Risk and Global Change: Developing scientific methods for advocacy and awareness raising

Peduzzi, Pascal

UNIL | Université de Lausanne

FACULTE DES GEOSCIENCES ET DE L'ENVIRONNEMENT
INSTITUT DE GEOMATIQUE ET D'ANALYSE DU RISQUE (IGAR)

Risk and Global Change:

Developing scientific methods for advocacy and awareness raising

THÈSE DE DOCTORAT

présentée à la

Faculté des Géosciences et de l'Environnement
de l'Université de Lausanne

pour l'obtention du grade de

Docteur en géosciences et environnement
par

Pascal PEDUZZI
Master of Science (remote sensing)
James Cook University of North Queensland
(Australie)

Directeur de thèse
Professeur Michel JABOYEDOFF

Jury
Professeur Torsten VENNEMANN, Président
Professeur Stuart LANE, expert interne
Docteur Ashbindu SINGH, expert externe
Docteur Hy DAO, expert externe

LAUSANNE
2012

UNIL | Université de Lausanne
Faculté des géosciences et de l'environnement
bâtiment Amphipôle
CH-1015 Lausanne

IMPRIMATUR

Vu le rapport présenté par le jury d'examen, composé de

Président de la séance publique :	M. le Professeur Torsten Vennemann
Président du colloque :	M. le Professeur Torsten Vennemann
Directeur de thèse :	M. le Professeur Michel Jaboyedoff
Expert interne :	M. le Professeur Stuart Lane
Expert externe :	M. le Docteur Ashbindu Singh
Expert externe :	M. le Docteur Hy Dao

Le Doyen de la Faculté des géosciences et de l'environnement autorise l'impression de la thèse de

Monsieur Pascal PEDUZZI

Licence en géographie, Université de Genève

Master en Sciences (Remote Sensing for Environmental Studies), James Cook University of North Queensland, Australie

intitulée

RISK AND GLOBAL CHANGE : DEVELOPING SCIENTIFIC METHODS FOR ADVOCACY AND AWARENESS RAISING

Lausanne, le 13 janvier 2012

Pour le Doyen de la Faculté des géosciences et de l'environnement

Professeur Torsten Vennemann, Vice-Doyen

à Corinne,
Antoine et Gaétan,
mes amis et ma famille,
aux générations futures.

Table of Content

List of acronyms

ANN	Artificial Neuronal Network
ATSR	Along-Track Scanning Radiometer
BCPR	Bureau of Crisis Prevention and Recovery
CFC	Chlorofluorocarbons
COP	Conference of the Parties
COPASA	Cooperación Peruana Alemana de Seguridad Alimentaria
CRED	Centre of Research for the Epidemiology of Disasters
DDI	Disaster Deficit Index
DFO	Dartmouth Flood Observatory
DRI	Disaster Risk Index
DRR	Disaster Risk Reduction
EMDAT	Emergency Database
ERD	Emergency Response Division
GAR	Global Assessment Report on Disaster Risk Reduction
GDP	Gross Domestic Product
GHG	Green House Gazes
GIS	Geographical Information System
GLOF	Glacial Lake Outburst Flood
GRID-Geneva	Global Resource Information Database, Geneva
GTZ	Deutsche Gesellschaft f¨ur Technische Zusammenarbeit
HDC	High Developed Countries
HDI	Human Development Index
HFA	Hyogo Framework for Action
IDNDR	International Decades for Disaster Reduction
IGAR	Intstitut de Géomatique et d'Analyse du Risque
IPCC	Intergovernmental Panel for Climate Change
IUCN	International Union for Conservation of Nature
LDC	Least Developed Countries
MRI	Mortality Risk Index
NDVI	Normalized Difference Vegetation Index
NOAA	National Oceanic and Atmospheric Administration
OCHA	Office of Coordination for Humanitarian Action
PEDRR	Partnership for Environment and Disaster Risk Reduction
PPP	Purchasing Power Parity
PREVIEW	Project for Risk Evaluation, Vulnerability Information and Early Warning
UNDP	United Nations Development Programme
UNDRO	United Nations Disasters Relief Organization
UNEP	United Nations Environment Programme
UNESCO	United Nations Educational, Scientific and Cultural Organization
UNISDR	United Nations International Strategy for Disaster Reduction
UNPD	United Nations Population Division
USGS	United States Geological Survey
WMO	World Meteorological Organization
WWF	World Wildlife Fund

Résumé

Les catastrophes sont souvent perçues comme des événements rapides et aléatoires. Si les déclencheurs peuvent être soudains, les catastrophes, elles, sont le résultat d'une accumulation des conséquences d'actions et de décisions inappropriées ainsi que du changement global. Pour modifier cette perception du risque, des outils de sensibilisation sont nécessaires. Des méthodes quantitatives ont été développées et ont permis d'identifier la distribution et les facteurs sous-jacents du risque.

Le risque de catastrophes résulte de l'intersection entre aléas, exposition et vulnérabilité. La fréquence et l'intensité des aléas peuvent être influencées par le changement climatique ou le déclin des écosystèmes, la croissance démographique augmente l'exposition, alors que l'évolution du niveau de développement affecte la vulnérabilité. Chacune de ses composantes pouvant changer, le risque est dynamique et doit être réévalué périodiquement par les gouvernements, les assurances ou les agences de développement. Au niveau global, ces analyses sont souvent effectuées à l'aide de base de données sur les pertes enregistrées. Nos résultats montrent que celles-ci sont susceptibles d'être biaisées notamment par l'amélioration de l'accès à l'information. Elles ne sont pas exhaustives et ne donnent pas d'information sur l'exposition, l'intensité ou la vulnérabilité. Une nouvelle approche, indépendante des pertes reportées, est donc nécessaire.

Les recherches présentées ici ont été mandatées par les Nations Unies et par des agences œuvrant dans le développement et l'environnement (PNUD, l'UNISDR, la GTZ, le PNUE ou l'UICN). Ces organismes avaient besoin d'une évaluation quantitative sur les facteurs sous-jacents du risque, afin de sensibiliser les décideurs et pour la priorisation des projets de réduction des risques de désastres.

La méthode est basée sur les systèmes d'information géographique, la télédétection, les bases de données et l'analyse statistique. Une importante quantité de données (1,7 Tb) et plusieurs milliers d'heures de calculs ont été nécessaires. Un modèle de risque global a été élaboré pour révéler la distribution des aléas, de l'exposition et des risques, ainsi que pour l'identification des facteurs de risque sous-jacent de plusieurs aléas (inondations, cyclones tropicaux, séismes et glissements de terrain). Deux indexes de risque multiples ont été générés pour comparer les pays. Les résultats incluent une évaluation du rôle de l'intensité de l'aléa, de l'exposition, de la pauvreté, de la gouvernance dans la configuration et les tendances du risque. Il apparaît que les facteurs de vulnérabilité changent en fonction du type d'aléa, et contrairement à l'exposition, leur poids décroît quand l'intensité augmente.

Au niveau local, la méthode a été testée pour mettre en évidence l'influence du changement climatique et du déclin des écosystèmes sur l'aléa. Dans le nord du Pakistan, la déforestation induit une augmentation de la susceptibilité des glissements de terrain. Les recherches menées au Pérou (à base d'imagerie satellitaire et de collecte de données au sol) révèlent un retrait glaciaire rapide et donnent une évaluation du volume de glace restante ainsi que des scénarios sur l'évolution possible.

Ces résultats ont été présentés à des publics différents, notamment en face de 160 gouvernements. Les résultats et les données générées sont accessibles en ligne (http://preview.grid.unep.ch). La méthode est flexible et facilement transposable à des échelles et problématiques différentes, offrant de bonnes perspectives pour l'adaptation à d'autres domaines de recherche.

La caractérisation du risque au niveau global et l'identification du rôle des écosystèmes dans le risque de catastrophe est en plein développement. Ces recherches ont révélés de nombreux défis, certains ont été résolus, d'autres sont restés des limitations. Cependant, il apparaît clairement que le niveau de développement configure une grande partie des risques de catastrophes. La dynamique du risque est gouvernée principalement par le changement global.

Abstract

Disasters are often perceived as fast and random events. If the triggers may be sudden, disasters are the result of an accumulation of actions, consequences from inappropriate decisions and from global change. To modify this perception of risk, advocacy tools are needed. Quantitative methods have been developed to identify the distribution and the underlying factors of risk.

Disaster risk is resulting from the intersection of hazards, exposure and vulnerability. The frequency and intensity of hazards can be influenced by climate change or by the decline of ecosystems. Population growth increases the exposure, while changes in the level of development affect the vulnerability. Given that each of its components may change, the risk is dynamic and should be reviewed periodically by governments, insurance companies or development agencies. At the global level, these analyses are often performed using databases on reported losses. Our results show that these are likely to be biased in particular by improvements in access to information. International losses databases are not exhaustive and do not give information on exposure, the intensity or vulnerability. A new approach, independent of reported losses, is necessary.

The researches presented here have been mandated by the United Nations and agencies working in the development and the environment (UNDP, UNISDR, GTZ, UNEP and IUCN). These organizations needed a quantitative assessment of the underlying factors of risk, to raise awareness amongst policymakers and to prioritize disaster risk reduction projects.

The method is based on geographic information systems, remote sensing, databases and statistical analysis. It required a large amount of data (1.7 Tb of data on both the physical environment and socio-economic parameters) and several thousand hours of processing were necessary. A comprehensive risk model was developed to reveal the distribution of hazards, exposure and risk, and to identify underlying risk factors. These were performed for several hazards (e.g. floods, tropical cyclones, earthquakes and landslides). Two different multiple risk indexes were generated to compare countries. The results include an evaluation of the role of the intensity of the hazard, exposure, poverty, governance in the pattern and trends of risk. It appears that the vulnerability factors change depending on the type of hazard, and contrary to the exposure, their weight decreases as the intensity increases.

Locally, the method was tested to highlight the influence of climate change and the ecosystems decline on the hazard. In northern Pakistan, deforestation exacerbates the susceptibility of landslides. Researches in Peru (based on satellite imagery and ground data collection) revealed a rapid glacier retreat and give an assessment of the remaining ice volume as well as scenarios of possible evolution.

These results were presented to different audiences, including in front of 160 governments. The results and data generated are made available online through an open source SDI (http://preview.grid.unep.ch). The method is flexible and easily transferable to different scales and issues, with good prospects for adaptation to other research areas.

The risk characterization at a global level and identifying the role of ecosystems in disaster risk is booming. These researches have revealed many challenges, some were resolved, while others remained limitations. However, it is clear that the level of development, and more over, unsustainable development, configures a large part of disaster risk and that the dynamics of risk is primarily governed by global change.

Chapter 1 Introduction

1.1. The evolution of disaster risk science: from hazard to global change

The perception of disaster risk as a dynamic process interlinked with global change is a fairly recent concept. It gradually emerged as an evolution from new scientific theories, currents of thinking and lessons learned from large disasters since the 1970s.

Until the late 1970s, researches conducted on risk were predominantly hazard-orientated (Maskrey 1993; Burton, 2005). The choice of the terminology "*natural disasters*", for referring to large human and/or economic losses from natural hazards, reflects the historical idea that these exceptional events were thought to be random events, acts of nature (Burton, 2005).

Pioneering work from Gilbert White (White, 1974) introduced the social dimension of disasters as a research field (Maskrey, 1993; Turner, 2003). By the end of the 1970s, this change of perspective had translated into the - now prevailing - definition of risk which emerged from the United Nations Disaster Relief Organization (UNDRO) group experts meeting (UNDRO, 1979). This definition is commonly used either in its original forms or as a basis for the multiple derivatives that followed. The UNDRO (1979) defines risk by three components: hazard, element at risk and vulnerability (Burton *et al.*, 1993; Blaikie, 1996). The recognition of human vulnerability was a revolutionary change in risk perception, as disasters were no longer seen as purely natural random phenomena (not mentioning acts of God). Publications such as Hewitt *et al.* (1983) participated in a globalized social theory of natural disasters (Maskrey, 1993). During the 1980s, the concept of vulnerability gained in importance, supported by the community of social-scientists (Schneiderbauer and Erlich, 2004).

Engineers, social scientists and insurances were mostly concentrating on a local to national scale. The impetus for a global perspective in risk analysis emerged in the mid-1980s. The Chernobyl accident (1986) and the ozone hole (Montreal Protocol was signed in 1987) contributed to the awareness that environmental impacts do not stop at the borders of countries and that a more global approach was needed.

It is also at this time that a group of scientists took up the challenge posed by Dr Frank Press (president of the American National Academy of Science) to use scientific development in order to reduce the loss of lives from natural hazards (Jeggle, 2005). Under the influence of the technical and scientific communities, a proposal for an international initiative led to the adoption by the United Nations General Assembly to proclaim 1990-99, the International Decade for Natural Disaster Reduction (IDNDR) (Jeggle, 2005).

Several global datasets on natural hazards were produced or initiated during this decade; for example, the Global Seismic Hazard Assessment Program (GSHAP) 1992 – 1998 (Giardini *et al.*, 1999). This dataset is a global compilation of earthquakes' peak ground accelerations (PGA) for a specific probability (50 years 10% excess) over a certain recurrent period (475 years). The ATSR World Fires Atlas (Arino *et al.*, 2005) was the start of the daily monitoring of high temperature events (i.e. biomass fires) over the planet. The Global Burnt Area 2000 was the first global inventory of fire scars (Tansey *et al.*, 2004a, 2004b). In 1999, UNEP launched the Project for Risk Evaluation, Vulnerability Information and Early Warning (PREVIEW). This is the centralisation, visualisation and dissemination of global hazard datasets in one interactive mapping web application (Peduzzi, 1999; Peduzzi, 2000). This project generated the first global tropical cyclones dataset with asymmetric windfield profiles (Herold *et al.*, 2002; Mouton *et al.*, 2005).

An alternative entry to this field of research followed the emergence of the scientific field of global environmental change, which emerged in the late 1980s and developed through the 1990s (Burton, 2005). Turner identified two types of global environmental change: systemic and cumulative (Turner *et al.*, 1990). Global systemic changes, includes localised sources of changes leading to global effect. The emissions of Green House Gases (GHG) fall in this category: the sources of these emissions are highly concentrated (40% are produced by two countries, namely USA and China), but their impacts affect the entire planet. The second type is the global cumulative changes, which include multiple transformations having local impacts, but which are nevertheless global because they are occurring on a worldwide scale. Loss of biodiversity and soil erosion fall in this category. Biomass burning is a global change which has both systemic and cumulative effects. Fires are emitting GHG which have a systemic impact, while they cause deforestation producing cumulative impacts, e.g. on biodiversity and soils (Turner et al, 1990). The term "change" was deliberately chosen for its neutral meaning (a change can be either good or bad), but what is usually meant is global environmental degradation (Burton, 2005).

The development of global environmental change research is a by-product of the studies conducted on the ozone hole and climate change. These researches revealed that there was also a cluster of other global concerns (deforestation, pollution, decline of natural resources,…), which were threatening the ecosystems which sustained human well-being (Turner, 1990). The Rio 1992 conference contributed in raising awareness of these environmental issues at both governmental and public levels.

As a result of these developments, progressively, the idea that natural disasters are a construction resulting from human behaviours was getting a firmer grip. The un-natural status of natural disasters was unveiled (Maskrey, 1993). Far from being sudden, disasters are the results of cumulative consequences of incremental changes from every day actions and inappropriate decisions (Hewitt, 1997). The conclusion from the US Natural Hazard Assessment "disasters are designed" could no longer be denied (Miletti, 1999).

Gradually through the 1990s, a change in perspective occurred. Disasters are not random events without underlying causes, but result from inappropriate choices (or lack of choices) in organising human settlements and infrastructures (including agricultural areas).

Climate change and ecosystem decline started to be considered as part of the issue of risk. In this framework, disasters can no longer be considered as being natural, a fatality, but as consequences of poorly thought through human activities (Burton, 2005) and also as part of a much broader process of global environmental change (Burton, 2005).

The 1990s were coming to an end and the decade, which aimed at reducing the losses from natural disasters, ended with several mega-disasters affecting large areas. In 1998, a hurricane called Mitch devastated Central American countries killing 18,820 people (EMDAT, 2011) mostly in Honduras (14,600) and Nicaragua (3,332). While Mitch was an extreme hurricane, it set off multiple collateral disasters triggered by flash floods and landslides, resulting from decades of unsustainable patterns of land use, territorial occupation and natural resource mismanagement (Maskrey, 1999).

The El Niño 1997/1998 was one of the strongest of the 20th century (Glantz, 2005). It disrupted regional climate, triggering droughts in Indonesia, Philippines, Bolivia, Southern Africa, Northeast Brazil and Central America and heavy rains in parts of Kenya, Peru and Southern Brazil. It led to losses of tens of billions of dollars (Glantz, 2005). Drought set the conditions for large wildfires which hit Indonesia, far-east Russia, Central America, Canada and Brazil (Levine *et al.*, 1999).

More localised disasters occurred such as the earthquake Izmit (1999) which struck Turkey. Venezuela was hit by severe rainfall triggering a large landslide (1999). It was obvious that the work could not stop with the IDNDR. Hence, in 2000, the UN General Assembly decided to create the United Nations International Strategy for Disaster Reduction (UNISDR), as a follow up of IDNDR (UNISDR, 2005).

If the concept that disasters are the result of incremental actions, which lead to risk accumulation (Hewitt, 1997) was spreading within the disaster risk community, this was not necessarily the prevailing understanding in governments, not to mention the general public. Except for drought, the public (and governments) perceived disasters predominantly as sudden events that struck societies, people and their welfare. The main perception was (and this belief still persists in many places) that disasters are random natural phenomenon (Burton, 2005). This means that most actions, from governments and specialised agencies, were (and in many cases, still are) focussed on how best to coordinate relief support after such events, rather than rethinking ways of development and land planning (Hamilton, 2005).

In order to mainstream the idea that disaster risk is an unresolved issue of development, the UNDP/ERD (future UNDP/BCPR) decided to develop an index for comparing countries and to identify the underlying factors of risk in a quantitative way.

After four years of research and development the Disaster Risk Index (DRI) was published as an on-going research in the UNDP report Reducing Disaster Risk a challenge for development (UNDP, 2004). The DRI was the first global attempt to produce a global quantitative approach to risk due to multiple hazards. It identified the role of vulnerability parameters such as poverty, underdevelopment, urban growth, or deforestation. However, at the time of these publications, there were still several gaps and issues. The methodology and the final version of the DRI was only published in 2009 (Peduzzi et al, 2009) and is one of the core publications in this thesis (see part 3.2).

The UNDP 2004 report was the first analysis to include exposure to natural hazards with a global focus. It was computed using population distribution models at a 5x5 km resolution and placed emphasis on the identification of vulnerability parameters. The risk was calibrated on past losses but then modelled using multiple regression analysis. It also provided a vulnerability proxy in the form of a ratio observed killed / average exposed per year (UNDP, 2004; Peduzzi, 2006). The risk was provided at national level. The DRI includes four hazards (tropical cyclones, drought, earthquakes and floods) although the data on drought was initially published as an on-going research.

In 2005, the World Bank launched the report "Natural Disaster Hotspots: a global risk analysis" (Dilley *et al.*, 2005) with the first global estimation of economic risk and human loss at subnational, albeit coarse resolution (between 0.5 x 0.5 degree to 2.5 x 2.5 degree depending on hazard). It included an assessment for six hazards (tropical cyclones, drought, floods, earthquakes, landslides and volcanoes). Its primary focus was to identify areas/regions which were affected by multiple hazards.

The DRI and the Natural Disaster Hotspots collaborated, the former providing the PREVIEW global dataset on tropical cyclones and PREVIEW volcanic eruption dataset, the second providing the drought dataset. Both these studies included multiple hazards and had a global coverage. They were pioneers in modelling exposure to hazard at a global level. As in any pioneering work, not all issues could be covered and several gaps were still to be addressed. The main problem was the use of average exposure over a 21 year period. This precluded taking the intensity of event into consideration for risk models. Flood models were also inappropriate as both studies used population at the watershed levels thus largely overestimating exposure.

2005 was also the year a very interesting report was published which introduced new methodologies developed in South American countries. However, the project was largely conceptual, requiring data that were not yet readily available (Cardona, 2005).

If these three reports (UNDP, 2004; Dilley *et al.*, 2005, Cardona, 2005) contributed to a better understanding of risk, risk trend and their distribution at the global level, none of them took climate change into consideration for estimating risk.

The last decade (2000s) saw some additional changes in risk perception. The 2003 heatwave took European countries by surprise, killing more than 84,000 people (EMDAT, 2011) and generating high economic losses (De Bono *et al.*, 2003). It came as a reminder that developed countries were not immune from large disasters triggered by natural hazards. This was further demonstrated when the Hurricane Katrina (2005) led to a major disaster in southern USA, killing more than 1,800 and generating US$ 125 billion damages (EMDAT, 2011).

At the end of 2004, the Indian Ocean tsunami devastated thousands of kilometres of coast mostly in Indonesia, Thailand, India, Sri Lanka, Maldives, but also as far away as Kenya and

Seychelles. It killed more than 226,000 people (EMDAT, 2011).

By a coincidence of calendar, the Kobe conference was held a mere three weeks after this disaster. It galvanised the willingness of the international community and 160 countries ratified the Hyogo Framework for Actions (HFA). This text set the roadmap for safer societies. It includes five priority actions (see box 1).

The 2004 Indian Ocean Tsunami also heightened the interest for ecosystems services in reducing disaster risk. This was mostly triggered by Friend of the Earth International (Friend of the Earth International, 2005, Khor, 2005). A tense scientific debate followed, led by Kthiresan and Rajendran, (2005), who stated that mangroves could mitigate tsunami. This position was opposed by other scientists (Kerr *et al.*, 2005). Some other scientists tried to support Kthireesan and Rajendran (Vermaat and Thampanya, 2006), but Vermaat and Thampanya finally admitted a mistake in their analysis and issued an erratum (Vermaat and Thampanya, 2007) stating "*We used a zero intercept in our statistical analysis where this should not have been the case…*".

The claim that mangroves and coral may help to reduce tsunami rapidly appeared to lack scientific basis whether based on research from the field (Kerr *et al.*, 2006; Baird and Kerr, 2008) by GIS modelling (Chatenoux and Peduzzi, 2007) or even after a thorough literature review (Cochard *et al.*, 2008). Nevertheless, this rebuttal did not necessarily mean that ecosystems could not provide such protection for other types of hazards (Chatenoux and Peduzzi, 2007; Peduzzi, 2009; UNEP, 2010). For example, mangroves can be very useful for protecting from impacts of hydro-meteorological hazards and for reducing the costs of dike maintenance in Vietnam (IFRC, 2002). The theory had however already been adopted by the media, UN agencies and NGOs and the debate escaped from the scientific arena.

The public at large and development agencies did not follow the scientific debate and the belief among the public, that mangroves can protect from tsunami is still well anchored. This led to vast plantations of mangroves in non-suitable areas, which quickly perished (see Figure 1).

Figure 1 Photo in Bandah Aceh, showing 98% and 100% of dead mangroves, 1 year after plantation. Photo. B. McAdoo, January 2006

The year 2005 broke previous temperatures records in the northern hemisphere and tropical cyclones reached unprecedent level of activities. With 28 storms over the north Atlantic, this year largely exceeded the previous record (21) in 1933. 15 became tropical cyclones and 7 supercyclones (Beven *et al.*, 2008).

2005 had the highest economic losses from climatic events: US$ 200 billion losses. (Katrina alone: US$125 billions) it had the strongest winds and the lowest central pressure ever recorded (Wilma gusts of winds reaching 330 km/h and lowest central pressure at 882 hPa) (Beven *et al.*, 2008).

With the all time record of tropical cyclones in 2005 and the 2003 heatwave, the idea that climate change may influence hazard frequency and severity was gaining support among the public. Scientific research also showed that severe heatwaves, such as the 2003 European one, had twice the probability of occurring due to anthropogenic impacts on climate (Stott and Allen, 2004).

The years 2006-2007 spurred the highest momentum of concern about climate change in the general public and governments. Three different milestones represented the most important efforts made for the generalisation of concerns regarding the impacts of climate change. The Stern Review Report: the economics of climate change (Stern *et al.*, 2006) captured the attention of the economic community, the Intergovernmental Panel on Climate Change (IPCC) fourth assessment report (Solomon *et al.*, 2007; Parry *et al.*, 2007; Metz *et al.*, 2007) had preponderant influence on the policy makers, governments and the scientifics community, while the movie "*An Inconvenient Truth*" featuring Al Gore (Guggenheim, 2006) participated in a large diffusion of the message to the general public. The IPCCs and Al Gore’s work on building up and disseminating knowledge about man-made climate change and measures needed to counteract such change, received recognition with the joint attribution of the Nobel Peace Prize in 2007.

Using the momentum generated by the 2004 Indian Ocean tsunami, environmental agencies, e.g. United Nations Environment Programme (UNEP), International Union for Conservation of Nature (IUCN), World Wildlife Fund (WWF) were all eager to demonstrate the role of ecosystems for disaster risk reduction.

Quantitative approaches and scientific replicable methodologies, can offer useful tools to help in the decision making process. It may help in better understanding on the interaction between human activities and impacts from ecosystem decline or climate change.

1.2. A closer look at risk

Risk is an evaluation of potential future losses for a specific hazard, location and time period (Tobin and Montz, 1997). It results from the combination of three components: the hazard occurrence probability, the element at risk (population, assets, ecosystems,..., located in hazard-prone areas) and the vulnerability of these elements (Burton *et al.*, 1993; Blaikie, 1996). Vulnerability being "the degree of loss to each element should a hazard of a given severity occur." (Coburn *et al.* 1991). Vulnerability is the most difficult concept, one cannot measure vulnerability directly. Cardona (2003) describe vulnerability as "the degree of loss to a given element at ris or set of such elements resulting from the occurrence of a natural phenomenaon of a given magnitude and epxressed on a scale from 0 (no damage) to 1 (total loss)". However, what is responsible for this variability in percentage of losses? This is most probably not one single factor, but arrises through a wide array of parameters: "physical, social, economic, and environmental factors". (UNISDR, 2011). Approaching vulnerability, would request to compile information on various contextual parameters, on economic, demographic, environmental, level of development, early warning capabilities, level of governance, health, eduction, as well as physical vulnerabiltiy (e.g. building and infrastructures quality). The ratio of losses is also depending on coping capacity: early warning, evacuation plan, transport (for evacuation), number of hospitals, civil servants, physicians, nurse, emergency relief, in prorata of the population exposed. Vulnerability in this study, will following Cardona's definition (i.e a ratio of losses), hence includes coping capacity. The definitions are further explained in point 2.2.4.

Hazards, elements at risk and their related vulnerability are subject to change, hence risk is not static. Population density is increasing (UN population, 2010) and new infrastructures are being built, thus increasing the number of assets. The organisation of our societies is evolving, with improved technologies, which may decrease our vulnerability, but may also expose potentially dangerous infrastructures leading to secondary hazards (e.g. the Fukushima nuclear accident following the earthquake and tsunami in March 2011). While progress is being made and more understanding on risk processes gained (UNISDR, 2011), large parts of humanity living under poor conditions are suffering disproportionate mortality from natural hazards as compared with more developed societies (UNDP, 2004). The succession of disasters may have a negative effect on their development (UNDP, 2004).

Because of its dynamic nature, risk needs to be re-evaluated periodically. Studying risk requires the understanding of all its components: the distribution, frequency and intensity of natural hazards; the potential influence of climate change on hazard; the change in population and assets density, the evolution of socio-economic contextual parameters associated with human vulnerability and the understanding of potential impacts of the decline of ecosystems and natural resources on disaster risk.

Except for drought, we tend to see disasters as sudden. Far from being sudden, the risk accumulation is slow and continuous (Hewitt, 1997). As an analogy, the creation of a risk bubble can be compared with playing with a house of cards, stacking playing cards one on top of each other and raising as many floors as possible. It will collapse if you place it on shaky foundations, or expose it to wind. It will also collapse if any of the necessary supporting elements is removed. In fact, it will always collapse!

The process of risk threatening our societies, like a house of cards, is slowly built by inappropriate decisions (e.g. from land planners and governments) or lack of choice (e.g. from poor population), and can be suddenly released by the shock of a hazardous event.

Figure 2 House of cards (photo credit: anonymous)1

The outcome of the risk will depend on whether hazard and population's vulnerability were taken into account when developing the area. This is why in this research (except in quotes) the expression "*Natural Disasters*" is not used, but replaced by expressions such as "*Disasters triggered by natural hazards*".

The question why are people living in hazard prone areas differ from social groups. Wealthy population may live close to flood prone areas for the aesthetical view on the river, while poor communities, may live close to a river due to lack of any other affordable/available alternative (Collins, 2008). They may even been force to live there by local elite, due to concentration of power and wealth in few hands (Mustafa, 1998).

Wealthy population are usually more influent, their assets also provide quicker return on hazard reduction measures against disaster losses savings, hence such reasoning may lead authorities to production of unequal risk, i.e. to spend large investements in areas where least vulnerable people are living, while poor population may be just relocated (Collins, 2008).

Also, people are balancing risk from natural hazards with other risk, such as risk of not being located close enough to employement capabilities, such as poor peasants turning to a new for of livelihood next to cities and occupying hazard prone areas in informal setllements next to cities (Collins, 2010) or simply because the location offers other rewards (Collins, 2008).

As seen previously, even the concept of "*natural hazard*" raises questions (Maskrey, 1993). Aside from tectonic hazards (e.g. earthquakes, tsunamis and volcanic eruptions), human activities can exacerbate a natural hazard. By emitting Green House Gases (GHG) human activities are changing the climate (IPCC, 2007). This is likely to affect hydro-meteorological hazard patterns, changing their frequency, intensity or even their spatial

[1] Anonymous, House of cards, photo. http://s666.photobucket.com/albums/vv25/seraiwallpapers2/HH/?action=view&current=Houseofcards.jpg&mediafilter=images, last checked: 26 April 2011.

distribution and extent (Solomon *et al.*, 2007). Developing tools and methodologies for highlighting the consequences of climate change on disaster risk is important as a contribution to the discussion on GHG mitigation, but also to flag areas where climate adaptation is needed.

Aside from climate change, transformation of the natural environment impacts natural hazards. By deforesting slopes and building roads, humans are increasing susceptibility to landslides (Niederer and Schaffner, 1989). Paving road and urban expansion is waterproofing soils, thus reducing water infiltration. Inadequate drainage to cope with this, is increasing the occurrence of urban floods (De la Fuente *et al.*, 2009, p.72-73). Fires are used for slash and burn practices and converting forest to cropland; these practices are responsible for the majority of biomass fires (Levine *et al.*, 1999; Peduzzi *et al.*, 2004).

Due to both climate and land cover changes, some natural hazards are becoming less natural and the causes now include a larger proportion related to human activities.

1.3. The mandates

As a follow up to the work conducted for UNDP/BCPR in developing the DRI, the UNISDR in 2007 wanted to design a new methodology addressing the gaps of both the DRI and Hotspots studies. This required the building of a team of partners and collaborators, the design of new datasets for floods and droughts, the improvement of datasets of other hazards, the development of a new methodology for identifying the underlying risk factors and a better characterisation of the spatial risk distribution.

In parallel, UNEP and other environmental agencies (e.g. IUCN, WWF,…) were interested in developing more research for quantifying the role of ecosystems in Disaster Risk Reduction (DRR). The methodology designed for the evaluation of the potential role of environmental factors in Tsunami disaster risk reduction (Chatenoux and Peduzzi, 2007) was well suited for its transposition to other hazards and ecosystems.

Finally, the *Deutsche Gesellschaft für Technische Zusammenarbeit* (GTZ) set out to quantify glacier retreat and remaining ice volume on the Coropuna glacier (Peru). Glacier retreat is threatening the water supply in this region.

These three mandates were different in nature and scale, but all addressed the same issue: a broader understanding of risk, integrating social vulnerability, development, decline of ecosystems or climate change. Furthermore a similar process for the quantitative analysis could be framed.

The results of these researches were mostly to be published in United Nations reports. Because of their targeted audience, these reports do not include the methodology to explain how the results or advocacy tools were generated. Also, in the process of developing these researches, some gaps and potential improvements were identified, which due to time and resource constraints, could not be addressed at that time. This thesis includes scientific publications which explain how results and tools were generated. When possible, improvements were made to fill the identified gaps. For example the Disaster Risk Index (DRI) published as an on-going effort (UNDP, 2004), has now been finalised (Peduzzi *et al.*, 2009b). The Global Risk Analysis (Peduzzi *et al.*, 2009a) was a major effort between 2007 and 2009 to bring risk data to a new level of complexity and higher definition, with broader and more complete data collection across more natural hazards. The most complex research and added value, is the one made on tropical cyclones, for which a detailed account of the methodologies used is provided here (Peduzzi *et al.*, submitted).

For understanding the consequences of harm to ecosystem and climate change impacts on risk, higher data resolution is needed (Nadim *et al.*, 2006). Global datasets are too coarse. So these studies were based on small study areas using higher resolution data. The links between deforestation and landslides in north Pakistan was part of a project carried out in collaboration with the IUCN (Peduzzi, 2010). This study focussed on a small study area of 3600 Km^2; while the research on impacts of climate change on glacier retreat focussed (Peduzzi et al, 2010) on an area of 700 Km^2. This allowed the use of high resolution datasets.

1.3.1. Specific questions

Least developed countries represent 11% of the population exposed to hazards but account for 53% of casualties (Dao and Peduzzi, 2004). On the other hand, the most developed countries represent 15% of human exposure to hazards, but account for only 1.8% of all victims. For the same scale of event, a significant discrepancy in the number of victims can be observed, depending on whether the disaster is located in a developed or less developed country (Dao and Peduzzi, 2004; Peduzzi, 2006). This observation leads to numerous questions.

Why such large differences? Are they due to levels of development or differences in exposure to hazard types, frequencies and intensities? Which hazards are more dangerous and where are these hazards distributed? Which specific socio-economic parameters of development are mainly responsible: poverty, education, health and sanitation, corruption, governance, building quality, rapidity of population growth, lack of early warning? There is no shortage of hypotheses, but can the main underlying factors be identified? Can the relative role of exposure, intensity and socio-economic parameters be quantified? Does the relative weight of each variable change depending on hazard types and/or intensities? Can the risk faced by each country, taking into account all (or at least most of) the natural hazards that this country is facing, be measured? If yes, is it possible to rank countries according to their risk level? And in this case, how can large and small countries be compared? How can countries affected by drought be compared with those affected by earthquakes? Can trends in disaster risk be observed? For example is the risk increasing because of the higher number of people living on the planet? Can an increase in risk due to climate change or due to decline of ecosystems be observed? Can the role of ecosystems in reducing disaster risk be quantified?

These are all challenging questions which require extensive standardisation, methodology development and data processing.

This research "*Risk and Global Change: developing scientific methods for advocacy and awareness raising*" aims at addressing questions related to the underlying factors contributing to risk. Although global level analysis cannot be used for local land use planning, they have their own purpose. At the global scale, tools are needed for advocacy (convincing governments to take actions), United Nations (UN) and development agencies need to prioritise their actions to see which countries and regions require more attention (funds, projects for DRR).

It also provides methodologies for quantifying some specific impacts of climate change (in this case on glacier retreat) as well as quantifying the role of ecosystems in mitigating hazards (such as forests for reducing landslides).

1.3.2. The need for a comprehensive approach

Why study risk in the context of global change? Developing tools for understanding the impacts of global change on risk is necessary. Evaluating risk requires physical sciences for modelling the hazards and exposure, as well as social sciences for the estimation of the vulnerability and environmental/climate sciences to understand underlying factors. No proper estimation of risk can be achieved by looking only at the physical or social sciences. Moreover, risk is a dynamic issue. An increase in population changes the exposure, climate change and ecosystem decline may also induce changes in hazards susceptibility, coverage, frequency and severity. Governance, level of development, early warning capabilities, level of education and training,… all have an effect on vulnerability. So far most reports on risk are using past losses.

Reported mortality and economic losses are recorded by several international databases. Munich RE and Swiss RE are maintaining the NatCat and the Sigma databases respectively. However these databases are not accessible and only aggregated figures are made available. The Centre of Research in Epidemiology of Disasters (CRED) with its EMDAT database is the only centre which provides access to data on losses due to disasters with a global coverage.

When looking at the number of disasters reported through time (Figure 3, there is a marked increase. EMDAT defines a disaster accoring to the following criteria:

Ten or more people killed, 100 wounded, call for international assistance. During the 41 year-period (1970 - 2010), more than 50% of the reported disaster events (droughts, earthquakes, tropical cyclones and floods) occur in the last 12 years. Can we infer that the number of disasters has increased? Or is it the number of reported disasters which has increased due to improvement in access to information? If the former hypothesis is correct, is it due to the rise in population density which is increasing the exposure to hazard, an increase in vulnerability or due to change in hazard probability and/or intensity, e.g. due to climate change?

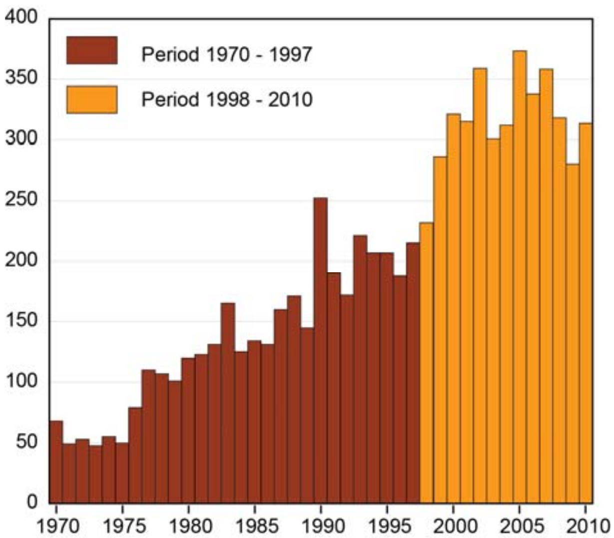


Figure 3 Number of reported disasters per year in EM-DAT. Droughts, earthquakes, tropical cyclones and floods. In brown 1970-1997, in orange 1998-2010.

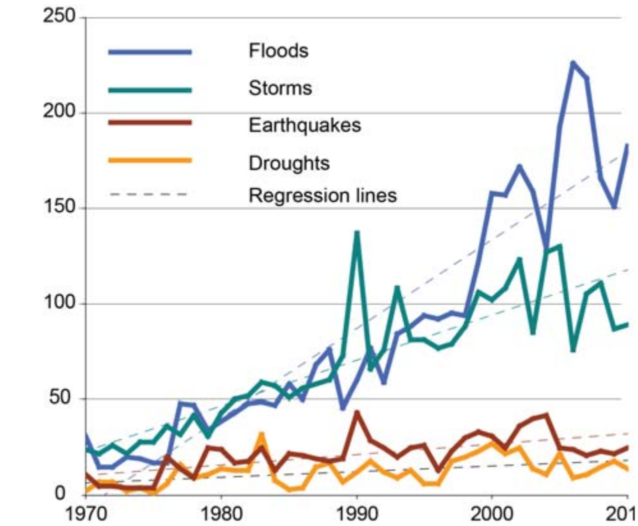


Figure 4 Trend of reported events by hazard type in EM-DAT (1970 - 2010)

The greater increase in the number of reported floods and tropical cyclones disasters as compared with the number of reported earthquakes disasters (Figure 4) is intriguing. Earthquakes are least susceptible to be influenced by climate change and can be used as a benchmark for access to information. The greater increase in hydro-meteorological reported disasters would tend to suggest that climate change has already a significant influence on the occurrence of these disasters.

However, it can also be due to the fact that the global monitoring of these hydro-meteorological disasters is improving significantly.

Without denying the potential impacts of climate change on hydro-meteorological hazards, our study revealed that there are stronger links with increase of population and increase in access to information (see points 3.2.3 and 3.7). This is probably due to improvement of information technologies (satellite, internet, media coverage). These improvements have introduced a bias in information access through time.

International databases on losses are not comprehensive; information quality and completeness vary by region and time period. These databases do not tell us whether high losses result from high exposure, high intensity or high vulnerability. Hence, they are not suited for risk trend analysis. Despite these significant limitations, most global reports (e.g. World Bank, 2007; ESCAP and UNISDR, 2010;, IFRC, 2010; ICHARM and UNESCO, 2009, DARA, 2010) are based on figures from international databases (mostly EMDAT). The same limitations apply to economic losses, but with even more problematic issues. EMDAT has a threshold of US$ 100,000 for including a disaster event into the database. However, US$ 100,000 does not have the same purchasing power value in Bangladesh and the USA and a dollar in 1970s does not have the same value as in 2000s. The value of real estate has increased sharply in the last decades. However, the losses included in EMDAT (and in Munich RE as well) do not adjust for inflation or for local purchasing power.

If the losses recorded in databases are not comprehensive and are influenced by access to information, how can we assess the risk level and trends independently from these databases? To overcome the limitations of the qualitative approach, a quantitative approach including hazard exposure and vulnerability might resolve these issues.

Quantifying the role of selected parameters, not only helps to convince, but also allows insight into the complexity of the process by assigning weights to each parameter. Stating that poverty or corruption kills is one thing, but being able to quantify these underlying triggers is much more powerful. It helps to convince decision makers to take action for disaster risk reduction.

In chapter 3, the research focuses on characterising risk at the global level, to map the distribution of hazards, exposure and risk as well as identify the underlying sources of vulnerability.

In chapter 4, the research shows that these tools of spatial and statistical analysis developed for risk from natural hazards are transversal. They can be applied to assess disaster risk, from rapid onset hazard. However such developments are also useful for assessing risk associated with creeping hazards. They can be applied to estimate the rate of ice volume reduction of a glacier, to help decisions in improving water supply under drier conditions. They can alert authorities to the need for protecting / restoring environmental features necessary to reducing the susceptibility of landslides or for mitigating beach erosion and its effects on related livelihoods (tourism).

The research presented here was mandated by United Nations agencies, development organizations or by governments. Although most of the results are too recent to evaluate their successful application, an evaluation of their potential impacts will be provided in the discussion.

Quantifying the components of risk is a needed advocacy tool to identify the responsibilities of the different risk components. It is hoped that quantitative analysis will convey a more factual message based on statistical evidence, thus reducing the subjectivity as compared with expert-based analysis.

Making the case for the existence of links between poverty, climate change, ecosystems degradation and disaster risk would be much more convincing if supported by quantitative analysis. This study shows how Geographical Information Systems (GIS), remote sensing and statistical analysis can be used for producing such advocacy tools. Mapping risk participates in making visible the invisible.

1.4. References

Arino, O., Plummer, S., Defrenne, D., Fires disturbance: the ten year time series of the ATSR World Fire Atlas, European Space Agency, 1-6, 2005. http://envisat.esa.int/workshops/meris_aatsr2005/participants/342/paper_Arino.pdf

Baird, A.H., Kerr, A.M., Landscape analysis and tsunami damage in Aceh: comment on Iverson and Prasad (2007), Landscape *Ecology*, **23** (1), 3-5, 2008.

Beven II, J.L., Avila, L.A., Blake, E.S., Brown, D.P., Franklin, J.L., Knabb, R.D., Pasch, R.J., Rhome, J.R., and Stewart, S.R., Atlantic Hurricane Season of 2005. *Mon. Wea. Rev.*, **136**, 1109–1173, 2008.

Blaikie, P. *et al.*, *At Risk: Natural Hazards, Peoples Vulnerability and Disasters* (Routledge), 284 p., 1996.

Burton, I., Kates, R.W. and White, G.F., *The Environment as Hazard*, 2nd Edition. New York/London: Guilford Press, 290 pp., 1993.

Burton, I., The social construction of natural disasters: an evolutionary perspective, *Know risk*, 35-36,United Nations International Strategy for Disaster Reduction, United Nations, Geneva, Switzerland, 2005.

Cardona, O.D., The notion of disater risk: conceptual framework for integrated risk management, IADB/IDEA Program on indicators for disaster risk management Universidad National de Colombia, Manizales, 2003.

Cardona, O.D., Hurtado, J.E., Chardon, A.C., Moreno, A.M., Prieto, S.D., Velásquez, L.S., Duque, G., Indicators of disaster risk and risk management. Program for Latin America and the Caribbean, summary report for the world conference on disaser reduction. IDB/IDEA program of indictors for disaster risk management, national university of Columbia, Interamerican Development Bank, 2005.

Chan, J.C.L., Comment on "Changes in Tropical Cyclone Number, Duration, and Intensity in a Warming Environment, *Science* **311**, 1713b (2006).

Chatenoux, B., Peduzzi, P., Impacts from the 2004 Indian Ocean Tsunami: analysing the potential protecting role of environmental features, *Natural Hazards*, **40** (2), 289-304, 2007.

Coburn, A.W., Spence R.J.S., Pomonis A., Vulnerability and risk assessment. *UNDP Disaster Management Training Program*, **57**, 1991, p.49.

Cochard, R., Ranamukhaarachchi, S.L., Shivakoti, G.P., Shipin, O.V., Edwards, P.J., Seeland, K.T., The 2004 tsunami in Aceh and Southern Thailand: A review on coastal ecosystems, wave hazards and vulnerability, *Perspectives in Plant Ecology, Evolution and Systematics*, **10** (1), 3-40, 2008.

Collins, T.W., The production of unequal risk in hazardscapes: An explanatory frame applied to disaster at the US-Mexico border. *Geoforum*, **40**, 589-601, 2009.

Collins, T.W., Marginalization, Facilitation, and the Production of Unequal Risk: The 2006 Paso del Norte Floods. *Antipode*, **42**, 258-88, 2010.

Dao, H., Peduzzi, P.: Global evaluation of human risk and vulnerability to natural hazards, *Enviroinfo 2004*, Sh@ring, Editions du Tricorne, Genève, **1** , 435-446, 2004.

DARA, *Climate vulnerability monitor 2010: the state of the climate crisis*, Development Assistance research Associates (DARA), 261 pp., 2010.

Darthmouth Flood Observatory, University of Colorado, Boulder, USA. http://floodobservatory.colorado.edu/, last accessed: 30 April 2011.

De Bono, A., Peduzzi, P., Kluser, S., Giuliani, G., Impacts of Summer 2003 heatwave in Europe, Environment Alert Bulletin, 2, 1-4, United Nations Environment Programme, 2004. http://www.grid.unep.ch/product/publication/download/ew_heat_wave.en.pdf, last accessed: August 2011.

De la Fuente, A. Revi, A., Lopez-Calva, L.F., Serje, J. Ramirez, F., Rosales, C. And Dercan, S., Deconstructing disaster: risk patterns and poeverty trends at the local level, Risk and poverty in a changing climate, 2009 Global Assessment Report on Disaster Risk Reduction, United Nations International Disaster Risk Reduction, chapter 3, Geneva, Swizerland, 59-113, 2009.

Dilley, M., Chen, R.S., Deichmann, U.Lerner-Lam, A.L., Arnold, M., Agwe, J., Buys, P., Kjekstad, O., Lyon, B., Yetman, G., *Natural disaster hotspots: a global risk analysis*, World Bank Publications, 2005.

EM-DAT: The OFDA/CRED International Disaster Database, Université Catholique de Louvain, Brussels (Belgium). http://www.emdat.be, last consulted December 2010.

ESCAP,UNISDR, *Protecting Development Gains, Reducing Disaster Vulnerability and Building resilience in Asia and the Pacific*, ESCAP, UNISDR, 129 pp., 2010.

Friends of the Earth International statement made by Chair Meena Raman in a January 2005 Reuters news agency report. Friend of the Earth, (2005), annual report 2004, p.16.

http://www.foei.org/en/resources/publications/annual-report/archive/ar2004.pdf/at_download/file

Giardini, D., Grünthal, G, Shedlock, K.M., Zhang, P., The GSHAP global seismic hazard map, *Annali di geofisica*, **42**(6), 1225-1230, 1999.

Glantz, M., El Niño, in *Natural Disaster Management*, 78-79, Cooper Trowbridge, Tudor Rose Holdings Limited, 1999.

Hamilton, R., Evolution in approaches to disaster reduction, *Know Risk*, p. 31-32 United Nations International Strategy for Disaster Reduction, United Nations, Geneva, Switzerland, 2005.

Hewitt, K., Regions of risk: a geographical introduction to disasters, Longman. Harlow, U.K., 389 pp., 1997.

Hewitt, K., The idea of calamity in a technocratic age, in Hewitt, K. (Ed.), *Interpretation of Calamities*, Allen & Unwin, Boston, MA, pp. 3-32.Hoyos, C.D., Agudelo, 1983.

P.A., Webster, P.J., Curry, J.A., Deconvolution of the Factors Contributing to the Increase in Global Hurricane Intensity, *Science* **312**, 94-97 (2006).

ICHARM, UNESCO, *Global trends in water-related disasters: an insight for policymakers*, ICHARM, UNESCO, 24 pp., 2009.

IFRC, Mangrove planting saves lives and money in Vietnam, World Disaster Report 2002, International Federation of Red Cross and Red Crescent Societies (IFRC), 2002.

IFRC, *World disasters report: focus on early warning, early action*, IFRC, 208 pp., 2009.

Jeggle, T., The goals and aims of the decade, in *Natural Disaster Management*, 24-27, Cooper Trowbridge, Tudor Rose Holdings Limited, 1999.

Kathiresan, K., Rajendran, N., Coastal mangrove forests mitigated tsunami, *Estuar. Coast. Shelf Sci.* **65**, 601-606, 2005.

Kerr, A.M., Baird, A.H., Campbell, S.J., Comments on "Coastal mangrove forests mitigated tsunami" by K. Kathiresan and N. Rajendran [Estuar. Coast. Shelf Sci. 65 (2005) 601-606]. *Estuarine, Coastal and Shelf Science*, **67** (3). pp. 539-541, 2006.

Kerr, A.M., Baird, A.H., Campbell, S.J., Comments on Coastal mangrove forests mitigated tsunami, *Estuar. Coast. Shelf Sci.* **67**, 539-541, 2005.

Khor M (2005), Save the Mangroves to fight tsunamis, Third World Network, http://www.twnside.org.sg/title2/gtrends39.htm

Levine, J.S., Bobbe, T., Ray, N., Witt, R.G., Singh, A., *Wildland fires and the environment: A global synthesis*, United Nations Environment Programme, 52 pp., 1999.

Maskrey, A., *Los Desastres No Son Naturales*, La Red de Estudios Sociales en Prevención de Desastres en América Latina, 137 pp., 1993.

Maskrey, A., Reducing global disasters, Natural disaster management, , pp. 84-85, Tudor Rose, ISDR, 320 pp. 1999.

Mileti, D. Disasters by design: a reassessment of natural hazard in the United States, Joseph Henry Press. Washington D.C. 351p., 1999.

Mustafa, D., Structural causes of vulnerability to flood hazard in Pakistan, *Economic Geography*, **74**(3), 289-305, 1998.

Nadim, F., Kjekstad, O., Peduzzi, P., Herold C., Jaedicke, C., Global landslide and avalanche hotspots, *Landslides*, **3**(2), 159-173, 2006

Niederer, S. and Schaffner, R.: Landslide problems and erosion control in Murree and Kahota tehsils of Rawalpindi Distt. Report of the fact finding mission, SDC, Ministry of Foreign Affairs, Govt. of Switzerland, CH-3003, Bern, 1989.

Parry ML, Canziani OF, Palutikof JP, van der Linden PJ, Hanson CE, eds., *Climate Change 2007: Impacts Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, UK: Cambridge Univ. Press, 2007.

Peduzzi, P., Chatenoux, B., Dao, H., De Bono, A., Herold, C., Kossin, J., Mouton, F., Nordbeck, O., Global Trends in Human Exposure, Vulnerability and Risk from Tropical Cyclones, submitted.

Peduzzi, P., Insight of Common/Key Indicators for Global Vulnerability Mapping, presentation for the Expert meeting on vulnerability and risk analysis and indexing, UNDP/DSSP, at the International House of Environment, Geneva, on 11-12 September 2000, UNEP/GRID-Geneva, 1-12, 2000.

Peduzzi, P., Is climate change increasing the frequency of hazardous events? *Environment & Poverty Times*, **3**, p.7, Special Edition for the World Conference on Disaster Reduction January 18-22, 2005, Kobe, Japan, 2005. http://www.grid.unep.ch/product/publication/download/article_climate_change_hazards.pdf, last checked: 27 April 2011.

Peduzzi, P., Kluser, S., Debono, A., Giuliani, G., Wildland Fires, a double impact on the planet, *Environment Alert Bulletin*, **2**, 1-4, United Nations Environment Programme, 2004.

Peduzzi, P., Project for Risk Evaluation, Vulnerability, Information and Early Warning (PREVIEW), http://www.grid.unep.ch/preview, 2000a.

Peduzzi, P., The Disaster Risk Index: Overview of a quantitative approach, *Measuring Vulnerability to Natural hazards*, 171-181, United Nations

University, United Nations University Press, Tokyo, New York, Paris, 524 pp., 2006.

Peduzzi, P., Dao, H., Herold, C., and Mouton, F.: Assessing global exposure and vulnerability towards natural hazards: the Disaster Risk Index, *Nat. Hazards Earth Syst. Sci*., **9**, 1149-1159, 2009.

Peduzzi, P., Herold, C., and Silverio, W.: Assessing high altitude glacier thickness, volume and area changes using field, GIS and remote sensing techniques: the case of Nevado Coropuna (Peru), *The Cryosphere*, **4**, 313-323, 2010.

Peduzzi, P.: Landslides and vegetation cover in the 2005 North Pakistan earthquake: a GIS and statistical quantitative approach, *Nat. Hazards Earth Syst. Sci*., **10**, 623-640, 2010.

Schneiderbauer, S. Ehrlich, D., Risk, Hazard and people's vulnerability to natural hazards: a review of definitions, concepts and data, brussels: european Commission - joint Research Centre (EC-JRC), 2004.

Solomon, S., Qin, Manning, D. M., Chen, Z., Marquis, M., Averyt, K.B., Tignor, M., and Miller, H.L. (eds.), *Climate Change 2007: The Physical Science Basis — Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge Univ. Press, Cambridge, UK, New York, USA, 2007.

Stern, N., The Stern Review Report: *the Economics of Climate Change*. London, HM Treasury, 603 p., 2006.

Stott, P.A., Allen, M.R., Human contribution to the European heatwave of 2003, *Nature*, **432**, 610-614, 2004.

Tansey K., J-M., Gregoire, Binaghi E., Boschetti L.,Brivio P., Ershov D., Flasse S., Fraser R., Graetz D., Maggi M., Peduzzi P., Pereira J., Silva J., Sousa A., Stroppiana D., A Global Inventory of Burned Areas at 1 Km Resolution for the Year 2000 Derived from Spot Vegetation Data, *Climatic change*, **67**(2), 345-377(33), 2004.

Tansey, K.; Grégoire, J-M; Stroppiana, D; Sousa, A; Silva, J; Pereira, J M. C.; Boschetti, L; Maggi, M; Brivio, P A; Fraser, R; Flasse, S; Ershov, D; Binaghi, E; Graetz, D; Peduzzi, P., Vegetation burning in the year 2000: Global burned area estimates from SPOT Vegetation data, *Journal of Geophysical Research*, **109**, 2004.

Tobin, G.A. & B.E., Montz, *Natural Hazards: explanation and integration*, Guilford Press, New York, 388p., 1997.

Turner II, B.L, Roger E. Kasperson, William B. Meyer, Kirstin M. Dow, Dominic Golding, Jeanne X. Kasperson, Robert C. Mitchell, Samuel J. Ratick, Two types of global environmental change: Definitional and spatial-scale issues in their human dimensions , *Global Environmental Change*, **1**(1), 14-22, 1990.

Turner II, B.L., Kasperson, R.E., Matson, P.A., McCarthy, J.J., Corell, R.W., Christensen, L., Eckley, N., Kasperson, J.X, Luers, A., Martello, M.L., Polsky, C., Pulsipher, A., Schiller, A., A framework for vulnerability analysis in sustainability science, *PNAS*, **100**(14), 8074-8079, 2003.

UNDP, *Reducing Disaster Risk: a challenge for development*, United Nations Development Programme, Bureau for Crisis Prevention and Recovery, 146 p., New York, NY 10017, USA, 2004.

UNISDR, 2011 Global Assessment Report on Disaster Risk Reduction, United Nations International Strategy for Disaster Reduction, United Nations, Geneva, Switzerland, pp. 178.

UNISDR, *Hyogo Framework for Action 2005-2015: building the Resilience of Nations and Communities to Disasters*, United Nations International Strategy for Disaster Reduction, 25 pp., 2005. http://www.unisdr.org/eng/hfa/docs/Hyogo-framework-for-action-english.pdf, last accessed: 29 April 2011.

UNISDR, *Know Risk*, p29, United Nations International Strategy for Disaster Reduction, United Nations, Geneva, Switzerland, 2005, pp.376.

United Nations Disasters Relief Co-Ordinator (UNDRO), Natural Disasters and Vulnerability Analysis, Report of Expert Group Meeting, 9-12 July 1979, Geneva, Switzerland.

Vermaat, J.E., Thampanya, U., erratum to Mangrove mitigated tsunami damage: a further response, *Estuar. Coast. Shelf Sci.* **75**, 564, 2007.

Vermaat, J.E., Thampanya, U., Mangrove mitigated tsunami damage: a further response, *Estuar. Coast. Shelf Sci.,* **69**, 1-2, 2006.

White, G.F., *Natural Hazards*, Oxford, New York, 1974.

World Bank, Development Actions and the Rising Incidence of Disasters, Evaluation Brief #4, Independent Evaluation Group, the World Bank, Washington, DC, 34 pp. (2007).

Chapter 2 Risk and Global Change: concepts and definitions

2.1. General hypothesis

The purpose of this thesis is to see whether quantitative analysis can provide evidences on the links between risk and global change.

Through population growth and increase in individual demand, the natural resources are being exploited at an accelerating rate. With forest being converted to cropland, the use of fossil fuel for energy and increased amount of cattle for meat and milk production are degrading soils and emitting GHG, thus inducing climate change. The decline of ecosystems, such as deforestation or overfishing may increase hazard susceptibility or decrease human resilience or coping capacity.

The hypothesis is that Global Change has direct impacts on the risk losses through multiple processes: population growth is increasing exposure to hazards; climate change may change hazard frequency, severity or spatial distribution. Global change is also increasing global wealth, at least in short/mid term, however there is a significant inequity in wealth distribution. Poor people are suffering disporoportinal losses from natural hazards. Climate, environmental and socio-economic changes may be linked with risk.

The question are: can we build tools that can highlight these processes? If yes, can we quantify the role of each components? Can we localize areas (population) most at threat?

To study the capacity of quantitative to provide support for advocacy, two levels of analysis will be tested.

Firstly, a global level of analysis on assessing the possibility to evaluate and understand mortality risk from main natural hazards. This analysis do not aim to produce a probabilistic approach for evaluation of future risk, but will try to identify the underlying factors which lead to higher mortality risk and the respective role of all risk components, i.e, hazard (intensity, frequency), exposure (population) and vulnerability. The vulnerability will include coping capacity and part of resilience (resist, and absorb a shock), but not the recovering aspect of resilience. Recovery being irrelevant for a study on mortality risk.

Secondly, this thesis will try to highlight links between climate change, the declining of ecosystems and risk. This will be done at the local level. The same tools will be used at different scales. Zooming at the local scale may allow depicting the links between landcover changes and risk. These changes being extremely localised, they are likely not to be identify at the global scale.

2.2. Risk and its components

Because several disciplines have been studying risk, from engineering to social science, definitions have evolved in parallel, creating a confused Babel amongst the risk communities (Thywissen, 2006). No less than six different schools can be identified for the sole concept of vulnerability (Birkman, 2006). This is the result of both historical developments and different disciplines. Historically risk evolved from a purely physical event perspective to a more integrated approach taking account of the socio-economic factors influencing human vulnerability. Different disciplines such as natural science, engineering, social-science, humanitarian and development communities, had their own focus and used the same words, alas with different connotations.

The differences between concepts and definitions of various schools are very well explained in Birkman (2006) and Thywissen (2006) and it is not the purpose of this study to explain these differences in detail. It is important to recognise that there are different communities of practices all having their own reasons for employing their own definitions. Because the definitions are not univocal, a clarification on how the concept of risk and related terms are used in the current study is needed.

It is not implied that the definitions used in this thesis are more correct than the ones used in other reports or research. The following definitions are only provided here to ensure a common language for the discussion of concepts and notions. The choice of these definitions was dictated by the context of the research undertaken (United Nations agencies) and thus closely follows the uses that prevail in UNDP and UNISDR. In order to reduce confusion, UNISDR provides an on-line source of terminology with a list of definitions (since 2004), but even here, some of the definitions have been revised. The definitions provided here are mostly derived from this on-line terminology source as of August 2011 (UNISDR, 2011).

2.2.1. Risk

Risk is "*the combination of the probability of an event and its negative consequences*" (UNISDR, 2011). More specifically, Tobin and Montz (1997) define the risk as "*a measure of the expected losses due to hazard event of a particular magnitude occurring in a given area over a specific time period.*" Risk should not be confused with losses. Losses or impacts refer to the number of human losses; the number of infrastructures or amount of crops damaged; the amount of economic losses; or the environmental losses. They are sometimes referred to "*realized risk*" or "*disaster losses*". Disaster losses may impact livelihood in sectors such as tourism, housing, fisheries, transport, communication, or agriculture, to name just a few.

In common popular usage, risk is used as the probability of occurrence (e.g. “the risk of an accident”). The probability of occurrence is part of the hazard. A commonly used terminology was provided by the United Nations Disaster Relief Organization (UNDRO) in their report "*Natural Disasters and Vulnerability Analysis in Report of Expert Group Meeting*" in 1979 (Burton *et al.*, 1993; Blaikie, 1996) , they state that the risk results from three components: the hazard occurrence probability, the element at risk and the vulnerability. This is a well-recognised definition, also referred to as risk being a function of hazard, exposure and vulnerability. Exposure is used here instead of elements at risk. Depending on the disciplines, people use vulnerability including coping capacity and resilience; others will treat these three parameters separately. In this thesis – and in the articles included – coping capacity and resilience are included as negative vulnerability parameters.

For Tobin and Montz (1997), risk is the product of some probability of occurrence and expected loss. Van Dissen and McVerry (1994) obtained risk (for earthquakes) by multiplying probability and vulnerability (which in their definition includes exposure). Similarly Mitchel (1990) uses a multiplicative approach of the components of risk. By multiplying the components of risk as described by UNDRO (1979), the risk is the outcome of the interaction between a hazard phenomenon, the elements at risk in the community, and the vulnerability of those elements. This is justified because should any of the components "Hazard, Exposure or Vulnerability" be null, then the risk is null (Peduzzi *et al.*, 2001, Peduzzi *et al.*, 2002; UNDP, 2004), (see Eq. 1).

$$R = H \cdot E \cdot V \qquad (1)$$

Where:

R = Risk (expected losses for a specific length of time, hazard type and intensity)
H = Hazard (frequency for a specific intensity)
E= Elements at Risk (number of people or assets)
V= Vulnerability (percentage)

These components are described in details below.

2.2.2. Hazards

Hazards: "*A dangerous phenomenon, substance, human activity or condition*"[…]. *Hazards are described quantitatively by the likely frequency of occurrence of different intensities for different areas, as determined from historical data or scientific analysis*" (UNISDR, 2011).

It is important to note that hazard is not the physical event itself but the probability of occurrence of a hazardous event type at a specific location, time period and strength (as measured in intensity, magnitude or toxicity). Hazard is the probability of occurrence of a physical phenomenon which may threaten human lives, lead to injuries, property damage or dysfunction of social and economic systems or the degradation of natural ecosystems, depending on related vulnerability or the elements exposed (UNISDR, 2011).

Hazards can be of natural origin, this category includes tectonic hazards (such as earthquakes, tsunamis, volcanic eruptions,...), hydro-meteorological hazards (floods, tropical cyclones,...), biologic hazards (plague, epidemics,...) and climatic hazards (drought, heat wave, cold wave). They can also be of anthropogenic origins, such as pollutions (oil or chemical spills, nuclear accidents,...), fires, wars, or explosions (see Figure 5). Most anthropogenic hazards are slow and continuous, they are also called creeping hazards (Glantz, 1999) such as soil erosion or deforestation (UNISDR, 2011). Some hazards can trigger secondary hazards (see Box 2), which in some cases lead to greater impacts than the initial hazard. For example, the 2011 Japanese earthquake, led to a devastating tsunami, which in turn led to a major nuclear accident. The natural hazards triggering technological disasters are sometimes referred as “Natech” hazards (Cruz *et al.*, 2006).

A hazard can be simple, sequential, or combined (in both origins and effects). Each hazard can be characterised by its location, frequency, strength (measured in magnitude, intensity or toxicity) (UNISDR, 2011). The frequency or the return period of a certain event (type and strength) can be defined by its probability of occurrence. The probability can be high or low, or certain (for continuous hazards). Each hazard type differs in rapidity of onset. It can be sudden (e.g. earthquakes), rapid (e.g. tropical cyclone), continuous (e.g. deforestation) or slow (e.g. drought). In the case of drought, one may not know when it starts; furthermore drought is not only a lack of precipitation, it depends on soil water content, possibility of irrigation, presence of lakes, aquifers, or glaciers.

Some hazards affect small surfaces (e.g. landslides), others affect much larger areas (e.g. drought, tropical cyclones). Hazards may have fuzzy boundaries (e.g. drought) or clear boundaries (e.g. floods). The potential destructive power of a hazard depends on the magnitude, duration, location, and timing of the event (Burton *et al.*, 1993).

Some consequences can be irreversible (at least at human life scale) such as certain radioactive isotopes resulting from a nuclear accident (which might last hundreds or thousands of years). Other consequences can last a few days or weeks (such as floods) while impacts might last a few years. So, while consequences result largely from exposure and vulnerability (see below), the intensity and severity are significant parameters.

Hazards’ predictability is variable. For instance tropical cyclones can be detected by satellites and warning can be provided several days before populations are hit. While for earthquakes early warning is mostly limited to a probability of a returning period for a specific intensity - research on early warning for earthquakes is still preliminary, offer a few seconds to a few minutes warning and their validity are highly dependant on local conditions (Fletcher *et al.*, 2007).

Ultimately the resulting impacts from a hazard depend on the vulnerability of the people or infrastructures exposed, as well as their number and concentration.

To summarise, each hazard has its own capacity of destruction which depends on its magnitude and level of predictability (usually in proportion to the rapidity of onset). Its impacts vary depending on the surface affected and duration of impact. For instance, a landslide can be very sudden, but the area affected will be limited and the duration of impact very short (couple of minutes) and it will have fixed boundaries. While a drought can be very long (several months, even years) and affect a large area with fuzzy boundaries.

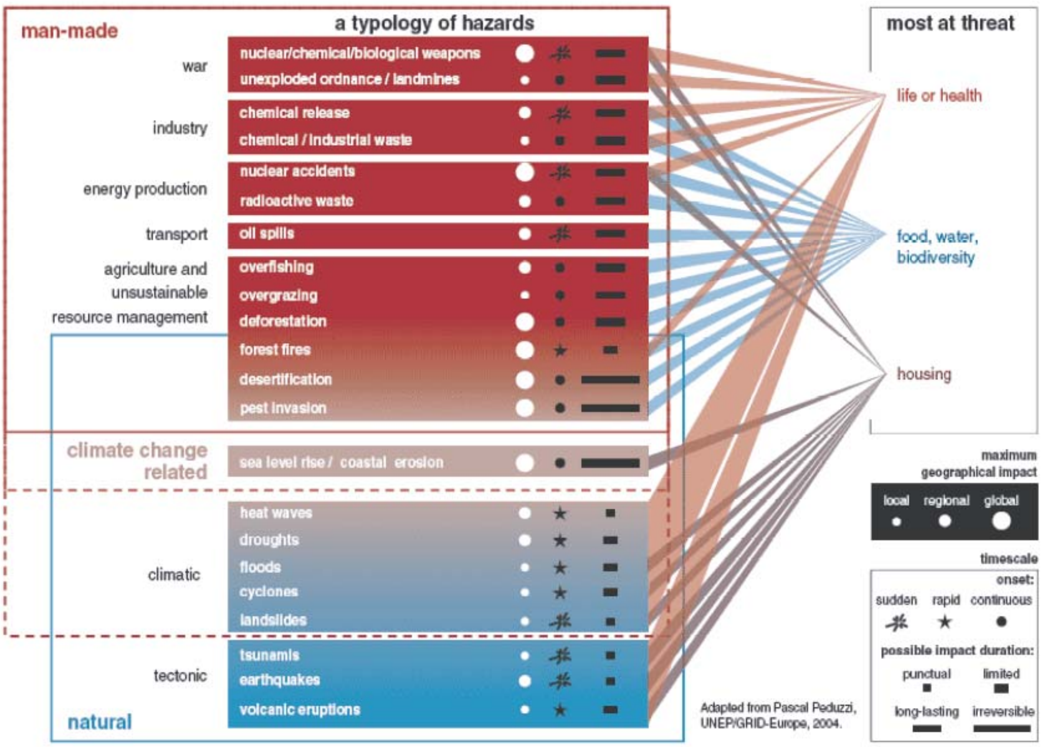


Figure 5 Typology of hazards (Peduzzi, 2005)

Table 1 Type of exposure

	Without frequency	With Frequency
Human exposure	The number of people living in hazard-prone area	Yearly average number of people exposed to hazards
Economic exposure	Number of assets located in hazard-prone area (houses, GDP, crops)	Yearly average amount of assets exposed to hazards.
Environmental exposure	Animals, plants, soils, water and other environmental features located in hazard-prone area.	Yearly average amount of animal, plants, soils, water and other environmental features exposed to hazards

2.2.3. Exposure

The exposure is the number of "*people, property, systems, or other elements present in hazard zones that are thereby subject to potential losses.*" (UNISDR, 2010). Each hazard depending on its severity, frequency and its specificities can pose different threats to different exposures such as population, assets or environmental features (Table 1). Earthquakes do not have major impacts on natural ecosystems (some impacts from resulting landslides) but can be devastating in urban and industrialised areas. Forest fires cause large impacts to vegetation and fauna, also leading to high losses for agriculture and housing; however few people die from forest fires. While populations can be evacuated to prevent human life losses (following efficient early warning), this is not the case of crops and infrastructures.

Measures of exposure can include the number of people or types of assets in an area. An intersection between area potentially affected by a hazard and population or economic assets can be performed, e.g. using GIS to identify how many people (or assets) are living (respectively located) in hazard prone area.

The average number of people potentially affected during a certain time period, e.g. average number of people (respectively assets) affected per year are obtained by multiplying the frequency of hazard (at a given intensity) by the population living (respectively assets located) in the hazard-prone area. These figures are referred in this publication as the physical exposure for population and economic exposure for assets.

This concept is valid for direct losses. Indirect losses have different type of exposure. Insurances, and other investors, may suffer losses because they are dependant or have investments in elements that are exposed. This is usually complex and can only be approached through case studies or local/sectoral scenarios.

2.2.4. Vulnerability

Vulnerability is probably the most complex component to understand. Timmerman (1981) defines vulnerability as "*the degree to which a system acts adversely to the occurrence of a hazardous event of a given intensity*". For UNISDR, vulnerability includes "*the characteristics and circumstances of a community, system or asset that make it susceptible to the damaging effects of a hazard. […] arising from various physical, social, economic, and environmental factors.*" (UNISDR, 2011). Coburn *et al.* (1991) define vulnerability as " *the degree of loss to each element should a hazard of a given severity occur.*" (Coburn *et al.* 1991). Vulnerability can be computed as a percentage of losses as compared with total exposure (hence varies between 0 and 1) (UNDRO, 1991).

Vulnerability as such is not easy to characterise. The idea in this study is to approach vulnerability by contextual parameters associated with vulnerability. These can be: poverty, capacity of early warning, knowledge on how to react, appropriate evacuation plans or presence of shelters, appropriate design of buildings (for earthquakes, floods and cyclones). When information is not necessarily available directly, we may try to find proxies. For example, evaluation of evacuation plan or early warning capacities are not available for all countries. However, some proxies can be used based on related existing indicators. Appropriate evacuation plans come from good governance. The number of radios per inhabitant can be a useful indicator of early warning capacity.

There are several hypotheses that would be interesting to test. For example to provide statistical evidence that vulnerability is different for each hazard. For example people may not be vulnerable to drought in the same way that they are to earthquakes. Drought is more related to food insecurity and thus should have higher effect on rural populations because urban centres are already importing food, meaning that it can be brought more easily as compared with remote areas. In the same way, proximity to main cities may be a valid indicator to test for access to health care as well as easier accessibility for rescue operations. An earthquake in itself is not dangerous. It is the buildings people are living or working in and the objects nearby that can harm or kill. This means that rural populations working in the fitelds should be less at threat than urban populations living or working (mostly) in or nearby buildings. Rural versus urban populations are interesting indicators. For selected sudden onset hazards, the time of onset (day or nigh) is also a potentially significant variable. These hypotheses will be tested (see parts 3.5).

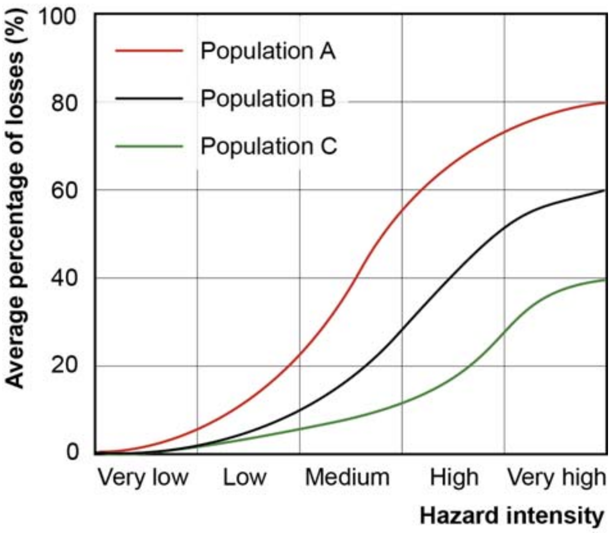


Figure 6 Different curves of vulnerability classes for different populations, with percentage of losses according to hazard intensities.

The percentage of losses is a function of the hazard intensity (see Figure 6). However, due to differences in planning practices, type of habitats, infrastructures, early warning, degree of preparedness (acquired from past events or from training), prevention (structural or operational), capacity of evacuation,... the degree of losses can differ significantly from one country, one region, or event, one community to another.

The vulnerability curve can be obtained by plotting the percentage probability of losses versus hazard intensity (Rossettoa and Elnashai, 2005). Vulnerability is a dynamic feature and varies over time from learning experience, improvement in governance which translates in building codes, enforcements and other DRR actions and practices.

Other notions are related to vulnerability:

Coping capacity: "*The ability of people, organizations and systems, using available skills and resources, to face and manage adverse conditions, emergencies or disasters*." (UNISDR, 2011). Vulnerability and coping capacity can be merged together. Coping capacity can be seen as an inverse of vulnerability, although, in theory, the vulnerability is more associated to the individual and coping capacity associated with external (societal, relief,...) capabilities.

Resilience: "*The ability of a system, community or society exposed to hazards to resist, absorb, accommodate to and recover from the effects of a hazard in a timely and efficient manner, including through the preservation and restoration of its essential basic structures and functions*". (UNISDR, 2011). Resilience is used in engineering to compute the solidity of buildings (e.g. resistance to a shock). It has a similar connotation for population at least at the community level. (Van Aalst *et al.*, 2008).

For a building, the resilience can be physically measured. It will depend on the materials (metal beams, concrete wall) and its level of engineering. The resilience of individual components to different shock types can be measured: thermal expansion, torsion, shaking, impact or pressure.

A negative way of measuring infrastructures' resilience is called the **structural vulnerability**. Information on structural vulnerability (resilience) is usually not accessible (at least globally), proxies can however be used. People do not build badly just for the fun of it. Badly designed structures may result from socio-economic vulnerabilities such as e.g. poverty, low education, and lack of a building code. Direct measurements of vulnerability factors might not always be possible, but some indicators can be used as proxies in absence of data on building quality for global level analysis (see Table 2). For local level assessments, data on building quality can (and should) be collected through survey if this is not already available.

There are also several issues when decreasing hazard or vulnerability with structural resilience. This can be achieved by building dikes or dams (for avoiding flood hazards), retrofitting buildings, or improving building codes (e.g. for making them more resilient to higher earthquakes and cyclones intensities). However, such structural resilience may increase exposure and lead to a disaster should the hazard be stronger than the maximum envisaged when building this infrastructure. This is where change in hydro-meteorological hazards from climate change, may induce the highest impacts (Mustafa, 1998).

Table 2 Hypotheses of indicators which may be used as substitute in absence of data on building resilience.

Factors for low building resilience	Probable associated socio-economomic vulnerability	Possible indicators used as proxy
Use of poor materials	Lack of resources, poverty	Gross Domestic Product per capita (ideally at purchasing power parity)
Lack of know-how	Low level of education	Illiteracy rate, school enrolment
Inappropriate building standards or no standards.	Lack of building codes, low political consideration, policy gap(s).	Governance, rule of law
Buildings not designed according to standards	Lack of law enforcement, lack of political willingness	Voice and accountability, corruption

For a society, measuring resilience can be challenging. It is more a concept that can be approached by looking at the level of wealth, education, information, preparedness, regular exposure to the hazard, quality of planning, level of governance, participation of the civil society, culture and perception of risk. In other words, there is not a physical way of measuring vulnerability, resilience and coping capacity, but a number of methods that attempt to grasp these concepts and characterise them as closely as possible (Birkmann *et al.*, 2006). It can be done through community consultations, calibration based on historical losses or modelled based on expert judgements. Vulnerability assessment can be qualitative or quantitative.

2.2.5. The risk equation

Risk is often approached by a multiplicative model. Such as a product of probability and consequence (Jones and Boer, 2003). Risk is the outcome of the interaction between a hazard phenomenon, the elements at risk in the community, and the vulnerability of those elements. This is the classic definition as already provided by UNDRO (1979) and widely used. See equation 1.

In some model, the vulnerability includes element at risk. For example in Tobin and Montz (1997), risk is seen as the product of some probability of occurrence and expected loss.

R = P(h) x V (2)

Where:

P(h) = probability of occurrence of a specific hazard type at a given intensity

V = vulnerability (but in this case includes both exposure, i.e. number of people or assets and vulnerability, hence in this case, vulnerability is the percentage of exposure losses, expressed in numbers).

This model does not differ from previous equation, but provides less flexibility, as the exposure and related vulnerability cannot be adjusted individually. Also using probability of occurrence might be restrictive in some cases (as probability is between 0 and 1, whereas frequency can be higher than 1).

For Fournier d'Albe (1979), risk is the expected number of lives losses, persons injured, damage to property and disrupted of economic activity due to a particular natural phenomenon and his approach for modelling it is as follows:

Risk = [Hazard (probability) x Loss (expected)]/Preparedness(loss mitigation). (3)

The loss expected is basically the same as the vulnerability definition used by Cardona (2003). The interesting part being the preparedness which divides the loss expected. However, knowing the level of preparedness of a given exposure, should inform on the expected losses. From this definition, some parameters are acting at increasing losses (e.g. poverty) and other at decreasing losses (e.g. preparedness). It is mostly a question of indicators. For example, poverty can be replaced by wealth. High poverty or low wealth. If we use GDP as a proxy of poverty, a low GDP would be associated to high vulnerability. Good preparedness may arise from high education, good governance, high scientific and technical levels, early warning systems in place, evacuation plan, means for evacuations, … all of this will have an influence on the expected losses, the distinction between these two components is necessary, at least for producing a sound mathematical model.

The equation 1 is presenting several advantages: it has a finer flexibility (as compared with equation 2), it simplifies the issue of interaction between vulnerability, coping capacity, resilience, by including all of them (except recovery) into vulnerability. This is well adapted for mortality losses. Direct or indirect economic losses, would need to include possibility to measure recovery, and absorption (such as based on savings) as well as risk transfer (e.g. insurances). But for mortality risk, such approach, by its simplicity seems relevant. The main issue in this approach is how to include the probabilities of different hazard intensity?

Intensity and probability

The issue with equation 1, is that you have to differentiate several intensities.

Several authors are using the same three components as in equation 1 (hazard, exposure and vulnerability, but use a convolution between them (Cardona, 2003).

R = f(H, E, V) (4)

The concept of convolution is not very different from the multiplication. Basically the difference between multiplying the element of using convolution functions is a question of being able to evaluate the continuous array of intensity and related exposure and vulnerability curves or an approximation based on discrete scenarios.

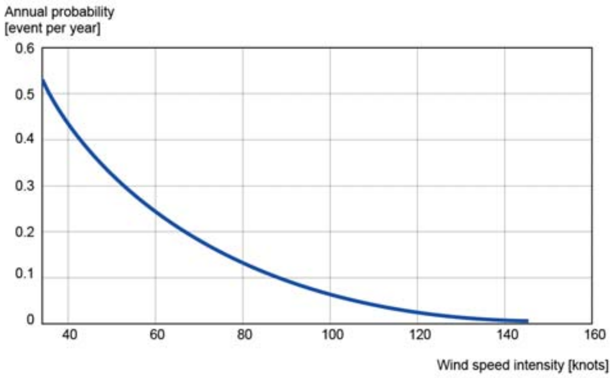
The general idea from risk model is that the level of risk is a function of the hazard intensity, frequency, the exposure and related vulnerability.

One of the problem we are confronted with lies in the non-continuous approach of our function. A computation using convolution, requires that each function is fully known, with continuous hazard, exposure and vulnerability curves. In the DRI (see 3.2) analysis, the approach is simplified. The intensity is not included. A single threshold is used to decide whether a hazardous event is strong enough or not. This is necessary in this approach, because the analysis is conducted at the country level by averaging losses over a period. To include intensity, the analysis has to be performed at the event level (see 3.5 and 3.7), however, in these cases, we are using different categories of hazard intensities (e.g. 3 for floods, 4 for earthquakes and 5 for tropical cyclones intensities). The function is not continuous, but the approach is simplified using discrete values.

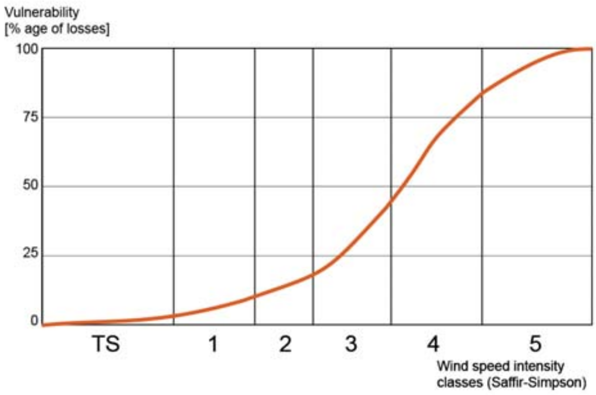
Below, the difference between a continuous and a discrete approach.

$$Exp_i = \sum_{i=0}^{i=\infty} H_i \cdot E_i \qquad (5)$$

Where:
Exp_i = exposure at different intensities.
H_i = probability of the hazard at different intensity "i".
E_i = Elements present in the hazard prone area at different intensities "i".



Model of exposure Continuous



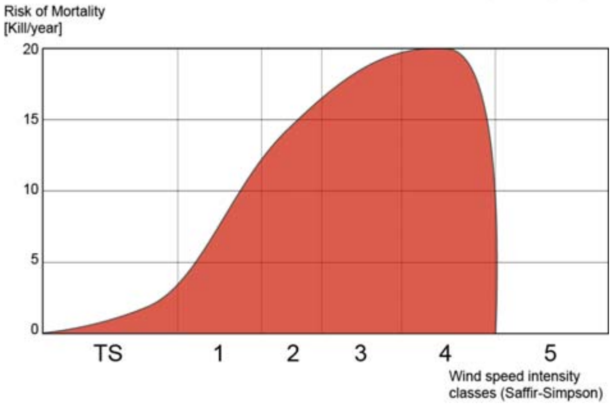


Figure 7 Continuous probability of TC wind hazard (top) and computation of related exposure (second from top). Continuous theoretical vulnerability curve function (third from top). Risk is a convolution between hazard and vulnerability function, with the integer below the risk curve providing risk level (bottom).

In this model, the risk is a convolution between the hazard and the exposure including its related vulnerability. The risk is the integer below the curve across all the intensity.

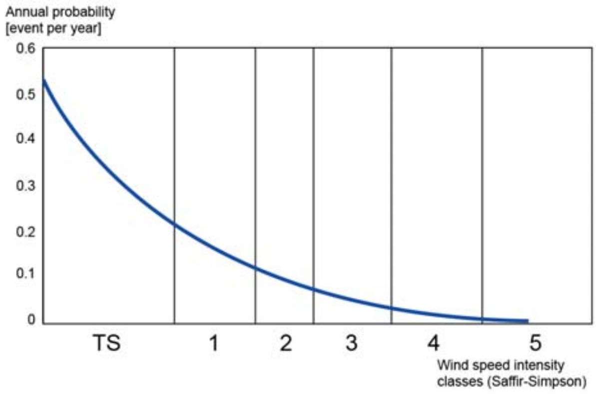
Where:

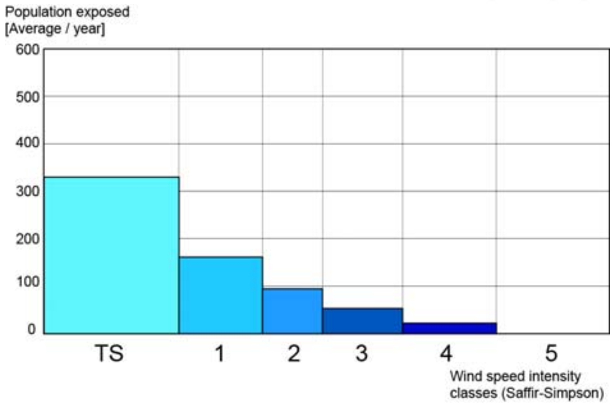
R_i = Risk of mortality from a specific hazard type (all intensities), for a specific location and time period.

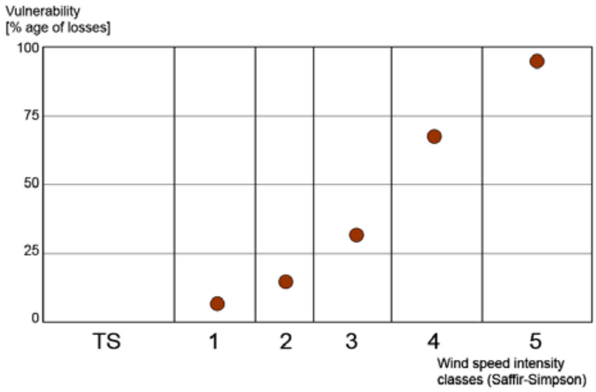
H_i = is the probability of a specific hazard type (e.g. tropical cyclones) according to different intensities, for a specific location and time period.

E_i = Number of people living in the hazard prone areas for different hazard intensities, for a specific hazard type, location and time period.

V_i = Vulnerability, the percentage of losses (mortality) for different intensities, for a specific hazard type, location and time period.







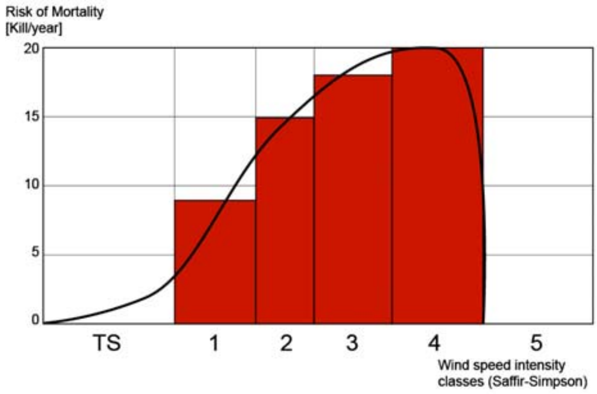


Figure 8 Consequences of using discrete approach on the risk model. TC winds hazards by Saffir-Simpson categories (top), Exposure by TC wind hazard category (second from top). Approximation of the vulnerability curve using discrete model (third from top). Approximation of the risk integer, by a discrete approach.

In this view, the multiplicative approach is a simplification of a convolution approach using a discrete number of categories. It significantly simplifies the computation for a global approach. Grouping events by categories, also ensure that there are enough records for a sound statistical analysis (enough degree of fredom).

Using equation 1 and the above definitions, a more elaborated version of the risk equation can be achieved. Risk is a function of hazard, exposure and vulnerability (coping capacity is merged as inversion of vulnerability). However, we do not know how the different components of risk relate to each other. They might not be linear and might not have similar weight. To allow for flexibility in the equation, exponent and weights should be added in the multiplicative model. (see Eq. 2).

$$R = \alpha H^a \cdot \beta E^b \cdot \gamma V^c \qquad (6)$$

Where :

H (Hazard) varies in type (floods, tropical cyclones, earthquakes, drought,...), frequency (periodicity) and strength (intensity, magnitude or toxicity), with α as associated weight and "a" as associated exponent.

E (Exposure) varies in kind (population, house, crops, environmental features,...) and in number (quantity). With β as associated weight and "b" as associated exponent.

V (Vulnerability) is the percentage of losses as compared with total exposure, hence varies between 0 and 1. With γ as associated weight and "c" as associated exponent. (UNDRO, 1979). Note that the vulnerability may require to be approached by several indicators, each of them having their own weight.

The link between the dependant and the independent variables is not necessarily linear. To ensure this flexibility, the variables can be transformed (e.g. taking the square root or exponented at different power). The main advantages in using linear regressions is the ease to re-apply the model to GIS raster files. It does not prevent from transforming independent variables to adapt for non-linear relations.

The formula can be modified depending on the use of linear or logarithmic regressions (see Equation 8). Logarythmic regressions offer several advantages. *It can linearize the relationships between the response and predictor variables. It can stabilize the model error variance so that the assumption of a constant variance is more closely met. It can remove serial correlation among the residuals.* (Stow *et al.*, 2006). There are also limitations with logarithmic regressions. One major limitation is that the dependent variables cannot be smaller or equal to zero. This is however, not an issue when looking at risk of disasters losses, because these cannot be smaller of equal to zero. Zero killed would not be a disaster when looking at mortality. Logarythmic regression are particularly well adapted in the case of reponse variables which are bounded (Stow *et al.* 2006), such as the number of killed which cannot be less than zero. Logarithmic regressions for risk can be as in Equation 8.

$$Ln(R) = \alpha Ln(H) + \beta Ln(E) + \gamma Ln(V) + C \qquad \textbf{(7)}$$

Risk equations will be described in detail in the different researches. However, all equations used in this study are based on a multiplicative approach.

The publications in Chapter 3 address this point (at the global level), by mapping the hazards and exposure, by identifying underlying factors of vulnerability and by assessing the risk both at a pixel[2] and national levels.

Taking actions for reducing disaster risk, first requires knowledge about hazards exposure and vulnerability. This necessitates knowledge about the fact of being exposed to hazards and then the quantification of the level of exposure. Quantitative risk assessment and visualisation of spatial risk distribution are the first necessary steps in order to take decisions on land planning and other DRR measures.

The Hyogo Framework for Action (HFA) is the main instrument (or process) for the United Nations ISDR system for listing and encouraging DRR activities (see Box 1).

If good land planning (taking into account disaster risk) is in place, risk is only reduced to unexpected hazards. However, in many places, the structure of the land planning is largely inherited from the past and thus disaster risk may not have been taken into account.

[2] A pixel in GIS is the smallest unit of a raster coverage. It is a square representing a geographical area (meaning it includes information on geolocation) associated with a value (or several values). The length of height (or width) of the square provide information on the resolution, i.e. the spatial precision of the dataset.

The Hyogo Framework for Action (HFA) was adopted in 2005 by 168 countries. The HFA was built based on the conclusions from The World Conference on Disaster Reduction held from the 18th to 22nd of January 2005 in Kobe. It includes five priorities for action:

1. Ensure that disaster risk reduction is a national and a local priority with a strong institutional basis for implementation.
2. Identify, assess and monitor disaster risks and enhance early warning.
3. Use knowledge, innovation and education to build a culture of safety and resilience at all levels.
4. Reduce the underlying risk factors.
5. Strengthen disaster preparedness for effective response at all levels.

The work presented in Chapter 3: contributes (at the global level) to part of key activities 1, 3 and 4 of HFA Priority 2: Identify, assess and monitor disaster risks and enhance early warning.

Key activity 1: National and local risk assessments

a. Develop, update periodically and widely disseminate risk maps and related information to decision-makers, the general public and communities at risk in an appropriate format.

b. Develop systems of indicators of disaster risk and vulnerability at national and sub-national scales that will enable decision-makers to assess the impact of disasters on social, economic and environmental conditions and disseminate the results to decision-makers, the public and populations at risk.

c. Record, analyse, summarize and disseminate statistical information on disaster occurrence, impacts and losses, on a regular basis through international, regional, national and local mechanisms.

Key activity 3: capacity

i. Support the development and sustainability of the infrastructure and scientific, technological, technical and institutional capacities needed to research, observe, analyse, map and where possible forecast natural and related hazards, vulnerabilities and disaster impacts.

j. Support the development and improvement of relevant databases and the promotion of full and open exchange and dissemination of data for assessment, monitoring and early warning purposes, as appropriate, at international, regional, national and local levels.

k. Support the improvement of scientific and technical methods and capacities for risk assessment, monitoring and early warning, through research, partnerships, training and technical capacity- building. Promote the application of in situ and space-based earth observations, space technologies, remote sensing, geographic information systems, hazard modelling and prediction, weather and climate modelling and forecasting, communication tools and studies of the costs and benefits of risk assessment and early warning.

l. Establish and strengthen the capacity to record, analyze, summarize, disseminate, and exchange statistical information and data on hazards mapping, disaster risks, impacts, and losses; support the development of common methodologies for risk assessment and monitoring.

Key activity 4: Regional and emerging risks

m. Compile and standardize, as appropriate, statistical information and data on regional disaster risks, impacts and losses.

n. Cooperate regionally and internationally, as appropriate, to assess and monitor regional and trans-boundary hazards, and exchange information and provide early warnings through appropriate arrangements, such as, inter alia, those relating to the management of river basins.

o. Research, analyse and report on long-term changes and emerging issues that might increase vulnerabilities and risks or the capacity of authorities and communities to respond to disasters.

In Chapter 4:, publications presented there contribute to the key activity 1 (at the local level) of the HFA Priority 4: Reduce the underlying factors.

Key activity 1: Environmental and natural resource management

a. Encourage the sustainable use and management of ecosystems, including through better land-use planning and development activities to reduce risk and vulnerabilities.

b. Implement integrated environmental and natural resource management approaches that incorporate disaster risk reduction, including structural and non-structural measures, such as integrated flood management and appropriate management of fragile ecosystems.

Box 1 Presentation of the relevant points of the Hyogo Framework for Action points for this thesis.

2.3. What is global change?

Changes are inherent to the planet earth system. Without changes, there would be no life. What is new (at a geological scale) is that before human impacts most of the changes were from natural phenomenon such as volcanism, tectonic movement, erosion from rivers and glaciers and modification of our planet’s rotation. Most of these changes were slow, allowing for the adaptation of the species.

Rapid natural phenomena, such as the meteorite that hit our planet 65.5 million years ago (Schulte *et al.*, 2010; Pope *et al.*, 1998), led to the fifth massive extinction of biodiversity. Ecosystems are not designed for quick adaptation. Life adapts through evolutionary processes (Darwin, 1879) which takes multiple generations for adapting to new conditions, hence after such a shock, it took ten to 40 million years to recover a similar level of biodiversity (Alroy, 2008).

Humans are now the primary force of transformation, shifting 1.5 times more material than the world’s rivers (Radford, 2005).

Today, more than 50% of the terrestrial planet has been transformed (Sanderson *et al.*, 2002). The remaining relatively unspoiled areas are the north of Canada and parts of Alaska, Siberia, the Tibetan plateau, Mongolia, the centre of Australia, the Sahara and less than 80% of Amazonia (see Figure 8). To feed the world, large tracts of forest are being cleared and converted into cropland. In 2010, 13 million ha of forest were deforested (FAO, 2010). The largest deforestation occurs in Amazonia. However, this is also the case in the Borneo and Sumatra islands (Indonesia) and in Africa as well as in boreal forest of Canada and Russia. One example is the Ivory Coast. In 1900, this West African country was covered by 14.5 million ha of primeval forest, in 1955 there were still 11.8 million ha (Sayer, Harcourt and Collins, 1992). However, by 2010, only 0.63 million ha of primeval forest remains (FAO, 2010). This is a 95.65% deforestation rate.

Mines, exploitation for energy (petrol, tar sand, uranium,...), metal (gold, copper,...) are not only transforming landscape locally, but are a significant source of pollution for rivers (Hettler *et al.*, 1997; Malm, 1998).

Figure 9 Aluminium Oxide spills, Hungary, 2010.

October 4, 2010, an accident occurred at the Ajkai Timföldgyár alumina (aluminum oxide) plant in western Hungary. A corner wall of a waste-retaining pond broke, releasing a torrent of toxic red sludge down a local stream. (NASA, 2010)

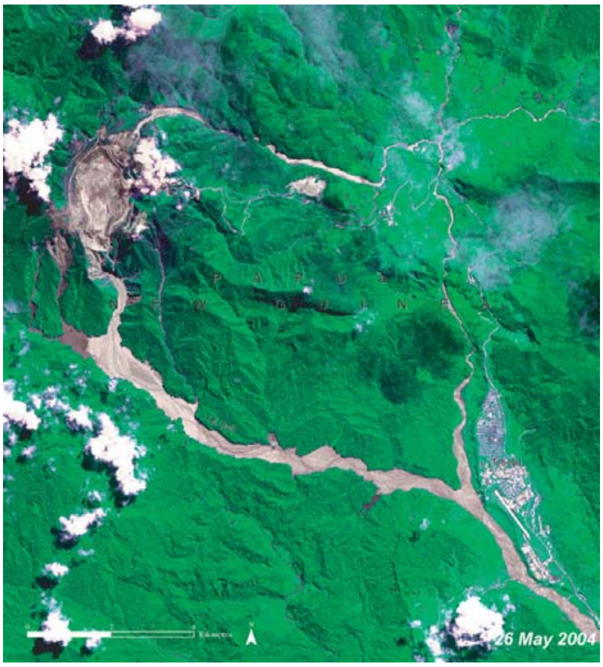


Figure 10 Ok Tedi Mine in Papua New Guinea

The uncontrolled discharge of 70 million tonnes of waste rock and mine tailings annually has spread more than 1 000 km down the Ok Tedi and Fly rivers, raising river beds and causing flooding, sediment deposition, forest damage, and a serious decline in the area's biodiversity. (UNEP, 2005).

Recently, a significant interest for remaining arable land can be seen with rich states and multinational companies purchasing 100,000 of ha of arable lands, principally in Africa (Zoomers, 2010). Every year, 3.9 million Km^2 of land are burnt, this represents a surface 94 times that of Switzerland or comparable to half of Australia (Tansey *et al.*, 2004a; Tansey *et al.* 2004b).

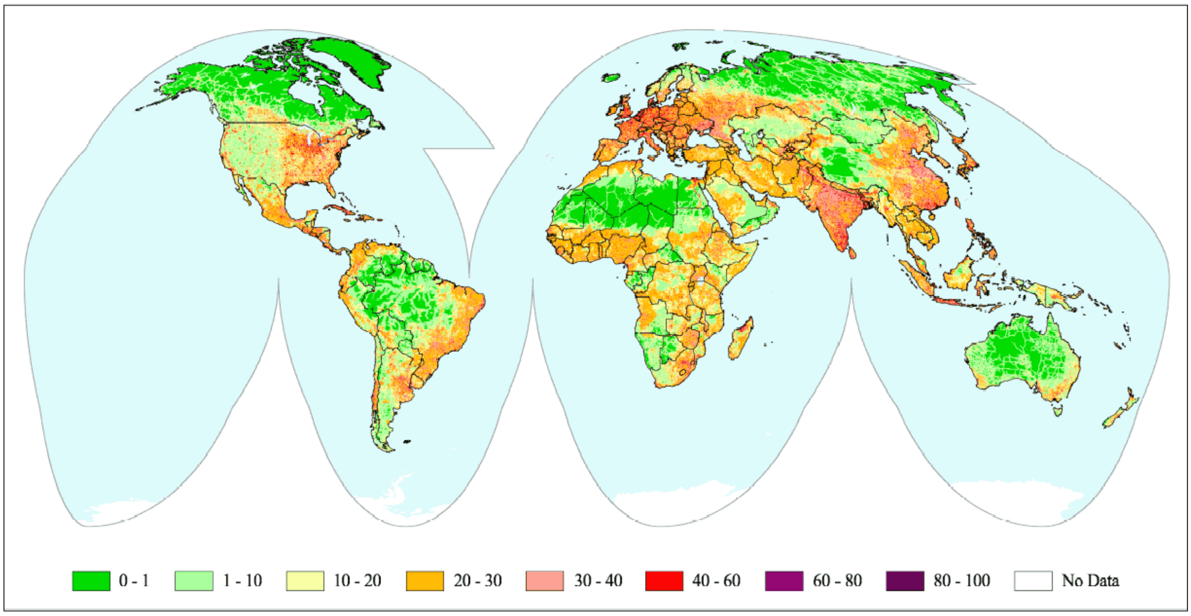


Figure 11 The human footprint (courtesy of Sanderson *et al.*, 2002)

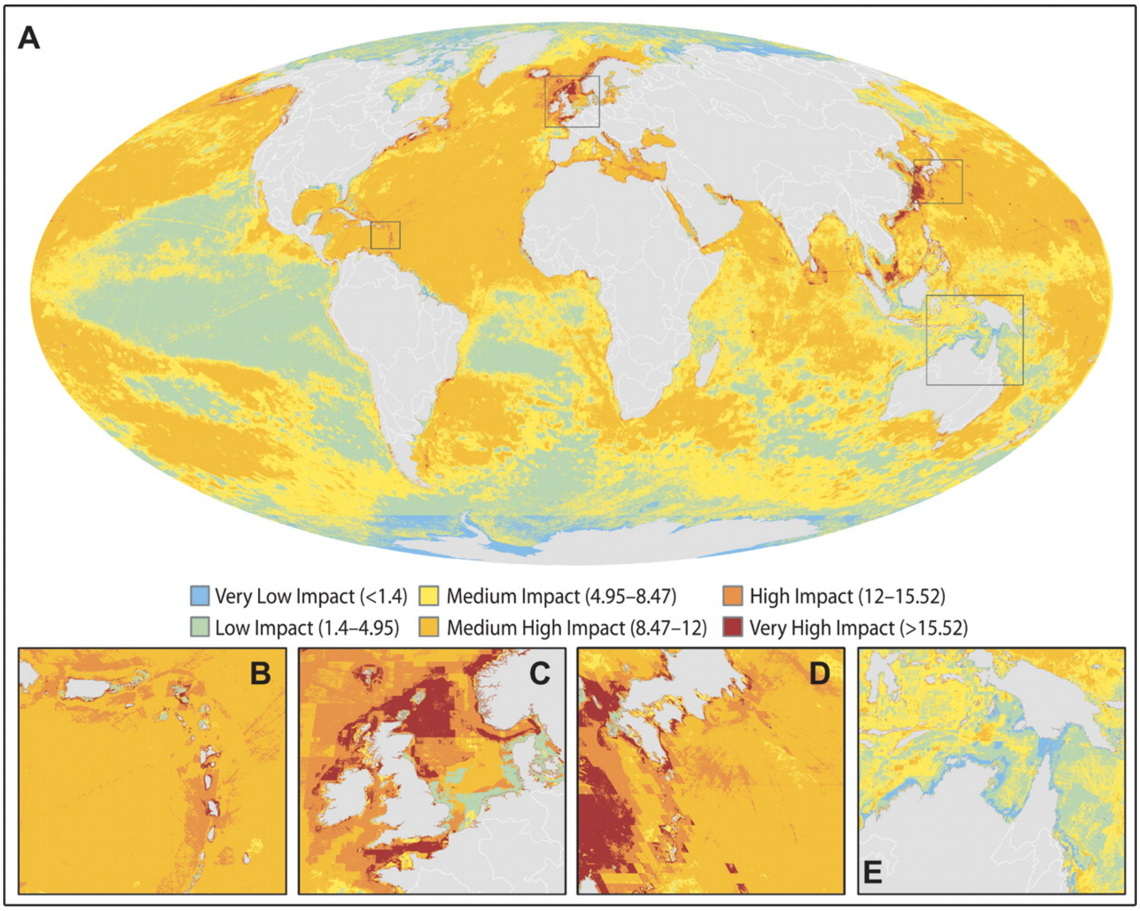


Figure 12 Global map (A) of cumulative human impact across 20 ocean ecosystem types. (Insets) Highly impacted regions in the Eastern Caribbean (B), the North Sea (C), and the Japanese waters (D) and one of the least impacted regions, in northern Australia and the Torres Strait (E). Courtesy from Halpern *et al.* (2008).

Oceans are also affected by human activities. Oceans can be polluted by oil spills, chemical released, fertilisers and wastes. It is estimated that approximately 6.4 million metric tons of waste enter the Oceans every year and that "*over 13,000 pieces of plastic litter are floating on every square kilometre of ocean*". (UNEP, 2010). Fish stocks are being depleted: 72% of the ocean are exploited to their limit or overfished (FAO, 2002). Only 10% of the tuna fish population remains and individual fish are between twice and five times smaller as compared with 1950th. (FAO, 2002; Alder, 2003; Giuliani *et al.*, 2004).

All these changes are now occurring at a rate which is too rapid for species adaptation. We may be experiencing the sixth massive biodiversity extinction (Barnosky *et al.*, 2011). Scientists estimate that extinction rates today are about 1000 times higher than the background rates of the past. (Wilson, 1992; McPhee and Flemming; 1999; Thomas *et al.*; 2004; Jackson, 2008). As opposed to the five previous mass extinctions, current biodiversity loss is mostly of human origin (Vitousek, 1994).

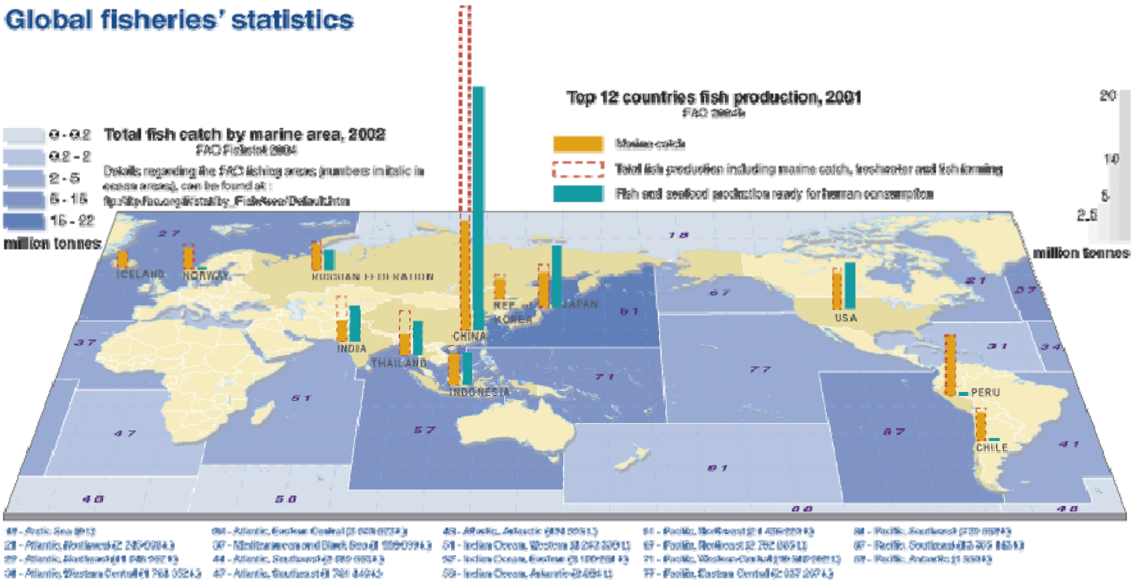


Figure 13 A majority of the oceans are exploited to their limit or overexploited (map from Stéphane Kluser, UNEP/GRID-Geneva in Giuliani *et al.*, 2004)

The use of petrol and other fossil fuel produces Green House Gases (GHG) of which higher concentration in the atmosphere is responsible for climate change (Solomon *et al.*, 2007).

What are the causes of such rapid change? The main triggers are interconnected: demographic growth, unsustainable use of natural resources as well as climate change resulting from GHG emission. How do they link with risk?

2.3.1. Change in population and urbanisation

The positive balance between human births and deaths is increasing the world population at a rate of more than 2.5 inhabitants per second, i.e. 80 million people per year (UNPD, 2010)[3]; in other words, adding each year the equivalent of the population of Germany or Vietnam. In 2010, the world population was 6.9 billion and is expected to exceed 9 billion by 2050 (UNPD, 2010). The increase in population is not the same in all places. Poor countries are still increasing at fast rates[4]: Liberia (+4.5%), Afghanistan (+3.9%), Burundi, Niger (+3.5%), Uganda (+3.2%). other countries see their population decreasing. This includes some small islands: Cook islands (-2.2%), Niue (-1.8%), east European countries: Ukraine (-0.8%), Russian Federation (-0.5%), Poland (-0.2%), or high income countries: Germany (-0.1%), Japan (0%). Even within countries, the population change is not evenly distributed (see Figure 12).

Population does not only change in number. The structure of societies is also changing. Since 2006, more than 50% of the world population is urban (UNPD, 2010). This is not

[3] Comparison between 2010 and 2000 world population, figures for these years are from United Nations Population Division in *Geodata portal*, UNEP, 2010. http://geodata.grid.unep.ch, last consulted 25 April 2010.

[4] Population growth for 2010 as consulted in the UNEP Geodata portal, 2010. http://geodata.grid.unep.ch, last consulted 25 April 2010.

bad in itself. However, the proportion of urban population living in slums is 23.2% (UNHABITAT, 2010) and even 32.7% of urban population in developing countries. While this proportion is decreasing, their absolute number has risen because of rapidly growing urban populations (UNHABITAT, 2010). Urban centres and coastal areas are attracting populations from rural areas and megacities are found mostly on coastal areas (Nicholls, 1995).

Between 1970 and 2010, the world population increased by a factor of 1.9. This is mostly due to urban population which was multiplied by 2.6, while rural population was multiplied by 1.5 (see Figure 14). But in the same period, the Gross Domestic Product (GDP) was multiplied by 3.6. The amount of assets has increased faster than the population. This is not only a question of having more assets (e.g. more houses) as the same assets increased in value. Thus while people are only increasing in number, the economic assets are increasing in number, in value and in volume.

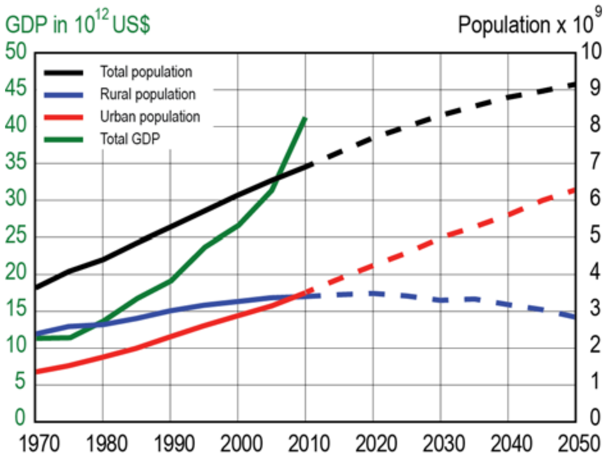


Figure 14 World population 1970 – 2050, total (black), rural (blue) and urban (red) projections in dash lines; GDP 1970-2010 (green).

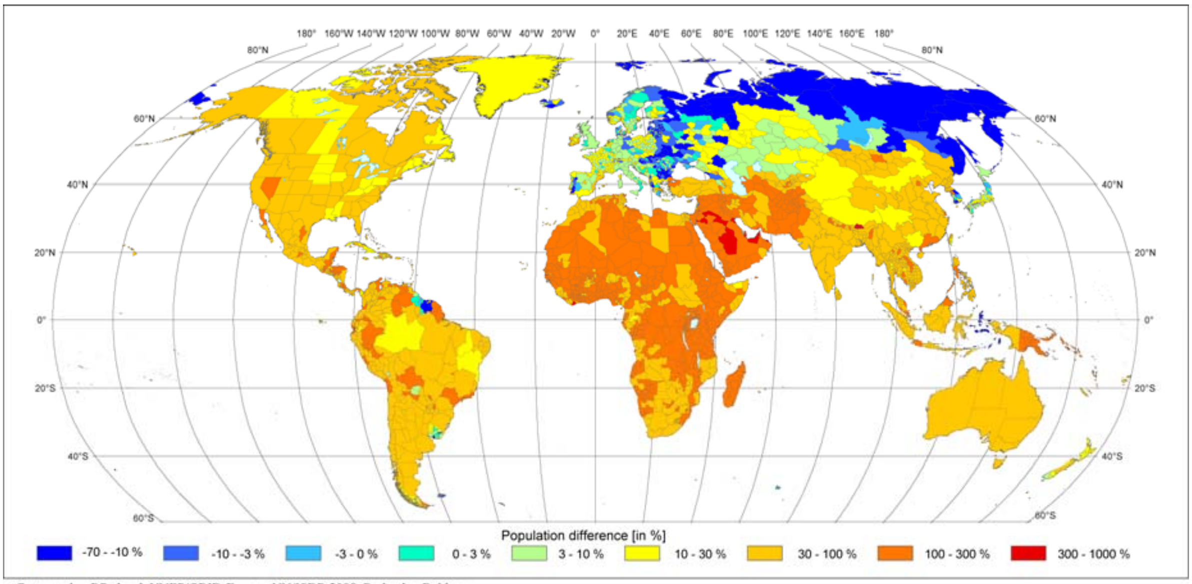
Data sources: UN Population Division, in UNEP geodata portal; Gross Domestic Product (GDP), World Development Indicators (WDI), The World Bank, 2011.

Hypotheses on relevance of changes in demography with regards to disaster risk

An increase in population will increase the number of humans exposed to natural hazards. Addressing these issues requires precise raster models of populations and a methodology for modelling population changes through time (both past and future). Furthermore, city dwellers are highly vulnerable to floods, landslides or tropical cyclones. Not only do slum habitats offer little protection against these hydro-meteorological hazards, but corrugated iron roofs and wood planks can transform into deadly flying objects in tropical cyclones wind conditions. Therefore, it would be interesting to test whether urban populations are more vulnerable to earthquakes, and rural populations more vulnerable to hydro-meteorological hazards.

Numerous large cities (Istanbul, Teheran, Kathmandu, …) are located in very active seismic zones. These include old buildings and retrofitting them is very costly. In the case of earthquakes it would be interesting to know whether urban population are more vulnerable than rural population. This would seem logical as during the day, rural populations are mostly in the fields, whereas urban populations are concentrated in buildings. Also, populations living in slums should suffer fewer impacts from earthquakes. While a corrugated iron roof can be very dangerous during tropical cyclones winds, it should induce limited casualties following an earthquake event. If such hypotheses are confirmed, it would show that the vulnerability of the same population differs depending on the type of hazard exposure and most probably also under different hazard intensities. To study all these hypotheses, statistical regressions, with differentiation between urban and rural population, were carried out. Results are provided in Chapter 3.

The link between demographic and economic growth and risk is not straightforward. Increased exposure does not necessarily mean increased risk. The question of vulnerability needs to be addressed. To identify the underlying factors of risk, such as vulnerability contextual parameters, exposure and hazard intensity, the idea is to see if multi-regression techniques can be used to provide the individual weight associated with each parameter. The methodologies and results are presented in the present thesis (see the part 3.2; published article as part of this thesis) on the Disaster Risk Index (Peduzzi *et al.*, 2009b) for analysis on tropical cyclones, drought, earthquakes and floods) as well as in the Global Risk Analysis (Peduzzi *et al.*, 2009a, Peduzzi *et al.*, 2010) provided in Chapter 3). A more detailed description of the individual event approach and trends in hazard, exposure, vulnerability and risk for tropical cyclones is provided in Chapter 3 (see part 3.5).



Cartography: P.Peduzzi, UNEP/GRID-Europe, UN/ISDR 2008, Projection Robinson
Data sources: Administrative Boundaries - First Level (WHO, 2001), Global Rural - Urban Mapping Project (GRUMP) – CIESIN, Columbia University

Figure 15 Population difference (2007 - 1975)

2.3.2. Unsustainable use of natural resources

As seen above, we may be experiencing (and triggering) the sixth biological extinction (Barnosky, 2011). This is due to habitat destruction (e.g. fragmentation, urbanisation, deforestation); spreading of exotics plants and animals; pollution; over-harvesting (e.g. overfishing); disease; pollution and climate change (Wilson, 1992; McPhee and Flemming; 1999; Thomas *et al.*; 2004; Jackson, 2008). Species are interdependent, thus the initial loss of a few, might lead to exponential losses (Wilson, 1992).

Humans are dependant on biodiversity for surviving: without plants, there would be no oxygen in the atmosphere. There was no oxygen in the form of O_2 in the primitive Earth atmosphere and O_2 appears as a by-product (or waste) of the photosynthesis from algae (Kasting and Siefert, 2002). Our food supplies depend on bacteria and earthworms for soil regeneration (Nicolino and Veillerette, 2007), pollinators (such as bees) for crop pollination (Kluser *et al.*, 2011). Fish represent 16% of our protein intake. Biodiversity also supplies new pharmaceuticals (Barbier and Aylward, 1996).

The increase in population (as well as increasing individual demands) has other effects, which can lead to further environmental vulnerability. To meet the demand of consumers, more crops are grown, more meat is being produced. This requires more water, more agricultural space (or pastures) or more chemicals. Agriculture production has changed by being more intense (more chemicals and industrial processes) as well as more extensive (more areas converted to crop land).

The so called "*green revolution*", boosted the productivity by hectare, but at the expenses of a large dependency on fossil resources, indirectly through the synthesising of large quantities of chemicals (fertilisers, pesticides,...) and directly through extensive needs in agriculture machines for plantation, treatment, harvest, transport, transformation, exportation and packaging of the food (Woods *et al.* 2010). While, this has increased the productivity by hectare, it has - energy wise - a very weak productivity. Each calorie of food produced (from field to the table) requires an average of 7.3 calories of energy input (Heinberg and Bomford, 2009). The increased use of pesticides is causing pollution threatening human health (Nicolino and Veillerette, 2007) and threatening pollinators (Forster, 2009; Bortolotti, 2009; Alaux *et al.* 2010; Wu *et al.* 2011). This is of concern given that about a third of our food is dependant on honeybee pollination, representing a yearly food production valued at US$ 200 billion (Kluser *et al.*, 2011). Some pesticides induce a high mortality rate on natural pest predators (Preetha *et al.*, 2009; Paine *et al.*, 2011), thus potentially requiring more chemicals. They may also inhibit litter breakdown by killing non-target invertebrates such as earthworms (Kreutzweiser *et al.*, 2009; Van Herk *et al.*, 2008).

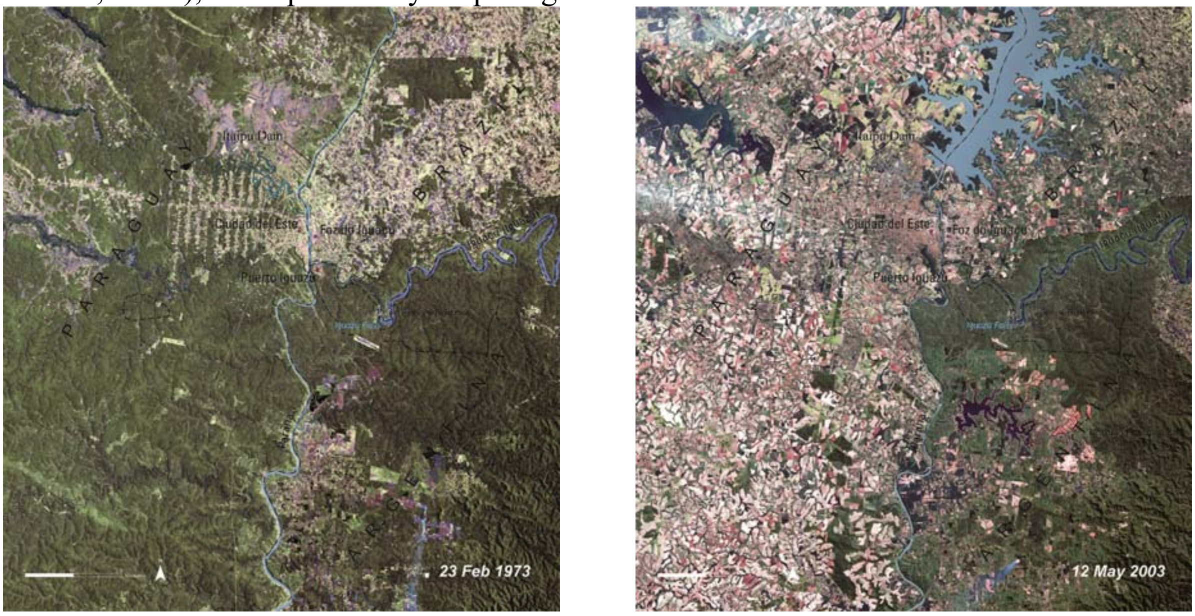


Figure 16 Iguaçu region in 1973 and in 2003 (source: UNEP, 2005)

The increase in area converted to cropland, has several consequences. Firstly the additional space is taken from natural ecosystems. Every year humans are cutting down 130,000 Km^2 of forests (FAO, 2010), mostly for conversion to cropland (Figure 13). In Brazil, between 1996 and 2005 the average clearing was 19,500 km^2/year. This forest conversion to pasture and farmland released 0.7 to 1.4 billion tons of CO_2 equivalents per year to the atmosphere (Nepstad *et al.*, 2009). In 2007, due to reduction of Soya bean prices and Brazilian government action, the deforestation rate was reduced to 11,000 Km^2 (Mahli *et al.*, 2008). Indonesia and Malaysia account for 86% of global palm oil production (Fargione *et al.*, 2008), which is the main cause of deforestation in this region. Palm oil is an important source of edible oil (Corley, 2008) but could also be used for biofuel (Tan *et al.*, 2007). The destruction of tropical rainforests for palm oil releases 17 to 420 times more CO_2 than the annual greenhouse gas (GHG) reductions that these biofuels would provide by displacing fossil fuels (Fargione *et al.*, 2008). Such deforestation has impacts on biodiversity, local and global climate, soil erosion and water supply.

There are large discrepancies between human footprints. Each individual has different standard of living. In 2010, the ratio between highest average GDP per capita (Luxembourg: US$/56,000 year) and lowest (Democratic Republic of the Congo: US$/100 year) was 560. The map in Figure 14 presents an interesting view of the world (as of 2000) showing GDP in anamorphosis, highlights the inequity of wealth distribution. This translates in highly different consumption patterns across the world. In 2007, an USA inhabitant withdrew on average 130 times more water as compared with a Ugandan (1.7 million litres and 13,000 litres per capita respectivelly). An inhabitant from Quatar uses 784 times more energy than an inhabitant from Bangladesh (102 and 0.13 tons equivalent petrol (TEP) per year and per inhabitant, respectively).

The global demand for energy has more than doubled between 1975 and 2007 (IEA, 2009). To feed the world and to transport people and produce goods, the energy required is steadily increasing. In 2010, the demand was over 12,000 Megaton of oil equivalent (Mteo) and there might well be a 36% increase by 2035 (i.e. more than 16,300 Mteo) (WEO, 2010). The demand in China accounts for almost all of the increase (WEO, 2010). There are two issues. Firstly, there is no such thing as petrol producers. The only petrol producers are bacteria and it takes them 200 million years to transform 24 tons of fern into one litre of petrol (Radford, 2005). Imagine placing 24 tons of fern in your tank to do a mere 20 km, this is not very handy; especially if you have to wait 200 millions years before you can use your petrol. This demonstrates how unsustainable our dependency on oil is.

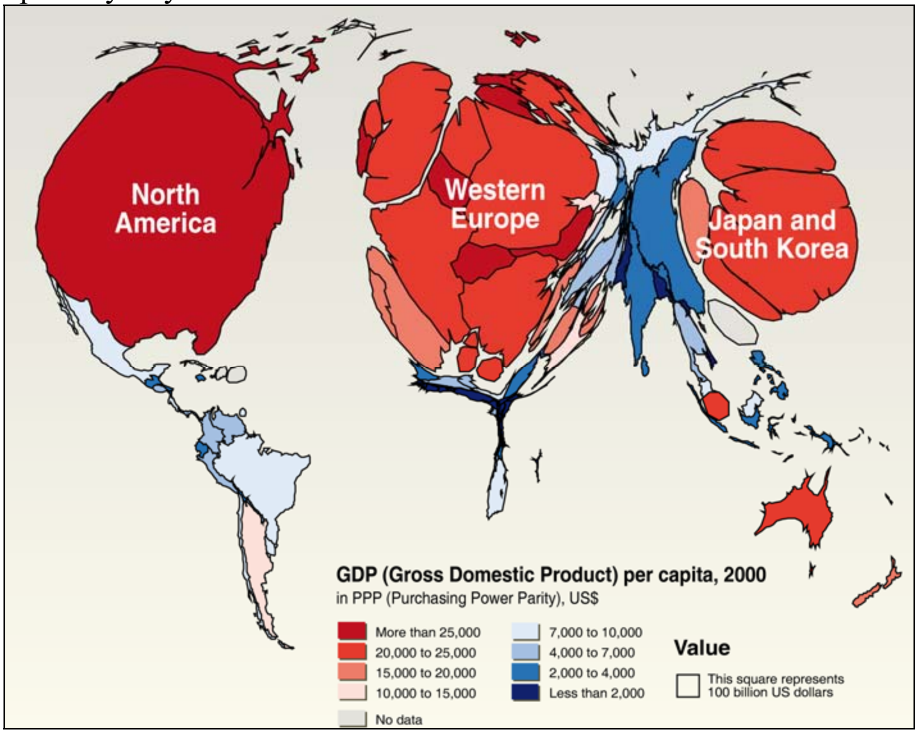


Figure 17 Difference in GDP 2000 (anamorphosis)

Sources: Philippe Rekacewicz, UNEP/GRID-Arendal, Vladimir S. Tikunov

Not only is the number of individuals increasing, but so is their individual demand. Gains in engine efficiency are offset by the increasing number of cars by inhabitants and the longer average distance travelled per year as well as the new fashion for SUV (25% of the new vehicles sold in Switzerland in 2006). The total distance travelled by cars in Switzerland in 2007 adds up to 87.5 billion km (OFS, 2011), i.e. 227,626 times the distance Earth - Moon. The Swiss population has increased by 16% between 1990 and 2010, however, the number of cars showed a 43% increase. The number of cars per thousand inhabitants in Switzerland, increased from 596 to 735 (OFS, 2010).

Most economic growth is based on extraction of natural resources at an unsustainable rate. One cannot catch more fish than the numbers that hatch each year, or cut more trees than the number that grow. This is not a new concept, already in the 1950s, Kenneth Boulding made a now famous statement: "*to believe in unlimited growth in a finite world one had to be either a fool or an economist!*". In their report The Limits of Growth (Meadow *et al.*, D.H., 1972) the Club of Rome came to the same conclusion. This report was heavily criticised in the 1970s by economists, even going as far as saying that the conclusions in the report were "*complete nonsense*". Alas, the hypothesis with a 30 years reality check appears to be largely confirmed and reflects what is currently happening (Meadows *et al.*, 2004; Turner, 2008). In his paper, Turner compares the different scenarios from the Club of Rome and 30 years of historical data. His analysis shows that a business-as-usual scenario (called the "*standard run*" scenario) would result in collapse of the global system midway through the 21st Century. Other economists have highlighted the need for zero growth. For example, Georgescu-Roegen (1971; 1979), applied Newton’s law of thermodynamics to the economy to demonstrate the impossibility for economic growth to continue. Other mathematical models were used to criticize the neoclassical growth theory (Nelson and Winter, 1982). Nevertheless, calls for reducing human footprints to avoid general collapse (Kitzes *et al.* 2007) were largely ignored. Although common sense dictates that continual growth based on finite resources is not feasible; a simple observation on current uses of natural resources indicates that common sense does not prevail.

Relevance of the unsustainable use of natural resources with regards to disaster risk

Priority 4 of The Hyogo Framework for Action (HFA) "*encourages the sustainable use and management of ecosystems,* [for] *reducing the underlying risk*" (UNISDR, 2005). The interest for the use of ecosystems in DRR showed a sharp increase following the 2004 Indian Ocean Tsunami. However, in this case the claims regarding the protection of coral reefs as well as mangroves appeared to lack scientific basis (Kerr *et al.*, 2006; Chatenoux and Peduzzi, 2007; Baird and Kerr, 2008; Cochard *et al.*, 2008). A scientific approach for quantifying and demonstrating the role of ecosystems in mitigating hazard is needed. This would help to restore (or maintain) these ecosystems and related contribution for DRR. However, to quantify the role of ecosystems in DRR, tools are needed, which allows for the isolation from the other factors (see 4.4).

The decline of ecosystems may influence the hazard susceptibility. Deforestation is also brought about by forest fires. Biomass burning constitutes a major contribution to global emissions of carbon dioxide, carbon monoxide, methane and aerosols (Tansey *et al.*, 2004). Deforestation induces several impacts on the climate. It emits about 17.4% of GHG (Solomon *et al.*, 2007) hence contributing to higher temperatures (red feedback in Figure 18). Deforestation also reduces precipitations (Hasler *et al.*, 2009). Hence, this might lead to more frequent/severe drought and under drought conditions, forest fires are more likely to occur (Van der Werf *et al.*, 2008) (orange feedback in Figure 18).

Higher CO_2 concentrations, were supposed to increase photosynthesis (Nemani *et al.*, 2003) ; but recent measurements on the warmest decades (2000-2009) show that the creation of biomass is decreased. (Zao and Running, 2010). CO_2 is not the only material needed for photosynthesis, it also requires H_2O as well as fertile soils, which may be the limiting factors. With less biomass produced, less CO_2 is being absorbed (grey feedback in Figure 18).

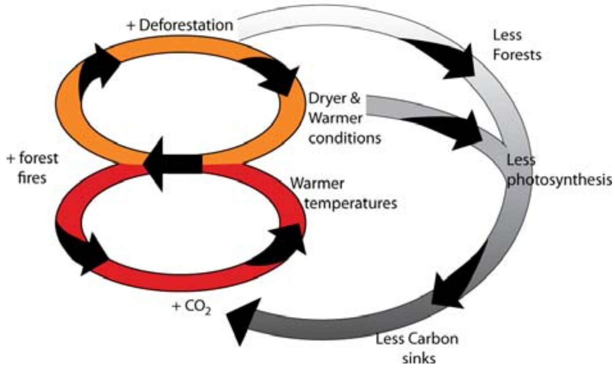


Figure 18 Triple positive feedbacks between deforestation, drought, forest fires and climate change. Graph P. Peduzzi 2011 (IPCC, in prep.)

Forests (and other biomass) might also reduce the susceptibility to landslides (Popescu, 2002¸ Vanacker *et al.*, 2003). The presence of coastal vegetation and coral reef may also contribute to mitigate disaster risk associated with storm surges and may reduce coastal erosion (UNEP, 2010; Peduzzi *et al.*, in prep.). However, to validate such statements, scientific tools and studies are needed. These are presented in point 4.4, for links between vegetation density and landslide susceptibility.

2.3.3. Climate change

While the decline of ecosystems occur locally (with the exception of overfishing) and mostly impact local populations in sustaining their livelihood (cumulative change), climate change is different since the consequences can differ in time and space with the causes. For instance GHG is largely emitted by inhabitants and industries of the northern hemisphere , with two countries, China and USA emitting approximately 40% of global CO_2 emissions, and about 35% of total GHGs (Leggett *et al.*, 2008). Emissions are far from small islands, which may nevertheless loose part of their territory as a result of the rise in sea level triggered by global warming (systemic change). Also, effects are not immediate and there could be several decades (hence generations) between emissions of GHG and consequences from related global warming.

Global temperatures rose by 0.74°C since 1900 (Solomon *et al.*, 2007); our climate is warming up at an increasing rate (Solomon *et al.*, 2007). To the natural greenhouse effect (e.g. produced by gas released by volcanic eruptions, swamps,…), is added the effect resulting from human activities. As compared to pre-industrial era, carbon dioxide (CO_2) concentration in the atmosphere is 35% higher (mostly due to the use of fossil fuel and forest fires). Concentration of methane (CH_4) is 148% higher, (mostly due to agriculture, cattle,...). Other GHG include tropospheric O_3, N_2O, black carbon on snow and linear contrails, while some substances have a cooling effect: such as stratospheric O_3, aerosol, cloud albedo (see Figure 19). However, the overall resulting radiative forcing (RF) is 1.66 W m^{-2} (Solomon *et al.*, 2007).

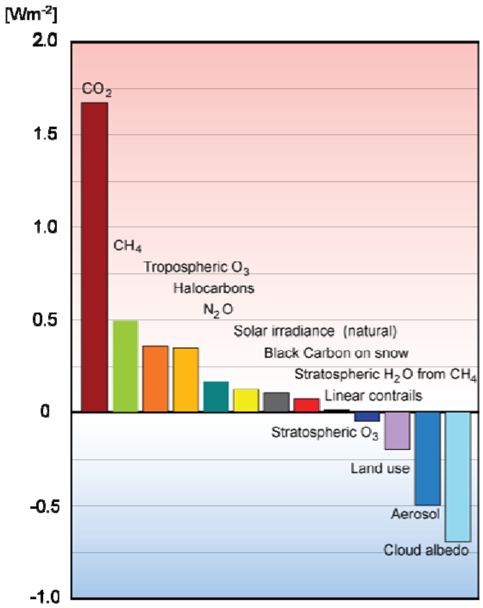


Figure 19 GLobal mean radiative forcing (RF) [W m-2], the resulting from anthropogenic RF is 1.66 Wm-2

data sources, IPCC, AR4, **Climate Change 2007: Working Grou**p I: The Physical Science Basis.) graph. Modified after IPCC (Solomon *et al.*, 2007).

The concentration of CO_2 in 2006, was one third higher than in the past 600,000 years (see Figure 20).

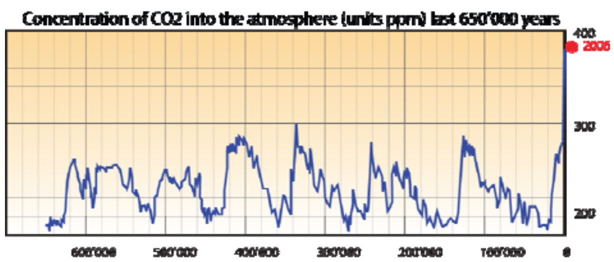


Figure 20 $_{CO2}$ concentration reached 380 ppm. Prior to the industrial era, the level of 300 ppm was never crossed in the last 650'000 years (data sources: Sources: http://www.realclimate.org/index.php/archives/2005/11/650000-years-of-greenhouse-gas-concentrations/) Graph modified after IPCC (Solomon *et al.*, 2007).

In the last two decades global temperatures are the warmest since records began in 1855 (see Figure 21).

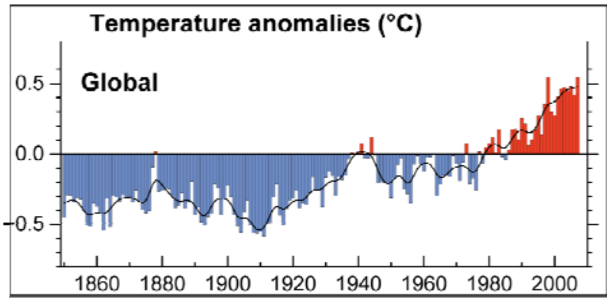


Figure 21 Past global temperatures as recorded (Solomon *et al.*, 2007).

Attempts to reduce GHG (called mitigation actions) have failed to meet the targets set (see results from COP 15, Copenhagen, Denmark). In COP 16 (Cancun, Mexico, 2010) Japan threatened to oppose the establishment of the second commitment period, arguing the need for a new international legally-binding framework with the participation of all major economies, including the USA and China, Despite the fact that these two countries are jointly responsible for 40% of global energy-related CO_2 emissions neither is not committed to emission reduction targets under the Kyoto Protocol.

The Montreal protocol has been hailed as a major success (Farman, 2001). It is an example of a problem perceived and attempts to solve it and showing encouraging results (still not guaranteed). Without saying that it was easy, it was at least eased by the fact that it was addressing a single issue: chlorofluorocarbons (CFCs) emissions, for which substitutes were available (Farman, 2001). Climate change is another kettle of fish. Figure 22 shows that climate change has multiple roots embedded at the heart of human activities: agriculture, forestry, deforestation, waste, energy supply, transport, residential and industry (Solomon *et al.*, 2007).

In some situations (extreme events or extreme impacts) adaptation may no longer be an option and might lead to extreme interventions such as evacuating the population of a selected region, the abandon of a whole economic sector in a specific location, or the extinction of species.

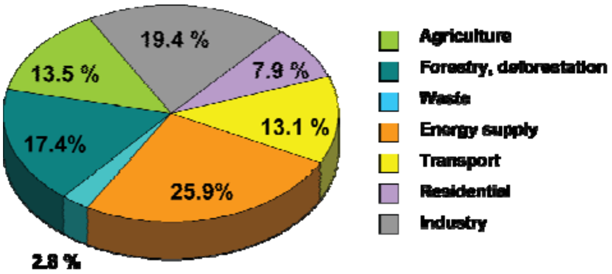


Figure 22 Share of GHG emission by sectors

data sources, IPCC, AR4, Climate Change 2007: Working Group I: The Physical Science Basis.) graph modified after IPCC (2007).

This is specifically of concern to some societies and cultures living in places highly sensitive to climate change: e.g. population living in low elevation coastal areas (especially islands) whose territories may be submerged by a rise in sea levels or by storm surges; populations living in areas where water supply during the dry season is provided by glaciers; agriculture in dry land facing decrease in precipitation and crop failure risk (Parry *et al.*, 2007). Tourism is a sector of activities which, in some locations, can be deeply affected by extreme events or by extreme impacts from incremental changes. This is true for tourism depending on beaches facing coastal erosion from sea level rise, diving activities where coral bleaching may decrease the attractivity of diving spots; but also low elevation ski resorts, where warming temperatures will reduce length (or confidence) of snowy season or increase the variability in snow precipitations (Beniston, 2003).

In our globalised world, individuals may migrate (at least in theory) and economic sectors may change to seek alternative forms of revenues. However, this is not the case of several ecosystems, e.g. polar (Post *et al.*, 2009; Parmesan, 2006) and mountainous ecosystems (Beniston, 2003; Easterling *et al.*, 2000) or coral reefs (Aronson *et al.*, 2000) here there are temperature thresholds above which survival of selected species is no longer possible. In these cases, the only hope depends on international efforts in mitigating GHG.

Climate change is also inducing its own dynamics. Positive feedbacks are being identified, such as the decline of permafrost releasing large quantities of CH_4 (Christensen *et al.*, 2004). Another example is the ice albedo feedback. When the extent of sea ice reduces (due to global warming), the albedo is also largely reduced, thus more energy can reach the sea and water warms up, further decreasing the extent of sea ice. Such positive feedbacks are well described (Parkinson, 2004). The comparison between maximum sea ice extent in 1979 and 2007 shows an acute retreat of arctic see ice (Figure 23). Interestingly one study (Kato *et al.*, 2006) shows a surprising increase in cloudiness over the Arctic which has helped to compensate the decline of sea ice albedo, at least between 2000 and 2004.

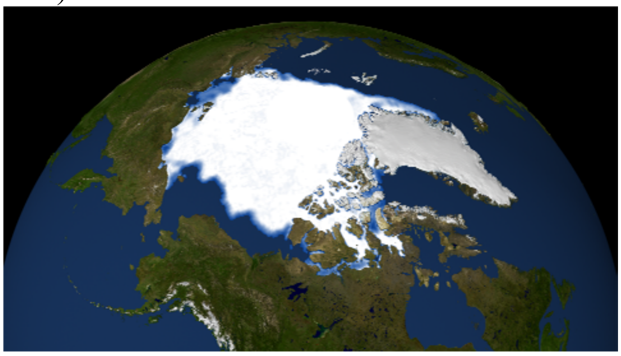
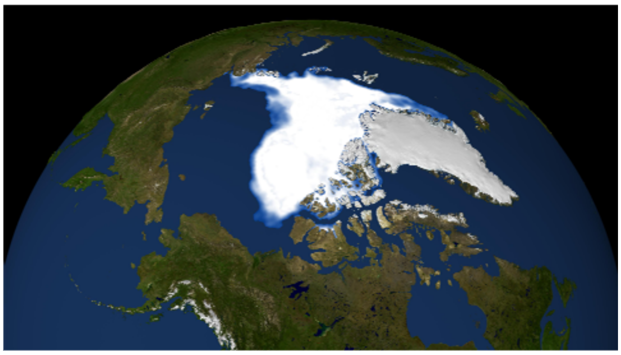



Figure 23 Reduction of artic ice cap beween 1979 and 2007, NASA.

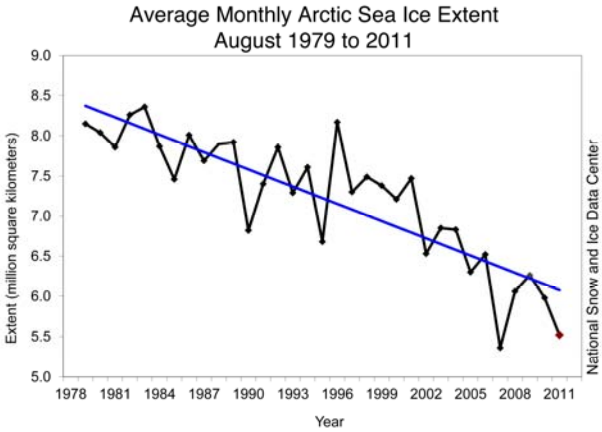


Figure 24 Average monthly arctic sea ice extent 1979 to 2011 (NSIDC, 2011)

Relevance of climate change with regards to risk

Climate change has multiple consequences on risk. Firstly it may impact the frequency and severity of hydro-meteorological hazards (see Table 3).

Table 3 Climate change impacts on natural hazards (frequency and intensity), probability of attribution to human activities

Phenomenon and direction of trend	Likelihood that trend occurred in late 20th century (typically post 1960)	Likelihood of a human contribution to observed trend	Likelihood of future trends based on projections for 21st century using SRES scenarios
Warmer and fewer cold days and nights over most land areas	Very likely	Likely	Virtually certain
Warmer and more frequent hot days and nights over most land areas	Very likely	Likely (nights)	Virtually certain
Warm spells/heat waves. Frequency increases over most land areas	Likely	More likely than not	Very likely
Heavy precipitation events. Frequency (or proportion of total rainfall from heavy falls)increases over most areas	Likely	More likely than not	Very likely
Area affected by droughts increases	Likely in many regions since 1970s	More likely than not	Likely
Intense tropical cyclone activity increases	Likely in some regions since 1970	More likely than not	Likely

Sources: IPCC, AR4, Climate Change 2007: Working Group I: The Physical Science Basis.

The question of the influence of climate change on tropical cyclone hazard has been strongly debated (Webster *et al.*, 2005; Chan, 2006; Webster *et al.*, 2006; Kerry, 2005; Hoyos, 2006). Such research is complex and under high scrutiny from both the scientific and political communities. Trends in tropical cyclone hazards are rendered difficult to map due to the lack of long-time data series or lack of comparable data. Improvements in methodologies and instruments for recording data (such as increase in satellite sensors resolution, day night detection, or improvement in the Dvorak methodologies) may drastically limit the possibility to assess changes (Landsea *et al.*, 2006).

But climate change has also indirect impacts on risk. One of them is to induce a rapid glacier retreat (Zemp *et al.*, 2008, Bates *et al.*, 2008). In regions were rains are concentrated in a few rainy season months; the higher altitude limit between rain and snow precipitations induces a high amount of water in the rainy season (with higher altitude, the collection of liquid water is over a larger areas); thus it might result in higher frequency of floods. During the dry months, the reduction of snow and ice volume leads to less water from melting glaciers, thus potentially inducing more frequent/severe agricultural droughts (Benistion, 2003; Parry *et al.*, 2007).

The retreat of glaciers also uncovers debris, which might lead to debris flows under high precipitations. Creation of high altitude lakes is also common. These lakes have fragile natural dams made of moraines. These may collapse, e.g. as a consequences of earthquakes. Also, avalanches and other material may fall into these lakes leading to overflows. This is particularly of concern in the Andean and Himalayans mountains as well as in central Asia, due to high seismicity (see Box 2).

Box 2 The Yungai disaster 1970.

On 31 May 1970, a violent earthquake (7.9 on Richter scale) located on the coast of Peru (9.2° South, 78.8° West), killed 66,794 people. However, one third of them did not die directly from the earth shaking. Rather, the earthquake shook Monte Huascarán, causing the loosening of large ice cornices which fell into a high altitude glacial lake. The overflow brought 50 to 100 million of m3 of mud and debris flow which surged at an average speed of 280 km per hour down the slopes of Mount Huascarán North (Peru). It devastated a 25 km long strip of the valley, wiping out the cities of Ranrahirca and Yungay and killing 18 to 22 thousand people (UNEP/GRID-Geneva, 2002, USGS, 2010).

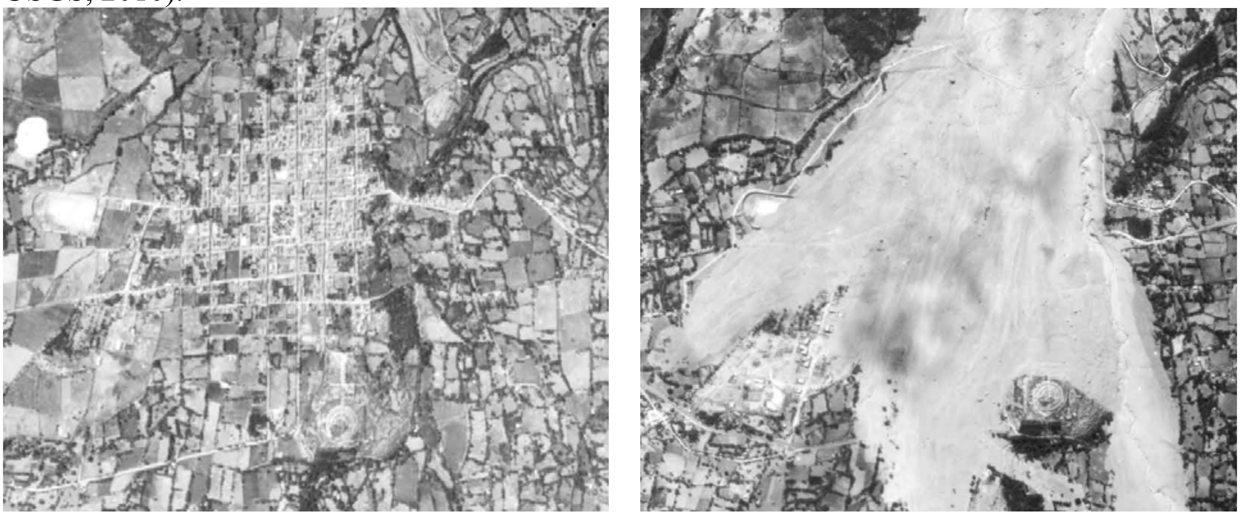


Figure 25 Pictures of Yungai (Peru) in 1962 (left) and after the avalanche of 1970 (right). Almost nothing remains of Yungay city, literally erased by the avalanche. (Silverio, 2002)

A succession of events can lead to complex situations. While climate change has no major effect on seismicity (except from post-glacial rebound due to the isostasy effect (Peltier, 1998; Sella *et al.*, 2007), it has a significant impact on glacier retreat (Zemp *et al.*, 2008; Bates *et al.*, 2008) thus leading to the formation of high altitude lakes. As a result of an earthquake, large quantity of material may fall into these lakes, creating Global Lake Outburst Flood (GLOF). Hence through complex interactions, climate change may exacerbate risk from earthquake hazards.

In this publication, GIS and remote sensing methodologies are developed to monitor the glacier retreat over Coropuna glacier (Peru) and to estimate the remaining ice (see part 4.2).

During the heatwave that affected Europe in 2003, several disruptions were recorded. The record high level of temperatures associated with drought conditions, led to high mortality rates as well as disruption of inland navigation, irrigation and nuclear power-plant cooling. Some of these nuclear power plants had to be shut down (Beniston and Díaz, 2004; De bono *et al.*, 2004). Temperatures were also very high in North America in 2003. The demand for electricity for air conditioning exceeded the capacity of the electricity network, leading to a major black out affecting 65 millions inhabitants. In Figure 26, the city of Toronto and Long Island can no longer be seen on the right image due to the blackout.

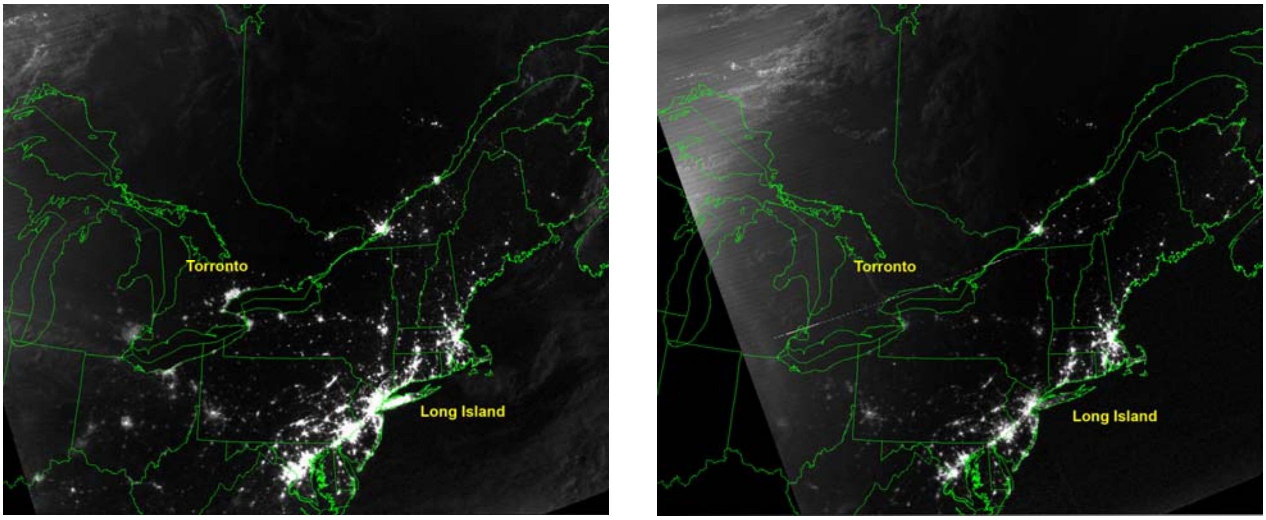


Figure 26 Image of 14 August 2003 (left) and 15 August 2003 (right) showing the 2003 North American black out, as seen from the Defence Meteorological Satellite Program (DMSP), Image sources : US Air Force (NASA, 2003)

Climate change is also inducing an accelerated sea level rise (ASLR). While the observed rate of sea level rise was about 1.8 ± 0.5 mm per year during the period 1961 - 2003, the rise was of 3.1 ± 0.7 mm per year during the years 1993 - 2003 (IPCC, 2007). Several processes are triggering this ASLR. Thermal expansion (58%), the decline of glaciers and ice caps (28%) and the decline of ice sheets (15%) (IPCC, 2007). Sea level rise increases coastal erosion, exacerbates impacts from storm surges and reduces the territories of low-lying small islands and coastal areas (Solomon *et al.*, 2007).

2.4. References

Alaux,C., Brunet, JL., Dussaubat, C., Mondet, F., Tchamitchan, S., Cousin, M., Brillard, J., Baldy, A., Belzunces, LP., Le Conte, Y., Interactions between Nosema microspores and a neonicotinoid weaken honeybees (Apis mellifera), *Environmental Microbiology*, **12**(3), 774–782, 2010.

Alder D.P.J., Bennett E., Christensen V., Tyedmers P., Watson R., The Future for Fisheries. *Science* **302**, 1359-1361, 2003.

Alroy, J. Dynamics of origination and extinction in the marine fossil record. *Proc. Natl Acad. Sci. USA* **105**, 11536–11542, 2008.

Aronson, R.B., W.F. Precht, I.G. Macintyre, and T.J.T. Murdoch, Coral bleach-out in Belize. Nature, **405**(6782), 36, 2000.

Baird, A.H., Kerr, A.M., Landscape analysis and tsunami damage in Aceh: comment on Iverson and Prasad (2007), Landscape Ecology, 23 (1), 3-5, 2008.

Barbier, E.B. and Aylward, B.A., Capturing the pharmaceutical value of biodiversity in a developing country,

Barnosky, A.D., Matzke, N., Tomiya, S., Wogan, G.O.U., Swartz, B., Quental, T.B., Marshall, C., McGuire, J.L., Lindsey, E.L., Maguire, K.C., Mersey B., Ferrer, E.A., Has the Earth's sixth mass extinction already arrived?, *Nature*, **441**, 51-57, 2011.

Bates, B.C., Z.W. Kundzewicz, S. Wu and J.P. Palutikof, Eds.,: *Climate Change and Water*. Technical Paper of the Intergovernmental Panel on Climate Change, IPCC Secretariat, Geneva, 210 pp., 2008.

Beniston, M., Diaz, H.F., The 2003 heat wave as an example of summers in a greenhouse climate? Observations and climate model simulations for Basel, Switzerland, *Global and Planetary Change*, **44**(1-4), 73-81, 2004.

Beniston, M., Climatic change in mountain regions: a review of possible impacts. *Climatic Change*, **59**, 5-31, 2003.

Birkman, J., conceptual frameworks and definitions, *Measuring vulnerability to promote disaster-resilient societies*, 9-54, United Nations University, United Nations University Press, Tokyo, New York, Paris, 527 pp., 2006.

Birkmann, J., and others, *Measuring Vulnerability to natural hazards, towards disaster resilient societies*, United Nations University, 527 p., TERI Press, New Delhi, India, 2006.

Blaikie, P. *et al.*, *At Risk: Natural Hazards, Peoples Vulnerability and Disasters* (Routledge), 284 p., 1996.

Bortolotti, L., Gloria Sabatini, A., Mutinelli, F., Astuti, M., Lavazza, A., Piro, R., Tesoriero, D., Medrzycki, P., Sgolastra, F., Porrini, C., Spring honey bee losses in Italy, Hazards of pesticides to bees – 10th International Symposium of the ICP-Bee Protection Group, *Julius-Kühn-Archiv* **423**, 148-152, 2009.

Burton, I., Kates, R.W., and White, G.F., *The environment as hazard*, 2nd Ed. New York: Guilford Press, 1993.

Chan, J.C.L., Comment on "Changes in Tropical Cyclone Number, Duration, and Intensity in a Warming Environment, *Science* **311**, 1713b (2006).

Cardona, O.D., The need for rethinking the concepts of vulnerability and risk from a holistic perspective: a necessary review and criticism for effective risk management, in *Mapping vulnerability: disasters, development and people*, Bankoff, G., Frerks, G., Hilhorst, D. (Ed), Earthscan Publishers, London.

Chatenoux, B., Peduzzi, P., Impacts from the 2004 Indian Ocean Tsunami: analysing the potential protecting role of environmental features, *Natural Hazards*, **40** (2), 289-304, 2007.

Christensen, T.R.,Johansson, T., Åkerman, H.J., Mastepanov, M., Malmer, N., Friborg, T., Crill, P., Svensson, B.H., Thawing sub-arctic permafrost: Effects on vegetation and methane emissions, Geogphysial research letters, 31, 1-4, 2004.

Coburn, A.W., Spence R.J.S., Pomonis A., Vulnerability and risk assessment. *UNDP Disaster Management Training Program*, **57**, 1991, p.49.

Cochard R., Ranamukhaarachchi S.L., Shivakoti G.P., Shipin O.V., Edwards P.J., Seeland K.T., The 2004 tsunami in Aceh and Southern Thailand: A review on coastal ecosystems, wave hazards and vulnerability, Perspectives in Plant Ecology, *Evolution and Systematics*, **10** (1), pp. 3-40, 2008.

Corley, R.H.V. How much palm oil do we need? *Environmental Science & Policy*, **12**(2), 134-139, 2009.

Cruz, A.M., Steinberg, L.J., Vetere-Arellano, A.L., Emerging Issues for Natech Disaster Risk Management in Europe, *Journal of Risk Research*, **9**(5), 483-501, 2006.

Darwin, C., *On the Origin of Species by Means of Natural Selection, or the Preservation of Favoured Races in the Struggle for Life*, London: John Murray, pp. 502, 1879.

De Bono, A., Peduzzi, P., Kluser, S., Giuliani, G., Impacts of Summer 2003 Heat Wave in Europe, *Environment Alert Bulletin*, UNEP/GRID-Geneva, **2**, 1-4, 2004.

http://www.grid.unep.ch/product/publication/download/ew_heat_wave.en.pdf, last checked: 26 April 2011.

Easterling, D.R., G.A. Meehl, C. Parmesan, S.A. Changnon, T.R. Karl, and L.O. Mearns, Climate extremes: observations, modeling, and impacts, *Science*, **289**(548), 2068-2074, 2000.

Environmental and Resource Economics, **8**(2), 157-181, 1996.

FAO, *Global Forest Resources Assessment 2010*, Food and Agriculture Organization of the United Nations, 378 pp., Rome, 2010. http://www.fao.org/docrep/013/i1757e/i1757e.pdf, last accessed 30 April 2011.

FAO, *The State of the World Fisheries and Aquaculture*. Rome, 2002.

Fargione, J., Hill, J., Tilman, D., Polasky, S., and Hawthorne, P., Land Clearing and the Biofuel Carbon Debt, *Science*, **319** (5867), 1235-1238, 2008.

Farman, J., Halocarbons, the ozone layer and the precautionary principle, *Late lessons from early warnings: the precautionary principle 1896-2000*, European Environment Agency, Copenhagen, Denmark, p.76-83, 2001.

Fletcher, L.E., Christensen, I.A., Liberda, J.J., Rojas G.J.I., Borrero del Pino, C., Nuria, B.D., Methods of Multivariable Earthquake Precursor Analysis and a Proposed Prototype Earthquake Early Warning System, 2007. http://upcommons.upc.edu/e-prints/bitstream/2117/1467/1/TREMOR-AGU-Paper_Ver6.pdf, last accessed: 29 April 2011.

Forster, F., Bee poisoning caused by insecticidal seed treatment of maize in Germany in 2008, *Julius-Kühn-Archiv* **423**, 2009.

Fournier d'Albe, E.M., Objectives of volcanic monitoring and prediction, *Journal of the Geological Society*, **136**, 321-326, 1979.

Georgescu-Roegen, N., *Demain, la décroissance: entropie-écologie-économie*, Pierre Marcel Favre, 1979.

Georgescu-Roegen, N., *The entropy law and the economic process.* Harvard University Press. Cambridge, Massachusetts, 457 p., 1971.

Giuliani, G., De Bono, A., Kluser, S., Peduzzi, P., Overfishing, a major threat to the global marine ecology, *Environment Alert Bulletin* **4**, 1-4, UNEP/GRID-Geneva, 2004.

Glantz M. H., editor. *Creeping environmental problems and sustainable development in the Aral Sea basin.* Cambridge University Press, Cambridge, UK, 1999.

Tobin, G.A. and Montz, B.E., *Natural Hazards: Explanation and Integration*. Guilford Publishing: New York, 388 p., 1997.

Halpern, B.S., Walbridge S., Selkoe K.A., *et al.*, 2008. A global map of human impact on marine ecosystems. *Science*, **319** (5865), 948–952, 2008.

Hasler N., Werth D. and Avissar R., Effects of Tropical Deforestation on Global Hydroclimate: A Multimodel Ensemble Analysis, *J. Climate* **22**, 1124–1141, 2009.

Heinberg, R. & Bomford, M., *The Food and Farming Transition: towards a post carbon food system*. Post Carbon Institute, 39 pp., 2009.

Hettler, J., Irion, G., Lehmann, B., Environmental impact of mining waste disposal on a tropical lowland river system: a case study on the Ok Tedi Mine, Papua New Guinea, *Mineralium Deposita*, 280-291, 1997.

Hoyos, C.D., Agudelo, P.A., Webster, P.J., Curry, J.A., Deconvolution of the Factors Contributing to the Increase in Global Hurricane Intensity, *Science* **312**, 94-97 (2006).

IEA, *World Energy Outlook*, International Energy Agency,736 pp., 2010

IEA, Final Energy Consumption (1971 - 2007), International Energy Agency (IEA), 2009, in *Geodata portal*, UNEP, 2010. http://geodata.grid.unep.ch, last consulted 25 April 2010.

Image courtesy Chris Elvidge, U.S. Air Force, accessed from the NASA Earth Observatory, 2003. http://earthobservatory.nasa.gov/NaturalHazards/view.php?id=11982, last accessed: 30 April 2011.

Jackson J.B.C., Ecological extinction and evolution in the brave new ocean. *Proc Natl Acad Sci USA* **105**(Suppl):11458–11465, 2008.

Jones, R.N. and Boer, R., Assessing Current Climate Risks, in Lim, B., Carter, I. and al Huq, S. (eds). *Adaptation Policy Framework*, Technical Paper 4, United Nations Development Programme, New York, 2003.

Kasting, J.F., Siefert, J.L., Life and the Evolution of Earth's Atmosphere, *Science*, **296**, 1066-1068, 2002.

Kato S., Loeb, N.G., Minnis, P., Francis, J.A., Charlock, T.P., Rutan, D.A., Clothiaux, E.E., and Sun-Mack, S., Seasonal and interannual variations of top-of-atmosphere irradiance and cloud cover over polar regions derived from the CERES data set. *Geophysical Research Letters*, **33**, L19804, 2006.

Kerr, A.M., Baird, A.H., Campbell, S.J., Comments on "Coastal mangrove forests mitigated tsunami" by K. Kathiresan and N. Rajendran [Estuar. Coast. Shelf Sci. 65 (2005) 601-606]. *Estuarine, Coastal and Shelf Science*, **67** (3). pp. 539-541, 2006.

Kerry, E., Increasing destructiveness of tropical cyclones ove the past 30 years, *Nature* **436** (4), 686-688, 2005.

Kitzes, J., Peller, A., Goldfinger, S., Wackernagel, M., Current Methods for Calculating National Ecological Footprint Accounts, *Science for Environment & Sustainable Society*, **4** (1), 1-9, 2007.

Kluser, S., Neumann, P., Chauzat, M.P., Pettis, J.S., Global honey bee colony disorders and other threats to insect pollinators, *UNEP emerging issues*, 1-12, 2010.

Kreutzweiser, D.P., Thompson, D.G., Taylor, A., Scarr, T.A., Imidacloprid in leaves from systemically treated trees may inhibit litter breakdown by non-target invertebrates, *Ecotoxicology and Environmental Safety* **72**,1053–1057, 2009.

Landsea, C.W., Harper, B.A. , Hoarau, K. , Kaff, J. . Can we detect trends in extreme tropical cyclones?, *Science*, **313**, 452-454 (2006).

Leggett, J.A., Logan, J., Mackey, A., China's Greenhouse Gas Emissions and Mitigation Policies, Congressional research Service Report for Congress, 32 pp., 2008. http://www.fas.org/sgp/crs/row/RL34659.pdf, last accessed 30 April 2011.

MacPhee R.D.E., Flemming C., *In Extinctions in Near Time: Causes, Contexts, and Consequences*, ed MacPhee RDE (Plenum, New York), 333–372, 1999.

Malhi, Y., Roberts, J.T. Betts, R.A., Killeen, T.J., Li, W., Nobre, C.A., Climate Change, Deforestation, and the Fate of the Amazon, *Science* **319**, 169 (2008).

Malm, O., Gold Mining as a Source of Mercury Exposure in the Brazilian Amazon, *Environmental Research*, **77**(2), 73-78, 1998.

Meadows, D.H. and others, *The Limits of Growth. A Report for The Club of Rome's Project on the Predicament of Mankind*, Universe Books, 381 Park Avenue South, New York, 1972.

Meadows, D.H., Meadows, D.L. and Randers, J., *Limits to Growth: The 30-Year Update*. Chelsea Green, Publishing Company, White River Junction, Vermont, 2004.

Mitchell, J.K. Human dimensions of environmental hazards, complexity, disparity, and the search for guidance, 1990, In Tobin, G.A. & B.E., Montz., *Natural Hazards: explanation and integration*, Guilford Press, New York, 1997.

Mustafa, D., Structural causes of vulnerability to flood hazard in Pakistan, *Economic Geography*, **74**(3), 289-305, 1998.

NASA, 2010: Toxic Sludge in Hungary, Earth Observatory. http://earthobservatory.nasa.gov/NaturalHazards/view.php?id=46360, last accessed: 30 April 2011.

Nelson, R. and Winter, S., *An evolutionary theory of economic change*, Belknap, Cambridge, Mass., Harvard University Press, 439 p., 1982.

Nemani, R., Keeling, C., Hashimoto, H., Jolly, W., Piper, S., Tucker, C., Myneni, R., Running, S., Climate-driven increases in global terrestrial Net Primary Production from 1982 to 1999. *Science*, **300** (5625), 1560-1563, 2003.

Nepstad, D., and others, The End of Deforestation in the Brazilian Amazon, *science*, **326** (5958), 1350-1351, 2009

Nicholls, R.J., Coastal megacities and climate change, *GeoJournal*, **37**(3), 369-379, 1995.

Nicolino, F. and Veillerette, F., Pesticides : révélation sur un scandale français, Fayard, pp. 379, 2007.

NSIDC, *Average monthly arctic sea ice extent 1979 to 2011,* National Snow and Ice Data Center, 2011. Http://nsidc.org/. Last accessed: September 2011.

Number of cars registered in Switzerland, Office Fédéral de la Statistique, http://www.bfs.admin.ch/, last consulted 25 April 2010.

OFS, *Environnement Indicateurs, Transport et mobilité - Prestations de transport de personne*, Office fédéral de la statistique, 2011. http://www.bfs.admin.ch/bfs/portal/fr/index/themen/02/06/ind13.indicator.130405.1374.html

Paine, T.D., Hanlon, C.c., Byrne, F.J., Potential risks of systemic imidacloprid to parasitoid natural enemies of a cerambycid attacking Eucalyptus, *Biological control*, **56**(2), 175-178, 2011.

Parkinson, C., Southern Ocean sea ice and its wider linkages: insights revealed from models and observations. *Antarctic Science*, **16** (4), 387-400, 2004.

Parmesan, C., Ecological and evolutionary responses to recent climate change. *Review of Ecological and Evolution Systems*, **37**, 637-669, 2006.

Parry ML, Canziani OF, Palutikof JP, van der Linden PJ, Hanson CE, eds., *Climate Change 2007: Impacts Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, UK: Cambridge Univ. Press, 2007.

Peduzzi, P., Chatenoux, B., Dao, H., De Bono, A., Deichmann, U., Giuliani, G., Herold, C., Kalsnes, B., Kluser, S., Løvholt, F., Lyon, B., Maskrey, A., Mouton, F., Nadim, F., Smebye, H., The Global Risk Analysis for the 2009 Global Assessment Report on Disaster Risk

Reduction, International *Disaster and Risk Conference (IDRC) Davos 2010*, 1-6, 2010a. http://www.grid.unep.ch/product/publication/download/peduzzi_etal_IDRC2010.pdf, last checked: 26 April 2011.

Peduzzi, P., Dao, H., Herold, C., Rochette, D., Sanahuja, H., Feasibility Study Report On Global Risk And Vulnerability Index –Trends per Year (GRAVITY), scientific report for For United Nations Development Programme Emergency Response Division, UNDP/ERD, UNEP/GRID-Geneva, 79 pp., 2001.

Peduzzi, P., Deichmann, U., Maskrey, A., Nadim, F., Dao, H., Chatenoux, B., Herold, C., Debono, A., Giuliani, G., Kluser, S., *et al.*, Global disaster risk: patterns, trends and drivers, *ISDR (2009) Global Assessment Report on Disaster Risk Reduction*, United Nations, Geneva, Switzerland, chapter 2, pp. 17-57, 2009.

Peduzzi, P., Is climate change increasing the frequency of hazardous events? *Environment & Poverty Times*, **3**, p.7, Special Edition for the World Conference on Disaster Reduction January 18-22, 2005, Kobe, Japan, 2005.

Peduzzi, P., Velegrakis, A., Chatenoux, B., Estrella, M., Kluser, S., Karambas, Th., Quantifying the role of marine ecosystems in reducing coastal erosion: the RiVAMP study in Negril Jamaica, in prep.

Peduzzi, P., Dao, H., Herold, C., and Mouton, F.: Assessing global exposure and vulnerability towards natural hazards: the Disaster Risk Index, *Nat. Hazards Earth Syst. Sci*., **9**, 1149-1159, 2009.

Pope, K.O., D'Hondt, S.L., Marshall, C.R., Meteorite impact and the mass extinction of species at the Cretaceous/Tertiary boundary, *PNAS,* **95** (19), 11028-11029, 1998.

Popescu, M. E.: Landslide causal factors and landslide remediatial options, on-line technical document, Illinois Institute of Technology, Chicago, USA, pp. 1–21, 2002. http://www.geoengineer.org/Lanslides-Popescu.pdf, last checked: 26 April 2011.

Post, E., M.C. Forchhammer, M.S. Bret-Harte, T.V. Callaghan, T.R. Christensen, B. Elberling, A.D. Fox, O. Gilg, D.S. Hik, and T.T. Hoye, Ecological Dynamics Across the Arctic Associated with Recent Climate Change, *Science*, **325**(5946), 1355-1358, 2009.

Preetha, G., Stanley, J., Suresh, S., Kuttalam, S., and Samiyappan, R., Toxicity of selected insecticides to Trichogramma chilonis: Assessing their safety in the rice ecosystem, *Phytoparasitica* **37**:209–215, 2009.

Radford, T., It's the way you tell them, *Environment & Poverty Times* **3**, Special Edition for the World Conference on Disaster Reduction January 18-22, 2005, Kobe, Japan, 2005. UNEP/GRID-Arendal http://www.environmenttimes.net/

Rossettoa,T. Elnashai, A., A new analytical procedure for the derivation of displacement-based vulnerability curves for populations of RC structures, *Engineering Structures*, **27**, 397–409, 2005.

Sanderson E.W., Jaiteh, M., Levy, M.A., Redford, K.H. Wannebo, A.V., Woolmer, G., The human footprint and the last of the wild. *Bioscience.* **52** (10):891-904, 2002.

Sayer J.A., Harcourt, C.S., and Collins, N.M., The Conservation Atlas of Tropical Forests, Africa. New York, IUCN, 1992.

Schulte, P. and others, The Chicxulub Asteroid Impact and Mass Extinction at the Cretaceous-Paleogene Boundary, *Science* **327**, 1214-1218, (2010).

Silverio, W., Cordilera Blanca, global change, UNEP/GRID-Geneva, 2002. http://www.grid.unep.ch/activities/global_change/cordillera.php, last checked: 27 April 2011.

Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor, and H.L. Miller (eds.), *Climate Change 2007: The Physical Science Basis — Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge Univ. Press, Cambridge, UK, New York, USA, 2007.

Stow, C.A., Reckhow, K.H., Qian, S.S., A Bayesian approach to retransformation bias in transformed regression, *Ecology*, **87**(6), 1472-1477, 2006.

Tan, K.T., Lee, K.T., Mohamed, A.R., Bhatia, S., Palm oil: Addressing issues and towards sustainable development, *Renewable and Sustainable Energy Reviews*, **13**(2), 420-427, 2009

Tansey K., J-M., Gregoire, Binaghi E., Boschetti L.,Brivio P., Ershov D., Flasse S., Fraser R., Graetz D., Maggi M., Peduzzi P., Pereira J., Silva J., Sousa A., Stroppiana D., A Global Inventory of Burned Areas at 1 Km Resolution for the Year 2000 Derived from Spot Vegetation Data, *Climatic change*, **67**(2), 345-377, 2004a.

Tansey, K., Grégoire, J-M; Stroppiana, D., Sousa, A., Silva, J., Pereira, J M. C., Boschetti, L., Maggi, M., Brivio, P.A., Fraser, R., Flasse, S., Ershov, D., Binaghi, E., Graetz, D., Peduzzi, P., Vegetation burning in the year 2000: Global burned area estimates from SPOT VEGETATION data, *Journal of geophysical research*, **109**, D14S03, 2004b.

Thomas, C.A., Green, R.E., Bakkenes, M., Beaumont, L.J., Collingham, Y.C., Erasmus, B.F.N., Ferreira de Siqueira, M., Grainger, A., Hannah, L., Hughes, L., Huntley, B., van Jaarsvel, A.S., Midgley, G.F., Miles, L., Ortega-Huerta, M.A., Townsend Peterson, A., Phillips, O.L., Williams, S.E., Extinction risk from climate change. *Nature* **427**, 145–148, 2004.

Thywissen, K., Core terminology ofisater reduction: a comparative glossary, *Measuring vulnerability to promote disaster-resilient societies*, 448-4496, United Nations University, United Nations University Press, Tokyo, New York, Paris, 524 pp., 2006.

Tobin, G.A. & B.E., Montz, *Natural Hazards: explanation and integration*, Guilford Press, New York, 388 p., 1997.

Turner, G.M., A comparison of the limits to growth with thirty years of reality, *Global Environmental Change*, **18** (3), 397-411, 2008. http://www.csiro.au/files/files/plje.pdf, last checked: 26 April 2011.

UNDP, *Reducing Disaster Risk: a challenge for development*, United Nations Development Programme, Bureau for Crisis Prevention and Recovery, 146 p., New York, NY 10017, USA, 2004.

UNDRO, *Mitigating Natural Disaster: Phenomena, Effects and Options. A Manual for Policy Makers and Planners*, United Nations, New York, 1991.

UNEP, One Planet Many People, atlas of our changing environment, United Nations Environment Programme, 322 pp., 2005.

UNEP, Annual report 2010, 124 pp., United Nations Environment Programme, 2011. http://hqweb.unep.org/annualreport/2010/pdfs/UNEP-AR-2010-FULL-REPORT.pdf, last accessed 30 April 2011.

UNEP, PIOJ, *Risk and Vulnerability Assessment Methodology Development Project (RiVAMP), Linking Ecosystems to Risk and Vulnerability Reduction: The Case of Jamaica. Results of the Pilot Assessment*, United Nations Environment Programme, Planning Institute of Jamaica, 130 pp., 2010. http://www.nat-hazards-earth-syst-sci.net/10/623/2010/nhess-10-623-2010.html, last accessed: 14 August 2011.

UNHABITAT, *State of the World's Cities 2010/2011, Bridging The Urban Divide*, (p.32), UNHABITAT, Nairobi, Kenya, pp. 220, 2010.

UNISDR, *Hyogo Framework for Action 2005–2015: Building the Resilience of Nations and Communities to Disasters*,World Conference on Disaster Reduction, Kobe, Hyogo, Japan, 25 pp., 2005.

UNISDR, terminology, Preventionweb, http://www.preventionweb.net/english/professional/terminology/?pid:6&pih:2, last checked: 27 April 2011.

UNPD, Population Projection, United Nations Population Division in *Geodata portal*, UNEP, 2010. http://geodata.grid.unep.ch, last consulted 25 April 2010.

Urban Population - Percent of Total Population, United Nations Population Division in *Geodata portal*, UNEP, 2010. http://geodata.grid.unep.ch, last consulted 25 April 2010.

USGS, Historic Earthquakes, Peru, 1970 May 31 20:23:27 UTC, Magnitude 7.9, USGS, 2010. From Earthquake Information Bulletin, September - October 1970, **2** (5). http://earthquake.usgs.gov/earthquakes/world/events/1970_05_31.php, last checked: 27 April 2011.

Van Aalst, M.K., Cannon, T., Burton, I., Community level adaptation to climate change: The potential role of participatory community risk assessment, *Global Environmental Change*, **18**(1), 165-179, 2008.

Van der Werf G. R., Dempewolf J., Trigg S. N., Randerson J. T., Kasibhatla P. S., Giglio L., Murdiyarso D., Peters W., Morton D. C., Collatz G. J., Dolman A. J. and DeFries R. S., Climate regulation of fire emissions and deforestation in equatorial Asia, *Proc. Natl. Acad. Sci. USA*, **105**, 20350–20355, 2008.

Van Dissen, R., and McVerry, Earthquake hazard and risk in new Zealand, 1994, in Tobin, G.A. & E.M. Burrel, *Natural Hazards: explanation and integration*, Guilford Press, New York, 1997.

Van Herk, W.G., Vernon, R. S. , Tolman, J. H., and Ortiz Saavedra, H., Mortality of a Wireworm, Agriotes obscurus (Coleoptera: Elateridae), after Topical Application of Various Insecticides, *Journal of Economic Entomology* **101**(2), 375-383, 2008.

Vanacker, V., Vanderschaeghe, M., Govers, G., Willems, E., Poesen, J., Deckers, J., and De Bievre, B.: Linking hydrological, infinite slope stability and land-use change models through GIS for assessing the impact of deforestation on slope stability in high Andean watersheds, *Geomorphology*, **52**, 299–315, 2003.

Vitousek, P.M., Beyond Global Warming: Ecology and Global Change. *Ecology* **75**, 1861–1876, 1994.

FAO, Water Use - Total Water Withdrawal, FAO (aquastats) 2007, in *Geodata portal*, UNEP, 2010. http://geodata.grid.unep.ch, last consulted 25 April 2010.

Webster, P.J., Curry, J.A., Liu, J., Holland, G.J., Response to Comment on Changes in Tropical Cyclone Number, Duration, and Intensity in a

Warming Environment, *Science* **311**, 1713c (2006).

Webster, P.J., Holland, G.J., Curry, J.A., Chang, H.R., Changes in Tropical Cyclone Number, Duration, and Intensity in a Warming Environment, *Science* **309**, 1844-1846 (2005).

Wilson, E.O., *The diversity of life*, Belknap Press of Harvard University Press, Cambridge, Massachusetts,USA, 1992.

Woods, J., Williams, A., Hughes, J.K., Black, M., Murphy, R., Energy and the food system, *Phil. Trans. R. Soc. B* **365** (1554), 2991-3006, 2010.

Wu, JY, Anelli, CM, Sheppard, WS, Sub-Lethal Effects of Pesticide Residues in Brood Comb on Worker Honey Bee (*Apis mellifera*) Development and Longevity. *PLoS ONE* **6**(2): e14720, 2011.

York/London: Guilford Press, 290 pp., 1993.

Zemp, M., Roer, I., K¨a¨ab, A., Hoelzle, M., Paul, F., and Haeberli, W.: WGMS: Global Glacier Changes: facts and figures, UNEP, World Glacier Monitoring Service, Zurich, Switzerland, 88 pp., 2008. http://www.grid.unep.ch/glaciers/, (last access: August 2010).

Zemp, M., Roer, I., Kääb, A., Hoelzle, M., Paul, F. and Haeberli, W. (eds.), *WGMS: Global Glacier Changes: facts and figures*. UNEP, World Glacier Monitoring Service, Zurich, Switzerland: 88 pp., 2008.

Zhao M., and Running S. W., Drought-Induced Reduction in Global Terrestrial Net Primary Production from 2000 through 2009, *Science* **329**, 940, 2010.

Zoomers, A. Globalisation and the foreignisation of space: seven processes driving the current global land grab. *Journal of Peasant Studies*, **37**(2): 429–447, 2010.

Chapter 3 Global Natural Hazard Risk Assessment and links with Development

According to NatCat (Figure 27) tectonic events (e.g. earthquakes, tsunamis, volcanic eruptions) represent 29% of the number of large disasters recorded since 1950, but lead to 56% of the fatalities. Climatic and hydro-meteorological events (e.g. droughts, floods, tropical cyclones, heatwaves) are more frequent representing 71% of the events. They account for 44% of fatalities, two third of the economic losses and 89% of the insured losses. However, reinsurance companies are restricting the access of their database to aggregated level. To better understand the losses, disaggregated values are needed.

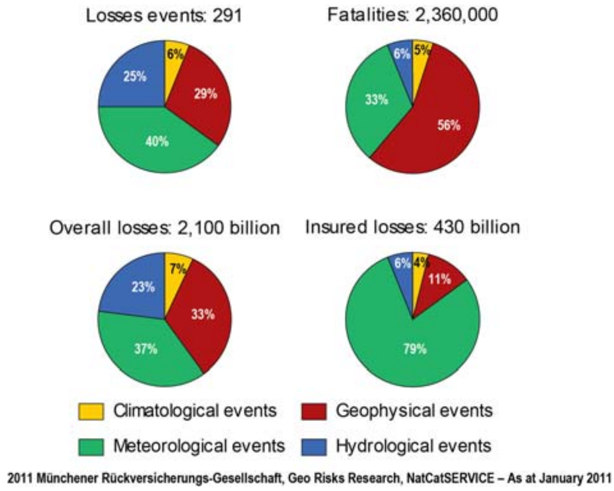


Figure 27 Great natural catastrophes world-wide 1950-2010, sources: NatCatSERVICE, Munich RE, 2011

Table 4 Disasters with more than 10,000 reported killed (period 1975 – 2010 + Japan 2011 earthquake/tsunami)

Year	Countries	Hazards	Name	Reported killed
1983	Ethiopia	Drought		300,000
1976	China P Rep	Earthquake	Tangshan	242,000
2004	**South Indian Ocean**	**Tsunami**	**Indian Ocean**	**226,408**
2010	**Haiti**	**Earthquake**		**222,570**
1983	Sudan	Drought		150,000
1991	Bangladesh	Tropical cyclone	Gorky	138,866
2008	**Myanmar**	**Tropical cyclone**	**Nargis**	**138,366**
1981	Mozambique	Drought	Southern Mozambique	100,000
2008	**China P Rep**	**Earthquake**	**Sishuan**	**87,476**
2003	**Europe**	**Heatwave**	**European**	**84,345**
2005	**Pakistan**	**Earthquake**	Kashmir	**73,338**
2010	**Russia**	**Heat wave**		**55,736**
1990	Iran Islam Rep	Earthquake	Manjil-Rudbar	40,000
2011	**Japan**	**Earthquake/tsunami/nuclear**		**28,114***
2003	**Iran Islam Rep**	**Earthquake**	**Bam**	**26,796**
1988	Soviet Union	Earthquake	Spitak	25,000
1978	Iran Islam Rep	Earthquake	Tabas	25,000
1976	Guatemala	Earthquake		23,000
1985	Colombia	Volcano	Nevado del Ruiz	21,800
2001	**India**	**Earthquake**	**Gujarat**	**20,005**
1999	Turkey	Earthquake	Izmit	17,127
1998	Honduras	Tropical cyclone	Mitch	14,600
1977	India	Tropical cyclone	Andhra Pradesh	14,204
1985	Bangladesh	Tropical cyclone		10,000
1975	China P Rep	Earthquake	Haicheng	10,000
			Total	**2'094'751**

Data sources: EM-DAT (as of 28 April 2011), * estimation from reliefweb.

The Disaster Inventory System (DesInventar) methodology (Osso, La Red, 1998-2011) provides detailed level of analysis on past losses, but covers only 31 countries. So the only database which offers access to individual past losses events with a global coverage is the Emergency Events Database (EM-DAT). It is maintained since 1988 by the Centre for

Research on the Epidemiology of Disasters (CRED, 2011).

A rapid analysis of past reported losses, shows that the losses are highly concentrated in a limited number of events. Between 1975 and 2010, EM-DAT reported 9,646 disasters from natural origin, killing more than 2.6 million people. Of these, 25 mega-disasters (see Table 4) killed more than 2 million people, mainly in developing countries. In other words, 0.26% of the events accounted for 79.9% of the mortality. In the same period (+ the 2011 Japanese earthquake / tsunami / nuclear accident), recorded economic losses were nearly US$ 2,000 billion (1,998). Table 5 lists the 25 mega-disasters that represented only 0.26% of the events, yet accounted for 50.4% of that loss, mainly in developed countries. These figures show that the losses (both human and economic) are concentrated in very few mega-events. A large proportion of them occurred in the last decade. Five of the top 10 events (in terms of mortality) are within the last 8 years. Ten out of the top 25 occurred in the last decade, and account for 46% of the events in the top 25, in terms of the number of reported killed. Heatwaves are recently making their way in the top 25, for both mortality and economic losses.

Table 5 Top 25 reported economic losses 1975 – 2011

Data sources: EM-DAT (as of 28 April 2011), * estimation from various sources.

Year	Countries	Hazards	Name	Reported loss [billion US$]
2011	**Japan**	**Earthquake/tsunami/nuclear**	**Fukushima**	**300-400***
2005	**United States**	**Tropical cyclone**	**Katrina**	**125**
1995	**Japan**	**Earthquake**	**Kobe**	**100**
2008	**China P Rep**	**Earthquake**	**Sichuan**	**85**
2008	**United States**	**Tropical cyclone**	**Ike**	**30**
2010	**Chile**	**Earthquake**		**30**
1998	**China P Rep**	**Flood**	**Yangtze**	**30**
2004	**Japan**	**Earthquake**	**Chuetsu**	**28**
1992	**United States**	**Tropical cyclone**	**Andrew**	**26.5**
2008	**China P Rep**	**Heatwave**		**21.1**
1980	**Italy**	**Earthquake**	**Irpinia**	**20**
2004	**United States**	**Tropical cyclone**	**Ivan**	**18**
2010	**China P Rep**	**Flood**		**18**
1997	**Indonesia**	**Wild Fires**		**17**
1994	**United States**	**Earthquake**	**Northridge**	**16**
2004	**United States**	**Tropical cyclone**	**Charley**	**16**
2005	**United States**	**Tropical cyclone**	**Rita**	**16**
1995	**Korea Dem P Rep**	**Flood**		**15**
2005	**United States**	**Tropical cyclone**	**Wilma**	**14.3**
1999	**Taiwan (China)**	**Earthquake**	**Chichi**	**14.1**
1988	**Soviet Union**	**Earthquake**	**Spitak**	**14**
1994	**China P Rep**	**Drought**		**13.8**
1991	**China P Rep**	**Flood**	**Eastern China**	**13.6**
1996	**China P Rep**	**Flood**	**Yellow river**	**12.3**
2007	**Japan**	**Earthquake**	**Niigataken Chuetsu-oki**	**12.5**
			Total	**1,007**

While it seems striking to see that 7 out of the top 10 economic losses are all in the last 7 years and that more than half (13) of the top 25 reported economic losses, are within the last 10 years (in bold) and represent 61.5% of the top 25 economic losses, some caution should be taken with the economic losses. Firstly because they are usually rough estimations, but more importantly because EM-DAT is providing the value of economic losses at the time of the event (i.e. not as e.g. constant 2005 US$), thus placing a higher weighting for more recent events. So, one shouldn't too quickly conclude from such table, that economic risk is increasing. This requests a correction for inflation (Blake *et al.*, 2011), change of currency against dollars and looking at difference in purchasing power. One way to correct for these artefacts is to translate the losses as a share of GDP (at the time of the event) (see Figure 71 in 3.5.7). 15 of the top 25 are triggered by hydro-meteorological hazards. The 2005 tropical cyclone season in North Atlantic has 3 disasters listed in the top 25 economic losses. Earthquakes account for 62.6% of the top damages (however, before the 2011 Japanese event, they accounted for 45.3% and hydro-meteorological for 54.7%). The 2003 European heatwave generated US$ 12.1 billion losses and is just outside of the 25 listed here.

But are we all in the same boat when confronted by hazardous events? Well, even if we were, the following story shows that equal chances cannot be guaranteed.

On 15 April 1912, the "S.S. Titanic" sank after hitting an iceberg. 67.7% of the 2201 passengers died, the rest were rescued by the ship "S.S Carpathia" (Hall, 1986). It appeared that the percentage of victims varied according to the travelling class of the passengers, with 37.5, 58.6 and 74.8% victims for 1st, 2nd and 3rd class respectively (Hall, 1986).

Several hypotheses were attempted to explain such differences (Hall, 1986). They ranged from higher consideration of the crew towards first class passengers, which may have been prioritised (socio-economic factors), to the proximity of the first class passengers to the lifeboats (spatial factors) or by the fact that some of the people in the third class could not speak any English and therefore may not have received the appropriate instructions (access to information, education). Women and children were prioritised by the crew (gender policy) explaining why 30.1% of woman died versus 75.3% of men, but the percentage of women who died varies significantly depending on their travelling class(2.7, 11.1 and 57.8% for 1st, 2nd and 3rd class respectively).

If the victims from the Titanic are not the subject of this study, similarities can be drawn with societies. For the same scale of event, a significant discrepancy in the number of victims can be observed, depending on whether the disaster is located in a developed or less developed country (UNDP, 2004; Peduzzi, 2006). Density of population, differences in wealth, building quality and in organisation of the society are likely contributing factors to this discrepancy.

The countries with least economic power present a lack of means for setting up appropriate preparedness, or for improving their capacities of both response and mitigation. The reverse statement may also be true: as high exposure toward natural hazards could lead to slow economic development by scaring the investors away, or by requiring costly infrastructures (UNDP, 2004). Over-arching development differences, countries are not equally exposed to natural hazards. Differences in geophysical factors (slopes, elevation, proximity from the shore or geological fault, inter-tropical location, …) are parameters leading to higher occurrence and severity of hazards (Burton, 1993). Can we distinguish and quantify separately the risk components linked with geophysical factors from those linked with socio-economic factors?

3.1. Risk analysis at the global level

In order to prioritise areas for DRR, United Nations and development agencies need a global assessment of disaster risk. Where is this risk located? Reported number of events and mortality suggests that the losses are increasing. However this could also be due to improved access to information, or in the case of economic losses, increases in the value of properties and exposed assets. If the risk is really increasing, is this due to higher population density in exposed areas, higher vulnerability or higher frequency/intensity of flood events? Answering these questions requires a significant exercise of standardisation, compilation of existing data as well as generation of missing data.

3.1.1. Developing a methodology for building the Disaster Risk Index

On September 11-12 2000, the United Nations Development Programme (UNDP) organised the "*Expert Meeting on Vulnerability and Risk Analysis and Indexing*". The aim of this meeting was to brainstorm on the possibility to create an index for comparing risk across countries. A highly sceptical presentation was made about such a project (Peduzzi, 2000), flagging several points that would need to be considered and limitations:

- Which hazards should be included?
- Where to access precise global coverage of frequencies of hazards such as floods, droughts, landslides, and tropical cyclones (only existed at that time at 5 x 5° cell)?
- What length of time should be taken into account? Ideally, one would have the longest time records for hazards; on the other hand vulnerability is changing very quickly.
- Should human induced hazard such as mines, pollution, nuclear wastes and accidents be incorporated?
- How to compare the situation of earthquakes in South America with the problem of drought in Africa?
- How to compare small countries with large countries (e.g. Costa Rica and China)
- How can we reflect the global quality of infrastructures? Gross Domestic Product (GDP) may be useful to reflect it. Other indicators could be incorporated such as the level of education, the capacity of response to hazards: but how to incorporate this without specific indicators? And how to weight them in the process?

Despite (or because of) the criticisms, I was mandated to develop the index. The mandate received from UNDP/BCPR required that the index should:

- allow comparisons across hazards and countries based on impacts from natural hazards.
- be global, simple and robust.
- be based on existing data.
- identify socio-economic parameters leading to highest vulnerability
- include possibilities to be extended to other hazards in the future (e.g. landslides, volcanic eruptions,…)

3.2. *Assessing global exposure and vulnerability towards natural hazards : the Disaster Risk Index*

P. Peduzzi[1,2], H. Dao[3], C. Herold[1] and F. Mouton[4]
[1]{UNEP/GRID-Europe, Geneva, Switzerland}
[2]{Institute of Geomatics and Analysis of Risk (IGAR), University of Lausanne, Switzerland}
[3]{Department of Geography, University of Geneva, Switzerland}
[4]{UFR de Mathématiques, Université J. Fourier, Grenoble, France}
Correspondence to: P. Peduzzi (pascal.peduzzi@grid.unep.ch)

Status: Published, references:
Peduzzi, P., Dao, H., Herold, C., and Mouton, F.: Assessing global exposure and vulnerability towards natural hazards: the Disaster Risk Index, *Nat. Hazards Earth Syst. Sci*., **9**, 1149-1159, 2009.
http://www.nat-hazards-earth-syst-sci.net/9/1149/2009/nhess-9-1149-2009.html

Abstract. This paper presents a model of factors influencing levels of human losses from natural hazards at the global scale, for the period 1980–2000. This model was designed for the United Nations Development Programme as a building stone of the Disaster Risk Index (DRI), which aims at monitoring the evolution of risk. Assessing what countries are most at risk requires considering various types of hazards, such as droughts, floods, cyclones and earthquakes. Before assessing risk, these four hazards were modelled using GIS and overlaid with a model of population distribution in order to extract human exposure. Human vulnerability was measured by crossing exposure with selected socio-economic parameters. The model evaluates to what extent observed past losses are related to population exposure and vulnerability. Results reveal that human vulnerability is mostly linked with country development level and environmental quality. A classification of countries is provided, as well as recommendations on data improvement for future use of the model.

Keywords Disaster risk, natural hazards, vulnerability assessment, physical exposure, indexing countries

3.2.1. Introduction

According to available global statistics, least developed countries represent 11% of the population exposed to hazards but account for 53% of casualties (Peduzzi *et al.*, 2002). On the other hand, the most developed countries represent 15% of human exposure to hazards, but account only for 1.8% of all victims. Obviously, similar exposures with contrasting levels of development lead to drastically different tolls of casualties. These are general figures, however, in order to better understand what development parameters are associated with risk, each exposure to specific hazard types should be analysed separately.

This paper presents the methodology and the results of the Disaster Risk Index (DRI), the central component of the report “Reducing Disaster Risk” by the United Nations Development Programme (UNDP/BCPR, 2004). The mandate from UNDP was to analyse potential links between vulnerability to natural hazards and levels of development. The DRI is the first model providing a statistical evidence of such links at the global scale. By setting reference risk values for the period 1980–2000, this model will be the basis for comparisons with subsequent calculations of the DRI in the 21st century.

Since the publication of this report, several other global and regional efforts have been published. The World Bank/University of Columbia published a report (Dilley *et al.*, 2005) including numerous hazard- exposure- and risk maps, also using similar datasets. This study placed more emphasis on the effect of multiple hazards exposure. Abovementioned studies did not try to model and address vulnerability by grouping past losses per exposed by countries and territories (thereafter referred to as countries+) of similar levels of economic development. At the other extreme, a report also published by the Inter-American Development Bank (Cardona, 2005) in 2005 proposed different sets of complex indicators, e.g. they compared the likely economic loss attributed to a major disaster in a given time period with the economic coping capacity of the country, resulting in an indicator known as the Disaster Deficit Index (DDI). The DDI can therefore be considered as an indicator of a country's economic vulnerability to disaster. Unfortunately, at present the indicator has only been applied in Latin America and the Caribbean, and therefore it is impossible to identify global trends. There is a need for a global index for comparing countries, including an identification of human vulnerability, which can be used by aid organisations and governments. Our first version of the DRI was published as on-going work (UNDP/BCPR, 2004), it included several gaps and recommendations that we try to address in this present paper. There are different challenges when comparing risk levels for different countries, e.g. how to compare large countries with small ones, or how to compare countries affected by earthquakes and those affected by droughts? Because of the specific nature of each hazard type (rapidity of onset, spatial extent and destruction potential), exposures to different hazard types cannot be compared. Being affected by drought differs drastically from being exposed to earthquakes. In the first case, infrastructures generally do not suffer, the impact is slow and gradual, but the duration is long, while the inverse is true for earthquakes. Complexity is higher than considered here as primary hazards often unfold into different secondary hazards (e.g. tropical cyclones triggers storm surges leading to coastal flooding, tempestuous rains and winds leading to landslides). However, this is a level of simplification that has to be accepted once dealing with global risk assessments. To overcome part of the difficulties associated with different types of exposures, the model is based on hazard-specific risk models (cyclones, droughts, earthquakes and floods), which are further combined in a multiple DRI allowing a classification of countries+.

The model is built on both available and newly created global datasets. Exposure, vulnerability and risk have been estimated by means of statistical and Geographical Information Systems (GIS) methodologies which are presented in this article.

3.2.2. Defining and measuring risk

In this research, the term risk follows the definition by the Office of the United Nations Disaster Relief Co-ordinator (UNDRO) and "refers to the expected losses from a particular hazard to a specified element at risk in a particular future time period. Loss may be estimated in terms of human lives, or buildings destroyed or in financial terms" (Cardona, 2005; Burton, 1978). There are different sorts of losses from natural hazards: human, economic, cultural, etc. However, this study concentrates on life losses for two main reasons. First, the number of killed people is the most reliable and least subjective figure that can be found in the Emergency Disasters Data Base (EM-DAT, Centre for Research on the Epidemiology of Disasters, http://www.em-dat.net/), the only publicly available global database on human impacts from hazardous events. By comparison, the definition and estimation of other variables like "homeless", "affected" and "total affected" are not reliable and depend largely on gross evaluations. Another reason was the difficulty of using economic data since EM-DAT only records events with estimated losses above 100 000 US$, ignoring many smaller events affecting developing countries. Yet, the socio-economic impacts of a 100 000 US$ loss is not the same when considering countries like USA and Bangladesh, thus inducing a statistical bias since most of the records including economic losses concern developed countries. It is to be noted that EM-DAT includes only medium to large-scale disaster events. Thus, disasters with less than 10 killed are not included.

However, considering the number of killed people does not solve the problem of comparison between countries+. If the raw number of killed is taken, more populated countries+ will always be on the top of the list (e.g. China, India), whereas several countries+

having in total an equivalent population would not be well represented. If the percentage of population killed is used, then the reverse problem appears: small islands and less populated countries+ will always be ranked first and the equity of one person killed is no longer ensured. In order to enable relevant comparisons between hazards and countries+, a risk indicator was computed combining both the total number and the percentage of killed people (Dao and Peduzzi, 2003).

3.2.3. Choice of hazard types and time period

The study focussed on droughts, earthquakes, tropical cyclones and floods, the four hazards accounting for 94% of casualties reported for the period 1980–2006 in the EM-DAT database. The period 1980–2006 was chosen for its homogenous level of information quality and completeness.

For identifying the period for which the access to information is comparable worldwide, a ratio between physically recorded earthquakes (magnitude>5.5) on land and reported earthquakes in EM-DAT was used. The choice of earthquakes as a benchmark was made because this hazard is not suspected of being influenced by climate patterns. The ratio of reported versus physically recorded events is rather low until 1979 (average of 11%) and suddenly increases in 1979 (average of 26%) and then remains steady around this value. From the previous observation, a time span of twentyone years was chosen (1980–2000), completed by a period used for comparison (2001–2006). For hydro-meteorological hazards, the same time span was chosen; however, for tectonic events, frequencies were computed over a longer period (1965–2006).

An even longer time period would have been relevant for hazards like earthquakes, but reports on casualties were probably not as homogenous before the 1980's and the problem of finding the corresponding vulnerability variables would have arisen. Given the significance of the four major hazards, modelling others would not have had a significant effect on the final classification of countries+, except for few specific countries+ affected mostly by tsunamis, landslides, volcanic eruptions or extreme temperatures (e.g. Equator, Papua New Guinea). The EM-Dat dataset was split into two parts: 1980– 2000 was used for the calibration of vulnerability to produce a model. The records 2001–2006 were used for comparison with recent events.

3.2.4. Modelling risk

By UN definition (Cardona, 2005), the risk of losses is a function of three components: hazard, element at risk and vulnerability. In the case of risk of human losses, the element at risk is the exposed population. The hazard occurrence refers to the frequency of returning period at a given magnitude, whereas the vulnerability is "the degree of loss to each element should a hazard of a given severity occur" (Blaikie *et al.*, 1994).

A hypothesis was made that risk follows a multiplicative formula as described in the simplified Eq. (1).

$$R = H_{fr} \cdot Pop \cdot Vul \qquad (1)$$

<u>*Where:*</u>

R = number of expected human impacts [killed/year].

Hfr = frequency of a given hazard [event/year]

Pop = population living in a given exposed area [exposed population/event].

Vul = vulnerability depending on socio-politico-economic context of this population [non-dimensional number between 0-1].

According to this formula, if there is no hazard, then the risk is null (the same if population or vulnerability is null).

3.2.5. Identifying Physical Exposure

The combination of both yearly average frequency of hazards and exposed populations provides the physical exposure and can be computed, depending on cases, using Eqs. (2) or (3).

$$PhExp = \sum_{i}^{n} F \cdot Pop_i \qquad (2)$$

<u>*Where:*</u>

PhExp = yearly average physical exposure for the spatial unit [exposed population/year]

F = annual frequency of a given magnitude event [event/year]

Popi = total population living in the spatial unit for each event "i". [exposed population/event]

n = number of events considered

$$PhExp = \sum \frac{Pop_i}{Y_n} \quad (3)$$

Where:

PhExp = yearly average physical exposure for the spatial unit [exposed population/year]

Popi = population living in affected area for each event "i" [exposed population/event]

Yn = length of time [year]

The frequency and geographical extent of each hazard were modelled and further used for extracting the exposed population (Figure 28). Equation (1) for risk was then transformed into Eq. (4) for computing the physical exposure:

$$R = PhExp \cdot Vul \quad (4)$$

3.2.6. Approaching human vulnerability

2.2.1 The use of indicators

The last component, vulnerability, is less easily apprehended. It is a concept to be quantified using indicators. A selection of 32 socio-economic and environmental variables (Supplementary material A: http://www.nat-hazards-earth-syst-sci.net/9/1149/2009/ nhess-9-1149-2009-supplement.pdf) was introduced in a database for further statistical analysis.

A correlation study (matrix-plot and correlation-matrix) was performed to ensure that the variables were independent before applying the regression analysis. This was for instance not the case for the highly correlated Human Development Index (HDI) and Gross Domestic Product per capita (at Purchasing Power Parity). In order to keep a valid sample size, a preference was given to variables with the lowest number of missing values.

2.2.2 Parametric model used

A generalisation of the multiplicative approach (Eq. 4) was defined with the following parametric model (Eq. 5):

$$K = C(PhExp)^{\alpha} \cdot V_1^{\alpha 1} \cdot V_2^{\alpha 2} \ldots V_n^{\alpha n} \cdot \quad (5)$$

Where:

K = number of persons killed by a certain type of hazard.

C = multiplicative constant.

PhExp = physical exposure : population living in exposed areas multiplied by the frequency of occurrence of the hazard.

Vi = socio-economic variables.

i = exponent of V i, which can be negative (for ratio).

Taking the logarithms in Eq. (5) gives Eq. (6):

$$\ln(K) = \ln(C) + \alpha \ln(PhExp) + \alpha 1 \ln(V_1) + \alpha 2 \ln(V_2) + \ldots + \alpha p \ln(V_p) \quad (6)$$

Significant socio-economic variables Vi (transformed when appropriate, see below) and exponents αi were determined by means of linear regressions that were carried out for each hazard. The variable K to be estimated was the number of killed people as reported by EM-DAT.

2.2.3 Transformation of variables

Since socio-economic indicators fluctuate across time, a weighted average was computed for each variable:

$$V' = (V_{1980} \cdot K_{1980} + V_{1981} \cdot K_{1981} + \ldots + V_{2000} \cdot K_{2000}) / K_{tot} \quad (7)$$

Where:

V 0 = weighted average of a given variable.

Vi = value of the variable for the year i.

Ki = number of recorded casualties for the year i.

Ktot = total number of recorded casualties for all years.

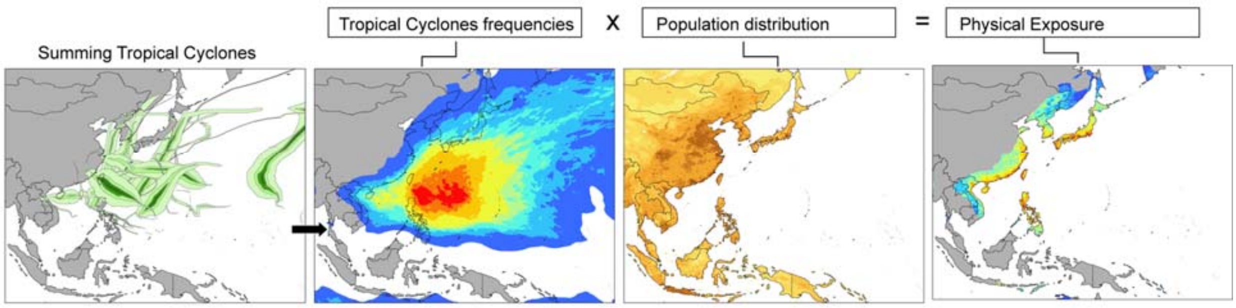


Figure 28. Example of physical exposure extraction (tropical cyclones).

Once the spatial extents of individual cyclones are modelled, each cell is used to count the average cyclone frequency over the available period. The average frequency is then multiplied by the population identified in each cell (population distribution) in order to obtain the physical exposure. This cell-by-cell physical exposure is further aggregated (summed) at national level.

The result of Eq. (7) is an averaged value that is obtained from yearly values weighted according to the number of casualties in each year. For example, this process avoids taking the Gross Domestic Product of a selected year if the bulk of the victims occurred 10 years before or after (see example in Table 6).

Table 6. Cyclone casualties and HDI in El Salvador (1980-2000)

Year	K	V (HDI)	V * K
1988	28	0.781	21.879
1996	3	0.810	2.429
1996	51	0.810	41.300
1998	8	0.815	6.523
Total	**90**		**72.132**

V' = 72.132 / 90 = 0.801

Since the population is also changing through time, this affects the computation of the physical exposure (PhExp). The same formula was applied to the physical exposure. For the variables with unlimited positive values (e.g. population) the logarithms were computed directly, but for others expressed in percent, a logistic transformation was applied,

$V^* = V' / (1- V')$, so that their logarithms range between $-\infty$ and $+\infty$. This appeared to be relevant as some of the transformed variables proved to be significant in the final results. For others, no logarithm was needed: for instance the urban growth U_g already behaves in a cumulative way.

3.2.7. Calibration of the risk model hazard per hazard

In the regression analysis, physical exposure (PhExp) was considered as an explanatory variable and proved to be statistically significant in all cases detailed below, thus validating the methodology developed for obtaining PhExp.

Tropical cyclones

Exposed populations to each cyclone were estimated by computing buffers along the cyclone track, where windspeed is greater than a certain threshold [42.5 m/s]. These buffers had to be generated for the study by modifying a wind profile model initially developed by Greg Holland (Holland, 1980). The modification adds the movement of cyclone's centre, leading to asymmetric buffers (Mouton *et al.*, 2002). A global dataset was produced using tracks of tropical cyclones available on the internet from different meteorological centres. Information on latitude/longitude, date, hour, windspeed and central pressure are usually included, although each centre has its own way and units for measuring cyclone characteristics. The PreView Global Cyclones Asymmetric Windspeed Profile dataset developed for this study provides users with a standardised version, with units converted into the metric system. Using the areas derived from the asymmetric windspeed profiles, it was possible to extract the physical exposure using Eq. (3).

The variables highlighted by the statistical analysis are PhExp, the GDPcap and the percentage of country+ area dedicated to cropland. According to the

analysis, the number of killed people is growing with PhExp and decreasing with the GDPcap. The percentage of cropland can also be understood as a proxy of the type of population/habitat, i.e. rural, scarcely distributed population being more vulnerable than urban population. This statistical result is in line with what was expected by consulted experts (IWTC-V, 2002). After a tropical cyclone, an economy relying on the tertiary sector is less affected than one relying on agriculture, the fields having been devastated. These results confirm that poor populations are more vulnerable to tropical cyclones. With a considerable part of variance explained by the regression (R^2=0.81), a high degree of confidence in the selected variables (p-values<0.05) over a sample of 34 countries+ and a residual analysis showing no particularity or abnormality, the model achieved is robust. Notice that although the consequences of hurricane Mitch (in 1998) could easily be depicted, Honduras and Nicaragua were far off the regression line (significantly underestimated) and were not used for the model. This is explained by the incredible difference of intensity between Mitch and other hurricanes. Cuba's in risk reduction (i.e. by evacuating population exposed to a coming cyclone) is confirmed by the analysis: observed casualties are so much lower than the expected values, that this country was identified as an outlier. The partial correlation analysis highlights that the physical exposure explains the major part of the casualties, followed by GDPcap and then percentage of country dedicated to cropland. The plot of observed versus expected values delineates a linear distribution as seen in Figure 29**. The model is the following (see**

Table 7):

$$\ln(K) = 0.621 \ln(PhExpCy) - 0.534 \ln(GDPcap) + 0.347 \ln(CROPpca) - 0.487 \quad (8)$$

<u>*where:*</u>

K = number of estimated killed.
PhExp = physical exposure to tropical cyclones.
GDPcap = transformed value GDP purchasing power parity per capita.
CROPpca = transformed value of the percentage of the country dedicated to Crop land.

Table 7 Model for tropical cyclones

Variables	Coefficients	St. Err.	t Stat	P-value
Intercept	−0.487	1.897	−0.257	0.799278
GDPcap	−0.534	0.197	−2.719	0.010767
CropPC	0.347	0.152	2.283	0.029714
PhExp	0.621	0.067	9.301	0.000000

Droughts

Drought is a complex process to model as it is not clear when a drought starts both in spatial and temporal terms. The same deficit in precipitation may not induce similar impacts depending on types of soil, vegetation and agriculture as well as on differences in irrigation infrastructures. Moreover, casualties are not directly induced by physical drought but rather by food insecurity which is not purely a natural hazard as it includes human induced causes (such as conflicts, poor governance, etc.). However, a global approach on risk to human development would not be achieved without drought, as most of Africa is affected mainly by food insecurity.

A first attempt to identify physical drought was developed by Brad Lyon and his team (Dilley *et al.*, 2005) from the International Research Institute for Climate Prediction (IRI), who produced several methods with different thresholds on duration (3 and 6 months) and shortage of precipitation (50%, 25% and 10%) at 2.5° resolution. For this research, their method was re-applied to a 0.5° resolution raster dataset from the Climatic Research Unit (University of East Anglia, Norwich). This proved to significantly improve results as compared to the original IRI data at 2.5° resolution. Secondly, physical exposure was computed on a cell-by-cell basis using Eq. (2) and was further aggregated at the national level. During this research, a calibration using reported casualties identified the best global match with the thresholds set at 50% of precipitation shortage during a period of 3 months. The indicators identified by the statistical analysis are Ph- Exp, GDPcap and the percentage of arable land. This latter variable was computed in order to take into account the percentage of arable land, over the country, excluding deserts.

Computing the percentage of arable land(for droughts)

The original figure for percentage of arable land came from the FAO database. It was modified in order to take into account the percentage of arable land excluding deserts.

$$mAL\ pc = ALA(TA - DA) \quad (9)$$

<u>*Where*</u>:
mAL pc = modified percentage of arable land.
ALA= arable land area (in km^2).
TA= total area (in km^2).

DA= desert area (in km^2).

The desert areas were identified using the Global Land Cover 2000 dataset. This is to avoid the case of countries+ largely covered by deserts where populations are concentrated on a small portion of the territory. According to the analysis, the number of killed people from physical drought grows with PhExp, decreases as the GDPcap grows and decreases if the percentage of arable land grows. The interesting point is that, as opposed to the other hazards, the main contribution to casualties is poverty (low GDP) followed by physical exposure and percentage of arable land.

A country with a large portion of arable land is less likely to be totally affected by a drought and might still be able to provide enough food for its inhabitants.

Again, the part of variance explained by the regression (R^2 = 0.70) is important and p-values are smaller than 0.05.

The plot can be seen on **Figure 29**. The residual analysis shows no abnormality or particular structure (see), which validates the regression:

$$\ln(K) = 1.373 \ln(PhExpDr) - 1.322 \ln(mAL\ pc) - 4.535 \ln(GDPcap) + 10.536 \quad (10)$$

Where:
K = number of estimated killed.
PhExpDr = physical exposure to drought.
GDPcap = GDP purchasing power parity per capita.
mAL pc = modified percentage of arable land.

It is worth noticing that Sudan and Swaziland were rejected by the model. The food shortage in Sudan is more likely due to conflict rather than climatic conditions. The case of Swaziland is a problem of country size. The raster layer at 0.5° resolution was not precise enough to provide an accurate model for this country.

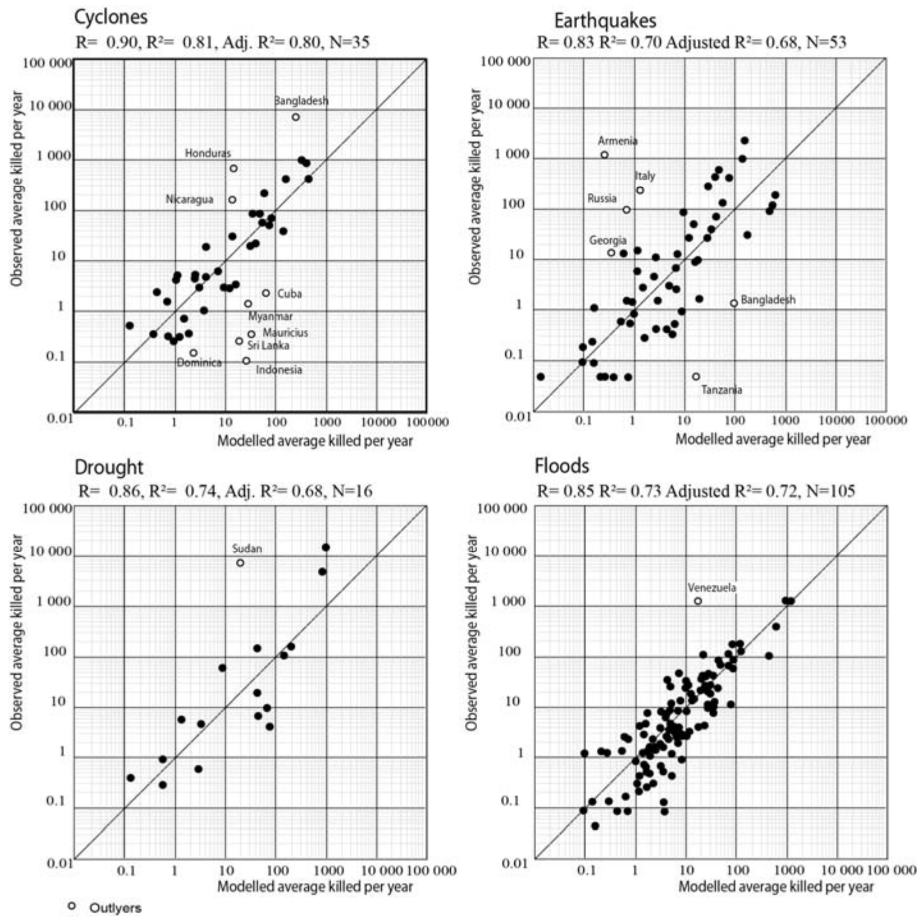


Figure 29. Regressions between observed and modelled casualties (log / log scale). Observed casualties are the number of people killed per year during the period 1980-2000, according to the EM-DAT database (CRED). Modelled casualties are derived from the statistical model based on socio-economic indicators of vulnerability and physical exposures for each hazard.

According to the analysis, the number of killed people from physical drought grows with PhExp, decreases as the GDPcap grows and decreases if the percentage of arable land grows. The interesting point is that, as opposed to the other hazards, the main contribution to casualties is poverty (low GDP) followed by physical exposure and percentage of arable land.

A country with a large portion of arable land is less likely to be totally affected by a drought and might still be able to provide enough food for its inhabitants.

Again, the part of variance explained by the regression (R^2 = 0.74) is important and p-values are smaller than 0.05. The plot can be seen on Figure 29. The residual analysis shows no abnormality or particular structure, which validates the regression (Eq.1)

Table 8. Model for drought

Variables	Coef.	St. Err.	t Stat	P-value
Intercept	10.536	6.637	1.588	0.138375
GDPcap	-4.535	1.087	-4.172	0.001294
PhExp	1.373	0.408	3.365	0.005620
mAL_pc	-1.322	0.478	-2.764	0.017148

Where:
K = number of estimated killed
PhExpDr = physical exposure to drought
GDPcap = GDP purchasing power parity per capita
mAL_pc = modified percentage of arable land

3.2.8. Earthquakes

Earthquakes affecting seismic hazard zones were modelled using the seismic catalogue of the CNSS (Council of the National Seismic System). Hypocentres records of the last 40 years (1965-2004) with magnitude equal to, or higher than, 5.5 on the Richter scale were used to generate circular buffers of Modified Mercalli Intensity (IMM). The radius of each buffer was based on intensity derived from depth of hypocentre and magnitude based on Kawasumi equations (Kawasumi, 1951).

Kawasumi equation (earthquakes)

IJMA = -0.3 + 2M - 4.6log(d) - 0.0018d
when d < 100 km
IJMA = -4.0 + 2M - 2.0log(X) - 0.0167X
when d > 100 km

Where:
IJMA = intensity of Japan Meteorological Agency
M = magnitude
d = distance from epicentre (km)
X = distance from hypocentre (km)

For each buffer, the whole range of intensity (1-12) was taken into account. This is a general approach that does not take into account any regional effects, for instance soil conditions or geotectonic characteristics. Physical exposure to earthquakes was then calculated and aggregated at country levels.

Physical exposure to earthquakes was then calculated and aggregated at country levels using Eq. 3. The variables retained by the regression are PhExp, Ug (rate of urban growth) and percentage of forest cover.

A high exposure and a high urban population growth being positively correlated to high risk of casualties, whereas a high forest coverage was correlated with less risk of casualties. This can be interpreted as high rates of population influx to cities as a synonymous of low quality urban planning and building standards. Or newcomers are living in areas previously empty because of the risk from earthquakes (unstable land, slopes, etc.). The percentage of forest, although with a low significance in the model, can be understood as the consequence of deforestation on slopes, thus leading to higher risk of landslides in earthquake prone areas.

The model is the following (see Eq. 2):

$$\ln(K) = 1.097 \cdot \ln(PhExp40_{Eq}) + 25.696 \cdot Ug - 0.425 \cdot \ln(WoodPC) - 17.344 \quad (2)$$

Table 9. Model for earthquakes

Variables	Coeff.	St. Err.	t Stat	P-value
Intercept	-17.344	1.934	-8.970	0.000000
WoodPC	-0.425	0.135	-3.141	0.002856
Ug	25.696	4.342	5.918	0.000000
PhExp	1.097	0.126	8.714	0.000000

Where:
K = number of estimated killed
PhExp40 = average population exposed to earthquakes (1964-2004)
Ug = percentage of urban growth (computed using a three-year moving average)
WoodPC = percentage of country forest coverage

The part of explained variance is smaller than for droughts or cyclones ($R^2 = 0.70$); however, considering the small length of time taken into account (36 years as compared to earthquakes long return period), the analysis delineates a reasonably good relation. Physical exposure is as relevant as in previous cases.

3.2.9. Floods

Although floods can be modelled using GIS, they request highly detailed data and complex procedures. For this study, a more generalised model was achieved by using the "comments" information in the EM-DAT database (Peduzzi *et al.*, 2005). The locations found in EM-DAT were used to select the watersheds in the HYDRO1k Elevation Derivative Database (U.S Geological Survey, http://edc.usgs.gov/products/elevation/gtopo30/hydro/) as approximations of the flooded areas as explained in previous study (Peduzzi *et al.*, 2002; Peduzzi *et al.*, 2005). This constitutes a global flood dataset taking into account 21 years covering 82.2% of the events (the one that had the necessary information) and 85.4% of the victims. Once the watersheds were identified, a computation of physical exposure was performed using the Eq. 3.

The variables identified by the statistical analysis are PhExp and GDPcap. Once again, GDPcap being highly correlated with HDI, this latter could have been chosen as well. The GDPcap was chosen due to a slightly better correlation between the model and observed casualties, and also due to lower p-values. Not surprisingly, the regression proves that highly exposed and poorer populations are more subject to suffer casualties from floods. The part of explained variance ($R^2 = 0.73$) associated with significant p-value on 90 countries+, as well as correct residual analysis, confirm a solid confidence in the selection of the variables.

The model is the following (see Eq.3):

$$\ln(K) = 0.905 \cdot \ln(PhExp_{Fl}) - 0.697 \cdot \ln(GDP_{cap}) - 4.799 \qquad (3)$$

Table 10. Model for floods

Variables	Coeff.	St. Err.	t Stat	P-value
Intercpt	-4.799	1.055	-4.551	0.000015
GDPcap	-0.697	0.102	-6.812	0.000000
PhExp	0.905	0.057	15.824	0.000000

Where:
K = number of estimated killed
GDPcap = normalised Gross Domestic Product per capita (purchasing power parity)
PhExpFl = average number of persons living in watersheds affected by floods

3.2.10. Multiple risk and categories

Multiple risk figures were computed by summing up modelled human losses from droughts, earthquakes, floods and tropical windstorms. For 16 out of 38 countries+ with missing data (i.e. either socio-economic parameters or exposure data), an estimated risk value of 0 was assigned because the exposure was considered to be negligible (less than 1000 people or 2% of the total population of the country exposed).

The DRI was computed for each country by taking into account both the absolute (killed per year) and the relative multiple risk figures (killed per year as percentage of the total country population). First of all, the log value of the two variables were normalised into 0-1 scales using the following thresholds: 0.5-500 killed per year and 0.1-10 killed per million per year (Figure 30).

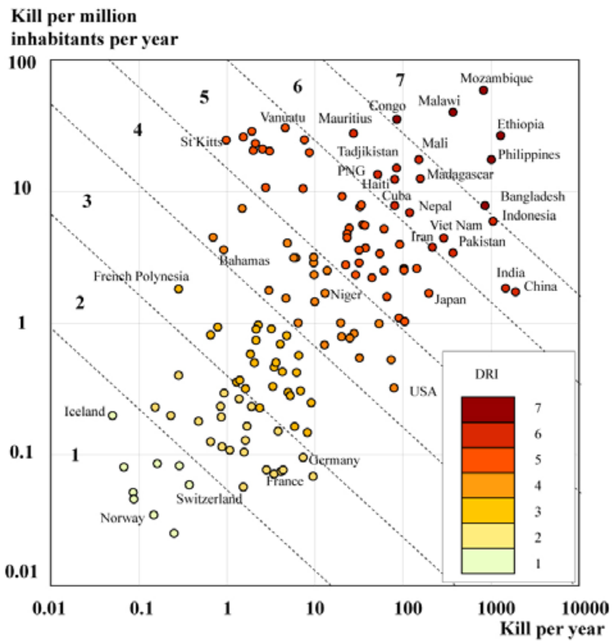


Figure 30. Two dimensional classification in categories of risk

Then, the two normalised absolute and relative variables were averaged and classified using an equal-interval classification scheme (see Table 11), which was also applied to the observed data from EM-DAT for further comparison.

Table 11 DRI classes

DRI value	DRI class
-∝	0 (no killed)
]-∝, 0]	1
]0.0, 0.2]	2
]0.2, 0.4]	3
]0.4, 0.6]	4
]0.6, 0.8]	5
]0.8, 1.0]	6
> 1.0	7

3.2.11. Discussion

Identifying human vulnerability

Although a significant database was generated on vulnerability parameters (32 indicators) only five of them were finally retained by the multiple regression analysis (i.e. GDP purchasing power parity per capita, modified percentage of arable land, percentage of urban growth, percentage of country forest coverage, transformed value of the percentage of the country dedicated to Crop land). The selection was made by statistical tests (hence without subjectivity). Poverty (low GDPcap) is the most selected indicator, many other indicators are strongly correlated with poverty (such as Human Development Index (HDI), Urban Growth, number of physicians per inhabitants, etc.). Given that we cannot place two indicators that are strongly correlated in the same model, the selected indicators are those that provided the best R^2, the smallest p-value and also the best countries+ and time coverage. However, GDPcap can most often be replaced by HDI or other correlated indicators, also with less precision in the model or with less countries+ covered).

Geographical distribution

The DRI could be computed for 215 countries+ (86% of the 249 countries+, representing 96% of the world population and 79% of the killed from EM-DAT). The main countries+ not included in the multiple model were: North Korea, Afghanistan, Somalia, Taiwan, Puerto Rico (missing socio-economic data), Swaziland, Tanzania (bad exposure data). These seven countries+ account for 99.7% of the missing killed from EM-DAT that could not be modelled. Other missing countries+ include several small island territories (see Table 12)

.

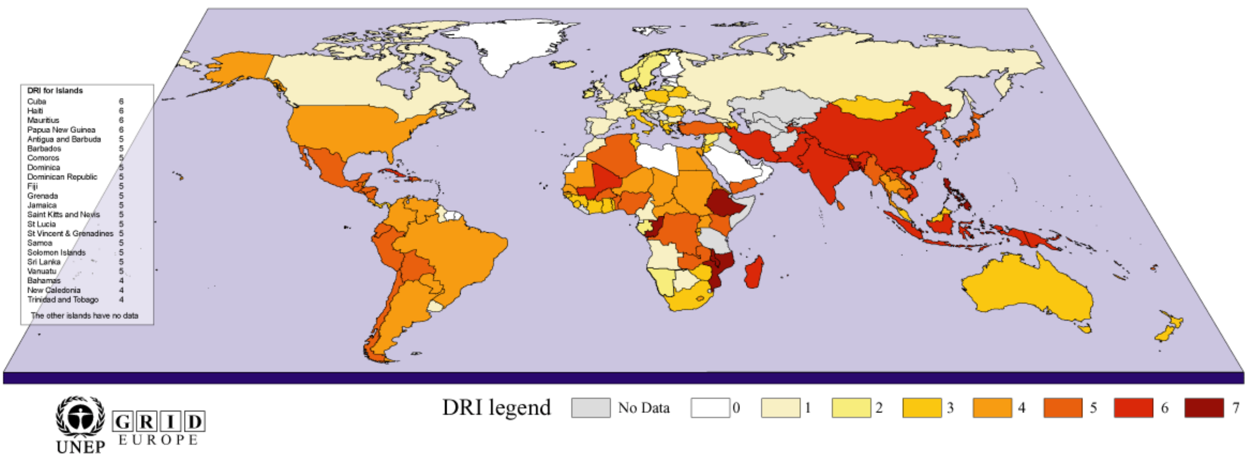


Figure 31. Spatial distribution of DRI classes

Without much surprise the top countries at risk in terms of killed per year are the most populated countries (China, India, Indonesia, Bangladesh), whereas small islands states (Vanuatu, Dominica, Mauritius, Antigua and Barbuda, St Kitts and Nevis, Solomon Islands, Grenada,etc.) come first in terms of killed per million inhabitants per year. Once the two indicators are combined to obtain the DRI, six of the top 10 countries are in Africa, the other countries+ being located in Asia. Islands states rank high in the DRI (Figure 31).

Some countries could not be modelled due to lack of data (see Table 12).

Table 12. List of countries+ that could not be modelled due to lack of data

independent states	Micronesia, Tonga
Territories	American Samoa, Anguilla, Bermuda, British Virgin Islands, Cook Islands, Guadeloupe, Guam, Martinique, Montserrat, Netherlands Antilles, Niue, Puerto Rico, Reunion, Turks and Caicos Islands, United States Virgin Islands, Wallis and Futuna

All the DRI values are provided in Supplementary material B.

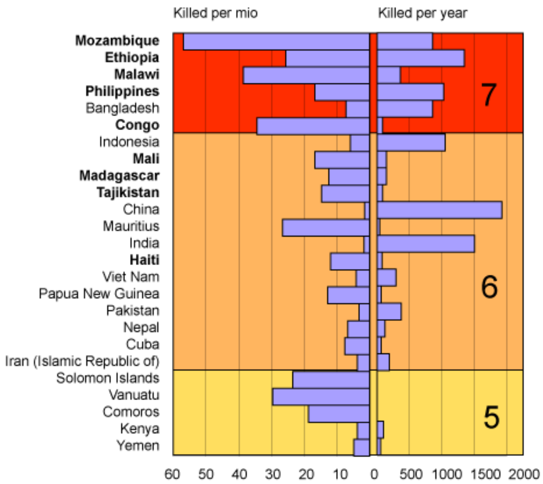


Figure 32. Top 25 countries+ according to DRI (in bold: countries+ with both indicators in the top 25)

For nine countries (in bold in Figure 32) the weights have little influence on the DRI since they are ranked high (in the top 25 countries+) in both indicators.

Unexpected DRI values

Although more than 90% of the modelled classes have a difference of 2 or less classes (50% with no difference, 30% with a difference of one class, and 9.3% with a difference of 2). There are some unexpected values. When comparing DRI classes based on the models with those derived from observed data (EM-DAT), 9 countries show a difference greater than 3 classes (see Table 13). This does not necessarily reflect limits of the models. Underestimated values rather highlight countries affected by extraordinary events (such as cyclone Mitch in 1998, earthquake in Armenia in 1988, floods in Venezuela in 1999). Overestimated values concern countries that are either drought prone areas or cyclone prone islands : in these cases, there were problems when computing physical exposure and/or in the classification of the victims in EM-DAT (e.g. the dubious value of 0 reported killed from droughts in Mali). Spatial comparisons between modelled and observed values can be seen in Figure 33.

Comparison of the model with 2001-2006 observed casualties

The DRI cannot be used for estimating future number of casualties, e.g. it underestimated Pakistan (2005 earthquake) and Iran (Bam 2003) or Haiti (hurricane Jeanne, 2004). However, these three countries were correctly classified (based on 1980-2000 data) as countries facing very high risk (class 6). The comparison of modelled and observed categories of risk shows that 71% of the countries have 1 class or less difference. Six countries show a difference of 4 classes : Morocco (underestimated, earthquakes in 2004), Congo, Papua New Guinea, Mali (overestimated for drought), Mauritius, Laos (overestimated for cyclones).

3.2.12. Conclusion : a flexible classification system to use with care

The DRI takes into account both an absolute and a relative risk indicator, allowing to consider populated and small countries+ in different manners. The somewhat arbitrary choice was to place a similar weight on killed per year and killed per inhabitant; any other combination would be possible according to the users' choice since the two indicators are provided along with the DRI.

Table 13. Major class differences between observed data and model

	Country	DRI (model)	DRI (with CRED data)	Difference	Main cause of under/over-estimation
Underestimation	Armenia	2	7	-5	Earthquakes
	Chad	4	7	-3	Droughts
	Mauritania	4	7	-3	Droughts
	Venezuela	4	7	-3	Floods
	Sudan	4	7	-3	Droughts
	Italy	3	6	-3	Earthquakes
	Morocco	2	5	-3	Floods
	Georgia	2	5	-3	Earthquakes
Overestimation	Mali	6	2	+4	Droughts
	Mauritius	6	2	+4	Cyclones
	Eritrea	4	0	+4	Droughts
	Senegal	4	0	+4	Floods
	Grenada	5	0	+5	Cyclones
	Zambia	5	0	+5	Droughts
	Barbados	5	0	+5	Cyclones
	Congo	7	1	+6	Droughts

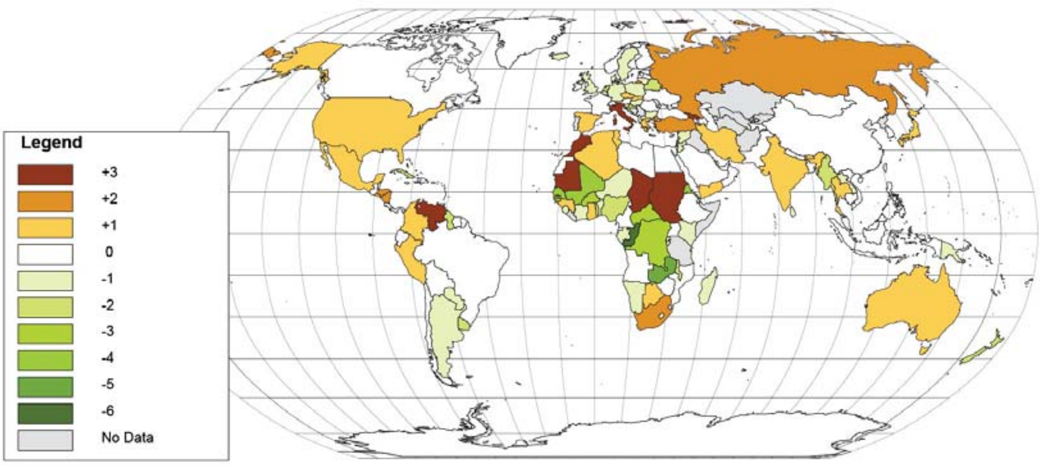


Figure 33. Maps of differences between DRI modelled and DRI observed.

For other countries+, the flexibility of the DRI classification system allows the users to specify whether more weight should be given to killed per year or to killed per inhabitant. Typically, the users interested in Small Island Developing States (SIDS) will obviously choose the second solution. This model also remains open to adding future components to the DRI, such as the economic losses once the input data are improved.

Correlations between modelled and observed risks for each hazard type were surprisingly high and relevant, given the heterogeneity of the data sources and the coarse resolution of the data at the global scale. They successfully demonstrate a correlation between high levels of development and low numbers of casualties from these four types of hazards. This correlation can be understood both ways: low development may lead to high casualties, and high disaster occurrence may also lead to low economic development as it destroys infrastructure and crops as well as deterring investors .

As EM-DAT does not include small-scale disasters, the models calibrated on past events cannot address these kinds of events, which are more frequent and may cumulate, to be of concern for the developing process in poor countries. Further studies might be carried out on more detailed databases (e.g. based on DesInventar) to identify patterns of small disaster hazards.

There is a gap between the resolution of the hazard and exposure (5 x 5 km cells) and the vulnerability parameters (country level). Some indicators are now being generated at sub-national level, but so far only for a limited number of countries+ and indicators. Given that the DRI is provided at a national level, this is less of an issue. However, in large countries+ with significant discrepancies, (e.g. China, India) more disaggregated figures should be used in the future.

Even though the model was designed for understanding past casualties (1980-2000), by using modelled losses based on 2005 physical exposure and vulnerability parameters (as opposed to recorded losses), the DRI offers a picture of risks (due to natural hazards) at a specific time. This provides a risk level that is comparable; it doesn't depend on quality of country reporting and demographic changes are taken into account. However, this model should not be used in a predictive way to estimate potential casualties that are usually also highly dependent on proximal parameters such as the time of the day (working hours, people asleep,etc.). The DRI does not differentiate risk from rare severe events and equivalent risk resulting from less severe, yet more frequent events. To overcome this issue, future modifications to the model should focus on less aggregated analyses and use event-based analysis to include hazard severity. Additionally, models should be made at sub-national levels with much higher resolution data, leading to danger maps for planning prevention and relief. In some cases, early warning systems and prevention measures can be implemented, while in others, the country is affected too frequently for coping with the new event : the high recurrence makes each new event worse than the previous ones, leading to what is called the ratchet effect.

The DRI is being used by UNDP\BCPR to identify countries+ in highest need for prevention and development. This study sets the basis of risk status for the period 1980 – 2000. Risk (from natural hazards) is likely to increase in the coming decades, since higher exposure to hazardous events will occur following population increases. However, exposure is not the only risk component that is likely to increase: depletion of natural resources and increasing gaps between rich and poor populations, political unrest and AIDS will probably have an impact on human vulnerability. Hydro-meteorological hazard frequencies and magnitudes might also change in the near future due to climate change and/or environmental degradation. To better understand where risk might increase in the future and to prepare for these future risk patterns, further refined analysis should be carried out on the three risk components. DRI can be used to prioritize where such detailed studies should be carried out and where improvements on data collection are needed; this is, however, not a final goal per se. Rather, final results will be achieved when proper risk reduction measures are implemented leading to an observed decrease in casualties.

Contributions

Redaction: Pascal Peduzzi with inputs from all other co-authors. General concept and methodology: Pascal Peduzzi. Modelling earthquake hazard: Christian Herold. Modelling tropical cyclones hazards: Christian Herold, based on a methodology developped by Ola Nordbeck, Frédéric Mouton, Christian Herold and Pascal Peduzzi. Modelling floods: based on Peduzzi *et al.* (2005), Extraction of exposure: Christian Herold. Preparation of vulnerability database: Hy Dao. Statistical analysis: Pascal Peduzzi under a mathematical methodology developped by Frédéric Mouton. Generation of the Disaster Risk Index: Pascal Peduzzi and Hy Dao. Maps and graphs: Pascal Peduzzi.

Acknowledgements

Assistants in geo-referencing EM-DAT: O. Nordbeck, A. Martin Diaz, T. Ton-That and B. Widmer. Modelling drought, Bruno Chatenoux, based on a modified methodology initially developped by Brad Lyon.

References

1. Peduzzi, P., Dao, H., Herold, C.: Global Risk And Vulnerability Index Trends per Year (GRAVITY), Phase II: Development, analysis and results, United Nations Environment Programme, technical document, UNEP/GRID-Geneva, 2002.

2. UNDP/BCPR, A Global Report: Reducing Disaster Risk, A Challenge for Development (UNDP/BCPR, New York, 2004), pp. 146.
3. Dilley, M., Chen, R. Deichmann, U., Lerner-Lam, A., Arnold, M., Natural Disaster Hotspots, a global risk analysis, the World Bank, 2005, pp. 112.
4. Cardona, O. D, Indicators for Disaster Risk and Risk Management. Program for Latin America and the Caribbean: Summary Report. Manizales, Columbia: Instituto de Estudios Ambientales, Universidad Nacional de Columbia, 2005.
5. Burton, I., Kates, R. W., White, G. F.: *The environment as hazard* (Oxford University Press, New York, 1978), pp. 240.
6. UNDRO, "Natural Disasters and Vulnerability Analysis : Report of Expert Group Meeting (9-12 July 1979)", UNDRO, 1979.
7. Dao, H., Peduzzi, P.: Global Risk And Vulnerability Index Trends per Year (GRAVITY), Phase IV: Technical annex and multiple risk integration, (Tech. Rep. UNDP/BCPR, Geneva, 2003).
8. Dao, H., Peduzzi, P.: Global evaluation of human risk and vulnerability to natural hazards, *Enviroinfo 2004*, Sh@ring, Editions du Tricorne, Genève, **1**, 435-446, 2004.
9. Blaikie, P., *et al.*, *At Risk: Natural Hazards, Peoples Vulnerability and Disasters* (Routledge, London, 1996).
10. Peduzzi, P., Dao, H., Herold, C.: Mapping Disastrous Natural Hazards Using Global Datasets, *Natural Hazards*, **35**(2), 265 – 289, 2005.
11. Coburn, A. W., Spence, R. J. S. , Pomonis, A.: Vulnerability and Risk Assessment (UNDP Disaster Management Training Program, 1991).
12. Holland, G. J.: *Monthly Weather Review* **108**, 1212, 1980.
13. Mouton, F., Nordbeck, O., Peduzzi, P.: Cyclone Database Manager, A tool for converting point data from cyclone observations into tracks and wind speed profiles in a GIS, (Tech. Rep. UNEP/GRID-Europe, Geneva, 2002).
14. Fifth International Workshops on Tropical Cyclones - IWTC-V, (Cairns, December 2002)
15. Dilley, M., Chen, R. S., Deichmann, U., Lerner-Lam, A. L., Arnold, M.: Natural Disaster Hotspots, a global risk analysis, The World Bank, 132 p., 2005.
16. Kawasumi, H., Bull. Earthq. Res. Inst. Univ. Tokyo 29, 469−482, 1951.

Hazard and exposure data

Hazard and exposure data created for this study can be freely accessed at:
http://www.grid.unep.ch/activities/earlywarning/preview/data/
They can be visualised using the PREVIEW – Global Risk Data Platform:
http://preview.grid.unep.ch/

3.3. Assessing global exposure and vulnerability towards natural hazards : the Disaster Risk Index (Supplementary material)

3.3.1. Maerial A. List of Variables tested for vulnerability assessment

Categories of vulnerability	Indicators	Source
Economic	Gross Domestic Product per inhabitant at purchasing power parity	World Bank
	Human Poverty Index (HPI)	UNDP
	Total dept service (% of the exports of goods and services),	UNDP
	Inflation, food prices (annual %),	World Bank
	Unemployment, total (% of total labour force)	World Bank / ILO
Type of economic activities	%age of arable land	FAO
	%age of urban population	UNPOP
	%age of country dedicated to cropland	FAO
	%age of agriculture's dependency for GDP	World Bank
	%age of labour force in agricultural sector	FAO
Quality of the environ.	Forests and woodland (in %age of land area),	FAO
	%age of irrigated land	FAO
	Human Induced Soil Degradation (GLASOD)	FAO / UNEP
Demography	Population growth,	UNPOP
	Urban growth,	GRID
	Population density,	GRID
	Age dependency ratio,	World Bank
Health and sanitation	Average calorie supply per capita,	FAO
	%age of people with access to adequate sanitation,	WHO / UNICEF
	%age of people with access to safe water (total, urban, rural)	WHO / UNICEF
	Number of physicians (per 1000 inh.),	World Bank
	Number Hospital Beds	World Bank
	Life Expectancy at birth for both sexes	UNPOP
	Under five year old mortality rate	UNPOP
Politic	Transparency's CPI (index of corruption)	TI
Early warning capacity	Number of Radios (per 1000 inh.)	World Bank
Education	Illiteracy Rate,	World Bank
	School enrolment,	UNESCO
	Secondary (% gross),	UNESCO
	Labour force with primary, secondary or tertiary education	World Bank
Development	Human Development Index (HDI)	UNDP

3.3.2. Supplementary material B. All DRI values

Countries+	Indicator 1 (killed per year)	Indicator 2 (killed per mio)	DRI	DRI class
Mozambique	1.08	1.38	1.23	7
Ethiopia	1.14	1.21	1.17	7
Malawi	0.96	1.29	1.13	7
Philippines	1.10	1.11	1.11	7
Bangladesh	1.08	0.94	1.01	7
Congo	0.75	1.27	1.01	7
Indonesia	1.11	0.88	0.99	6
Mali	0.83	1.12	0.97	6
Madagascar	0.83	1.05	0.94	6
Tajikistan	0.74	1.08	0.91	6
China	1.19	0.61	0.90	6
Mauritius	0.58	1.21	0.90	6
India	1.16	0.63	0.89	6
Haiti	0.74	1.04	0.89	6
Viet Nam	0.92	0.81	0.87	6
Papua New Guinea	0.67	1.06	0.86	6
Pakistan	0.96	0.76	0.86	6
Nepal	0.80	0.92	0.86	6
Cuba	0.74	0.94	0.84	6
Iran (Islamic Republic of)	0.88	0.78	0.83	6
Solomon Islands	0.40	1.19	0.79	5
Vanuatu	0.32	1.24	0.78	5
Comoros	0.41	1.14	0.78	5
Kenya	0.76	0.79	0.78	5
Yemen	0.70	0.85	0.78	5
Nicaragua	0.61	0.94	0.77	5
Lao People's Democratic Republic	0.61	0.94	0.77	5
Turkey	0.83	0.70	0.76	5
Jamaica	0.54	0.97	0.75	5
Dominican Republic	0.63	0.87	0.75	5
Bolivia	0.62	0.87	0.74	5
Japan	0.87	0.61	0.74	5
Democratic Republic of the Congo	0.78	0.70	0.74	5
Republic of Korea	0.77	0.69	0.73	5
Sri Lanka	0.68	0.76	0.72	5
Dominica	0.20	1.22	0.71	5
Benin	0.57	0.85	0.71	5
Samoa	0.27	1.15	0.71	5
Ecuador	0.63	0.78	0.70	5
Honduras	0.56	0.84	0.70	5
Fiji	0.39	1.00	0.69	5
Algeria	0.70	0.69	0.69	5
Saint Lucia	0.24	1.15	0.69	5
Grenada	0.21	1.18	0.69	5
Guatemala	0.60	0.78	0.69	5
El Salvador	0.56	0.82	0.69	5

Antigua and Barbuda	0.17	1.20	0.68	5
Saint Vincent and the Grenadines	0.20	1.15	0.68	5
Cambodia	0.60	0.72	0.66	5
Peru	0.65	0.67	0.66	5
Myanmar	0.71	0.60	0.65	5
Saint Kitts and Nevis	0.10	1.19	0.65	5
Nigeria	0.78	0.50	0.64	5
Zambia	0.55	0.72	0.64	5
Mexico	0.76	0.51	0.63	5
Chile	0.59	0.68	0.63	5
Burkina Faso	0.56	0.71	0.63	5
Barbados	0.24	1.01	0.63	5
Chad	0.48	0.70	0.59	4
Costa Rica	0.43	0.75	0.59	4
Thailand	0.68	0.49	0.59	4
Eritrea	0.44	0.72	0.58	4
Trinidad and Tobago	0.33	0.80	0.57	4
Paraguay	0.43	0.68	0.56	4
Mauritania	0.36	0.74	0.55	4
Bhutan	0.36	0.74	0.55	4
Belize	0.16	0.93	0.55	4
Niger	0.47	0.61	0.54	4
Brazil	0.72	0.35	0.54	4
Colombia	0.59	0.45	0.52	4
Venezuela	0.54	0.50	0.52	4
Senegal	0.44	0.58	0.51	4
Argentina	0.57	0.44	0.50	4
United States of America	0.74	0.25	0.49	4
Sudan	0.54	0.45	0.49	4
Egypt	0.60	0.37	0.49	4
Central African Republic	0.33	0.59	0.46	4
Uganda	0.47	0.41	0.44	4
Lesotho	0.26	0.62	0.44	4
New Caledonia	0.05	0.82	0.44	4
Rwanda	0.37	0.49	0.43	4
Bahamas	0.09	0.77	0.43	4
Burundi	0.33	0.45	0.39	3
Cote d'Ivoire	0.38	0.37	0.37	3
Togo	0.27	0.47	0.37	3
Guinea	0.31	0.42	0.36	3
Mongolia	0.22	0.49	0.36	3
Panama	0.21	0.47	0.34	3
Ghana	0.37	0.31	0.34	3
Albania	0.21	0.43	0.32	3
Tunisia	0.29	0.34	0.32	3
Greece	0.31	0.31	0.31	3
Romania	0.38	0.24	0.31	3
South Africa	0.42	0.19	0.31	3
Azerbaijan	0.28	0.33	0.31	3
Australia	0.33	0.23	0.28	3

New Zealand	0.19	0.37	0.28	3
Malaysia	0.34	0.22	0.28	3
Guinea-Bissau	0.07	0.48	0.27	3
Moldova, Republic of	0.21	0.34	0.27	3
French Polynesia	-0.08	0.62	0.27	3
Belarus	0.27	0.25	0.26	3
Gambia	0.04	0.45	0.24	3
Italy	0.40	0.08	0.24	3
Poland	0.36	0.10	0.23	3
Sierra Leone	0.15	0.28	0.21	3
Israel	0.17	0.24	0.21	3
Jordan	0.14	0.27	0.20	3
Zimbabwe	0.23	0.17	0.20	3
Morocco	0.30	0.08	0.19	2
Bulgaria	0.20	0.18	0.19	2
Germany	0.39	-0.01	0.19	2
Georgia	0.15	0.21	0.18	2
Russian Federation	0.43	-0.09	0.17	2
Uruguay	0.09	0.23	0.16	2
Angola	0.18	0.10	0.14	2
United Kingdom of Great Britain and Northern Ireland	0.32	-0.06	0.13	2
Armenia	0.07	0.18	0.13	2
France	0.31	-0.06	0.12	2
Cameroon	0.17	0.05	0.11	2
Croatia	0.08	0.14	0.11	2
Guyana	-0.08	0.29	0.11	2
Ukraine	0.28	-0.08	0.10	2
Spain	0.25	-0.07	0.09	2
Netherlands	0.17	0.01	0.09	2
Belgium	0.11	0.02	0.06	2
Hungary	0.11	0.01	0.06	2
Lebanon	-0.01	0.12	0.06	2
Austria	0.08	0.03	0.06	2
Slovakia	0.04	0.05	0.04	2
Botswana	-0.11	0.15	0.02	2
Canada	0.16	-0.13	0.02	2
Cyprus	-0.17	0.17	0.00	2
Ireland	-0.08	-0.05	-0.06	1
Switzerland	-0.04	-0.12	-0.08	1
Iceland	-0.33	0.15	-0.09	1
The former Yugoslav Republic of Macedonia	-0.16	-0.04	-0.10	1
Gabon	-0.29	-0.05	-0.17	1
Kuwait	-0.25	-0.15	-0.20	1
Czech Republic	-0.10	-0.31	-0.20	1
Norway	-0.18	-0.23	-0.20	1
Slovenia	-0.25	-0.17	-0.21	1
Namibia	-0.37	-0.31	-0.34	1
Luxembourg	-0.65	-0.41	-0.53	1

Sweden	-0.46	-0.81	-0.64	1
Syrian Arab Republic	-0.53	-1.01	-0.77	1
Cape Verde	-1.46	-1.59	-1.53	1
Lithuania	-2.02	-2.96	-2.49	1
Denmark	-2.47	-3.72	-3.10	1
Andorra	n. d.	n. d.	n. d.	0
Antarctica	n. d.	n. d.	n. d.	0
Aruba	n. d.	n. d.	n. d.	0
Bahrain	n. d.	n. d.	n. d.	0
Baker Island	n. d.	n. d.	n. d.	0
Bouvet Island	n. d.	n. d.	n. d.	0
British Indian Ocean Territory	n. d.	n. d.	n. d.	0
Brunei Darussalam	n. d.	n. d.	n. d.	0
Cayman Islands	n. d.	n. d.	n. d.	0
Christmas Island	n. d.	n. d.	n. d.	0
Cocos (Keeling) Islands	n. d.	n. d.	n. d.	0
Equatorial Guinea	n. d.	n. d.	n. d.	0
Estonia	n. d.	n. d.	n. d.	0
Falkland Islands (Malvinas)	n. d.	n. d.	n. d.	0
Faroe Islands	n. d.	n. d.	n. d.	0
Finland	n. d.	n. d.	n. d.	0
French Guiana	n. d.	n. d.	n. d.	0
French Southern and Antarctic Territories	n. d.	n. d.	n. d.	0
Gibraltar	n. d.	n. d.	n. d.	0
Glorioso Islands	n. d.	n. d.	n. d.	0
Greenland	n. d.	n. d.	n. d.	0
Guernsey	n. d.	n. d.	n. d.	0
Heard Island & McDonald Islands	n. d.	n. d.	n. d.	0
Holy See	n. d.	n. d.	n. d.	0
Howland Island	n. d.	n. d.	n. d.	0
Isle of Man	n. d.	n. d.	n. d.	0
Jarvis Island	n. d.	n. d.	n. d.	0
Jersey	n. d.	n. d.	n. d.	0
Johnston Atoll	n. d.	n. d.	n. d.	0
Juan De Nova Island	n. d.	n. d.	n. d.	0
Kiribati	n. d.	n. d.	n. d.	0
Latvia	n. d.	n. d.	n. d.	0
Libyan Arab Jamahiriya	n. d.	n. d.	n. d.	0
Liechtenstein	n. d.	n. d.	n. d.	0
Macau, China	n. d.	n. d.	n. d.	0
Maldives	n. d.	n. d.	n. d.	0
Malta	n. d.	n. d.	n. d.	0
Marshall Islands	n. d.	n. d.	n. d.	0
Mayotte	n. d.	n. d.	n. d.	0
Midway Islands	n. d.	n. d.	n. d.	0
Monaco	n. d.	n. d.	n. d.	0
Nauru	n. d.	n. d.	n. d.	0
Norfolk Island	n. d.	n. d.	n. d.	0
Northern Mariana Islands	n. d.	n. d.	n. d.	0
Occupied Palestinian Territory	n. d.	n. d.	n. d.	0

Oman	n. d.	n. d.	n. d.	0
Palau	n. d.	n. d.	n. d.	0
Paracel Islands	n. d.	n. d.	n. d.	0
Pitcairn Island	n. d.	n. d.	n. d.	0
Qatar	n. d.	n. d.	n. d.	0
Saint Helena	n. d.	n. d.	n. d.	0
Saint Pierre and Miquelon	n. d.	n. d.	n. d.	0
San Marino	n. d.	n. d.	n. d.	0
Sao Tome and Principe	n. d.	n. d.	n. d.	0
Saudi Arabia	n. d.	n. d.	n. d.	0
Seychelles	n. d.	n. d.	n. d.	0
Singapore	n. d.	n. d.	n. d.	0
South Georgia and the South Sandwich Islands	n. d.	n. d.	n. d.	0
Spratly Islands	n. d.	n. d.	n. d.	0
Suriname	n. d.	n. d.	n. d.	0
Svalbard and Jan Mayen Islands	n. d.	n. d.	n. d.	0
Tokelau	n. d.	n. d.	n. d.	0
Tuvalu	n. d.	n. d.	n. d.	0
United Arab Emirates	n. d.	n. d.	n. d.	0
Wake Island	n. d.	n. d.	n. d.	0
Western Sahara	n. d.	n. d.	n. d.	0
Afghanistan	n. d.	n. d.	n. d.	n. c.
American Samoa	n. d.	n. d.	n. d.	n. c.
Anguilla	n. d.	n. d.	n. d.	n. c.
Bermuda	n. d.	n. d.	n. d.	n. c.
Bosnia and Herzegovina	n. d.	n. d.	n. d.	n. c.
British Virgin Islands	n. d.	n. d.	n. d.	n. c.
Cook Islands	n. d.	n. d.	n. d.	n. c.
Democratic People's Republic of Korea	n. d.	n. d.	n. d.	n. c.
Djibouti	n. d.	n. d.	n. d.	n. c.
Guadeloupe	n. d.	n. d.	n. d.	n. c.
Guam	n. d.	n. d.	n. d.	n. c.
Iraq	n. d.	n. d.	n. d.	n. c.
Kazakhstan	n. d.	n. d.	n. d.	n. c.
Kyrgyzstan	n. d.	n. d.	n. d.	n. c.
Liberia	n. d.	n. d.	n. d.	n. c.
Martinique	n. d.	n. d.	n. d.	n. c.
Micronesia (Federated States of)	n. d.	n. d.	n. d.	n. c.
Montserrat	n. d.	n. d.	n. d.	n. c.
Netherlands Antilles	n. d.	n. d.	n. d.	n. c.
Niue	n. d.	n. d.	n. d.	n. c.
Portugal	n. d.	n. d.	n. d.	n. c.
Puerto Rico	n. d.	n. d.	n. d.	n. c.
Reunion	n. d.	n. d.	n. d.	n. c.
Somalia	n. d.	n. d.	n. d.	n. c.
Swaziland	n. d.	n. d.	n. d.	n. c.
Taiwan	n. d.	n. d.	n. d.	n. c.
Tonga	n. d.	n. d.	n. d.	n. c.
Turkmenistan	n. d.	n. d.	n. d.	n. c.

Turks and Caicos Islands	n. d.	n. d.	n. d.	n. c.
United Republic of Tanzania	n. d.	n. d.	n. d.	n. c.
United States Virgin Islands	n. d.	n. d.	n. d.	n. c.
Uzbekistan	n. d.	n. d.	n. d.	n. c.
Wallis and Futuna	n. d.	n. d.	n. d.	n. c.
Yugoslavia	n. d.	n. d.	n. d.	n. c.

n. d. = no data
n. c. = not classified

3.4. From DRI to MRI, bridging the gaps

The DRI allows for comparisons between small to big countries and countries affected by earthquakes with those affected by drought. Designing such index, posed a certain number of challenges. Georeferencing past disasters in an automatic way requested the development of new methods (Peduzzi *et al.*, 2005). Using mortality was a logical way for comparing countries affected by different hazards. It may looks reductive to consider only mortality, however, the quality of the economic losses data did not allow for the comparison of risk across time and countries.

The main challenge was to find a way of comparing small and large countries. If the absolute number of people killed was considered, large countries like China, India would rank first and small countries would be relegated to the last rows. Using the percentage of killed over population is better, but then has the inconvenient that individuals from different countries do not have the same consideration: one killed in Costa Rica would worth 160 killed in China. At the end of the day, this is a political decision. In absence of such guidance from UNDP who mandated us for such study, the use of both axes was an elegant way to show risk in both dimension.

The DRI is a quantitative index. It's development provided the first evaluation of human exposure to four natural hazards. It was also the first study to provide insight on triggers of vulnerability at the global level and provided scientific evidences that risk was an unresolved issue from development. This was soon used in media and special reports with headlines such as “poverty kills” (Wahrurst, 2006). In terms of impacts, the DRI was first published as an on-going process in the UNDP/BCPR report (UNDP, 2004). This report was launched in 14 different locations and benefitted from a large media coverage. UNDP/BCPR used the DRI for deciding the number of professional dispatched in each region.

The DRI included three dimensions: kill per year, killed per million inhabitants per year and a vulnerability proxy provided by the ratio killed / exposed. It revealed some surprises. For example Cuba having less killed per exposed than USA from tropical cyclones. This is interesting because it shows that even poorer countries with limited resources can be more efficient if DRR actions are being implemented. It shows that risk is not a fate of poor countries, but also a question of governance.

Another conclusion from the DRI is the complexity of drought disaster. It revealed that drought is more a geopolitical hazards than a natural hazard. In Figure 34, the group of countries which are the most vulnerable from drought (highest ratio killed per exposed) are North Korea, Mozambique, Ethiopia and Sudan, all four countries were facing very difficult political situations and / or conflict during the period 1980-2000.

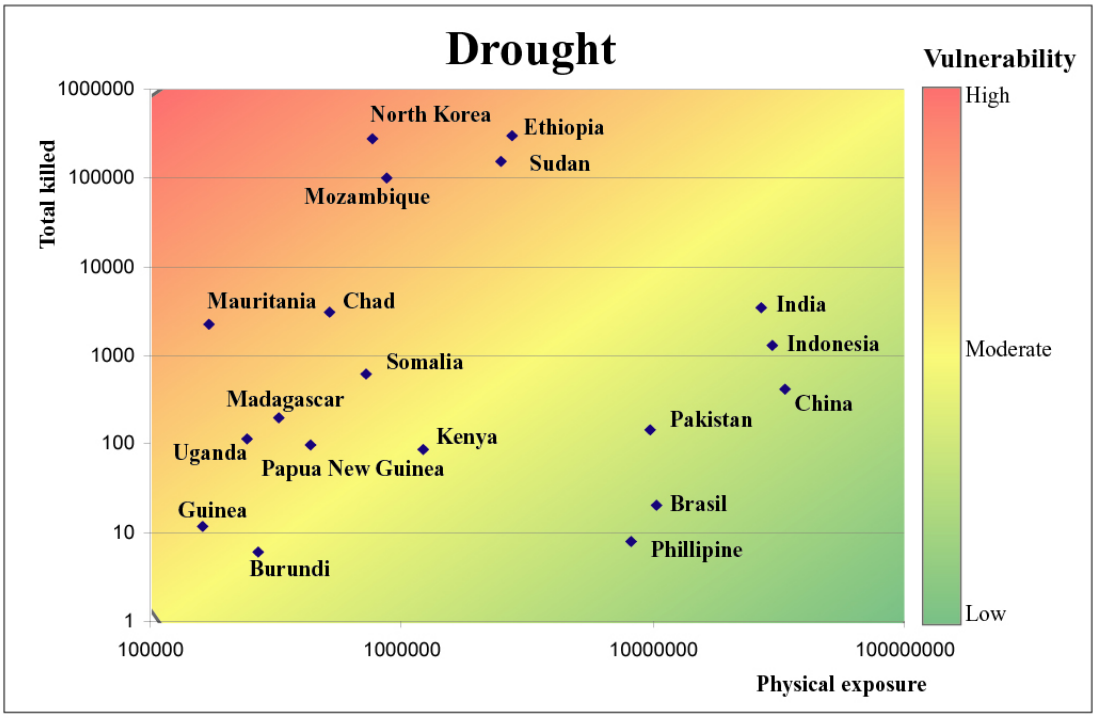


Figure 34 Drought killed versus exposed.

The most vulnerable countries are in the top left, while least vulnerable are found in the lower right. Countries with no killed resulting from drought are not represented.

Still the DRI included several limitations. The DRI was only based on mortality risk. There were no analysis on economic losses. In term of hazard, drought was not modelled in a much detailed way. It uses the methodology developed by the International Research Institute on Climate Prediction (IRI).

Floods were identified by watershed affected, the exposure to floods is therefore exaggerated. Only 21 years of hazard were covered, thus for long returning period hazards (e.g. earthquakes) countries which were not hit during this period will have a risk that may be under estimated.

The main limitation flagged was the lack of inclusion of the hazard intensity. This was the result of using average exposure and average vulnerability parameters over a 21 year-period.

All these limitations were attempted to be addressed in the Global Risk Analysis.

3.5. Global disaster risk: patterns, trends and drivers

Author: Pascal Peduzzi[1,2,3,] Uwe Deichmann[4] and others.

1 United Nations International Strategy for Disaster Reduction (UNISDR), Global Assessment Report (GAR) Unit, Switzerland
2 United Nations Environment Programme (UNEP) GRID-Geneva, Global Change and Vulnerability Unit, Switzerland.
3 Institute of Geomatics and Analysis of Risk (IGAR), University of Lausanne, Lausanne, Switzerland
4 World Bank, Washington, United States of America

Status: Published. This article is the Chapter 2 of the 2009 Global Assessment Report on Disaster Risk Reduction, published by UNISDR in May 2009. The original layout has been modified. References: Peduzzi, P., Deichmann, U., Maskrey, A., Nadim, F., Dao, H., Chatenoux, B., Herold, C., Debono, A., Giuliani, G., Kluser, S., *et al.*, Global disaster risk: patterns, trends and drivers, *ISDR (2009) Global Assessment Report on Disaster Risk Reduction*, United Nations, Geneva, Switzerland, chapter 2, pp. 17-57, 2009. http://www.preventionweb.net/english/hyogo/gar/report/documents/GAR_Chapter_2_2009_eng.pdf

3.5.1. Introduction

An observation of disaster risk patterns and trends at the global level allows a visualization of the major concentrations of risk described in the previous chapter and an identification of the geographic distribution of disaster risk across countries, trends over time and the major drivers of these patterns and trends.

The analysis presented in this chapter, developed by a large, interdisciplinary group of researchers from around the world, makes global disaster risk more visible – a key step towards mobilizing the political and economic commitment needed to reduce it.

Given the growing influence of climate change, the centrepiece of this chapter is an analysis of the mortality and economic loss[4] risk for three weather-related hazards: tropical cyclones, floods and landslides. In addition new insights have been gained into other hazards such as earthquakes, tsunami and drought.

3.5.2. Summary of findings

1. Risk concentration

Disaster risk is geographically highly concentrated. A very small portion of the Earth's surface contains most of the risk and most future large-scale disasters will occur in these areas. Risk will increase further if exposure continues to increase, for example in tropical cyclone prone coastal cities.

2. The uneven distribution of risk

Disaster risk is very unevenly distributed. Hazards affect both poorer and richer countries. For example, tropical cyclones hit both Japan and Bangladesh. Severe earthquakes occur in the United States and in India. However, for hazards of a similar severity, countries with higher incomes and, importantly, higher human development levels generally experience lower mortality and smaller losses when measured against the country's total wealth. In absolute terms economic losses are higher in richer countries, but less so once they are seen as a share of overall wealth.

3. Risk drivers

In addition to hazard severity and exposure a range of other risk drivers related to economic and social development play a crucial role in the configuration of disaster risk. These include not only income and economic strength, but also governance factors such as the quality of institutions, openness and government accountability. Income is a driver in its own right, but also conditions other drivers. Wealthier countries tend to have better institutions, more effective early-warning, and disaster preparedness and response systems, and more open government that tends to be more supportive of disaster risk reduction.

4. Disaster risk is increasing

Risk levels for most of the hazards are increasing over time, even assuming constant hazard frequency and severity. Economic loss risk is increasing faster than mortality risk. These increases in risk are being driven by the growing exposure of people and assets, for example through rapid economic and urban growth in cyclone prone coastal areas and earthquake prone cities. Vulnerability decreases as countries develop, but not enough to compensate for the increase in exposure.

5. Climate change

Weather-related hazard is critically important in the configuration of global risk patterns. Two of the principal global datasets on disaster losses[5] agree that more than two thirds of the mortality and economic losses from internationally reported disasters is associated with meteorological, climatological and hydrological hazard.

The IPCC has confirmed that the geographic distribution, frequency and intensity of these hazards is already being altered significantly by climate change[6]. Changes are already occurring in the amount, intensity, frequency and type of precipitation. This is associated with increases in the extent of the areas affected by drought, in the numbers of heavy daily precipitation events that lead to flooding, and increases in the intensity and duration of certain kinds of tropical storms.

Individual events, such as recent large tropical cyclones in the United States and Myanmar, cannot be attributed to climate change. However, given the concentration and uneven distribution of risk described above, the impact of any increases in weather-related hazard will be highly asymmetric. Poorer countries that concentrate most existing risk will be disproportionately affected by climate change.

6. Economic resilience, vulnerability and development constraints

A group of developing countries, including many SIDS, LLDCs and others with small and weak economies are particularly vulnerable to economic loss, have low resilience to that loss and are particularly exposed to climate change. Disaster impacts compromise their prospects for economic growth, poverty reduction and development at large, to the extent that the capacity of the most vulnerable countries to benefit from their insertion in the global economy is severely constrained.

3.5.3. *Method and data*[7]

Improvements in methodology and data now enable a much more accurate characterization of disaster risk than was possible when comprehensive global assessments were published by the UNDP and the World Bank[8] five years ago. Several factors have contributed to these improvements, outlined in Box 2.1.

Following the basic risk model that guides this Report (Box 1.1), disaster risk for a given location is determined by the probability that a hazard event of a given magnitude will occur, the number of exposed people or the value of exposed assets, and the level of vulnerability. The latter refers to characteristics of the exposed population, public infrastructure and economic assets that increase or decrease the likelihood of damages when a hazard event occurs, as well as factors such as effective governance and higher levels of social coherence, which influence and condition those characteristics.

Improved estimates of global disaster risk have been made possible by: Higher resolution and more complete data on geographic and physical hazard event characteristics, especially for floods, tropical cyclones and earthquakes. Improved high resolution exposure data on population and economic assets (sub-national GDP).

Enhancements in geographic and physical modelling of hazard extent, frequency and severity – especially for floods, landslides and tsunamis – allowing hazard intensity or severity to be calculated.

Explicit linking of hazard event outcomes (i.e. losses) with the geographic and physical characteristics of the event. This permits event-level analysis of the influence of exposure, vulnerability and hazard severity and the imputation of disaster losses for events for which no loss data were recorded. Incorporation of new global data sets on social, economic and other vulnerability factors, such as governance and corruption.

Box 3 Innovations in data and methodology

Analysing the mortality and economic loss experienced in past disasters permits an assessment to be made of the role played by each of the three main risk factors – hazard event characteristics, exposure and vulnerability – in configuring risk. With data for each of these risk factors for many individual disaster events, their relative importance can be statistically analysed. For instance, controlling for the magnitude of a tropical cyclone and the size of the population or economy in the affected area, it is possible to measure how vulnerability factors (such as a country's institutional quality) affect mortality or the size of economic losses. Box 2.2 presents the methodology that was followed for each hazard type.

While understanding of disaster risk has increased steadily, data limitations combined with the unpredictable and unique nature of hazard mean that much uncertainty remains. Rapid increases in vulnerability and in the exposure of population and economic assets, as well as the possibility of shifting climatic conditions affecting hazard location, frequency or magnitude, imply that risk cannot be modelled deterministically. Despite improvements in disaster reporting, loss information for individual events is incomplete and suffers from inconsistent measurement of damages and broader losses, particularly in the case of economic losses. Box 2.3 illustrates the difficulties in obtaining accurate data. While disaster mortality data are considered to be better recorded and more robust than economic loss data, uncertainties still exist.

Sub-national data on the exposure of economic assets and vulnerability factors are scarce or non-existent, meaning that proxies have to be used. Higher resolution data on disaster impacts that capture smaller-scale events and locally specific hazards are not globally available. Steady improvements in data collection will address these shortcomings and national data collection efforts will filter up to provide better global information, but these processes will take time.

The application of the risk model involved the following steps for each hazard type:1. Compile geographical and physical information on specific hazard events such as tropical cyclone track data, areas of flood extent, or earthquake location and magnitude.

2. For each hazard event, determine the footprint or area of impact, such as the area where a tropical storm exceeded tropical cyclone-force wind speed. See Figures 2.1, 2.2 and 2.3. 3. For each impact area, compute exposure as the number of people and economic assets within that area.

4. Link available loss information for each hazard event (sourced from EM-DAT) to the hazard event information (hazard severity and exposure).

5. Add information on vulnerability. Since global data on direct vulnerability factors such as building quality are unavailable, this analysis uses country-level indicators for the year in which the event occurred, such as government accountability or per capita income. 6. Estimate empirical loss functions that relate event mortality or economic losses to risk factors (hazard characteristics, exposure and vulnerability) using statistical regression techniques.

7. Derive an estimate of expected average annual losses and exposure. The estimated loss functions are used to impute disaster outcomes for all recorded events, whether or not a loss estimate is available in EM-DAT or not. This is done using data on exposure and vulnerability for 2007 such that annualized average estimates reflect current conditions.

Classes	Absolute risk (average killed per year)	Relative risk (killed per million peryear)	Mortality Risk Index (average of both indicators)
10	> 3 000	> 300	Extreme
9	1 000 to 3 000	100 to 300	Major
8	300 to 1 000	30 to 100	Very High
7	100 to 300	10 to 100	High
6	30 to 100	3 to 10	Medium high
5	10 to 30	1 to 3	Medium
4	3 to 10	0.3 to 1	Medium low
3	1 to 3	0.1 to 0.3	Low
2	0.3 to 1	0.03 to 0.1	Very Low
1	> 0 to 0.3	> 0 to 0.03	Negligible
0	0	0	Unknown exposure

8. Apply estimates to all pixels in a geographic grid. The loss estimates are aggregated at different levels (1 km x 1 km cells; sub-national administrative areas; countries) allowing the identification of geographic concentrations of risk. Mortality risk is classed in deciles using a logarithmic index with values ranging from 1 = negligible to 10 = extreme risk (see below). Economic loss risk is calculated for World Bank regions and country income groups.

9. The above procedure differed slightly between hazards. A full description of the methodology is given in Appendix 1, Technical Note 1.1: Methodology.

Box 4 Risk analysis procedure

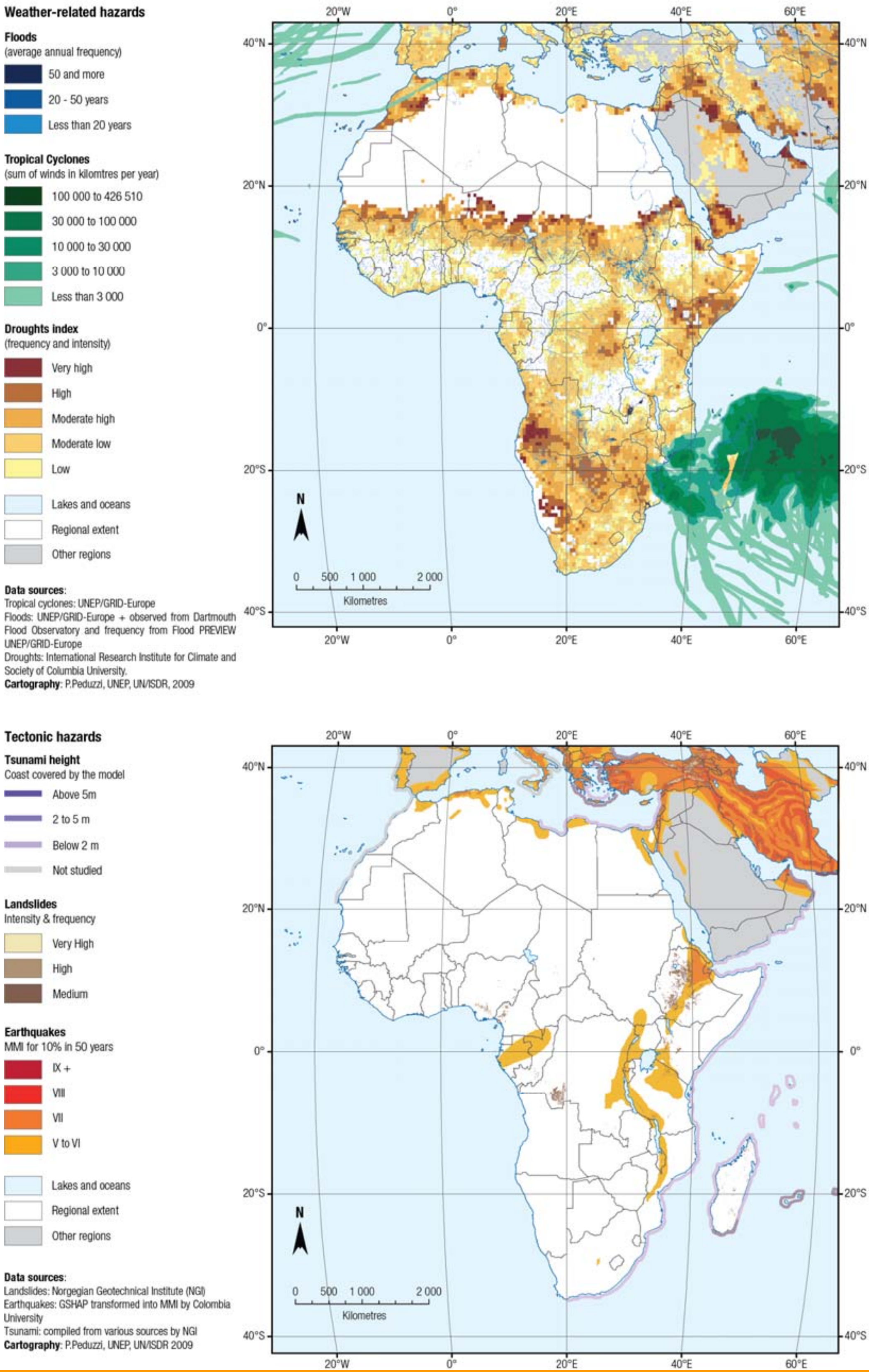
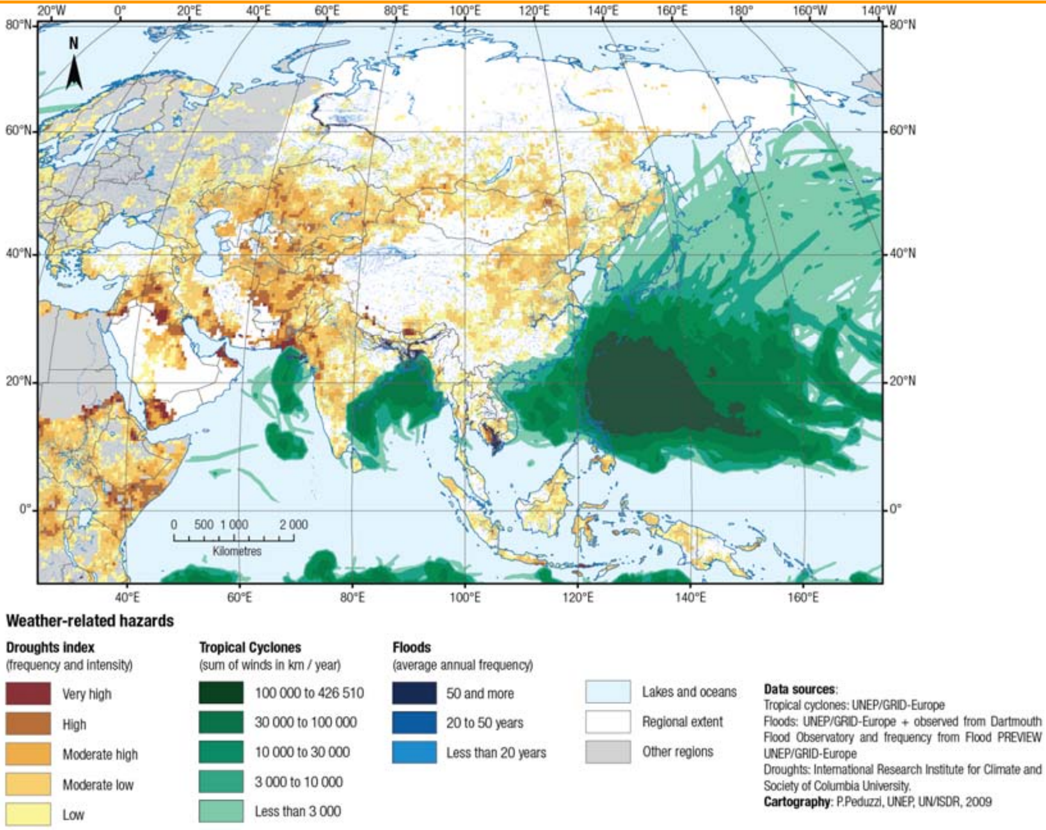


Figure 35: Multi-hazard map of Africa

Data sources: Tropical cyclones: UNEP/GRID-Europe; Floods: UNEP/GRID-Europe + observerd from Dartmouth Flood Observatory and frequency from Flood PREVIEW UNEP/GRID-Europe; Droughts: IRI, Columbia University; Landslides: Norwegian Geotechnical Institute; Earthquakes: GSHAP transformed into MMI by IRI, Columbia University; Tsunami: compiled from various sources by the Norwegian Geotechnical Institute; Cartography: P. Peduzzi, UNEP/GRID-Europe, 2009.



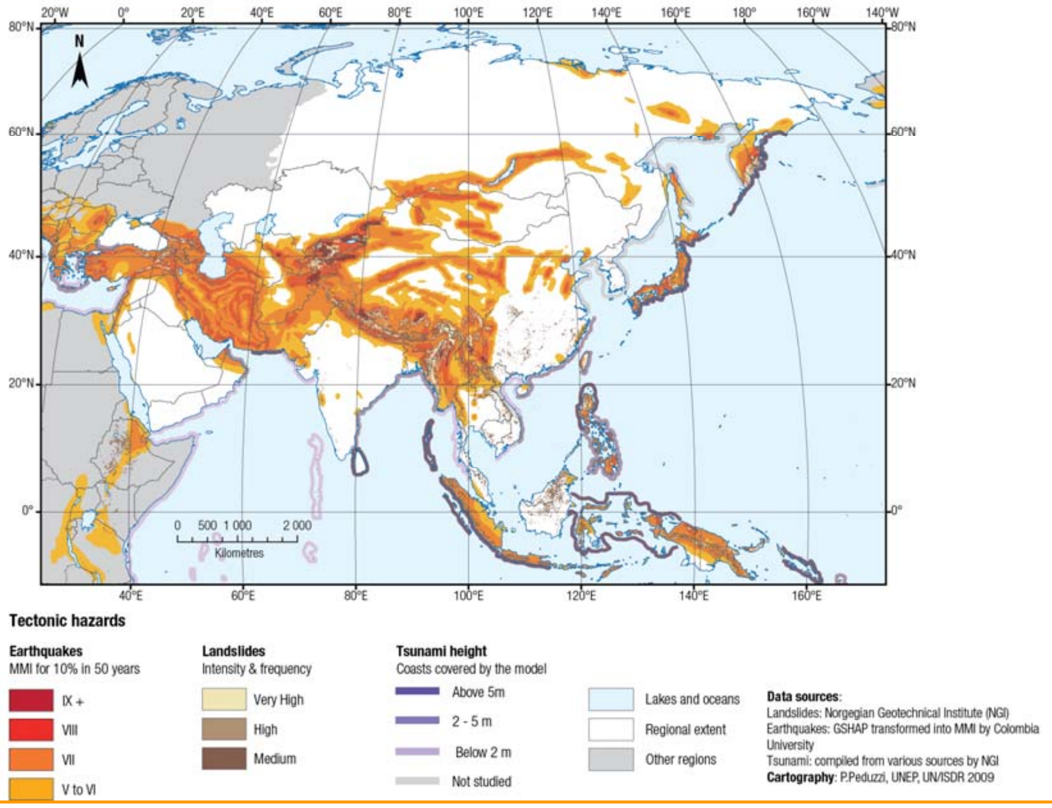


Figure 36 Multi-hazard map of Asia

Data sources: Tropical cyclones: UNEP/GRID-Europe; Floods: UNEP/GRID-Europe + observerd from Dartmouth Flood Observatory and frequency from Flood PREVIEW UNEP/GRID-Europe; Droughts: IRI, Columbia University; Landslides: Norwegian Geotechnical Institute; Earthquakes: GSHAP transformed into MMI by IRI, Columbia University; Tsunami: compiled from various sources by the Norwegian Geotechnical Institute; Cartography: P. Peduzzi, UNEP/GRID-Europe, 2009.

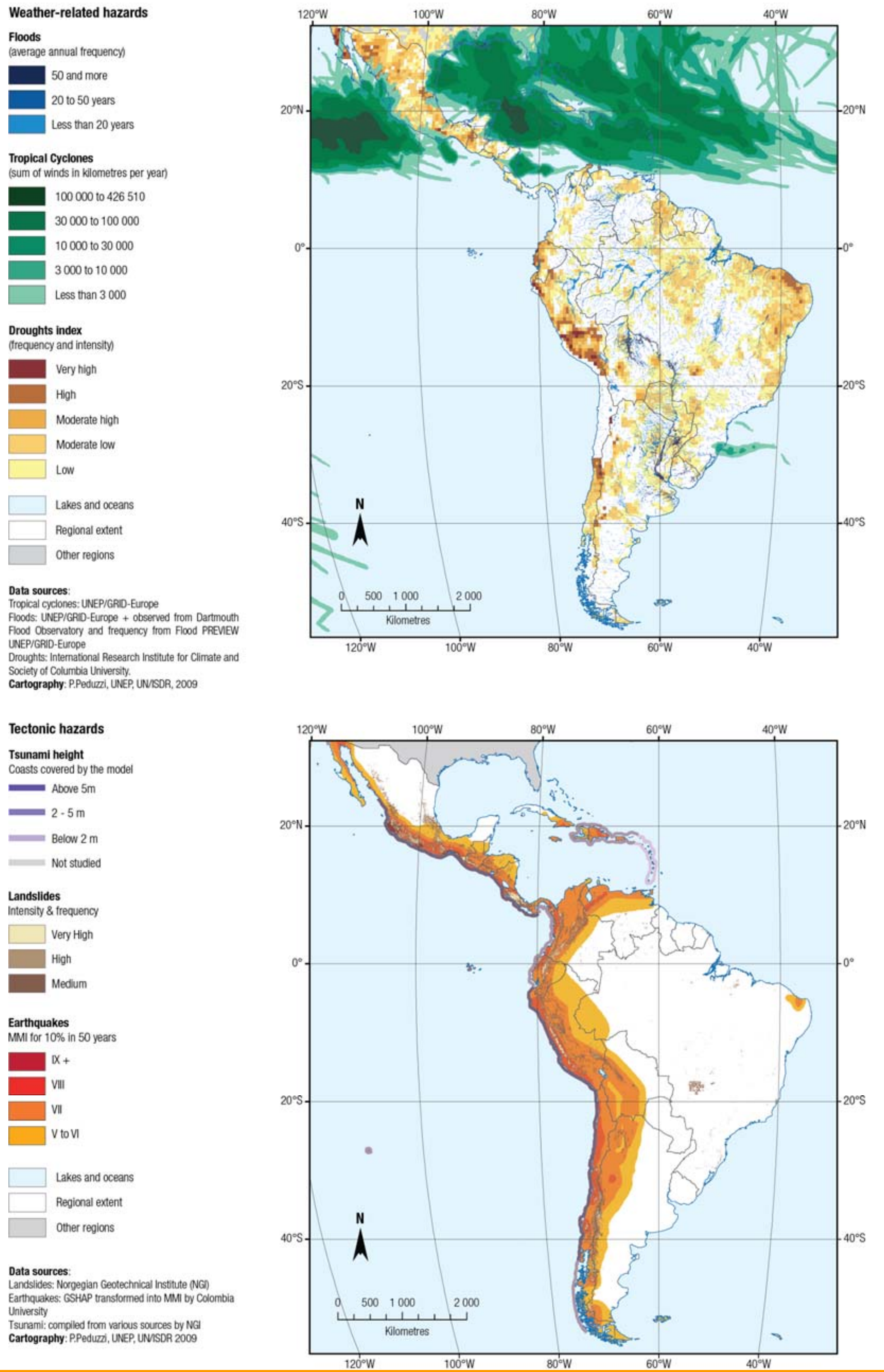


Figure 37 Multi-hazard map of Latin America and the Caribbean

Data sources: Tropical cyclones: UNEP/GRID-Europe; Floods: UNEP/GRID-Europe + observerd from Dartmouth Flood Observatory and frequency from Flood PREVIEW UNEP/GRID-Europe; Droughts: IRI, Columbia University; Landslides: Norwegian Geotechnical Institute; Earthquakes: GSHAP transformed into MMI by IRI, Columbia University; Tsunami: compiled from various sources by the Norwegian Geotechnical Institute; Cartography: P. Peduzzi, UNEP/GRID-Europe, 2009.

In 2000, the World Bank, describing the impact of natural catastrophes in 1999, stated that *"the landslides in Venezuela alone caused 50,000 fatalities"* [9]. The EM-DAT database records 30,000 deaths due to the same set of floods, mudslides and landslides, which occurred in December 1999 and affected 11 states of Venezuela, mostly the State of Vargas but also Miranda and the country's capital, Caracas. Research by anthropologist Rogelio Altez[10] of the Universidad Central de Venezuela puts forward a very different picture. After a forensic investigation into the deaths occurred in Vargas state, Altez documented a total of only 521 corpses attributed to the disaster, including 290 that had never been identified. In addition only 331 people had been reported missing. Given the likelihood that some of those reported missing were amongst the 290 unidentified corpses, Altez concluded that *"the total number of deaths does not exceed 700"*.

After flying over the affected area, the then Secretary General of the International Federation of Red Cross and Red Crescent Societies (IFRC) had declared that Venezuela's disaster was *"certainly at least two or three times worse than Mitch as far as the death toll is concerned"* and that *"as many as 50,000 people may have been killed"* [11]. According to Altez, statements of this kind began to be quoted as objective data and later became accepted international statistics. The key message from Altez's study is that there are still major deficiencies in the way corpses are dealt with after many large natural disasters around the world, with documented cases of mass cremations and burials without an adequate process of identification or even quantification of the victims, often due to unjustified fear of epidemics. While the Venezuelan case may be unique, it does highlight the need for a critical approach when dealing with disaster mortality data.

Box 5 Disaster mortality data – when the dead

Common statistical techniques, as employed in this study, are suitable for estimating average patterns and trends but are not able to predict extreme events, given the data limitations described (in particular limitations in the use of country-level vulnerability indicators) and the unpredictability of individual hazard events. This means that if the models in this analysis predict an annual average of 1,000 people killed by a given hazard type globally, there could be one event killing 10,000 people followed by 9 years of almost no casualties. A number of hazard types have been left out or covered less comprehensively in this global analysis. Most importantly, although new indicators of drought occurrence have been developed and are discussed, the analysis did not yield sufficiently accurate estimates of global risk. This is a significant gap especially for sub-Saharan Africa, where drought is a major hazard facing rural populations. As a slow onset hazard, drought impacts are very different from those in sudden impact disasters such as earthquakes or storms. Many droughts with very severe social and economic consequences do not, in fact, show recorded mortality in international disaster databases[12]. The Report looks briefly at forest and other biomass fires, which account for a mere 0.1% of the fatalities recorded in EM-DAT, but have major impacts on climate change, deforestation, soil productivity and biodiversity. This hazard is both exacerbated by and influences climate change, and is the second largest source of human-related greenhouse gas (GHG) emissions.

Given these limitations and uncertainties the estimates of exposure and risk provided can only be taken as indicative. They do not describe and cannot predict disaster risk in specific locations. As such, while many of the results can be displayed at quite high geographic resolutions, these should not be used for planning or decision making at the national or local levels. The purpose of this global risk analysis is to decipher global patterns and trends in risk and it does not and cannot substitute for detailed national and local-level risk assessments.

3.5.4. Weather-related disaster risk

Tropical cyclones

Tropical cyclones, also called typhoons and hurricanes, are powerful storms generated over tropical or sub-tropical waters. They have multiple impacts including extremely strong winds, torrential rains leading to floods or landslides, high waves and damaging storm surge, leading to extensive coastal flooding. Tropical cyclone risk has been modelled using the procedure described in Box 2.2 and further elaborated in Appendix 1.

Disaster risk for tropical cyclones has been calculated taking into account hazard associated with both wind speed and storm surge for different categories of cyclones on the Saffir–Simpson scale.

Figure 2.4 shows the geographic distribution of mortality risk for 10 km × 10 km squares in Asia, Africa and the Americas. Figure 2.5 shows the distribution of both absolute and relative mortality risk from all categories of tropical cyclones aggregated at the country level. Absolute risk is the average annual expected mortality; relative risk describes the average annual expected number of deaths as a proportion of national population. The statistical level of confidence in the model is good, particularly for Category 4 and 5 cyclones[13]. However, these are average annual estimates and cannot be used to predict specific events.

The top ten countries on the Mortality Risk Index and their respective values are Bangladesh (8.5), the Philippines (6.5), India (6), Madagascar (6), the Dominican Republic (6), Haiti (6), Myanmar (5.5), Vanuatu (5.5), Mozambique (5) and Fiji (5).

Geographically, tropical cyclone mortality risk is highly concentrated. For example, 75.5% of the expected mortality is concentrated in Bangladesh and 10.8% in India. There are also large differences in risk between different groups of countries. Relative mortality risk is approximately 200 times higher in low-income countries than in OECD countries and approximately 30 times greater in low human development countries than in high human development countries.

Economic loss risk due to tropical cyclones can be estimated using a model similar to that for mortality. However, the results tend to be less reliable because loss estimates are available for fewer events. There are also difficulties in defining and estimating losses, and there is an incentive to exaggerate damages in anticipation of greater external support. Because of these data constraints this chapter reports economic loss risk aggregated by broad regions and categories of countries.

As Table 2.1 shows, OECD countries including those prone to tropical cyclones such as Japan, the United States of America and Australia, account for almost 70% of estimated annual economic losses in absolute terms, followed by East Asia and the Pacific, and Latin America and the Caribbean. Sub-Saharan African countries, such as Madagascar and Mozambique, suffer the highest relative economic loss risk as a proportion of the size of the affected economy. Across all regions, estimated economic losses are highly concentrated in a few countries. The top five countries account for 80% of all estimated losses, with the remainder spread over more than 50 countries and areas.

When expressed as a proportion of exposed GDP, estimated losses in East Asia and the Pacific, Latin America and the Caribbean, and South Asia are between 5 and 7 times higher than those of the OECD countries, indicating a far higher vulnerability of their economic infrastructure.

Risk drivers and vulnerability factors

Tropical cyclone hazard (for each category of cyclone) is shown for each region in the regional multi-hazard maps presented in Figures 2.1, 2.2 and 2.3.

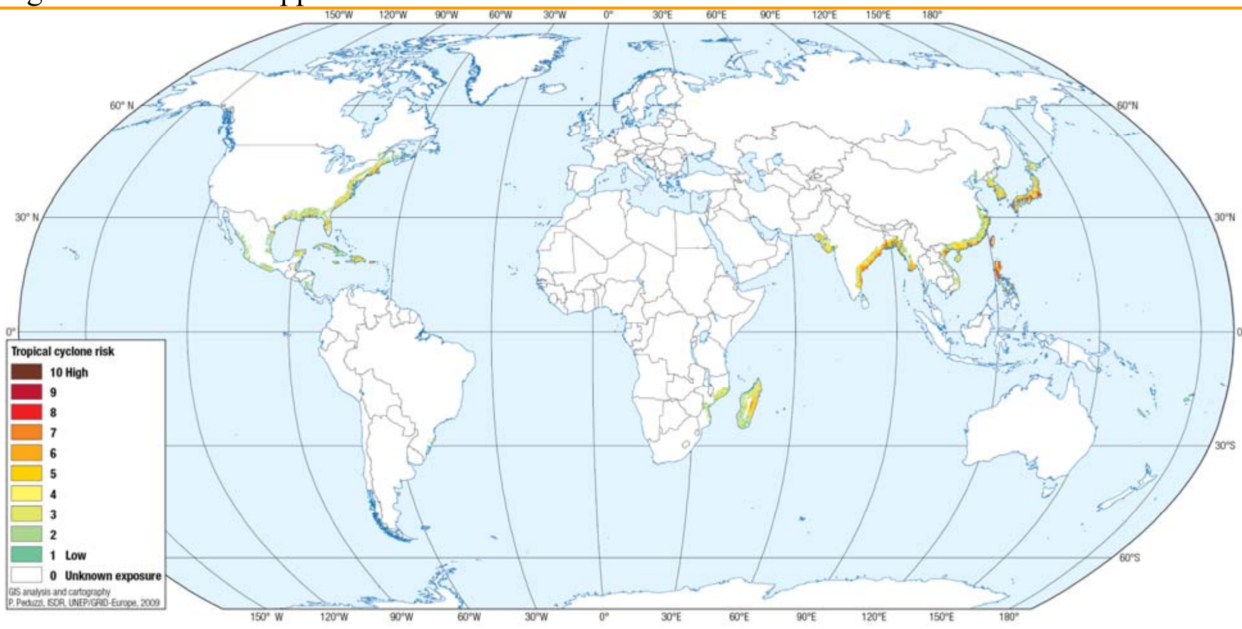


Figure 38 Distribution of mortality risk associated with tropical cyclones (10 × 10 km)

GIS and cartography: P. Peduzzi, ISDR, UNEP/GRID-Europe, 2009.

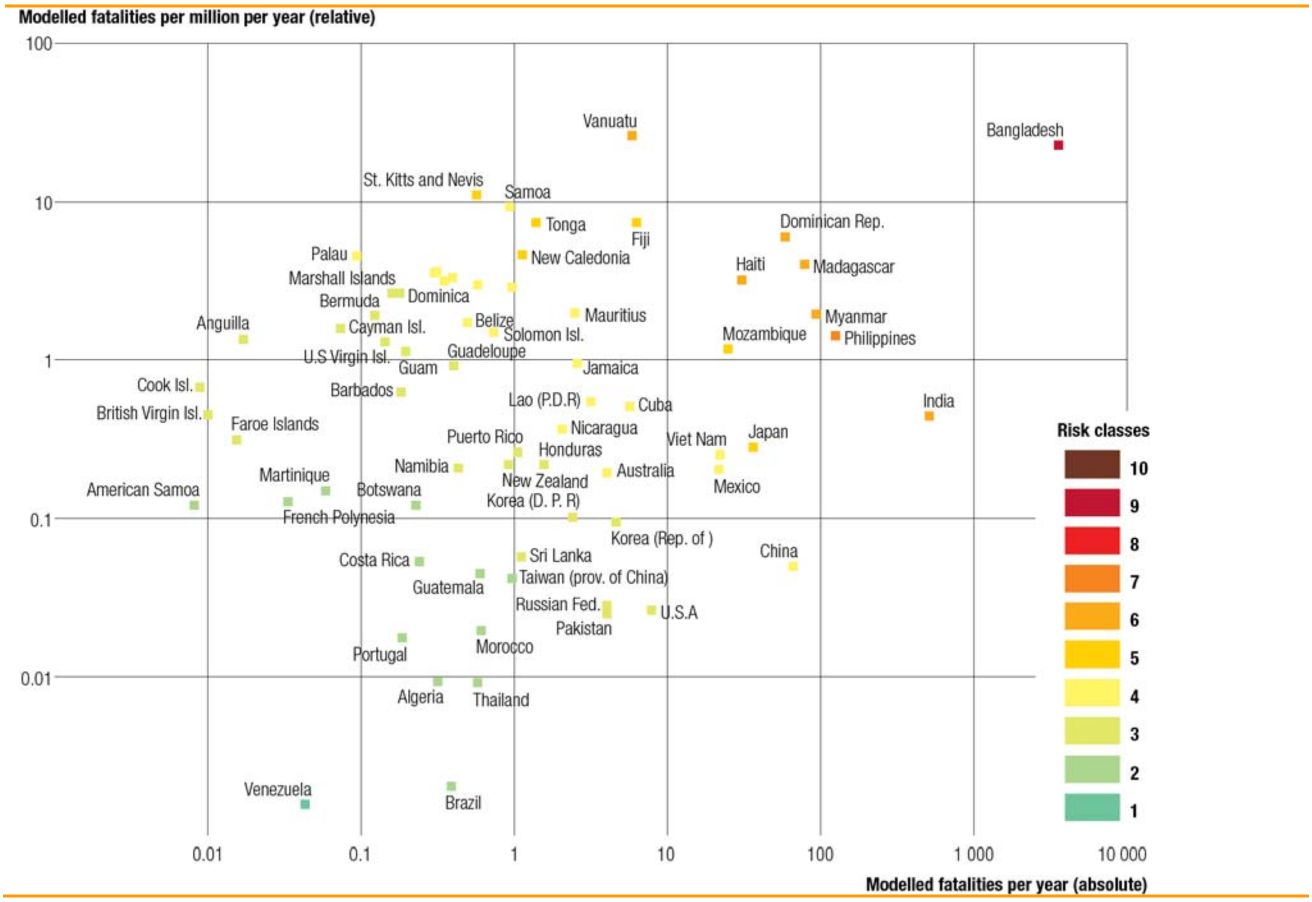


Figure 39: Absolute and relative mortality risk for tropical cyclones

Region	**Average annual number of reported tropical cyclones 1975–2007**	**Average annual estimated economic loss** (million constant 2000 US$)	**Average annual GDP exposure** (million constant 2000 US$)	**Percent of global total economic loss**	**Estimated average annual economic loss as % of GDP in affected countries**	**Ratio of economic loss to GDP exposure** (global mean = 100)
East Asia and Pacific	8.8	5,835	44,136	15.1	0.22	438
Europe and Central Asia*	–	–	–	–	–	–
Latin America and Caribbean	3.2	2,465	14,656	6.4	0.13	557
Middle East and North Africa*	–	–	–	–	–	–
South Asia	1.2	1,054	8,380	2.7	0.11	417
Sub-Saharan Africa	1.9	306	3,467	0.8	0.55	292
OECD	11.1	27,451	1,060,431	71.2	0.13	86
Other high income countries	3.5	1,434	176,010	3.7	0.19	27
Total	**29.7**	**38,545**	**1,307,080**	**100**		

Table 14 Summary of predicted losses from tropical cyclone events14

Table 2.2 shows the number of people and GDP exposed to tropical cyclones and related storm surge hazards, for different tropical cyclone categories. An average of 78 million people worldwide are exposed each year to tropical cyclone wind hazard and a further 1.6 million to storm surge. Asian countries have the largest absolute population exposed, while SIDS have the highest proportion of their population exposed. In particular, SIDS have a far greater relative exposure to highly destructive Category 3 and 4 storms than larger countries. Some countries, such as the Philippines have a very high absolute and relative exposure.

In terms of economic exposure, an annual average of US$ 1,284 billion of GDP is exposed to tropical cyclones. The country with the highest absolute exposure is Japan. The countries with the highest relative exposure, however, are almost all SIDS.

The strength of a tropical cyclone and the number of people or exposed economic assets in the area affected explain a large part of the risk (see Figures 2.7, 2.8 and 2.9). However, even for comparable storms and exposure, large differences persist between countries (also see Box 2.4 for unexpected events).

For the first time since monitoring of tropical cyclones began a tropical storm in the South Atlantic reached a force of Category 1 on 26th March, 2004 (Figure 2.6). By the 28th it had strengthened to Category 2, when it reached Santa Catarina Province of Brazil. Even though it weakened somewhat before landfall, it caused US$ 350–425 million damage (15), killing 4 people and injuring 518 others (16)

It was commonly thought that tropical cyclones could not be generated in the South Atlantic Ocean. Today there is still no scientific agreement on the cause of the Catarina cyclone, but it provides a clear demonstration that unexpected events can occur in places where they have not happened before. Longer-term changes in the Earth's oceans and atmosphere may bring more such surprises.

Box 6 Unexpected risks: tropical cyclone Catarina, 2004

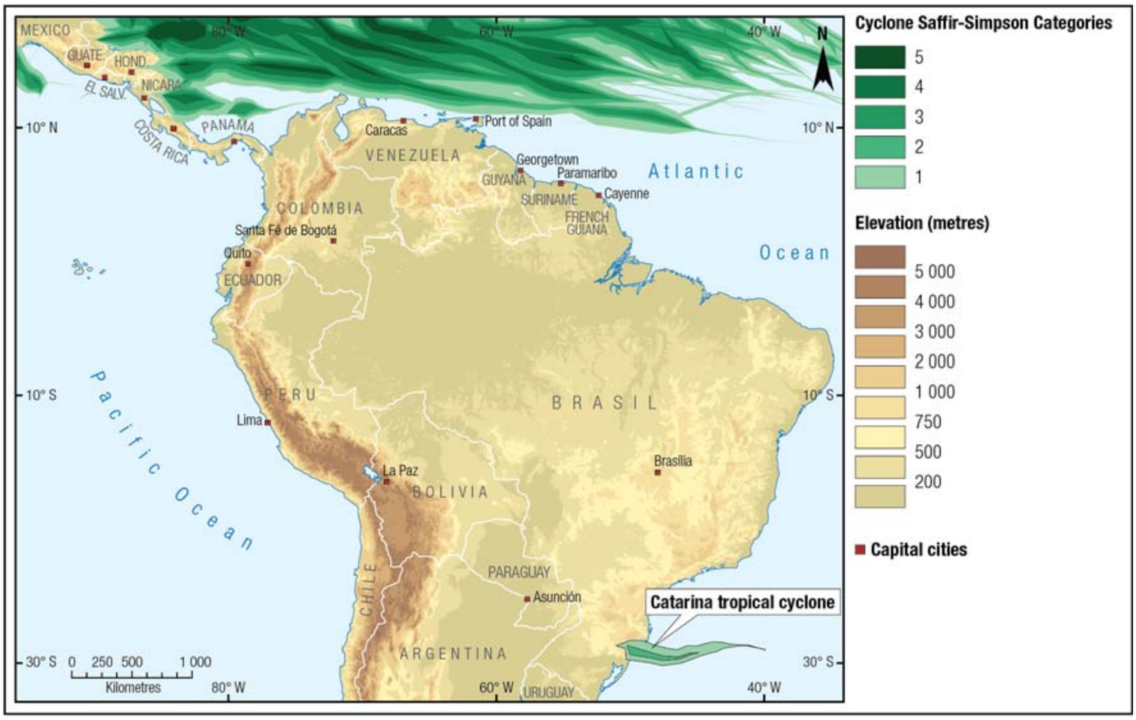


Figure 40 Tropical cyclones over a 30-year period

Cyclone category	Annual population exposure (millions)	Annual GDP exposure (US$ millions)
Category 1: Winds (Km/hour) 118–153, Surge: less than 2 m	57.8	942,300
Category 2: Winds (Km/hour) 154–177, Surge: 2–3 m	13.5	229,025
Category 3: Winds (Km/hour) 178–210, Surge: 3–4 m	5.5	100,684
Category 4: Winds (Km/hour) 211–249, Surge: 4–5 m	0.8	11,623
Category 5: Winds (Km/hour) more than 249, Surge 5–10 m	0.2	824
Total	**77.7**	**1,284,456**

Table 15 Annual exposure to tropical cyclones by classes of intensity (Saffir–Simpson)
* Source: Adapted from the U.S. National Oceanic and Atmospheric Administration (NOAA), National Hurricane Center (NHC) 17 * Modelled

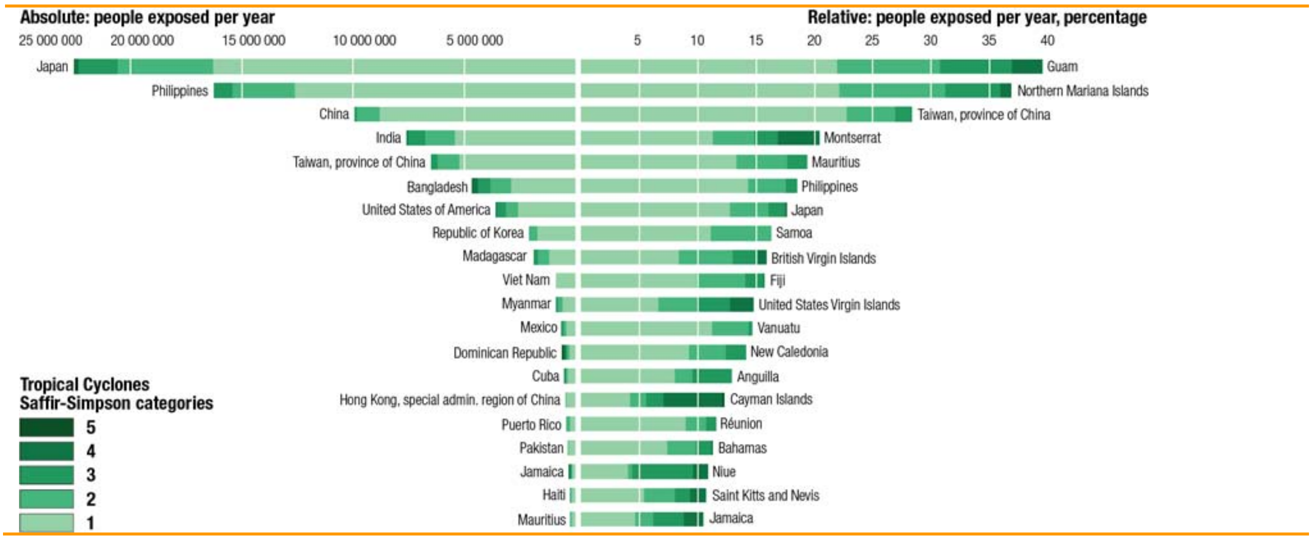


Figure 41 People exposed to tropical cyclones (wind speed categories)

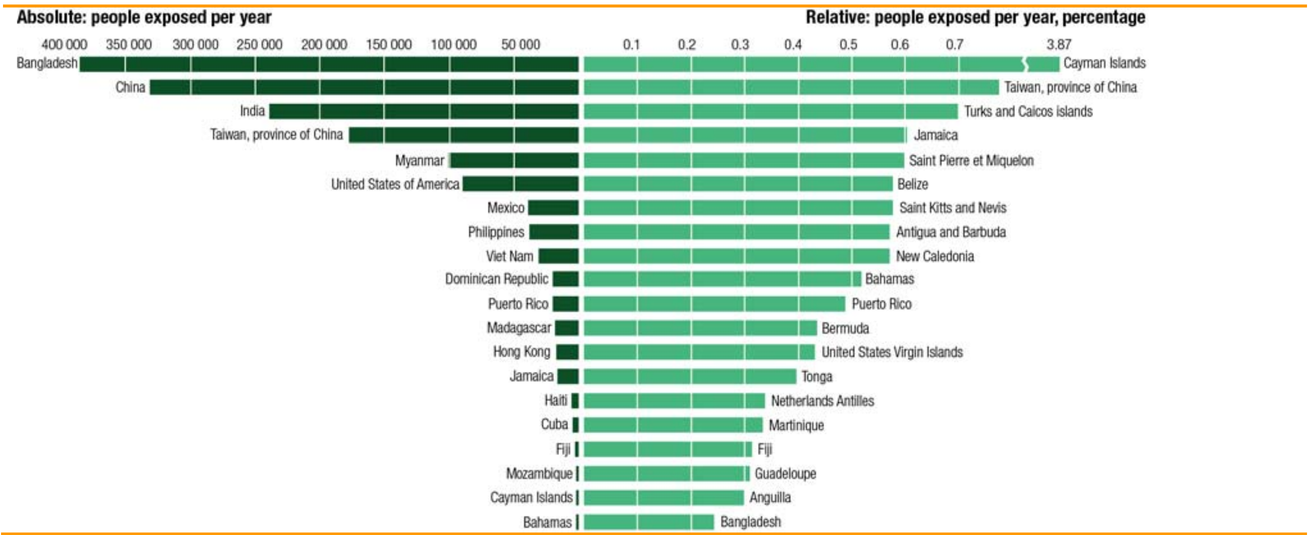


Figure 42 People exposed to storm surge for all categories of tropical cyclone

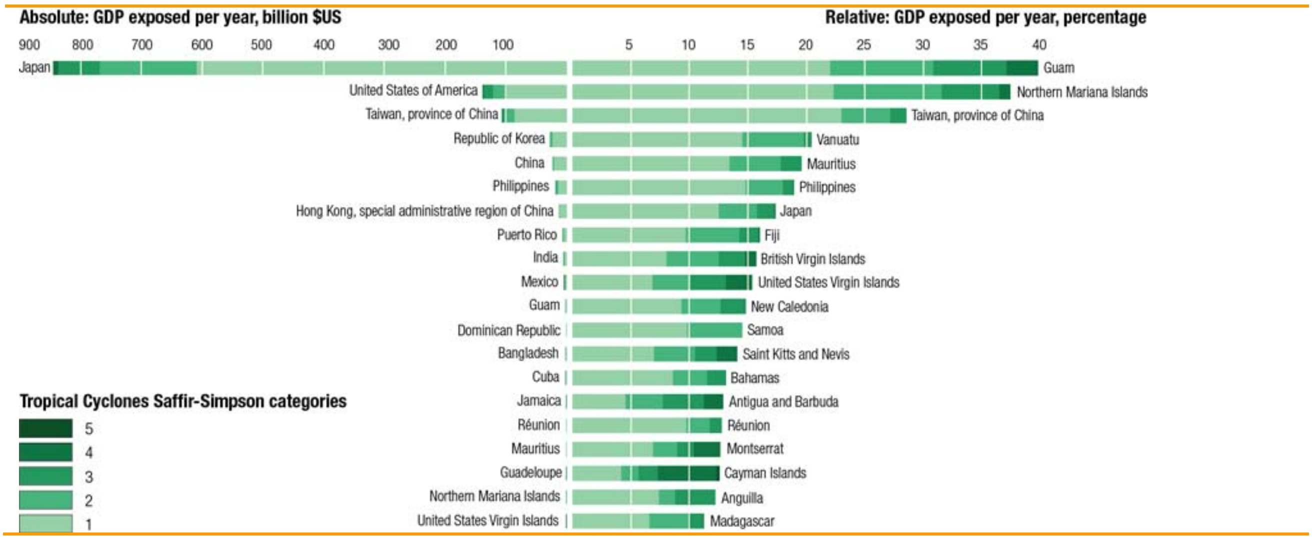


Figure 43 GDP exposed to tropical cyclones

Figure 2.10 shows that in general, low-income countries are far more likely to suffer mortality for a given number of people exposed and, in particular, for powerful Category 3 and 4 tropical cyclones. Similarly, lower-middle income countries are much more likely to suffer economic loss across all categories of cyclone intensity.

The key vulnerability factors that contribute to mortality risk are low GDP per capita and remoteness. As exposure increases and income decreases there is a greater risk of tropical cyclone mortality. Areas that are remote with respect to the main administrative and economic centre of the country, tend to suffer more. The case of tropical cyclone Nargis in Myanmar in 2008 is an example. Densely populated, very poor remote rural areas were devastated by a Category 4 tropical cyclone and associated storm surge.

In the case of economic losses, well-governed countries seem to experience lower damages in comparable tropical cyclones with similar magnitude and exposure, than poorly governed countries. In contrast, income inequality is associated with higher levels of damage. To illustrate the effect of these variables, the economic risk model suggests that if Bangladesh had the significantly higher institutional quality and lower levels of inequality found in Japan, its annual economic loss from tropical cyclones could be about 60% lower, even if exposure and hazard severity remained unchanged.

Finally, even after controlling for population size, SIDS generally experience greater economic losses.

Floods

Disaster risk for floods has been calculated for large rural flood events. The risk calculations do not include flash floods or urban flooding from inadequate drainage.

Figure 2.11 shows the geographic distribution of mortality risk for 10 km × 10 km squares of the Earth's surface. Figure 2.12 shows the distribution of both absolute and relative mortality risk for floods aggregated at the country level. As with cyclones, absolute risk is the average annual expected mortality, while relative risk is measured as the average annual expected number of deaths as a proportion of national population. The geographical distribution of flood mortality risk mirrors that for exposure. It is heavily concentrated in Asia, especially in India, Bangladesh and China. Between them these countries concentrate 75% of the modelled annual global mortality. Viet Nam also has high absolute and relative flood risks. The top ten countries on the Mortality Risk Index for floods and their respective values are India (7.5), Bangladesh (6.5), China (6), Viet Nam(6), Cambodia (6), Myanmar (5.5)

Sudan (5.5), Democratic People's Republic of Korea (5.5), Afghanistan (5), Pakistan (5).

Figure 44 Mortality and economic loss from tropical cyclones compared to exposure for income classes

The regional distribution of economic loss risk is shown in Table 2.3. Severe flooding affects more countries than tropical cyclones [18]. Flood losses are also somewhat less concentrated across countries than tropical cyclone losses. The top five countries account for 68%, and the top 10 for 78%, of total modelled economic losses. By region, OECD countries (especially the United States of America and Germany) account for the largest share of average annual modelled damages. But the East Asia and Pacific region and South Asia experience almost similar levels of losses. China, Indonesia and Thailand combined account for 25%, as do India, Pakistan and Bangladesh. By far the largest economic losses in relation to the size of economies occur in South Asia, followed by sub-Saharan Africa and East Asia.

The ratio of losses to GDP exposure in the OECD countries is far higher than in Latin America and the Caribbean, or South Asia. This probably indicates the differential impact of flooding on primary sector activities, such as agriculture and fishing in the latter two regions, compared to the impact on industry and services in the OECD.

Figure 2.13 illustrates why global hazard identification cannot be used for local risk mapping. In August 2008, a dyke breach led to a large flood in Bihar, India. The red areas are those that actually flooded, while the blue areas represent modelled flood hazard. The global model cannot take into account locally specific risk factors, such as the strength of dykes, even though these have a critical influence on the distribution and magnitude of losses.

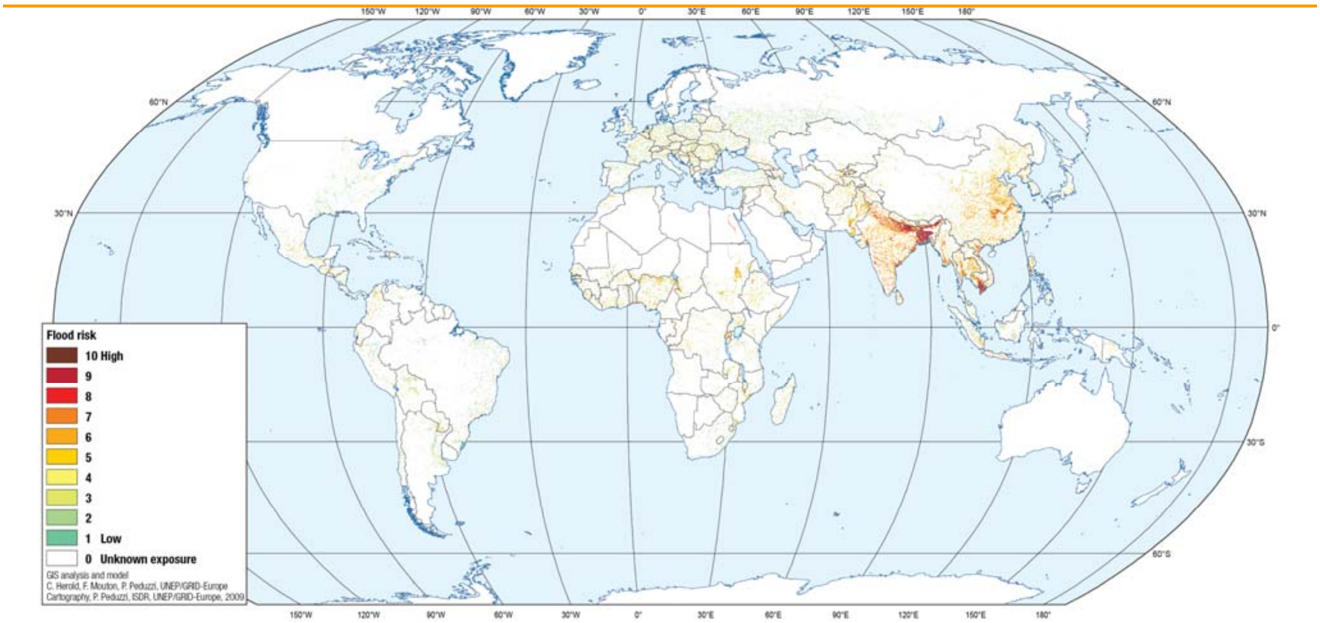


Figure 45 Distribution of mortality risk associated with floods (10 x 10 km)

GIS and cartography: C. Herold, P. Peduzzi, UNEP/GRID-Europe, 2009

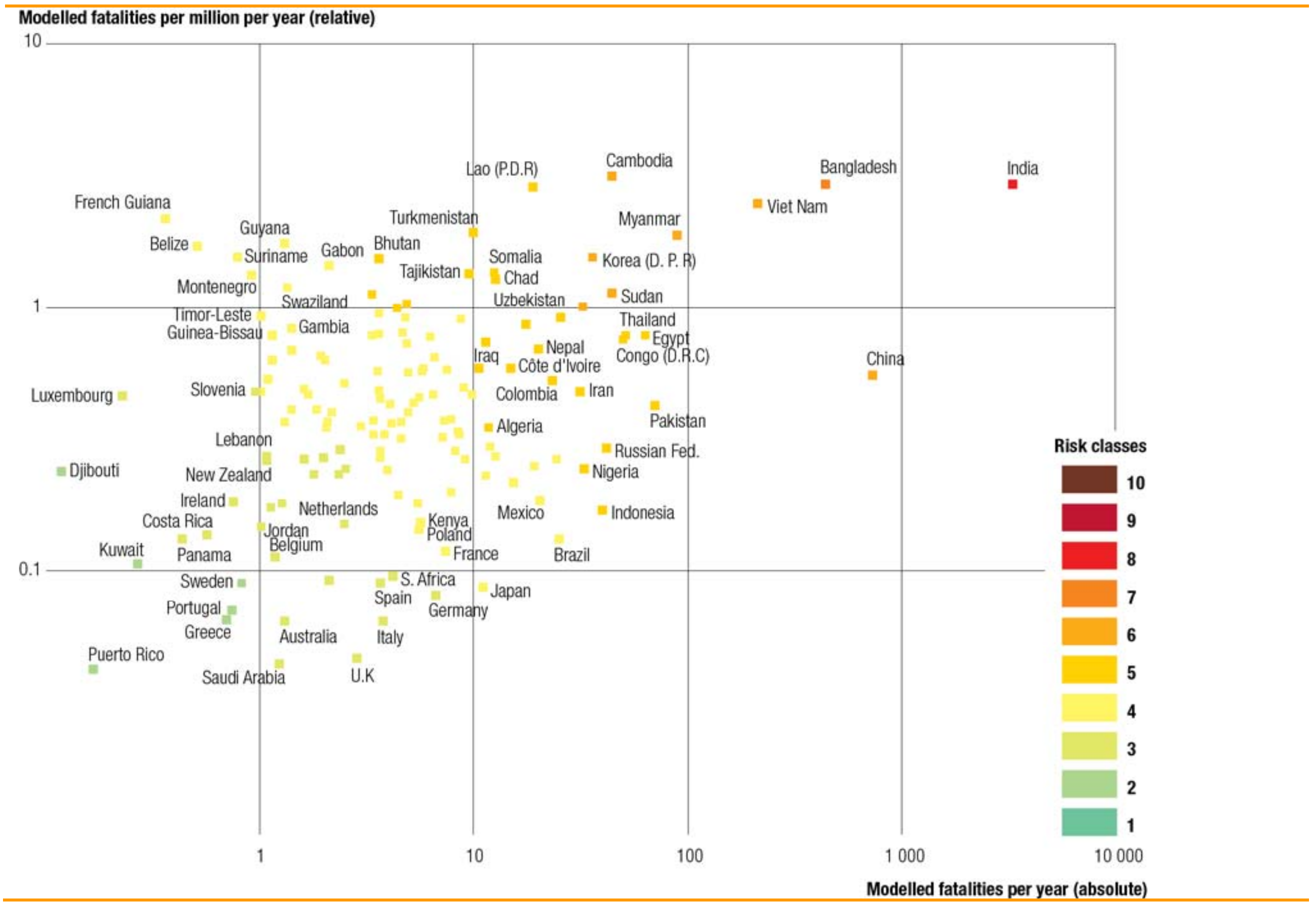


Figure 46 Absolute and relative mortality risk for floods

Region	Average annual number of reported floods 1999–2007	Average annual modelled economic losses (million constant 2000 US$)	Average annual GDP exposure (million constant 2000 US$)	Percent of total global economic loss	Modelled average annual economic loss as % of GDP in affected countries	Ratio of economic loss to GDP exposure (global mean = 100)
East Asia and Pacific	4.0	4,935	8,707	27.4	0.16	128
Europe and Central Asia	4.9	1,382	3,156	7.7	0.11	99
Latin America and Caribbean	3.2	470	1,818	2.6	0.02	59
Middle East and North Africa*	–	–	–	–	–	–
South Asia	5.7	4,807	13,817	26.7	0.49	79
Sub-Saharan Africa	8.6	767	867	4.3	0.19	201
OECD	4.2	5,536	12,113	30.7	0.03	104
Other high income economies*	–	–	–	–	–	–
Total	**30.6**	**17,897**	**40,478**	**100**		

Table 16 Summary of predicted losses from flood events

***insufficient observations**

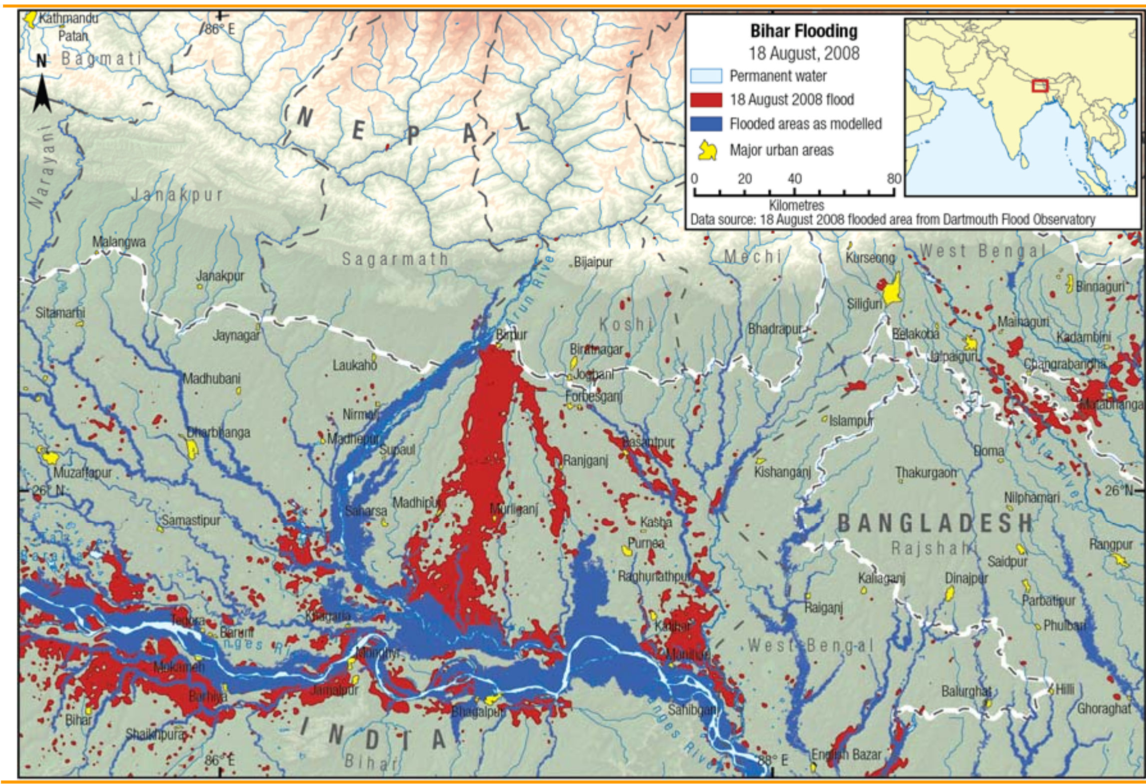


Figure 47 Example of one limitation of the model
Cartography and GIS analysis: UNEP/GRID-Europe Data source for detected Bihar flood event: courtesy of Dartmouth Flood Observatory.

Risk drivers and vulnerability factors

Flood hazard is shown for each region in the regional multi-hazard maps presented in Figures 2.1, 2.2 and 2.3.

As Figure 2.14 shows, human exposure to floods is heavily concentrated in Asia. The top ten most exposed countries – in absolute and relative terms – are in South and South-East Asia, where a number of heavily populated river deltas and watersheds are located. GDP exposure is also heavily concentrated in Asia (see Figure 2.15). However, developed countries such as the United States of America, Germany, Japan and France also have high absolute GDP exposure, while African countries, such as Benin, the Sudan and Chad have high relative GDP exposure.

Compared to their exposure, lower-middle income countries have higher mortality rates and higher levels of economic loss (Fig. 2.16).

Mortality from flood events 19 is closely associated to the size and growth rate of exposed rural populations. Lack of voice and accountability were also identified as significant factors. Flood mortality risk is thus highest in heavily populated rural areas in countries with weak governance.

In the case of economic risk, smaller, more concentrated floods appear to cause relatively greater economic damages than floods with a larger extent. The former may affect areas with higher population density more severely, while the latter might mostly impact relatively lower value agricultural lands. The effect of a country's wealth is much less pronounced for floods than for other disaster types. While mortality is concentrated in developing countries, significant economic damages from floods also occur regularly in North America and Central Europe, for instance.

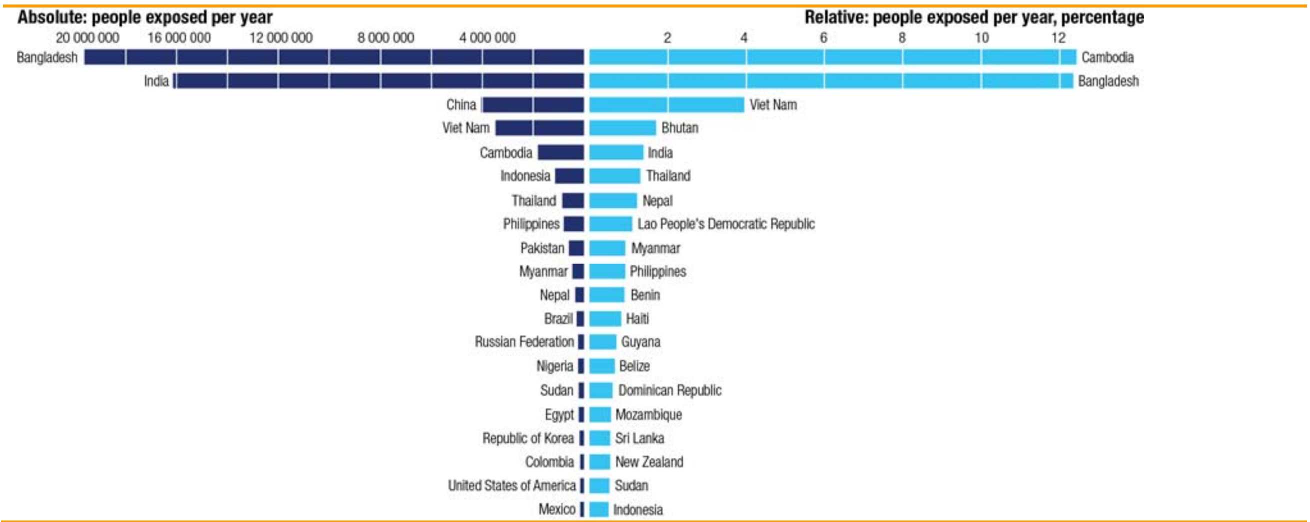


Figure 48 People exposed to floods

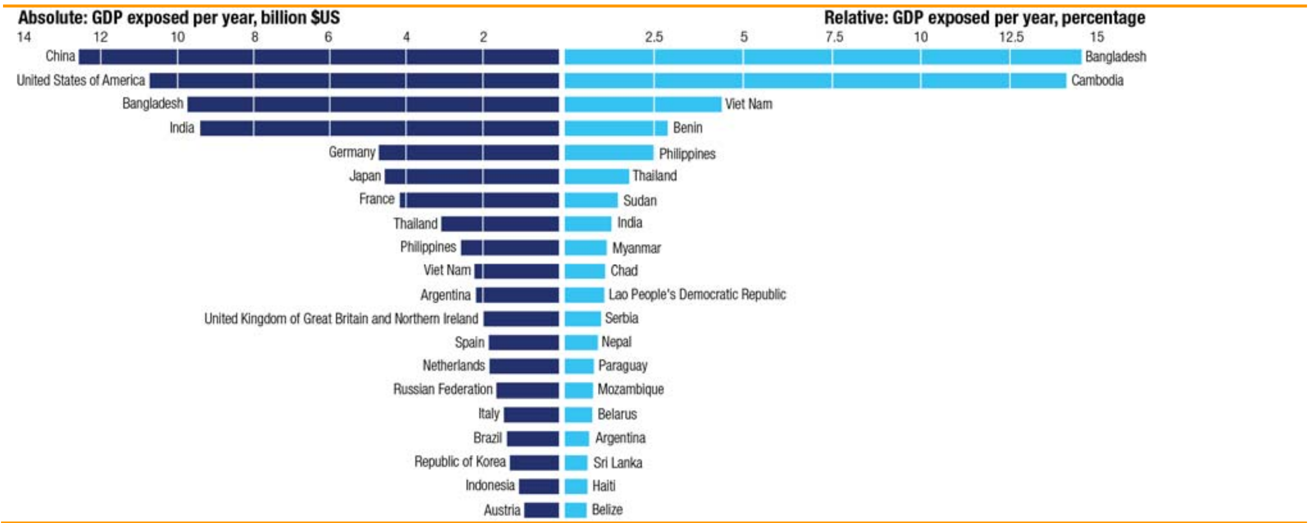


Figure 49 GDP exposed to floods

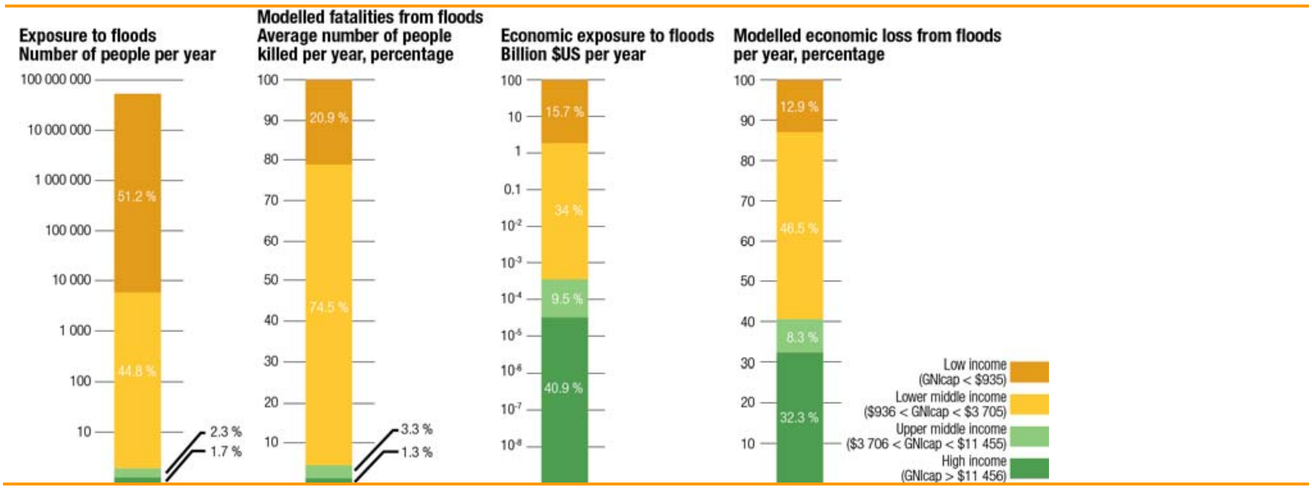


Figure 50 Exposure, mortality and economic loss to floods by income class

Landslides

Observed mortality in landslides triggered by high precipitation is approximately six times higher than in landslides triggered by earthquakes. The risk model therefore focuses on precipitation triggered landslides (Fig. 2.17). Exposure, however, has been calculated for both kinds of landslide.

Figure 2.18 shows absolute and relative mortality risk for precipitation triggered landslides. Countries with very high absolute and relative risk include Guatemala, Nepal and Papua New Guinea. Compared to other hazards, global landslide mortality risk is relatively low, although many small landslide events causing deaths are not internationally reported. The predicted mortality risk, even in very large countries such as India or China, is less than 100 deaths per year. Absolute mortality risk is highest in countries such as Ethiopia, Indonesia and India. Relative mortality risk is highest in small islands, notably in Dominica and the Comoros. Approximately 55% of mortality risk is concentrated in 10 countries, which also account for 80% of the exposure. The top ten countries on the Mortality Risk Index for landslides and their respective values are Comoros (6.5), Dominica (6), Nepal (5.5), Guatemala (5.5), Papua New Guinea (5.5), Solomon Islands (5.5), Sao Tome and Principe (5.5), Indonesia (5), Ethiopia (5), and the Philippines (5).

Risk drivers and vulnerability factors

Landslide hazard is shown for each region in the regional multi-hazard maps presented in Figures 2.1, 2.2 and 2.3. Figures 2.19 and 2.20 illustrate the relative and absolute exposure of people and GDP to both earthquake and precipitation triggered landslides. Approximately 2.2 million people are exposed to landslides worldwide. In absolute terms, exposure is very high in a number of large Asian countries, especially India, Indonesia and China. Relative exposure is highest in small countries with steep terrain including a number of small island nations. The relative importance of the triggering mechanism varies widely among countries.

Taiwan, Province of China, has the highest absolute GDP, as well as the highest relative GDP exposure, both due to earthquake triggered landslides. As illustrated in Figure 2.21, lower-middle income countries in general experience greater mortality with respect to the population exposed.

This is confirmed by the identification of vulnerability factors. Precipitation triggered landslide mortality is best explained by the exposure of the population and by local GDP per capita. As in the case of tropical cyclones, poor countries have significantly more landslide mortality than wealthier countries.

Data limitations prevent the analysis of economic losses due to landslides.

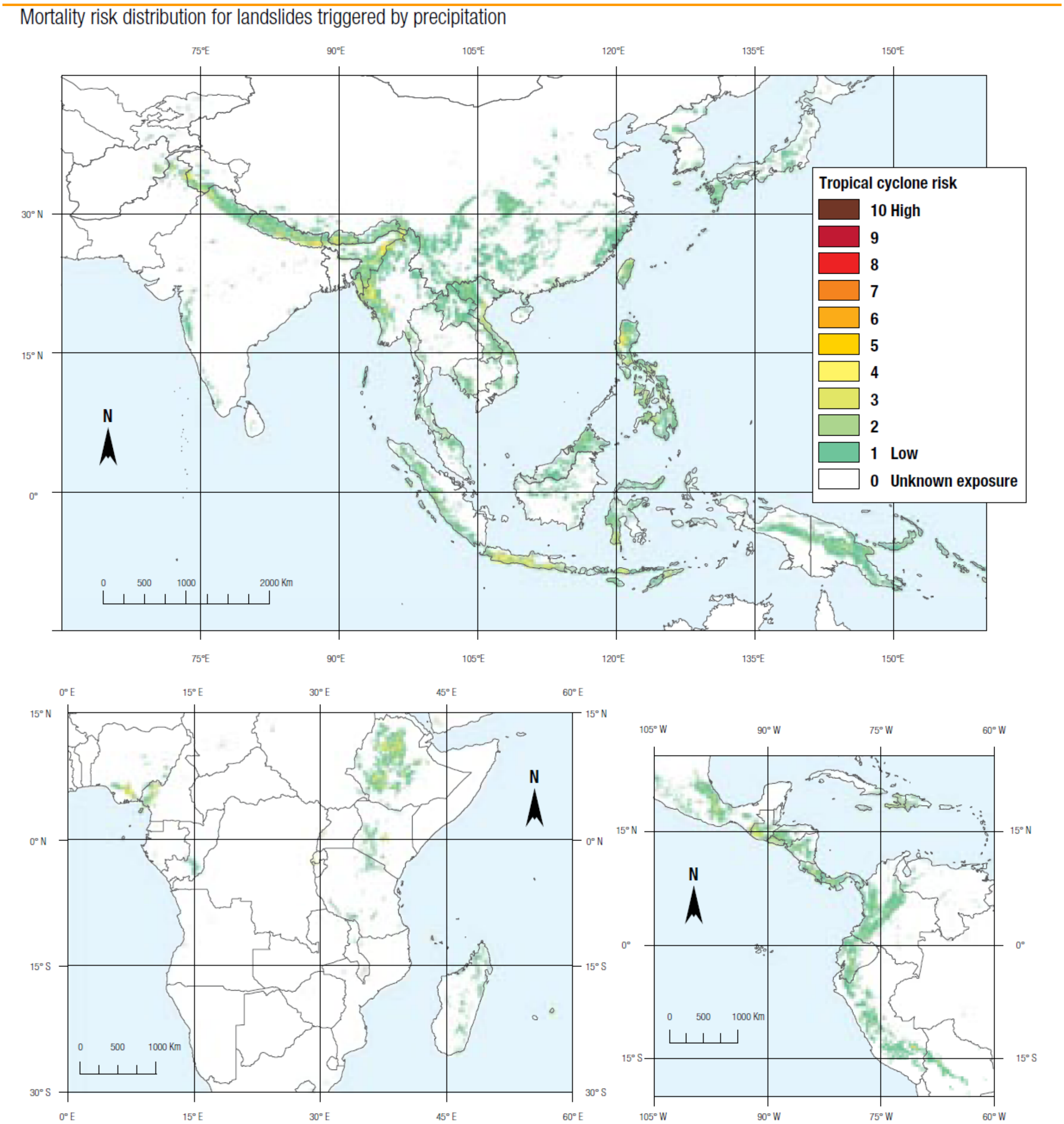


Figure 51 Distribution of mortality risk associated with precipitation triggered landslides (10 × 10 km)
GIS and cartography: P. Peduzzi, ISDR, UNEP/GRID-Europe, 2009.

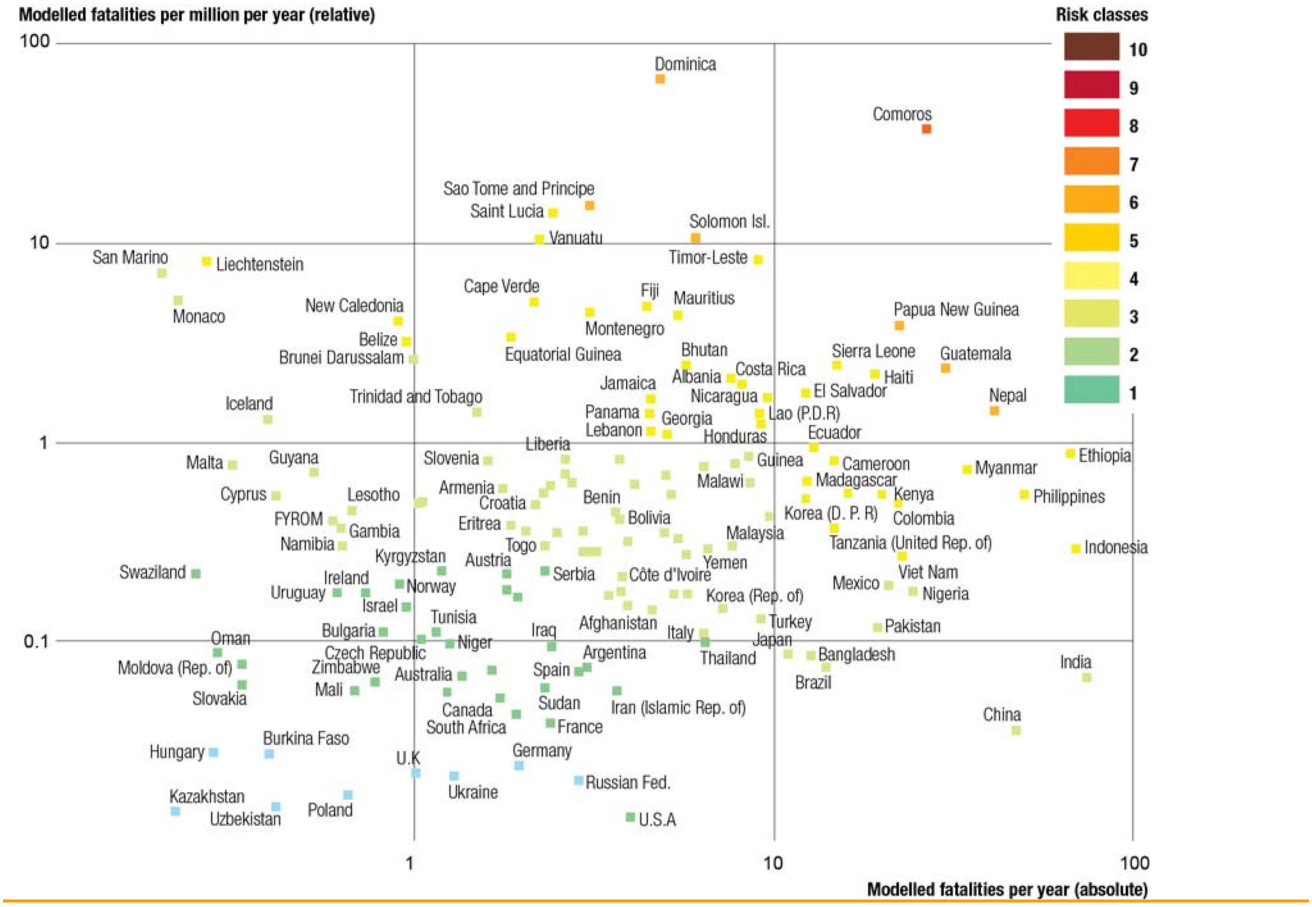


Figure 52 Absolute and relative mortality risk for precipitation triggered landslides

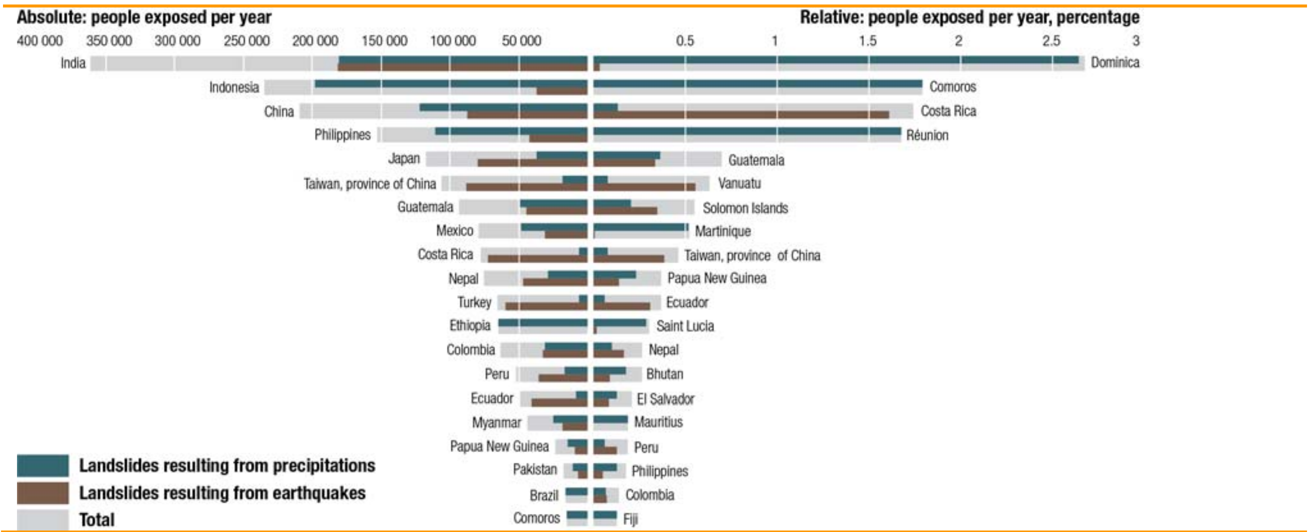


Figure 53 People exposed to landslides triggered by precipitation or earthquake

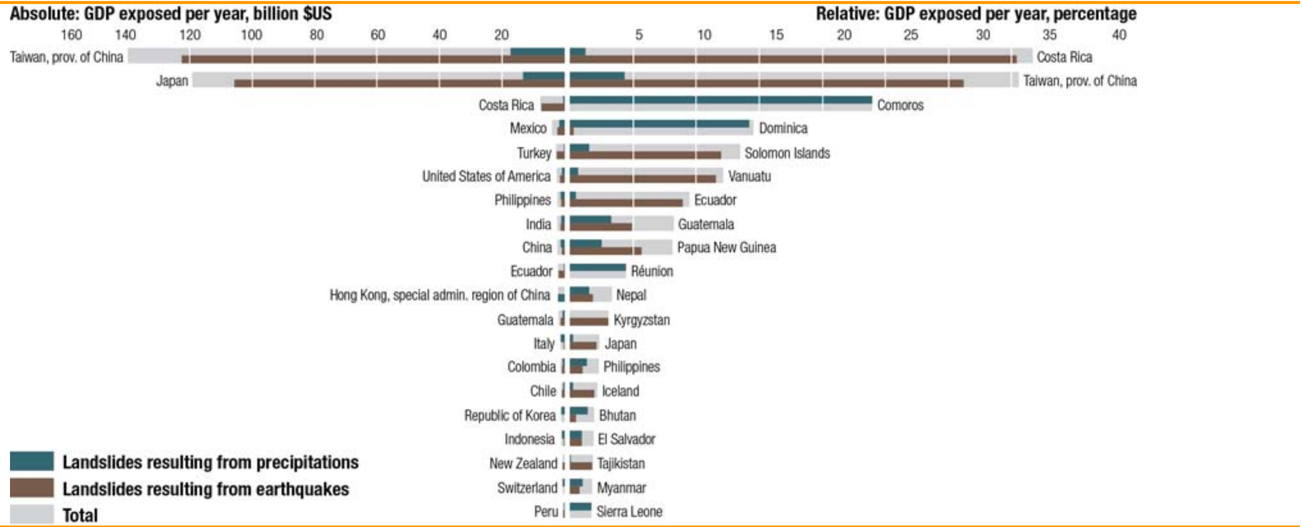


Figure 54 GDP exposed to landslides triggered by precipitation or earthquake

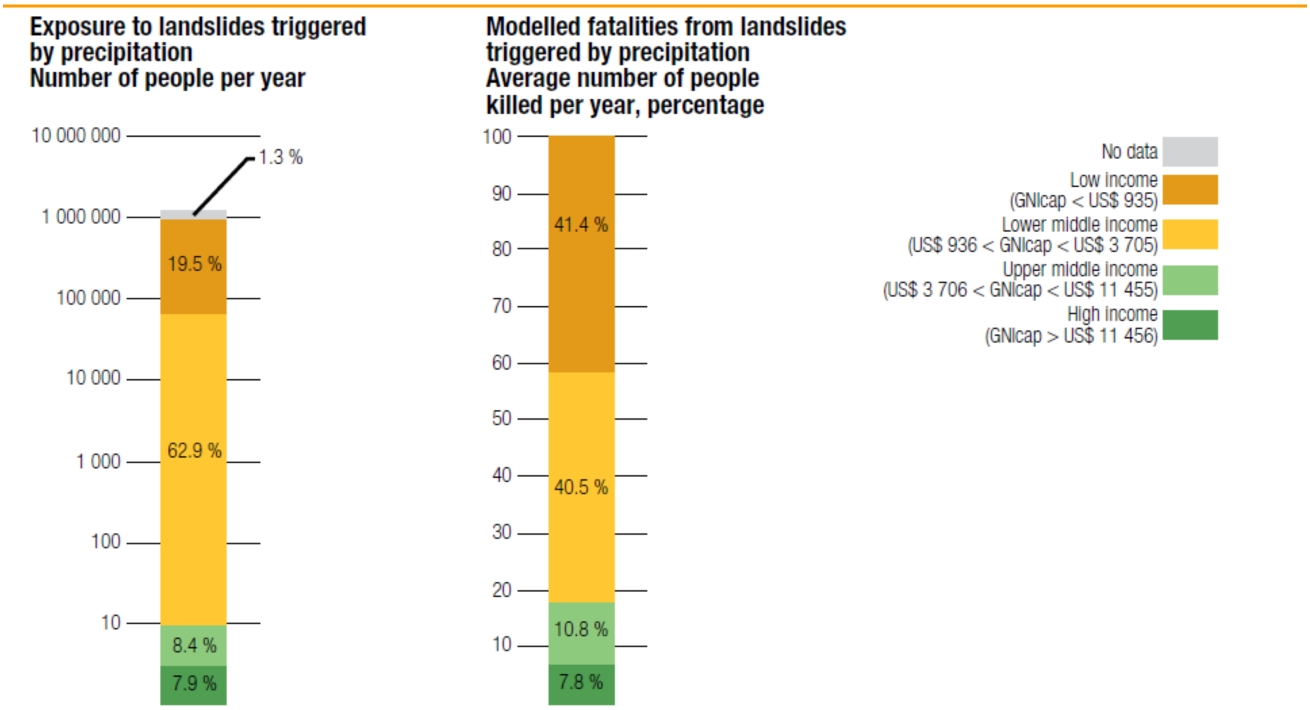


Figure 55 Mortality and exposure to landslides by income class

3.5.5. *Other hazards*

Earthquakes

Earthquake risk has been calculated using four categories of seismic intensity, corresponding to values between V and XII on the Modified Mercalli Intensity scale (MMI) (see Table 2.4). Different exposure models were used to calculate mortality risk and economic loss risk and results are presented with a medium level of confidence. As with other hazards, economic loss risk is calculated only for groups of countries (regions and income classes).

Categories 1 and 2 include 93.0% and 5.8% respectively of the population exposure, but account for only 0.6% of the mortality risk. Most mortality risk is concentrated in earthquakes of higher intensities (Categories 3 and 4).

Figure 2.22 shows the geographic distribution of mortality risk as modelled for each 10 km × 10 km square of the Earth's surface. Figure 2.23 shows the distribution of both absolute and relative mortality risk from all categories of earthquakes aggregated at the country level.

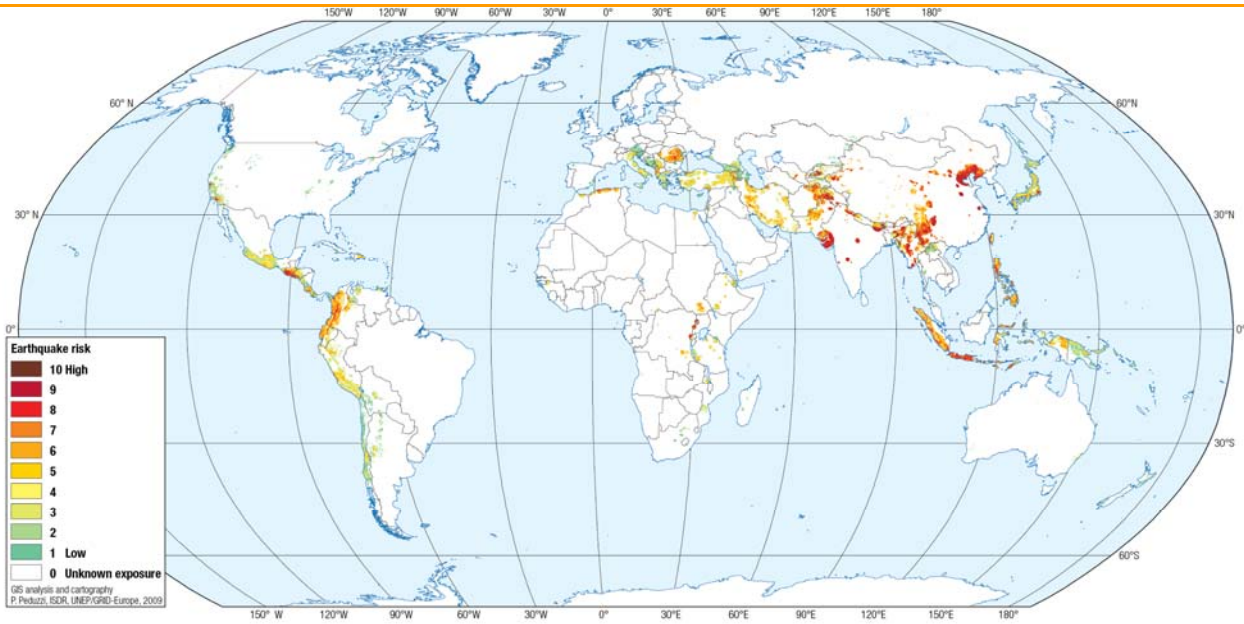


Figure 56 Distribution of mortality risk associated with earthquakes (10 × 10 km)
GIS and cartography: P. Peduzzi, ISDR, UNEP/GRID-Europe, 2009.

China, India and Indonesia are the countries with the highest absolute mortality risk, while some smaller countries, such as El Salvador and Guatemala have very high relative risk. Some countries, such as the Democratic Republic of the Congo, that have not experienced recent major earthquake disasters have high levels of both absolute and relative mortality risk. Mortality risk is highly concentrated. The model suggests that 86% of mortality risk is manifested in disasters with more than 10,000 fatalities.

Categories	1	2	3	4
MMI	V to VI	VII	VIII	IX to XII

Table 17 Categories of seismic intensity

This is consistent with the observed losses. Of the 246,200 people killed by earthquakes over the last ten years 20, 226,000 (91.8%) were killed in just five mega-disasters 21. The top ten countries on the Mortality Risk Index for earthquakes and their respective values are China (8.5), India (8.5), Indonesia (8.5), Colombia (8.5), Myanmar (8.5), Guatemala (8), Pakistan (7.5), Afghanistan (7.5), Iran (7.5) and Peru (7.5).

Table 2.5 shows the modelled economic losses from earthquakes. OECD countries account for 58% of the modelled annual total losses. East Asia also has high absolute modelled economic losses, followed by Latin America and the Caribbean. Relative to GDP, modelled losses are most significant in the Middle East and North Africa region, followed by Eastern Europe and Central Asia. The vulnerability of economic infrastructure appears to be much higher in both Asia and the Pacific, and Eastern Europe and Central Asia, than elsewhere. The ratio of modelled damages to exposed GDP is between 8 and 10 times greater in these two regions than in OECD countries.

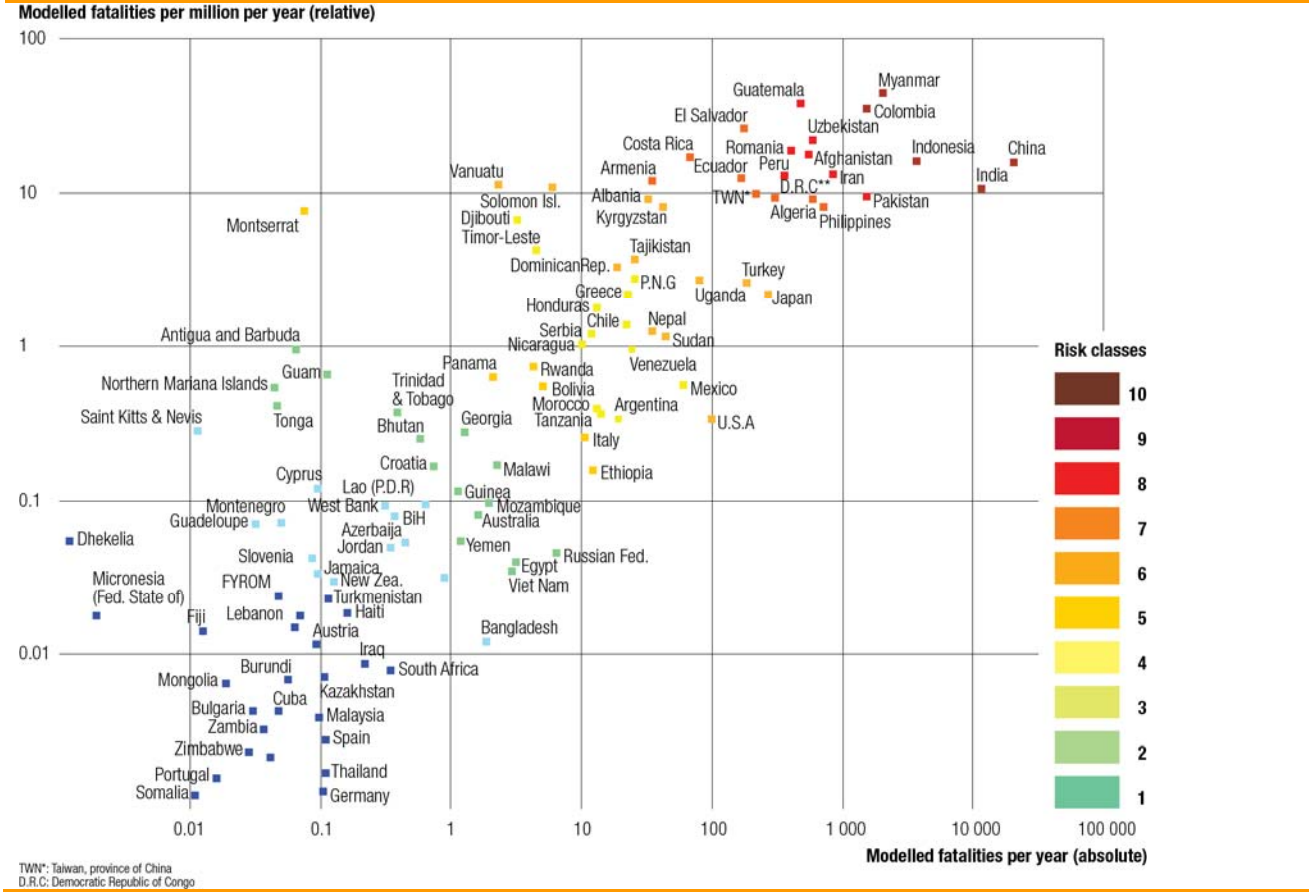


Figure 57 Absolute and relative mortality risk for earthquakes

Note: BIH, Bosnia and Herzegovina; DRC, Democratic Republic of the Congo; FYROM, Former Yugoslav Republic of Macedonia; PNG, Papua New Guinea; TWN, Taiwan, province of China.

Risk drivers and vulnerability factors

Earthquake hazard is shown for each region in the regional multi-hazard maps presented in Figures 2.1, 2.2 and 2.3. Figure 2.24 shows the number of people exposed to each category of earthquake hazard. More than one hundred million people worldwide (103.2 million) are exposed to an average of 144 earthquake events per year, with intensities higher than V on the MMI scale. As with other hazard types, absolute exposure is concentrated in large countries, particularly in Asia, but also in the United States of America and parts of Latin America. Relative exposure is higher in smaller countries.

Figure 2.25 shows that exposure is higher in lower middle-income countries than in all other income classes. However, altogether, 85.3% of mortality risk is concentrated in lower middle-income countries. Upper middle and high-income countries concentrate only 1.7% and 0.9% of the risk respectively. This means that the countries with the highest human vulnerability are lower middle-income countries. Both low- and high-income countries have relatively lower levels of vulnerability. This suggests that earthquake vulnerability is highest in countries with relatively higher levels of economic and urban growth, but that have not yet put in place planning and regulatory frameworks capable of factoring disaster risk reduction considerations into urban development. Structural collapse of buildings is more frequent in countries with fast rates of urbanization and weak enforcement of building codes, especially where informal construction is prevalent. Some low-income countries have yet to urbanize sufficiently to increase their earthquake risk. High-income countries on the other hand have been able to regulate development through tools such as building codes and land-use zoning and have invested in retro-fitting buildings to withstand strong shaking.

Region	Average annual number of reported earthquakes 1975–2007	Average annual modelled economic losses (million constant 2000 US$)	Average annual GDP exposure (million constant 2000 US$)	Percent of total economic losses	Modelled average annual economic losses as a % of GDP in affected countries	Ratio of economic losses to GDP exposure (global mean = 100)
East Asia and Pacific	3.8	3,266	1,888	14.4	0.12	702
Europe and Central Asia	1.9	1,301	974	5.7	0.15	542
Latin America and Caribbean	2.7	2,010	3,812	8.9	0.12	214
Middle East and North Africa*	1.8	1,277	1,774	5.6	0.31	292
South Asia	1.3	401	570	1.8	0.04	286
Sub Saharan Africa	–	–	–	–	–	–
OECD	2.2	14,446	90,448	63.6	0.07	65
Other high income economies*	–	–	–	–	–	–
Total	**13.7**	**22,701**	**99,466**	**100**		

Table 18 Summary of predicted economic losses from earthquake events by region
***insufficient observations**

Examination of the risk drivers associated with earthquake damage reinforces these findings. Earthquake mortality for all categories is correlated positively with exposure and, in the case of Category 1 and 3 earthquakes, negatively with GDP per capita. In the case of Category 2 earthquakes, mortality was correlated with rapid urban growth [22], while Category 4 earthquakes mortality was negatively correlated with voice and accountability. Typically, therefore, poorer countries with high exposure, rapid urban growth and weaker governance have the highest mortality.

In the case of economic loss risk, richer countries have higher absolute, and poorer countries greater relative, damages from earthquakes. A country with a GDP of US$ 20,000 per capita would experience 2.3 times the absolute economic losses of a country with a GDP of US$ 2,500 per capita [23]. But relative to GDP, economic losses in the rich country would be only 43% of those in the poorer country. Institutional quality as measured by voice and accountability, and government effectiveness were also identified as relevant to economic loss risk. The model suggests that a country with average per capita income and the highest score in the voice and accountability indicator would experience only a quarter of the economic losses from a Category 4 earthquake than a country with the lowest institutional quality. This provides further evidence that earthquake loss risk is strongly associated with the quality of urban governance, and in particular with the lack of regulation of urban development and the ineffectiveness of building codes.

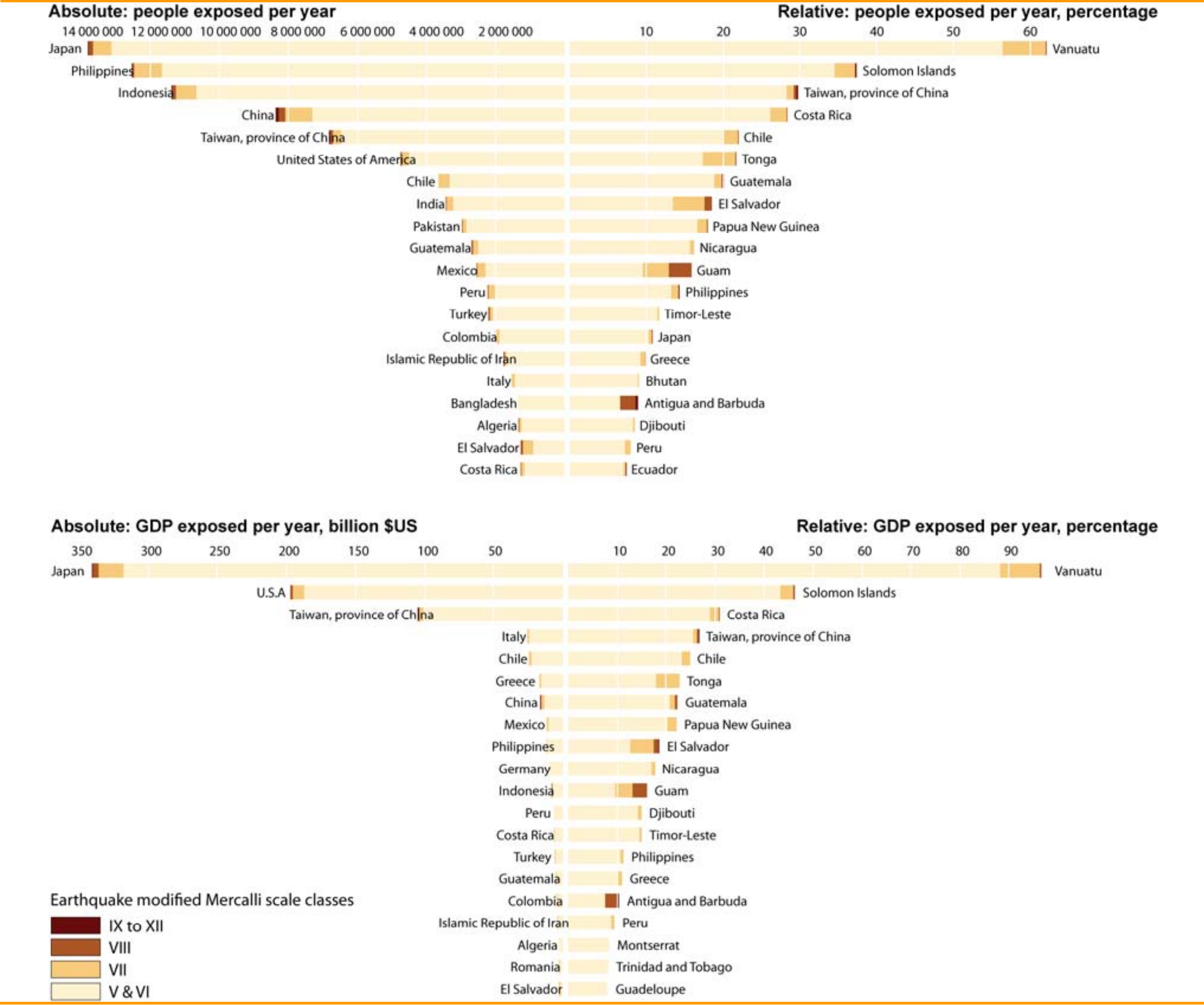


Figure 58 People and GDP exposed to earthquakes

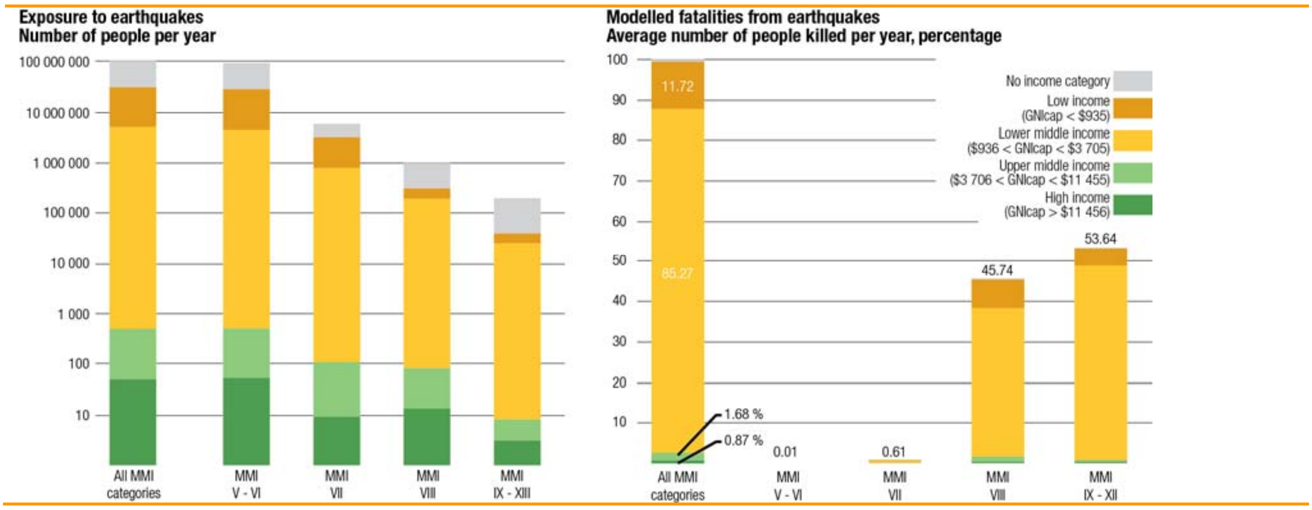


Figure 59 Exposure and mortality risk for earthquakes of different intensities by income class

Drought

Drought differs from other hazard types in several ways. First, unlike earthquakes, floods or tsunamis that occur along generally well-defined fault lines, river valleys or coastlines, drought can occur anywhere (with the exception of desert regions where it does not have meaning). Secondly, drought develops slowly, resulting from a prolonged period (from months to years) of precipitation that is below the average, or expected, value at a particular location. Drought ultimately represents a condition of insufficient water supply relative to demand, both being highly location specific. For example, a few months of deficient rainfall may adversely affect rain-fed agriculture but not a reservoir system with substantial storage capacity, and defining what constitutes 'deficient' precipitation depends on the local climate. Scientists therefore distinguish between three general categories of drought: meteorological, agricultural and hydrologic. Meteorological drought refers to a prolonged period of deficient precipitation, while agricultural drought occurs when soil moisture is depleted to the point where crops, pastures or rangelands are impacted. Hydrologic drought refers to a prolonged period with below-average water levels in rivers and streams, lakes and reservoirs, or groundwater.

Drought also differs from other hazard types in the way losses are incurred. Few droughts lead directly to mortality. Those that do cause mortality have generally occurred during a political crisis or civil conflict where aid could not reach the affected population. In these cases the mortality should more properly be attributed to the conflict than to the drought. Impacts might also be highest even after the meteorological drought event has ended, for instance when people have exhausted their food supplies long before the next harvest.

Overall, the unique characteristics of drought make it difficult to analyse vulnerability and risk in the same framework as the other hazard types. Available loss data sets do not provide information on the factors contributing indirectly to drought mortality, while mortality itself is not a good indicator of impact. Similarly, there is also no clear way to translate meteorological drought into agricultural drought since it depends on the farming system and even on individual crop choice. Specific risk and vulnerability to droughts and how they affect income, consumption, health, human development and productivity are therefore best analysed in detailed local and context specific studies (see Chapter 3) 24.

Given the varying impacts of drought, several drought indicators are in use around the globe. These include the Standardized Precipitation Index (SPI) and the coefficient of variation (CV) 25. Drought intensity and frequency are captured by the SPI. The CV gives additional information since it is a summary measure of how large the variability of precipitation is from year-to-year, relative to the amount of mean annual rainfall. The CV tends to be high in semi-arid regions, where there tends to be both high variability of rainfall and a small mean annual rainfall. In Figures 2.1, 2.2 and 2.3 drought hazard was calculated by multiplying the SPI-defined drought event frequency by the CV therefore combining drought intensity, frequency and information on where interannual precipitation variability is high or low (Fig. 2.26).

Approximately 400 geo-referenced drought disasters recorded in EM-DAT were also compared with various SPI drought indicators. The EM-DAT disasters were best matched with severe droughts identified using a SPI indicator for six-month total precipitation. This is consistent with the observation that the majority of EM-DAT drought disasters are in tropical areas that experience a distinct rainy season with a typical duration of six months or less. Again, the drought indicator showing the best correspondence with EM-DAT disasters (or other impacts) may vary locally.

Drought Exposure

Figures 2.27 and 2.28 show the number of people and areas of crops exposed to drought hazard as measured by the six month SPI. In terms of relative exposure, sub-Saharan African countries are highly exposed in both categories. For the reasons explained above, exposure does not necessarily indicate a risk of mortality, crop or economic loss.

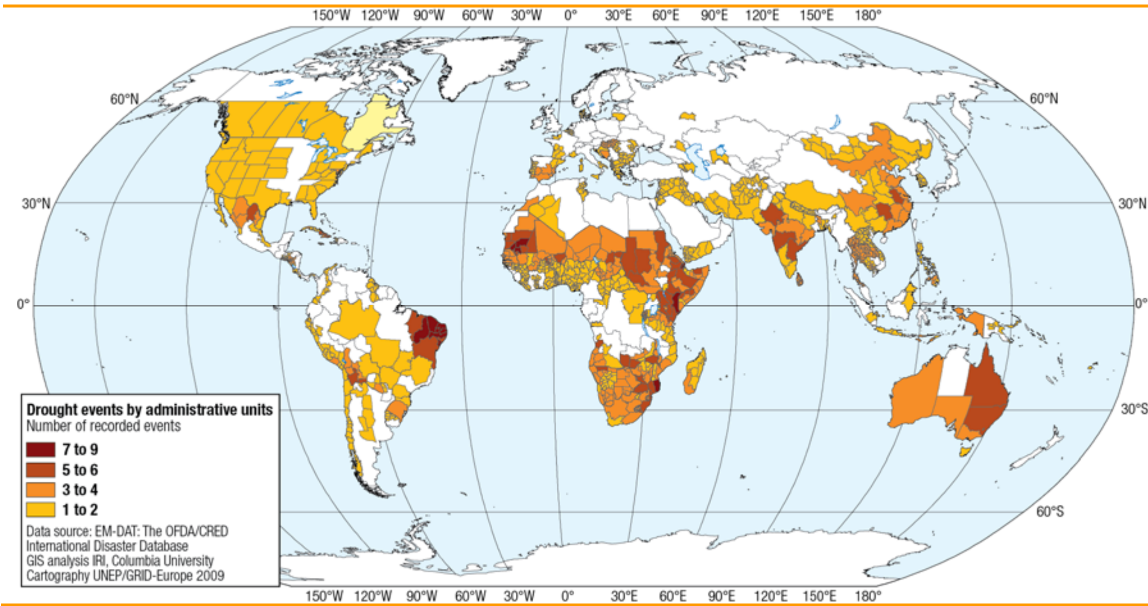


Figure 60 Number of drought disasters as recorded by EM-DAT (1974–2004)

Data source: EM-DAT: The OFDA/CRED International Disaster Database: www.emdat.net; GIS analysis: IRI, Columbia University; Cartography: UNEP/GRID-Europe, 2009.

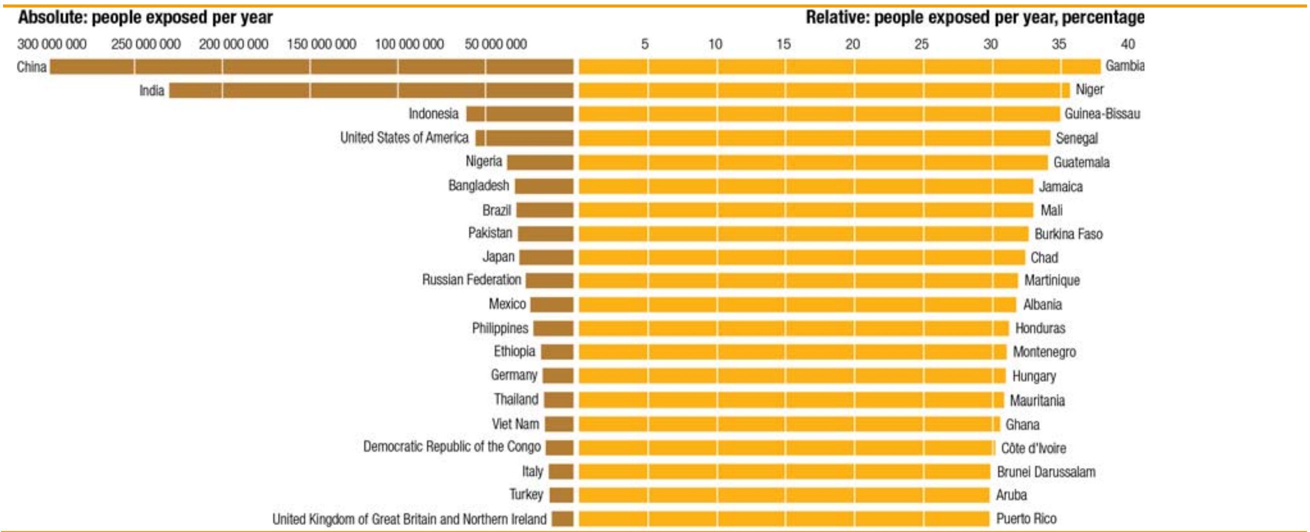


Figure 61 People exposed to drought

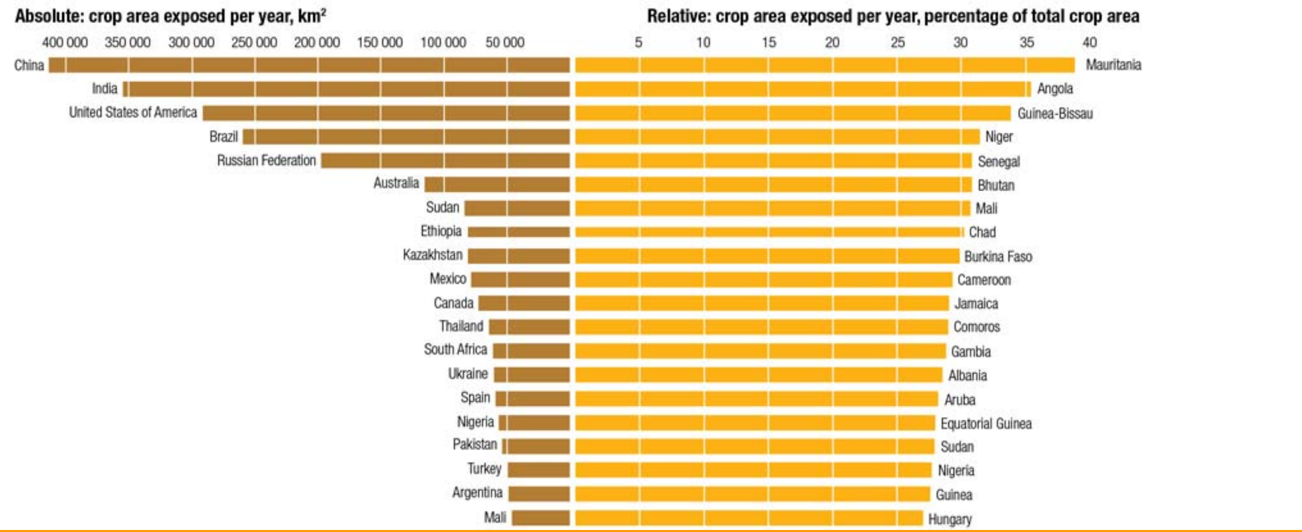


Figure 62 Crop area exposed to drought

Tsunamis

Tsunamis are relatively infrequent with only 5–10 events reported globally per year, but as demonstrated in the Indian Ocean in 2004 they can be devastating. Tsunamis are waves set in motion by large and sudden forced displacements of sea water caused by submarine earthquakes or landslides as well as other causes such as submarine volcanoes or asteroid impacts. When the tsunami is generated, its speed in the open sea can reach several hundred kilometres per hour, reaching distant coastlines in relatively short times. Tsunamis slow down as they approach the shoreline but their height increases. Because of their relatively large wavelength, tsunamis may travel far inland, and because of their relatively short wave period, they cause flooding faster than tidal waves and storm surges. Their enormous capacity to erode the landscape and destroy buildings makes them highly destructive both in terms of mortality and economic loss. The Indian Ocean tsunami is estimated to have caused area 210,000 deaths and more than US$ 10 billion in damages. Figure 2.29 shows the distribution of tsunami hazard globally.

Large and infrequent, but highly destructive tsunami events generally pose greater mortality risk than the cumulative effect of smaller and more frequent events. The tsunami exposure analysis therefore focuses on extreme events generated by large earthquakes with return periods of approximately 500 years (formally, a probability of 10% of an event occurring in 50 years). Large Asian countries such as Indonesia and Japan account for a large proportion of people living in tsunami prone areas, while SIDS account for the highest proportion of their population (Figure 2.30). Countries on the Pacific coast of South America, notably Chile and Peru have a very high number of people living in tsunami prone areas in both absolute and relative terms. It is worth noting that given the low probability of tsunami occurrence, Figure 2.30 provides the number of people living in tsunami- prone areas and not the average yearly exposure as provided for other hazards.

As shown in Figure 2.31, Japan has the highest absolute GDP exposed to tsunamis, but relative exposure is higher in SIDS and some South American countries, such as Ecuador and Peru.

The time between the triggering event and the tsunami's landfall is a key variable as it influences the effectiveness of tsunami early warning systems and the possibility of evacuation. Chile, India, Indonesia, Myanmar, Peru, the Solomon Islands, Portugal, Tonga, Pakistan, Papua New Guinea and the Philippines all have particularly high levels of hazard, given that tsunamis could hit the shoreline in less than 15 minutes with wave heights in excess of 6 metres.

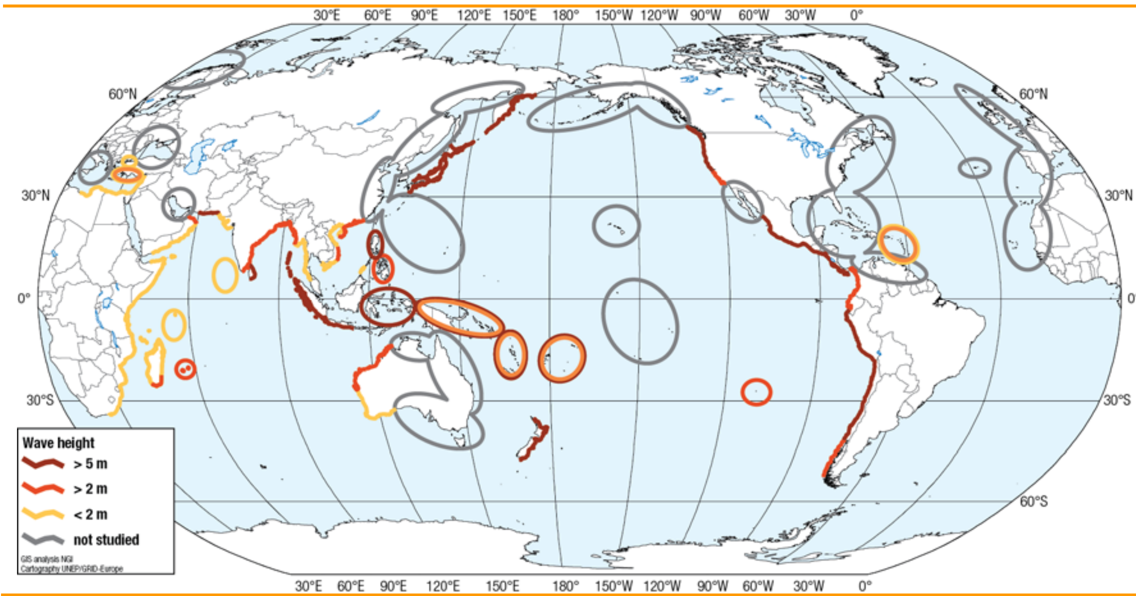


Figure 63 Sketch of global tsunami hazard

GIS analysis: Norwegian Geotechnical Institute; Cartography: UNEP/GRID-Europe, 2009

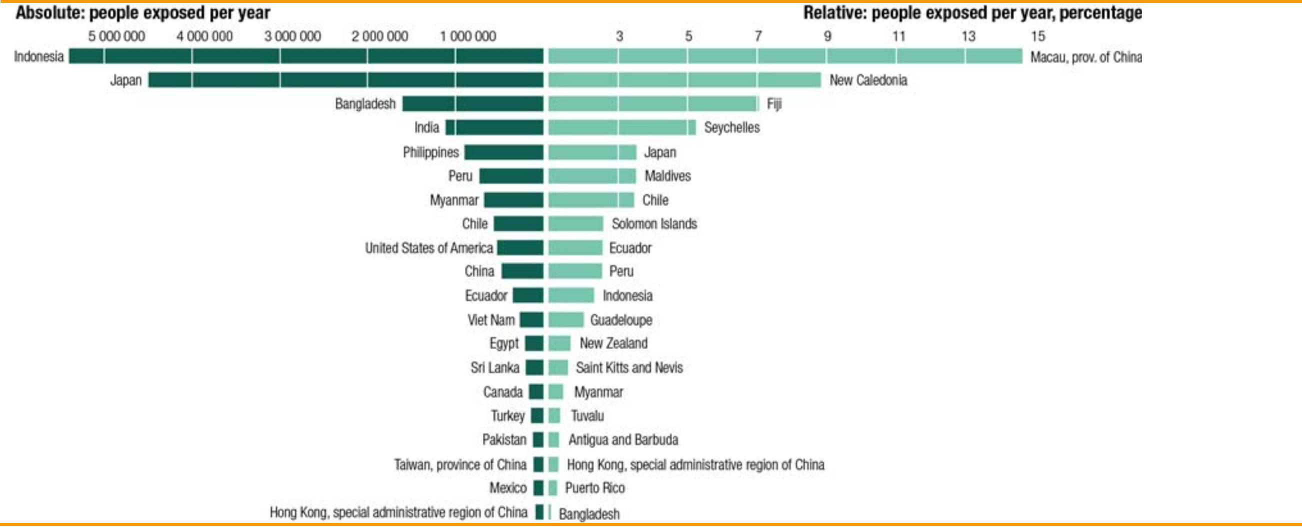


Figure 64 Number of people living in areas potentially affected by tsunamis

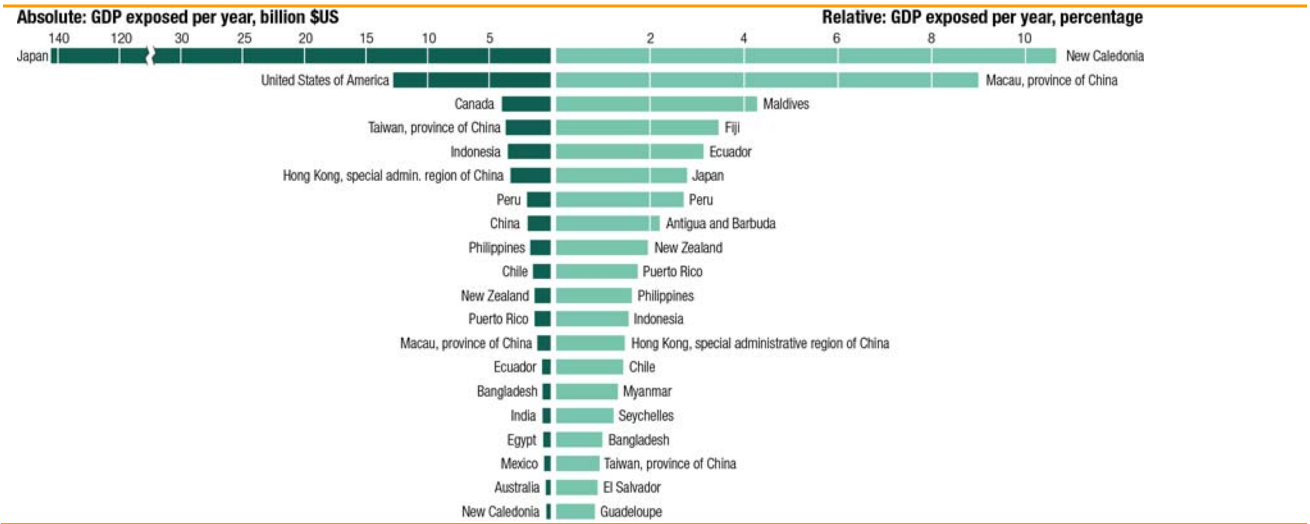


Figure 65 GDP exposed to tsunamis

Figure 66 Tsunami modelling of Manila Bay (the Philippines)

It is important to emphasize once again that hazard is modelled with a 10% probability of occurrence every 50 years, or in other words, a 500-year return period. Similarly, the actual tsunami hazard in any particular area in these countries depends on local topography, bathymetry and other factors. For example, while the Philippines could be subject to wave heights of up to 16 metres hitting the shoreline in only 9 minutes, Figure 2.32 shows that the most severe impact zones are outside of the city of Manila.

Forest and other biomass fires

According to a recent inventory [26] wild land fires and other biomass fires annually burn a total land area of between 3.5 and 4.5 million Km^2, equivalent to the surface area of India and Pakistan together, or more than half of Australia. This makes it makes it one of the most spatially prevalent hazards after drought.

Emissions from biomass burning inject pollutants into the atmosphere, as well as GHGs. The IPCC attributes 17.3% of total anthropogenic emissions to biomass burning[27], making it the second largest source of GHGs from human activities after the burning of fossil fuel. However, this figure may in reality be even higher, as it is based on pre-2000 data. Biomass fire is the only hazard that has both an impact on, and is exacerbated by, climate change. Most fires have human causes.

Figure 2.33 shows the average density of fires per 100 Km^2, between 1997 and 2008. Not all high temperature events are biomass fires, as gas flares and other high temperature events are also detected. However, most fires are due to biomass burning.

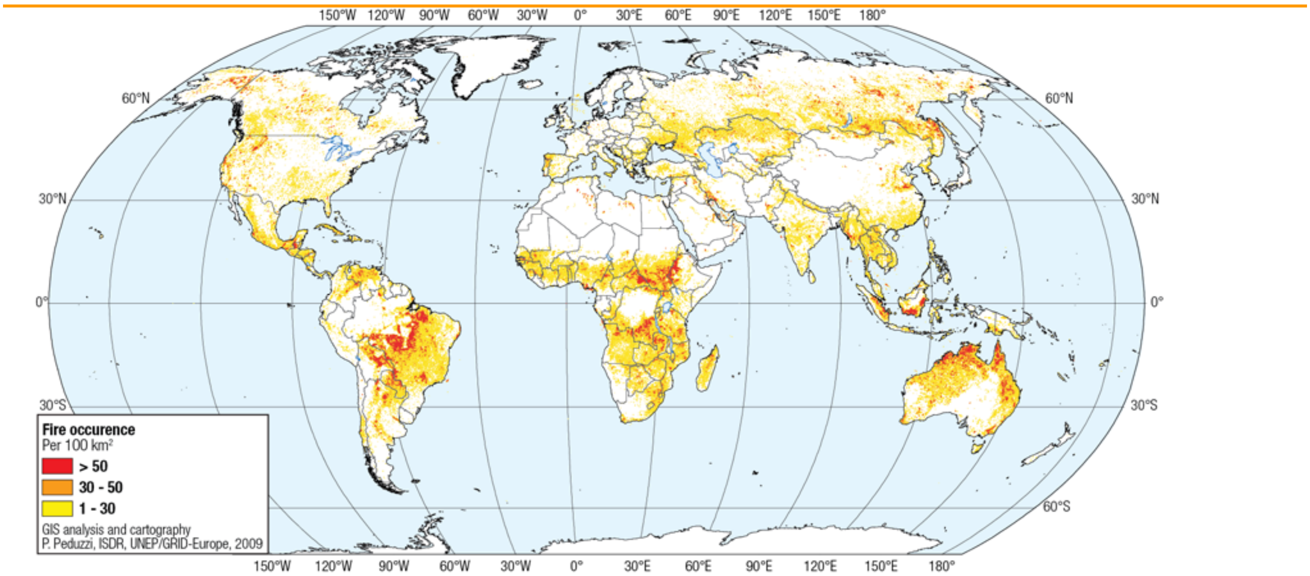


Figure 67 Distribution of average density of fires per 100 Km^2 (1997–2008)

GIS analysis and cartography: P. Peduzzi, ISDR, UNEP/GRID-Europe, 2009

3.5.6. Multi-hazard and risk identification

Multi-hazard risk

Figure 2.34 shows multi-hazard risk for tropical cyclones, floods, earthquakes and landslides. Given that drought is not represented, mortality risk is underestimated for countries in some regions, particularly in Africa.

Figure 2.35 shows the spatial distribution of mortality risk accumulated for tropical cyclones, floods, earthquakes and landslides.

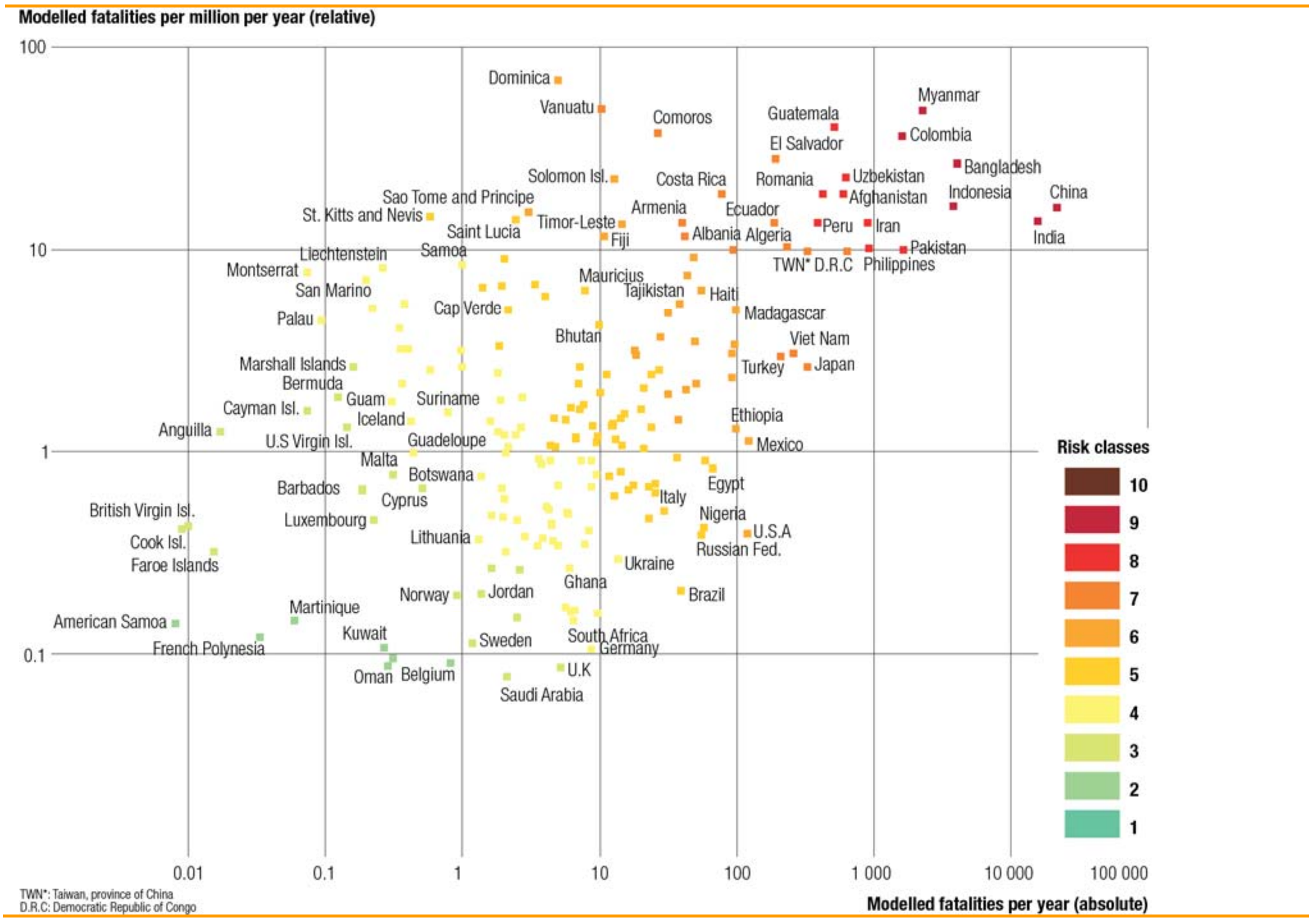


Figure 68Absolute and relative multi-hazard mortality risk for tropical cyclones, floods, earthquakes and landslides

Note: DRC, Democratic Republic of the Congo; TWN, Taiwan, province of China; UK, United Kingdom of Great Britain and Ireland; USA, United States of America.

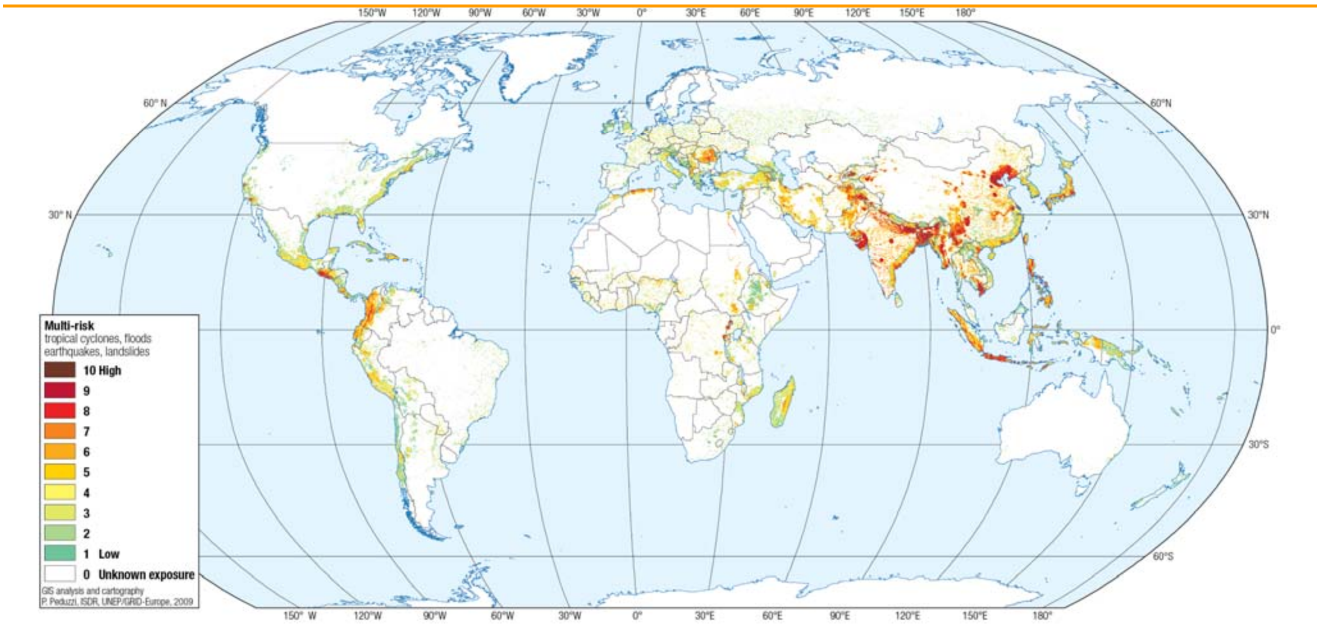


Figure 69 Global distribution of multiple hazards mortality risk

GIS analysis and cartography: P. Peduzzi, ISDR, UNEP/GRID-Europe, 2009.

3.5.7. Trends in global disaster risk

Both mortality and economic loss risk are increasing in absolute terms for all the principal hazards, except for landslides, where the tendency appears to be stable. However, relative risk when measured as a proportion of population or GDP is stable and, in the case of mortality, may be declining.

Many readers will be familiar with graphs such as Figure 2.36, which show an exponential increase in economic loss from disasters since the 1970s. Figure 2.37 shows that when these losses are adjusted for inflation and expressed as a percentage of global GDP, the trend is far less pronounced and statistically insignificant.

Risk, exposure and vulnerability

In order to see how risk patterns are changing over time, modelled mortality and economic loss in 1990 and 2007 were compared, assuming constant levels of hazard.

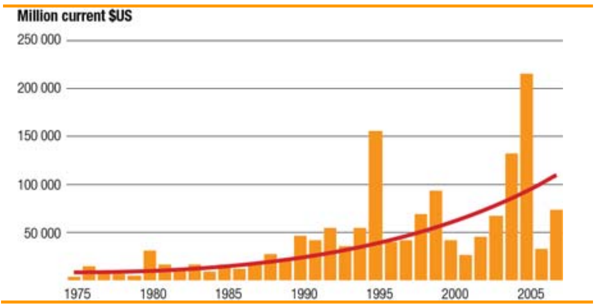


Figure 70 Total reported economic losses from natural disasters 28

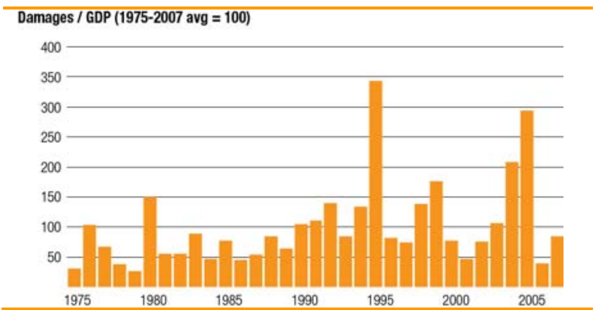


Figure 71 Inflation adjusted economic losses as a share of global GDP

In the case of floods, modelled mortality increased by 13% from 1990 to 2007. This increase was driven by a 28% increase in modelled exposure. Vulnerability actually declined by 11%.

Modelled economic loss over the same period increased by 33%, while GDP exposure increased by 98%. Vulnerability actually declined by 33%. This concurs with the fact that globally GDP increased by 64% over the same period, but countries with very high flood exposure, such as China and India, increased their GDP by more, in this case 420% and 185% respectively.

In the case of landslides, mortality risk was stable from 1990 to 2007 (the model indicates a decrease of 1%). Exposure increased by 23%, while vulnerability decreased by 20%, reflecting GDP growth in the countries exposed.

These simulations of risk indicate that increases in weather-related disaster risk are principally being driven by increases in exposure. Vulnerability actually appears to be going down although these simulations do not indicate which specific factors are increasing or decreasing over time.

The overall implication is that while economic development can reduce vulnerability, at the same time it drives increased exposure of people and economic assets in areas prone to weather-related hazards, particularly urban and coastal areas. Economic loss risk appears to be increasing faster than mortality risk, reflecting a faster increase in GDP exposure than population exposure.

Since 1975, for example, the global population has increased by 63% [29]. In terms of economic assets, between 1975 and 2007, global GDP grew by 166%, from US$ 14.8 trillion to US$ 39.4 trillion (in constant 2000 US$), far faster than world population which grew from 4.1 to 6.6 billion. GDP per capita therefore grew from US$ 3,600 to US$ 5,900 [30]. But these gains have not been uniform. The economies of richer countries and some successful lower-income countries grew faster than those of many poor countries, especially in Africa and South Asia.

Although solid data are hard to come by, there is evidence that economic activities, assets and productive infrastructure are also further concentrated within countries. Growth has been fastest in coastal regions and near large navigable rivers, many of which are prone to natural hazard events 31. Urban growth has added significant economic assets to large cities in developing countries, some of which are located in geologically unstable areas. Earthquake prone Tehran and Istanbul, for instance, experienced faster urban and economic growth than the Islamic Republic of Iran and Turkey as a whole. As populations concentrate and economic activity in those centres grows even faster, exposure also increases significantly.

It is also likely that risk is increasing fastest in low and lower-middle income countries with rapidly growing economies. These countries have rapidly increasing exposure at the same time as only slowly improving vulnerability indicators. In contrast, most high-income countries experience more sedate increases in exposure, with very low vulnerability.

Is hazard increasing?

The above simulations of loss trends assume constant hazard levels. Yet hazard is changing, due to climate change, urbanization and environmental degradation.

In the case of tropical cyclones, Table 2.6 shows that there has been an increase in the frequency of Category 4 events during warm years. These results are in line with findings published recently [32] in which it was calculated that a 1ºC increase in sea surface temperatures would result in a 31% increase in the global frequency of Category 4 and 5 storms per year. This is also consistent with the IPCC's 4th Assessment report (p. 795)[33] which states that *"Tropical cyclones (including hurricanes and typhoons), are likely to become more intense with sea surface temperature increases."*

Table 2.6 shows that the average number of tropical cyclones between cold, average and hot years is fairly stable (between 56 and 58 tropical cyclones per year). However, Category 3 and 4 cyclones show a marked increase in average and hot years compared with cold years. Global sea surface temperature data are available only since 1985. The "No data" years (1976–1984) show more Category 1 and fewer Category 3, 4 and 5 cyclones.

Any increase in the severity of cyclones will magnify the unevenness of disaster risk distribution. For example, the economic risk model shows that 1.9% of the GDP of Madagascar is at risk annually from Category 3 cyclones, but only 0.09% of the GDP of Japan. If these cyclones were to increase to Category 4 storms, 3.2% of the GDP of Madagascar would be at risk, but only 0.16% of the GDP of Japan.

Group by average sea surface temperature (SST)	Number of cyclones for the period*	Number of years	Average number of events/ year	Number events Cat. 1	Number events Cat. 2	Number events Cat. 3	Number events Cat. 4	Number events Cat. 5
No data on SST	494	9	54.9	22.7	12.7	12.9	6.2	0.6
Cold SST	407	7	58.1	25.4	13.9	10.4	7.1	1.3
Average SST	448	8	56.0	18.0	13.9	14.0	9.3	1.9
Hot SST	460	8	57.5	20.4	11.6	16.1	8.1	1.3

*Analysis covers the period 1977–2006; sea surface temperature (SST) data were available from 1985–2006; cyclones for the period 1977–1984 were grouped as one category (no data on SST).

Table 19 Tropical cyclone intensity and occurrence (1977–2006) grouped by sea surface temperature for 1985–2006

3.5.8. *Economic resilience, vulnerability and development constraints in developing countries*

Previous research has confirmed that the level of economic losses experienced by a country is not a good indicator per se of the country's capacity to absorb the impact of a major hazard event and recover, even when expressed in relation to the size of a country's GDP or exposed GDP. In the development of the Disaster Deficit Index [34], for example, it was proposed that countries with access to insurance and reinsurance payments (for example through participation in a catastrophe pool), with disaster reserve funds, with access to external credit and with internal reserves would in general be more resilient to catastrophic disaster loss than countries without.

The stock of physical (economic) capital has always been considered as a determinant factor in economic growth, a perspective that has been enriched by incorporating other forms of capital (human, social-relational and natural capital) as well as institutions and knowledge, as *endogenous capacities* contributing to explaining growth [35].

Estimates prepared for this report show that disasters have a major impact on the accumulation of capital stock in a small number of vulnerable countries. The top three countries in this situation, in which the ratio of economic losses to capital stock was highest are all SIDS, namely Samoa, Saint Lucia and Grenada. The next two most affected countries, Afghanistan and Tajikistan, are land-locked countries [36].

Figure 2.38 clearly shows the differential impact of economic loss in countries with different characteristics.

In Samoa, for example, economic losses in a series of disasters including a tropical storm and forest fire in 1983, and a series of back-to-back tropical cyclones between 1989 and 1990 appear to have set back the country's economy by about 30 years. It was not until 2000 that the island's capital stock recovered to its 1970's level. A similar pattern is presented in Saint Lucia due to the impacts of Hurricane Allen in 1980 and Hurricane Gilbert in 1986. Madagascar shows a different pattern but a clear impact of disaster loss on cumulative net capital formation. In contrast, the impact of major disasters on high-income countries such as the United States of America is imperceptible, even though that country has experienced disasters with enormous absolute economic loss. Similarly, the effect in large low-income countries such as India or middle-income countries such as Colombia is not so significant.

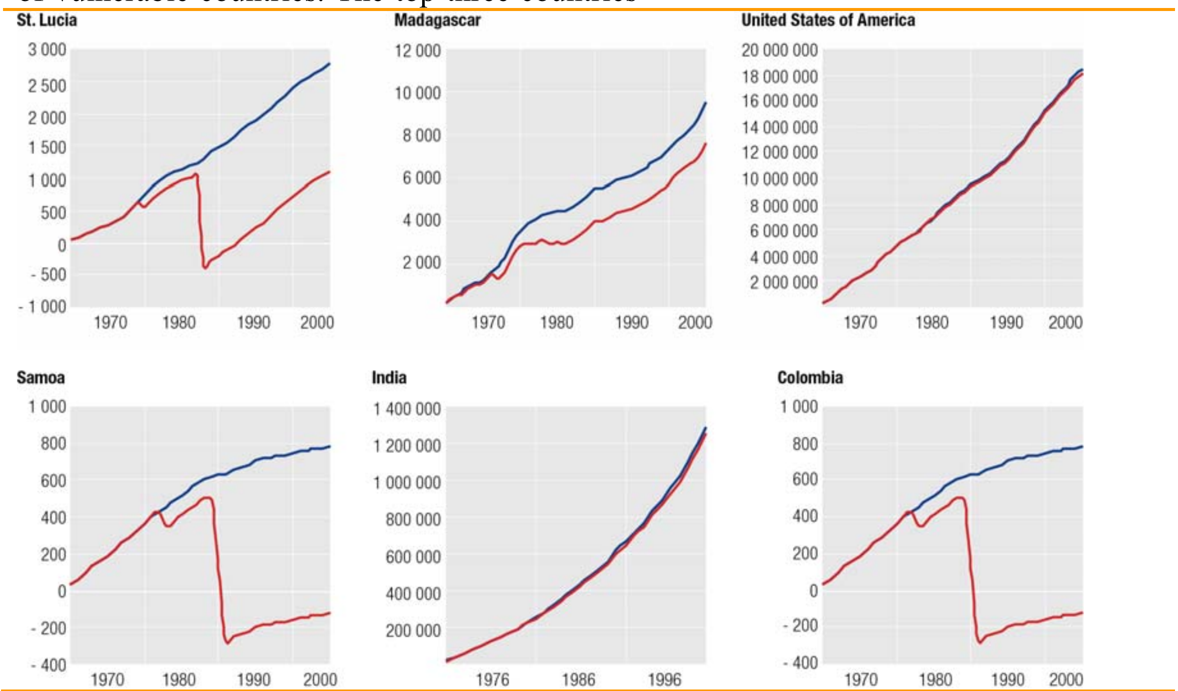


Figure 72 Impact of economic loss

Cumulative net capital formation (NCF) from 1970 to 2006, in millions of constant 2000 US$, with (red lines) and without (blue lines) the effect of economic losses in disasters.

Hurricane Gilbert in 1986. Madagascar shows a different pattern but a clear impact of disaster loss on cumulative net capital formation. In contrast, the impact of major disasters on high-income countries such as the United States of America is imperceptible, even though that country has experienced disasters with enormous absolute economic loss. Similarly, the effect in large low-income countries such as India or middle-income countries such as Colombia is not so significant.

The implications are that disasters do not have a significant impact on economic growth in countries with large economies, but a devastating impact on those with small economies. Such economies are highly vulnerable to disaster loss. While in large countries disasters may have a devastating impact on the localities and regions where they occur, as Hurricane Katrina demonstrated, this is not necessarily translated into a national impact unless the affected area concentrates a significant proportion of a country's capital.

Approaches to measuring the resilience of a country to economic shocks have included the Disaster Deficit Index, mentioned above, and others [37]. Another approach is to use net savings as a proxy of a country's ability to absorb the impact and recover from disaster losses. Net savings is probably a better proxy of resilience than GDP per capita because it more accurately estimates the available internal resources, which could be invested in the recovery of losses including capital stock.

However, the factors that influence a country's resilience (i.e. its capacity to recover from deviations in its development path caused by disaster impacts) are complex and cannot be reduced easily to any one variable. Nevertheless, five groups of countries can be identified that share common characteristics in terms of their vulnerability and resilience to disaster loss and their development limitations, particularly their capacity to benefit from international trade [38].

Table 2.7 shows the countries in this classification. Groups 4 and 5 are those with high and very high economic vulnerability to natural hazards. The table also shows the number of developing countries (including LLDCs) in those groups that experience extreme limitations in their ability to benefit from international trade. Countries suffering extreme trade limitations are characterized by a very low participation in world export markets (less than 0.1%) and simultaneously show low export diversification, which render them highly exposed to trade shocks.

The higher the vulnerability of a group to natural hazard risks, the higher the number of developing countries in it that suffer extreme trade limitations [39]. In the groups with high and very high vulnerability (i.e. Groups 4 and 5), 81% of all countries suffer extreme trade limitations (reaching 100% in Group 5), while in groups with very low, low and medium vulnerability (Groups 1, 2 and 3), only 4% suffer such limitations.

It is also clear that SIDS and LLDCs represent the majority of countries with high and very high vulnerability and those suffering extreme trade limitations. In fact, SIDS and LLDCs together constitute 60% and 67% of all countries in Groups 4 and 5 respectively, and about two thirds of all countries in the groups affected by extreme trade limitations.

Given that the risk circumstances of many SIDS and LLDCs are likely to worsen because of climate change trends, in the absence of particular attention from the international community, their prospects for a positive insertion in the global economy will further deteriorate, and even their economic and social viability as nations could be seriously compromised.

Given the limitations on economic loss data mentioned in Section 2.2, it is likely that with more complete information, the specific countries identified in each of those groups would change. The exercises mentioned above should, therefore, be considered illustrative only. Nevertheless, a key conclusion is that SIDS, landlocked countries, LLDCs and others with small and vulnerable economies and low levels of resilience to economic loss will require a specific policy focus that takes into account the complexity of the factors involved. This conclusion will be revisited in the recommendations of the report in Chapter 7.

Short vulnerability characterization	Groups of countries according to their economic vulnerability to natural hazards		Vulnerability factors relative to all countries	
	Countries in the group	Developing countries in the group experiencing extreme trade limitations (Very Low Revealed Competitiveness; High Exposure to Trade Shocks)(3)(4)	Relative economic loss (1)	Economic resilience (2)
1 Very Low	(16) Bahrain; Finland; Gabon; Iraq; Ireland; Kuwait; Lybian Arab Jamahiriya; Luxembourg; Macau; Malta; Norway; Qatar; Saudi Arabia; Singapore; Suriname; United Arab Emirates	0	In the best (lowest) 25% of the world	In the best (highest) 25% of the world
2 Low	(33) Albania; Austria; Belgium; Botswana; Bulgaria; Canada; Congo, Rep. of; Cyprus; Czech Republic; Denmark; Egypt; Equatorial Guinea; France; Germany; Hong Kong; Iceland; Kiribati; Lithuania; Malaysia; Netherlands; New Zealand; Oman; Panama; Russian Federation; Slovenia; South Africa; Sweden; Switzerland; Trinidad & Tobago; Tunisia; United Kingdom; Uruguay; Venezuela.	(2) Equatorial Guinea; Kiribati	In the second quartile (Between 25% and 50% of the world)	In the third quartile (Between 50% and 75% of the world)
3 Medium	(23) Algeria; Antigua & Barbuda; Azerbaijan; Bahamas; Chile; China; Costa Rica; Dominican Republic; Fiji; India; Iran, Islamic Republic of; Jamaica; Liberia; Mauritius; Moldova; North Korea; Peru; Portugal; Phillipines; Romania; Somalia; Sudan; Turkey	0	In the third quartile (Between 50% and 75% of the world)	In the second quartile (Between 25% and 50% of the world)
4 High	(33) Bangladesh; Barbados; Bermuda; Bolivia; Bosnia-Herzegovina; Cape Verde; Chad; Cuba; Ecuador; Georgia; Grenada; Guyana; Honduras; Jordan; Madagascar; Malawi; Mauritania; Mongolia; Nauru; Nepal; Pakistan; Papua New Guinea; St Kitts & Nevis; St Lucia; Seychelles; Solomon Islands; Sri Lanka; Swaziland; Tajikistan; Tuvalu; Vanuatu; Vietnam; Zimbabwe	(25) Bangladesh; Barbados; Bermuda; Bolivia; Cape Verde; Cuba; Ecuador; Grenada; Guyana; Honduras; Jordan; Madagascar; Malawi; Mauritania; Mongolia; Nepal; Nicaragua; Papua New Guinea; St Kitts & Nevis; St Lucia; Sri Lanka; Swaziland; Tajikistan; Tuvalu; Vanuatu	...Either in the worst (highest) 25% of economic losses and between 25% and 50% of resilience simultaneously, ...	
			...Or in the worst (lowest) 25% of resilience and between 50% and 75% of economic losses simultaneously	
5 Very High	(18) Afghanistan; Armenia; Belize; Cambodia; Comoros; Dominica; El Salvador; Guatemala; Haiti; Kyrgyzstan; Lao People's Democratic Republic; Former Yugoslav Republic of Macedonia; Mozambique; Myanmar; St Vincent & The Grenadines; Samoa; Senegal; Tonga	(18) Afghanistan; Armenia; Belize, Cambodia; Comoros; Dominica; El Salvador; Guatemala; Haiti; Kyrgyzstan; Lao People's Democratic Republic; Former Yugoslav Republic of Macedonia; Mozambique; Myanmar; St Vincent & The Grenadines; Samoa; Senegal; Tonga	In the worst (highest) 25% of the world	In the worst (lowest) 25% of the world

(1) Economic losses relative to GDP and/or to capital stock are used to proxy fragility; (2) Net savings per capita is used as a proxy for economic resilience; (3) A share of 0.10% or less of world export market in is used for very low revealed competitiveness; (4) Being in the worst 50% of the world in terms of trade diversification is used as an indicator of high exposure to trade shocks

Table 20 Five groups of countries characterized in terms of their economic vulnerability to natural hazards, and developing countries in each group experiencing extreme limitations in international trade.

3.5.9. Endnotes

1 The LandScan™ Dataset comprises a worldwide population database compiled on a 30” × 30” latitude/longitude grid. Census counts (at sub-national level) were apportioned to each grid cell based on likelihood coefficients, which are based on proximity to roads, slope, land cover, nighttime lights and other information. LandScan has been developed as part of the Oak Ridge National Laboratory Global Population Project for estimating ambient populations at risk: http://www.ornl.gov/sci/landscan/index.html

2 The ShakeMap Atlas: http://earthquake usgs.gov/eqcenter/pager/prodandref/index php; Allen, T. I., Wald, D. J., Hotovec, A., Lin, K., Earle, P. and Marano, K. (2008) *An Atlas of ShakeMaps for Selected Global Earthquakes*. U.S. Geological Survey. Open File Report 2008–1236. USGS.

3 Wald, D. J., Earle, P.S., Porter, K., Jaiswal, K. and Allen, T. I. (2008) *Development of the U.S. Geological Survey’s Prompt Assessment of Global Earthquakes for Response (PAGER) System*. Proceedings of the 14th World Conference on Earthquake Engineering, October 12–17, 2008. Beijing, China.

4 Normally economic loss in disasters is divided into direct economic loss referring to the value of destroyed and damaged assets, and indirect economic loss, referring to knock-on effects in broader economic flows. The term economic loss risk in this chapter refers specifically to the former, although in practice it is often impossible to know whether reported loss estimates include indirect losses..

5 MunichRe NatCatService, GeoRisiko-Forschung, Great Natural Disasters 1950–2007: http://www.munichre.com/en/ts/geo_risks/natcat service/default.aspx; EM-DAT, 2008; analysis by ISDR (data as of September 2008).

6 IPCC (Intergovernmental Panel on Climate Change) (2007b) *Summary for Policymakers*. In: Parry, M. L., Canziani, O. F., Palutikof, J. P., Linden, P. J. v. d. and Hanson, C. E. (Eds.) *Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the IPCC (Intergovernmental Panel on Climate Change).* Cambridge, UK. Cambridge University Press.

7 Detailed information on data sources and methodology is provided in Appendix 1 and in the technical background papers produced for this chapter. Maps, figures and tables illustrating key highlights of the findings are presented in this chapter. User-generated maps and graphs may be created on http://preview.grid.unep.ch

8 UNDP/BCPR (United Nations Development Programme, Bureau for Crisis Prevention and Recovery) (2004) *Reducing Disaster Risk: A Challenge for Development.* New York. UNDP/BCPR.
Dilley, M., Chen, R.S., Deichmann. U., Lerner-Lam, A.L. and Arnold, M. (2005) Natural Disaster Hotspots: A Global Risk Analysis. Washington DC. World Bank and Colombia University.

9 World Bank (2000) *World Development Report 2000/01: Managing Economic Crises and Natural Disasters*. Washington, DC. World Bank.

10 Altez, R. (2007) Muertes Bajo Sospecha: Investigación Sobre el Número de Fallecidos en el Desastre del Estado Vargas, Venezuela, en 1999. *Cuadernos de Medicina Forense*, **13**(50).
Altez, R. and Revet, S. (2005) Contar los Muertos Para Contar la Muerte: Discusión en Torno al Numero de Fallecidos en la Tragedia de 1999 en el Estado Vargas – Venezuela. *Revista Geografica Venezolana*, Numero especial 2005, 21–43.

11 BBC, 29 December, 1999. Venezuala disaster ‘worst this century’: http://news.bbc.co.uk/2/hi/americas/581579.stm

12 Cormac, Ó. G. (2007) Making famine history. *Journal of Economic Literature* XLV (March) 5–38.

13 The level of confidence of the model for Category 1 events was (R^2 = 0.417), Category 2 (R^2 = 0.413), Category 3 (R^2 = 0.450), Category 4 (R^2 = 0.681) and Category 5 (R^2 = 0.998).

14 Estimates are based on EM-DAT reported damages and predicted losses for cyclone events during 1975–2007 for which no damage estimates were available.

15 McTaggart-Cowan, R., Bosart, L. F., Davis, C. A., Atallah, E. H., Gyakum, J. R. and Emanuel, K. A. (2006) Analysis of Hurricane Catarina (2004). *Monthly Weather Review* 134(11), 3029–3053.

16 Marcelino, E. V., Marcelino, I. P. V. d. O. and Rudorff, F. d. M. (2004) *Cyclone Catarina: Damage and Vulnerability Assessment.* Florianópolis, Brazil. Santa Catarina Federal University.

17 NOAA/NHC (United States National Oceanic and Atmospheric Administration/National Hurricane Center): http://www.nhc.noaa.gov/aboutsshs.shtml

18 The difference would be smaller if extra-tropical storms were included in the analysis.

19 As observed by the Dartmouth Flood Observatory between 1980 and 2001.

20 As reported by CRED/EM-DAT for earthquakes between 1999 and 2008; EM-DAT, 2008; analysis by ISDR (data as of September 2008).

21 Izmit (Turkey, 1999; 17,000 killed); Bhuj (Gujarat, India, 2001; 20,000 killed); Bam (Iran, 2003; 26,800 killed); Jammu/Kashmir (Pakistan/India, 2005; 74,000 killed) and Sichuan (China, 2008; 87,900 killed).

22 GDP per capita, voice and accountability, and urban growth were highly correlated and therefore could not be used in the same regression. For Categories 1 and 3 earthquakes, GDP per capita was the best fit; for Category 2 urban growth, and for Category 4 voice and accountability.

23 Assuming average earthquake magnitude, exposure and institutional quality.

24 Fuente, A. d. l. and Dercon, S. (2008) *Disasters, Growth and Poverty in Africa: Revisiting the Microeconomic Evidence*. Background paper for: Global Assessment Report on Disaster Risk Reduction, ISDR (International Strategy for Disaster Reduction) Secretariat. Geneva. United Nations.

25 See Appendix 1 for details. http://www.preventionweb.net/english/hyogo/gar/2011/en/bgdocs/GAR-2009/GAR_Postlims_2009_eng.pdf

26 Lehsten, V., Tansey, K., Balzter, H., Thonicke, K., Spessa, A., Weber, U., Smith, B. and Arneth, A. (2009) Estimating carbon emissions from African wildfires. *Biogeosciences* 6: 349–360.

27 IPCC (Intergovernmental Panel on Climate Change (2007c) Synthesis Report. p.36. http://www.ipcc.ch/pdp/assessment_report/ar4/syr/ar4_syr.pdf

28 EM-DAT, accessed 12 December 2008

29 Data sources: UN Population Division, on UNEP geodata portal: http://geodata.grid.unep.ch

30 GDP data: DDP, 2008. Population data: UN Population Division, 2006.

31 McGranahan, G., Balk, D. and Anderson, B. (2007) The rising tide: assessing the risks of climate change and human settlements in low-elevation coastal zones. *Environment and Urbanization* 19(1)**,** 17–37.

32 Elsner, J. B., Kossin, J. P. and Jagger, T. H. (2008) The increasing intensity of the strongest tropical cyclones. *Nature* 455**,** 92–95.

33 IPCC (Intergovernmental Panel on Climate Change) (2007a) *Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the IPCC (Intergovernmental Panel on Climate Change)*. In: Parry, M. L., Canziani, O. F., Palutikof, J. P., Linden, P. J. v. d. and Hanson, C. E. (Eds.) *Fourth Assessment Report of the IPCC*. Cambridge, UK. Cambridge University Press.

34 Cardona, O. D. (2005) *Indicators for Disaster Risk and Risk Management. Program for Latin America and the Caribbean: Summary Report*. Manizales, Colombia: Instituto de Estudios Ambientales, Universidad Nacional de Colombia.

35 Corrales and Miquilena (2008) Disasters in Developing Countries. Sustainable Development: A conceptual framework for strategic action. Background paper for 2009 Global Assessment Report on Disaster Risk Reduction. Unpublished.

36 Baritto, F. (2009) *Disasters, Vulnerability and Resilience from a Macro-Economic Perspective, Lessons from the Empirical Evidence*. Background paper for: Global Assessment Report on Disaster Risk Reduction, May 2009, ISDR (International Strategy for Disaster Reduction) Secretariat. Geneva. United Nations.

37 For example, Brugiglio's Economic Vulnerability Index, and Economic Resilience Index

38 Risk factors used were the per capita net savings, a proxy for resilience, and the ratio of economic losses to capital stock, as a proxy of vulnerability. The capacity to benefit from insertion in the global economy was expressed in terms of the 'revealed competitiveness' of countries (the market share of world exports), and the concentration of exports in a few export lines, an indicator of the country's exposure to trade shocks. The indicators of development outcomes were the human development index, and countries' per capita GDP.

39 Corrales and Miquilena (2008) Disasters in Developing Countries. Sustainable Development: A conceptual framework for strategic action. Background paper for 2009 Global Assessment Report on Disaster Risk Reduction. Unpublished.

3.5.10. List of contributors and acknowledgments

Chapter co-authors are Pascal Peduzzi (UNISDR and UNEP/GRID-Europe), and Uwe Deichmann (World Bank). Cartography and graphs were prepared by Stéphane Kluser (UNEP/GRID-Europe) and Pascal Peduzzi.

The chapter was developed in collaboration with the UNDP led Global Risk Identification Programme (GRIP), the World Bank Global Facility for Disaster Reduction and Recovery, UNEP/GRID Europe PREVIEW (Project for Risk Evaluation Vulnerability Information and Early Warning), the Norwegian Geotechnical

Institute and the Earth Institute at Columbia University. Close coordination was maintained with a study on Risk Assessment and Mitigation Measures for Natural- and Conflict-Related Hazards in Asia–Pacific, undertaken by the United Nations Office for Coordination of Humanitarian Affairs (OCHA), Regional Office for Asia and the Pacific. Both that study and the present analysis are underpinned by common hazard data sets, in order to avoid duplication and enable comparability.

The mortality risk analysis was developed and coordinated by Pascal Peduzzi and the economic loss risk analysis by Uwe Deichmann. The advisory group included: Maxx Dilley and Carlos Villacis (UNDP/BCPR); Hy Dao (UNEP/GRID-Europe); Oddvar Kjekstad and Farrokh Nadim (Norwegian Geotechnical Institute); Art Lerner-Lam and Brad Lyon (Earth Institute at Columbia University); Uwe Deichmann, Andrew Maskrey and Pascal Peduzzi.

The population distribution (1975–2007) used in this chapter was prepared by Hy Dao, based on the LandscanTM population model, kindly provided by the Oak Ridge National Laboratory (1). The GRUMP population distribution was also tested. It was generated by Greg Yetman (Columbia University) and used to compute the GDP raster distribution (1975–2007) prepared by Uwe Deichmann, Siobhan Murray and Mahyar Eshragh-Tabary (World Bank).

Social and economic indicators were compiled by Hy Dao, Andrea De Bono (UNEP/GRID-Europe) and Uwe Deichmann. The historical disaster loss data used was from EM-DAT: the OFDA/CRED International Disaster Database. Munich Reinsurance provided economic loss data aggregated at the country level. Maryam Golnaraghi and Jean Baptiste Migraine (WMO) coordinated the scientific peer review of the hazard models for tropical cyclones, floods and droughts. Badaoui Rouhban, Takashi Imamura and Juliana Chaves Chaparro (UNESCO) coordinated the scientific peer review of the hazard models for landslide, earthquake and tsunami.

The tropical cyclones hazard model was developed by Bruno Chatenoux (UNEP/GRID-Europe) and Pascal Peduzzi, based on previous work by Christian Herold, Frédéric Mouton, Ola Nordbeck and Pascal Peduzzi (UNEP/GRID-Europe). Events in the EM-DAT database were geo-referenced by Andrea De Bono and human and economic asset exposure was calculated by Bruno Chatenoux. The cyclone storm surge hazard model was developed and exposure calculated by Andrea De Bono. The vulnerability and risk analysis and models were done by Pascal Peduzzi (for human losses) and Uwe Deichmann (for economic losses) with Michael M. Lokshin (World Bank). Scientific peer review of the hazard models was carried out by Koji Kuroiwa and Taoyong Ping (WMO) with Jim Davidson (Bureau of Meteorology, Queensland, Australia), Woo-Jin Lee (Korean Meteorological Administration) and Linda Anderson-Berry (Bureau of Meteorology, Melbourne, Australia).

The hazard model for floods was developed by Christian Herold and Frédéric Mouton (University of Grenoble, Institut Fourier) with code contributed by James and Kristin Verdin (USGeological Service). All information associated with flood events was processed by Christian Herold based on floods detected by remote sensing by Bob Brackenridge and his team at the Dartmouth Flood Observatory. Disaster losses and exposure were geo-referenced and calculated by Christian Herold. The vulnerability and risk analysis and models were done by Pascal Peduzzi (for human losses) and Uwe Deichmann (for economic losses). Advice on development of the flood hazard model was given by James and Kristin Verdin, Bob Brackenridge and Wolfgang Grabs (WMO). Scientific peer review of the hazard models was carried out by Ayinash Tyagi (WMO) and Wolfgang Grabs with Zhiyu Liu (Bureau of Hydrology, Ministry of Water Resources, China).

The hazard model for drought was developed by Brad Lyon, Greg Yetman, Maria Muniz, Liana Razafindrazay and Vilentia Mara (Columbia University). Drought exposure was calculated by Gregory Guiliani (UNEP/GRID-Europe) and Andrea De Bono. Scientific peer review of the hazard model was carried out by Mannaya Sivakumar and Robert Stefanski (WMO) with Simone Orlandini (Department of

Agronomy and Land Management, University of Florence, Italy), Harlan D. Shannon (US Department of Agriculture, World Agricultural Outlook Board), Mark Svoboda (National Drought Mitigation Center, School of Natural Resources, University of Nebraska-Lincoln, USA) and Orivaldo Brunini (Instituto Agronomico, Sao Paulo, Brazil).

The landslide hazard model was developed by Helge Smebye and Bjorn Kalsnes (International Centre for Geohazards, Norwegian Geotechnical Institute, Norway) and Pascal Peduzzi calculated exposure. The vulnerability and risk analysis and models were done by Pascal Peduzzi (for human losses) and Uwe Deichmann (for economic losses). Scientific peer review of the hazard models was carried out by Kyoji Sassa (University of Kyoto, Japan), Nicola Casagli (University of Firenze, Italy), Lynn Highland (USGS), Dwikorita Karnawati (Gadjah Mada University, Indonesia) and Alexander Strom (Institute of Geospheres Dynamics, Russia).

The intensities and spatial extent of past earthquake events were compiled from the ShakeMap Atlas2 developed under the auspices of the US Geological Survey's Prompt Assessment of Global Earthquakes for Response (PAGER)3, kindly provided for the project by USGS. Losses were geo-referenced by Andrea De Bono. Human and economic exposure was computed by Bruno Chatenoux. The vulnerability and risk analysis and models were done by Hy Dao and Pascal Peduzzi (for human losses) and Uwe Deichmann (for economic losses). The global intensity hazard earthquake distribution was developed by Arthur Lerner-Lam and Liana Razafindrazay. Scientific peer review of the hazard models was carried out by Avi Shapira (Israel Geophysical Institute), Kunihiko Shimazaki (University of Tokyo, Japan), Giuliano Panza (University of Trieste, Italy) and Mihail Garevski (Institute of Earthquake Engineering and Engineering Seismology, Former Yugoslav Republic of Macedonia).

The tsunami hazard model was developed by Finn Løvholt, Natalia Zamora, Sylfest Glimsdal and Helge Smebye (International Centre for Geohazards, Norwegian Geotechnical Institute, Norway) with Greg Yetman. Exposure was calculated by Hy Dao. Scientific peer review of the hazard models was carried out by Jörn Behrens and Alfred Wegener (Institute for Polar and Marine Research, Germany), Stefano Tinti (University of Bologna, Italy) and Kenji Satake (University of Tokyo, Japan).

The study on economic resilience was carried out by Felipe Barrito, Werner Corrales and Tanya Miquelena (independent consultants).

3.6. Global risk analysis and MRI

MRI was a request by UNISDR which wanted new development for assessing risk and trends of risk. They needed something with a spatial distribution of risk which would be much finer than the previous attempts (UNDP, 2004, Dilley *et al.*, 2005).

The Global Risk Analysis is a collaborative effort involving UNISDR (institutional coordination), UNEP/GRID-Europe (flood and tropical cyclones modelling, human and economic exposure, risk model for four hazards, scientific coordination), World Bank (economic analysis), Columbia University (drought hazard), Norwegian Geotechnical Institute (characterisation of tsunami and landslides hazards) and data contribution from many partners: Dartmouth Flood Observatory, United States Geological Survey…

It was financed by UNDP/BCPR (GRIP), UNISDR, UNEP, World Bank, the governments of Norway and Switzerland. A review process (on hazard modelling methodologies) was organised by UNESCO and WMO who selected 24 independent experts.

It aims to provide a spatial distribution of seven natural hazards and associated human and economic exposure, identification of risk/vulnerability drivers, spatial risk distribution patterns (human and economic), an index for comparing countries at risk, a risk trend analysis and to provide full access to data for end users.

As compared with the DRI (UNDP, 2004; Peduzzi *et al.*, 2009), or with the Disasters Risk Hotspots (Dilley *et al.*, 20005), the Global Risk Analysis presented several innovations. First it benefited from newly released global datasets (see below); but more interestingly a thorough rethinking of the methodology. The use of individual events for modelling risk addressed the main critics that followed the released of the DRI. As compared with the Disasters Risk Hotspots, it provides a much finer resolution for the characterisation of risk (about 10 x 10 km at the equator). Marked improvements were achieved in the hazard modelling, especially for floods and landslides.

While this study was on-going (2007-2009), several new global datasets were released which greatly enhance the research.

Name	Type	Resolution	Authors	Released
GlobeCover	**Landcover**	**300 m**	**ESA**	**August 2008**
Landscan 2007	**Population distribution**	**1 km**	**Oak Ridge Laboratory**	**2008**
SRTM vs 3	**DEM**	**90 m**	**NASA**	**2002**
GDP 1975 - 2008	**GDP**	**1 km**	**World Bank**	**2008**
Hydroshed	**Hydrological model based on SRTM**	**90 m**	**USGS/WWF**	**2008-2009**
ShakeMaps (5000 earthquakes)	**Earthquake footprints with MMI**	**vectors**	**USGS**	**2008**
DFO flood	**Flood footprints**	**250 m**	**DFO**	**2008**

Table 21 Datasets newly released and used for the Global Risk Analysis

The newly released (August 2008) ESA Land cover : GlobeCover ESA, at 300 m resolution, provided the urban mask as well as crop land. The population distribution was based on Landscan 2007, 1 km resolution and extrapolations were made by UNEP/GRID-Europe to get population from 1975 to 2008. The elevation as detected by SRTM, allowed for a much improved characterisation of slopes for landslides. The World Bank produced a Gross Domestic Product with difference between urban and rural GDP and extrapolation between 1975 and 2008.

The hydroshed produced by USGS for WWF, is based on the 90m resolution SRTM but corrected for hydrology. It was under development when we modelled floods and the flood modelling was processed as soon as a new tile of the world was made available through 2008 and 2009.

The newly realeased USGS ShakeMaps provided an archive of more than 5000 earthquakes footprints in Modified Mercalli Intensity (MMI) scale. These were used for the extraction of exposure and links were made with EM-DAT to georeference the impacts.

For floods, more than 600 past floods events as detected by satellite sensors, 250m resolution, by Dartmouth Flood Observatory (DFO) were provided. The events had to be merged as they resulted from the treatment of about 3600 satellite images each of them in their own projection. One flood event could be represented in anything between 1 and 10 files. Merging them and linking them with EM-DAT requested two months of work.

More than 2500 past tropical cyclones data from 1975 to 2008 were modelled by UNEP/GRID-Europe to transform cyclones best tracks into wind buffers and areas flooded by storm surges.

Finally, 43 parameters on socio-economic context, including governance, corruption, urban growth,… with values from 1975 to 2007 were compiled.

In itself the simple compilation of all this data is already an achievement, but the Global Risk Analysis provided the spatial distribution of 7 hazards (cyclones, floods, earthquakes, drought, forest fires, landslides and tsunamis). It uses a new methodology so called "event per event" approach, which was performed on floods, earthquakes and tropical cyclones allowing the inclusion of each individual events specificities and contextual parameters. Specifically it made possible to take the intensity into account.

3.6.1. Limitations

Despite all these improvements there are still limitations that users need to consider carefully.

Although it used detailed datasets, this is still based on global models and should not be used for local land planning

Drought and tsunami risk could not be estimated

Trend analysis on hazards is still at very early stage

Reports on economic losses still not very accurate and prevented to achieve the same level of analysis as compared with mortality.

GDP as a mesure of asset is limited (revenu not assets)

Mortality is not necessarily the best proxy (livelihood would be better)

Earthquake risk is based on location of 5000 earthquakes and not from a probabilistic model. It means that while the capacity to identify the underlying factors of earthquakes risk is appropriate, the extrapolation to future risk as limited value.

3.6.2. Differences in MRI between GAR 2009 and Tropical Cyclones article

There is a difference between the tropical cyclones MRI published in GAR 2009 (see part 3.5) and the one published in Nature Climate Change (see part 3.7, Peduzzi *et al.*, in press). The difference comes from the consideration on the use of the median in the former and in the use of the mean and bias corrector in the later. In order to be fully transparent, this point is explains in details below.

The MRI is based on five models for tropical cyclones (one for each Saffir-Simpson class) one model for flood, one for landslides and four for earthquakes. These provide the modelled mortality for each type of event. To obtain the mortality risk for 2010, the values of exposure and vulnerability were replaced by 2010 corresponding values. The number of killed are then summed by country and divided by the number of years or records to obtain an average killed per year.

The models being based on logarithmic regressions, the sum of modelled killed cannot be done in the logarithm space (an addition of the logarithm results in a multiplication in the linear scale) and thus, the modelled values need to be translated in the original metric. This is mathematically performed using anti-log function. In the case of the median being relevant (and not the mean), the transformation only requires to be *detransformed* the fitted linear model (i.e., apply the inverse transformation) (Miller, 1984). This results in a model of the median response in the original variable space (Miller, 1984). However, should the mean be more relevant, such simple translation - also called naïve retransformation (Stynes, 1986) - introduced a bias, which is resulting from ignoring the model error term. This is well explained in Stow *et al.* (2006), they used the following example to show the problem :

$$LnY = c + \beta LnX + \varepsilon \quad (2)$$

Hence when translating it back to linear metrics, the equation is:

$$Y = aX\beta\ \varepsilon$$

One of the technique to reduce the bias, is to used the "quasi maximum likelihood estimator" (QMLE) (Cohn *et al.* 1989; Gilroy *et al.* 1990),

$$QMLE = \exp(0.5\sigma^2) \quad (3)$$

Where σ^2 is the variance of the residual computed as follows (Beauchamp and Olson, 1973):

$$\sigma^2 = \sum_{i=0}^{i=n} (y_i - y'_{ii})^2 / (n-2) \quad (4)$$

Where:
y = reported killed per event
y' = modelled killed per event
n = number of events having both information on reported killed and for modelling killed.

The equation of risk of mortality in logarithm space is:

$$LnK = \alpha LnE + \beta LnV_1 + \ldots + \omega LnV_n + C + 0.5\sigma^2 \quad (5)$$

Where:
K = killed.
E = people exposed.
V = vulnerability parameters.
α, β, γ, ω = weights provided by the statistical regression.
C = intercept
σ^2 = Variance of the residual

When "translating" the regression back in linear space, there is a need to take into consideration the standard error σ as in equation 5 (Stow *et al.* 2006).

$$K = E^{\alpha} \times V_1^{\beta} \times \ldots \times V_n^{\omega} \times \exp(C) \times \exp(0.5\sigma^2) \quad (6)$$

Multiplying by "$\exp(0.5\sigma^2)$" introduces a correction to the bias (Cohn *et al.* 1989; Gilroy *et al.* 1990). Without such corrector, the results would be an underestimation of the risk. Because the tropical cyclones mortality model is based on five different models, countries would be underestimated in a different way depending on which category of tropical cyclones is affecting them.

However, the use of a corrector such as a QMLE is only relevant if the error is normally distributed (Manning, 1998). Failing to consider the error distribution may lead to large error (Manning, 2001). If the error is not following a normal distribution or is unknown, a smearing estimate should be used (Duan, 1993).

The literature suggests that further steps are needed (Manning, 2001): qualify the errors distribution (to chose between QMLE or smearing estimate), but more importantly, to collect elements which support whether the median or the mean is more relevant (Stynes, 1986; Miller, 1984; Haneman, 1984). In some cases, when a very small number of events account for a large proportion of the total, i.e. when dealing with extremely skewed distributions, the use of the median should be considered over the use of the mean (Haneman, 1984). The median is more robust and tends to be less influenced by outliers and extreme values (Haneman, 1984). In such case, the median may be preferred and the log transformation adjustments should not be applied (Stynes, 1986).

According to the test conducted, there is no suspicion that the error distributions do not follow a normal distribution. Hence, in case we need to use the mean, at least we know that the QMLE can be used. However, deciding whether the median or the mean is more appropriate revealed to be more problematic.

The data distribution in the case of mortality from natural hazard is highly skewed. Between 1975 and 2010, EM-DAT reported 9,646 disasters (EM-DAT, 2011). The top 25 disasters (i.e. 0.26% of the events) accounted for 79.9% of the mortality. There are known issue regarding large error in reported losses, one of the most striking one being the case of the Venezuela 1999 flood disaster, where 30000 killed were reported (EM-DAT, 2011). A detailed recount led to a maximum of 700 killed (Altez *et al.*, 2005). In the case of such extremely skewed distribution and potential spurious data, the use of a more robust indicator may be justified. Using the median (i.e. without bias corrector) is, in this view, a valid option. The judgment of the experts consulted (Mouton, 2011; Velegrakis, 2011) and the literature review support this appreciation.

I compared the distribution of reported killed versus modelled (median) and reported killed versus modelled (mean bias corrected) for tropical cyclones. On an event by event level, the R^2 is very similar (save values up to the fourth digit) and thus is not conclusive to support the choice for one option or another. However, the sum of all modelled killed were closer to the sum of all reported killed when using the QMLE. Both uses of median and mean were producing a smaller part of the reported killed (56% in the former and 66% in the later using QMLE). The mean with QMLE bias corrector provided a sum of killed closer to the sum of reported killed for comparable events.

Without formally proving one option or another, the improvement achieved using a QMLE is an element in favour of the use of the mean over the median, at least in the case of tropical cyclones. The test conducted on the distribution of errors, suggest that it follows a normal distribution. These two conditions (use of the mean and errors distribution) are supporting the decision of using a bias corrector such as the QMLE.

Hence, for tropical cyclones, a correction was applied to each event, using QMLE according to the different categories (see Table 22).

Table 22 Standard error and correction factors for the five models of tropical cyclones

	1	2	3	4	5
σ^2	1.301	1.340	1.521	1.096	0.179
QMLE	1.916	2.014	2.140	1.730	1.094

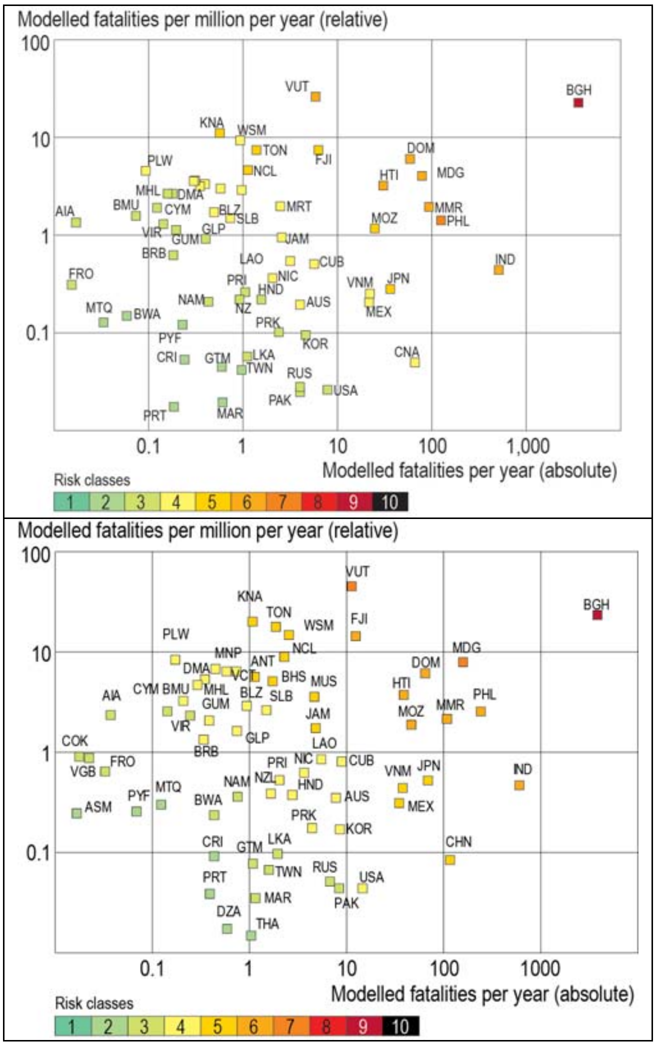


Figure 73 Tropical Cyclones MRI without bias correction (top) and after bias correction (bottom).

For flood, more researches are needed to test whether the median or the mean is more relevant. At the time of the GAR study, we used the median because it seemed more robust. But further tests should be made. In case the mean is relevant, the error distribution seems to follow a normal distribution and thus a QMLE could be used. For the flood model, the σ^2 = 2.11 and thus the QMLE is 2.88. Because there is only one model, all the countries would be moving in direction of the upper right corner.

For earthquakes there were four categories. The σ^2 and the QMLE are provided in Table 23.

Category	1	2	3	4
σ^2	1.293	1.302	2.184	1.816
QMLE	1.909	1.917	2.980	2.479

Table 23: Standard error and correction factors for the four models of earthquakes

For landslides, the situation is different. Because landslides were not based on an event per event approach, they were modelled like in the DRI (i.e. using an average human exposure by country over the period and average vulnerability parameters). The results were provided in logarithmic scale, hence the bias correction is not necessary.

While both options might be suitable estimators (or at least can be defended), the use of the mean - in the case of tropical cyclones - is at least providing closer results and give more support for the inclusion of the QMLE. Nevertheless this is an evidence based judgment and the readers in similar situation may prefer to dissent from this choice and use the robustness offered by the median. This is an interesting point and more researches are needed regarding the validity of the median versus the use of the mean with a bias corrector. The impacts on the predicted would be significant. A formal mathematical study should be conducted, not only on tropical cyclones, but also on floods and earthquakes as the conditions to use log-normal distribution in science varies from one subject to another (Limpert *et al.*, 2001).

3.6.3. References

Altez, R. Revet, S., Contar los muer tos para contar la muer te: discusión en torno al número de fallecidos en la tragedia de 1999 en el estado Vargas–Venezuela, Revista Geografica Venzolana, Número especial 2005, 21-43, 2005.

Beauchamp, J.J., Olson, J.S., Corrections for bias in regression estimates after logarithmic transformation, *Ecology*, **54**(6), 1403-1407, 1973.

Cohn, T.A., DeLong, L.L., gilroy, E.J., Hirsch, R.M., and Wells, D.K., Estimating constituent loads, *Water Resourcse Research*, **25**, 937-942, 1989.

Dilley, M., Chen, R. Deichmann, U., Lerner-Lam, A., Arnold, M., *Natural Disaster Hotspots, a global risk analysis*, the World Bank, pp 112, 2005.

Duan, N., Smearing estimate: a nonparametric retransformation method, Journal of the American Statistical Association, **78**(383), 605-610, 1983.

EM-DAT: The OFDA/CRED International Disaster Database, Université Catholique de Louvain, Brussels (Belgium). http://www.emdat.be, last consulted December 2011.

Gilroy, E. J., R. M. Hirsch, and T. A. Cohn, Mean Square Error of Regression-Based Constituent Transport Estimates, *Water Resources Research*, **26**(9), 2069-2077, 1990.

Hanemann, W.M., Welfare evaluations in contingent valuation experiments with discrete responses, American Journal of Agriculture Economics, **66**(3), 332-341, 1984.

Limpert, E., Stahel, W.A., Abbt, M., Log-normal Distributions across the Sciences: Keys and Clues, BioScience, **51**(5), 341-352. 2001.

Manning, G.W., Mullahy, J., Estimating log models: to transform or not to transform?, Journal of health Economics, **20**, 461-494, 2001.

Manning, G.W., The logged dependent variable, heteroscedasticity, and the retransformation problem, Journal of Health Economics, **17**, 283-295, 1998.

Miller, D.M., Reducing transformation bias in curve fitting, The American Statistician, **38**(2), 124-126, 1984.

Mouton, F. Mathematician, Institut Fourrier, University of Grenoble, personal communication, 28 November 2011.

Peduzzi, P., Chatenoux, B., Dao, H., De Bono, A., Herold, C., Kossin, J., Mouton, F., Nordbeck, O., Tropical cyclones: global trends in human exposure, vulnerability and risk, *Nature Climate Change*, (in press).

Stow, C.A., Reckhow, K.H., Qian, S.S., A Bayesian approach to retransformation bias in transformed regression, *Ecology*, **87**(6), 1472-1477, 2006.

Stynes, D.J., Peterson, G.L., Rosenthal, D.H., Log transformation bias in estimating travel cost models, Land Economics, **62**(1), 94-103, 1986.

UNDP, *Reducing Disaster Risk: a challenge for development*, United Nations Development Programme, Bureau for Crisis Prevention and Recovery, 146 p., New York, NY 10017, USA, 2004.

Velegrakis, A., prof. in oceanography, Agean University, personal communication, 20 December 2011.

3.7. Tropical Cyclones: Global Trends in Human Exposure, Vulnerability and Risk

Authors : P. Peduzzi[1,2], B. Chatenoux[1,3], H. Dao[1,4], A. De Bono[1,3], C. Herold[1,3], J. Kossin[5], F. Mouton[6], O. Nordbeck[1]*

[1] Global Change and Vulnerability Unit, DEWA/GRID-Geneva, United Nations Environment Programme, 11, ch. Anémones, 1219 Châtelaine, Geneva, Switzerland. * e-mail: Pascal.Peduzzi@unepgrid.ch

[2] Institute of Geomatics and Risk Analysis (IGAR), Faculty of GeoSciences and Environment, Amphipôle, University of Lausanne, 1015 Lausanne, Switzerland

[3] Institut F.A. Forel, Faculty of Sciences, University of Geneva, 10, Route de Suisse, 1290 Versoix, Switzerland

[4] Department of Geography, University of Geneva, Faculty of Economic and Social Sciences, Uni Mail, 40, Bd du Pont-d'Arve, 1211 Geneva, Switzerland.

[5] National Climatic Data Center/NOAA, 151, Patton Avenue, Asheville 28801-5001, North Carolina, USA.

[6] Institut Fourier, University of Grenoble, 100, rue des maths, BP 74, 38402 St Martin d'Hères, France.

Status: accepted for publication in Nature Climate Change. References:
Peduzzi, P., Chatenoux, B., Dao, H., De Bono, A., Herold, C., Kossin, J., Mouton, F., Nordbeck, O., Tropical cyclones: global trends in human exposure, vulnerability and risk, *Nature Climate Change*, (in press).

3.7.1. Summary

The impact of tropical cyclones on humans depends on the number of people exposed and their vulnerability, as well as the frequency and intensity of storms. How will the cumulative effects of climate change, demography and vulnerability affect risk? Conventionally, reports assessing tropical cyclone risk trends are based on reported losses, but these figures are biased by improvements to information access. Here we present a new methodology based on thousands of physically observed events and related contextual parameters. We show that mortality risk depends on tropical cyclone intensity, exposure, levels of poverty and governance. Despite the projected reduction in the frequency of tropical cyclones, projected increases in both demographic pressure and tropical cyclone intensity over the next 20 years can be expected to largely increase the number of people exposed per year and exacerbate disaster risk, despite potential progression in development and governance.

3.7.2. Why a new approach to evaluating tropical cyclone risks is needed

Tropical cyclones (TCs) are common in many regions of the world and affect nearly all tropical areas (see Figure 74). They are associated with extreme winds, torrential rains triggering floods and/or landslides, high waves and damaging storm surges leading to extensive coastal flooding. Between 1970 and 2009, singular TC events inflicted the highest death toll (Bhola, Bangladesh, 1970, 300000 killed) and greatest damages (Katrina, USA, 2005, US$ 125 billions of losses) on record. They claimed a cumulated reported 789000 lives during this period[1]. Mortality and losses vary extensively from one event to another. Understanding the probability of losses requires an identification of all the components of risk[2,3], which are the hazard (frequency and intensity), the exposure (the number of people; assets or crops) present in the hazard-prone area[4] and the vulnerability (the degree of loss to each element should a hazard of a given severity occur[5]). Given that hazard, exposure and vulnerability are changing, the risk is dynamic and needs to be re-assessed periodically.

Regarding TC hazard, the influence of observed climate change on past TC frequency and intensity is uncertain, and confidence that there have been detectable long-term trends remains low[6]. However, due to consistency among the models and their agreement with theory, there is greater confidence in 21st century projections of TC activity under warming scenarios. Specifically, while it is likely that overall global TC frequency will decrease (or remain roughly constant), it is also likely that mean intensity will increase. Such an increase is expected to manifest notably in the most intense storms[7] and increases in the

		1970s	1980s	1990s	2000s
A	Number of TC physical events (recorded)	88.4	88.2	87.2	86.5
B	Number of TC events making landfall (recorded)	34.4	34.4	35.6	35.2
C	Weighted average intensity over landfall*	1.7	1.8	1.8	1.8
D	Number of times that TC hit countries (recorded)	142.1	144.0	155.0	146.3
E	TC Disasters in EM-DAT (reported)	21.7	37.5	50.6	63.0
F	Killed (x 1000) by TC in EM-DAT (reported)	35.7	4.7	21.1	17.4
G	Reported disasters versus countries hit by TC (in %)	15%	26%	33%	43%

Table 24 Events as recorded by instruments (lines A to D) versus trend of reported tropical cyclone disasters (lines E and F, average per year). The percentage of reported disasters increased three-fold, while the number of TC remains stable.

* Weighted average is the sum of all maximum intensity, divided by the number of observed tropical cyclones.

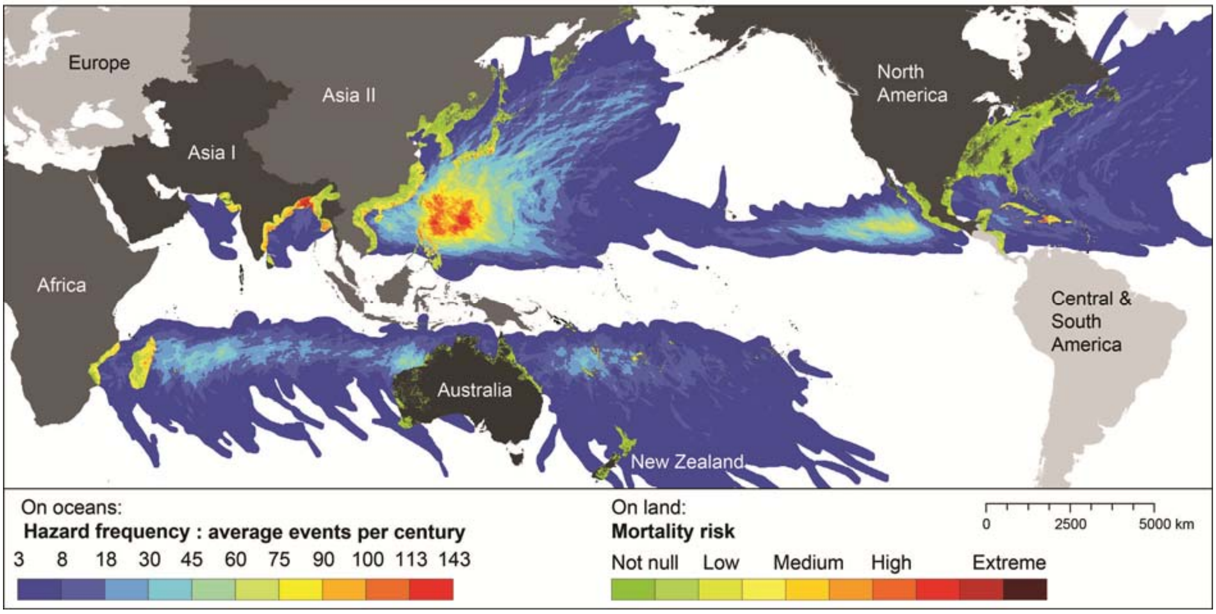


Figure 74 Map showing distribution of hazard frequency and mortality risk from TC for the year 2010. Estimates are applied to all pixels on a geographic grid. Mortality risk is categorised from low to extreme.

frequency of the strongest storms are possible[6,8].

More than the trend in hazards, the governments and the insurance industry need information on the trend in mortality and economic risk induced by these hazards. Most global reports looking at trend in disaster risk, are based on past reported losses from international databases (mostly from EMDAT)[1].

The number of reported TC disasters by EMDAT has nearly tripled between 1970s and 2000s (see line E in Table 24). Although one cannot discard impacts from climate change on hazard, the improved access to information may be responsible for spurious increases and needs to be assessed.

Performing a trend analysis presupposes that such databases are comprehensive or at least consistent through time. However, by comparing observed TC events (as detected by satellite) and reported disasters, there are some large differences in trend. The average observed global TC frequency remained steady in the past 40 years (see line A in Table 24). The number of TCs making landfall, their intensity and the number of countries struck is also stable (lines B, C and D[5]). The world population increased 86% between 1970 and 2010[9] (from 3.7 to 6.9 billion) and the exposure has therefore increased. However, this has not translated into higher reported mortality, which has fluctuated but is on a downward trend (see line F in Table 24).

So either the increase in exposure was compensated by a significant decrease in vulnerability, and/or the observed increase in reporting is mostly induced by improved access

[5] One tropical cyclone event can affect several countries. For example Hurricane Mitch lead to disasters in 8 different countries and is recorded as 8 disasters in EMDAT.

to information. The latter is quite probable given the improvements in global TV coverage, internet, cell phone- and satellite networks[10].

Without undermining the value of international loss databases, these simple statistics show that these are likely to be biased by improvements to technology and information access; they are not comprehensive and they do not indicate whether high losses result from high exposure, high intensity or high vulnerability. Hence, they are not suited for risk trend analysis. Despite these significant limitations, most global reports are based on figures from reported losses[11,12,13,14,15]. A new approach is needed. The method introduced here provides a trend analysis on mortality risk based on GIS and statistical regression. It is independent from international loss databases, which are only used for initial calibrations.

3.7.3. *Results*

The new layers of information produced include: TC hazard global distributions such as average TC frequency; maximum intensity recorded between 1970 and 2009 as well as total sum of winds. We also provide the TC exposure distribution (population and GDP for each class of intensity) and mortality risk distribution by class (see Figure 74). These layers of information are made available in different GIS format. The GIS raster values on exposure and risk were also aggregated (summed) at country level in a tabular format Table S35 (in part 3.8.9).

The multiple regression analysis shows that the intensity of the hazard, the level of population exposure, the level of poverty and the level of governance were the main factors accounting for risk. It also showed that vulnerability parameters have more weight for less intense TC and conversely, the role of population exposure in mortality risk grows with the intensity of the TC. Exposure accounted for 9.0%, 46.4%, 52.7% and 62.9% of mortality losses for TC category I, II, III and IV respectively (see 3.8.6). For category V, human exposure to winds and number of the coastal population living in low-lying areas accounted for 68.9% of the model's losses. However, for this latter category there were too few events for a sound statistical analysis. Poverty levels (low GDP per capita) accounted for 91% of the mortality loss for category I TC and 37.1% for category IV (and 31.1% of category V). This shows that poverty levels are less significant when facing very intense TC, whereas at lower intensities, only the poorest suffer heavy losses.

Coastal population living in low-lying areas (less than 10 km from the coast) were found to explain a large share of losses from high category TC, while remoteness was also identified as triggering more vulnerability. According to this analysis, TCs appear to be more dangerous in rural / remote areas as compared with cities. This can be due to several factors such as: improved early warning, better infrastructure, quicker access to external rescue and aid and from humanitarian services in urban areas. Remote locations are more disconnected and less accessible.

3.7.4. *The Tropical Cyclone Mortality Risk Index*

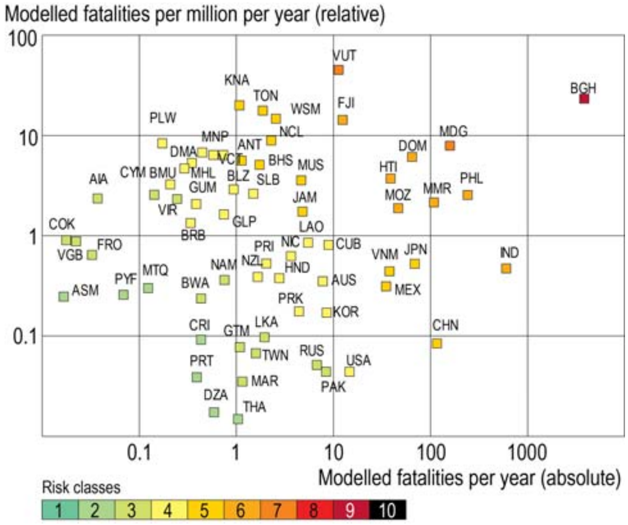


Figure 75: Tropical Cyclones Mortality Risk Index (TC-MRI). The risk categories are based on both average number or people killed per year as modelled (X axis) and average number of killed per million inhabitants (Y axis).

The mortality risk was aggregated at country level according to two logarithmic scales: number of average expected killed per year (absolute risk) and number of killed per million inhabitants (relative risk). If absolute risk is employed, large countries will rank first whilst if relative risk is utilized, small islands will appear foremost. To overcome this issue, the two scales were combined to produce 10 categories of countries at risk. This provides a TC Mortality Risk Index (see Figure 75). The detailed ranking and categories of countries are provided in Table S35 (in part 3.8.9). The TC-MRI provides a standardised tool for comparing countries. The rank is produced by sorting countries by decreasing TC-MRI value, decreasing relative risk, and then by decreasing absolute risk.

As a limitation, the model cannot take mega-disasters (such as Mitch 1998 or Nargis 2008) into account. These are too rare events and thus were statistical outliers in the analysis. The TC-MRI is probably too high for countries that are pro-active in DRR (e.g. Bangladesh, Japan and Cuba). The reason being that data on DRR (number of shelters, early warning quality, etc.) are not readily available. Comparing tropical cyclone Sidr (Bangladesh, 2007) and Nargis (Myanmar, 2008) provides an example of differences from DRR practices. By improving the early warning system, building shelters, and reforesting coastal areas, Bangladesh has succeeded in drastically reducing the number of fatalities related to tropical cyclones[34]. Despite the fact that Sidr hit a larger population with stronger winds, it resulted in 30 times fewer victims in Bangladesh than did Nargis in Myanmar[1]. Myanmar's official warning to population was provided in page 15 of the newspaper The New Light of Myanmar[35], suggesting that officials did not take the threat seriously. Bangladesh has drastically reduced the mortality risk, but risk remains high due to high exposure and poverty levels.

Also, the historical global TC records suffer from well-known heterogeneities due to improvements of methodologies and instruments for measuring TC. Estimates of TC maximum winds are particularly sensitive to these improvements.[36] This sensitivity can influence the size of the buffers considered in this study and result in a spuriously inflated trend in exposure. To minimize this effect, only the events from 1978 and onward were taken for the event analysis. The results based on TC frequency are less sensitive to data heterogeneity, given the smoothing function applied. The full range of data since 1970 were used in order to cover as much TC-prone areas as possible. A smaller sample of records would have resulted in an underestimation of the TC-prone areas and associated frequencies.

3.7.5. Trend analysis of Tropical Cyclones Mortality Risk between 1970 and 2010

A given population living in a hazard prone area is not impacted every year by hazardous events. The average number of people exposed annually to hazards is called "physical exposure" and mathematically can be obtained by multiplying the number of people living in hazard prone area by the annual frequency of occurrence of a selected hazard. In 2010, an estimated 1.53 billion people were living in TC prone areas in 81 different countries and territories. The average yearly number of people exposed to TCs is estimated at 133.7 million. An average of 1901 billion US$ are exposed annually to TCs, out of the 16281 billion located in TC prone areas. Computing trends in

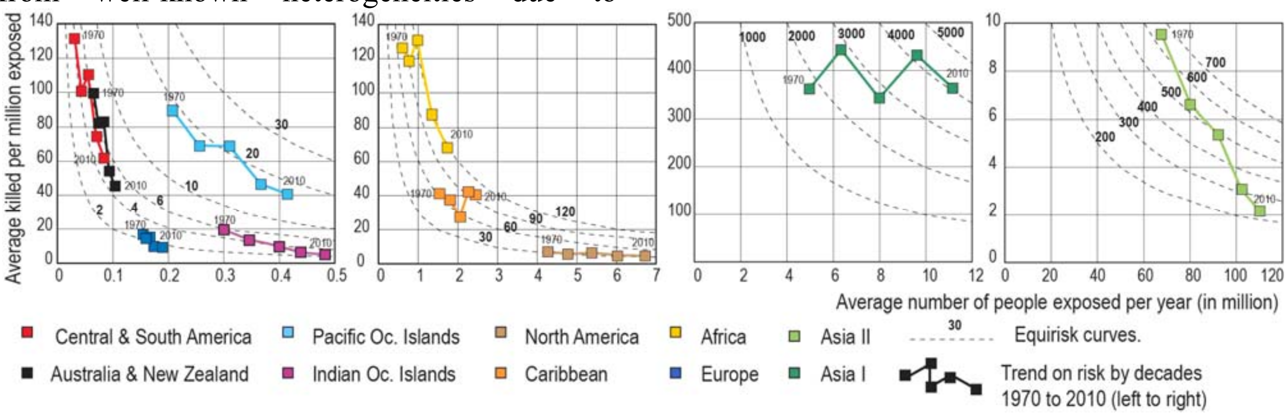


Figure 76 Trends in TC exposure, vulnerability and risk by IPCC regions from 1970 to 2010. Y-axis represents the vulnerability (in killed per million exposed), X-axis represents the number of exposed (in million). The area of the virtual rectangles where the bottom left corner is the origin (0,0) and each colored square is the top right corner, equals the level of risk. The dash lines represent equirisk levels.

physical exposure requires information on both hazard frequencies and demographic changes (see 3.8.6).

In the model, values of exposure and vulnerability were replaced by values for the specific years (1970, 1980, 1990, 2000 and 2010) and used to identify trends based on vulnerability and exposure while holding hazard constant. This allows removing the effect of seasonal variations.

At constant hazard, risk is a product of exposure and vulnerability. In Figure 76, the Y-axis is the vulnerability (expressed in killed per million exposed). The X-axis is the number of people exposed (in millions). The multiplication of vulnerability by exposure provides the risk. Each point in Figure 76 is the top-right corner of a rectangle whose area equals the level of risk. In this way it is possible to see if the risk is triggered more by exposure or by vulnerability. The dashed lines represent the equirisk levels, where, for example, the increase in exposure is exactly compensated by corresponding decrease in vulnerability in such a way that risk remains unchanged. This is the case for North America, where despite a 58% increase in exposure between 2010 and 1970, the risk remained constant due to a corresponding decline in vulnerability. All regions have an increasing exposure due to demographic pressure, but some regions manage to reduce their risk despite an increase in exposure. For example, in Asia II (Asian countries on Pacific ocean, see Figure 74), the level of risk was reduced by 300% due to a drastic reduction in vulnerability (i.e. more than 70% reduction since 1970). The trend in this region is largely influenced by China. In Asia I (India, Bangladesh and Myanmar), the vulnerability remains very high and fluctuates around 400 killed per million exposed. Progress in DRR has been made in Bangladesh (e.g., number of shelters built). However, such indicators were not available globally for inclusion in the models. Both the exposure and risk more than doubled in this region since 1970.

3.7.6. *Scenarios for 2030*

The UN projection for world population in 2030 is 8.3 billion people[9] (8.2 - 8.5)[37]. This change in demography will influence the exposure to hazards. Since 2010, more than 50% of the population is urban. Our study reveals that urban population are usually less vulnerable to TC hazards. However, about a third of the urban population live in slums, and such habitat often does not provide safe haven compared to areas with better construction. Instead of providing shelter, the construction material can actually escalate the risk (e.g. flying corrugated roofing material). The population in the slums is also often from rural areas and may be less prepared for and informed about TCs.

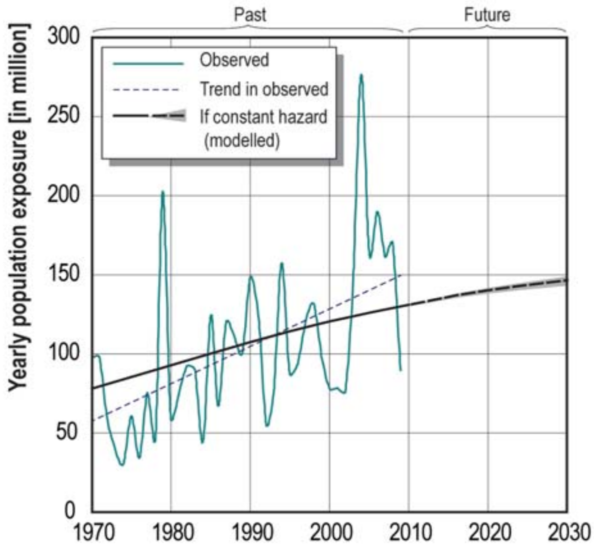


Figure 77: Change in TC population yearly exposure through time. For the period 1970 - 2009 the exposure is provided for both observed as well as average trend (assuming constant hazard). Period 2010-2030 include only the average trend under constant hazard, with uncertainty from population growth (-2.2 to 1.0 %).

In Figure 77, yearly exposure depends on several factors, the main parameters being the number of intersections of TC events with land, the population density at the affected locations, and the size of the TC footprint. The observed exposure reveals high variability. However, the trend follows the theoretical average exposure (assuming constant hazard), although the average trend in observed exposure is steeper than the modelled trend (which suggests either a change in hazard or influence in instruments and/or methods improvements). For the extrapolation to 2010 to 2030, only the average exposure is provided (see Figure 77).

Assuming constant hazard, the population growth would increase the average population exposed per year to 149.3 million (+11.7%) by 2030. In relative terms, the main percentage increase in physical exposure to TC will be in

Africa with + 54% (i.e. mostly Madagascar and Mozambique). In absolute terms, about 90% of exposure to TC will occur in Asia. This region will face the highest increase of annual exposure with +10.7 million for Pacific Asia and + 2.5 million for Indian Ocean Asia (see Table S30).

According to Knutson *et al.* (2010)[5], owing to climate change, global TC frequency is likely to decrease or remain essentially unchanged (-6 to -34% by year 2100) while some increase in the mean maximum wind speed of tropical cyclones is likely (+2 to +11% globally). While it is understood that climate and TC activity exhibit substantial natural variability on a range of time-scales, here we assume constant linear trends for illustration purposes, and to explore how exposure may change according to summaries of current global TC projections from Knutson *et al.* (2010). Under this assumption, the projections of Knutson *et al.* (2010) translate to a -1.3 to -7.6% change in frequency and between +0.4 to +2.4% change in intensity by 2030. Figure 78 shows the influence of these changes in hazard frequency and intensity on human exposure.

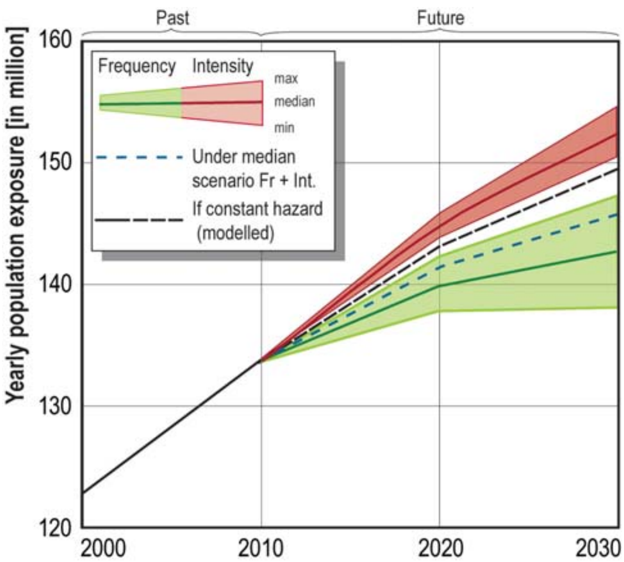


Figure 78: Scenarios until 2030. Influence of hazard on exposure for increase in intensity (red) and change (decrease) in frequency (green) and median scenario (dash line in blue).

The influence of frequency on exposure is linear. Following the projections of Knutson *et al.* (2010)[5], the potential range of exposure from frequency change would be between 135.5 and 144.6 million people per year (median: 140.1 million) exposed by 2030. The effect of increasing intensity is harder to estimate as more intense TCs often have bigger footprints, thus further compounding the increases in exposure. Also to be taken into account is the possibility for a higher rate of population increase on coastal areas.

Despite uncertainties about these values on the future evolution of TC, we show that independently from the scenarios, there will be an increase in exposure to TC triggered mainly by population growth. This is a global trend, and the regional trends include much higher variations (see 3.8.7), but also with less confidence in the projections. Even under the most optimistic scenario (7.6% decrease in TC frequency and no increase in TC intensity) on climate change influences on TC, changes in human exposure will increase exposure to TC.

3.7.7. Conclusions

This method proved to be successful in identifying underlying factors of risk, where poverty, intensity and exposure appear to be the main explanatory variables. The modelling of tropical cyclone footprints allows for a refined measure of exposure and modelled of average exposure.

In future research, the model used here could be improved. Parameterisation of the TC wind field with the Holland (1980) model can suffer from inaccuracies and tends to overestimate the area of strong winds[25,26,27] although there is no expectation that these will project strongly on the trends shown here (see discussion in 3.8.1).

Another improvement could be made by using subnational values for vulnerability indicators. The use of national values, especially for large countries such as India and China, does not reflect the significant variations within the countries.

The demographic pressure and the development of new infrastructure will increase the exposure in the coming decades. Regardless of uncertainties in TC projections, the likelihood of increased risk and human exposure suggests that the principle of caution should be observed and should galvanize governments to action.

So far the reduction in vulnerability has compensated the increase in exposure. If projections of TC intensity increases are confirmed, the outcome could be different since exposure trends tend to increase at higher intensities as exposure plays a heavier role with high intensity TC. Further investigations include continuing research on the impacts of climate change on the intensity of TC as well as introducing these impacts into the footprints and risk models.

3.7.8. Method

Modelling TC wind fields and tracks using mathematical formulas associated with Geographical Information System (GIS) techniques is a well recognised approach[16,17]. Characterisation of the hazard is generally based on linear interpolation through Monte-Carlo simulation of best tracks (or synthetic tracks) for computing probability of occurrence of windspeed hazards[18,19,20,21,22]. Surfaces covered by TC are usually modelled either through kernel smoothing of best tracks[20] or the creation of circular buffers derived from the maximum sustained wind speed[23]. But mathematical models based on central pressure and maximum windspeed provide more realistic results. The Holland model[24] and its derivatives, is probably the most used and recognised hurricane hazard model, despite a known tendency in overestimating the radius of maximum wind[25,26,27]. It produces windspeed profiles for a specific time[17]. We transformed this model to produce TC windspeed surfaces through time.

Most studies including hazards and change in exposure have mostly focused on small areas[16,28] or one country[23]. Risk analyses have mainly focused on economic losses[16,18,29]. None of the aforementioned studies attempt to cover the whole world.

We provide here results from 3D modelling (windspeed profile footprints through time) of all individual TC events available (4182) from 1970 to 2009 for the entire globe. We intersected these modelled surfaces of wind intensities with models of human and economic distribution (at a resolution of 30 arc second) for the corresponding years in order to compute the exposures under each hazardous event footprint. We then linked these footprints with reported losses (killed and economic losses) as well as contextual vulnerability parameters using indicators of economy, development level, governance, political(?) corruption, quality of environment, demography, as well as remoteness, proximity from the coast and other parameters (see Table S27 in supplementary material). To this end, we compiled a vulnerability database with 124000 records on about 40 indicators for 40 years and 208 countries and territories. Some indicators were not available and data gaps remain a limitation for selected indicators. Exposure and vulnerability parameters were used to infer the loss functions using statistical multiple regressions. This provides the TC hazard distribution for the five different Saffir-Simpson intensity classes; the distribution of human and economic exposure; an identification of the vulnerability parameters which are associated with TC risk; a quantitative evaluation of the role of exposure and vulnerability in configuring risk. The risk was mapped to show its geographic distribution and values were aggregated at the national level for comparing countries. We also replaced original values of exposure and vulnerability for the corresponding values of 1970, 1980, 1990, 2000 and 2010 to identify the trend in risk. Finally, values of exposure were extrapolated for year 2030 in order to evaluate the respective influences of both climate change and population growth on future human exposure to TC.

The method follows an eight-step process (see 3.8.1 for details), starting from hazard modelling, evaluation of human and economic exposure (using Landscan population model and a Gross Domestic Product (GDP) distribution model), and identification of contextual vulnerability parameters from a list of about 40 parameters. It allows the creation of a mortality risk index for comparing countries.

3.7.9. References

1. EM-DAT: The OFDA/CRED International Disaster Database, Université Catholique de Louvain, Brussels (Belgium). http://www.emdat.be, last consulted May 2011.
2. Tobin, G.A. & Montz, B.E., *Natural Hazards: explanation and integration*, Guilford Press, New York, 1997.
3. UNDRO (United Nations Disater Relief Coordinator) 1979: Natural Disasters and Vulnerability Analysis in Report of Expert

Group Meeting (9-12 July 1979). Geneva: UNDRO. 49 pp. (1979).

4. UNISDR, terminology, Preventionweb, http://www.preventionweb.net/english/professional/terminology/?pid:6&pih:2, last consulted: 27 April 2011.
5. Coburn, A.W., Spence R.J.S., Pomonis A., Vulnerability and risk assessment. *UNDP Disaster Management Training Program*, **57** (1997), p.49.
6. Knutson, T.R., McBride, J.L., Chan, J., Emanuel, K., Holland, G., Landsea, C., Held, I., Kossin, J.P., Srivastava, A. K. & Sugi, M. Tropical cyclones and climate change, *Nature Geoscience,* **3**, 157 – 163,(2010).
7. Elsner, J.B., Kossin, J.P., Jagger, T.H. The increasing intensity of the strongest tropical cyclones, *Nature*, **455**, 92-95, (2008).
8. Bender, M.A., Knutson, T.R., Tuleya, R.W., Sirutis, J.J., Vecchi, G.A., Garner, S.T., Held, I.M. Modeled Impact of Anthropogenic Warming on the Frequency of Intense Atlantic Hurricanes, *Science*, **327**, 454-458 (2010).
9. United Nations Population Division. Population 1960-2010, last update: 11.06.2009, http://geodata.grid.unep.ch/
10. Peduzzi, P., Dao, H., Herold, C. and Mouton, F. Assessing global exposure and vulnerability towards natural hazards: the Disaster Risk Index. *Nat. Hazards Earth Syst. Sci*, **9,** 1149-1159 (2009).
11. World Bank, *Development Actions and the Rising Incidence of Disasters, Evaluation Brief #4*, Independent Evaluation Group, the World Bank, Washington, DC, 34 pp. (2007).
12. ESCAP,UNISDR, *Protecting Development Gains, Reducing Disaster Vulnerability and Building resilience in Asia and the Pacific*, ESCAP, UNISDR, 129 pp. (2010).
13. IFRC, *World disasters report: focus on early warning, early action*, IFRC, 208 pp. (2009).
14. ICHARM, UNESCO, *Global trends in water-related disasters: an insight for policymakers*, ICHARM, UNESCO, 24 pp. (2009).
15. DARA, *Climate vulnerability monitor 2010: the state of the climate crisis*, Development Assistance research Associates (DARA), 261 pp., (2010).
16. Davidson, R., Zhao, H., Kumar, V., Quantitative model to forecast changes in hurricane vulnerability of regional building inventory, *Journal of Infrastructure systems*, **9**(2) 55-64 (2003)
17. Vickery, P.J. Skerlj, P.F., Steckley, A.C., Twisdale, L.A., Hurricane wind field model for use in hurricane simulations, *J. Struct. Eng.* **126** (10), 12036-1221 (2000a).
18. Jain, V.K., Davidson, R., Roswosky, D. modeling changes in hurricane risk over time, *Natural hazards review*, **6**(2), 88-96 (2005).
19. Apivatanagul, P., Davidson, R., Blanton, B., Nozick, L., Long-term regional hurricane hazard analysis for wind and storm surge, *Coastal Engineering* **58**, 499-509 (2011).
20. Poulos, H.M. Spatially explicit mapping of hurricane risk in New England, USA using ArcGIS. *Nat Hazards* **54**, 1015-1023 (2010).
21. Rumpf, J., Weindl, H., Höppe, P., Rauch, E. & Schmidt, V. Tropical cyclone hazard assessment using model-based track simulation. *Nat Hazards* **48**, 383-398 (2008).
22. Legg, M.R., Nozick, L.K., Davidson, R.A. Optimizing the selection of hazard-consistent probabilistic scenarios for long-term regional hurricane loss estimation, *Structural Safety*, **32**, 90-100, 2010.
23. Esteban, M. & Longarte-Galnares, G. Evaluation of the Productivity Decrease Risk Due to a Future Increase in Tropical Cyclone Intensity in Japan. *Risk Analysis* **30**, 1789-1802 (2010).
24. Holland, G. J. An analytic model of the wind and pressure profiles in hurricanes, *Mon. Wea. Rev*, **108**, 1212-1218 (1980).
25. Willoughby, H. E., Rahn, M. E. Parametric Representation of the Primary Hurricane Vortex. Part I: Observations and Evaluation of the Holland (1980) Model. *Mon. Wea. Rev*., **132**, 3033–3048 (2004).
26. Willoughby, H.E., Rahn,M.E., Darling, R.W.R. Parametric Representation of the Primary Hurricane Vortex. Part II: A New Family of Sectionally Continuous Profiles, *Mon. Wea. Rev*., **134**, 1102-1120 (2006).
27. Holland, G. A revised hurricane pressure-wind model, *Monthly Weather Review*, **136**, 3432-3445, (2008).
28. Jain, V.K., Davidson, R., Rosowsky, D. Modelling changes in hurricane risk over time, *Natural Hazard Review*, **6**(2), 88-96, 2005.
29. Vickery, P.J., Masters, F.J., Powell, M.D., Wadhera, D., Hurricane hazard modeling: the past, present, and future, *J. Wind Eng. Ind. Aerodyn.* **97**, 392-405 (2009).
30. IBTrACS v02r01, *NCDC International Best Track Archive for Climate Stewardship Project*. Since Sept. 2010, a new dataset exist.
31. Landscan, Oak Ridge National Laboratory, http://www.ornl.gov/sci/landscan/
32. Balk, D., Pozzi, F., Yetman, G. Global Rural-Urban Mapping Project (GRUMP alpha), CIESIN, Columbia University, 2011. http://sedac.ciesin.columbia.edu/gpw/global.jsp, last consulted June 2011.
33. Peduzzi, P., Dao, H. and Herold, C. Mapping disastrous natural hazards using global datasets, *Nat. Haz.*, **35**, 265–289 (2005).
34. Paul, B. K. Why relatively fewer people died? The case of Bangladesh's Cyclone Sidr. *Natural Hazards*, **50**, 289-304, (2009).
35. Webster, P. J. Myanmar's deadly daffodil. *Nature Geoscience*, **1**, 488-490, 2008.
36. Landsea, C.W., Harper, B.A. , Hoarau, K. , Kaff, J. . Can we detect trends in extreme tropical cyclones?, *Science*, **313**, 452-454 (2006).

37. Raftery, AE., Alkema, L., Gerland, P., Clark, SJ., Pelletier, F., Buettner,T., Heilig, G., Li, N., Sevcikova, H., White Paper: probabilistic projections of the total fertility rate for all countries for the 2010 World population prospects, 2009. http://esa.un.org/unpd/wpp/Documentation/EGM-RFTF_P16_Raftery.pdf, last consulted June 2011.

Supplementary information accompanies this paper on www.nature.com/nclimate/.

3.7.10. Acknowledgements

Uwe Deichmann (World Bank) for providing the GDP distribution, Andrew Maskrey (UNISDR) for finding the finances to supporting this study, Ruth Harding for English corrections.

3.7.11. Author contributions

PP developed the methodology, performed the multiple-regression risk analysis, including trend, spatial risk distribution, developed the mortality risk index with HD. BC, CH, ON generated the spatial model for the Tropical cyclones buffers and extracted the human and economic exposure as well as contextual parameters. FM did the mathematical models for the tropical cyclone buffers. HD produced the model of population distribution for 1970 to 2030 and produced the database on socio-economic parameters. ADB georeferenced the losses and estimated the coastal population living in low-lying areas. JK and PP developed the method for extrapolating exposure and frequency for 2030 based on a review of different climate change scenarios. PP is the lead author, with advices and critical review from JK and key contributions from all co-authors.

3.7.12. Author information

The authors declare no competing financial interests. Reprints and permissions information is available at www.nature.com/reprints. Correspondence and request for materials should be addressed to Pascal Peduzzi (e-mail: Pascal.Peduzzi@unepgrid.ch).

3.8. *Article: Tropical Cyclones: Global Trends in Human Exposure, Vulnerability and Risk Supplemental material*

P. Peduzzi*[1,2], B. Chatenoux[1,3], H. Dao[4,5], A. De Bono[1,3], C. Herold[1,3], J. Kossin[6], F. Mouton[7], O. Nordbeck[1]

[1]Global Change and Vulnerability Unit, DEWA/GRID-Europe, United Nations Environment Programme, Geneva, Switzerland.
[2]Institute of Geomatics and Risk Analysis (IGAR), University of Lausanne, Switzerland
[3]Climatic Change and Climate Impacts Research Group, Institute for Environmental Sciences, University of Geneva, Switzerland
[4]Metadata & Socio-Economics Unit, DEWA/GRID-Europe, United Nations Environment Programme, Geneva, Switzerland.
[5]Department of Geography, University of Geneva, Switzerland.
[6]National Climatic Data Center/NOAA, Asheville, North Carolina, USA.
[7]Institut Fourier, University of Grenoble, France.

Status: accepted for publication in Nature Climate Change. References:
Peduzzi, P., Chatenoux, B., Dao, H., De Bono, A., Herold, C., Kossin, J., Mouton, F., Nordbeck, O., Tropical cyclones: global trends in human exposure, vulnerability and risk (supplemental material), *Nature Climate Change*, (in press).

Contents of supplemental material:

3.8.1. General description of the approach

The method follows an eight-step process:

1. The global model of tropical cyclone wind hazard is based on historical observations of tropical cyclones (TC) events (1970 – 2008) from IBTrACS v02r01[1] and 2009 from various sources (see 3.8.2). GIS techniques were applied to each TC event to produce an estimation of the TC wind speed profile using a parametric model. The model is adapted from Holland (1980)[2] and modified to take into consideration the cyclone's speed of motion (see 3.8.3). This model generates asymmetric wind speed surfaces and provides the footprints for each Saffir-Simpson category (the Saffir-Simpson scale classifies TCs into 5 categories; see 3.8.2) for 4,182 TC events (see Table S25). These were intersected with country borders, showing that countries were hit 5,874 times during this period.

2. To estimate the number of people exposed for each Saffir-Simpson category, we used a population model produced by Landscan 2008[3]. It was modified to provide one model for each year between 1970 and 2009 and one model for each projected population distributions for the years 2010, 2020 and 2030 (see 3.8.4). The distribution models are provided at 30 arc seconds (about 1 x 1 km at the equator). We applied the same method for estimating the exposure of Gross Domestic Product (GDP). GDP distribution was produced by the World Bank based on GRUMP population data[4].

3. Using the dates of TC landfall and the country name, it is possible to link the fatalities

or economic losses as reported by EMDAT, with individual TC events[5]. For each hazard, several factors were also computed, such as the duration of the event as well as the wind intensity factor.

4. In order to include the vulnerability parameters, a database of contextual parameters was designed (see 3.8.5). It includes 39 variables covering economy, demography, environment, development, early warning, governance, health, education, and also remoteness (distance to capital city). These 39 variables over 41 years and for 256 countries and territories created more than 200,000 records. Missing data were interpolated when relevant to fill the gaps.

5. If needed, the variables were transformed to obtain a more normal distribution (see S6.3) and grouped in different hypotheses using a correlation matrix. Each group was made of uncorrelated variables.

6. A vulnerability analysis was run to estimate empirical loss functions that relate event mortality to risk factors (hazard characteristics, exposure and vulnerability) using statistical regression techniques. It uses the reported losses to calibrate the weights of each variable. One model was produced for each Saffir-Simpson category (see 3.8.6). Adding exposure and intensity of past hazardous events in association with groups of hypotheses on contextual parameters and using multiple regression analysis, it was possible to assess which hypothesis best explains the losses.

7. Once this was achieved, a selection of variables and related weights could be used to compute the theoretical mortality rate for each recorded past event, including those for which no information on losses was available. By replacing all the values (exposure, and selected vulnerability indicators) by the value of a specific year (e.g. 1970, 2010) one could run hypothetical risk scenario for any given year. The sum of the losses divided by the number of years in the dataset, provide the average estimated losses for a selected year. This was used to compute trends in disaster risk (i.e. 1970, 1980, 1990, 2000 and 2010). For extrapolation in 2030, only exposure could be computed, as extrapolations on the vulnerability parameters would be weak.

8. Finally, we used the 4182 footprints to produce an average frequency for each intensity as well as an average sum of wind per year. A matrix of 100 by 100 km was used to smooth the random variability in TC tracks, and provided global hazard maps (see Figure 74 in main article). The mortality rates by country were distributed in proportion to the exposure distribution, to produce risk maps.

3.8.2. Modelling tropical cyclones past events and hazards distribution

In this section the modelling of the past TC events is described, in order to convert text information (on the eye of the cyclone location at a given time and date) into three dimensional surfaces (spatial extent and time) for wind hazards. It is also explained how the global distribution of tropical cyclones was made.

Data preparation (source IBTrACS 1970 – 2008)

IBTrACS (version v02r01)1 was downloaded in July 2010. It consists of a public and open global best track dataset combining storm information directly from all the Regional Specialized Meteorological Centres (RSMC), other international centres and individuals. It is endorsed by the World Meteorological Organization Tropical Cyclone Programme as an official archiving and distribution resource for tropical cyclone best track data.

As the present study focuses on the satellite era, the data between 1970 and 2008 (latest data available) was extracted to be processed.

Missing values were frequent within the dataset as Minimum Central Pressure (MCP) and/or Maximum Sustained Wind (MSW) speed were calculated on a 10 minute average. In order to maintain the dataset as complete as possible, multiple regression analysis was performed on each IBTrACS regions with the aim to model one of the missing parameter (MCP or MSW), to finally compute a single equation providing reasonable estimates:

$$MCP = 1024.688+0.055*Latitude-0.028*Longitude-0.0815*MSW \quad (R^2 = 0.90)$$

*MSW = 1131.816+0.064*Latitude-0.031*Longitude-1.1000*MCP (R^2 = 0.90)*

The Figure S79 shows all records in IBTrACS v02r01 with, in dark grey the complete records, in yellow the records with modelled Maximum Sustained Wind speed and in light blue the modelled Minimum Central pressure.

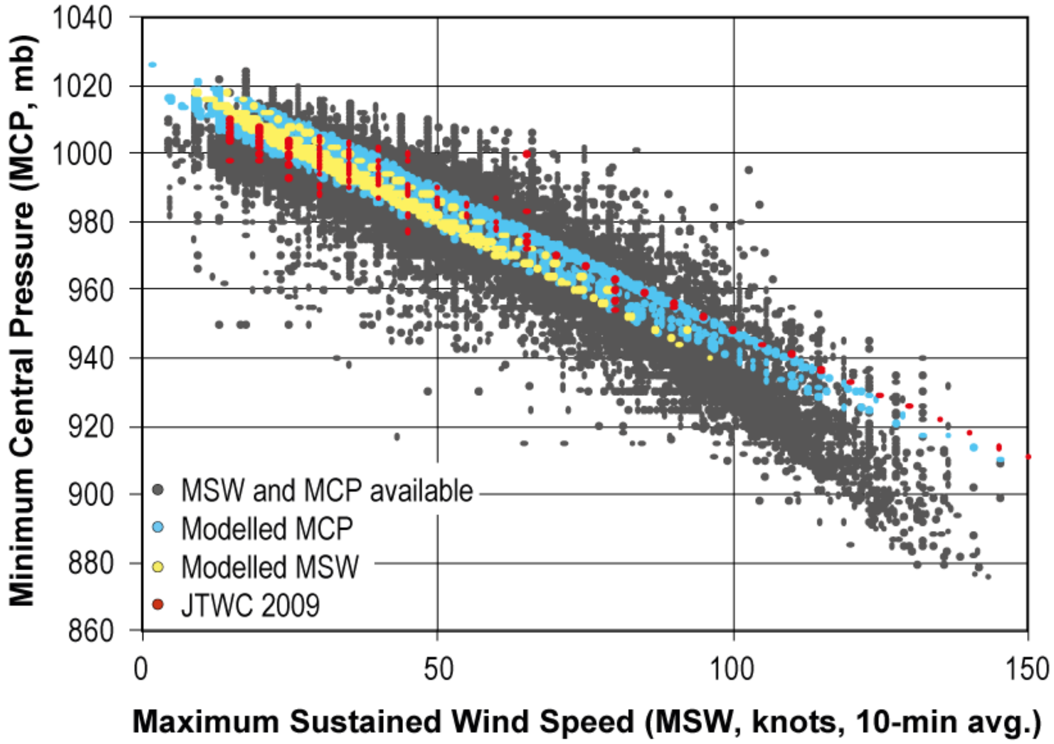


Figure S79: Minimum Central Pressure versus Maximum Sustained Wind speed during data completion process

Data preparation (update for year 2009)

As the time period of the IBTrACS stops in 2008, and in order to analyse a full four decades dataset, the year 2009 was acquired from several sources that are: Japan Meteorological Agency (JMA)[6], Joint Typhoon Warning Center (JTWC)[7], UNISYS[8] and Meteo France[9] websites and added to the existing dataset. Data from the Bureau of Meteorology of the Australian Government was sent by e-mail[10].

As for the IBTrACS dataset some MSW and/or MCP parameters were missing, and they were, when possible, similarly modelled for each data provider through the application of a multi-regression equation based on records containing all necessary parameters:

The JTWC dataset contained all parameters and consequently did not need to be completed. A quick visualization of MSW and MCP parameters shows (see red dots in Figure S79) that an similar process has been applied to the dataset.

The following equation was applied to the JMA dataset: MSW = 889.170-0.164*Latitude+0.100*Longitude-0.8626*MCP (R^2 = 0.96)

And on the Meteo France dataset: MSW = 1145.509-0.120*Latitude-1.119*MCP (R^2 = 0.97)
MCP = 1022.886-0.082*Latitude-0.863*MSW (R^2 = 0.97)

Finally on the UNISYS dataset: MCP = 1029.178-0.105*Latitude-0.029*Longitude-0.702*MSW (R^2 = 0.95)

Data processing

The complexity of the multiple forms of impacts triggered by tropical cyclones would call for a multiple model including wind, rains, storm surge and landslides. Here we concentrate on wind hazard, as global floods and landslides hazards, exposures and risks were being developed separately on other projects[11,12] and storm surges request global bathymetry at high resolution and tide effects that is beyond the scope of this study.

Modelling winds

The parametric model used in this process is based on an equation from Greg Holland2 derived from an original approach by Schloemer13. The model includes a formula for the wind speed at a given radius (Equation S7), i.e. the distance from a current point to the eye of the cyclone. For this model it is supposed that the cyclone is over the ocean, that the eye of the cyclone is stationary and that the surrounding winds follow a three-dimensional symmetry around a vertical axis (axymmetric winds).

$$V_h(R) = \sqrt{\frac{b}{\rho} \cdot \left(\frac{R_{\max}}{R}\right)^b \cdot (P_{env} - P_{centre}) \cdot e^{-\left(\frac{R_{\max}}{R}\right)^b} + \frac{R^2 f^2}{4}} - \frac{Rf}{2} \qquad \text{(S1)}$$

Equation S7: Greg Holland (1980) parametric model

Where:

$V_h(R)$: Gradient wind speed at distance R from the eye (in m/s)
b: Parameter that changes the shape of the radial profile
P_{centre}: Central pressure (in Pa)
P_{env}: The asymptotic environmental pressure (in Pa)
R_{max}: The radius of maximum winds (in meters)
R: The radius where wind speed is $V_h(R)$ (in meters)
ρ: The air density, assumed constant = 1.15 kg/m^3
f : The Coriolis parameter = 2*(Earth's angular velocity)*sin(latitude) where the Earth angular velocity equals 0.0000729 radians/s.

The wind field in tropical cyclones is rarely, if ever, symmetric. Asymmetries arise from a range of processes, including: cyclone movement; location and structure of the cloudy and clear regions around the cyclone, including the spiral cloud bands; external influences from surrounding weather systems; and occasional high intensity transients, such as meso vortices[14]. The only processes routinely included in current parametric wind models are those arising from the cyclone movement (Figure S80). The simplest way to include in the model the asymmetry due to the movement, is, in other words, to add the eye's speed vector (translation) to the stationary model's wind vector field (rotation).

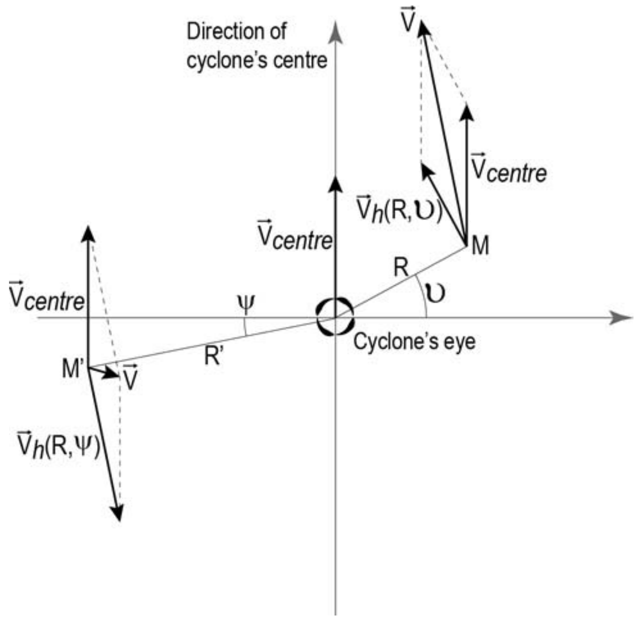


Figure S80: Eyes of the cyclone translation speed added to the Greg Holland parametric model

$$V(R,\vartheta) = \|\vec{V}(R,\vartheta)\| = \sqrt{V_h(R)^2 + V_{centre}^2 + 2V_h(R)V_{centre}\cos(\vartheta)} \qquad \textbf{(S2)}$$

Equation S8: Transformation of the Equation S7 to include the eye of the cyclone translation speed

This methodology was presented at the fifth Workshop on Tropical Cyclones, organised by WMO in Cairns in December 2002. For the detail of the modelling, please refer to the publication "Cyclone Database Manager"[15].

Estimation of Rmax

The *Rmax* parameter is theoretically independent of the relative values of ambient and central pressure and also of the *b* parameter. It could therefore not be determined by the cyclone intensity data nor by the shape of its profile. However, to be able to model the extension of the destructive winds within a tropical cyclone without the information about the cyclone's structure, the available data about the intensity has to be used. In order to estimate the *Rmax* of a cyclone, Mark Powell at NOAA (Personal contact, July 2001) suggested to stratify the cyclones into three different classes related to the central pressure: small, medium and large.

The three classes were defined by aggregating the Saffir-Simpson scale for the central pressure (p > 980, 980 > p > 965 and 965> p.). These classes were thereafter used to define relevant *Rmax* values based on examples of cyclone events with observed *Rmax*.

By studying earlier cyclone events and their *Rmax,* we were able to identify three likely distances for the *Rmax*. However, choosing a fixed value of *Rmax* for each of the three pressure classes leads to distinct differences between the classes and a piecewise linear function was therefore used between the determined classes. Further improvement of the *Rmax* estimation could be done by dividing the tropical cyclone's life cycle into three phases: growing, mature and declining. For these different phases the link between central pressure and *Rmax* is different and a great improvement of the buffer estimation could be achieved if reasonable estimations of *Rmax* were furnished by the providers.

Estimation of parameter b

The problem with choosing a constant value for the parameter b is that the theoretical maximum wind speed intensity depends almost uniquely upon the pressure value. This results sometimes in a great difference between the theoretical maximum values and the observed maximum speed intensities.
As the maximum theoretical values are obtained at distance *Rmax*, it is a simple computation to choose *b* such that the maximum theoretical value for stationary model equals the maximum relative (with respect to the centre) speed intensity:

$$b = \frac{\rho \cdot e \cdot (V_{\max obs} - V_{centre}) \cdot (V_{\max obs} - V_{centre} + R_{\max} \cdot f)}{P_{env} - P_{centre}} \qquad \text{(S3)}$$

Equation S9 Estimation of the b parameter

As the Coriolis term is negligible and because of the uncertainty in the determination of Rmax, an approximation was made:

$$b = \frac{\rho \cdot e \cdot (V_{\max obs} - V_{centre})^2}{P_{env} - P_{centre}} \qquad \text{(S4)}$$

Equation S10: Simplified equation for the estimation of the b parameter

In order to keep b between reasonable fixed physical limits (i.e. between 1 and 2.5). The b parameter is not fixed arbitrary, but estimated with the above equation.

From tracks to buffers

Practically, the geometrical parameters are calculated with a Macro (Visual Basic for

Applications) and implemented using an Arc Macro Language (AML) script in ArcInfo workstation. For each point the distance from the centre to the different Saffir-Simpson intersection of wind speed are computed. This allows to transform the tracks into a series of areas called wind speed buffers, each buffer corresponding to a given Saffir-Simpson intensity (see Figure S81 and Table S25).

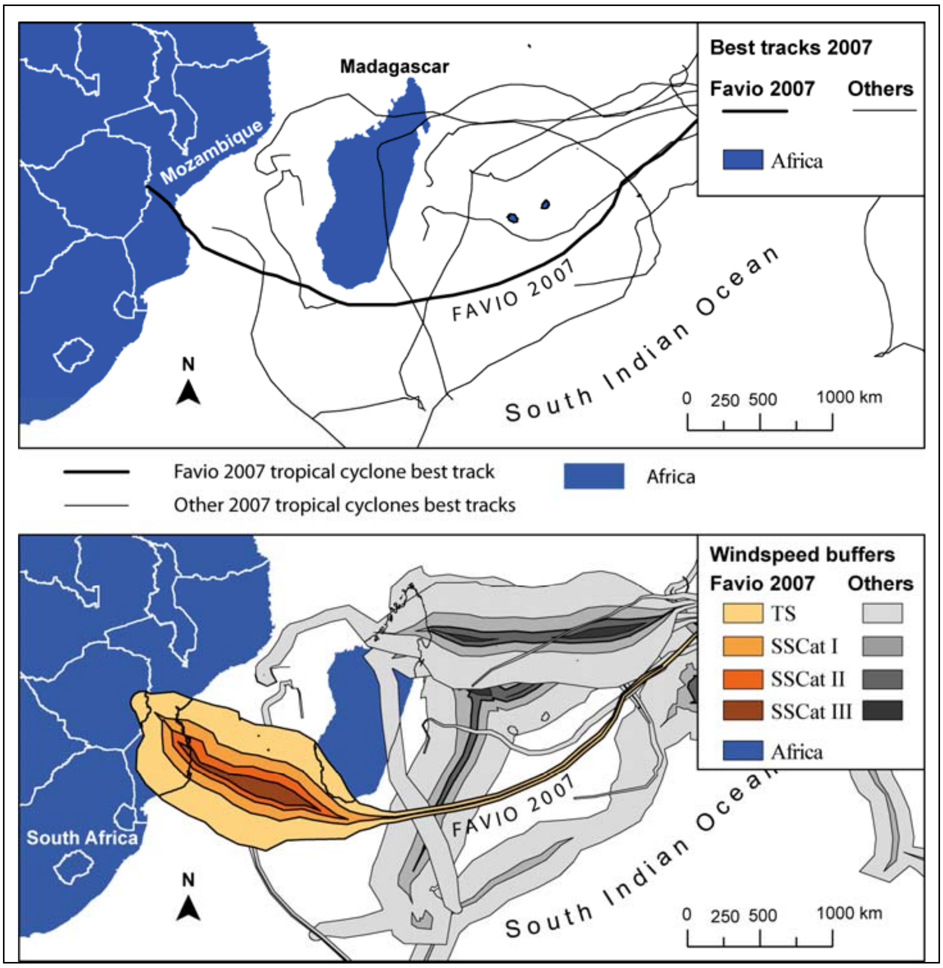


Figure S81: From best tracks to Saffir-Simpson buffers (South Indian Ocean, 2007)

Category	Pressure (mbar)	Winds (knots)	Winds (mpd)
Tropical Depression	--	less than 34	less than 39
Tropical Storm	--	34-63	39-73
Category 1 Hurricane	more than 980	64-82	74-95
Category 2 Hurricane	965-980	83-95	96-110
Category 3 Hurricane	945-965	96-113	111-130
Category 4 Hurricane	920-945	114-135	131-155
Category 5 Hurricane	less than 920	more than 135	more than 155

Table S25: Saffir-Simpson scale[16]

There are some limitations in using this approach. One of them is the improvements of methodologies and instruments for recording TC events. Increase in satellite sensors resolution, night detection and improvement in the Dvorak Techniques are influencing the estimation of the maximum winds[17], hence the size of the buffers. This is inherent to the datasets and cannot be corrected (at least at the moment).

Secondly, according to Holland (2008)[18] the application of the Dvorak analysis overestimates the maximum winds for TC (especially category 3, 4 and 5) and underestimates the effects of storm translation speed. Comparisons between use of the Holland 1980 model as compared with aircraft measurements from Willoughby and Rahn (2004)[19] and Willoughby *et al.* (2006)[20] found that it generally overestimated the area of strong winds, underestimated the maximum wind, and smoothed the eyewall structure. This leads to overestimates of the maximum wind and spreads the strongest winds too far around the maximum (Willoughby and Rahn, 2004)[19]. However, given that this is the case for all the modelled events, it is equivalent to considering a larger area for all TC events.

This model could be improved by using the new method provided by G. Holland (2008)[18] for the estimation of the b parameter. Where, in his equation, an estimation of b varies with central pressure, latitude, intensification rate, and storm translation speed.

Adding value to the dataset

From the event per event buffer dataset several products were derived at a global scale.

A frequency grid was computed by counting the number of events of a given Saffir-Simpson category in each place around the globe divided by the number of years of observations, thus providing the average number of events per year.

A footprint grid was also computed representing the maximum Saffir-Simpson category over the 40 year period of the dataset.

Grids of physical and economic exposure were also computed by multiplying the frequency grid by population and GDP grids from respectively Landscan 2008[21] and World Bank (unpublished), and calculated for the following decades 1970, 1980, 1990, 2000 and 2010 (see 0).

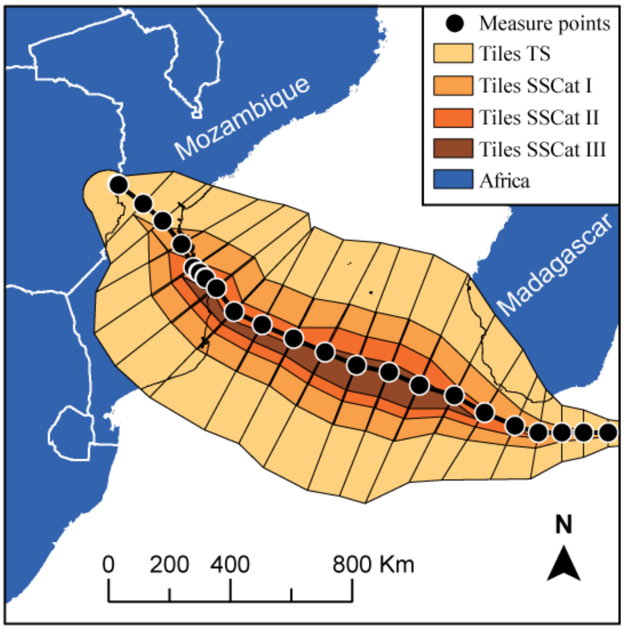


Figure S82: Adding values tile per tile (A tile was created for each Saffir-Simpson category between two measure points)

In addition six types of tropical cyclone severity indicators were calculated for every buffer of a measured point (named tile, Figure S82):

Sum of winds: estimated by summing the duration by the average wind speed of each Saffir-Simpson category.

ACE: Accumulated Cyclone Energy, calculated by summing the squares of the estimated 6-hourly maximum sustained surface wind speed while the system is either a tropical storm or hurricane[22].

PDI: Potential Destruction Index, sum of the cube of the maximum wind speed for each 6-hour period of all tropical storms and typhoons[23].

PD: Estimation of the total Power Dissipation, derived from Emanuel[24] and corresponding to the PDI multiplied by the size of the buffer.

Production of the annual frequency raster

From the event per event buffer dataset several products were derived at a global scale.

The global annual frequency raster is generated using the cyclone wind buffers derived from forty years of cyclone tracks records (A in Figure S83). The first step produces a raster with a one kilometre resolution, the pixels count every wind event of the buffer zones included in our forty year dataset. Each event has a weight of 1, independently from the Saffir-Simpson wind classes. The result is divided by forty to obtain the annual frequency raster (B in Figure S83).

Then, a spatial mean is applied to this annual frequency raster in order to smooth out unnecessary details. The matrix used in this process is a circle of 10 pixel radius (10 kilometres). Below the annual frequency of 0.05 (two events in forty years), the raster coverage is inevitably sparse. These zones show isolated buffers corresponding to track extremities of single events and to gaps surrounding zero frequency. Considering that these gaps are partly due to the limited size of our sample, another spatial mean in these areas was applied, using a wider circular matrix of 100 kilometres radius.

Finally, in order to integrate the raster produced by these two different treatments in one single and continuous output, isolines from these two annual frequency rasters were created. These isolines are integrated in a single coverage, and interpolated to produce the final annual frequency raster at a resolution of 2 kilometres (C in Figure S83).

A footprint grid was also computed representing the maximum Saffir-Simpson category over the forty year period of the dataset.

Grids of physical and economic exposure were also computed by multiplying the frequency grid by population and GDP grids from respectively Landscan 2008[21] and World Bank (unpublished), and calculated for the following decades 1970, 1980, 1990, 2000 and 2010 (see 0).

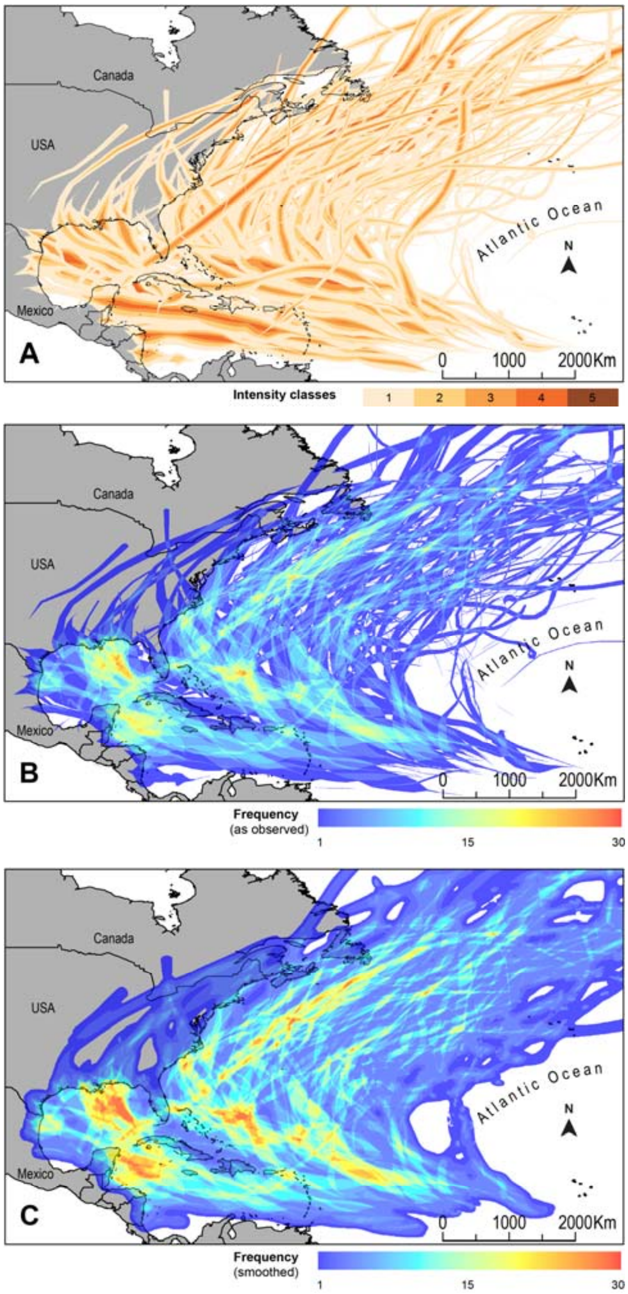


Figure S83 From tropical cyclones wind speed buffer (A) to observed annual frequencies (B) to smoothed modelled annual frequencies (C) over the North Atlantic ocean.

Tropical and extra-tropical cyclone automatic differentiation was not possible. Firstly because the information is not extensively available in IBTrACS dataset as 35% of the records are not documented between 1970 and 2008 or are conflicting between reporting centres. Secondly, due to the lack of scientific consensus on a methodology for determining the extratropical transition point[25], the differentiation was not achieved. Threshold was applied, using Evans and Hart (2003)[26] as references and the TC over Greenland, Island, Ireland, United Kingdom and continental

Europe were defined as extra-tropical cyclones and thus exposure to TC was removed in these region.

3.8.3. Geo-referencing cyclones from the CRED EM-DAT Database

Introduction

The OFDA/CRED EM-DAT[27] database (EM-DAT) plays a key role in global risk assessment studies, and remains probably the best source for reports of number of persons killed by natural hazards. Data are compiled from verifiable sources, including UN agencies, non-governmental organizations, insurance companies, research institutes and press agencies.

The major inconvenience of EM-DAT is that it does not provide a proper geo-reference of the reported events. Moreover, in the case of tropical cyclones, no geographical coordinates are provided. The most reliable geo-localization is done by the ISO country code.

The database for the period 1975-2007 included 2313 records under the category "wind storms" comprising: cyclones, hurricanes, storms, tornadoes, tropical storms, typhoons, winter storm and unclassified. The original assignation of each event to these sub-categories can be debated, for this reason the complete database was kept for our geo-referencing workflow.

Methodology

The methodology is based partially on a previous study[28], with some refining.

The EM-DAT database on wind storms (CRED db) was joined within the event per event buffer dataset created from cyclones tracks (see S1) named here "cyclone buffers".

The selected fields used in the process from both datasets are describe in Figure S84

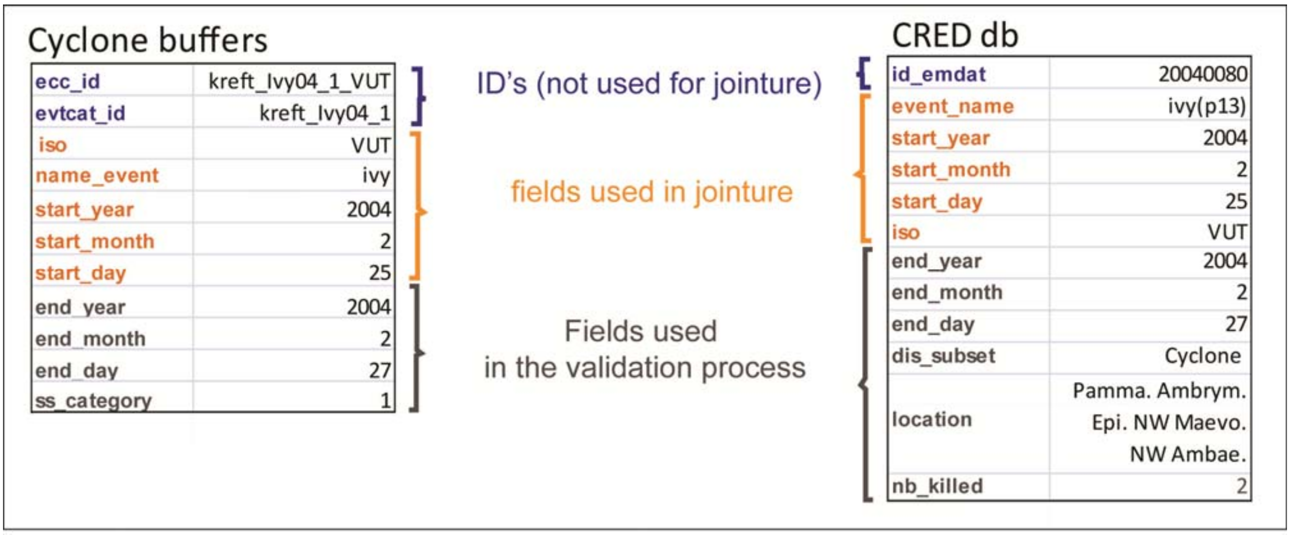


Figure S84: Useful fields in the process of geo-referencing from both EM-DAT and cyclone buffers tables.

Automated and semi-automated procedures were applied in order to process the data. Automated methods include the localization of the event by linking the Iso code to the period of the beginning of the event (using a filter of +/- 2 days of tolerance) from both tables. For cyclones that have a name in EM-DAT, a link was made using the cyclone's name, the country (ISO) code and the year. For more details refer to Figure S85.

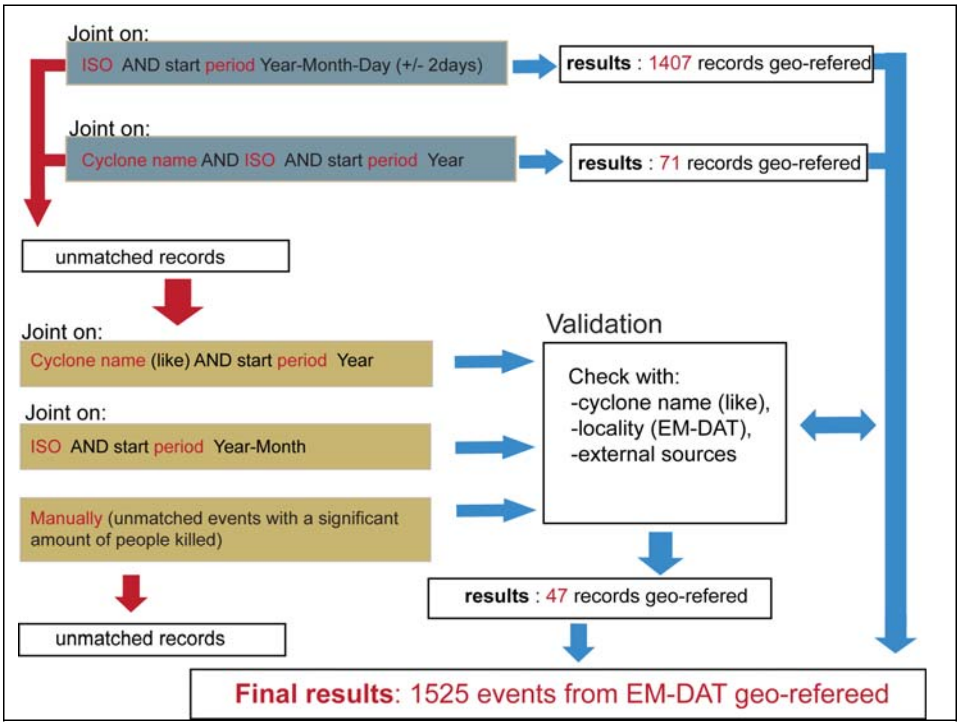


Figure S85: geo-referencing workflow

All the Unmatched records were further processed using a semi-automatic procedure, where verification by an operator was essential. This approach mainly includes links on cyclone name (or similar "like") and period (year) or ISO and period (year and month). The remaining unmatched events were classed by number of people killed, and the more significant cases were geo-referred manually. Validations especially for these last categories of events were made one by one by checking localities on "CRED db" fields (when reported) and by using external sources[1,8,29].

Results

As mentioned before CRED db includes 2313 records, but not all are associated to tropical cyclones. If only the events occurring in the countries present in both tables (buffer cyclones and CRED) are considered and excluding winter storms, there are 1832 events on CRED db that cover 83 % of the geo-referenced events including 87 % of the people killed.

3.8.4. Modelling population through time

This document describes the method followed for producing time series of population raster grids.

Gridded population data

The base data for the calculation of population exposure is the Landscan 2008[21]. This dataset is a model which uses "annual mid-year sub-national population estimates[30]. The allocation of population from administrative units (collected from various sources) to grid cells is made by means of a probability grid calculated with ancillary information such as transportation networks, land-cover, topography, urban settlements. The resulting data depicts a so-called **ambient population**, i.e. the average population that might by present in each grid cell over 24 hours during the year. The spatial resolution of the dataset is 30 arc seconds, i.e. 1/120th of a degree (about 1km at the Equator), which defines a grid of 43'200 columns by 21'600 rows (933 millions of cells) to cover the entire world.

Country population data

Population statistics at the country level were collected from the UNEP GEO Data Portal[31]. This site provides time-series population data originating from the World Population Prospects (Population Division of the Department of Economic and Social Affairs of the United Nations Secretariat). We selected annual data (in GIS vector format) for the period 1970-2009 and projections for the years 2010, 2020 and 2030.

Using UN/UNEP country figures to extrapolate Landscan 2008 data

The Landscan 2008 data were adjusted to the UNEP GEO figures and extrapolated to the 43 dates (years) of interests by means of GIS operations. Country population totals were first extracted from the Landscan 2008 grid. A comparison of these Landscan country totals with the UNEP GEO country data showed some minor discrepancies, caused by differences in population data sources. Grids of estimated population for each of the 43 selected years were then produced using the following formula (Equation S11):

$$PopEst_y = Landscan_{2008} \cdot \frac{CountryPopUN_y}{CountryPopLandscan_{2008}} \quad \text{(S5)}$$

Equation S11 Estimation of the population for previous year

where:

PopEst$_y$ is the estimated population grid for a given year *y*

Landscan$_{2008}$ is the Landscan 2008 population grid

CountryPopLandscan$_{2008}$ is the grid of country population totals for 2008 as extracted from Landscan 2008

CountryPopUN$_y$ is the grid of country population totals for the year *y* as from UN data (UNEP GEO)

To summarize, the outputs grids *PopEst*$_y$ are linear extrapolations of Landscan 2008 data based on UN country population figures. This approach may not reflect local/regional differences in population evolution, but at least it guarantees that the sums of pixels within each country match the UN/UNEP GEO figures.

Calculating population exposure to cyclones

The population exposed to each individual tropical cyclone event was calculated by summing up the population pixels falling in the cyclone buffer for the year of occurrence (e.g. a cyclone that occurred in 1980 was overlaid with corresponding population grid for 1980). Time-series of annual population exposures on a country by country basis (43 years x 256 countries) were also calculated by summing up the event by event exposures by year and country.

Finally, several products were computed at different levels of aggregation (country and IPCC regions):

Yearly average population exposed: using the smoothed annual frequency (see Figure S83c), the frequency was multiplied by the population distribution models of different years (1970, 1980, 1990, 2000, 2010, 2020 and 2030), in order to produce yearly exposure for the corresponding years. The sum of the product was then aggregated at both country and IPCC region levels. The figures are provided in Table S31.

Yearly average Gross Domestic Product (GDP) exposed: using the same method, the GDP exposed was computed and aggregated at both country and IPCC regions levels. The figures are provided in Table S33.

Population living in tropical cyclones prone areas: by replacing the frequency by 1 and multiplying by the population (i.e. using the frequency as a mask), the population living in the TC prone area was obtained. This was also computed for the seven decades (1970 to 2030). The figures are provided in Table S32.

GDP located in tropical cyclones prone areas : as for the population the GDP located in TC prone areas was computed with the same method. The results were used for the trend analysis. The figures are provided in Table S34.

Computation of coastal population living in low-lying areas using the SRTM

Population living in coastal low-lying areas may be more prone to suffer losses. This could be because they can be affected by storm surge or by flooding resulting from the large precipitations from tropical cyclones. Storm surge is an abnormal rise of water generated by a storm, over and above the predicted astronomical tides. To evaluate the number of people living in low-lying areas, we used the heights as recorded by the Shuttle Radar Topography Mission (SRTM), we intersected these with the cyclones buffers. Different heights were used for different wind speed categories (see Table 26) this is to take into consideration higher waves (or storm surge) with increasing TC intensity. The low-lying areas were then intersected with the population distribution model to provide an estimation of the number of population living in low-lying area. This factor was used as a complement to human exposure to qualify low-lying human exposure. The correlation between cyclone categories and waves highness is derived by the Saffir-Simpson (SS) scale, according to Shultz *et al.*[32].

Methodology

All the cyclone events for the period 1970-2007 and their impacts on coastal zones at global scale were considered.

TC category	DEM value (m)	DEM reclassified
-	-100 - 0	-1
-	0 - 1	0
1	1 - 2	1
2	2- 3	2
3	3- 4	3
4	4- 6	4
5	6 - 10	5

Table 26: Table used to reclassify the 90 meters Digital Elevation Model (DEM), according to the Saffir-Simpson scale for wave's height

The wind speed buffers, from tropical cyclones, calculated in 0 are intersected within a global DEM at 90 m of resolution from the Shuttle Radar Topography Mission Global (SRTM)33. The mains steps of the process are summarized as follows (see figure 2 for more details and an example).

- The DEM was limited to a coastal zone of 10 km from the shoreline. 584 tiles of 5 x 5 (Decimals degrees) were processed in order to ensure a global coverage
- The DEM was re-classified according to the corresponding wave's height of the SS classification in Table 26.
- Wind speed buffers and the re-classified DEM were intersected in order to identify the low-lying areas. Each resulting area is linked with a unique cyclone event.

From these areas several products where derived at a global scale:

1. A frequency grid was generated by considering the number of events per area of determined Saffir-Simpson category, divided by the number of years. This frequency could be used to provide number evaluation on average number of population (or economic revenues) located in low-lying tropical cyclones prone areas.

2. Human and economic exposure grids where also created by using the same methodology and datasets described in point 0.

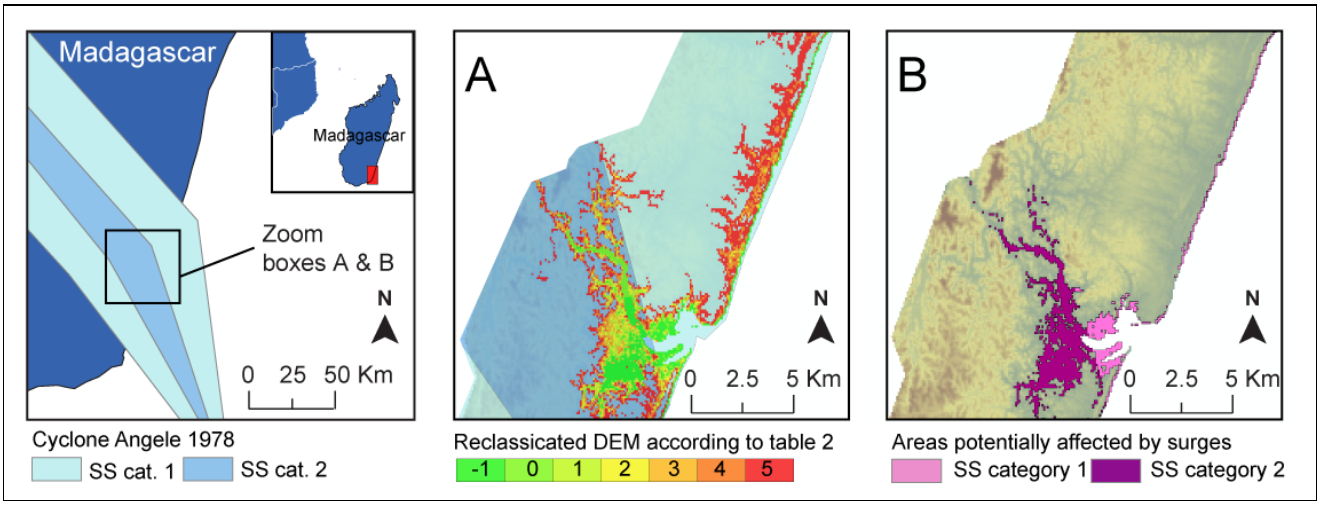


Figure S86: Example of methodology applied to buffer of "Angele" cyclone (ss cat 1 and 2) on the South-East coast of Madagascar. Box A: DEM reclassification and intersection with cyclone buffers; Box B: coastal low-lying areas potentially affected by surges from cyclones of SS cat 2.

3.8.5. *Vulnerability parameters*

This document describes the method followed for the preparation of vulnerability indicators.

Compilation of country statistics

Vulnerability is approached by means of a series of socio-economic indicators supposed to have a direct or an indirect influence on the level of human and economic losses. From international databases (such as UN institutions, World Bank) a set of 39 socio-economic and geographic variables including economic features, dependency on the environment quality, demography, health and sanitation, governance, infrastructure, early warning and capacity of response, education and development was compiled. For each of these variables, data at national level and for the years 1970-2010 were collected and stored as a table in a spreadsheet.

Extrapolations

Some variables showed many missing data. For instance, the Corruption Perception Index (CPI, from Transparency International) for the period 1980-1995 was only available for 54 countries and two dates. This was a potential problem for the subsequent statistical analysis, which should be based on a maximum number of observations. Therefore, estimations were done on missing data when possible, using alternative data sources and linear extrapolation/interpolation.

For example, Table S27 below shows how Gross Domestic Product (GDP) data from World Bank (World Development Indicators 2008) were completed:

Country	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984
Canada	23142	23416	23695	23976	24251	24516	24770	25016	25267	25539
Saint Pierre and Miquelon	5.9	5.9	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0
United States of America	220165	222226	224323	226466	228662	230917	233239	235627	238070	240552
Anguilla	7.0	7.0	7.0	7.0	7.0	7.0	7.0	7.0	7.0	7.0
Antigua and Barbuda	76.336	76.295	76	75	73	72	71	71	70	69
Aruba	59.091	59.406	59.661	59.927	60.297	61	62	63	64	64
Bahamas	189	193	197	201	206	210	215	219	224	229
Barbados	246	246	247	247	248	249	251	253	255	258
Bermuda	54	55	55	55	56	56	56	57	57	57
British Virgin Islands	10	11	11	11	11	11	11	12	12	13
Cayman Islands	13	14	15	16	17	17	18	19	19	20
Cuba	9432	9536	9625	9700	9765	9823	9874	9917	9962	10016
Albania	2400.8	2454.3	2508.0	2562.1	2616.5	2671.3	2725.1	2777.7	2831.8	2891.1
Bosnia and Herzegovina	3747.1	3780.6	3812.6	3844.3	3877.6	3913.5	3949.8	3985.0	4022.8	4067.8
Bulgaria	8720.7	8754.9	8784.2	8810.3	8835.6	8861.5	8888.4	8914.9	8938.1	8954.2
Croatia	4263.3	4285.5	4308.3	4331.4	4354.3	4376.6	4398.6	4420.2	4440.3	4457.6
Cyprus	609.2	607.7	606.7	606.6	607.9	611.0	616.1	623.1	631.3	639.6

Table S27 Example of missing data estimations : the case of Gross Domestic Product (GDP) from World Bank

Legend

Source/Manipulation	Color	Source/Manipulation	Color
Original data untouched from WDI 2008	24516	Extrapolated (linear trends)	92
Original data untouched from WDI 2007	23142	From World Energy Outlook 2008 (IEA)	271
(PPP form CIC) * (GDP local currency from UNSD)	246	Calculated from trends based on "non ppp" GDP (UNSD)	3845

Linking statistical data to cyclones events

To each cyclone event the corresponding statistical variables were linked using the information on ISO country codes and years that are present in both the event and statistical tables. The result is a table of 2312 rows (cyclone events) x 40 columns (1 for population exposure and 39 for vulnerability variables).

The overall completeness is as follows: vulnerability data are available for 66.2% of the events, which represents 70.5% of the reported people killed. In terms of reported killed, the completeness percentage is higher than 90% for 56% of the variables (it is higher than 70% for 74% of the variables).

Variable by variable, theses completeness figures range from 0.4% of the reported killed

(4.0% of the events) for the variable "access to electricity" to more than 99.5% of reported killed for variables such as Gross Domestic Product, population growth, governance indicators.

Transformation of variables

As explained in S6 (the multiple regression analysis), some variables were transformed. As for example variables expressed in percentage, a logistic transformation was applied. For others, no logarithm was needed, for instance the urban growth already behaves in a cumulative way.

Variable code	Variable name	Theoretical min. value	Theoretical max. value	Transformation
agedep_0	Total age dependency rate	0	∞	Ln
aidspc_0	AIDS estimated deaths, aged 0-49 (% of tot. pop.)	0	100	transform + Ln
arabpc_0	Arable and Permanent Crops - % of non GLC2000 bare land	0	100	transform + Ln
cars_0	Motor vehicles in use - Passenger cars (thousand)	0	∞	Ln
carspc_0	Motor vehicles in use - Passenger cars (per inhabitant)	0	∞	Ln
comvehicpc_0	Motor vehicles in use - Commercial vehicles (per inhabitant)	0	∞	Ln
conflipc_0	Physical exposure to conflicts	0	100	not applicable
cpi_0	Corruption Perceptions Index (CPI)	0	10	transform + Ln
crop_0	Arable and Permanent Crops - Total	0	∞	Ln
croppc_0	Arable and Permanent Crops - Percent of Land Area	0	100	transform + Ln
ctrcor_0	Control of Corruption	-2.5	2.5	transform + Ln
deforpc_0	Deforestation rate	0	100	transform + Ln
elecacc_0	% of population with access to electricity	0	100	transform + Ln
forestpc_0	Forests and Woodland (% of Land Area)	0	100	transform + Ln
gdpcap_0	Gross Domestic Product - Purchasing Power Parity per Capita	0	∞	Ln
gdpppp_0	Gross Domestic Product - Purchasing Power Parity	0	∞	not applicable
gini_0	Inequality (Gini coefficient)	0	1	transform + Ln
glasodpc_0	Human Induced Soil Degradation (GLASOD)	0	1	transform + Ln
goveff_0	Government Effectiveness	-2.5	2.5	transform + Ln
hdi_0	Human Development Index (HDI)	0	1	transform + Ln
healthxp_0	Per capita government expenditure on health (PPP int. $)	0	∞	Ln
hosbedpc_0	# of hospital beds per 100000 habitants # of doctors	0	∞	Ln
infmort_0	Infant mortality and malnutrition (though are also factored into HDI)	0	1000	transform + Ln
iwatotpc_0	Improved Drinking Water Coverage - Total Population	0	100	transform + Ln
phonespc_0	Telecommunications (phone density per 100000 habitants)	0	∞	Ln
polsta_0	Political Stability	-2.5	2.5	transform + Ln
pop_0	Population (Persons (in Thousands))	0	∞	not applicable
popg3_0	Population growth on 3 past years	0	∞	none
popurbpc_0	Urban Population (% of Total Population)	0	100	transform + Ln
radiospc_0	Radio receivers (per thousand inhabitants)	0	∞	Ln
regqua_0	Regulatory Quality	-2.5	2.5	transform + Ln
rullaw_0	Rule of Law	-2.5	2.5	transform + Ln
schoo1pc_0	School enrolment, primary (per inhabitant)	0	1	transform + Ln
slumpopc_0	% of urban population living in slums / squatter settlements	0	100	transform + Ln
toubibpc_0	Physicians density (per 10 000 population)	0	10000	transform + Ln
u5mort_0	Under five years old mortality rate	0	1000	transform + Ln
unouripc_0	Undernourished (% of total population)	0	100	transform + Ln
urbg3_0	Urban Population Growth on past 3 years	0	∞	none
voiacc_0	Voice and Accountability	-2.5	2.5	transform + Ln

Table S28 Transformation of the vulnerability variables

3.8.6. *The multiple regression analysis*

This document describes the method followed in the statistical analysis. Figure S87 provides a synopsis of the process.

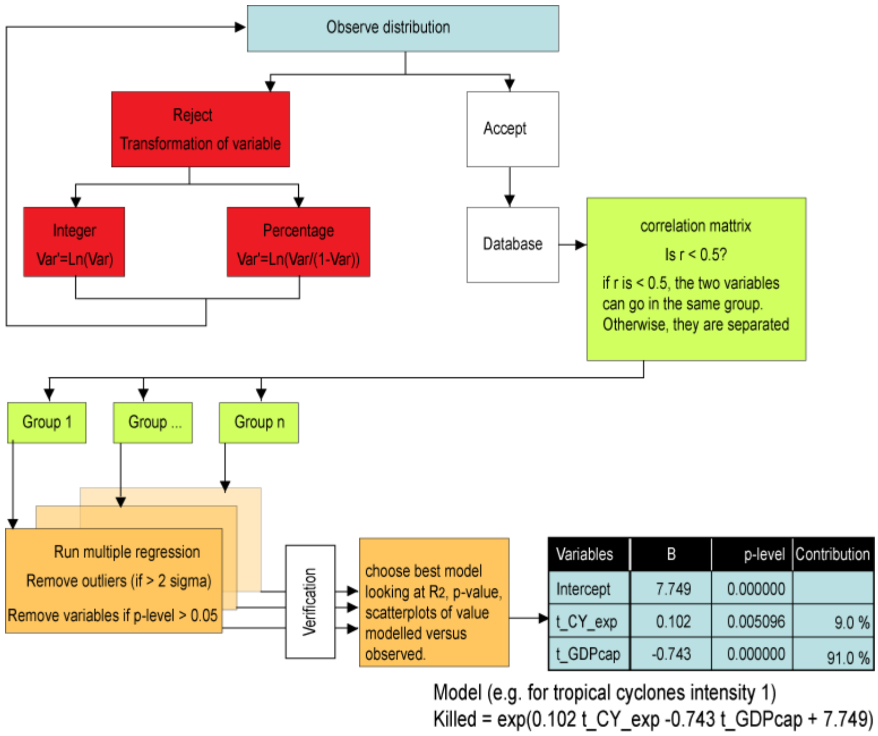


Figure S87 statistical process

Working definitions of risk hazards, exposure and vulnerability

Risk is "*the combination of the probability of an event and its negative consequences*" (UNISDR, 2011)[34]. Many other definitions exist, e.g. more specifically, Tobin and Montz (1997)[35] define the risk as "*a measure of the expected losses due to hazard event of a particular magnitude occurring in a given area over a specific time period.*" Hence, risk should not be confused with the losses. Losses or **impacts** refer to the number of human losses; the number of infrastructures or amount of crops damaged; the amount of economic losses; or the environmental losses. They are sometimes referred to "*realized risk*" or "*disaster losses*". Disaster losses may impact livelihood in sectors such as tourism, housing, fisheries, transport, communication, or agriculture, to name just a few.

Risk is the probability of losses (or potential losses) for some particular cause (hazard), in a specific place and for a specific time-period. A commonly used terminology was provided by the United Nations Disaster Relief Organization (UNDRO) in their report "*Natural Disasters and Vulnerability Analysis in Report of Expert Group Meeting*" in 1979[36,37] and states that the risk is resulting from three components: the hazard occurrence probability, the element at risk and the vulnerability. Risk is a function of **hazard**, **exposure** and **vulnerability**. Exposure is used here instead of element at risk. Depending on the schools of thought, people use vulnerability including coping capacity and resilience; others will treat these three parameters separately. In this study, coping capacity and resilience are included as negative vulnerability (see discussion below). The definitions on risk and related concepts, follow closely the one provided by the United Nations International Strategy for Disaster Reduction (UNISDR, 2011)[29].

Risk = function of (hazard, exposure, vulnerability, coping capacity) (S6)

Equation S12 General equation of risk

Hazards: "*A dangerous phenomenon, substance, human activity or condition […]. Hazards are described quantitatively by the likely frequency of occurrence of different intensities for different areas, as determined from historical data or scientific analysis.*"[29]

The exposure is the number of *"People, property, systems, or other elements present in hazard zones that are thereby subject to potential losses."*[29].

The vulnerability is *the degree of loss to each element should a hazard of a given severity occur.*" (Coburn *et al.* 1991)[38] and depends on *the characteristics and circumstances of a community, system or asset that make it susceptible to the damaging effects of a hazard. […] arising from various physical, social, economic, and environmental factors.*"[29]. Vulnerability can be computed as a percentage of losses as compared with total exposure (hence varies between 0 and 1). Vulnerability as such is not easy to characterise, but can be approached by contextual parameters associated with vulnerability, such as: poverty, capacity of early warning, knowledge on how to react, appropriate evacuation plan or presence of shelters, appropriate design of building (for earthquakes, floods and cyclones). Information is not necessarily available as such. For example appropriate evacuation plans or early warning capacities. However, some proxies can be used. Appropriate evacuation plans come from good governance (this indicator is available). The number of radios per inhabitant can be a useful indicator of early warning capacity.

General theoretical model: a multiplicative approach

The variable to be explained is the probability of people killed per event (i.e. mortality risk). Risk is a function of hazard, exposure and vulnerability[39,40,41]. The hypothesis is made that the relation between hazard, exposure and vulnerability follows a multiplicative model[42] such as:

$$R_i = H_i \cdot E_i \cdot Vul_i \qquad \text{(S7)}$$

Equation S13 Generic risk equation

Where:

i = Intensity based on Saffir-Simpson scale (ranging from 1 to 5).

R_i = Risk of human losses (mortality) from tropical cyclones, expressed by a transformed variable at intensity i.

H_i = Tropical Cyclone hazard which varies in frequency for each intensity "i".

Ei = Population exposure, transformed variable. Is the population living in the tropical cyclones prone-areas, or, in the case of an individual cyclone, the number of people exposed to this physical event, one can differentiate exposure for each intensity "i".

Vul_i = Vulnerability is a non dimensional number between 0 and 1 (transformed variable).

The multiplicative approach is justified since the three components (hazards, exposure and vulnerability) are linked between them: the risk is null if any of the components is equal to zero[42].

The vulnerability can be explained by different variables as explained in Equation S14:

$$Vul_i = C_i \cdot V_{i,1}^{\alpha_{i,1}} \cdot V_{i,2}^{\alpha_{i,2}} \cdot \ldots \cdot V_{i,n}^{\alpha_{i,n}} \quad \textbf{(S8)}$$

Equation S14 Interaction of factors for estimation of the vulnerability

Where:

Ci = multiplicative constant

$V_{i,1}$ ... = representing types of socio-economic contextual parameters such as e.g. governance, poverty, quality of the environment,... exponent α are necessary as the vulnerability is not directly proportional (or inversely proportional) to the losses, i.e. a population twice as poor might not suffer twice as many losses.

This is achieved using statistical regressions. Note that coping capacity and resilience are included in Vulnerability.

Given that an individual event approach is used, the equation can be simplified by suppressing the frequency of hazard (Equation S15): for a single event, the hazard frequency is equal to one. Still the risk is not necessarily in direct proportion of E_i, this is taken into consideration by putting an exponent μ on this exposure. This leads to the parametric model:

$$R_i = C_i \cdot E_i^{\mu} \cdot V_{i,1}^{\alpha_{i,1}} \cdot V_{i,2}^{\alpha_{i,2}} \cdot \ldots \cdot V_{i,n}^{\alpha_{i,n}} \quad \text{(S9)}$$

Equation S15 Risk equation for the multiplicative approach

To calibrate the models we are using past reported losses from each event. This requires first to georeference the losses (see S3). The reported losses do not follow a normal distribution. Most losses are low, with very few events having very high losses (see Figure S88). The easiest way to deal with such distributions is to use logarithmic regressions, based on natural logarithms (Ln) as seen on the Equation S16. An addition of Ln is a multiplication of the non transformed variables, so this is still a multiplicative model:

$$RR_i = \exp(LnC_i + \mu LnE_i + \alpha_{i,1} LnV_{i,1} + \alpha_{i,2} LnV_{i,2} + \ldots + \alpha_{i,n} LnV_{i,n}) \cdot \exp(0.5\sigma^2) \quad \text{(S10)}$$

Equation S16 Risk equation using a logarithmic model

Where:

i = Intensity based on Saffir-Simpson scale (ranging from 1 to 5).

RR_i = the Realised Risk: i.e. past reported losses used for calibration

E_i = Population exposed for each specific event

$V_{i,1} \ldots V_{i,n}$ = significant socio-economic variables

C_i = multiplicative constant

$\exp(0.5\ \sigma^2)$ = Bias corrector for logarithmic transformations, also referred as "quasi maximum likelihood estimator" (QMLE) as explained in Cohn *et al.* (1989)[43], in Gilroy *et al.* (1990)[44] and Stow *et al.* (2006)[45]

The number of variables should be limited (to avoid over-fitting). In order to validate the model, the exposure is included in the set of dependant variables (precisely two different variables are used as proxies for the exposure) and it is expected, for each regression, that at least one of those exposure variables is significant.

One difficulty to overcome is the different categories of wind-speed. Even under a tropical cyclone category 4, some people are "only" affected by low wind speeds if they are not close to the cyclones eye. Yet it does not mean that they will not suffer losses.

3.8.7. Transformation of variables

Many variables have particular distributions and need to be transformed in order to enable comparison (see Figure S88). For the integer variables the Natural Logarithm is computed. For variables including values between 0 and 1 ((0; 1), such as percentage…) a transformation function is used:

$$\overline{V} = Ln[V/(1-V)] \quad \text{(S11)}$$

Equation S17 transformation of variables including values between 0 and 1.

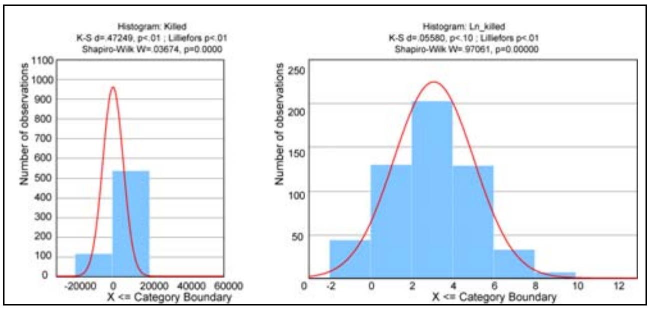


Figure S88 Logarithmic transformation of the variable "Killed".

Some variables might not follow a linear model, for example it might be the square of sum of wind that is correlated with the number of killed. So scatterplots of each variables and the Ln of numbers killed was produced to observe whether variables need to be transformed taking the square root, the Ln or the square.

Formulating hypotheses

The idea was to work by category of Saffir-Simpson, as being exposed to category 4 is not equivalent to being exposed to category 1. But even within the wind category, the duration and sum of wind can make significant difference. Ultimately, what influences directly the level of casualties is the quality of the buildings, the design of land planning, the knowledge of individuals and the organisation of the society to face such events (early warning, evacuation plan, shelters,...). However, these variables cannot be measured directly. So a range of proxies are being used (e.g. number of radios per inhabitant as a proxy for early warning; or voice and accountability as a proxy for good governance).

On the hazard and exposure, the hypothesis was made that the number of reported killed should be positively correlated with: power of winds (Saffir-Simpson category, Sum of winds, Maximum winds); the duration (also as a proxy for amount of precipitations) and the number of people exposed.

Vulnerability (including coping capacity and resilience as above) can be explained by several socio-economic variables:

1) *Demography*: the hypothesis is that with rapid population growth, people end-up living in hazard prone areas, due to lack of available space. Improvement of infrastructures fails to cope with the rapidity of population growth (or urban growth). The indicators include: annual population growth and urban growth, both should be positively correlated with the number of killed.
2) *Poverty*: the hypothesis is that low level of development or high level of poverty should lead to higher casualties, since this translates in poor building and infrastructures quality, lack of coping capacity, lower education, less technological early warning. The indicators include Human development Index (HDI), Gross Domestic Product per capita (GDPcap) expressed both in absolute term and in Purchasing Power Parity (ppp).
3) *Governance*: the hypothesis is that an efficient government will take care of the population, provide appropriate guidance, planning, provide good early warning and anticipation of the hazard occurrence translating in better prevention and preparedness. Indicators include voice and accountability, government efficiency, political stability, control of corruption, rule of law. All these variables should be negatively correlated with the number of killed.
4) *Remoteness*: The hypothesis is that the further away from national government, the worse the infrastructures and coping capacity, and the longer the time for accessing people in need of assistance. The indicators include: average distance from capital city and minimum distance from capital city; percentage of crop land (as a proxy of rural habitat), percentage of rural versus urban population in exposed area. These indicators should all be positively correlated with the number of killed.
5) *Early warning*: the hypothesis is that better early warning (advance warning associated with evacuation plan and a population trained to react to these warning, will translate in reduced amount of casualties. Indicators: number of radios per inhabitant, number of phones per inhabitant. Should be negatively correlated with the number of killed.
6) *Quality of the environment*: the hypothesis is that a good environment quality will translate in less landslides, and coastal vegetation can act as a buffer and reduce storm surge energy. Indicators include deforestation rates (should be positively correlated with the number of killed).
7) *Education*: the hypothesis is that a well educated population will have better knowledge on how to deal with the emergency and will know what to do. Indicators: school attendance (negative correlation with killed is expected), illiteracy rate (positive correlation with killed is expected).

For several indicators, the availability of data to cover both the maximum number of countries affected and maximum number of years for the time span (1970-2009), was an issue. Section S4 provides the level of completeness of the data for countries presenting human losses. Nearly 100 variables were computed.

Selection of uncorrelated variables

Socio-economic variables

The majority of the socio-economic parameters are correlated between themselves, either because poverty (low GDP cap) is also translated in low level of physicians, or because some variables are built from others. Typically the Human Development Index (HDI) which is computed based on the Gross Domestic Product (GDP), literacy rate and life expectancy. The HDI is correlated at 85% with GDP, hence it cannot be used in the same selection of explanatory variables.

A correlation matrix was run to see which variables can be used together (uncorrelated variables). A threshold of correlation (using pearson r) was fixed (r < 0.50).

The matrix can also be used to see which variables can be substituted by others. This can be useful when some variables are not available globally (e.g. GDP_Cap is a good proxy for voice accountability and other governance indicators). For the vulnerability parameters, all the following variables show a significant link with the variable Ln_killed. However, only few can be used together in the same model (see Table S29).

Variables	Short name	Ctrcor	Goveff	Polsta	Radiopc	Rullaw	Urbg3	Voiacc	Cropst	GDPcapt	Pop_gt	HDIt
Corruption Control	Ctrcor											
Government efficiency	Goveff	0.90										
Political stability	Polsta	0.69	0.60									
Number of radio per inhabitant	Radiopc	0.88	0.89	0.50								
Rule of law	Rullaw	0.91	0.94	0.73	0.85							
Urban growth (3 years)	Urbg3	-0.72	-0.78	-0.69	-0.63	-0.83						
Voice & accountability	Voiacc	0.80	0.73	0.68	0.76	0.81	-0.66					
Cropland affected (in %)	Cropst	-0.29	-0.16	-0.60	-0.14	-0.21	0.21	-0.30				
Gross Domestic Product per capita	GDPcapt	0.82	0.91	0.66	0.85	0.89	-0.88	0.77	-0.30			
Population growth (over 10 years)	Pop_gt	-0.55	-0.56	-0.67	-0.38	-0.66	0.85	-0.37	0.11	-0.65		
Human Development Index	HDIt	0.83	0.92	0.63	0.84	0.90	-0.86	0.75	-0.20	0.97	-0.70	
Logarithm of the reported Killed	Ln_killed	-0.44	-0.31	-0.49	-0.33	-0.38	0.42	-0.51	0.51	-0.48	0.30	-0.44

Table S29 Sample of correlation matrix for vulnerability parameters. In bold, the variables that can be used together. In black, the indicative correlation between Ln_killed and the selected variable.

This matrix in Table S29 is very useful. It shows that all indicators of governance are well correlated with GDPcap. Demography (pop_gt) is also highly (but negatively) correlated with GDPcap. The percentage of crops is not correlated with any other and thus can be used in nearly all models. Other variables which can be used in all models (not correlated with other variables) but not shown here due to lack of space are: e.g. distance to capital city (Dcap) or school enrolment.

Hazard variables

The Hazard varies in duration and intensity. Given that several indicators were computed, a correlation matrix (see Table S30) provides the list of the hazard variables and their related correlation. Choice of best hazard severity indicators was made using matrix provided in Table S30.

Variables on TC Hazard	Short name	LnAv_Dur	LnSum_Dur	LnMax_Dur	LnSum_WS	LnMax_WS
Average duration (Ln)	LnAv_Dur					
Sum_Dur (Ln)	LnSum_Dur	0.84				
Maximum Duration (Ln)	LnMax_Dur	0.92	0.89			
Sum of wind speed (Ln)	LnSum_WS	0.84	0.99	0.85		
Maximum Wind speed (Ln)	LnMax_WS	0.89	0.83	0.93	0.86	
Reported killed (Ln)	Ln_Killed	0.22	0.15	0.18	0.14	0.16

Table S30 Correlation matrix of hazard parameters. The average duration of the event seems to have the best correlation with the reported killed. We can only include one parameter as they are all correlated.

This matrix shows that duration and intensity are highly correlated and thus both indicators cannot be used together. The best indicator is “average duration” (which was our proxy for amount of precipitation). This is not surprising since when using Saffir-Simpson classes, wind speed is already partly taken into consideration.

The five models

Thanks to the previous steps (using availability of data, transformation of variables and the correlation matrix), the choice between variables was reduced from 98 to 6 variables. Using past reported killed from EM-Dat for calibration, the following variables for each of the five Saffir-Simpson categories were seleted.

Category 1

R= 0.646 R^2= 0.417 Adjusted R^2= 0.410

N=167	Beta	Std.Err.	B	Std.Err.	t(164)	p-level	Rel. Con.[f]
Intercept			7.749019	0.891944	8.68778	0.000000	
Ln_Exposure	0.178274	0.062791	0.102395	0.036065	2.83914	0.005096	9.0%
Ln_GDPcapt	-0.567315	0.062791	-0.743028	0.082240	-9.03492	0.000000	91.0%

N= 167, 6 outliers.

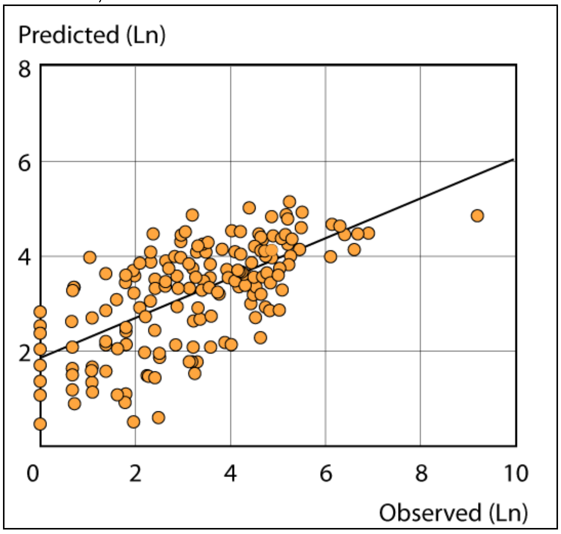


Figure S89 Predicted versus observed for category 1

Category 2

R= 0.643 R^2= 0.413 Adjusted R^2= 0.402

N=115	Beta	Std.Err.	B	Std.Err.	t(112)	p-level	Rel. Con.
Intercept			5.032	1.134	4.438	0.000022	
Ln_Exposure	0.434	0.075	0.278	0.048	5.799	0.000000	46.41%
GDPcapt	-0.466	0.075	-0.695	0.112	-6.232	0.000000	53.59%

N= 115, 4 outliers.

[f] Rel. Con. = Relative contribution of the variable to the model.

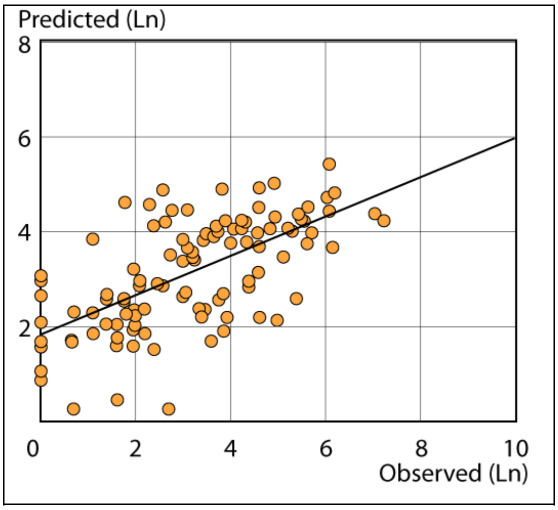


Figure S90 Predicted versus observed for category 2

Category 3

R= 0.671 R^2= 0.450 Adjusted R^2= 0.430

N=87	Beta	Std.Err.	B	Std.Err.	t(83)	p-level	Rel. Con.
Intercept			-0.751	1.482	-0.507	0.613375	
Ln_Exposure	0.467	0.082	0.408	0.072	5.685	0.000000	52.75%
GDPcapt	-0.400	0.081	-0.470	0.096	-4.908	0.000005	38.74%
Dcapt	0.187	0.082	0.311	0.136	2.286	0.024815	8.51%

N= 87, 4 outliers.

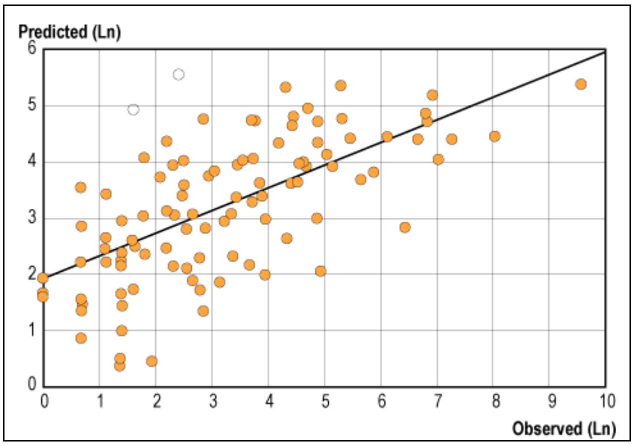


Figure S91 Predicted versus observed for category 3

Category 4

R= 0.825 R^2= 0.681 Adjusted R^2= 0.663

N=39	Beta	Std.Err.	B	Std.Err.	t(36)	p-level	Rel. Con.
Intercept			0.409	1.569	0.260	0.795989	
Ln_Exposure	0.587	0.097	0.455	0.075	6.028	0.000001	62.95%
GDPcapt	-0.450	0.097	-0.457	0.099	-4.625	0.000047	37.05%

N= 39, 2 outliers.

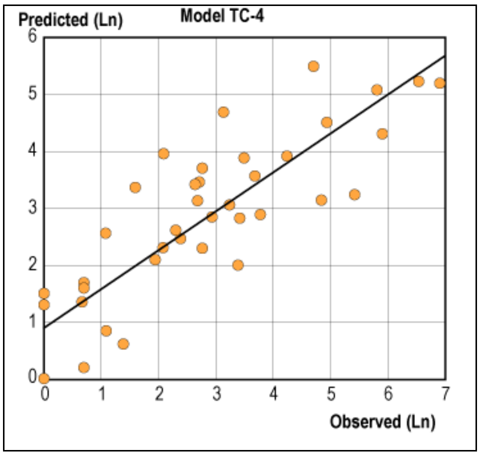


Figure S92 Predicted versus observed for category 4

Category 5

R= 0.999 R^2= 0.998 Adjusted R^2= 0.997

N=8	Beta	Std.Err.	B	Std.Err.	t(4)	p-level	Rel. Con.
Intercept			-11.342	1.205	-9.411	0.000711	
Ln_Exposure	0.680	0.0212	1.214	0.038	32.000	0.000006	68.89%
Ln_exposure in costal low-lying areas	0.404	0.029	0.325	0.024	13.808	0.000159	24.36%
GDPcapt	-0.213	0.031	-0.582	0.085	-6.855	0.00237	6.75%

Exclude cases: 138 (Mitch in Honduras)

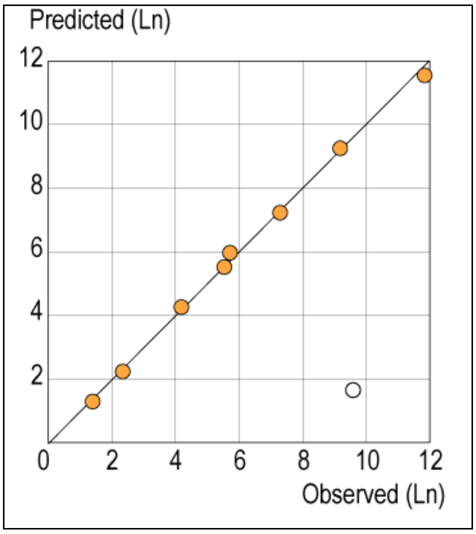


Figure S93 Predicted versus observed for category 5

The quality of the correlation varies from one model to another. Models 1, 2 and 3 are of average to fair quality (r between 0.64 to 0.67). Model 4 is of good quality (r=0.83), while model 5 would be of exceptional quality (r=0.999), however, given that these events are very rare, only 8 valid cases, such a model should only be seen as informative.

The sample size varies greatly, there are much more events of categories 1 and 2 (167 and 115 valid cases) as compared with stronger wind categories (87 cases for category 3, 39 for category 4 and only 8 for category 5). The outliers were only removed if their residual value was more than 2 sigma.

Several tests were made to ensure the solidity of the model:

1) Distribution of Raw residuals and predicted were analysed. There is no indication that it does not follow a normal distribution. The distribution of predicted values seems to follow a normal distribution (despite the relatively small number of cases in models 4 and 5).

2) Looking at the distribution of predicted versus residuals, the predicted versus residuals do not show any remaining pattern. The predicted versus observed provided a fair fit.

3) Three tests of normality were applied, (Normal expected frequencies, Kolmogorov-Smirnov & Lilliefors test for normality, Shapiro Wilkinson W test). None of them let any suspicion of non-normality for residuals.

4) Given the small size of certain samples, there is a possibility of having the regression weights to be data-driven. In order to test the solidity of the model, a "bootstrap" method was applied. This function allows to randomly suppress some records to see how it affects the weights of each variable in the model. 1000 iterations were run for each model.

Interpretation of the results

Most of the variable show high significance (very small p-values as compared with the threshold of < 0.05). The results all follow the hypotheses: killed are positively correlated with human exposure and with distance to capital city. It is negatively correlated with GDPcap.

The profile of countries at higher risk are poor countries, with high populations living in coastal areas, (e.g. Small Islands Developing States, SIDS).

Several models were computed; it is usually possible to replace GDPcap by HDI or by indicators of governance (such as voice and accountability, corruption control, but GDPcap was usually preferred because this information is available for all countries. The best models achieved were all based on exposure and level of wealth (GDPcap). Remoteness is also highlighted. The indicators on governance and on corruption provided good results but presented three main issues. Firstly they are not complete for all countries and years, hence it resulted in models based on a smaller sample (less degree of freedom). Secondly, the level of GDP can be computed locally with population and GDP distribution models. This ensures a more localised level of vulnerability, while governance and / or HDI are national values. Finally, it is easier to generate risk raster maps based on GDPcap since this value is also a raster. So these models were chosen also for these criteria.

Figure 7 shows a very interesting result. The vulnerability component has more weight (more important role) at lower intensity, while the role of exposure increases along with intensity. This was expected as only most vulnerable population (or most fragile houses) are being killed (destroyed) at low intensity. At high intensity, even high quality buildings are being destroyed, placing their inhabitant at higher risk.

The models were used to compute the risk for several years. The values of the different variables were changed to reflect the values of a selected year (e.g. 1970, 1980, 1990, 2000, 2010) and divided by the number of years of the period covered. This produces an estimation of the risk for each selected year assuming a constant hazard (average risk). It allows the comparison of the risk level across time, taking the evolution of the exposure and vulnerability parameters into consideration. For future risk (e.g. 2030), the same process may be applied, however, only the exposure is known with enough confidence. There is not enough confidence on the evolution of socio-economical parameters to produce such models for the future. However, the level of exposure was computed taking into consideration forecasted evolution of hazard frequency and demographical changes.

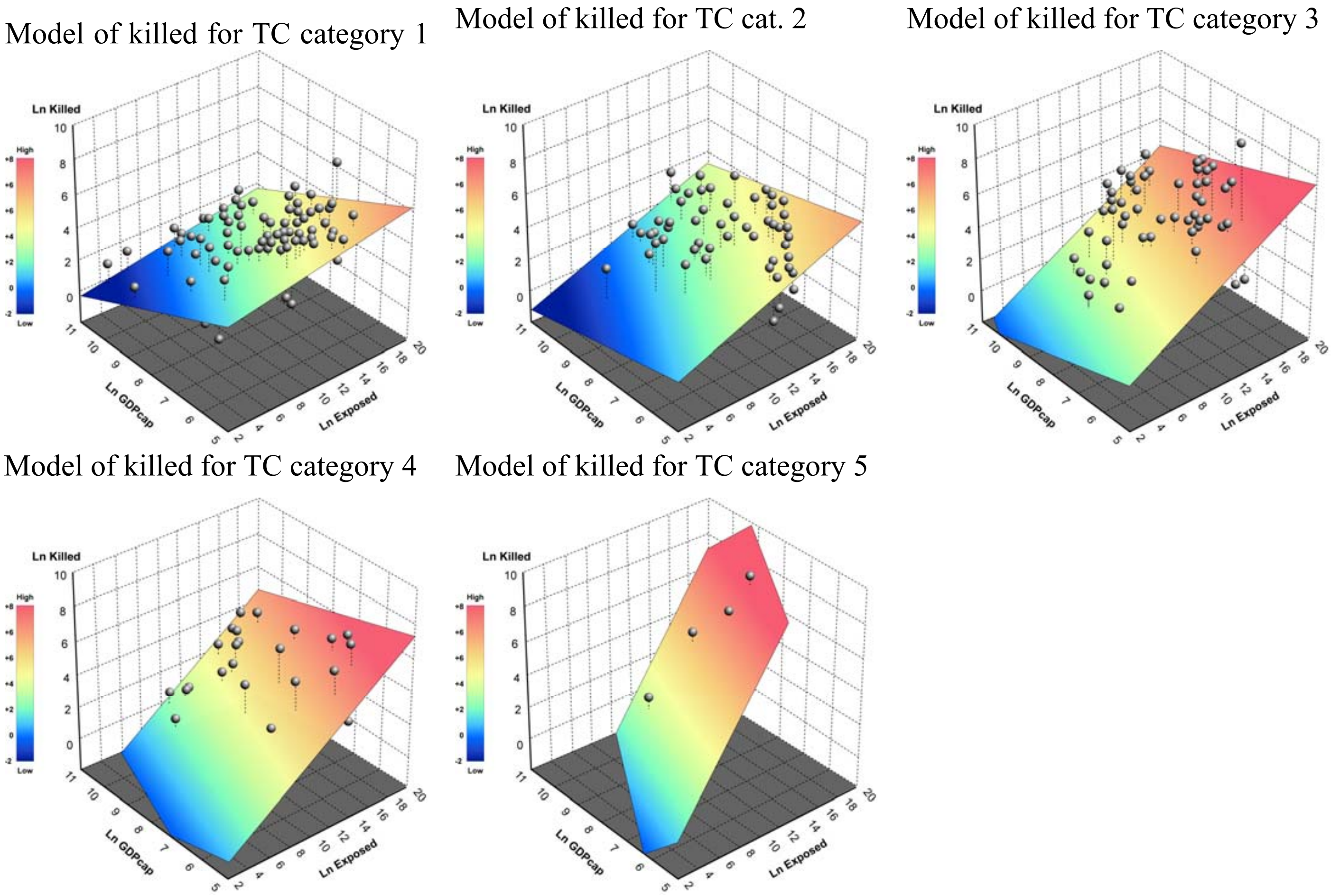


Figure S94 Ln of killed versus GDPcap and Ln of population exposed in 3D plots. The weight (role) of the vulnerability (GDPcap) decreases with intensity, while the weight of exposure increases.

3.8.8. Expected impacts of climate change on TC frequency, intensity and exposure

We cannot talk about future change in exposure, without including the potential effects of climate change on tropical cyclones. Knutson *et al.* (2010)[46] made estimations on the influence of climate change on tropical cyclones for 2100. There are multiple issues about such estimations. Models are based on different resolutions and for different climate scenarios. However, the idea is to provide guidance on likelihood of direction and magnitude of changes. We are basing our analysis up to 2030 for two reasons, firstly because projection on population changes are less precise after this date and secondly because policy makers have difficulties in projecting decisions for 2100. For Knutson *et al.* (2010)[46], TC frequency is likely to decrease or remain essentially unchanged (-6 to -34% by 2100) while some increase in the mean maximum wind speed of tropical cyclones is likely (+2 to +11% globally). Knutson *et al.* (2010)[46] also provided regional differences, but for which the confidence is lower. Figure S96 show that there is a higher agreement on global estimates as compared with regional estimates. The resolution of models varies between 9 and 120 km. From Figure S96 it seems that by taking higher resolution, models have a higher agreement, but this can also be due to the reduction of number of models considered. Given the large variations of estimates at the regional level, only the global values were considered in this article. At the global level, Knutson *et al.* (2010) reviewed 22 models on change in frequency (see Figure S95). In order to take into account the uncertainty, we considered all the models (22 for frequency and 8 for intensity). Placing a restriction on the resolution would have drastically reduced the number of models, especially for intensity. The agreement – for the global level - is high.

We first looked at the impacts of resolution on the models.

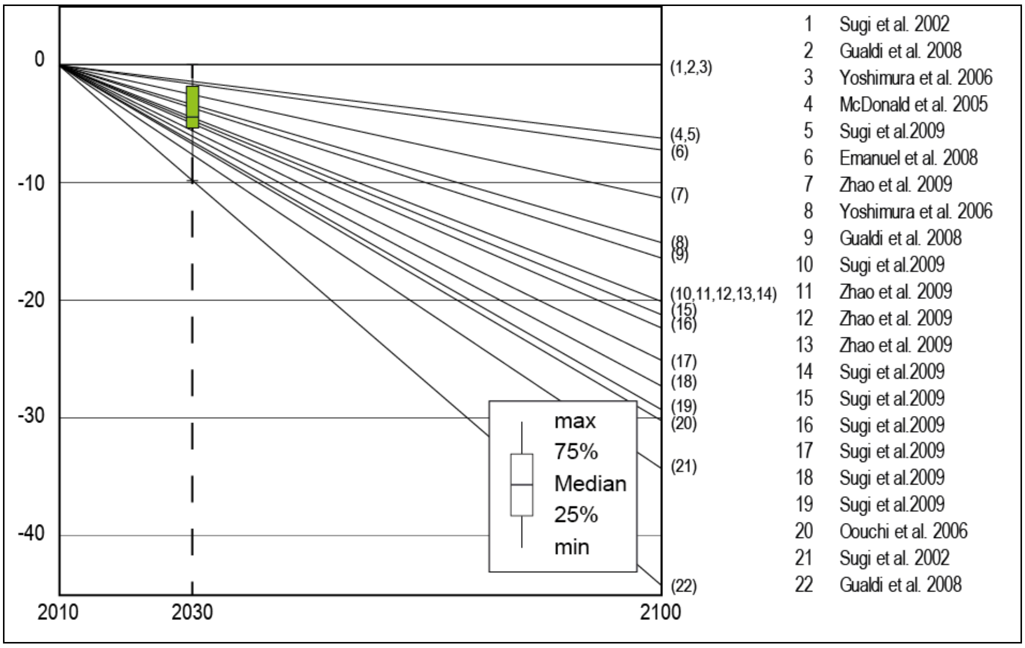


Figure S95 Estimated change in frequency for 2030 based on 22 models as reviewd by Knutson et al. 2010.

To find a corresponding change for 2030, we assumed linear impacts from climate change. This is based on the projection graphs in Knutson *et al.* (2010)[46]. We have assumed that the change in mean tropical cyclone intensity will be the same as the changes in the maximum intensities that were given in Knutson *et al.* (2010). Support for equating changes in mean intensity to changes in maximum intensity comes from Emanuel (2000)[47].

To find the corresponding values in changes, the projection for 2100 were divided by 4.5 (90 years between 2010 and 2100 and 20 years to 2030 (90/20 = 4.5). These values translated in a -1.3 to -7.6% (median -4.4%) change in frequency and between +0.4 to +2.4% (median +1.4%) change in intensity for 2030.

The change in frequency on yearly exposure is linear. So we multiplied the expected minimum, median and maximum values of expected frequencies for 2030 by the expected average yearly global exposure to TC in 2030 at constant hazard (i.e. frequency and intensity remaining as of today's average, is estimated at 149.3 million people per year). Under scenarios from Knutson *et al.* (2010) of average decrease in frequency the exposure would be 147.4 millions ((100 – 1.3)*149.3); 142.7 ((100-4.4)*149.3) and 138.3 millions ((100-7.6)*149.3) for minimum decrease, median and maximum decrease.

Increase in intensity will also have an impact on exposure. The more intense TCs are (in average) covering larger areas, thus more people are exposed. Should this be done at the regional level, the best way to do such estimations would be to increase the initial wind speed by the values of Knutson *et al.* (2010) and re-run the generation of the TC buffers. This in an interesting lead for future research, but was not achievable in the scope of this article. In order to obtain an estimation at the global level, a quicker evaluation was performed.

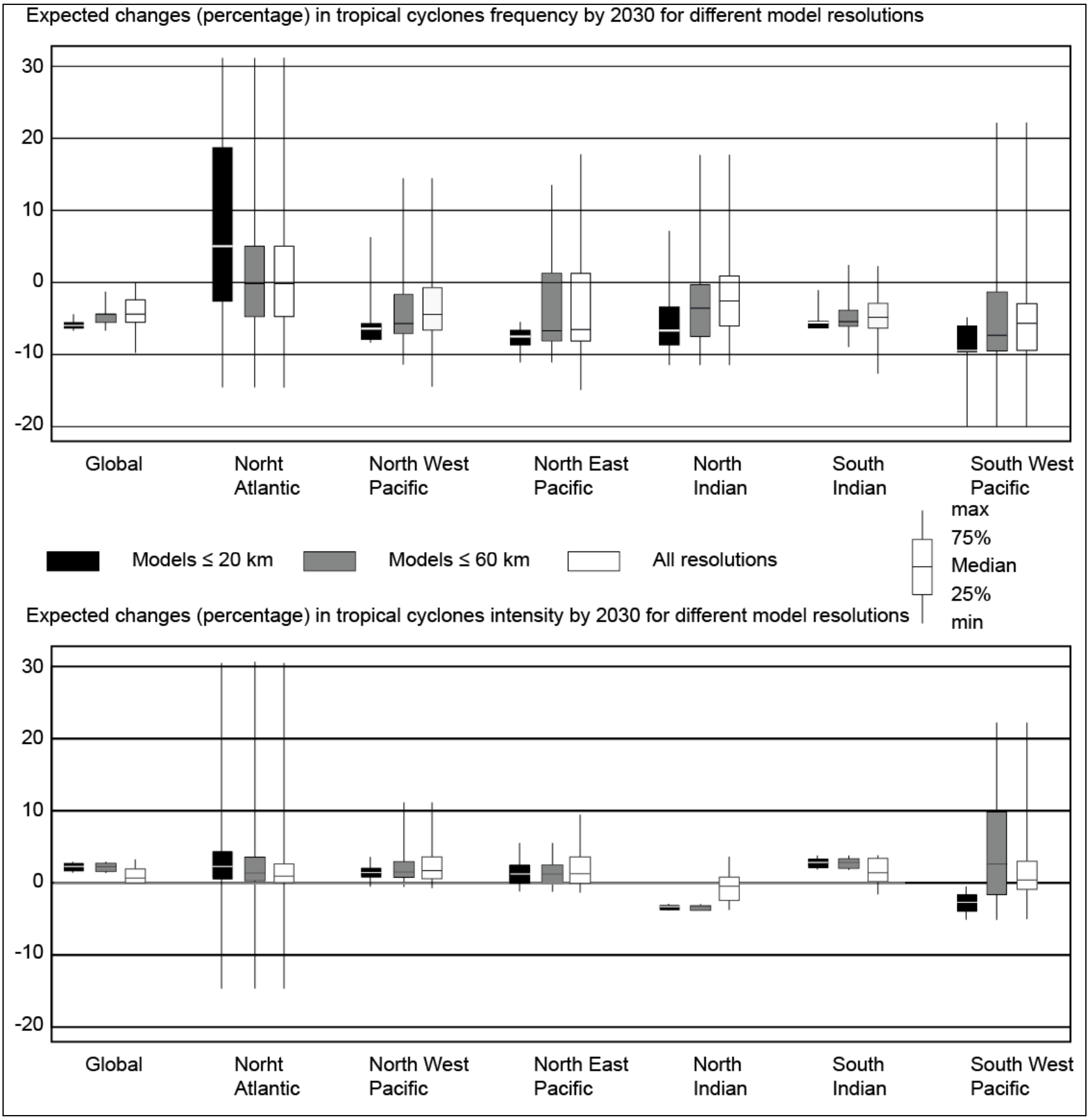


Figure S96 range of expected changed in frequency (above) and intensity (below) values for different models for 2030 (as adapted from Knutson et al. 2010)

With an increase in intensity, a percentage of TC category 1 will be more intense and thus a portion of them will be of category 2. However, a portion of category two will also be more intense and thus will be category 3. For the purpose of a first estimation of influence in change in intensity a simplification was used and the influence of intensity change on TC number of each category was computed as follows:

$$TC_a^y = TC_{(a-1)} \cdot (1 + \Delta i) + TC_a - TC_a \cdot (1 + \Delta i) \quad \text{(S12)}$$

Equation S18 Estimation of expected new number of TC by Saffir-Simpson category.

Where:

TC = Global average number of Tropical Cyclones per year
y = Future year considered, e.g. 2030.
a = Category of Saffir-Simpson intensity
Δi = Percentage of intensity change (e.g. +0.4% or +2.4%)

These values were computed for the minimum, the maximum and the median of all intensity global models.

We then looked at the average influence of the intensity on the area of land. We applied this difference in area and the difference in number of TC for each category to obtain a ratio for multiplying exposure for 2030.

The population distribution for 2030 is based on estimates from the United Nations, assuming a uniform distribution of the population increase. This is a simplification, however it is considered conservative, because coastal population have so far increased at a faster rate as compared with the average national increase. Given that the results show already a matter for concern, this is most probably below the real magnitude of increase that will be observed.

3.8.9. Tables and index

Human and economic trend exposure to TC by IPCC regions

In order to take the climate regional variation into consideration, the IPCC regions were slightly modified so that Asia is separated into Asia I (exposed to Indian Ocean TC) and Asia II (exposed to North West Pacific TC). The islands were separated in Caribbean, Indian Ocean, Pacific Ocean islands. Human exposure is based on Landscan[21] 2008™, further modified to reflect population distribution in 1970, 1980, 1990, 2000, 2010, 2020 and 2030. The economic exposure is based on a dataset designed by the World Bank (see S4 for more details).

IPCC	1970	1980	1990	2000	2010	2020	2030	Change 2030 - 2010
North America	4.3	4.8	5.4	6.1	6.7	7.3	7.8	16.30%
South America	0	0	0.1	0.1	0.1	0.1	0.1	34.40%
Caribbean	1.5	1.8	2	2.3	2.5	2.6	2.7	10.50%
Africa	0.6	0.8	1	1.3	1.7	2.2	2.7	53.80%
Asia 1	5	6.4	8	9.6	11.2	12.6	13.7	22.80%
Asia 2	67.6	80.3	92.3	102.4	110.5	117.2	121.2	9.70%
Australia and NZ	0.1	0.1	0.1	0.1	0.1	0.1	0.1	17.80%
Pacific islands	0.2	0.3	0.3	0.4	0.4	0.5	0.5	20.80%
Indian Ocean Isl	0.3	0.3	0.4	0.4	0.5	0.5	0.5	12.00%
World	**79.6**	**94.8**	**109.6**	**122.7**	**133.7**	**143.1**	**149.3**	**11.67%**

Table S31 Average yearly population exposure to tropical cyclones, assuming constant hazard (in million inhabitants)

IPCC	1970	1980	1990	2000	2010	2020	2030	Change 2030 - 2010
North America	156.5	174.9	196.1	222.3	245.2	267.2	285.3	16.4%
Central America	2.2	2.9	3.8	4.8	5.8	6.8	7.8	34.5%
Caribbean	24.9	29.2	33.7	37.9	41.5	44.6	47.1	13.5%
Africa	10.7	14	17.5	23.6	30.6	38.4	46.6	52.3%
Asia 1	154.6	196.6	247	298.1	346.1	390.4	425.7	23.0%
Asia 2	518.3	619	716.6	796	854.4	903.3	928.6	8.7%
Australia and NZ	3.5	4	4.4	4.9	5.4	5.9	6.3	16.7%
Pacific islands	1.4	1.7	2.1	2.4	2.7	3	3.3	22.2%
Indian Ocean Isl	1.5	1.8	2	2.3	2.6	2.8	3	15.4%
World	**874**	**1'044**	**1'223**	**1'392**	**1'534**	**1'662**	**1'754**	**14.3%**

Table S32 Trend in population (as modelled) living in TC prone areas, assuming constant hazard (in million inhabitants)

IPCC	1970	1980	1990	2000	2010
North America	69.2	96.7	132	182.3	214.8
Central America	0.1	0.1	0.1	0.2	0.2
Caribbean	4.6	6.8	9.5	12.5	18.9
Africa	0.2	0.2	0.3	0.3	0.5
Asia 1	1.2	1.5	2.4	4	7.8
Asia 2	465.7	746.6	1141.3	1408.9	1648.1
Australia and NZ	0.7	0.9	1.2	1.7	2.2
Pacific islands	1.2	1.8	3	4.4	5.5
Indian Ocean Isl	0.8	1.2	1.8	2.5	3.3
World	**543.7**	**855.8**	**1291.6**	**1616.8**	**1901.3**

Table S33 Average yearly Gross Domestic Product to tropical cyclones, assuming constant hazard (in billion US$)

IPCC	1970	1980	1990	2000	2010
North America	2512.7	3500.8	4775.6	6583.7	7747
Central America	3.8	5.3	6.2	8.9	12.7
Caribbean	65.2	97.2	132.4	170.4	270
Africa	3.8	4	4.3	5.5	8.3
Asia 1	37.8	48.3	80.6	134.5	261.8
Asia 2	2013.3	3213.3	4972.5	6277.5	7834.1
Australia and NZ	37.8	46.9	59	80.2	102.3
Pacific islands	6.1	8.7	14.1	19.3	24.6
Indian Ocean Isl	7.2	10.3	14	18.3	21.9
World	**4687.7**	**6934.8**	**10058.7**	**13298.3**	**16282.7**

Table S34 Trend in Gross Domestic Product (as modelled) located in TC prone areas, assuming constant hazard (in billion US$)

Exposure, Vulnerability and risk at country level

The model of risk is based on logarithmic regressions, therefore there is a large margin of error. To overcome this issue, the risk is provided in ten categories. Given that it is not possible to compare large and small countries (e.g. China and Jamaica), the results are provided for absolute numbers, for relative numbers (i.e. percentage of total) and as a combination of the two. The Figure S97 provides the legend for the category of risk.

Classes	Absolute risk (average killed per year)	Relative risk (killed per million peryear)	Mortality Risk Index (average of both indicators)
10	> 3 000	> 300	Extreme
9	1 000 to 3 000	100 to 300	Major
8	300 to 1 000	30 to 100	Very High
7	100 to 300	10 to 100	High
6	30 to 100	3 to 10	Medium high
5	10 to 30	1 to 3	Medium
4	3 to 10	0.3 to 1	Medium low
3	1 to 3	0.1 to 0.3	Low
2	0.3 to 1	0.03 to 0.1	Very Low
1	> 0 to 0.3	> 0 to 0.03	Negligible
0	0	0	Unknown exposure

Figure S97 Legend for risk in ten categories for absolute risk, relative risk and Mortality Risk Index.

ISO3	Country name	Region IPCC	Population living in TC prone area (1000 inhab.)	Population living in TC prone area (%)	GDP located in TC prone areas (mio $)	GDP located in TC prone areas (%)	Average number of people exposed in 2010	People exposed in 2010 (%)	Average GDP exposed in 2010 (mio $)	GDP exposed in 2010 (%)	Risk absolute (class)	Risk relative (class)	TC risk Index (class)
BGD	Bangladesh	Asia 1	107'166	65.18	57'384	69.5	4'147.00	2.52	2'365.20	2.86	10	7	9
VUT	Vanuatu	Pacific islands	245	100	334	100	50.2	20.46	69.3	20.74	5	8	6
MDG	Madagascar	Africa	20'107	100	5'411	100	1'365.00	6.79	388.9	7.19	7	6	6
FJI	Fiji	Pacific islands	856	100	1'868	100	149.2	17.43	328	17.56	5	7	5
DOM	Dominican Republic	Caribbean	10'225	100	32'370	100	463.2	4.53	1'490.80	4.61	6	6	6
HTI	Haiti	Caribbean	10'189	100	4'201	100	383.3	3.76	161.5	3.84	6	6	6
PHL	Philippines	Asia 2	88'991	95.07	110'565	95.46	26'075.20	27.86	31'443.30	27.15	7	5	5
MMR	Myanmar	Asia 1	24'498	48.56	11'405	52.97	836	1.66	384.4	1.79	7	5	6
IND	India	Asia 1	197'247	16.24	166'771	18.02	5'489.70	0.45	4'700.80	0.51	8	4	7
ZWE	Zimbabwe	Africa	586	4.65	183	4.18	7.5	0.06	2.3	0.05	6	5	7
MOZ	Mozambique	Africa	9'895	42.34	2'739	34.41	323.9	1.39	83.4	1.05	6	5	6
KNA	Saint Kitts and Nevis	Caribbean	52	100	400	100	5.1	9.67	38.7	9.67	3	7	5
TON	Tonga	Pacific islands	104	100	171	100	10.5	10.06	16.4	9.58	3	7	4
WSM	Samoa	Pacific islands	179	100	300	100	16.2	9.04	27	9.01	3	7	4
MUS	Mauritius	Indian Ocean islands	1'296	100	6'657	100	358.9	27.68	1'845.20	27.72	4	6	4
JPN	Japan	Asia 2	127'011	100	4'864'041	100	30'670.60	24.15	1'156'929.80	23.79	6	4	4
VNM	Viet Nam	Asia 2	66'169	74.34	52'053	83.54	3'219.70	3.62	1'635.60	2.63	6	4	5
MEX	Mexico	North America	25'193	22.8	123'049	18.77	904.4	0.82	5'159.40	0.79	6	4	5
NCL	New Caledonia	Pacific islands	253	100	3'485	100	43.8	17.32	614.7	17.64	3	6	4
ANT	Netherlands	Caribbean	201	100	3'189	100	8.2	4.07	123.4	3.87	3	6	4

ISO3	Country name	Region IPCC	Population living in TC prone area (1000 inhab.)	Population living in TC prone area (%)	GDP located in TC prone areas (mio $)	GDP located in TC prone areas (%)	Average number of people exposed in 2010	People exposed in 2010 (%)	Average GDP exposed in 2010 (mio $)	GDP exposed in 2010 (%)	Risk absolute (class)	Risk relative (class)	TC risk Index (class)
	Antilles												
BHS	Bahamas	Caribbean	345	100	7'253	100	31.3	9.05	659.5	9.09	3	6	4
JAM	Jamaica	Caribbean	2'731	100	8'747	100	228	8.35	714.5	8.17	4	5	4
CHN	China	Asia 2	456'997	34.55	1'430'936	46.21	30'254.20	2.29	100'547.80	3.25	7	2	5
VCT	Saint Vincent and the Grenadines	Caribbean	111	100	451	100	3	2.66	12	2.67	2	6	4
ATG	Antigua and Barbuda	Caribbean	89	100	912	100	9.6	10.8	98.7	10.82	2	6	4
MNP	Northern Mariana Islands	Pacific islands	88	100	3'285	100	36.2	40.94	1'344.90	40.94	2	6	3
FSM	Micronesia	Pacific islands	99	88.98	137	80.66	3.9	3.48	3.8	2.24	2	6	4
DMA	Dominica	Caribbean	67	100	324	100	3.4	5.18	16.9	5.23	2	6	4
MHL	Marshall Islands	Pacific islands	18	27.9	54	39.42	0.2	0.39	0.8	0.58	2	6	5
SLB	Solomon islands	Pacific islands	323	60.26	231	55.92	5.8	1.08	4.1	1	3	5	5
LAO	Lao	Asia 2	2'145	33.43	1'055	31.96	37.3	0.58	18.9	0.57	4	4	5
CUB	Cuba	Caribbean	11'215	100	95'719	100	718.3	6.4	6'126.50	6.4	4	4	4
NIC	Nicaragua	South America	923	15.87	717	14.01	21.7	0.37	16.9	0.33	4	4	5
AUS	Australia	Australia and New Zealand	1'730	8.07	44'898	8.36	60.3	0.28	1'528.90	0.28	4	4	5
PLW	Palau	Pacific islands	20	99.88	178	100	0.6	2.7	4.8	2.66	1	6	4
BMU	Bermuda	North America	65	100	5'302	100	7	10.71	558.8	10.54	1	6	3
BLZ	Belize	South America	311	100	1'270	100	20.9	6.71	88.1	6.94	2	5	3

ISO3	Country name	Region IPCC	Population living in TC prone area (1000 inhab.)	Population living in TC prone area (%)	GDP located in TC prone areas (mio $)	GDP located in TC prone areas (%)	Average number of people exposed in 2010	People exposed in 2010 (%)	Average GDP exposed in 2010 (mio $)	GDP exposed in 2010 (%)	Risk absolute (class)	Risk relative (class)	TC risk Index (class)
GUM	Guam	Pacific islands	180	100	6'680	100	72.3	40.21	2'686.50	40.21	2	5	2
GLP	Guadeloupe	Caribbean	467	100	6'502	100	34.4	7.36	470.3	7.23	2	5	3
BRB	Barbados	Caribbean	257	100	3'714	100	11.2	4.35	161.9	4.36	2	5	3
PRI	Puerto Rico	Caribbean	3'998	100	81'022	100	342.9	8.58	6'976.10	8.61	3	4	3
NZL	New Zealand	Australia and New Zealand	3'698	86.33	57'403	87.43	44.6	1.04	664.4	1.01	3	4	4
HND	Honduras	South America	2'641	34.71	2'836	33.63	55.6	0.73	54.2	0.64	3	4	4
PRK	Dem People's Rep of Korea	Asia 2	23'983	100	11'937	100	560.9	2.34	278.5	2.33	4	3	4
KOR	Republic of Korea	Asia 2	48'507	100	744'160	100	3364.3	6.94	50'594.10	6.8	4	3	3
USA	United States of America	North America	197'711	62.28	7'127'585	61.9	5'350.40	1.69	194'301.60	1.69	5	2	4
CYM	Cayman Islands	Caribbean	57	100	2'625	100	8.90	15.63	408.10	15.55	1	5	2
AIA	Anguilla	Caribbean	15	100	149	100	1.9	12.26	18.3	12.26	1	5	2
VIR	United States Virgin Islands	Caribbean	109	100	4069	100	13.1	11.94	485.9	11.94	1	5	3
RUS	Russian Federation	Asia 2	3506	2.49	9'595	2.38	73.2	0.05	221.2	0.05	4	2	5
PAK	Pakistan	Asia 1	12'067	6.53	7'546	6.56	158.2	0.09	92.3	0.08	4	2	4
COK	Cook Islands	Pacific islands	19	93.9	110	97.84	1	4.88	5.4	4.81	1	4	2
VGB	British Virgin Islands	Caribbean	23	100	1177	100	3.2	13.57	159.7	13.56	1	4	2
FRO	Faroe Islands	Europe	50	100	1'530	100	1.5	3.07	47	3.07	1	4	2
LKA	Sri Lanka	Asia 1	4049	19.84	3'583	13.68	64.5	0.32	57.8	0.22	3	2	4

ISO3	Country name	Region IPCC	Population living in TC prone area (1000 inhab.)	Population living in TC prone area (%)	GDP located in TC prone areas (mio $)	GDP located in TC prone areas (%)	Average number of people exposed in 2010	People exposed in 2010 (%)	Average GDP exposed in 2010 (mio $)	GDP exposed in 2010 (%)	Risk absolute (class)	Risk relative (class)	TC risk Index (class)
GTM	Guatemala	South America	426	2.96	720	2.74	5	0.04	8.5	0.03	3	2	5
TWN	Taiwan	Asia 2	23130	100	465603	100	12596.2	54.46	255064.6	54.78	3	2	2
MTQ	Martinique	Caribbean	406	100	6'344	100	33.60	8.27	524.40	8.27	1	3	2
PYF	French Polynesia	Pacific islands	257	94.23	4'701	96.88	10.8	3.97	196.1	4.04	1	3	2
ASM	American Samoa	Pacific islands	69	100	2'590	100	5.4	7.81	202.2	7.81	1	3	1.5
CRI	Costa Rica	South America	541	11.66	2'308	9.73	5.7	0.12	24.2	0.1	2	2	4
THA	Thailand	Asia 2	2'934	4.31	2'396	1.35	41	0.06	31.2	0.02	3	1	4
GBR	U.K.	Europe	15015	24.34	294564	18.12	165.7	0.27	3268.9	0.2	n.d.	n.d.	n.d.
HKG	Hong Kong	Asia 2	7389	100	131'982	50.6	1378.9	18.66	48272.5	18.51	n.d.	n.d.	n.d.
IDN	Indonesia	Asia 2	3069	1.32	1'472	0.55	36.6	0.02	17.1	0.01	n.d.	n.d.	n.d.
OMN	Oman	Asia 1	1'106	38.02	15'149	41.53	15.1	0.52	205.7	0.56	n.d.	n.d.	n.d.
REU	Réunion	Indian Ocean islands	837	100	10'515	100	110.2	13.17	1302	12.38	n.d.	n.d.	n.d.
TTO	Trinidad and Tobago	Caribbean	531	39.52	6'214	42.72	4.5	0.34	51.00	0.35	n.d.	n.d.	n.d.
MAC	Macau	Asia 2	416	100	8'232	38.98	59.3	14.26	3011.7	14.26	n.d.	n.d.	n.d.
COM	Comoros	Indian Ocean islands	271	39.23	95	37.96	2.6	0.37	0.9	0.35	n.d.	n.d.	n.d.
MYT	Mayotte	Indian Ocean islands	199	100	4'595	100	5.9	2.96	135.9	2.96	n.d.	n.d.	n.d.
LCA	Saint Lucia	Caribbean	174	100	802	100	8	4.61	37	4.61	n.d.	n.d.	n.d.
KHM	Cambodia	Asia 2	114	0.76	54	0.71	1.3	0.01	0.6	0.01	n.d.	n.d.	n.d.
ABW	Aruba	Caribbean	107	100	2'303	100	2.7	2.5	57.5	2.5	n.d.	n.d.	n.d.

ISO3	Country name	Region IPCC	Population living in TC prone area (1000 inhab.)	Population living in TC prone area (%)	GDP located in TC prone areas (mio $)	GDP located in TC prone areas (%)	Average number of people exposed in 2010	People exposed in 2010 (%)	Average GDP exposed in 2010 (mio $)	GDP exposed in 2010 (%)	Risk absolute (class)	Risk relative (class)	TC risk Index (class)
GRD	Grenada	Caribbean	104	100	424	100	3.1	2.99	12.7	2.99	n.d.	n.d.	n.d.
IMN	Isle of Man	Europe	80	100	2'160	100	1	1.27	27.4	1.27	n.d.	n.d.	n.d.
TCA	Turks and Caicos islands	Caribbean	33	100	1'006	100	2.1	6.4	65.7	6.53	n.d.	n.d.	n.d.
PNG	Papua New Guinea	Asia 2	25	0.37	10	0.21	0.5	0.01	0.20	0	n.d.	n.d.	n.d.
WLF	Wallis and Fortuna	Pacific islands	16	100	339	100	0.8	5.23	17.8	5.24	n.d.	n.d.	n.d.
SPM	Saint Pierre et Miquelon	North America	6	100	137	100	0.4	7.37	10.1	7.36	n.d.	n.d.	n.d.
MSR	Montserrat	Caribbean	6	100	39	100	0.5	8.22	3.2	8.22	n.d.	n.d.	n.d.
TUV	Tuvalu	Pacific islands	5	51.13	4	23.27	0.1	0.72	0	0.28	n.d.	n.d.	n.d.
NFK	Norfolk Island	Pacific islands	2	100	45	100	0	1.59	0.7	1.6	n.d.	n.d.	n.d.
NIU	Niue	Pacific islands	1	100	19	100	0.2	11.71	2.2	11.71	n.d.	n.d.	n.d.
TKL	Tokelau	Pacific islands	1	100	12	100	0	1.88	0.2	1.8	n.d.	n.d.	n.d.
CCK	Cocos (Keeling) Islands	Pacific islands	1	100	16	100	0	4.61	0.7	4.59	n.d.	n.d.	n.d.
MSR	Montserrat	Caribbean	6	100	39	100	0.5	8.22	3.2	8.22	n.d.	n.d.	n.d.
TUV	Tuvalu	Pacific islands	5	51.13	4	23.27	0.1	0.72	0.00	0.28	n.d.	n.d.	n.d.
NFK	Norfolk Island	Pacific islands	2	100	45	100	0	1.59	0.7	1.6	n.d.	n.d.	n.d.

Table S35 Exposure, Vulnerability and risk, values aggregated at country level. For several countries and territories (mostly islands), some missing variables prevented the computation of the risk (see n.d. in the table)

3.8.10. References

1. IBTrACS v02r01, NCDC *International Best Track Archive for Climate Stewardship Project*. Since Sept. 2010, a new dataset exist. IBTrACS: http://www.ncdc.noaa.gov/oa/ibtracs/
2. Holland, G. J. An analytic model of the wind and pressure profiles in hurricanes, *Mon. Wea. Rev*, **108**, 1212-1218 (1980).
3. Landscan, Oak Ridge National Laboratory, http://www.ornl.gov/sci/landscan/
4. Balk, D., Pozzi, F., Yetman, G. Global Rural-Urban Mapping Project (GRUMP alpha), CIESIN, Columbia University, 2011. http://sedac.ciesin.columbia.edu/gpw/global.jsp, last consulted June 2011.
5. Peduzzi, P., Dao, H. and Herold, C. Mapping disastrous natural hazards using global datasets, *Nat. Haz.*, **35**, 265–289 (2005).
6. Japan Meteorological Agency (JMA): http://www.jma.go.jp/jma/jma-eng/jma-center/rsmc-hp-pub-eg/trackarchives.html
7. Joint Typhoon Warning Center (JTWC): http://www.usno.navy.mil/NOOC/nmfc-ph/RSS/jtwc/best_tracks/
8. UNISYS, Hurricane/Tropical Data: http://weather.unisys.com/hurricane/
9. Meteo france: http://www.meteo.fr/temps/domtom/La_Reunion/webcmrs9.0/anglais/index.html
10. Alan Sharp, personal communication.
11. Herold, C., Mouton, F. Global flood hazard mapping using statistical peak flow estimates, *Hydrol. Earth Syst. Sci.* (in prep.).
12. Nadim, F., Kjekstad, O., Peduzzi, P., Herold, C., Jaedicke, C., Global landslide and avalanche hotspots, *Landslides*, **3** (2), 159-173 (2006).
13. Schloemer, R.W., (1954). Analysis and synthesis of hurricane wind patterns over Lake Okehoee, *FL. Hydromet Rep.* **31**, 49 pp. [Govt. Printing Office, No. C30.70:31].
14. Holland , G. J. Survey of Current Risk Models: Horizontal Winds, RPI Technical Reports: Hurricane Winds Over Land: Recommendations for Research, 28-30 May 1997. http://www.bios.edu/rpi/public/pubs/pre2000/paper/landmain.html
15. Nordbeck, O., Mouton, F., Peduzzi, P. Cyclone Data Manager: A tool for converting point data from cyclones observations into tracks and windspeed profiles in a GIS. UNEP/GRID-Europe (2005). http://www.grid.unep.ch/product/publication/download/article_PREVIEW_TropCyclones.pdf
16. National Oceanic and Atmospheric Administration (NOAA), The Saffir-Simpson Hurricane Wind Scale Summary Table, National Hurricane Center. http://www.nhc.noaa.gov/sshws_table.shtml
17. Landsea, C.W., Harper, B.A. , Hoarau, K. , Kaff, J. . Can we detect trends in extreme tropical cyclones?, *Science*, **313**, 452-454 (2006).
18. Holland, G. A revised hurricane pressure-wind model, *Mon. Wea. Rev*, **136**, 3432-3445, (2008).
19. Willoughby, H. E., Rahn, M. E. Parametric Representation of the Primary Hurricane Vortex. Part I: Observations and Evaluation of the Holland (1980) Model. *Mon. Wea. Rev.*, **132**, 3033–3048 (2004).
20. Willoughby, H.E., Rahn,M.E., Darling, R.W.R. Parametric Representation of the Primary Hurricane Vortex. Part II: A New Family of Sectionally Continuous Profiles, *Mon. Wea. Rev.*, **134**, 1102-1120 (2006).
21. LandScan™ Global, Oak Ridge National Laboratory, http://www.ornl.gov/sci/landscan/
22. Bell, G. D., and Chelliah, M. Leading Tropical Modes Associated with Interannual and Multidecadal Fluctuations in North Atlantic Hurricane Activity*, Journal of Climate* **19**(4), 590-612 (2006).
23. Chan, J. C. L. Comment on "Changes in tropical cyclone number, duration, and intensity in a warming environment". *Sciences*, **311**, 1713b (2006).
24. Emanuel, K. Increasing destructiveness of tropical cyclones over the past 30 years, *Nature*, **436** (4), 686-688 (2005).
25. Kofron, D.E., Ritchie, E.A. & Tyo, J.S. Determination of a Consistent Time for the Extratropical Transition of Tropical Cyclones. Part I: Examination of Existing Methods for Finding "ET Time."*Mon. Wea. Rev.* **138**, 4328-4343 (2010).
26. Evans, J.L. & Hart, R.E. Objective Indicators of the Life Cycle Evolution of Extratropical Transition for Atlantic Tropical Cyclones. *Mon. Wea. Rev.* **131**, 909-925 (2003).
27. OFDA/CRED International Disaster Database, from the Centre for Research on the Epidemiology of Disasters (CRED), Université Catholique de Louvain (sources: www.emdat.be).
28. Peduzzi, P., Dao H., Herold, C. Mapping Disastrous Natural Hazards Using Global Datasets, *Natural Hazards*, **35** (2), 265 – 289 (2005).
29. Relief Web: http://www.reliefweb.int/rw/dbc.nsf/doc100?OpenForm
30. Geographic Studies Branch, US Bureau of Census to allocate population counts within administrative units http://www.ornl.gov/sci/landscan/landscan_documentation.shtml
31. UNEP GEO Data Portal (http://geodata.grid.unep.ch)
32. UNISDR, terminology, Preventionweb, http://www.preventionweb.net/english/professional/terminology/?pid:6&pih:2, last checked: 27 April 2011.
33. Shultz, J. M., Russell, J., and Espine, Z. Epidemiology of Tropical Cyclones: The Dynamics of Disaster, Disease, and

Development, *Epidemiologic Reviews*, **27**, 21-35 (2005).

34. SRTM: The Shuttle Radar Topography Mission Global. 90m Digital Elevation Database v4.1 http://www.cgiar-csi.org/data/elevation/item/45-srtm-90m-digital-elevation-database-v41, last checked October 2011.
35. Tobin, G.A. & Montz, B.E., *Natural Hazards: explanation and integration*, Guilford Press, London, 2007.
36. Burton, I., Kates, R.W. and White, G.F., *The Environment as Hazard, Second Edition.* New York/London: Guilford Press, 290 pp., 1993.
37. Blaikie, P. *et al.*, *At Risk: Natural Hazards, Peoples Vulnerability and Disasters* (Routledge), 284 p., 1996.
38. Coburn, A.W., Spence R.J.S., Pomonis A., Vulnerability and risk assessment. *UNDP Disaster Management Training Program*, **57**, 1997, p.49.
39. UNDRO (United Nations Disater Relief Coordinator). Natural disasters and vulnerability: analysis in Report of Expert Group Meeting (9-12 July 1979). Geneva, UNDRO. 49 pp. (1979)
40. Blaikie, P., T. Cannon, I. Davis, and B. Wisner. 1994. *At Risk: Natural Hazards, People's Vulnerability, and Disasters*. London: Routledge (1994).
41. Wisner, B., Blaikie, P., Cannon, T. and Davis, I. *At risk, natural hazards, people's vulnerability and disasters*, (2nd ed.). London: Routledge (2004)
42. Peduzzi, P., Dao, H., Herold, C., and Mouton, F.: Assessing global exposure and vulnerability towards natural hazards: the Disaster Risk Index, *Nat. Hazards Earth Syst. Sci.*, **9**, 1149-1159 (2009).
43. Cohn, T.A., DeLong, L.L., gilroy, E.J., Hirsch, R.M., and Wells, D.K., Estimating constituent loads, *Water Resourcse Research*, **25**, 937-942, (1989).
44. Gilroy, E. J., R. M. Hirsch, and T. A. Cohn, Mean Square Error of Regression-Based Constituent Transport Estimates, *Water Resources Research*, **26**(9), 2069-2077, (1990).
45. Stow, C.A., Reckhow, K.H., Qian, S.S., A Bayesian approach to retransformation bias in transformed regression, *Ecology*, **87**(6), 1472-1477, (2006).
46. Knutson, T.R., McBride, J.L., Chan, J., Emanuel, K., Holland, G., Landsea, C., Held, I., Kossin, J.P., Srivastava, A. K. & Sugi, M. Tropical cyclones and climate change, *Nature Geoscience*, **3**, 157 - 163 (2010).
47. Emanuel, K.A., A statistical analysis of tropical cyclone intensity. *Mon. Wea. Rev.* **128**, 1139-1152 (2000).

3.9. Other references for chapter 3

Birkmann, J., and others, *Measuring Vulnerability to natural hazards, towards disaster resilient societies*, United Nations University, 527 p., TERI Press, New Delhi, India, 2006.

Burton, I., Kates, R.W. and White, G.F., *The Environment as Hazard*, 2nd Edition. New York/London: Guilford Press, 290 pp., 1993.

Blake, E.S., Landsea, C.W., Gibney, E.J., The deadliest, costliest, and most intense united states tropical cyclones from 1851 to 2010 (and other frequently requested hurricane facts), National weather Service, National Hurricane Centre, Miami, Florida, 2011. http://www.nhc.noaa.gov/pdf/nws-nhc-6.pdf

Cardona, O.D., *Indicators for Disaster Risk and Risk Management. Program for Latin America and the Caribbean: Summary Report*, Manizales, Columbia: Instituto de Estudios Ambientales, Universidad Nacional de Columbia, 2005.

Dao, H., Peduzzi, P.: Global evaluation of human risk and vulnerability to natural hazards, *Enviroinfo 2004*, Sh@ring, Editions du Tricorne, Genève, **1** , 435-446, 2004.

Dilley, M., Chen, R.S., Deichmann, U.Lerner-Lam, A.L., Arnold, M., Agwe, J., Buys, P., Kjekstad, O., Lyon, B., Yetman, G., *Natural disaster hotspots: a global risk analysis*, World Bank Publications, 2005.

EM-DAT: The OFDA/CRED International Disaster Database, Université Catholique de Louvain, Brussels (Belgium). http://www.emdat.be, last consulted September 2011.

Giuliani, G. and Peduzzi, P., The PREVIEW Global Risk Data Platform: A geoportal to serve and share global data on risk to natural hazards, a geoportal to serve and share global data on risk to natural hazards, *Nat. Hazards Earth Syst. Sci.*, **11**, 53–66, 2011.

Hall, W., Social class and survival on the S.S. Titanic, *Soc. Sci. Med.* **22**(6), 687-690, 1986.

Peduzzi, P., Dao, H., Herold, C., 2005: Mapping disastrous natural hazards using hlobal datasets , *Natural Hazards*, **35**(2), 265-289.

Peduzzi, P., Deichmann, U., Maskrey, A., Nadim, F., Dao, H., Chatenoux, B., Herold, C., Debono, A., Giuliani, G., Kluser, S., *et al.*, Global disaster risk: patterns, trends and drivers, *ISDR (2009) Global Assessment Report on Disaster Risk Reduction*, United Nations, Geneva, Switzerland, chapter 2, pp. 17-57, 2009.

Peduzzi, P., *Insight on common/key indicators for Global Vulnerability Mapping*, presentation at the UNDP Expert Meeting on Vulnerability and Risk Analysis and Indexing, Geneva 11-12 September 2000, on-line report, UNEP/GRID-Geneva, 12 pp., 2000. http://www.grid.unep.ch/product/publication/download/article_vul_risk.pdf, last accessed: April 2011.

Peduzzi, P., The Disaster Risk Index: Overview of a quantitative approach, *Measuring Vulnerability to Natural hazards*, 171-181, United Nations University, United Nations University Press, Tokyo, New York, Paris, 524 pp., 2006.

Peduzzi, P., Dao, H., Herold, C., and Mouton, F.: Assessing global exposure and vulnerability towards natural hazards: the Disaster Risk Index, *Nat. Hazards Earth Syst. Sci*., **9**, 1149-1159, 2009.

UNDP, *Reducing Disaster Risk: a challenge for development*, United Nations Development Programme, Bureau for Crisis Prevention and Recovery, 146 p., New York, NY 10017, USA, 2004.

Warhurst, A., Disaster prevention : a role for business ?, Maplecroft, Prevention consortium, 2006. http://www.proventionconsortium.org/themes/default/pdfs/business_case_DRR.pdf, last accessed : September 2011.

Chapter 4 Quantifying Impacts from ecosystems decline and climate change on disaster risk

Identifying disaster risk at the global level is needed for raising awareness. The indexes developed and the GAR report are advocacy tools and they can be used for prioritizing actions in Disaster Risk Reduction. However, the global level cannot tell the full story.

In the DRI, the level of development was clearly shown: Haiti and Dominican Republic, despite being located on the same island and thus affected by the same tropical cyclones events have different vulnerability. Haiti has a vulnerability proxy (killed per exposed) 4.5 higher as compared with Dominican Republic. However, what if – in this case – the rate of deforestation was more important than the level of development? (see Figure 98).

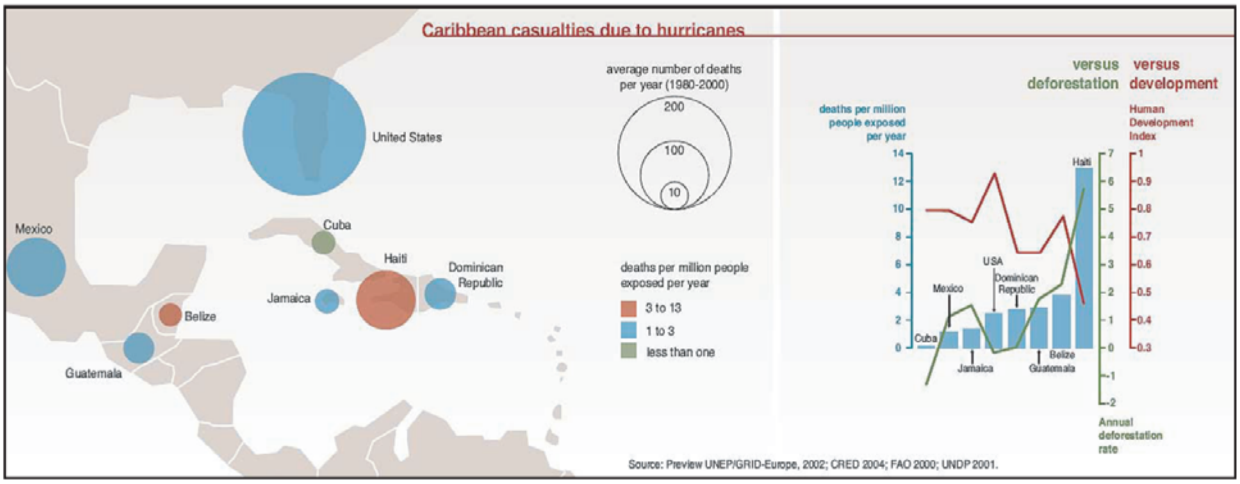


Figure 98 Killed from tropical cyclones in the USA, Caribbean and central America, level of developments or deforestation?

Sources : Peduzzi, 2005

Although not highlighted in this study, the difference in forest coverage between Haiti and Dominican Republic (3,2% and 28.4% respectively in 2000) may be determinant factor explaining part of the difference in risk (Peduzzi, 2005). Also there are no or little mangroves left in Haiti, compared with 69,600 hectares in the Dominican Republic (Peduzzi, 2005).

Reducing disaster risk requests actions at the local level, hence to convince local authorities and stakeholders. National level values (e.g. percentage of deforestation), are not sufficiently located to make the link between the role of ecosystems and risk. Raising awareness on the role of climate change, ecosystems decline and risk, request studies at much better resolution. The tools used at the global level (GIS for extraction of data, multiple regression analysis for identification of weight for each parameters and modelling using GIS), were adapted and modified so that they can be applied at more local level.

Another innovation in these studies is the use of remote sensing for acquiring missing data (as well as archive data), such as the glaciated area (in part 4.2); vegetation density, deforestation, size of landslides (in part 4.4) or classification of marine and coastal features (UNEP, 2010; Peduzzi *et al.*, in prep.). The idea is to ascertain whether the tools and methodologies which worked for identifying the underlying factors of risk at global level related to rapid onset hazards, are also efficient for quantifying the impacts from change in climate conditions or decline of ecosystems.

In order to understand how climate change and the decline of ecosystems may exacerbate risk, several methodologies are presented here. The understanding of the multiple interactions between climate, decline of ecosystems and societal impacts requests a holistic and integrated approach. This is difficult to achieve, and beyond the scope of this thesis. One way to achieve this, is to study the overall systems by watersheds. Hence, looking at issues from the highest elevation, down to the coastal zone. This kind of approach can be called Hill to Ocean (H_2O) or from Ridge to Reef (see GEF, 2004). Watershed approach might be - in some cases - transboundary, however such approach allows for a comprehensive understanding on environmental and societal issues. In this thesis, several tools and methodologies are being tested for different strata of watershed.

Highlands, glacier retreat and threat on water supply (in part 4.2)

This range from high altitude studies on the impacts of climate change on water supply, analysing trend in glacier retreat and modelling remaining ice volume as an example of methodology for highlands.

Hills and mountains: deforestation and susceptibility of landslides (see in part 4.4)

Further down the hills, a study on the potential impacts of deforestation on landslide susceptibility is provided as an example of methodology for hills and mountains.

This is not yet an integrated approach, but it presents different attempts at developing new methodologies for addressing these issues in a scientific and quantitative way. The purpose is to offer innovative advocacy tools and for awareness raising. Other researches using similar approaches have already addressed coastal zones issues (Chatenoux and Peduzzi, 2007; UNEP, 2010; Peduzzi *et al.*, in prep.).

4.1. References

Chatenoux, B., and Peduzzi, P.: Impacts from the 2004 Indian Ocean tsunami: analysing the potential protecting role of environmental features, *Natural Hazards*, **40**, 289-304, 2007.

GEF, 2004: *From Ridge to Reef, water, environment, and community security*, GEF Action on transboundary water resources, Global Environment Facility, 78 pp. http://www.thegef.org/gef/sites/thegef.org/files/publication/GEF_RidgetoReef_CRA_lores.pdf, last accessed: 27 April 2011.

Peduzzi, P.,: Tropical cyclones: paying a high price for environmental destruction, *Environment & Poverty Times,* ***3***, 3, Special Edition for the World Conference on Disaster Reduction January 18-22, United Nations Environment Programme, Kobe, Japan, 2005.

Peduzzi, P., Velegrakis, A., Chatenoux, B., Quantifying the role of marine ecosystems in reducing coastal erosion: the RiVAMP study in Negril Jamaica, in prep.

UNEP, PIOJ, 2010: *Risk and Vulnerability Assessment Methodology Development Project (RiVAMP), Linking Ecosystems to Risk and Vulnerability Reduction: The Case of Jamaica. Results of the Pilot Assessment*, United Nations Environment Programme, Planning Institute of Jamaica, 130 pp.

.

The Cryosphere, 4, 313–323, 2010
www.the-cryosphere.net/4/313/2010/
doi:10.5194/tc-4-313-2010

4.2. *Assessing high altitude glacier thickness, volume and area changes using field, GIS and remote sensing techniques: The case of Nevado Coropuna (Peru).*

Pascal Peduzzi[1, 2], Christian Herold[1] and Walter Silverio[3]
[1] United Nations Environment Programme, GRID-Europe, Global Change & Vulnerability Unit, 1219 Châtelaine, Switzerland}
[2] Institute of Geomatics and Risk Analysis (IGAR), University of Lausanne, Switzerland}
[3] University of Geneva, Climatic Change and Climate Impacts Research Group, Institute for Environmental Sciences, University of Geneva, Switzerland}
Correspondence to: P. Peduzzi (Pascal.Peduzzi@unepgrid.ch)
Received: 6 July 2009 – Published in The Cryosphere Discuss.: 6 October 2009
Revised: 5 August 2010 – Accepted: 6 August 2010 – Published: 23 August 2010

Status: published

References: Peduzzi, P., Herold, C., and Silverio, W.: Assessing high altitude glacier thickness, volume and area changes using field, GIS and remote sensing techniques: the case of Nevado Coropuna (Peru), The Cryosphere, 4, 313-323, doi:10.5194/tc-4-313-2010, 2010.

Can be accessed at:

http://www.the-cryosphere.net/4/313/2010/tc-4-313-2010.html

Abstract: Higher temperatures and changes in precipitation patterns have induced an acute decrease in Andean glaciers, thus leading to additional stress on water supply. To adapt to climate changes, local governments need information on the rate of glacier area and volume losses and on current ice thickness. Remote sensing analyses of Coropuna glacier (Peru) delineate an acute glaciated area decline between 1955 and 2008. We tested how volume changes can be estimated with remote sensing and GIS techniques using digital elevation models derived from both topographic maps and satellite images. Ice thickness was measured in 2004 using a Ground Penetrating Radar coupled with a Ground Positioning System during a field expedition. It provided profiles of ice thickness on different slopes, orientations and altitudes. These were used to model the current glacier volume using Geographical Information System and statistical multiple regression techniques. The results revealed a significant glacier volume loss; however the uncertainty is higher than the measured volume loss. We also provided an estimate of the remaining volume. The field study provided the scientific evidence needed by COPASA, a local Peruvian NGO, and GTZ, the German international cooperation agency, in order to alert local governments and communities and guide them in adopting new climate change adaptation policies.

4.2.1. *Introduction*

General context

Changes in glaciers and ice caps are good indicators of climate change (Zemp *et al.*, 2008) and the current trend shows that a majority of the world glaciers have undergone a reduction in their mass at an accelerating rate. The mass loss was greater in the period 1990/91 to 2003/04 than in the previous period 1960/61 to 1989/90 (Bates *et al.*, 2008). This is of concern given that about one-sixth of the world's population depend on glacier and snow melting for their water supply (Bradley *et al.*, 2006).

In Peru, the population growth and rising water demand for agriculture, domestic and economic activities generate an increased pressure on water resources. As the rainy season is concentrated during four months of the year, the role of glaciers is crucial for spreading out the water supply during the dry season. Higher limit between rain and snow precipitation reduces the buffering role of ice and snow, thus increasing flood risk during the wet season and reducing dry-season water supplies. This is of concern particularly in China, India and Asia, but also in the South American Andes, where a large fraction of the population relies on the glacial melt for water supply and hydropower (Barnett *et al.*, 2005). In the South American region, the glacier monitoring for the period 1970 – 1996 revealed an acute retreat of Andean glaciers, with glacier coverage decreasing from 725 km^2 in 1970 to 600 km^2 in 1996 in Cordillera Blanca, Peru (Silverio and Jaquet, 2005).

4.2.2. Assessing change of ice volume in Nevado Coropuna, Peru (6446 m above sea level)

The present study on the Coropuna Glacier was made at the request of the *Cooperación Peruana Alemana de Seguridad Alimentaria* (COPASA) Special Project of Arequipa Regional Government, in collaboration with the Deutsche Gesellschaft für Technische Zusammenarbeit (GTZ). They asked for scientific-based evidence of glacier area and volume changes, in order to assess whether climate change adaptation policies on water supply should be introduced at local government and communities levels.

The study was carried out by a team from UNEP/GRID-Europe and the University of Geneva. It assessed glacial retreat using both satellite imagery analysis and in situ measurements of the Coropuna Glacier.

This paper describes how glacier area was monitored through time and how to measure the change in volume of the glacier using different Digital Elevation Models (DEMs) as well as evaluate the current (2004) ice thickness. To this end, a field mission was carried out using a Ground Penetrating Radar (GPR) coupled with a Ground Positioning System (GPS). It provided profiles of ice thickness on different slopes, orientations and altitudes. These profiles were used for modelling the entire remaining glacier volume using Geographical Information System (GIS) and statistical multiple regression techniques.

Given the limited financial resources of the local governments and development organisations in Peru, simple and low-cost techniques to measure changes in glacier volume and the remaining ice volume were needed. The purpose of this paper is to test how, with limited budgets and using locally available hardware, scientific evidence of glacier area and volume variation as well as ice thickness can be obtained.

4.2.3. Study area and data sources

Study area

The Coropuna Glacier is the third highest summit in Peru, culminating at 6,446m. It is located at 15.546° S, 72.660° W, about 155 km northwest of the city of Arequipa (Figure 99). According to COPASA staff, 8,000 people depend on the Coropuna Glacier for their water supply and it is estimated that 30,000 people depend indirectly on the glacier for their livelihoods.

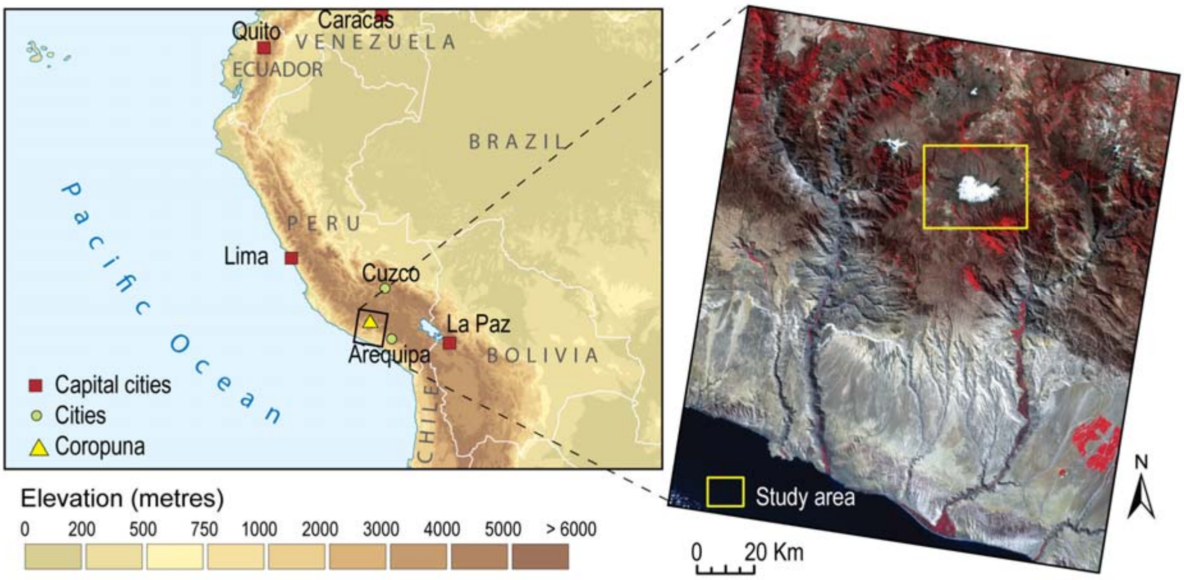


Figure 99 Location map and study area with 2003 Landsat 7 satellite image (band 2, 3, 4)

The study area covered 577 Km^2 around the Coropuna summit. This area includes the entire glacier surface as observed in 1955. A base camp was set up at 5,664 m, and ground measurements were collected at altitudes ranging between 5,870 and 6,446 m (see Figure 100).

4.2.4. Data sources

Passive satellite sensors images

To compute the difference in glaciers area loss we used a topographic map for the area in 1955 and four images from 1980, 1996, 2003 and 2008 (see Table 36). Only cloud-free images were used. Except the image 2003, which is still early in the season (May) and might still have some snow, all the others are taken far from the snow season.

Table 36 Data source for monitoring glaciated area

Image	Acquisition date
Topographic map	1955
Landsat-2 MSS	6 Nov. 1980
Landsat-5 TM	12 Jun. 1996
Landsat-7 ETM	7 May 2003
ASTER	25 Sept. 2008

Digital Elevation Models

In order to estimate the ice volume loss between 1955 and 2002, four Digital Elevation Models (DEMs) from different years were considered. Although eight DEMs in total were available for Coropuna, the period of data acquisition was the first criterion considered for selection to ensure adequate time span between datasets. The quality of the dataset was the second criterion. Four DEMs were thus selected from the following years: 1955, 1997, 2000 and 2002.

The DEM 1955 was generated by manually digitising the elevation contour lines from the topographic map of 1955. The DEM 1997 was purchased from the company SARMAP which produced it based on a pair of ERS-1 Synthetic Aperture Radar (SAR), a satellite from the European Space Agency. The DEM 2000 was based on radar measurements from the NASA Shuttle Radar Topographic Mission (SRTM, version 3). The DEM 2002 was derived from ASTER satellite data, DEM provided by United States Geological Survey (USGS) (see Table 37).

Table 37 Sources and general information for the Digital Elevation Models

DEM Year	DEM Month	Horizontal resolution	Proportion of no data	Sources
1955	Unknown	1 : 100 000	0 %	Instituto Geográfico Nacional de Peru. Printed map.
1997	October	25 m	24 %	SARMAP (http://www.sarmap.ch) based on ESA, ERS-1 SAR satellite images.
2000	February	90m	0 %	CGIAR, NASA / SRTM (version 3), downloaded from http://srtm.csi.cgiar.org/
2002	May	30 m	0 %	USGS, based on ASTER satellite image. https://lpdaac.usgs.gov/lpdaac/get_data/

Field measurements

The purpose of the expedition was to measure the depth of the ice as well as taking GPS points for the adjustment of the DEMs. The 14 day-mission was undertaken between 13 and 26 August 2004. The team was composed of two scientists and 11 support staff.

The scientific instruments were chosen based on local availability (as opposed to most efficient). The GPR Ramac X3M included a 100 MHz shielded antennas. Much lighter GPR exist; however, it was the only GPR available in Arequipa. Three Global Positioning System receptors (GPS) and two regular office laptops for controlling the GPR unit and recording the data were used. Due to the limitations of the computer's hard disk at low pressure conditions (the reading heads would touch the disks and damage them), hard disks were removed. Computers and software were booted on CDs, and measurements were recorded on USB cards.

4.2.5. Methodology

Estimation of ice thickness

Measuring the ice thickness was achieved using the GPR, with a sampling frequency of 438 MHz. Technical settings are specified inTable 38. The signal was assumed to travel through ice at 0.16 m/ns +/- 0.01 m/ns according to other studies performed in similar conditions (Gruber, Ludwig and Moore, 1996; Moorman and Michel, 2000; Descloitres *et al.* 1999). The depth of ice can be measured by recording the time lag between the emission and the reception of the signal (see Equation 19)

$$I = \frac{TC}{2} \qquad \text{Equation 19}$$

Where

I = Ice thickness [m]

T = Time [ns]

C = Speed of propagation through ice of the signal (0.16 [m/ns])

For example a time lag of 2000 ns = 160 m of ice thickness.

Table 38 GPR settings

Record parameters	Settings
Sampling frequency	438 MHz
Number of stacks	16
Time window	2055 ns
Trace interval	2 seconds
Antenna separation	0.5 metres

Each recorded depth was coupled with geographical coordinates obtained by a GPS so that the profiles could be geo-referenced and speed of radar over ground computed (given that for each GPS location, the time is also recorded). Due to time and access constraints, it was not possible to achieve a comprehensive coverage of the glaciated area. Instead, the mission proceeded along transects (shown on Figure 100). The selected transects were chosen to provide samples including different altitudes, slopes, and aspects (slope orientation). We proposed (and tested) the hypothesis that these three variables would explain most of the ice thickness. Using multiple regression analysis, depth was modelled in areas where no measurements were taken.

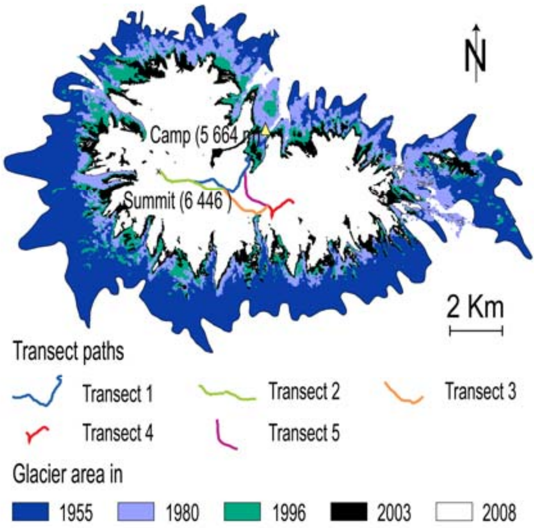


Figure 100 Georeferenced radar profiles and evolution of glaciated area (1955 – 2008).

During the mission, 10.6 km of transects were obtained from the GPR. Figure 100 shows the radar profiles. A GPR signal was recorded every two seconds, and a GPS location with hours, minutes and seconds approximately every 2 minutes. It was then possible to link GPS point with profile traces and accurately geo-reference the profiles. GPR transects were processed using the software “Reflex”, “Ground Vision” and “Kingdom Suite” to estimate ice depth. Due to the computer configuration that limited recording time windows, the bedrock was sometimes too deep to be detected (typically in volcanic craters, see Figure 107). However, as an approximation, profiles can be extrapolated by following ice stratification.

4.2.6. Estimation of ice volume loss

Although passive satellite sensors, such as Landsat TM, provide an estimate of the area covered by ice (see Figure 100) passive sensors do not provide information on the changes in ice thickness. However, the difference of ice volume may be estimated by using DEM time series.

Adjustment and corrections

The DEM from the 1955 topographic map, as explained in 2.2.1, was generated using elevation contour lines, which are not continuous; thus, a linear interpolation was applied to generate an average slope between elevation contour lines.

In order to compare the different DEMs, several operations were needed. Firstly, all the DEMs were re-sampled to 30 m to compensate for different spatial resolutions. They were then reprojected in Universal Transverse Mercator (UTM), projection 18 south, datum WGS84. Finally, they were geo-referenced so that they could be overlaid. This was performed using 32 control points, such as summits located outside the glacier area (on bare rocks).

The vertical accuracy of available digital elevation models remains very low. However in the case of this study, we are not interested in knowing with precision the altitude of a specific location, but the relative difference in altitudes between a series of DEMs taken at different dates. Hence, all the DEMs were transformed to optimise match with the reference DEM of 1955.

Previous studies highlighted the issue of DEMs such as ASTER or SRTM which appear to have a bias following altitude (Berthier *et al.*, 2004) or reveal significant errors when applied to rugged terrain and steep slopes (Kääb *et al.*, 2002). In all DEMs, a reference area was chosen on surfaces that were not covered by ice, snow or vegetation (i.e. rocky or bare ground). This corresponds to the area outside the glaciated area of 1955. A sample of 1009 points located on an ellipse outside the glaciated areas was used to extract information on easting (X), northing (Y), elevation, slope and aspect (slope orientation). These factors proved to influence the DEM errors in other studies (Gorokhovich and Voustianiouk, 2006). To verify whether the DEMs used were well-adjusted, the differences in altitude were computed against the reference area (DEM 2000 - DEM 1955; DEM 1997 - DEM 1955 and DEM 2002 – DEM 1955).

Then the differences between DEMs were plotted in 3D along with X and Y. Despite the fact that the DEMs are all in the same geographic projection, Figure 101 shows that they are not in the same plan, with DEM 1997 having the least distortions and DEM 2002 (ASTER) showing the worst distortion. If the DEMs are not in the same plan, a change in latitude and longitude can significantly influence the difference in elevation

This can be corrected using the following linear regression (see Equation 2):

$$DEMt = DEM - (aX + bY + c) \qquad \text{Equation 2}$$

Where DEMt is the new values corrected for the X and Y. The weights a, b, c used to correct the DEMs are provided in Table 39.

Table 39 Weights used to place the DEMs in the same plan as DEM 1955

	a	b	C
DEM 1997	0.00027	- 0.00115	9315
DEM 2000	0.00018	- 0.00218	17958
DEM 2002	-0.00111	-0.00420	35643

After this first correction, there were still some bias induced by aspect and elevation. To correct these, a quadratic equation was applied. The aspect variable was transformed by taking the cosine of the angle (expressed in radians). This is necessary as an orientation of 359° is close to an orientation of 1°.

This distortion from elevation and aspect was corrected using Equation 3:

$$DEMt2 = DEMt - (aEl + b\cos(As) + cEl \cdot \cos(As) + dEl^2 + e(\cos(As))^2 + f)$$

Equation 3

Where:

DEMt2 = DEMt further corrected with elevations and cosine of the aspects

El = Elevation

As = Aspect (slope orientation)

This second correction really improved the DEM 2002 (see

Table 40), while for the DEM 1997 and the DEM 2000, the standard deviation increased, so the second correction was not applied to them. The weights used to obtain the DEM2002t2 were as followed: a = 0.1455, b = 0.0012, c = -1.765*10-5, d = 9.843*10-8, e = 1.327*10-8 and f = -297.

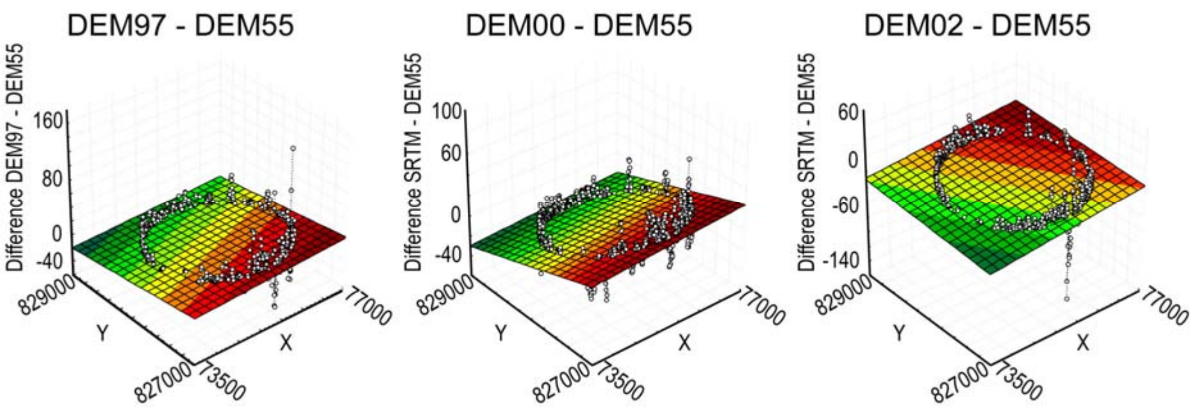


Figure 101 Difference between DEMs plotted along X and Y

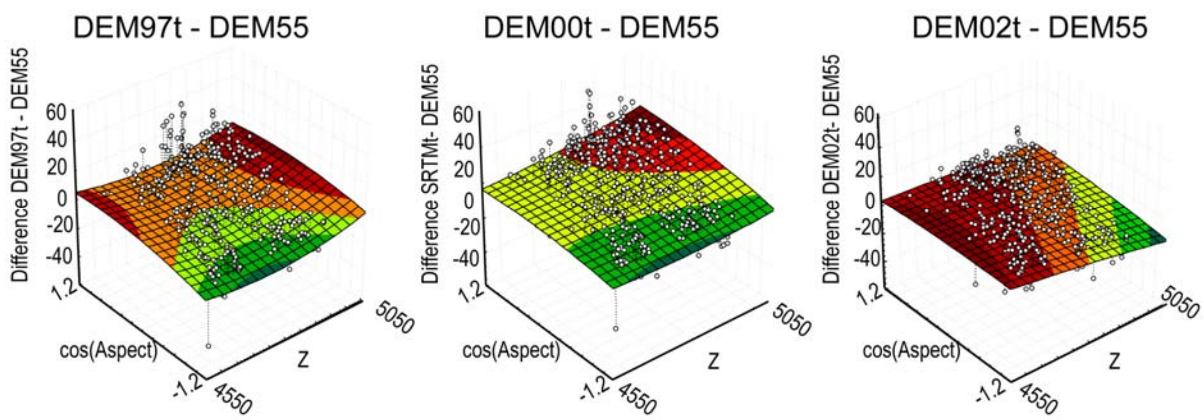


Figure 102 Difference on rocky areas versus elevation and aspect for ASTER 2002

Table 40 Assessing the DEMs accuracy before and after corrections (on rocky areas)

	Original image		Correction 1 (X & Y)		Correction 2 (El & As)	
	Difference	STDEV	Difference	STDEV	Difference	STDEV
DEM97-55	-0.24 m	18.6	**-0.24 m**	**16.1**	0.00	18.6
DEM00-55	0.04 m	18.2	**0.00 m**	**13.2**	0.00	13.2
Dem02-55	71.01 m	42.1	2.71 m	27.9	**3.28**	**14.4**

Table 40 shows that for the ASTER DEM it was possible to reduce the error by almost two thirds (from 42.1 to 14.4), although there was still an off-set of 3.28 .

The standard deviation (STDEV) and average difference are computed over all the rocky areas higher than 4400 m (i.e. 533,689 pixels). Errors calculated on exposed rock are not necessarily fully representative of the potential systematic errors on the glaciated terrain.

While this study was carried out in 2004 – 2005, a parallel study was ongoing using a similar approach on Coropuna, of which we were informed later (Racoviteanu *et al.*, 2007). They built a DEM based on a topographic map of 1955, but at a more precise scale of 1:50,000. They used DEM from ASTER 2001 and SRTM 2000 datasets. Although the initial approach is similar (with exception that we used an additional DEM from 1997 and the ASTER 2002), there are several significant differences in the results of the two studies:

Racoviteanu *et al.* succeeded to bring the standard deviation on rocky area to 9.5 m for SRTM (DEM 2000) as compared to 13.2 m in our study. This might be explained by the use of a more precise map (1:50,000 as compared to our 1:100,000), but could also be due to a smaller sample of reference points to compute the standard deviation (61 points in their study as compared with 533,689 in our present study for rocky areas).

However, we succeeded in decreasing the ASTER standard deviation to 14.4 m (in contrast to 26 m in their study), by using an additional correction based on a quadratic regression that corrected the ASTER 2002 DEM for bias induced by elevation and the cosine of aspect. The difference observed between DEM 2002t2 and DEM 1955 is -9.4 m (see **Table 41**), a result close to the results found between DEM 2000 and DEM 1955 (-8.75 m). Racoviteanu *et al.* (2007) found an elevation difference between 2001 and 1955 of + 28.5 m, which is extremely unlikely and not supported by both our and their GPS measurements. This is acknowledged in their article: "*Comparison of GPS points with corresponding ASTER elevations on glaciated areas shows that the ASTER DEM is too high on glaciated terrain, with a RMSEz error of 98.3 m with respect to GPS points*". This highlights the importance for further correcting the DEMs with elevation and cosine of aspect. It also highlights that obtaining more precise maps should not be underestimated.

Table 41 Altitude changes on glaciated areas on original and corrected images

	DEM97-55	DEM00-55	Dem02-55
Original DEMs	-1.35 m	- 5.05 m	+ 28.85 m
DEMs corrected	- 3.36 m	- 8.75 m	- 9.40 m[7]

4.2.7. Results

Change in ice cover

The identification of ice cover using images from passive satellite sensors is very straightforward in this location. As long as images are selected outside the snowy season (i.e. not between December and April), the ice detection is facilitated by the high contrast between the dark volcanic rock and the ice. The summits have a smooth shape, thus without much shadows (see Figure 103). The images

[7] Once the off-set of 3.28 is removed, otherwised the average difference on ice is -6.11.

were projected in UTM 18S (datum WGS84), they were georeferenced, classified. The classes corresponding to ice cover were transformed into vectors and the area computed using GIS.

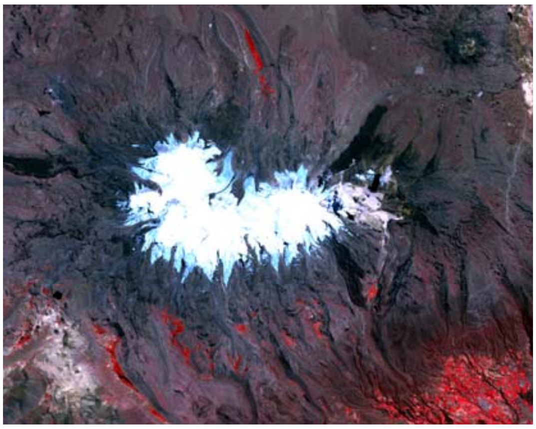


Figure 103 ASTER 2008 image (band 1, 2, 3)

The map in Figure 100 shows the ice cover changes for the five dates. This first analysis revealed that the Coropuna Glacier shrunk steadily from 122.7 Km^2 in 1955 to 48.1 Km^2 in 2008, i.e. losing more than 60 % of its surface in 53 years (Table 42).

Table 42 Evolution of ice cover

Date	Glacier surface (km^2)	Ice area loss (km^2/y)	Remaining ice cover *
1955	122.7	- - -	100 %
06 Nov. 1980	80.14	1.7	65.3 %
12 Jun. 1996	65.5	0.9	53.4 %
07 May 2003	57.3	1.2	46.7 %
25 Sept. 2008	48.1	1.8	39.2 %

*1955 as reference

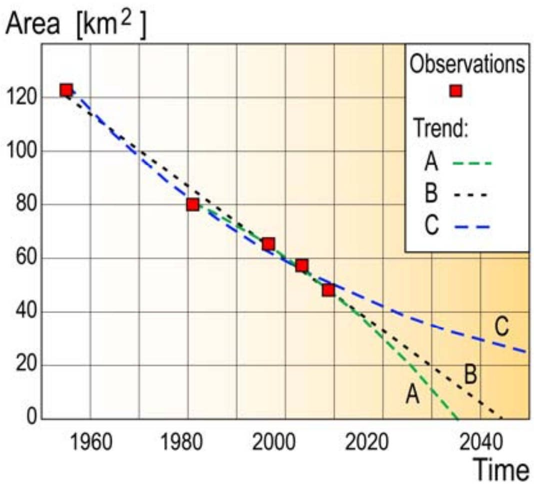


Figure 104 Glacier areas through time and different scenarios

By plotting glacier area through time (Figure 104) a clear declining trend appears. However with these observations it is not possible to predict whereas this will follow an accelerating trend (A) corresponding to smaller volume of ice having less inertia, thus shrinking faster. A linear trend (B), or a decelerating trend (C), where the shrinking will be slower when affecting higher altitudes. While scenarios A and B do not make much difference (total decline around 2040), in the scenario C, a small glaciated area would be maintained at the higher altitudes and slowly decline. The three scenarios have a very good fit with R^2 of 0.996, 0.989, 0.987 for A, B and C respectively. A better understanding of the rate of volume loss and remaining ice volume, might provide additional insight toward which scenario is most likely. For example if we see a decline below a certain altitude but a steady (or increasing) volume at higher altitude, this might provide indication that scenario C is more likely than scenarios A & B. Conversely if the decline is all over the glacier scenarios A or B would be more likely.

4.2.8. *Ice volume loss*

Except the DEM 1997 (of which 24% did not contain data especially with respect to glaciated area), both SRTM 2000 and ASTER 2002 provide similar elevation differences. According to these results the average elevation changes were - 8.75 +/- 13.2 m (DEM 2000) and – 9.4 m +/- 14.4 m (DEM 2002) at 95% confidence interval (see Table 41 for values and Table 40 for the margin of error). This corresponds to a yearly average loss of about - 0.2 m +/- 0.3 m per year (at 95% confidence interval). Once extrapolated to the volume, the loss of ice between 2002 and 1955 is estimated to be 1.2 km3. This corresponds to an ice volume decrease of 18% as compared with 1955. These figures should be taken with caution given the low accuracy of the DEM, as illustrated by the measured difference being lower than the margin of error.

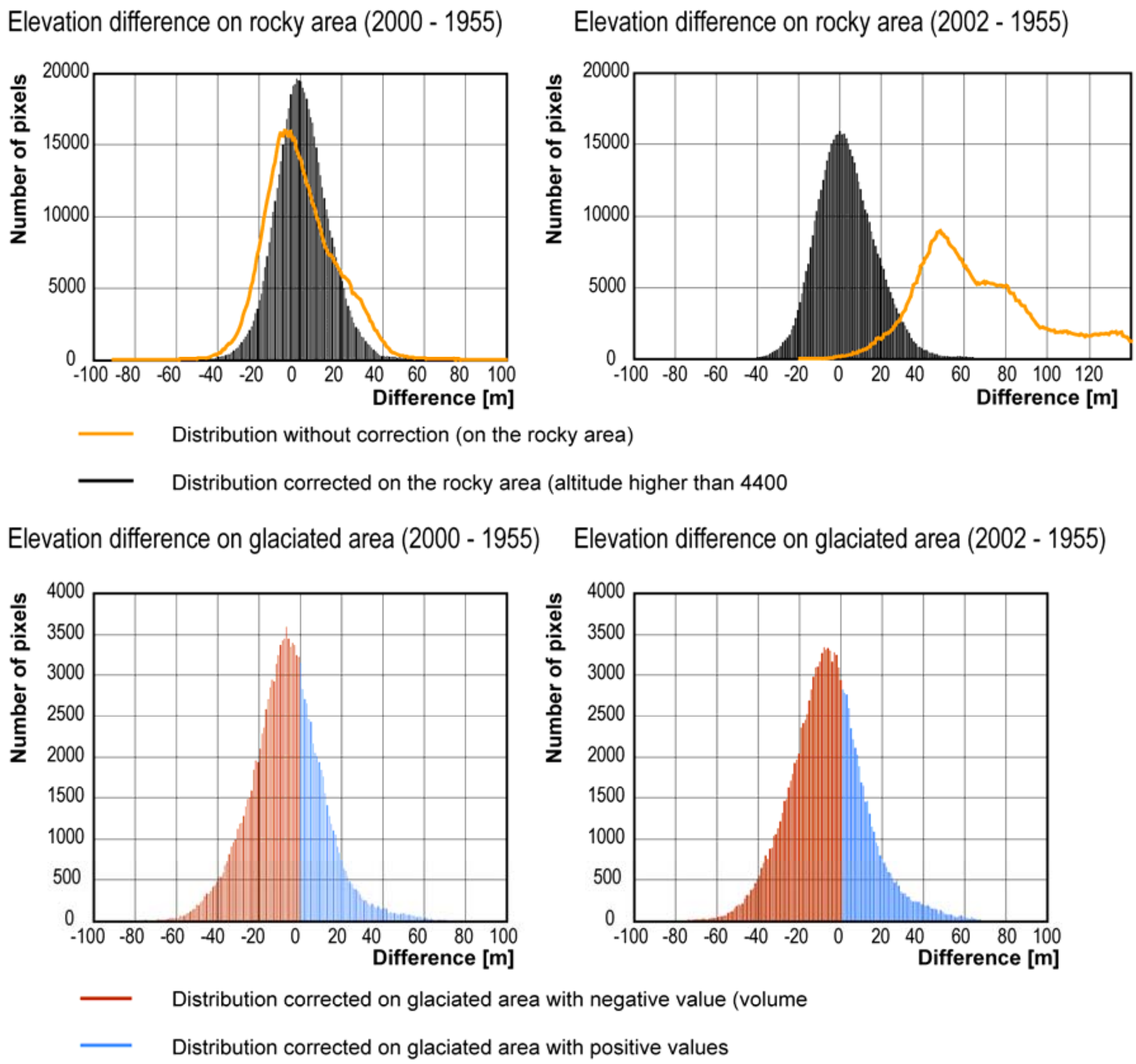


Figure 105 Elevation differences on rock and on glaciated areas

The much smaller differences observed in 1997 as compared with 2000 and 2002 are more likely due to data quality rather than linked with a 6 m decrease in ice thickness between 1997 and 2002.

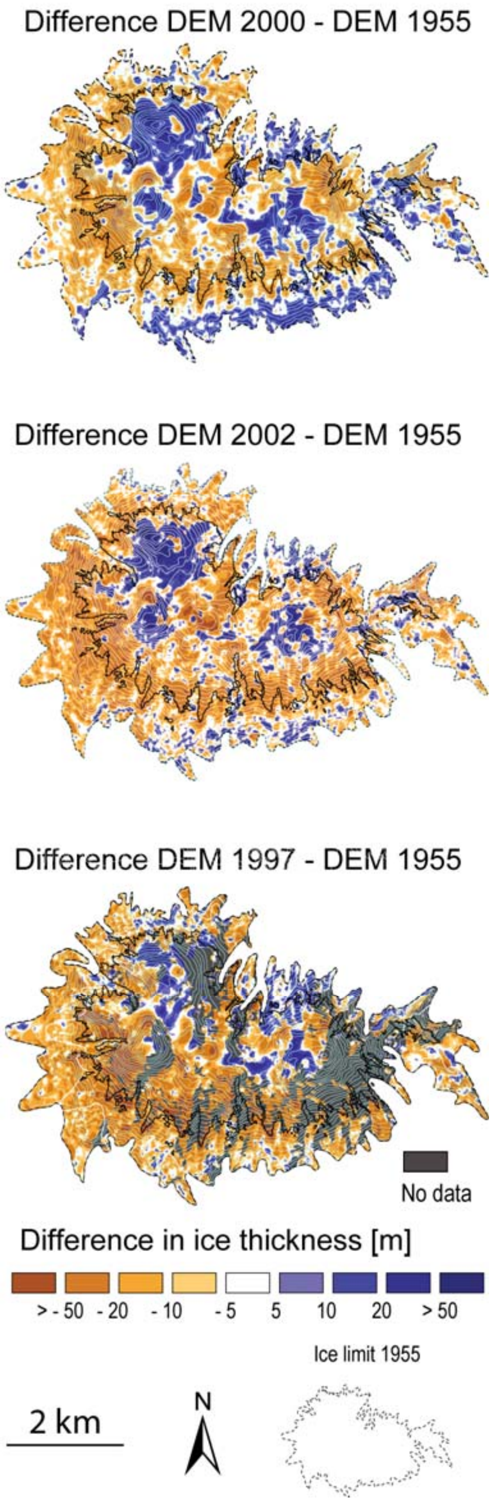


Figure 106 Estimation of ice loss between 1955 and 2000 and between 1955 and 1997

Figure 106 shows the differences between the DEMs based on the topographic map from 1955. The 1997 DEM includes 24% of no data (in black) due to shadow of relief. The loss of thickness is represented in orange. The losses and the gains are located in the same areas, which is a good indication of the method's robustness, as these results come from three different DEMs generated from three different types of sensors. The differences in the south (at the bottom of the glacier) might be explained by seasonal changes. The SRTM mission (DEM 2000) was in February at a time with high snow cover, while the DEM 1997 was acquired in October, at the end of the dry season. DEM 2002 was acquired in May.

4.2.9. Remaining ice

Analysing the transects

Figure 107 shows a portion (about 50%) of transect 2. This part is interesting as it shows that in some areas, the bedrock (in orange) is too deep to be recorded (see in the Crater).

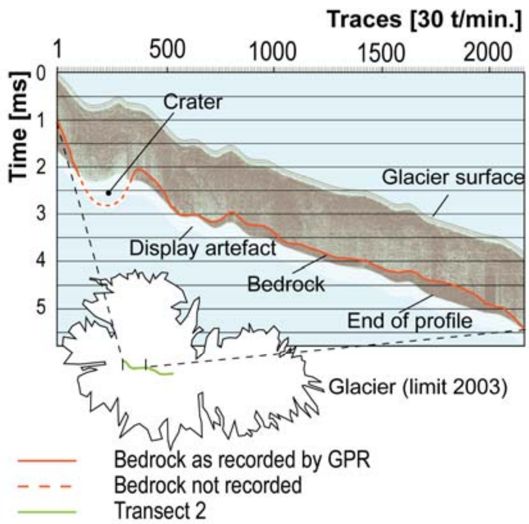


Figure 107 Example of interpreted profile of transect 2 from the GPR on the slope to the summit.

Modelling remaining ice: Results

In order to extrapolate the estimation of the ice volume to the rest of the map, the hypothesis was made that the depth of ice was dependent on the altitude, the aspect (slope's orientation) and the slopes. The assumption was made that ice thickness would depend on these three components. The amount of precipitation should be driven by altitude, slope and orientation. Orientation should also play a role due to predominant wind direction as well as different solar exposure (also probably less prominent in the tropics). Finally, snow accumulation should also be driven by slopes, based on the hypothesis that on steep slopes the ice should be thinner as the glacier is moving faster, whereas on gentle slopes, the ice accumulates as the glacier slows down.

To test these hypotheses, a statistical multiple regressions analysis was made using the recorded depth in relation to altitude, slope and orientation.

Table 43 Quality of regressions used for modelling ice thickness

Cases	Altitude	Slope	Orientation	Intercept	Pearson coefficient	% of variance explained	p-value
Alt. >6360	**-2.06**	---	---	**13294.65**	0.87	76%	$< 10^{-10}$
Alt. >=6100 and alt.<6360	**-0.11**	**-1.47**	---	**832.62**	0.94	88%	$< 10^{-10}$
Alt. <6100 and alt. >5980	**-0.14**	**-5.25**	---	**1021.47**	0.80	64%	$< 10^{-10}$
lt.<=5980 and orient.[91;270]	**1.00**	**2.22**	**0.15**	**-5852.65**	0.77	59%	$< 10^{-10}$
Alt. <=5980 and Orient. >270	**-2.19**	---	---	**13128.5**	0.64	41%	$< 10^{-10}$
Alt. <=5980 and orient. <91	**3.32**	**2.43**	---	**-19565.3**	0.93	87%	$< 10^{-10}$

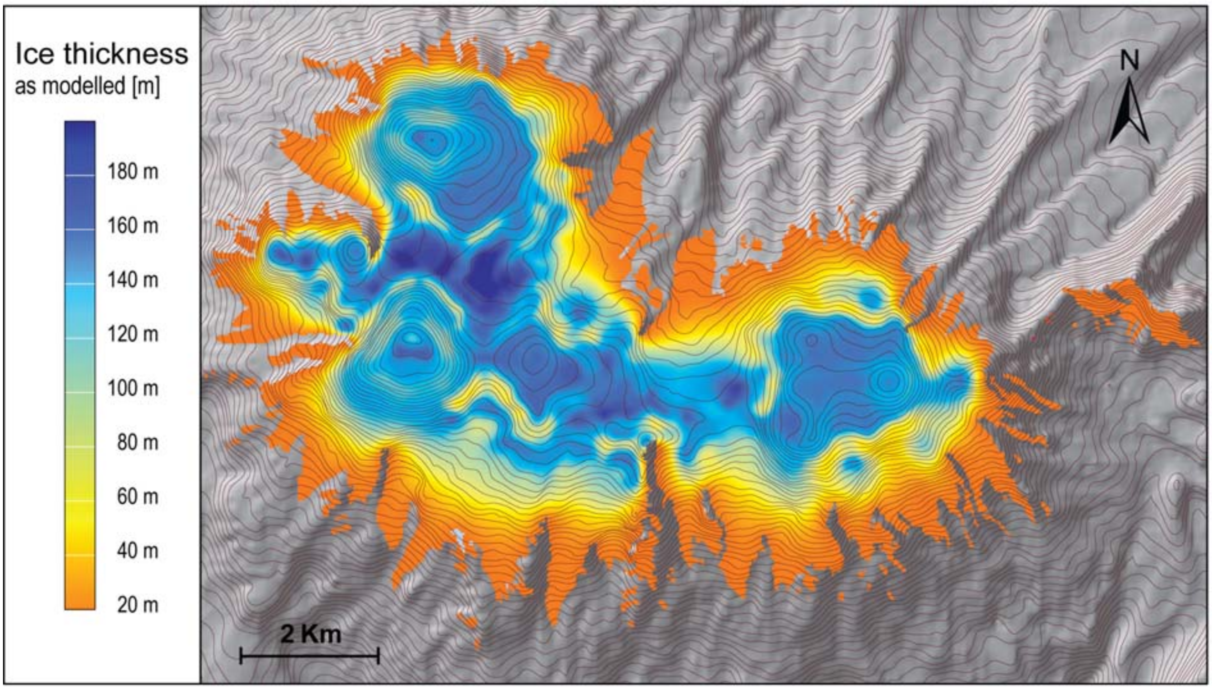


Figure 108 Estimation of ice thickness (model)

It was necessary to differentiate six cases (see Table 43): the top of volcanoes with altitudes higher than 6,360 m; areas with altitudes between 6,100 and 6,360 m; and altitudes between 5,980 and 6,100 m. The next categories used three differentiations of slope orientation. These were needed for altitudes lower than 5,980 m with the following aspects: higher than 270°, between 91° and 270° and smaller than 91°). Table 43 describes the variables (altitude, slope and orientation) and weight (in bold) used in the model according to the different thresholds. The quality of the models was assessed by looking at p-value[8] (all smaller than 10^{-10}) and Pearson coefficient (between 0.80 and 0.94 for altitudes higher than 5,980 m). The model becomes less accurate for lower elevations, which is reflected by a lower correlation (between 0.64 and 0.77 except one at 0.93).

Equations from Table 43 suggest that except for case 4 where orientation of slopes seems to play a role, in all the other cases, the depth of ice can be explained by altitude and slopes only. At the summit (altitude > 6,360 m) ice depth is

[8] In broad terms, a p-value smaller than 0.05, shows the significance of the selected indicator. A value of 10^{-10} is highly significant.

only linked with altitude. This is not surprising given that the smooth round summits of Coropuna are mostly flat (hence limited slopes and orientation). The map in Figure 108 shows the result of this model once extrapolated to the entire glacier.

The modelled thickness ranges between 20 and 200m, with an average thickness estimated at 80.8 m +/- 16.5 m (at 95% confidence interval). This gives an expected remaining ice volume of 4.62 km^3 (+/- 20.3%). The margin or error is fairly important at +/- 0.94 km^3; however, this result only provides a rough estimate.

The multiple regression analysis confirmed that altitude, slopes and orientation are factors influencing the ice thickness. This illustration includes transect 2, 3 and 4 (see Figure 100 for their locations), thus offering the longest stretch across the measurements. The modelled depth fits well with the recorded profiles. The Pearson correlation between ice depths measured and modelled is 0.87 with a standard deviation of 16.5 (at 95% confidence interval). Figure 109 provides the fit between the observed and modelled depths. Still, for obvious reason of access, we were not able to take measurements on steep slopes with the GPR. This lack of samples might have an effect on the model. The maximum ice thickness on steep slopes, especially below the west summit, might be a limitation of our model to capture these physical conditions. The DEM 2000 shows an increase in elevation in higher than 6160 (areas where the green line above the blue line in Figure 109). Elevation loss can be seen on lower summits (area where blue line is below green line in Figure 109).

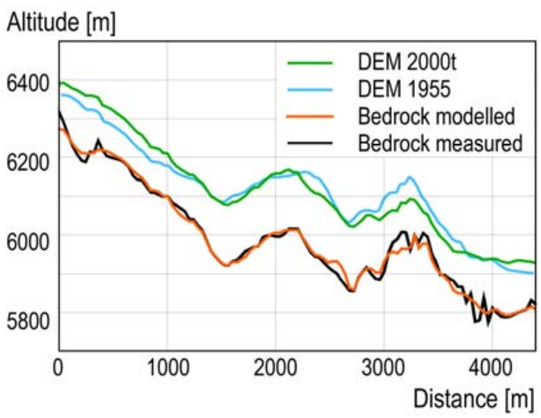


Figure 109 Ice thickness measured versus modelled (transects 2, 3 and 4)

4.2.10. Discussion

Estimation of the evolution in ice cover

This technique based on passive sensors provides simple and clear results. This is still the most effective method for quickly identifying a trend; however without remaining ice thickness and estimation of volume loss rate, it is difficult to say whereas the projected decline will be abrupt or slow. It is possible that with a new estimation in year 2015, the trend might be better identified.

Measuring ice thickness

The hypothesis made on the statistical link between altitude, slope and orientation proved to be successful, except for orientation, which plays a limited role (mostly non-significant except in one case). It was expected that orientation would play a bigger role due to direction of the predominant wind, precipitation coming mostly from one direction. The limited role played by orientation is probably due to the study area's location within the tropics where the sun is less predominant on a specific slope (such as south in northern latitudes or north in southern latitudes). For glaciers at higher (Northern Hemisphere) or lower (Southern Hemisphere) latitudes, slope orientation might play a bigger role and should not be disregarded in the model.

The accuracy of the model was better at high altitude than at lower altitude (< 5980). This is believed (although not tested) to be due to two factors. Firstly, there were more records made at high than at lower altitudes (due to the difficulty of access at the edge of the glacier). Secondly, it is believed that at the edges, site effects played a more significant role, hence making it more complex to model. This could be due to lower temperature inertia (thinner ice) and increased solar heat radiation from the surrounding rocks.

Limitations on measuring the difference in ice volume

In this analysis, the differences recorded on the rocky areas were significant and raised concerns on the ability to use DEMs. In any case, they could not be used without the adjustments. The corrections applied on easting and northing as well as on elevation and aspects (for DEM 2002) significantly improved the quality of the DEMs. The Radar DEM 1997 included numerous no-data. Another limitation lies in the fact that digital DEMs are fairly recent technologies, and the date of the oldest archive found for the Coropuna was 1997.

The methodology for identifying the ice volume loss using DEM is straightforward and less challenging compared to the estimation of remaining ice. The difficulty comes from the lack of precision of DEMs on rough terrain, and attempts to correct the distortions can be time-consuming.

4.2.11. Conclusions and perspectives

The simple computation of area decrease based on passive satellite sensors, show a rapid decline of Glacier Coropuna (-1.4 km^2 per year, -60% since 1955) and if this continues, it may be gone before 2045. This is why it was important to try to produce more complex evaluations in terms of volume loss and remaining ice.

The methodology chosen for ice thickness and ice volume loss estimation proved to be effective. The corrections applied on the DEMs through multiple regression models based on easting, northing, aspect and elevation reduced the uncertainties, although the margin of errors is still high.

The vertical accuracy for the differences computed between the DEM2000t, the DEM2002t and the DEM 1955 were estimated at +/- 13.2 and 14.4 m respectively, for elevation changes of -8.75 and -9.4 m on the ice (i.e. an average of 0.19 to 0.2 m of decrease per year, +/- 0.3 m). Errors calculated on exposed rock are not necessarily fully representative of the potential systematic errors on the glaciated terrain. Although this provides an estimate of ice loss trends, the difference in ice thickness is smaller than the margin or error, thus affecting the confidence in the measurements. This can only be improved by either satellite sensors with better precision or by pursuing research in finding methods for correcting the DEMs.

For the ice thickness, the methodology could be improved, notably by choosing a lighter GPR. This would have eased the data collection, for instance by using skis to cover a much bigger area. Using the profiles from the ground study and a statistical extrapolation (modelling), it was possible to estimate the ice thickness (in average 80.8 m +/- 16.5 m), which gives an estimated remaining volume of 4.62 km^3 +/- 0.94 km^3 (i.e. 3.2 million tonnes of water).

These results were presented to GTZ and COPASA in Arequipa in December 2005. It helped to raise awareness on the issue of shrinking glaciers. In 2006, COPASA obtained support from GTZ. We then presented our results to United Nations Development Programme (UNDP) and they agreed to support COPASA through their Global Risk Information Programme (GRIP). Later on, the Inter-American Development Bank (IADB) also joined. These institutions help to introduce new policies for climate change adaptation at both local government and community levels: between 2006 and 2009, the following actions were carried out:

A “Changing climate scenario” was developed for the Arequipa region; the socio-economic consequences of climate change were assessed. This led to a climate change adaptation strategy which was included (and implemented) in the Development Plans of six districts of Arequipa State; two urban and rural land use plans were developed in the Viraco and Machahuay districts; Guidelines were developed with the Ministry of Agriculture for the incorporation of climate change adaptation in agricultural procedures; several thematic networks of students and teachers have been created and are working on climate change topic; The issue has been brought to the attention of regional institutions, which then produced a regional strategy for climate change adaptation. Three university theses have studied climate change at the regional level; four educational brochures were developed and their use approved in primary and secondary schools; a board game was developed on Climate Change Adaptation to help children to learn while playing. Five mini reservoirs and 15 warehouses for forage were built in this area.

The recent 2008 ASTER image shows that the glacier area continues to shrink, however, the local authorities have now integrated this threat into their development plan. The threat on water supply might be increasing, but efforts are made to reduce the vulnerability of the local population.

4.2.12. Contributions

Generation of DEM 1955: Dr Walter Silverio.
Remote sensing analysis of ice cover: Walter Silverio (for 1955 and 2003) and Pascal Peduzzi (for 1980, 1996 and 2008).
Analysis on the difference in DEM for ice volume loss: Pascal Peduzzi.
Georadar and GPS ground data collection; Pascal Peduzzi and Christian Herold.
Interpratatin of georadar profile: Christian Herold.
Modelling remaining ice: statistical model: Pascal Peduzzi, GIS modelling: Christian Herold.
Maps, graphs and figures: Pascal Peduzzi
Redaction: Pascal Peduzzi with support from Christian Herold.

4.2.13. Acknowledgements

This work was supported by the GTZ/COPASA, Arequipa. We would like to thank Josef Haider, Juan Carlos Montero and all the team of GTZ/COPASA in Arequipa for the logistical support and for trusting us in conducting this study. We also would like to thank Carlos Zarate and all his team of guides, porters, cook, and drivers for the expedition on Coropuna, and the team of Peruvian Geophysical Institute in Arequipa. Without all this combined support, this research would not have been possible. For the help provided on seismic and GPR data acquisition and analysis, we would like to thank Milan Beres, Julien Fiore and Michaël Fuchs of the Department of Geology, University of Geneva; Jacques Jenny of Geo2x; François Marillier and Dieb Hammami of Geophysical Institute, University of Lausanne; and Ansgar Forsgren of Mala Geoscience. We also would like to thank Marisol Estrella and John Harding for kindly reviewing the English.

4.2.14. References

Bates, B.C., Z.W. Kundzewicz, S. Wu and J.P. Palutikof, Eds.,: Climate Change and Water. Technical Paper of the Intergovernmental Panel on Climate Change, IPCC Secretariat, Geneva, 210 pp., 2008. http://www.ipcc.ch/pdf/technical-papers/climate-change-water-en.pdf. Last accessed 2010.

Barenett, T. P., Adam, J. C. & Lettenmaier, D. P.: Potential impacts of a warming climate on water availability in snow-dominated regions. Nature, 438, 303-309, 2005.

Berthier, E., Arnaud, Y., Baratoux, D., Vincent, C. & Rémy, F.: Recent rapid thinning of the "Mer de Glace" glacier derived from satellite optical images. Geophysical research letters, 31, L17401, 1-4, 2004.

Bradley, R. S., Vuille, M., Diaz, H. F., and Vergara, W.: Threats to water supplies in the tropical Andes, Science, 312, 1755–1756, 2006.

Descloitres, M., Guérin, R., Ramirez, E., Gallaire, R., Ribstein, P., Valla, F.: Détermination de l'épaisseur des glaciers de Sarenne (Alpes) et de Chacaltaya (bolivie) par prospection radar au sol à 50 MHz, La Houille Blanche 5, 29–33, 1999.

Eisen, O., Nixdorf, U., Keck, L. and Wagenbach, D.: Alpine ice cores and ground penetrating radar: combined investigations for glaciological and climatic interpretations of a cold Alpine ice body, Alfred-Wegener-Institut für Polar- und Meeresforschung Bremerhaven, Institut für Umweltphysik, Universität Heidelberg, 2003.

Gorokhovich, Y., Voustianiouk, A.: Accuracy assessment of the processed SRTM-based elevation data by CGIAR using field data from USA and Thailand and its relation to the terrain characteristics, Remote Sensing of Environment, 104, 409–415, 2006.

Gruber, S., Ludwig, F. and Moore, J. C.: Application of Ground Penetrating Radar in Glaciology and Permafrost Prospecting, Geographisches Institut/JLU Gießen, 1996.

Kääb, A., Huggel, C., Paul, F., Wessels, R., Raup, B., Kiefer, H. and Kargel, J.: Glacier Monitoring from ASTER imagery: accuracy and applications, Proceedings of EARSeL-LISSIG- Workshop Observing our Cryosphere from Space, Bern, Switzerland, 2002.

Liu, Y., an evaluation of the data quality of SRTM DEM at the alpine and plateau area, north-western of

China, The International Archives of the Photogrammetry, ISPRS. 37, Part B1., 1123-1128, 2008.

Maijala, P., Moore, J. C., Hjelt, S.-E., Pälli, A. and Sinisalo, A.: GPR Investigations of Glaciers and Sea Ice in the Scandinavian Arctic, GPR98 - 7th International Conference on Ground-Penetrating Radar Proceedings., 143-148, 1998. http://kaares.ulapland.fi/home/hkunta/jmoore/pdfs/maijalagpr98.pdf. Last accessed : 2010

Moorman, B. J., Michel, F. A.: Glacial hydrological system characterization using ground-penetrating radar, Hydrol. Process., 14, 2645-2667, 2000.

NASA, SRTM mission statistics, http://www2.jpl.nasa.gov/srtm/statistics.html. Last accessed 2010.

Rabus, B., Eineder, M., Roth, A., and Bamler, R.: The shuttle radar topography mission - a new class of digital elevation models acquired by spaceborne radar. Photogramm. Rem. Sens., 57, 241−262, 2003.

Racoviteanu, A. E., Manley, W. F., Arnaud, Y. & Williams, M. W.,: Evaluating digital elevation models for glaciologic applications: An example from Nevado Coropuna, Peruvian Andes. Global and Planetary Change, 59, 110-125, 2007.

Sénéchal, G., Rousset, D., Salomé, A.-L. and Grasso, J.-R.: Georadar and seismic investigations over the Glacier de la Girose (French Alps), Laboratoire d'imagerie géophysique, Université de Pau, Laboratoire de géophysique interne et tectonophysique, Université Joseph Fourier, Grenoble (France), 2005.

Silverio. W. and Jaquet, J.-M.: Glacial cover mapping (1987-1996) of the Cordillera Blanca (Peru) using satellite imagery, Remote Sensing of Environment, pp. 342-350, 2005.

Vimeux, F., Ginot, P., Schwikowski, M., Vuille, M., Hoffmann, G., Thompson, L.G. and Schottererg, U.: Climate variability during the last 1000 years inferred from Andean ice cores: A review of methodology and recent results, Palaeogeography, Palaeoclimatology, Palaeoecology, 281, Issues 3-4, 229-241, 2009.

Vuille, M., Francou, B., Wagnon P., Juen, I., Kaser, G., Bryan G. M., Bradley R. S.: Climate change and tropical Andean glaciers: Past, present and future, Earth-Science Reviews 89, 79–96, 2008.

Zemp, M., Roer, I., Kääb, A., Hoelzle, M., Paul, F. and Haeberli, W. (eds.), WGMS: Global Glacier Changes: facts and figures. UNEP, World Glacier Monitoring Service, Zurich, Switzerland: 88 pp., 2008. http://www.grid.unep.ch/glaciers/. Last accessed: 2010.

4.3. *Use of the Coropona study*

The problem of glacier retreat was already known by the NGO, however they were unable to quantify the rate of the retreat and thus could not highlight the priority for accessing funds.

The funds obtained were used to:

- Integrate climate change concerns into risk analysis and development plans at the local and regional level;
- Implement concrete measures to adapt to the local consequences of climate change and to manage sustainably the available resources;
- Raise awareness on climate change and its effects through communication and education;
- Generate information on climate variability in the Coropuna region;

The practical outcomes include new policies at the local level, new irrigation plans, choices of seeds for crops that require less water, teaching the importance of adaptation to climate change in local schools.

On the technical side, it shows the need to improve the accuracy of the DEM which was disappointing. This project was challenging, especially due to altitude and meteorological conditions (low pressure, cold temperatures and strong wind), requiring innovative solutions for using regular laptops in such conditions (i.e. removing hard disk, booting on CD and recording data on USB cards as well as protection from wind and low temperatures).

Nat. Hazards Earth Syst. Sci., 10, 623-640, 2010
www.nat-hazards-earth-syst-sci.net/10/623/2010/

4.4. Landslides and Vegetation Cover in the 2005 North Pakistan Earthquake: a GIS and statistical quantitative approach

Pascal Peduzzi[1, 2]

[1] United Nations Environment Programme, GRID-Europe, Global Change & Vulnerability Unit, 1219 Châtelaine, Switzerland}
[2] Institute of Geomatics and Risk Analysis (IGAR), University of Lausanne, Switzerland}

Correspondence to: P. Peduzzi (Pascal.Peduzzi@unepgrid.ch)

Received: 15 July 2009 – Published in Natural Hazards and Earth System Sciences: 1 April 2010
Revised: 26 February 2010 – Accepted: 28 February 2010 – Published: 1 April 2010

Peduzzi, P.: Landslides and vegetation cover in the 2005 North Pakistan earthquake: a GIS and statistical quantitative approach, *Nat. Hazards Earth Syst. Sci.*, **10**, 623-640, 2010.
http://www.nat-hazards-earth-syst-sci.net/10/623/2010/nhess-10-623-2010.html

4.4.1. Abstract

The growing concern for loss of services once provided by natural ecosystems is getting increasing attention. However, the accelerating rate of natural resources destruction calls for rapid and global action. With often very limited budgets, environmental agencies and NGOs need cost-efficient ways to quickly convince decision-makers that sound management of natural resources can help to protect human lives and their welfare. The methodology described in this paper, is based on geospatial and statistical analysis, involving simple Geographical Information System (GIS) and remote sensing algorithms. It is based on free or very low-cost data. It aims to scientifically assess the potential role of vegetation in mitigating landslides triggered by earthquakes by normalising for other factors such as slopes and distance from active fault. The methodology was applied to the 2005 North Pakistan/India earthquake which generated a large number of victims and hundreds of landslides. The study shows that if slopes and proximity from active fault are the main susceptibility factors for post landslides triggered by earthquakes in this area, the results clearly revealed that areas covered by denser vegetation suffered fewer and smaller landslides than areas with thinner (or devoid of) vegetation cover. Short distance from roads/trails and rivers also proved to be pertinent factors in increasing landslides susceptibility. This project is a component of a wider initiative involving the Global Resource Information Database Europe from the United Nations Environment Programme, the International Union for Conservation of Nature, the Institute of Geomatics and Risk Analysis from the University of Lausanne and the "institut universitaire d'études du développement" from the University of Geneva.

4.4.2. Introduction

Overexploitation of natural resources and deforestation is one of the main triggers for the observed increase in landslide disasters along with increase in population exposure (Nadim *et al.*, 2006). While timber production, grazing or woodfuel collection are activities supporting livelihoods, their impact on vegetation cover needs to be addressed, as forests are being harvested, converted to crop land or pasture at an accelerating pace. Current deforestation reaches 13 millions ha per year (FAO, 2006). Conversely, restoration of vegetation coverage can be a cost-effective method for risk reduction. Planting mangroves for tropical cyclones protection revealed to be seven fold cheaper than dike maintenance, while also providing secondary benefits for local livelihoods (IFRC, 2005).

The Hyogo Framework for Action (HFA) "*encourages the sustainable use and management of ecosystems,* [for] *reducing the underlying risk*" (UNISDR, 2005). To achieve this goal, both local authorities and international decision-makers need to adopt improved environmental policies. Yet, convincing people to change their practices demands tangible evidence and clear examples of sound environmental management. Post-disaster situations might provide a favourable impetus to bring new concepts and to avoid rebuilding risk during the reconstruction phase. There is a need for a multiplication of scientific evidence and thus for developing simple methods allowing solid scientific assessments. Outputs from this quantitative analysis were used in an interdisciplinary study for disaster risk reduction (Sudmeier-Rieux *et al.*, 2008). It explored the relation between land use factors, such as deforestation, grazing, road building, etc. on the frequency of landslides and coping strategies developed by the population. It was applied and tested on the area affected by the earthquake that hit North Pakistan and India on 8 October 2005. The epicentre was located at 34.493°N, 73.629°E and had a recorded magnitude of 7.6 Mw on Richter scale (USGS, 2006). It devastated a large stretch of the region, killing 74,647, injuring 134,622 and leaving 5.15 million homeless and resulted in an economic loss evaluated at 6.2 billion US$ (CRED, 2009). While impressive, these figures fail to capture the level of despair of the surviving population. The heaviest damage arose in the Muzaffarabad area and Kashmir, where entire villages were destroyed. More than 30% of the victims were killed by landslides (Petley *et al.*, 2006). More than 2400 landslides were identified by remote sensing techniques (Sato *et al.*, 2007) following this earthquake. The biggest individual landslide triggered by the Kashmir Earthquake 2005 was the 68 millions m^3 Hattian Bala rock avalanche that killed about 1000 people (Dunning *et al.*, 2007). Understanding why landslides claim such a high death tolls is thus an important task. Not only to identify the potential future slope failure, but also to see if portion of past susceptibility can be attributed to human activities. This is particularly relevant in this context, as five months before the October 2005 earthquake, an IUCN-Pakistan report highlighted the risk "*from a possible human catastrophe due to the growing danger of landslides that was haunting the locals owing to heavy constructions, ruthless deforestation and massive quarrying.*" (IUCN, 2005).

Landslides are complex hazards requesting the collection of many different parameters to produce susceptibility maps: slopes, lithology, identification of recent deforestation, proximity from roads and presence of triggers (such as heavy precipitations or seismic activities) are the most commonly used factors in landslides modelling (Guzzetti *et al.*, 1999; Gorsevski *et al.*, 2001; Vanacker *et al.*, 2003; Ayalew and Yamagishi, 2005).

(Guzzetti *et al.*, 1999) describe five main categories of techniques for mapping landslides susceptibility (geomorphological hazard mapping, analysis of landslides inventories, heuristic or index based methods, functional, statistically based models, geotechnical or physically based models). They can be gathered in two broader categories: qualitative and quantitative (Ayalew and Yamagishi, 2005).

The most common types of qualitative methods simply use landslide inventories (Ayalew and Yamagishi, 2005). Landslide inventories attempts to predict future patterns of slope failure by preparing landslide density maps (Guzzetti *et al.*, 1999).

As part of a preliminary study (Sudmeier-Rieux *et al.*, 2007), a first landslide inventory was undertaken by computing the landslides density on different landcover, slope classes and geological formations.

It showed for instance that 57% of landslides occurred in the Murree geological formation. Although at first glance it seems that such gaeology is highly susceptible to landslides, this is less evident when knowing that such formation accounted for 52.3% of the area. Qualitative methods are useful in preliminary tests, but are only of interest if the ratio of percentage of landslides over percentage of coverage of the selected feature is showing significant over (or under) representation. In the case of the Murree geological formation, such ratio is about 1.1 (57/52.3). This is not to say that such geological formation has a neutral role, but only that this is not statistically relevant.

Looking at landcover was more interesting. While forests cover about 45% of the study area, it includes only 17% of total landslides, ratio = 0.36 (17/45), so forest are under-represented. Deforested and grazing areas covers 42% of the study area, but includes 54.8% of total landslides, ratio = 1.3 (45.8/42), so areas with no or low vegetation density are over-represented. However this can easily be a fluke correlation as one might argue that forested areas may potentially be more located on gentler slopes, or areas further away from fault line or on different geological formation.

Quantitative methods overcome the issue of potential interconnectivity between the susceptibility factors. The most robust method is based on a deterministic approach. This consists of an engineered evaluation of slope instability based on exhaustive collection of relevant data. Such exercises are very time consuming and costly. Deterministic approaches request comprehensive local assessments and are thus usually conducted over small areas (Ayalew and Yamagishi, 2005) and one might add: with high financial values given the resources needed.

For large areas, statistical quantitative approaches are more appropriate. In this category, logistic regression and discriminant analysis are the most frequently chosen models (Guzzetti *et al.*, 1999; Brenning, 2005). This requests first to identify past landslides (usually using remote sensing) and then prepare map layers for each potential susceptibility factors using GIS techniques (Guzzetti *et al.*, 1999; Ayalew and Yamagishi, 2005; Brenning, 2005; Vanacker *et al.*, 2003; Coe *et al.*, 2004). This allows for the identification and the estimation of the relative contribution of the instability factors and the cartography of different hazard degree (Guzzetti *et al.*, 1999).

Such multiple regression analysis associated with extraction of parameters using GIS, was already used for highlighting the role of deforestation in landslides (e.g. Vanacker *et al.* 2003). In their study, Vanacker *et al.* extracted slopes, aspect, distance to valley and type of landcover. They also used different sets of aerial photos taken at different years to look at the role of deforestation (and time since deforestation) for landslides susceptibility. They concluded, that in their area of study, the overall susceptibility of slope movement was highly dependent on recent land-use changes. Vegetation can reduce landslide susceptibility (both shallow and deep landslides) by reducing water content in the soil (Popescu, 2002) or may reduce shallow landslides with the mechanical role of roots in anchoring the soil. However, vegetation may also destabilize the forces by adding weight and acting as a surcharge as well as by wind forces on vegetation exposed (Popescu, 2002).

Remote sensing techniques are useful for estimation of crustal deformation using either passive sensors (Avouac *et al.*, 2006) or radar imagery. A remarkable study (Sato *et al.*, 2007) used Synthetic Aperture Radar (SAR) images from ENVISAT revealing a maximum six-meter uplift north of Muzaffarabad. In the same study, landslide detection performed by comparing a pair of pre- and post-event SPOT-5 images plotted over a Digital Elevation Model (DEM). Sato *et al.* showed that a majority of landslides (63.3%) occurred on slope steeper than 30 degrees and that gentler slopes were also affected by landslides when closer to active faults. However, they found that this was not systematic, as large-scale slope failures also occurred at slopes less than 30 degrees at a longer distance. Steeper slopes located further away from the active faults were not necessarily more affected. Slope and distance from active faults are thus only part of the story.

In order to highlight the potential role of vegetation in mitigating slope failure, this current study builds on similar methodologies developed for different hazard types (Peduzzi *et al.*, 2002; Chatenoux and Peduzzi, 2007). It uses multiple regressions to normalise geophysical and geographical parameters (such as slopes, distance from active fault, distance from rivers) to highlight other parameters related to human activities (presence of roads, vegetation removal). A logistic regression with stepwise variable selection proved to be adequate for landslide susceptibility modelling (Brenning, 2005). In order to ensure easy reproduction even for low-budget institutions, the research is based on free or low-cost data. It is thus based on published material and free global datasets, with the sole acquisition of a (low-cost) 30 m DEM derived from ASTER satellite sensor. This paper describes how spatial and statistical analysis using remote sensing and GIS techniques were applied (see Appendix E for the list of software used).

One of the key inputs consisted of the use of results from two previous assessment made by the *Service Regional de Traitement d'Image et de Télédétection* (SERTIT) and the National Engineering Services of Pakistan (NESPAK) which identified post-disaster landslides using satellite imagery. Both institutes kindly provided the two sets of detected landslides. To study which parameters are potentially linked with landslide susceptibility, a series of potential susceptibility factors were extracted using GIS techniques (slope variation and steepness, vegetation density, and distance from epicentres / active fault, rivers, roads or trails). Satellite imagery and simple remote sensing computation were also used to evaluate vegetation density. The Normalised Difference Vegetation Index (NDVI) is commonly used as a proxy for vegetation density (Tucker, 1979). It was computed and statistical regressions were run to identify potential susceptibility factors associated with observed slope failures. Once identified, the identified factors were introduced into the GIS to provide a landslide susceptibility map.

4.4.3. Data collection

Selection of the study area

The study area is a 60 by 60 km square (3,600 Km^2) delimited by the choice of the ASTER DEM covering Muzaffarabad and the Neelum valley (the bounding coordinates are: 73.23E, 34.65N, 73.86 E, 34.56 N; 73.72 E, 34.02 N; 73.09 E, 34.11 N). It lies in North Pakistan and India with more than half over the disputed territory of Jammu Kashmir (sovereignty status still unsettled). It includes the largest epicentre of 7.6 on Richter scale in the north of the study area, while numerous replicas are just outside in the northeast (see Figure 110).

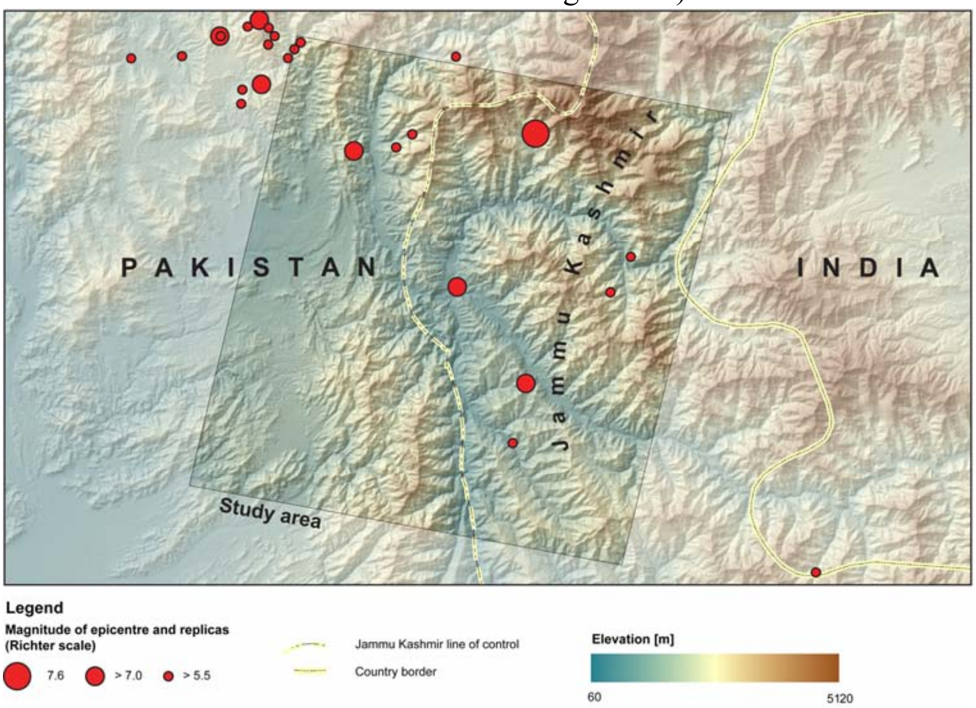


Figure 110 Map of the study area (the boundaries and names shown on this map do not imply official endorsement or acceptance by the United Nations or by the author)

The altitudes range between 552 m and 4476m (average around 1700 m) in this complex pattern featuring a rugged landscape. The rough relief of this mountainous area might be of concern for remote sensing processes, due to the areas in the shadow.

To overlay the different layers of information, the data were all projected in UTM 43 N (datum: WGS 1984). The full list of data sources is provided in Appendix A.

Hypothesis and data sources

The dependant variable to be explained is the size of landslides. The original data on detected landslides were obtained through the Humanitarian Information Centre for Pakistan (HIC) but generated by two different offices: (SERTIT) based on 5-metre SPOT-4 images and from the National Engineering Services of Pakistan (NESPAK) at a lower resolution. To explain the variation in landslide size, several hypotheses were made. Assuming that distance from active fault is an important factors, the Muzaffarabad and Tanda fault lines were manually digitalized (R. Klaus internship at UNEP/GRID-Europe) from a map extracted from (Nakata *et al.*, 1991) at a scale of 1: 100,000. From this dataset the distance from the active fault was computed for each pixel. Epicentres were geo-referenced based on latitude / longitude information retrieved from the Advanced National Seismic System (ANSS) composite catalogue, the Northern California Earthquake Data Center (NCEDC); The ANSS composite catalogue. Distances from epicentres (and replicas) were computed for three categories of epicentres: the first one includes epicentres comprised between 5.5 and 7 M_W on Richter scale, the second one for epicentres between 7 and 7.5 M_W, the last one consisting of the main epicentre at 7.6 M_W.

Another hypothesis was made that the presence of roads and trails could destabilise the slopes by either allowing infiltrations or by destabilising the balance slope of the material. Trails for pedestrians and cattle were distinguished from roads for cars and trucks. The data were provided (and digitalized) by the United Nations Joint Logistics Centre (UNJLC). Based on this dataset, distances from nearest roads and trails were computed for each pixel using GIS.

On the satellite image, numerous landslides appear to be located close to (or touching) rivers. The files for rivers were downloaded from the Data Repository of the Geographic Information Support Team (GIST). Distances from rivers were computed for each pixel. Soil types are also a central element for landslides susceptibility. At this stage, the soil coverage in this region is still a major gap in the analysis that needs to be bridged.

A main hypothesis is that slope is the primary causal factor of landslides (including debris flows, blocks fall and landslides). Two DEM were used. The Shuttle Radar Topography Mission (SRTM) version 3 (at 90m spatial resolution) was obtained from the CGIAR Consortium for Spatial Information (CGIAR-CSI) and the ASTER (at 30 m spatial resolution) purchased from United States Geological Survey (USGS). These datasets allowed the computation of slopes for each pixel and to derive the maximum, average and standard deviation of slopes within each landslide).

Finally, the aim of the study was to ascertain the role of vegetation in relation with landslides. A pre-event satellite image from Landsat ETM sensor was used (image path: 150, row 36 from 7 October 2002). It was obtained from Landsat.org, Global Observatory for Ecosystem Services, Michigan State University. A normalise difference vegetation Index (NDVI) was computed. This combination of recorded electromagnetic reflectance in near Infra-red (nIR) and red (Red) wavelengths is highly correlated with photosynthesis activity, hence with density of vegetation (Tucker, 1979). Being a complex ratio it also reduces the problem of shadows produced by topographic effects. This was particularly relevant over this mountainous area. The ratio is computed using the equation :

$$\mathrm{NDVI} = \frac{(nIR - \mathrm{Re}\,d)}{(nIR + \mathrm{Re}\,d)} \quad (1)$$

Where:
NDVI: Normalized Difference Vegetation Index
nIR: electromagnetic reflectance in Near Infra-Red (not equal to zero)
Red: electromagnetic reflectance in Red (not equal to zero)

4.4.4. Methodology

Role of vegetation cover and landslides

To understand why some areas led to large landslides while others suffered smaller landslides, some basic tests using correlation matrix between variables and area of landslides, or 3D surfaces can provide useful hints. However, to better understand the context, multiple regressions analysis should be run. The size of landslide was set as the dependant variable for the magnitude of landslides. Prior to testing whether variations in vegetation cover density have an effect on the size of detected landslides, standardisation of other parameters is needed. A hypothesis was made that slope failures, triggered by earthquakes, were related with slopes, type of soil (not tested due to lack of appropriate data), proximity from active fault or epicentres and proximity from rivers.

Once the geophysical and morphological parameters related to slope failure are identified, proximity from trails (or roads) as well as role of vegetation cover can be introduced to see what are the potential mitigation or enhancing effects of these features.

The dependant variable was set to be the size of landslides. Using the post-event detection of landslides by SERTIT and NESPAK (further corrected by UNEP/GRID-Europe as explained in the point: "*Data preparation*"), the area (in m^2) of each landslide was computed using GIS. This variable was then transformed by computing the natural logarithm (LN) of the size.

$$LS_{size} = \alpha V_1^a \cdot \beta V_2^b \cdot \ldots \cdot \gamma V_n^i$$

Factors to be tested

Other factors were extracted using GIS techniques and associated with each landslide. Examples of variables extracted are provided in Table 44 while the full list of tested variables (including transformed variables) is provided in the Appendix B).

Table 44 Examples of variables extracted for each detected landslide

Raw data	Derived variables	Type of values recorded for each landslide
Detected Landslides	Area	Area, maximum width and length.
DEM	Slope	Elevation difference, Maximum slope, average slope, standard deviation.
Epicentre locations	Distance from epicentres	Minimum distance between either edge of the landslides or centre of the landslide area.
active fault	Distance from fault line	Minimum distance between either edge of the landslides or centre of the landslide area.
Rivers	Distance from river	Minimum distance between either edge of the landslides or centre of the landslide area.
Road and trails	Distance from road and trails	Minimum distance between either edge of the landslides or centre of the landslide area.
Landsat ETM+ image	NDVI	Maximum, minimum and average NDVI value.

Transformation and normalisation of variables were needed because the links between landslide area and other contextual parameters are not necessarily linear and statistical linear regressions request variables that follow a normal distribution. In order to see how these variables behave, a visual test using histograms and scatter plots was performed and variables were transformed accordingly (as explained below).

Data preparation

The list of data sources is provided in Appendix A. The preparation of data involved:

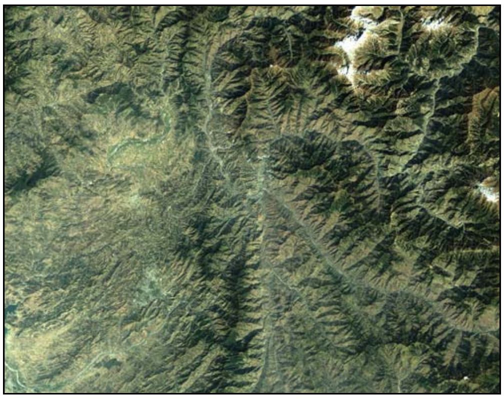
Improving the recorded landslides data

The recorded landslides from both SERTIT and NESPAK, did not take into account the trans-edge or trans-river effect. In other words, two landslides having the same origin at a mountain edge, or two landslides ending their courses in front of each other at the bottom of a valley, were recorded by SERTIT or NESPAK as one landslide. To correct for these issues, manual transformation of these two datasets were made (thanks to the work of Rafaël Klaus as part of his internship at UNEP/GRID-Europe).

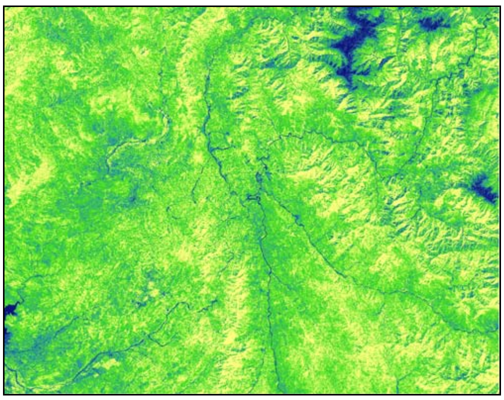
Computation of distances

Distances were computed for the following features: roads, trails, active fault and epicentres. This operation was performed in a GIS using a raster of 30m x 30m, where each cell includes the minimum distance to one of the selected feature as well as distance between the centre of each landslide and the selected features.

Computation of NDVI



Landsat image (Band 1, 2, 3)



NDVI

Figure 111 Computation of NDVI using Landsat band 3 and 4

In Figure 111 one can see that the computation of the NDVI strongly reduced the shadows produced by the relief. In the bottom image, low NDVI values are displayed in blue and include ice, snow, rivers and lakes, while green reflects the high NDVI values produced by dense vegetation.

Slopes

Slopes were computed using GIS, based on both ASTER (30m x 30m) and SRTM (90m x 90m) DEM datasets. The SRTM covers a larger area (in fact the whole world is available), whereas the ASTER DEM purchased, "only" covers 3,600 km^2. If the 90m resolution is sufficient, an extrapolation to a larger area using SRTM would be possible.

4.4.5. Data extraction, transformation and integration

Values extraction

By superimposing the detected landslides over the different layers of information, it was possible, for each individual landslide, to compute the minimum distance (or maximum, average…) from a specific feature (such as river, trails, roads, active fault, epicentres) or the maximum slope (average, standard deviation and square of maximum slope were also computed and extracted). The same process was applied to extract the minimum, maximum and average value of NDVI.

Transformation of variables

Prior to developing the statistical analysis, the variables need to be selected and transformed to ensure that they follow a normal distribution. The link between landslide area and other factors is not necessarily linear, so a visual interpretation followed to identify whether some functions can be applied to improve the link with landslide area. For example, in a scatter plot *landslide areas* seemed to present a link with the square of *maximum slope*. This function was hence computed for *maximum slope*.

The variables were transformed by taking the natural logarithm (LN) of scalar or, in some cases, the LN of transformed values. Transformations already proved to be efficient in previous studies (Peduzzi *et al.*, 2002) (Chatenoux and Peduzzi, 2007). For variables ranging between 0 and 1 (e.g. percentage, or NDVI) Equation 3 was applied.

$$V_i^{'} = LN\left(\frac{V_i}{1-V_i}\right) \qquad (3)$$

Where

Vi is the variable to be transformed and

Vi' is the transformed value.

The choice of logarithmic regression was made to reflect the interactivity between the different parameters, given the multiplicative effect on each other (an addition of LN being a multiplication of the exponents). This is believed to be pertinent, given the complexity of sites where one factor can mitigate or enhance another.

All the 36 variables (see Appendix B) computed and/or transformed for all the individual landslides were placed in a database and then introduced into statistical software for multiple regression analysis.

Groups of independent variables

A correlation matrix (see Appendix C) was computed between all the variables and used to discriminate variables that were too correlated to be taken together in regression analysis. Groups of independent variables were generated, each one corresponding to a specific hypothesis, which was tested by running multiple regression analysis. The selection of the most relevant hypothesis was based on relevance (p-level < 0.05) and maximisation of percentage of variance explained (R^2). This process allows the identification of combinations of parameters that best explain the landslide area and thus confirms or rejects the hypothesis on the potential role of the different environmental and geomorphologic features.

4.4.6. Statistical results

Hypothesis can be quickly tested using correlation matrix between variables and area of landslides. In some cases, plotting observed data in 3D surfaces can provide useful hints to show correlation of landslides area with two independent variables. For example Figure 112 shows that the landslides area decreases sharply when slopes decrease (until 30°) or when distance to active fault increase. It also shows that below a slope of 30°, landslides area may increase when located closer to active fault. This is in line with findings provided by Sato *et al.* (2007).

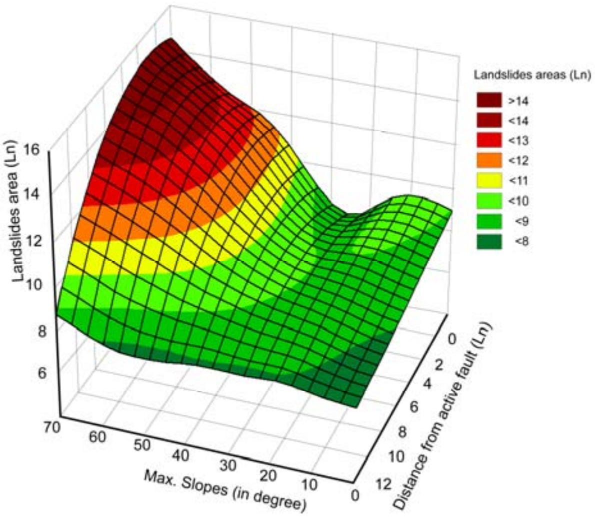


Figure 112 landslides area versus slopes and distance from active fault

Similarly, the effect of vegetation density can be quickly tested by looking at 3D surface between landslides area, maximum slope and a proxy of vegetation density (NDVI). Figure 113 highlights the role of vegetation density, where NDVI is inversely correlated with the Ln of landslides area.

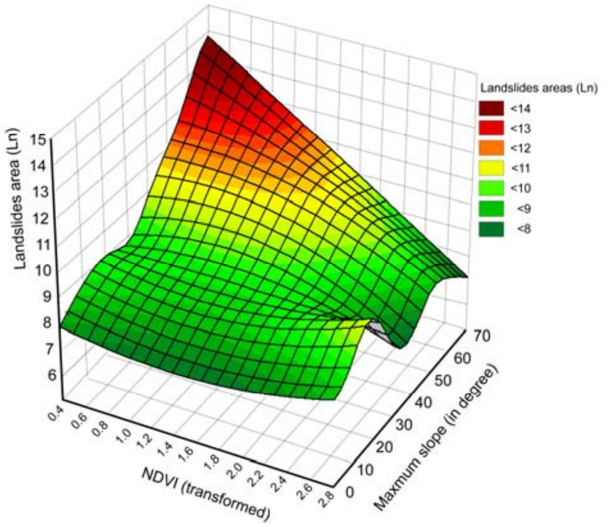


Figure 113 Landslides area versus slopes and vegetation density (NDVI)

However, 3D plots can only display the link with two explaining variables and some of the variations viewed in Figure 112 and in Figure 113 suggest that other variables play a role. For example, the increase in landslide area at gentle slope and high vegetation. Could it be along rivers? To really address the weight of each parameters and the potential multiplicative effect of variables, a multiple regression analysis is needed.

General model (all landslides considered – except outliers)

The multiple regressions analysis (Table 45) selected the following variables being associated with the landslides area (see Appendix F, for further details on how to read the information provided in the table). The regression coefficients (third column) represent the weight that should be multiplied by each independent variable to get the predicted dependent variable.

The expected LN of landslide area from this model would be :

$$LN\_LsArea = -0.125 D\_river\_\min Ln + 0.206 D\_trail\_avLn - 0.246 D\_fault\_\min Ln - 0.878 NDVIt\_avLn + 0.263 Slope\_\max^2 Ln + 7.913$$

However, a higher weight do not necessarily implies a higher degree of influence. This is because the units are not the same between the variables as they were not standardized to a mean of 0 and a standard deviation of 1. The magnitude of the "Beta" coefficients provide information on the relative contribution of each independent variable. From the "Beta" coefficient, the percentage of contribution to landslide area can be derived (see column "contribution". *Slopes* and *Distance from active fault* were both explaining most of the variance (about 35% each), the next one *Distance from river* explaining much less (about 12%), *NDVI* and *distance from trail* explain about 9% each.

All the signs are according to the common sense (the steeper the slope, the larger the landslides, the smaller the distances to active fault, river, trails, the larger the landslides and the smaller the NDVI the larger the landslides). The selection shows a high degree of confidence (p-level much smaller than 0.05; the highest p-level is associated with distance from trail with a value of 0.002, hence 99.8% (1 - 0.002) probability that the selection of distance from trail is not due to random process.

The percentage of variance explained (R^2) by the general model reaches 61.3% (Pearson = 0.78), baring in mind that the variables have been transformed and expressed here in logarithms. The total number of landslides considered for the analysis is 280, 262 had valid information for the variables studied. 246 cases were considered, excluding 16 outliers (+2.0 sigma).

Table 45 Results from multiple regression analysis

Variables	Beta	Coeffi-cient	p-level	Contri-bution
Intercept		7.913	0.000000	
D_river_minLn	-0.180	-0.125	0.000013	12.13%
D_trail_avLn	0.128	0.206	0.001859	8.63%
D_fault_minLn	-0.520	-0.246	0.000000	35.04%
NDVIt_avLn	-0.137	-0.878	0.001007	9.23%
Slope_max²Ln	0.519	0.263	0.000000	34.97%

r = 0.78, R^2 = 0.613, Adjusted R^2= 0.601, N = 246, outliers = 16

Where:

Intercept: Intercept value of the regression line

D_river_minLn : Logarithm natural of minimum distance between landslides and river

D_trail_avLn: Logarithm natural of minimum distance between landslides and trail

D_fault_minLn: Logarithm natural of minimum distance between landslides and active fault

$NDVI_t$_avLn: Logarithm natural of average transformed value of NDVI

Slope_max^{2}Ln: Logarithm natural of maximum slopes as detected from ASTER

The correlation matrix (Table 46) between the explicative variables shows no auto-correlations. Maximum slopes and distance from active fault area already strongly correlated with landslides area (0.505 and -0.533 respectively).

Transformation and normalisation of variables were needed because the links between landslide area and other contextual parameters are not necessarily linear and statistical linear regressions request variables that follow a normal distribution. In order to see how these variables behave, a visual test using histograms and scatter plots was performed and variables were transformed accordingly (as explained below).

Table 46 Correlation matrix

N=246	D_river_minLn	D_trail_avLn	D_fault_minLn	NDVIt_avLn	Slope_max²Ln
D_trail_avLn	0.045				
D_fault_minLn	0.105	0.035			
NDVIt_avLn	0.081	0.143	0.052		
Slope_max²Ln	-0.020	0.100	0.018	0.153	
Ls_areaLn	-0.251	0.134	-0.533	-0.081	0.505

Where:

Other factors as above mentioned and

Ls_areaLn: Logarithm natural of landslides area

The scatter plot featuring predicted versus observed values (Figure 114) shows a relatively good fit; however it seems that two groups can be identified with a gap between large landslides areas and smaller one.

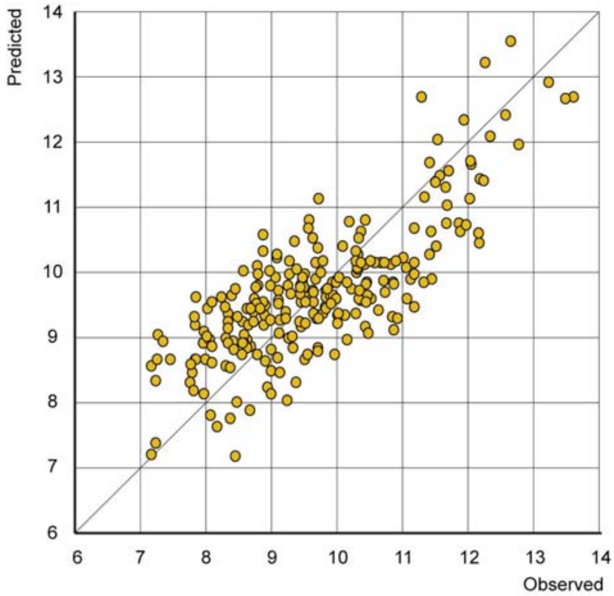


Figure 114 Predicted size of landslides versus observed, scale in Ln[m2]

Differencing landslides close and away from rivers

Numerous small landslides were observed along rivers (or close to rivers). Larger landslides seem to be following different rules. Given that distance from river might not be relevant for landslides away from rivers, a hypothesis was made that landslides might be modelled using differentiated regressions. Three different categories of landslides were made: those touching rivers, those close to rivers (but not touching) and those away from rivers (at a distance greater than 100 meters), this process was carried out using both Boolean conditions and a (GIS) buffer of 100 m around rivers to intersect with surrounding landslides.

Landslides away from river (minimum distance > 100 m)

The number of cases away from rivers is 98 (once excluding 3 outliers, with sigma > 2.0).
Percentage of variance explained is 54.0% (Pearson = 0.73).
The variables selected are as follows:

- Slope (square of Ln maximum slope)
- Minimum distance from active fault (Ln)
- NDVI (Ln of transformed values)

The level of significance is very high (all p-level much smaller than 0.05), no auto-correlation suspected, the signs are according to what was expected (see Table 47). According to the Beta coefficient the susceptibility factor most influencing the landslide area is slope (41.2%), followed by distance from active fault (38.9%) and then NDVI (19.9%).

Table 47 Results from multiple regression analysis for landslides away from rivers

Variables	Beta	Coeffi-cient	p-level	Contri-bution
Intercept		7.029	0.000000	
D_fault_minLn	-0.511	-0.219	0.000000	38.9%
NDVIt_avLn	-0.256	-1.540	0.000652	19.9%
Slope_max²Ln	0.541	0.373	0.000000	41.2%

r = 0.732, R^2 = 0.535, Adj. R^2 = 0.520, N = 98, outliers = 3

The distance from trails and the distance from rivers are no longer selected by the model, which makes sense for rivers, given the filters applied.

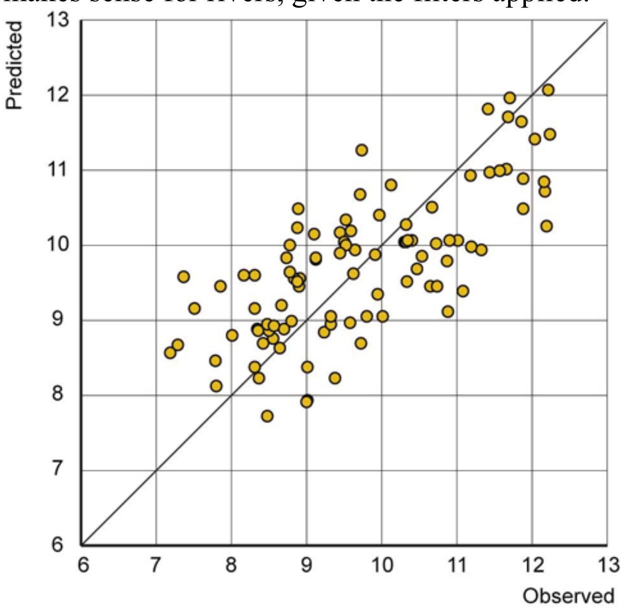


Figure 115 Predicted size of landslides versus observed: Landslides away from rivers (> 100 m), scale in Ln(m2)

Landslides close to river (at a distance from river < 100 m)

The number of valid cases was 178, with 169 considered and 9 outliers. The percentage of variance explained increased to 64.3% (Pearson = 0.80)

The variables selected were:

- Minimum distance from active fault (Ln)
- Maximum slopes (Ln^2)
- Distance from trails.

The level of significance is very high (all p-level much smaller than 0.05), no auto-correlation suspected (see Table 48). First contributor is slope (42.0%), followed by distance from active fault (36.8%) and then distance from trail (21.2%).

Table 48 Results from multiple regression analysis for landslides close (but not touching rivers)

Variables	Beta	Coeffi-cient	p-level	Contri-bution
Intercept		9.343	0.000000	
D_trail_avLn	-0.249	-0.172	0.000003	21.2%
D_fault_minLn	-0.433	-0.230	0.000000	36.8%
Slope_maxLn²	0.493	0.245	0.000000	42.0%

R = 0.802 R^2 = 0.643, Adj. R^2 = 0.636, N = 169, outliers = 9

Where:

Dist_trail_av_Ln: Logarithm natural of minimum distance between landslides and trail

Dist_fault_min_Ln: Logarithm natural of minimum distance between landslides and active fault

Slope_max_Ln^2: Square of logarithm natural of maximum slope as recorded by ASTER

The parameters distance from trail is selected, whereas NDVI is no longer considered by the model.

Landslides touching river

For this category of landslides (touching river), only the slope (52.3% of contribution) and the distance from active fault (47.7%) is relevant according to the statistical model. The explanation value is 53% (Pearson = 0.73). The level of significance is very high (all p-level much smaller than 0.05), no auto-correlation suspected (see Table 49). The distance from trails/roads and NDVI is no longer considered.

Table 49 Results from multiple regression analysis for landslides touching rivers

Variables	Beta	Coeffi-cient	p-level	Contri-bution
Intercept		8.630	0.000000	
D_fault_minLn	-0.490	-0.211	0.000000	47.7%
Slope_maxLn²	0.537	0.200	0.000000	52.3%

r= 0.730, R^2= 0.532, Adj. R^2 = 0.520, N = 82, outliers = 5

4.4.7. Cartographical results

Spatial model

The model was improved by looking at different distance from rivers, although following the theory, three sets of equation should be collected (touching rivers, < 100m from rivers and away from them), given that at such resolution only three pixels account for a distance of 90 meters, a simplified model based on results provided in Table 47 (away from rivers) and Table 49 (touching rivers) provides the following equations:

If Distance river > 100, then

$$Ls\_areaLn = - 0.219 * D\_fault\_Ln - 1.54 * NDVIt\_avLn + 0.373 * Slope^2Ln + 7.029 \quad (4)$$

Else

$$Ls\_areaLn = - 0.211 * D\_fault\_Ln + 0.2 * Slope\_Ln^2 + 8.63 \quad (5)$$

Buffers of 100 meters were generated on both sides of rivers for discriminating between first and the second case. For each pixel (of 30m x 30m) the distance from active fault, the slope and the NDVI were computed (with the relevant transformations and corresponding weights and exponents). This allows the creation of a susceptibility map as shown in Figure 116

.

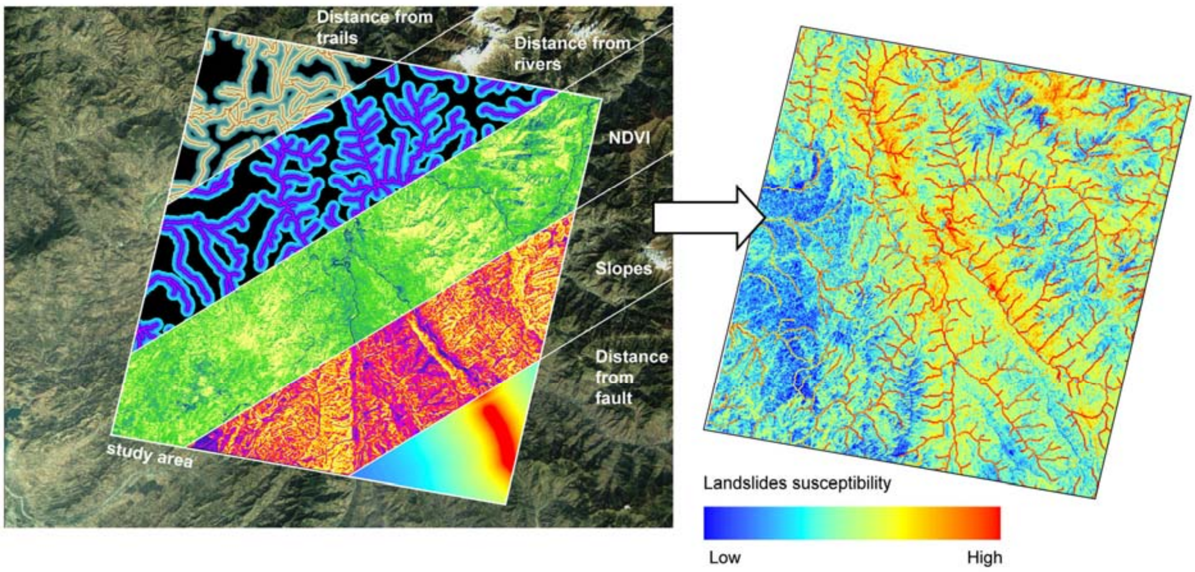


Figure 116 Map of landslides susceptibility as modelled

4.4.8. Discussion

The five factors identified as having an influence on landslide area fell in three categories, namely: slope, distance from linear features (active fault; trails or river) and vegetation cover density.

Slopes

Not surprisingly, the main parameter for landslides occurrence is slope. The positive sign associated to the parameters is indicating that the steeper the slope, the higher the landslide susceptibility, which is perfectly logical. Tests were made using the SRTM DEM (at 90 meters resolution), however the variance explained dropped significantly, hence extrapolation to larger areas was abandoned. The role of slopes being so predominant, a higher resolution is needed. Higher resolution DEM might improve the model. It may allow computation of concave and convex slopes as this was proven to be an improved explanatory factor in other study (Sato *et al.*, 2007).

Distance from features

The negative sign before the coefficient means that the closer from the active fault, river or trail/road, the larger the value of landslide area. This is consistent with the theory, the maximum energy being closer to the epicentres. Similar links with negative coefficients were found for rivers and trails, although the influences of these features are much more local and the range of influence on instability is not known. Trails could be replaced by roads (although there are fewer of them and thus the variance explained was slightly lower). If distances from trails and roads were highlighted in the general model, it was only selected for landslides near but not touching rivers. Indeed, most of the roads are along main rivers, so while selecting areas touching rivers, it spatially already includes these roads, hence the selection wasn't pertinent anymore. However, their selection in the general model is an indicator that these human infrastructures should be studied with attention.

Vegetation density (NDVI)

The use of NDVI proxy appears to be efficient in linking contextual vegetation density with susceptibility of landslides. Although the part of variance explained was not really high, the confidence in the selection (low p-level) clearly indicates that the presence of denser vegetation has a mitigation effect on landslide susceptibility. The close up using the verification model provides some striking examples for the entire map. When displayed to local decision makers, it had a large impact and will hopefully lead to improve environment management. Socio-economic studies on why forests have been cleared should now be conducted in order to see what solutions could be envisaged to reverse the trend. By running the model without the NDVI mitigation effect, the total susceptibility in the study rose by 15.13%. This delineates that vegetation cover is a significant component of risk reduction.

Verification of causality

Correlations between set of parameters do not necessarily imply causality. Providing this link is the usual weakness of statistical regression analysis.

One might argue that because areas on steep slope might be less covered by vegetation. Thus observing less dense vegetation might be an indirect way of looking at slope. To test if slopes and vegetation are correlated, a simple scatterplot of the two susceptibility factors can be computed using the function "scattergram" in the module GRID from ArcINFO workstation (see Figure 117). This scatterplot shows no correlation between the two variables. Hence, there is no indication that vegetation density is function of slope.

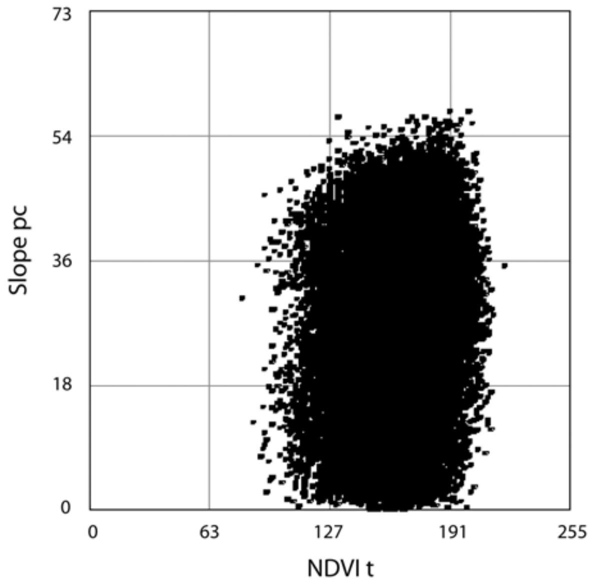


Figure 117 Scatterplot of vegetation density (NDVI t) versus slope (slope pc)

Another test can be run by looking for similar areas, where only one parameter is changing. For example, to test whether vegetation density has mitigation effect on landslide susceptibility, a model can be run without the NDVI component, thus normalising all the features but the vegetation. By plotting forest cover (pre-landslide) and landslides as recorded, landslides should be more frequently observed in areas with similar landslide susceptibility in areas with lower vegetation density as compared with areas covered with dense vegetation.

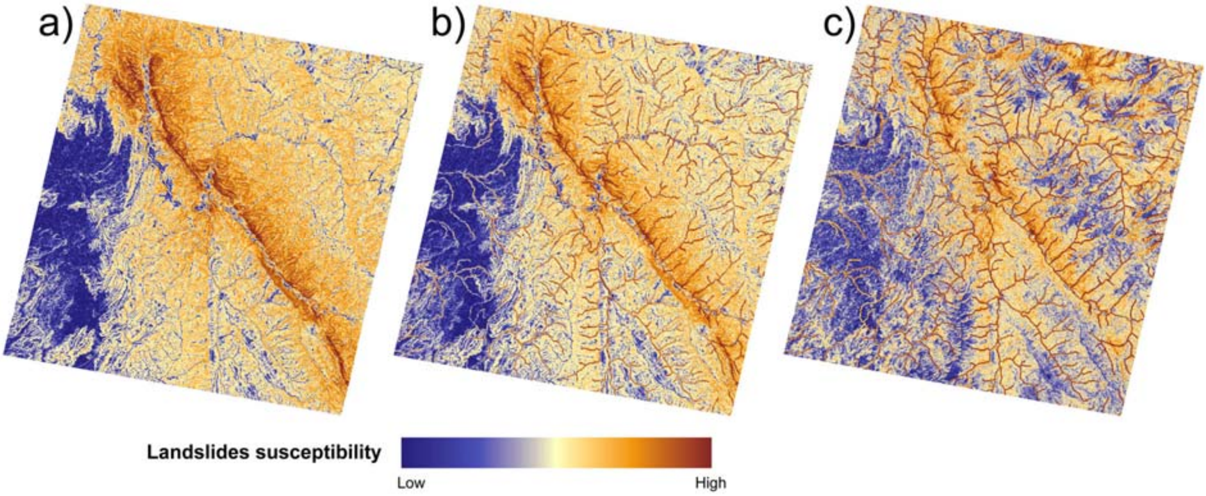


Figure 118 Different models of landslides susceptibility (a. including slope and active faults, b. adding distance from rivers, c. adding presence of vegetation).

The Figure 118 shows three different models, clearly looking at slopes and distance from active fault does not explain for all the landslides on river shores. Thus model "b" is already adding valuable information on susceptibility by adding distance from rivers; however, model "a" and "b" are presenting an area of landslide susceptibility that is much larger than observed impacts. Adding vegetation cover as parameters (model "c"), drastically reduces the area at risk and provides a much better match between observed landslides and the model.

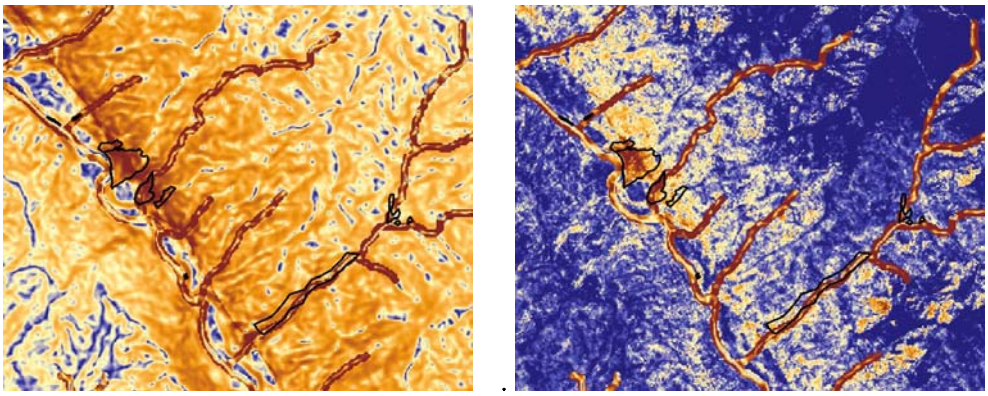


Figure 119 Close up without vegetation mitigation effect (model "b"), left and with vegetation mitigation effect (model "C"), right.

In Figure 119, the left-hand close up shows a model without a vegetation density component. In a way it shows a theoretical situation if all vegetation were removed. The susceptibility seems to be spread in most of the area, whereas observed landslides areas are featured in bold black. On the right-hand close up, the model includes the vegetation mitigation effect. The areas susceptible to landslides are much more concentrated and fit better with the observed impacts.

These results are encouraging. Although global datasets cannot (and should not) be used for local landuse planning, this method has some great potential as an advocacy tool or to determine where more detailed data should be acquired, allowing saving on – usually – high input costs.

4.4.9. Conclusion

The study confirmed the hypothesis that landslide occurrence is higher on steep slopes, close to rivers, trails, active fault and that vegetation cover seems to act as stabiliser in this region. The results from this research show that adding the mitigation effect of vegetation cover in the model drastically improves the model as compared with the observed landslide areas. This seems to indicate that, in this region, vegetation seems to play a significant role in decreasing landslide susceptibility. It shows that global available datasets can be used to select layers of information to be gathered and narrow the areas where deeper analysis should be conducted.

Given that this study uses of low costs data and free available data, the resolution of such data (at best 30m) is not appropriate for local land planning. But given the price of high resolution DEM and satellite sensors (e.g. IKONOS, Quickbird, GeoEye and alike), such study is very useful to identify areas where detailed data should be collected.

The applied method proved to be successful in providing statistical links between contextual parameters, vegetation density and size of landslides. The extrapolation of the model to the area provides a general quick look of the areas of potential high risk of landslide occurrence. The spatial precision of the DEM was the main reason for the success of this analysis; hence the extrapolation using lower spatial distribution (such as SRTM) was not possible without significant decrease in accuracy. New studies from University of Lausanne are now been implemented with very high resolution satellite data (Quickbird, 0.6 m resolution) to zoom in the Neelum Valley and bring more in depth analysis.

The role of small tracks in inducing risk of soil instability was highlighted. This parameter (along with vegetation cover, slope, distance from rivers and proximity from active fault) should be considered for landuse planning. Whereas for timber exploitation, pasture or access, such high risk areas cannot be managed without improved information in landslide occurrence. The larger gap to be bridged is the lack of data on soil types, which would most probably, increase the level of accuracy. It would, however, introduce a difficulty, as type of soil is not a continuous variable. It would request either to run several models (one for each type of soil), or to use expert judgment on the susceptibility of each soil type.

The methodology is quite simple, based on global datasets and/or easily accessible data. This was applied in the case of landslides triggered by earthquakes, but should now be tested on other areas with landslides triggered by heavy precipitation in deforested areas. It can be adapted to allow gathering evidence in different areas of the planet where heavy deforestation has been recorded, thus hopefully address the message that healthy ecosystems can help reduce disaster risk.

This model was presented to local authorities. The simple message it carries was well-received. It should be emphasized that reforestation cannot suppress all the susceptibility factors (such as slope, rivers and distance from active fault). Landuse planning in areas where such magnitude of earthquakes can take place is not an easy task. Planting trees and increasing vegetation density cannot be the only solution and should not be done blindly. Methodologies for reforesting using local useful species is one of the recommendations, however, some cities in the region are located straight on the active fault (or potentially active fault), on Quaternary rocks, where recorded vertical deformation of land (uplift) was between 1 and 6 meters. Clearly in these locations, forest cover will not be of sufficient protection. If delocalisation of population is to be carried out, it is hoped that the new settlements will be chosen with care not to recreate risk and that it will be done with more consideration for environmental features.

Appendix A: Raw data sources

Features	Raw data providers	URL link (if relevant)
Post event landslides	Service Régional de traitement d'image et de télédétection (SERTIT)	http://sertit.u-strasbg.fr/documents/asie/asia_en.html
Post event landslides	National Engineering Services of Pakistan (NESPAK), both obtained through the Humanitarian Information Centre For Pakistan (HIC)	
active fault	Manually digitalised from a map published by Nakata *et al.* (1991)	
Roads/trails	United Nations Joint Logistics Centre (UNJLC)	
Rivers	Data Repository of the Geographic Information Support Team (GIST)	https://gist.itos.uga.edu/index.asp?body=repository
Epicentres	Advanced National Seismic System (ANSS)	http://quake.geo.berkeley.edu/anss/
Vector country borders	NIMA Vmap level 0, UN Cartographic Section	www.mapability.com/info/vmap0_intro.html
Digital Elevation Model (DEM), 90m	Consortium for Spatial Information (CGIAR-CSI) SRTM version 3.	http://srtm.csi.cgiar.org
DEM, 30m	From ASTER data purchased at USGS	http://lpdaac.usgs.gov/aster/ast14dem.asp
Satellite imagery	Landsat 7 ETM+, path/row: 150/36, 7 Oct. 2001, original data sources: Landsat ETM from 7 Oct. 2001, path/row 150/36 obtained through the Global Observatory for Ecosystem Services, Michigan State University	http://landsat.org

Appendix B: Set of independent variables extracted

ID	Variable name	Description
V1	Geol_class	Classified lithology
V2	TYPES	Landslides shape (horizontal, vertical and large)
V3	EPI55_Ln	Log Natural (Ln) of Distance Epicentre>5.5 and centre of landslides
V4	EPI7_Ln	Ln of Distance Epicentre>7 and centre of landslides
V5	EPI8_Ln	Ln of distance between epicentre = 7.6 and centre of landslides
V6	DFPC2001	Dense forests % in 2001 (transformed and Ln)
V7	AFPC2001	All forest % in 2001 (transformed and Ln)
V8	DFPC1992	Dense forests % in 1992 (transformed and Ln)
V9	AFPC1992	All forest % in 1992 (transformed and Ln)
V10	DFPC1979	Dense forests % in 1979 (transformed and Ln)
V11	AFPC1979	All forest % in 1979 (transformed and Ln)
V12	D_AF_N	Deforestation 2001-1979 all forest, normalised et Ln
V13	D_DF_N	Deforestation 2001-1979 dense forest, normalised and Ln
V14	DEM_D_Ln	Difference in elevation en Ln
V15	SL_MAXPC	Slope max in %
V16	SLMEANPC	Slope min in %
V17	SLOPESTD	Slope standard dev.
V18	SL_MEDPC	Slope median %
V19	FAU_E_Ln	Ln distance fault (edge)
V20	FAU_C_Ln	Ln distance faille (centre)
V21	RIV_E_Ln	Ln distance to river (edge)
V22	RIV_C_Ln	Ln distance to river (centre)
V23	ROAD_ELn	Ln distance route (edge)
V24	ROAD_CLn	Ln distance route (centre)
V25	TRAILELn	Ln distance trail (edge)
V26	TRAILCLn	Ln distance trail (centre)
V27	LN__AS_D	Ln DEM Aster Difference DEM
V28	AS_SLMAX	Maximum slope max from ASTER DEM
V29	AS_SLAV	Slope average from ASTER DEM
V30	AS_STD	Slope standard deviation from ASTER DEM
V31	minR_Tc	Distance minimum between road and trail (centre)
V32	minR_Te	Distance minimum between road and trail (edge)
V33	MinNDVIt_Ln	Minimum NDVI transformed and Ln
V34	MaxNDVIt_Ln	Maximum NDVI transformed and Ln
V35	AVNDVIt_Ln	Average NDVI transformed and Ln
V36	$Slopemax^2\_Ln$	Ln of the square of the maximum slope
V37	$Slopemax\_Ln^2$	Square of the Ln of maximum slope

Appendix C: Example of a selection of non-correlated features using correlation matrix

Variables	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11
V1	- - -										
V2	**-0.611**	- - -									
V3	0.030	0.064	- - -								
V3	0.151	-0.021	0.681	- - -							
V5	-0.157	0.150	**0.511**	0.408	- - -						
V6	-0.306	0.263	0.397	0.291	**0.661**	- - -					
V7	-0.190	0.160	-0.054	0.010	**0.557**	0.379	- - -				
V8	**-0.574**	**0.509**	-0.018	-0.059	0.132	0.194	0.127	- - -			
V9	-0.027	-0.047	0.073	0.026	0.086	0.137	0.039	-0.110	- - -		
V10	0.246	-0.180	0.164	0.240	0.115	-0.034	-0.002	-0.191	0.006	- - -	
V11	-0.084	0.070	0.013	0.000	0.069	0.244	0.064	0.038	-0.030	-0.035	- - -
V12	0.322	-0.329	0.023	0.069	-0.111	0.004	-0.078	-0.358	-0.218	0.085	0.546

In bold the variables that cannot be placed in the same group of analysis.

Appendix D: Descriptions of acronyms used in this paper

Acronyms	Description
ANSS	Advanced National Seismic System
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
CGIAR-CSI	Consortium for Spatial Information
CNSS	Northern California Earthquake Data Center
CRED	Centre for Research on Epidemiology of Disasters
DEM	Digital Elevation Model
GIS	Geographical Information System
GIST	Geographic Information Support Team
HFA	Hyogo Framework for Action
HIC	Humanitarian Information Centre For Pakistan
IFRC	International Federation of Red Cross and Red Croissant Societies
ISDR	International Strategy for Disaster Reduction
IUCN	International Union for Conservation of Nature
IUED	Institut Universitaire d'Etude du Développement
NDVI	Normalised Difference Vegetation Index
NESPAK	National Engineering Services of Pakistan
NIR	Near Infra-Red
SAR	Synthetic Aperture Radar
SERTIT	Service Régional de traitement d'image et de télédétection
SRTM	Shuttle Radar Topography Mission
UNEP	United Nations Environment Programme
UNEP/GRID	United Nation Environment Programme, Global Resource Information Database
UNJLC	United Nations Joint Logistics Centre
UTM	Universal Transverse Mercator

Appendix E: List of software used for the analysis

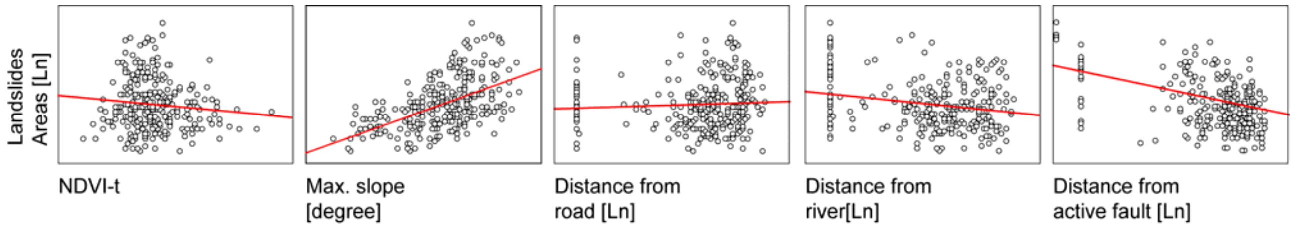
Tasks	Software
GIS	ArcGIS 9.2; ArcINFO workstation 9.2
Remote sensing	ERDAS IMAGINE 8.4
Statistics	Statistica 8, Minitab 15.1.30.0.
Cartography, graphs	Adobe Illustrators CS3, Photoshop CS3

Appendix F: Statistical concepts

For readers who are not familiar with some of the statistical concepts used in this paper, here is a small summary. This section is adapted from the on-line help of StatSoft Electronic Statistics Textbooks (http://www.statsoft.com/textbook/statistics-glossary/).

Multiple regression analysis

When addressing the potential link between one variable (e.g. slope) and a dependant variable (e.g. landslide areas) simple scatter plots provide useful information (See figure A1).



Some variables can directly be linked with landslide areas (e.g. slope), however, one variable is usually not enough to model the behaviour of a dependent variable. Variables can have a multiplicative effect when associated one to another.

To understand what the best combinations of susceptibility factors are and how they contribute to landslide area, a *multiple regression analysis* can be made. Such statistical process aims to highlight the relationship between a dependent variable (e.g. landslide area) and several independent variables (potential susceptibility factors, e.g. slopes, distance from active fault, presence of vegetation,...).

The aim is to obtain an equation such as:

$$LA = \alpha X_1 + \beta \cdot X_2 + ... + \theta \cdot X_n + I$$

Where

LA = Landslide area

X_1 = first susceptibility factor (e.g. slope)

X_2 = second suscpeptibility factor (e.g. distance from active fault)

X_n = last susceptibility factors (e.g. vegetation density)

α, β and θ = weights which multiplies the factors.

I = Intercept

The purpose is double, first it allows a better understanding of the underlying processes leading to landslides, secondly, it provides the weights associated with each susceptibility factors, allowing creating maps of landslides susceptibility. The main limitation being that although it shows potential link, it cannot ensure causality (see causality below).

Pearson coefficient, r

The independent variables in the model should not have influence between them. To produce group of independent variables a correlation matrix is computed and variables that are too correlated should not be tested in the same hypothesis. Thus group of uncorrelated variables should be created (see appendix C). The r is the pearson coefficient, it is computed as follows:

correlation coefficient, r, is computed as follow:

$$r = \frac{\sum (x-\bar{x}) \cdot \sum (y-\bar{y})}{\sqrt{\sum (x-\bar{x})^2 \cdot \sum (y-\bar{y})^2}}$$

where

$\bar{x}$ is the average for a observed dependant variable

$\bar{y}$ is the average for the modelled variable

In this study, two independent variables could be placed in the same group if $|r| < 0.5$.

R^2 and Adjusted R^2

R^2 is the square of r, it provides an indication of the percentage of variance explained.

Adjusted R^2 is a modification of R^2 that adjusts for the number of explanatory terms in a model. Meaning that by adding more explanatory variables you might increase the R^2, but it could also be by chance (over fitting models). The Adjusted R^2 is particularly useful in the selection of potential susceptibility factors as it takes into account the number of explanatory variables and only increase if the added explanatory variable explains more than as a result of a coincidence.

$$adj.R^2 = 1 - (1 - R^2) \cdot \frac{n-1}{n-p-1}$$

Where

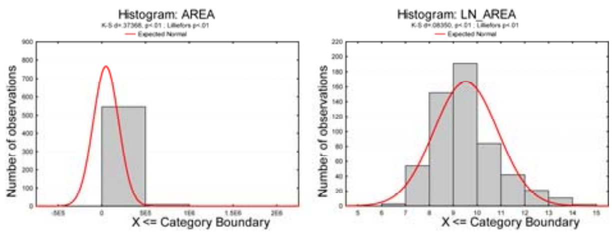
n = is the sample size, p is the number of independent variables in the model.

In general terms, the more explanatory variables you have the less the adj. R^2, because by introducing more independent variables, you increase the risk that the results is obtained by random. This is often called "overfitting".

Normal distribution

The variables should follow a normal distribution. This can be done by looking at histograms and by applying some statistical normality tests (e.g. Normal expected frequencies, Kolmogorov-Smirnov & Lilliefors test for normality, Shapiro-Wilk's W test.). If a variable do not follow a normal distribution, it needs to be transformed so that it does (e.g. computing the Ln, or using transformation formula). The figure below shows the distribution of landslide areas. Taking the Ln greatly improve the normality.

Figure A2: normality



Other functions can be used as specified in the article.

Outliers

Outliers are cases that do not follow the general assumption. In the real environment, it is difficult to take all the parameters reflecting the complexity of the situations. Some isolated cases, might have specific settings, and they don't follow the general trends. These outliers are easy to identify as they are distant to the rest of the data. They should be identified and removed so that the general rule can be better identified. However, an analysis of these outliers should be performed to ensure that they don't follow another rule. If this is the case, then the dataset might need to be split so that two (or more) models can be generated. For example, we differentiated landslides close to rivers and landslides away from rivers as it seems that these two groups follow different rules.

Causality

Correlation between two variables (e.g. A & B) do not imply that variation of A is the origin of the variation of B.

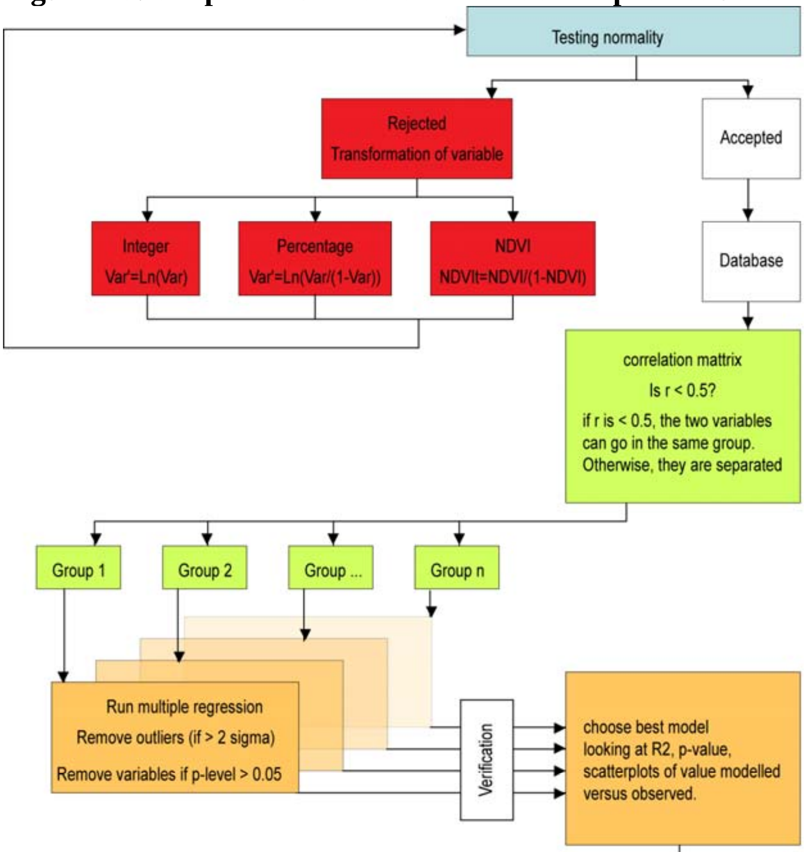
If multiple regression can show potential link, it cannot ensure causality.

What we aim to do is to say that factor A (e.g. vegetation density) influence B (landslide area). Now having a correlation between factors A & B can have several origins:

A is indeed having an influence on B or
B is influencing A or
C is influencing A & B.

The p-level provide good insight on the probability that the link is due to a coincidence. However, addressing causality is always the main challenge (see discussion under "verification of causality").

Figure A3: Simplified version of the statistical process used in this study



Variables	Beta	B	p-level	Contribution
Intercept		7.03	0.000000	
D_fault_minLn	-0.51	-0.22	0.000000	38.93 %
NDVIt_avLN	-0.26	-1.54	0.000652	19.85 %
Slope_max2Ln	0.54	0.37	0.000000	41.22 %

Model
LN(Landslide area)= -0.22D_fault_minLn -1.54NDVIt_avLN + 0.37Slope_max2Ln +7.03

In the final table (in blue) provided, the coefficient "Beta" provides information on the relative contribution of each susceptibility factor to landslides area. Slopes is the main one (0.54) and has a positive sign, hence the steeper the slope the bigger the landslide area; distance from active fault is the second contributor (-0.51) and has a negative sign, hence the further away from active fault line, the smaller the landslide areas and finally NDVI has a negative sign, hence denser vegetation (high NDVI) relates to smaller landslide areas.

One can even compute the percentage of contribution from each factor. For this we need to sum the absolute value of the Beta coefficient (0.51 + 0.26 + 0.54 = 1.31), then the ratio of each absolute value of the Beta coefficient provides the percentage of contribution for each variable: slope contributes for 41.22% (0.54/1.31), distance from active fault for 38.93% and NDVI for 19.85%. These percentage are provided in the last column (contribution).

The coefficient B (third column) provide the weights which can be used to model the landslide area (see equation of the model below the table).

The p-level indicates the probability that the variable was selected by coincidence. For example a p-level of 0.05 indicates that there is 5% of chance that the selected variable is a "fluke". This level is customarily treated as a "border-line acceptable" error level. So the lowest the p-level the highest the confidence in the selection. In this study the highest p-level was 0.0018, meaning the all the selected variables have less than 0.18% chance of being selected by coincidence.

Acknowledgements

Thank you to Raphaël Klaus for his valuable contribution on digitalisation of active faults and improvement of the recorded landslides dataset, to Karen Sudmeier-Rieux (University of Lausanne/IUCN) for successful collaboration with us on this subject and her useful editing suggestions, finally to Michel Jaboyedoff (University of Lausanne) for his review.

4.4.10. References

Avouac, J. P., Ayoub, F., Leprince, S., Konca, O., and Helmberger, D. V.: The 2005, Mw 7.6 Kashmir earthquake: Sub-pixel correlation of ASTER images and seismic waveforms analysis, Earth and Planetary Science Letters, 249, 514-528, 2006.

Ayalew, L., and Yamagishi, H.: The application of GIS-based logistic regression for landslide susceptibility mapping in the Kakuda-Yahiko Mountains, Central Japan, Geomorphology, 65, 15-31, 2005.

Brenning, A.: Spatial prediction models for landslide hazards: review, comparison and evaluation, Natural Hazards and Earth System Sciences, 5, 853-862, 2005.

Chatenoux, B., and Peduzzi, P.: Impacts from the 2004 Indian Ocean tsunami: analysing the potential protecting role of environmental features, Natural Hazards, 40, 289-304, 2007.

Coe, J. A., Michael, J. A., Crovelli, R. A., Savage, W. Z., Laprade, W. T., and Nashem, W. D.: Probabilistic assessment of precipitation-triggered landslides using historical records of landslide occurrence, Seattle, Washington, Environmental and Engineering Geoscience, 10, 103, 2004.

Dunning, S. A., Mitchell, W. A., Rosser, N. J., and Petley, D. N.: The Hattian Bala rock avalanche and associated landslides triggered by the Kashmir Earthquake of 8 October 2005, Engineering Geology, 93, 130-144, 2007.

FAO, U. N.: Global Forest Resources Assessment 2005. Progress Towards Sustainable Forest Management, Forestry Paper, 147, 737-750, 2006.

Gorsevski, P. V., Foltz, R. B., Gessler, P. E., and Cundy, T. W.: Statistical modeling of landslide hazard using GIS, Links, 2001.

Guzzetti, F., Carrara, A., Cardinali, M., and Reichenbach, P.: Landslide hazard evaluation: a review of current techniques and their application in a multi-scale study, Central Italy, Geomorphology, 31, 181-216, 1999.

IFRC: *Mangrove planting saves lives in Vietnam*, Press release issued by the International Federation of the Red Cross Red Crescent Societies in June 2002, the text is an excerpt from the IFRC's World Disasters Report 2002 – Focus on reducing risk republished by UNEP in *Environment and Poverty Times N°3*, Special Edition for the World Conference on Disaster Reduction January 18-22, 2005, Kobe, Japan.

http://www.grida.no/publications/et/ep3/page/2610.aspx

IUCN: Rapid Environmental Appraisal of Developments in and Around Murree Hills, 16 pp., 2005.

Nadim, F., Kjekstad, O., Peduzzi, P., Herold, C., and Jaedicke, C.: Global landslide and avalanche hotspots, Landslides, 3, 159-173, 2006.

Nakata, T., Tsutsumi, H., Khan, S. H., and Lawrence, R. D.: Active faults of Pakistan: map sheets and inventories, Research Center for Regional Geography, Hiroshima University, Hiroshima, 1991.

Peduzzi, P., Dao, H., Herold, C., and Mouton, F.: Global risk and vulnerability index trends per year (GRAVITY), phase II: development, analysis and results, 2002.

Petley, D. N., Dunning, S. A., Rosser, N. J., and Kausar, A. B.: Incipient landslides in the Jhelum Valley, Pakistan following the 8th October 2005 earthquake, Disaster Mitigation of Debris Flows, Slope Failures and Landslides, Frontiers of Science Series, 47, 47-56, 2006.

Popescu, M. E.: Landslide causal factors and landslide remediatial options, 2002, 78,

Sato, H. P., Hasegawa, H., Fujiwara, S., Tobita, M., Koarai, M., Une, H., and Iwahashi, J.: Interpretation of landslide distribution triggered by the 2005 Northern Pakistan earthquake using SPOT 5 imagery, Landslides, 4, 113-122, 2007.

Sudmeier-Rieux, K., Qureshi, R. A., Peduzzi, P., Jaboyedoff, M. J., Breguet, A., Dubois, J., Jaubert, R., and Cheema, M. A.: An interdisciplinary approach to understanding landslides and risk management: a case study from earthquake-affected Kashmir., Mountain Forum, Mountain GIS e-Conference, 2007, 16 pp.,

Sudmeier-Rieux, K., Jaboyedoff, M., Breguet, A., Dubois, J., Peduzzi, P., Qureshi, R., and Jaubert, R.: Strengthening Decision-Making Tools for Disaster Risk Reduction: An Example of an Integrative Approach from Northern Pakistan, Regions: Laboratories for Adaptation, 74-77 pp., 2008.

Tucker, C. J.: Red and photographic infrared linear combinations for monitoring vegetation., Remote Sensing of Environment 8, 127-150, 1979.

UNISDR: Hyogo Framework for Action 2005-2015: Building the Resilience of Nations and Communities to Disasters, World Conference on Disaster Reduction, Kobe, Hyogo, Japan, 2005, 25 pp.,

Vanacker, V., Vanderschaeghe, M., Govers, G., Willems, E., Poesen, J., Deckers, J., and De Bievre, B.: Linking hydrological, infinite slope stability and land-use change models through GIS for assessing the impact of deforestation on slope stability in high Andean watersheds, Geomorphology, 52, 299-315, 2003.

On-line references

USGS, Earthquake Hazards Program, (2006), http://earthquake.usgs.gov/eqcenter/eqinthenews/2005/usdyae/

USGS ASTER DEM, ASTER Digital Elevation Model, http://lpdaac.usgs.gov/aster/ast14dem.asp

EM-DAT: Emergency events Database (2007), Centre for Research on the Epidemiology of Disasters (CRED), Université Catholique de Louvain, http://www.emdat.be

ANSS, 2007, Advanced National Seismic System composite catalogue from the Northern California Earthquake Data Center (NCEDC), http://quake.geo.berkeley.edu/anss/

IUCN, 2005, Rapid Environmental Appraisal of Developments in and Around Murree Hills, http://www.waterinfo.net.pk/pdf/new_murre_report.pdf

SERTIT, Service Régional de traitement d'image et de télédétection (SERTIT), post landslides detection http://sertit.ustrasbg.fr/documents/asie/asia_en.html

StatSoft Electronic Statistics Textbooks http://www.statsoft.com/textbook/statistics-glossary

Chapter 5 Discussion

We saw that disaster risk assessments were initially focussing on hazard studies (Maskrey, 1993, Burton, 2005). From the mid-1970s, social scientists introduced the perspective that disaster risk was not only resulting from external shock (namely hazardous events), but also resulted from *various physical, social, economic, and environmental factors.* (White, 1974; Maskrey, 1999, Turner, 2003).

The different perspectives in risk studies have led to situations where similar words have different meaning for different risk communities (Thywissen, 2006). On one hand research predominantly focussing on hazard modelling has led (in some cases) to use risk instead of hazard (Cardona, 2003). Conversely, studies predominantly focussing on vulnerability led to the overuse of the term vulnerability, such as the use of "vulnerable groups of population" to refer to the elderly, children or women even in absence of a threat, i.e. without stating vulnerable to what? (Cardona, 2003).

There is a need to combine all the risk components: hazard, exposure and vulnerability to reflect risk (UNDRO, 1979). Some researchers have called for a Holistic approach, i.e. comprehensive and multidisciplinary evaluation of risk, with assessments of all the different characteristics in order to improve the effectiveness of risk managements (Cardona, 2003; UNISDR, 2005).

The methodology used in this thesis, aims at offering the possibility to deal with the different components of risk.

The vulnerability is probably the most difficult to assess (Birkmann, 2006). Poor people suffer disproportionate levels of losses compared to their exposure (UNDP, 2004), however vulnerability cannot be simply replaced by poverty. Some consequences of poverty (limitation of choices, decisions, limitation of access to certain resources) may result in higher vulnerability, e.g. the incapacity to survive a calamity (Chambers, 1989). We built a database including 43 different indicators, which were tested to see which one (or which combination of them) were, in association with hazard and exposure, the best proxy for approaching vulnerability. The results show that poverty plays a significant role, however it is associated with other parameters, such as low governance, remoteness or rapid urban growth.

The identification of conditions leading to higher losses has different terms, depending also on the scale of the studies: conditions of insecurity, dynamic pressures or root causes (Wisner, 1993; Cannon, 1994, Blaikie *et al.*, 1994), or underlying factors (UN, 2009). This profusion of terms reflects the complexity to grasp what lies behind vulnerability.

The universe of risk is large. It encompasses physical science, socio-economical science, land planning, and policies, laws and regulations, health and sanitation issues, which makes studies in this field both interdisciplinary and complex. Although models can not fully describe all the complexity of the reality, this thesis aimed at providing tools which help in dealing with such levels of complexity.

5.1. Choice of the method

Understanding risk from natural hazards can be achieved through different methods. Inventories, heuristic or index based methods, statistically based models (Guzzetti *et al.*, 1999). Deterministic approaches such as physically based models are used by engineers to determine the risk of a building or infrastructure failure (Cardona, 2003). Because we were dealing with the global scale, where quality of building and other such detailed data could not be introduced (due to both lack of availability for the global coverage and complexity of computation) a more simplified method was needed.

The most common way to deal with risk assessment at the global level are methods based on inventories of past losses (World Bank, 2007; ESCAP and UNISDR, 2010; IFRC, 2009; ICHARM and UNESCO, 2009; DARA, 2010).

Given the number of disasters worldwide, information on disasters has to be collected in a standardised and comparative way. The access to this information has to be provided. Several databases are doing this at national levels, e.g. DesInventar is a project which aims at generating new national inventories of disasters from hazardous events. DesInventar is now available for 38 countries and five Indian provinces (DesInventar, 2011). There are numerous other national initiatives following different methodologies (GRIP, 2011). However, only three databases have a global coverage: NatCat (from Munich RE), Sigma (from SwissRe) and EM-DAT (EM-DAT, 2011). Out of these three International databases on reported losses, EM-DAT is the only one offering public access to its content (UN, 2009).

While EM-DAT is a very useful tool and an essential effort for reporting losses world-wide, global assessment cannot be based only on EM-DAT. We showed that improved access to information reduces the possibility to compare situations across time and regions (Peduzzi *et al.*, in press, part 3.6). Another important issue, is the absence of information regarding what share of the losses comes from the magnitude of an event, the vulnerability of the elements exposed, or the number of elements exposed.

To overcome these issues, the choice of a quantitative approach was made. Logistic regression and discriminant analysis are the most frequently chosen models (Guzzetti *et al.*, 1999; Brenning, 2005), although other methods such as Artificial Neuronal Network (ANN), support vector machine, are now becoming increasingly popular (Xu, 2001; Pozdnoukhov and Kanevski, 2008).

Hazard and vulnerability are concomitant in producing risk, the methodology shall allow the incorporation of all the components of risk (Cardona, 2003). Multiple regression analysis, associated with extraction of parameters using GIS, was already successfully applied to highlight links between ecosystems decline and hazard susceptibility (Vanacker *et al.*, 2003; Chatenoux and Peduzzi, 2007). At the global level, such association between GIS and statistical regressions was already successfully used for identification of underlying factors of risk (UNDP, 2004).

There are numerous options to show statistical evidences between a dependent variables and explanatory variables. The choice for the Multiple Regression Analysis was used in these researches. Bayesian statistics would be a relevant alternative for such analysis. The choice of multiple regression analysis over Bayesian was also a question of simplicity of computation. Bayesian statistics requires integrations over uncertain parameters, which can be difficult to compute and may often not have an analytical solution, thus requesting intensive numerical integration (Eddy, 2004).

In all the cases studied, a single parameter (poverty, exposure, deforestation, slopes) was not enough to explain the dependent variable (e.g. mortality or area of landslides). The general purpose of multiple regressions is to quantify the relationship between several independent variables. It was therefore well-suited for the purpose of this thesis, because it is straightforward to implement, but it is clear that we miss the true nonlinear behaviour that can be catch by ANN for instance (Kanevski and Maignan, 2004). But as the main goal was to provide a world distribution, necessary shortcuts due to lack of data availability and to produce maps rapidly, the Multiple Regression Analysis was chosen.

5.2. Global level

5.2.1. Intro

The initial DRI (UNDP, 2004) and the World Bank / University of Columbia Global Risk Hotspots study (Dilley *et al.*, 2005) were pioneer works at mapping the risk distribution at the global level. However, as any study, there was room for improvements and some gaps and limitations were stated by the authors of these studies as lead for future developments.

The new article on DRI (Peduzzi *et al.*, 2009b, see part 3.2) solved some of the gaps of the initial DRI study (improved on drought, more completed tropical hazard data, production of the DRI). However, the issue of the non-inclusion of the intensity in the analysis was still a gap which remained to be addressed. Also, an acknowledged issue from initial global studies (UNDP, 2004; Dilley *et al.*, 2005) was the inappropriate model used for floods. In the absence of any global dataset on flood frequency, these pioneer researches used identification of watersheds flooded, leading to an overestimation of population exposed to floods.

The mandate provided to global risk assessment made for the 2009 GAR (Peduzzi *et al.*, 2009a, see part 3.3) was to solve (or at least improve) these issues. The inclusion of intensity into the analysis was made through an approach using individual events.

This new global study benefited from numerous new developments of global datasets. A more precise model of population distribution (Landscan, 2008; Balk *et al.*, 2011), a new global landcover (Arino *et al.*, 2008), the not so new (2000), but improved version of the global digital elevation model from the space shuttle (SRTM, 2008), a new hydrological model at 90 m resolution produced by USGS: hydroshed (Lehner *et al.*, , 2008), a more complete dataset of historical tropical cyclones IbTracks, (IbTracks, 2009), the footprints of past earthquakes intensity from ShakeMaps produced by USGS (Allen *et al.*, 2008; Wald *et al.*, 2008), the collection of flood footprints 2000 to 2008 from Dartmouth Flood Observatory (DFO, 2009), UNEP GEO collection of national indicators (UNEP, 2011); a set of indicators on governance from the World Bank, as well as a so far unpublished dataset on GDP per capital at raster level, produced by the World Bank specifically for this study.

These datasets were combined and transformed using GIS and statistical techniques to produced new datasets. Global hazard datasets (landslides, tropical cyclones, floods), exposure datasets (GDP distribution, back processing of exposure for 1970 to 2010), risk distribution for selected hazards.

In return, we provided access to all the main datasets that we generated. They are available on-line on the PREVIEW Global Risk Data Platform (Giuliani and Peduzzi, 2011) (see http://preview.grid.unep.ch). The compilation of vulnerability parameters was greatly helped by the UNEP geodata portal (http://geodata.grid.unep.ch), which provided a large collection of these indicators.

The improvement of flood information benefitted from two different approaches. Firstly, on individual events, the access provided by DFO on their collection of observed flood events as detected by satellite sensors (at 250 m or finer resolution) greatly improved the mapping of individual flood events extent. Secondly, funds were made available to generate a first attempt at generating a global flood model (Herold and Mouton, in prep.). This first global flood dataset based on the newly released Hydroshed (at 90 meters resolution) and an hydrological flood model modified from USGS, greatly improved the estimation of exposure.

The global flood model is a first generation model, there are several issues that need to be fixed. New developments are planned, including to compute several returning periods, improve the algorithm and the characterisation of the hazard in flat areas. Although the use of this global dataset was never intended for identifying individual future events, the comparison between the flood-prone areas as modelled for the 2009 GAR and the 2010 flood (as detected by satellite sensor) in Pakistan is interesting. In terms of hazard geolocation, the model presented in Figure 120 shows a reasonable good match between the hazard model and the observed flood in Pakistan (2010), i.e. for a global level perspective, not for a local level land planning perspective. The Figure 120 reveals areas where the model should be improved (typically in flat areas, see e.g. red areas north of Shikapur).

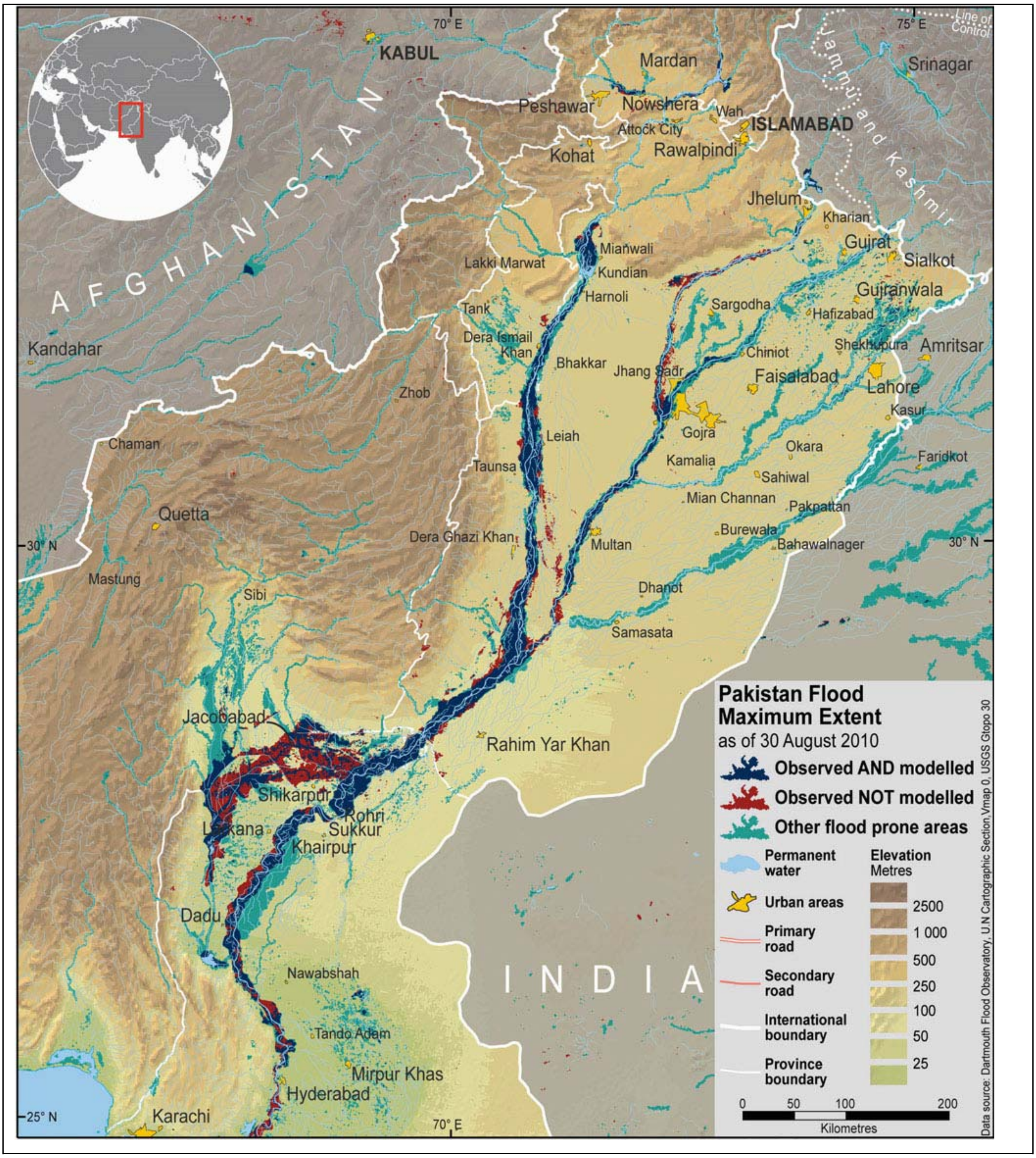


Figure 120 Flood hazard model versus observed in Pakistan 2010.

For the statistical analysis, we had the footprints of 8762 physical events: 5686 Earthquakes (provided by USGS shakemaps), 1106 floods (provided by Dartmouth Flood Observatory) and 4182 tropical cyclones (which we modelled based on tracks information provided by IBTrACS (IBTrACS, 2009)). For all these events, we extracted exposure and socio-economical contextual parameters. This generated a database of 124,000 records (over 40 years, 208 countries, 43 parameters. On vulnerability parameters, not all indicators were available for all countries and years, but the final database included more than 124,000 data cells.

Because not all hazardous events turn into disasters (hopefully, some of them had no significant impacts: without killed or drastic economic consequences) and because some disasters remain unreported, not all these events could be linked with reported losses for the analysis. We georeferenced 718 Earthquakes, 620 floods and 1525 tropical cyclones. The use of this database to identify the underlying risk factors, quantifying their respective role and for mapping disaster risk is the main output of the new global risk analysis.

As the aim was to build tools to support awareness raising and DRR, the map and graphics created by the proposed quantitative analysis proved to be efficient in getting the media's attention. Journalists were eager to get figures on exposure. The index for comparing countries was also a feature which helped to get the interest of the media.

5.2.2. Advantages and limitations

The main advantages of the proposed quantitative approach are to provide the possibility to identify and quantify the role of underlying risk factors and the geolocation of the risk assessment allowing mapping of its distribution.

This method offers some complementary advantages over the use of inventories (although we will see that it also introduces different limitations). The results of the global risk study (part 3.4) provide new material which includes: the footprints of past disasters at an acceptable resolution for a global study. This is an advantage over assessments based on EM-DAT, because EM-DAT can only provide the information at the national level. Some attempts of georeferencing EM-DAT used the first level administrative boundaries (Verelst, 1999; FAO 2001). However, similar approaches revealed that this is biased by the extreme variety in both size and populations of the administrative units (Clark and Rhind, 1992). The links between footprints of past events with EM-DAT reported losses, significantly improved the precision and the characterisation of the exposure (Peduzzi *et al.* 2005).

Maps were provided to show the distribution (again at a global scale) of selected hazards, exposure and risk. The use of improved models and more detailed datasets provided a better and more precise distribution of hazards, exposure and risk as compared with the previous global study at a subnational level (Dilley *et al.*, 2005).

We estimated the percentage of the losses which can be attributed to exposure, hazard intensity and vulnerability. Finally, an estimation of modelled losses was provided, even for events where no reported losses were available. This is possible, because we are using EM-DAT reported losses only for calibrating our models. Then, as long as all the variables needed for the models are available, we can compute the losses, independently from EM-DAT. The model being based on logarithmic regressions cannot be substituted for individual events (there is a large margin of error and the models only capture part of the losses, however, this can be useful for doing trend analysis. Even in the case of the DRI (based on yearly average), the use of models proved to be credible. For example, during the landslides triggered by floods in Venezuela (1999), the number of reported killed by EM-DAT was 30,000. A recount based on a ground survey and local verifications (Altez, 2007), found the number of killed to be at a maximum of 700. If this correction is applied, we get a total of 44 killed per year for the period 1980 - 2000. This is far from the 1440 of reported killed. Our model provides a yearly average of 15.4, much closer to the observed number of killed (see Figure 121).

Quantitative analysis cannot ensure fully objective results. The choice of the method, data, the margin of error, the interpretation of the results are all subjective choices and based on expert judgement.

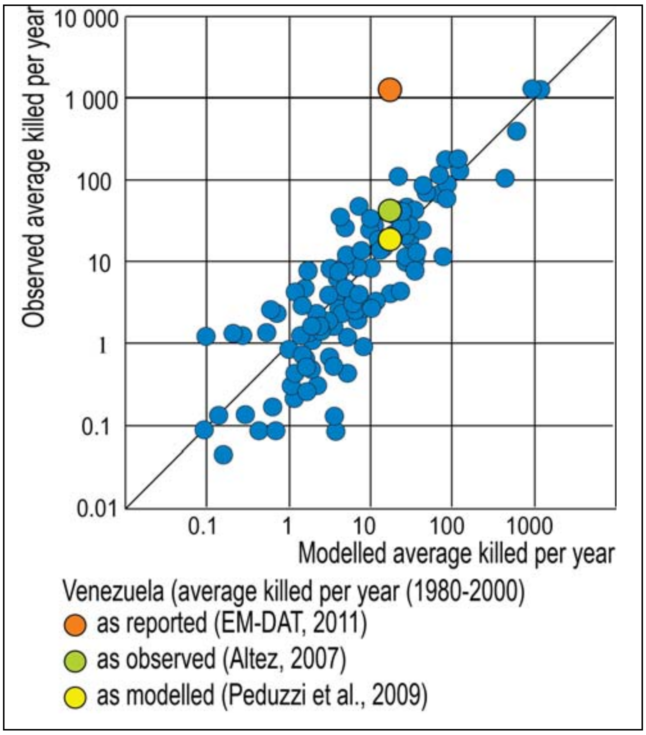


Figure 121 DRI model for flood showing the differences in Venezuela reported, observed and modelled values.

Recent studies also proposed to integrate more sophisticated models to quantify the impact of disasters, integrating for instance the growth of population and personal wealth for tropical cyclones in US (Blake *et al.*, 2011).

Some countries did not like the findings of the DRI, not because they were classified as high risk, but because they thought they were much more at risk (Worrell, pers. comm., 2004). By being placed in lower categories, it may be detrimental for them to get international support. Typically in the Caribbean the populations are regularly hit by hazardous events (earthquakes, floods, tropical cyclones, landslides,...). However, except for Haiti, this is not reflected in terms of high mortality. For example in Cuba, the efficiency of early warning, associated with compulsory evacuation of the local population, leads to very few casualties (UNDP, 2004; UN, 2009). However, given that fields and infrastructures cannot be evacuated, the Cuban population still suffers large economic / livelihood losses (UN, 2009). These losses are not reflected by the DRI or the MRI as these indexes were both designed to show mortality risk.

This is certainly a limitation of these two indexes (DRI, MRI), while populations can move and be secured, it is not the case of crops, harbours and infrastructures (bridge, roads, hotels, schools,...) and these events are likely to create significant setbacks on development, especially in small economies (small and poor countries (see part 3.5.8).

All in all, only 30% of EM-DAT events include information on economic losses. According to the World Bank team, this gap in the data was the main obstacle which prevented the creation of an Economic Risk Index (Deichmann, 2009). This shows the limitation of the quantitative approach. A proposed quantitative approach is limited by data accessibility unless it is possible to generate the data (as this was done at a local level, see below).

Another limitation of quantitative analysis lies in the precision of the data, each analysis is scale specific. This means one should not use the results from the global analysis for local applications. The resolution of the data is coarse, especially socio-economic data, which are in their vast majority, only available at national levels with global coverage. At sub-national levels, the availability drops significantly. At national levels, an indicator does not reflect the same precision in all countries. It is very detailed for a small island state such as Mauritius, but can arguably be questionable for countries like China and India.

For the global level analysis several shortcuts had to be taken. One of them is the linear approach in risk, i.e. in our model, the most frequently exposed are most at risk and this is not necessarily the case. For example in Figure 122, one may argue that the higher frequency event leads to higher risk. If a flood occurs every two to three years, people gain experience in dealing with such events, as it has been shown in Bangladesh and China: floods can be profitable or manageable if they are not catastrophic (Paul, 1984; Zong *et al.*, 2007). However, this was a necessary shortcut inherent in global analysis. A way to improve it, would be to introduce a variable of time lag between two extreme events. This is possible for TC or earthquakes for which we have comprehensive datasets (i.e. inventories), but not for floods or landslides. This would allow to test the hypothesis that least frequent hazards may be linked with higher vulnerability, through lack of experience, know-how and increased surprise effect on populations less frequently exposed to hazards.

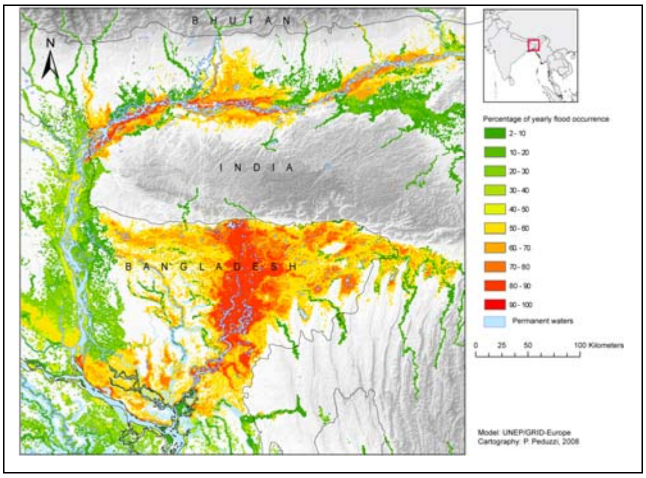


Figure 122 flood frequency map in North Bangladesh.

The use of transformed variables and especially logarithms proved to be efficient in identifying underlying risk factors. It usually induces large uncertainties when translating it back into the original metric, thus has limited value for forecasting. However, forecasting future risk was not the purpose of this research, where I wanted to concentrate on providing statistical evidences to support awareness raising.

The use of logarithm is well suited for skewed distributions, when mean values are low, variances large, and values cannot be negative (Limpert *et al.*, 2001) as in the case of mortality losses. The most common way to deal with such data, is to linearize the model via logarithmic transformations (Stynes, 1986). In the case of the MRI it was necessary to retransform the estimated functions by taking anti-logs. This may introduce a statistical bias (Stow *et al.*, 2006), depending if the median or the mean is the relevant indicator (Stynes, 1986).

When the median is preferred, the log transformation adjustments should not be applied (Stynes, 1986), resulting in a model of the median response in the original variable space (Miller, 1984). When the mean is more relevant, a correction for this bias should be applied (Manning, 2001), e.g. by using the "quasi maximum likelihood estimator" (QMLE) (Cohn *et al.* 1989; Gilroy *et al.* 1990). This can only be used if the errors follow a normal distribution (Maning, 1998), if not or if the distribution of the error is unknown, a smearing estimate can be used (Duan, 1983). When dealing with extremely skewed distributions, the use of the median should be considered over the use of the mean (Haneman, 1984; Stynes, 1986). The median is more robust and tends to be less influenced by outliers and extreme values (Haneman, 1984). Between 1975 and 2010 the top 25 disasters - out of 9,646 disasters reported (EM-DAT, 2011) - i.e. 0.26% of the events, led to 79.9% of the reported mortality. This highly skewed distribution justified the choice made in the MRI to use the median, also to account for potential spurious reported values (Altez, 2007).

Nevertheless, for the tropical cyclones, the QMLE was used as it provided values closer to the observed (see 3.6). Both options can be justified, and reflects that quantitative analysis is not devoid of subjectivity. (see part 3.6 for more explanations).

Finally, correlation between two variables (e.g. A & B) does not imply that variation of A is the origin of the variation of B. If multiple regression can show potential link, it cannot ensure causality. A correlation between a dependent variable A and an independent variable B can have several origins: B indeed has an influence on A, or A influences B, or C influences A & B. This is the main critic of the multiple regression analysis. In the case of links between vegetation density and landslides area, a causality analysis was made by visual interpretation of the models (see part 4.3.8).

5.3. Links with global change

We saw that global change can be systemic or cumulative (Turner *et al.*, 1990). Global systemic changes include localised sources of changes leading to global effect while cumulative change consist in widespread continuous changes occurring world-wide and together having a global impact.

Climate change belongs to the systemic type of global changes (Turner *et al.*, 1990). It also has an impact through time, meaning that it will continue to affect future generations. The examples presented in this thesis, are only a small part of the many challenges posed by climate change, a new assessment of the links between climate change and impacts from extreme event will be released shortly by IPCC, the summary for policy makers is already available (IPCC, 2011).

The observed decline (using remote sensing techniques) of the Coropuna glacier is a striking example of how quickly (a few decades) the situation can change. Although monitoring the change in ice extent through time was relatively easy in this case (no shadow effects, high contrast between ice and rocks, no rocks on the glacier and access to numerous cloud free images), the impacts on water supply would be much more complex to analyse. In Peru other glaciers are following similar rate of retreat. Bury *et al.* (2011) showed that the Yanamarey glacier (Peru) is retreating at an average annual rate of 30 m.

This is a global phenomenon affecting all regions world-wide (Zemp *et al.*, 2008; Bates *et al.*, 2008). Although the coverage of glacier monitoring is improving, it needs to be extended to more locations. Also needed is a better understanding of the hydrological consequences of glacial melt and its impact on individuals, social groups, the economy and institutions. This subject is one of the top 21 emerging issues for the XXI century selected by international experts in the UNEP Foresight Process (UNEP, in prep.).

Studies like the one produced in Coropuna help local decision makers to visualize the threat as well as providing a time horizon with the rate of glaciers retreat. This allows planning the action for climate change adaptation. This is needed not only in the Andean region, but also in many regions, such as in Central Asia and in the Himalayas (Immerzeeel *et al.*, 2010; Xu *et al.*, 2009).

5.3.1. Climate change impacts on natural hazard

The link between climate change and risk, through change in hazard frequency, intensity and new areas affected, is studied in depth in the coming IPCC special report on extreme events (IPCC, 2011). As one of the lead authors of this report (Lead author in Chapter 4: Changes in impacts of climate extremes: human systems and ecosystems, contributing author in Chapter 9: case studies). I have included several relevant parts of developments achieved through my contribution in this thesis. For example the link between deforestation, drought, forest fires and climate change (see Figure 18 in part 2.3.2), whose main interest is to highlight the role in land cover change on climate change.

The article on tropical cyclones (Peduzzi *et al.*, in press; see part 3.6) shows that climate change will have several impacts on TC risk. The expected increase in intensity (Knutson *et al.*, 2010) will exacerbate disaster risk in two ways, firstly by increasing the intensity of winds, storm surges and precipitations, secondly by affecting larger areas, thus potentially more people, despite a forecasted decrease in frequency (Knutson *et al.*, 2010). Given that our researches show that exposure plays an increasing role at higher intensity, risk is likely to be exacerbated by these changes.

The influence of observed climate change on past TC frequency and intensity is uncertain, due to changes in the resolution of satellite sensors and changes in methodologies (Landsea *et al.*, 2006; Knutson *et al.*, 2010). However, there is greater confidence in 21st century projections of TC activity under warming scenarios. An increase in intensity is expected notably in the most intense storms (Elsner *et al.*, 2008) with a potential increase in the frequency of the strongest storms (Knutson *et al.* 2010; Bender *et al.* 2010). Our study shows, however, that regardless of potential scenarios of future TC evolution as triggered by climate change, change in demography will be the preponderant factor in increasing human exposure (Peduzzi *et al.*, in press).

5.3.2. Population growth

Climate change will exacerbate disaster risk by magnifying the exposure and intensity. The main trigger for increase in hazard exposure will be pressure from demographic growth. Population growth is a cumulative change (although, it is more concentrated in developing countries). The studies at global level revealed the significant role of human exposure in risk. This role was also shown to have an increasing weight in the models when the hazard intensity was high. In this respect, current population growth is very likely to induce an increase in disaster risk. Population growth is drastically increasing exposure to hazards, to the point that progress in decreasing vulnerability can be erased and risk may increase despite the decrease in vulnerability. With population probably exceeding 9 billion by 2050 (Raftery *et al.*, 2009), it is important to understand what are the implications on hazard exposure.

To assess the role of population, two different population distribution models were tested The Global Rural-Urban Mapping Project (GRUMP) is based on census data and on urban population (Balk *et al.*, 2011). We also used Landscan which is also based on census data but uses various topographical data, such as land cover (Landscan, 2008) and provided better results. GRUMP being only based on census, it provides the resident population, while Landscan takes into account people on the road and people at work. This difference may be interesting if someone wants to use GRUMP for population during night time and Landscan for population exposure during day time.

To capture the exposure at the time of the event, the models of population were processed to produce a model population at the time of the event. This was performed using a simple ratio between country population at the time of the event, versus population 2007 (as we used Landscan 2007 for the global study). This ratio was then used to multiplied the pixel, tests were run to ensure that the sum of the pixels match the population of the country for each corresponding year. This is a simple model, which does not take into account internal migration, such as migration toward urban centres or other population moves within the countries. However, it provided a first level correction for population growth.

The studies included in chapter 3 of this thesis, all flagged the importance of population exposure on disaster risk. The one on TC provided a trend analysis showing the rapid increase in population growth. This trend analysis has also been recently provided as an input to the Global Assessment Report 2011 (UN, 2011, chapter 2). This underlines the importance and the impact of the population distribution on the results.

5.4. Specific comments for the local level

Each scale has its own complexity. The global level requested to handle a large quantity of data, sometimes at the limit of the computers capacity and was characterised by difficulties in accessing data of comparable quality to achieve a global coverage. By zooming in, it is possible to use more detailed data at a local level. It reveals some complexity that cannot be seen at the global level. Accessing quality data remains a challenge. Some data needs to be generated.

The study on landslides and deforestation in North Pakistan (Peduzzi, 2010) follows a similar methodology developed previously for our study on the Indian Ocean Tsunami (Chatenoux and Peduzzi, 2007). In the tsunami study, we showed that the width of the flooded area by the tsunami was larger behind coral and we could not assess the role of mangroves, as mangroves grow in already sheltered areas. This was not what we were aiming to show and such findings came as a surprise. However, these surprising results were confirmed by studies conducted on the ground (Baird and Kerr, 2008).

In the study in North Pakistan the method was able to provide statistical evidences on the role of vegetation density in mitigating hazard susceptibility. Correlation being not causality, some verifications and tests were provided. Following the 2004 Indian Ocean tsunami, numerous studies concentrated on coastal hazards (Alpine and Wotton, 2009), there is a need to expand on other types of hazards in other ecosystems. Multiple regression analysis, associated with extraction of parameters using GIS, was already used to highlight the role of deforestation in landslides (e.g. Vanacker *et al.*, 2003). Although not innovating, the study confirms that such impacts are needed in a world were 1.3 million ha are deforested yearly (FAO, 2010). One of the originality of this article was to introduce the quantification of the role of ecosystems using the beta coefficients.

"*The Beta coefficients are the regression coefficients you would have obtained had you first standardized all of your variables to a mean of 0 and a standard deviation of 1. Thus,* *the advantage of Beta coefficients (as compared to B coefficients, which are not standardized) is that the magnitude of these Beta coefficients allows you to compare the relative contribution of each independent variable in the prediction of the dependent variable."* (StatSoft, 2011).

The quantification of the role of each component in a model is very useful. Decision makers are interested to know whether some components play a major or a minor role. It must be pointed out that the proposed quantitative approach is one among other techniques, ANN, support vector machine, etc. are now getting very popular (Xu, 2001; Pozdnoukhov and Kanevski, 2008), but what can be claimed for our approach is that is is rather simple and easy to follow. In my own experience we get the following results:

> *The study in Peru, by quantifying the rate of ice losses and estimating remaining ice, gave credit to the threat on water supply in the region. It showed that scientific studies can help in quantifying issues. The ice area recorded by satellites provides information that can be verified and reproduced (Paul et al., 2007). Using a temporal series of the decrease in ice coverage is a mean of raising awareness and to trigger actions.*
>
> *After the scientific results on the rapid retreat of Coropuna Glacier (Peru), the local authorities and a NGO (COPASA) were able to attract funds from the UNDP, GTZ and the Inter-American Development Bank, supporting the proposed approach that leads to actions. GTZ decided to prolong their activities for an additional five years. The project benefited from US$. 205,000 (GRIP, 2011).*

In the case of a local approach, with remote sensing or ground collected data, it was possible to compensate the lack of data by directly generating them. This is limited in time, ground collected data can only be collected at the time of the study (unless this was performed on a regular basis). For remotely sensed data, satellite imagery, Landsat first images date from late 1972 and higher resolution images are much more recent. Before this we rely on either aerial photos - as in the case of RiVAMP (UNEP/PIOJ, 2010) - or on topographical maps (also derived from aerial photos) as in the case of the Coropuna study.

The need to translate the findings in monetary terms would be an advantage, but there still exist several solutions to perform such assessment (NRC, 1999; Blake *et al.*, 2011; Hallegatte, 2006, Hallegate *et al.*, 2007). Teaming with economists would help to increase the value of the results to convince politicians and some of the stakeholders.

5.5. Last points

Decision-makers need figures (preferably in dollars), graphs and maps in order to be convinced (Robinson, 2010) but also to convince others to invest in poverty reduction and environment programmes. Nevertheless, the impact of risk communications is in itself a research topic, and still under fast development (Morgan *et al.*, 2007).

Overall, the proposed quantitative approach used in this thesis appears to be valid if it is applied with caution in order to avoid bias as described above. In addition it is fairly easy to explain. Its flexibility was the main advantage, the same approach was easy to adapt for uses at different scales and on different hazard types. Poverty, by reducing choices and access to resources (Chambers, 2009), is increasing vulnerability. The global studies have highlighted this.

The signal of the role of ecosystem decline on hazard susceptibility can be detected. This requires, however, local scale type of studies (Nadim *et al.*, 2006; Vanacker, 2003). The role of deforestation on landslides susceptibility was significant in the case of the North Pakistan landslides. Other studies have revealed the strong role of coral and sea grass in mitigating beach erosion (Peduzzi *et al.*, in prep; UNEP, 2010).

The global level showed that the increase in human exposure has a prominent role in increasing risk. Such an increase is of concern in a context of a world which may exceed 9 billion inhabitants in 40 years (Raftery *et al.*, 2011). The increase in urban areas might also induce another shift, potentially a decrease in hydro-meteorological risk such as risk resulting from floods or tropical cyclones hazards. However, if buildings are not built according to safe building codes, the risk from earthquakes may increase.

The trend analysis revealed that the progresses made vulnerability reduction were sometimes erased by the rapidity in demographic increase. If poverty (as measured through GDP per capita) appears to be a good proxy for global vulnerability (this indicator is selected in most models) it is not the only one and governance, even in poor countries can make a significant difference (see Box 7).

Including the potential effect of climate change at the local level is possible, yet with high uncertainties. The future exposure levels can be run through several scenarios. To increase confidence, most studies concentrate their results for the horizon of 2100, under different climate change scenarios, this is not a time-scale that can be easily mainstreamed into political agendas.

Box 7 Governance versus poverty? A comparison between two disasters from tropical cyclone Sidr (Bangladesh 2007) and Nargis (Myanmar, 2008)

In 2007 Cyclone Sidr hit Bangladesh (Paul, 2009) and in 2008 Cyclone Nargis hit Myanmar (Webster, 2008). These two events were comparable in intensity but led to vastly different impacts. Sidr maximum wind speed reached 245 km/h and the storm surge reached between 5-6 m (Paul, 2009). Nargis had a maximum wind speed of 235 km/h and the storm surge reached about 4 m (Webster, 2008). Between 8 and 10 million people were exposed/affected by Sidr and the number of reported fatalities was about 4,200. For Nargis estimations are less precise but between 2 and 8 million people were exposed/affected. The fatalities exceeded 138,000 (UNEP and UNISDR, 2000-2011, 2011; EM-DAT, 2011), making Nargis the eighth deadliest cyclone ever recorded (Fritz *et al.*, 2009). Despite its lower intensity, exposure and storm surge, Nargis led to nearly 33 times more victims. Why?

Bangladesh has a significant historical record of large scale disasters and serious efforts to decrease risk from tropical cyclones have been made (Paul, 2009). The country has experienced 15 disasters of more than 1000 casualties since 1960, including the infamous Cyclone Gorky (April 1991, causing about 140,000 fatalities) and the November 1970 Cyclone Bhola which caused 300,000 deaths (EM-DAT, 2011). After the devastating cyclone of 1970, the government of Bangladesh initiated several structural and non-structural measures to reduce the cyclone risk (Paul, 2009). These measures consisted of three major actions: implementation of an early warning system; construction of public cyclone shelters and construction of shelters to provide protection for cattle during storm surges.

Nearly 43,000 volunteers have disseminated cyclone warnings among villagers via megaphones and by house-to-house contact and close to 4,000 cyclone shelters have been built. According to a field survey, 86% of the potentially exposed population were aware of the coming of Sidr and 3.2 million people were evacuated (Paul, 2009).

Environmental features also played an important role in limiting the impact of Sidr. The 590,000 ha of the Sunderban mangroves and coastal forests proved to be effective barriers during Cyclone Sidr (GOB, 2008). As opposed to tsunami wave (Chatenoux and Peduzzi, 2007), storm surge energy can be efficiently reduced by mangroves (IFRC, 2002). In Bangladesh, a coastal reforestation program was initiated in 1960, covering about 159,000 ha of coastal land, the riverine coastal belt, and abandoned embankments. These plantations reduced the impact of previous cyclones and floods as well as created employment opportunities (GOB, 2008). Cyclone Sidr showed that coastal reforestation protects embankments against cyclonic surge and monsoon waves – with the tremendous additional benefit of greatly reducing the impact of the storm surge (GOB, 2008).

In contrast to Bangladesh, Myanmar has had very little experience with previous natural disasters. Prior to Nargis, Myanmar had only experienced one tropical cyclone disaster with more than 1000 fatalities since 1960 (EM-DAT, 2011). The landfall of Nargis was the first time that Myanmar had experienced a cyclone of such a magnitude and severity (Lateef, 2009) and "the path of the storm could not have been worse" (Webster, 2008). Several unfavourable conditions were combined to transform this hazardous event into a large scale disaster. There was virtually no early warning for this event. The Indian meteorological department has the responsibility to issue cyclone warnings for the region, but has no mandate to provide storm surge forecasts (80% of the victims from Nargis were killed by the storm surge). Myanmar's official forecasts appeared on page 15 in the newspaper The New Light of Myanmar from 29 April to 2 May, suggesting that the media underestimated the potential impacts of the threat, which resulted in insufficient warning to the population (Webster, 2008).

In 2008, the estimated GDP for Bangladesh was $1,500, while it was $1,200 for Myanmar (CIA, 2009).

The relatively small difference in poverty (20%) cannot explain the discrepancy in the aftermaths between the two disasters. Good governance can make significant differences.

If looking at long-term impacts increases the confidence in models for climate change impacts, it is exactly the reverse for vulnerability parameters. How can we infer the socio-economic future by 2030 (let alone 2100)? If we look back 20 years from now, the world has changed drastically since 1991.

The current world economic and social situation is complex and unsettled. The Arab spring, the economic crisis, especially within the Euro zone, triggers large uncertainties even at short term (5-10 years). Running risk scenarios for 2100 or even for 2050 is therefore of little relevance. This is why in the article on TC we concentrated on scenarios for 2030 and only taking into account combined impacts of demography and climate change on human exposure.

5.6. References

Allen, T. I., Wald, D. J., Hotovec, A., Lin, K., Earle, P. and Marano, K., An Atlas of ShakeMaps for Selected Global Earthquakes. U.S. Geological Survey. Open File Report 2008–1236. USGS, 2008.

Alpine, K.G., Wotton, D., Conservation and the delivery of ecosystem services: a literature review, *Science for conservation*, **295**, New Zealand Department of conservation, Wellington, New Zealand, 81 pp. 2009. sprep.org/att/IRC/eCOPIES/Global/317.pdf

Altez, R., Muertes bajo sospecha: Investigación sobre el número de fallecidos en el desastre del estado Vargas, Venezuela, en 1999. *Cuad. med. forense*, **50**, 255-268, 2007.

Arino, O., Gross, D., Ranera, F., Bourg, L., Leroy, M., Bicheron, P., Latham, J., Di Gregorio, A., Brockman, C., Witt, R., Defourny, P., Vancutsem, C., Herold, M., Sambale, J., Achard, F., Durieux, L., Plummer, S., Weber, J.-L., GlobCover: ESA service for global land cover from MERIS, *Geoscience and Remote Sensing Symposium*, 2412 - 2415, 2008

Baird, A.H., Kerr, A.M., Landscape analysis and tsunami damage in Aceh: comment on Iverson and Prasad (2007), Landscape *Ecology*, **23** (1), 3-5, 2008.

Bajracharya, S.R., Mool, P. 2009. Glaciers, glacial lakes and glacial lake outburst floods in the Mount Everest region, Nepal. *Annals of Glaciology*, **50**, 81-86

Balk, D., Pozzi, F., Yetman, G. Global Rural-Urban Mapping Project (GRUMP alpha), CIESIN, Columbia University, 2011. http://sedac.ciesin.columbia.edu/gpw/global.jsp, last consulted June 2011.

Bates, B. C., Kundzewicz, Z. W., Wu, S., and Palutikof, J. P.: Climate Change and Water, Technical Paper of the Intergovernmental Panel on Climate Change, IPCC Secretariat, Geneva, 210 pp., available at: http://www.ipcc.ch/pdf/technical-papers/climate-change-water-en.pdf (last access: August 2010), 2008.

Bender, M.A., Knutson, T.R., Tuleya, R.W., Sirutis, J.J., Vecchi, G.A., Garner, S.T., Held, I.M. Modeled Impact of Anthropogenic Warming on the Frequency of Intense Atlantic Hurricanes, *Science*, **327**, 454-458 (2010).

Birkmann, J., and others, *Measuring Vulnerability to natural hazards, towards disaster resilient societies*, United Nations University, 527 p., TERI Press, New Delhi, India, 2006.

Blake, E.S., Landsea, C.W., Gibney, E.J., The deadliest, costliest, and most intense united states tropical cyclones from 1851 to 2010 (and other frequently requested hurricane facts), National weather Service, National Hurricane Centre, Miami, Florida, 2011. http://www.nhc.noaa.gov/pdf/nws-nhc-6.pdf

Bender, M.A., Knutson, T.R., Tuleya, R.W., Sirutis, J.J., Vecchi, G.A., Garner, S.T., Held, I.M. Modeled Impact of Anthropogenic Warming on the Frequency of Intense Atlantic Hurricanes, *Science*, **327**, 454-458 (2010).

Bernard, C., Director sustainable development and regional planning, Planning Institute of Jamaica, personal communication, December 2011.

Brenning, A.: Spatial prediction models for landslide hazards: review, comparison and evaluation, Natural Hazards and Earth System Sciences, 5, 853-862, 2005.

Burton, I., The social construction of natural disasters: an evolutionary perspective, *Know risk*, 35-36,United Nations International Strategy for Disaster Reduction, United Nations, Geneva, Switzerland, 2005.

Bury, J., Mark, B.G., McKenzie, J.M., French, A., Baraer, M., Huh, K.I., Zapata Luyo, M.A., Gomez Lopez, R.J. 2011. Glacier recession and human vulnerability in the Yanamarey watershed of the Cordillera Blanca Peru. *Climatic Change*, **105**, 179-206

Cannon, T., Vulnerability analysis and the explanation of "natural" disaster, in A. Varley (Ed) *Disasters, development and environment*, John Wiley and Sons Chichester, New York, Brisbane, Toronto and Singapore, pp. 13-29, 1994.

Cardona, O.D., The need for rethinking the concepts of vulnerability and risk from a holistic perspective: a necessary review and criticism for effective risk management, in *Mapping vulnerability: disasters, development and people*, Bankoff, G., Frerks, G., Hilhorst, D. (Ed), Earthscan Publishers, London.

Chambers, R., Vulnerability, coping and policy, *IDS bulletin 20*, Institue of Development Studies, Sussex, 1989.

Chatenoux, B., and Peduzzi, P.: Impacts from the 2004 Indian Ocean tsunami: analysing the potential protecting role of environmental features, Natural Hazards, 40, 289-304, 2007.

CIA, 2009: *The World Factbook 2009*. Central Intelligence Agency. Washington, DC, Central Intelligence Agency.

Clarke, J.T., Rhind, D.W. (Eds), Population data and global environmental change. International Social Science Council, Human Dimensions of global environmental change programme, Report No3, IISC/UNESCO, Paris, 1992.

Cohn, T.A., DeLong, L.L., gilroy, E.J., Hirsch, R.M., and Wells, D.K., Estimating constituent loads, *Water Resourcse Research*, **25**, 937-942, 1989.

DARA, *Climate vulnerability monitor 2010: the state of the climate crisis*, Development Assistance research Associates (DARA), 261 pp., 2010.

Darthmouth Flood Observatory, University of Colorado, Boulder, USA. http://floodobservatory.colorado.edu/, last accessed: 30 December 2011.

DesInventar, ISDR, UNDP, La RED, http://www.desinventar.net/, last accessed, December 2011.

Deichmann, U., personal communications, February 2009.

Dilley, M., Chen, R. Deichmann, U., Lerner-Lam, A., Arnold, M., *Natural Disaster Hotspots, a global risk analysis*, the World Bank, pp 112, 2005.

Duan, N., Smearing estimate: a nonparametric retransformation method, *Journal of the American Statistical Association*, **78**(383), 605-610, 1983.

Eddy, S.R., What is Bayesian statistics?, *Nature Biotechnology*, **22**, 1177 – 1178, 2004.

Elsner, J.B., Kossin, J.P., Jagger, T.H. The increasing intensity of the strongest tropical cyclones, *Nature*, **455**, 92-95, (2008).

EM-DAT: The OFDA/CRED International Disaster Database, Université Catholique de Louvain, Brussels (Belgium). http://www.emdat.be, last consulted September 2011.

ESCAP,UNISDR, *Protecting Development Gains, Reducing Disaster Vulnerability and Building resilience in Asia and the Pacific*, ESCAP, UNISDR, 129 pp., 2010.

FAO, Asia Fivims For Disaster Preparedness, In: *Report of the FAO Asia-Pacific Conference on Early Warning, Prevention, Preparedness and Management of Disasters in Food and Agriculture*, Chiangmai, Thailand, Annex XIII, 2001. Http://www.fao.org/DOCREP/005/AC120E/AC120E00.HTM.

FAO, *Global Forest Resources Assessment 2010*, Food and Agriculture Organization of the United Nations, 378 pp., Rome, 2010. http://www.fao.org/docrep/013/i1757e/i1757e.pdf, last accessed 30 April 2011.

Friends of the Earth International statement made by Chair Meena Raman in a January 2005 Reuters news agency report. Friend of the Earth, (2005), annual report 2004, p.16. http://www.foei.org/en/resources/publications/annual-report/archive/ar2004.pdf/at_download/file

Fritz, H. M., Blount, C. D., Thwin, S., Thu, M. K. & Chan, N., 2009: Cyclone Nargis storm surge in Myanmar. *Nature Geoscience*, **2**, 448-449.

Gilroy, E. J., R. M. Hirsch, and T. A. Cohn, Mean Square Error of Regression-Based Constituent Transport Estimates, *Water Resources Research*, **26**(9), 2069-2077, 1990.

Giuliani, G., Peduzzi, P., The PREVIEW Global Risk Data Platform: a geoportal to serve and share global data on risk to natural hazards. *Nat. Haz. Earth Syst. Sci*, **11**(1):53-66, 2011.

Government of Bangladesh (GOB) 2008: *Cyclone Sidr in Bangladesh: damage, loss and needs assessment for disaster recovery and reconstruction*. Governement of Bangladesh. Dhaka, Bangladesh. IN FINANCE, M. O. (Ed.) Economic Relations Division, Ministry of Finance. Dhaka, Bangladesh, Government of the People's Republic of Bangladesh.

GRIP, Global Risk Information Programme, list of losses databases, http://www.gripweb.org, last accessed in December 2011.

Guzzetti, F., Carrara, A., Cardinali, M., and Reichenbach, P.: Landslide hazard evaluation: a review of current techniques and their application in a multi-scale study, Central Italy, *Geomorphology*, **31**, 181-216, 1999.

Hallegatte, S., Hourcade, J.C.. Dumas, P., Why economic dynamics matter in assessing climate change damages: Illustration on extreme events. *Ecological Economics*, **62**(2) 330-340, 2007.

Hanemann, W.M., Welfare evaluations in contingent valuation experiments with discrete responses, *American Journal of Agriculture Economics*, **66**(3), 332-341, 1984.

IBTrACS v02r01, NCDC International Best Track Archive for Climate Stewardship Project. Since Sept. 2010, a new dataset exist.

ICHARM, UNESCO, *Global trends in water-related disasters: an insight for policymakers*, ICHARM, UNESCO, 24 pp., 2009.

IFRC, *World disasters report: focus on early warning, early action*, IFRC, 208 pp., 2009.

Immerzeeel, W.W., van Beek, L.P.H., Bierkens, M.F.P. Climate change will affect the Asian Water Towers. *Science*, **328**, 1382-1385, 2010.

IPCC, Summary for Policymakers. In: *Intergovernmental Panel on Climate Change Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation* [Field, C. B., Barros, V., Stocker, T.F., Qin, D., Dokken, D., Ebi, K.L., Mastrandrea, M. D., Mach, K. J., Plattner, G.-K., Allen, S. K., Tignor, M. and P. M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 30 pp., 2011.

Jolliffe, I.T., Discarding Variables in a Principal Component Analysis. I: Artificial Data, *Journal of the Royal Statistical Society. Series C (Applied Statistics)*, **21**(2), 160-173, 1972.

Kanevsky, M., and Maignan, M., Analysis and Modelling of Spatial Environmental Data. EPFL-Press, 304 pp., 2004.

Khor M (2005), Save the Mangroves to fight tsunamis, Third World Network, http://www.twnside.org.sg/title2/gtrends39.htm

Knutson, T.R., McBride, J.L., Chan, J., Emanuel, K., Holland, G., Landsea, C., Held, I., Kossin, J.P., Srivastava, A. K. & Sugi, M. Tropical cyclones and climate change, *Nature Geoscience*, **3**, 157 – 163, 2010.

Lateef, F., 2009: Cyclone Nargis and Myanmar: A wake up call. *Journal of Emergencies, Trauma and Shock*, **2**(2): 106–113.

Landscan, population distribution model, Oak Ridge National Laboratory, 2008. http://www.ornl.gov/sci/landscan/

Landsea, C.W., Harper, B.A. , Hoarau, K. , Kaff, J. . Can we detect trends in extreme tropical cyclones? *Science*, **313**, 452-454, 2006.

Lehner, B., Verdin, K., and Jarvis, A., New global hydrography derived from spaceborne elevation data, *Eos*, **89**(10), 93–104, 2008.

Limpert, E., Stahel, W.A., Abbt, M., Log-normal Distributions across the Sciences: Keys and Clues, *BioScience*, **51**(5), 341-352. 2001.

Manning, G.W., The logged dependent variable, heteroscedasticity, and the retransformation problem, *Journal of Health Economics*, **17**, 283-295, 1998.

Manning, G.W., Mullahy, J., Estimating log models: to transform or not to transform?, *Journal of health Economics*, **20**, 461-494, 2001.

Maskrey, A., *Los Desastres No Son Naturales*, La Red de Estudios Sociales en Prevención de Desastres en América Latina, 137 pp., 1993.

Maskrey, A., Reducing global disasters, *Natural disaster management*, ,84-85, Tudor Rose, ISDR, 320 pp. 1999.

Miller, D.M., Reducing transformation bias in curve fitting, *The American Statistician*, **38**(2), 124-126, 1984.

Morgan, M. G., Fischhoff, B., Bostrom, A., and Atman, C. J., *Risk communication: A mental models approach*. New York: Cambridge University Press. 2002.

Nadim, F., Kjekstad, O., Peduzzi, P., Herold C., Jaedicke, C., Global landslide and avalanche hotspots, *Landslides*, **3**(2), 159-173, 2006

NRC, The Impacts of Natural Disasters: A Framework for Loss Estimation Committee on Assessing the Costs of Natural Disasters, National Research Council, 80 pp., 1999. http://www.nap.edu/catalog/6425.html

Paul, B. K., Perception of and agricultural adjust ments to floods in Jamuna floodplain, Bangladesh. *Human Ecology,* **12**, 319, 1984.

Paul, B. K., Why relatively fewer people died? The case of Bangladesh's Cyclone Sidr. *Natural Hazards*, **50**, 289-304, 2009.

Paul, F., Kääb, A. and Haeberli, W., Recent glacier changes in the Alps observed from satellite: Consequences for future monitoring strategies. *Global and Planetary Change*, **56** (1/2), 111-122, 2007.

Peduzzi, P., Dao, H., Herold, C., Rochette, D., Sanahuja, H., Feasibility Study Report On Global Risk And Vulnerability Index –Trends per Year (GRAVITY), scientific report for For United Nations Development Programme Emergency Response Division, UNDP/ERD, UNEP/GRID-Geneva, 79 pp., 2001. http://www.grid.unep.ch/product/publication/download/ew_gravity1.pdf, last accessed on 5 May 2011.

Peduzzi, P., Dao, H., Herold, C., Mapping Natural Hazards, Human Impacts using global Datasets, Natural Hazards, 35(2), 265-289, 2005.

Peduzzi, P., Dao, H., Herold, C., Rochette, D., Sanahuja, H., Feasibility Study Report On Global Risk And Vulnerability Index –Trends per Year (GRAVITY), scientific report for For United Nations Development Programme Emergency Response Division, UNDP/ERD, UNEP/GRID-Geneva, 79 pp., 2001. http://www.grid.unep.ch/product/publication/download/ew_gravity1.pdf, last accessed on 5 May 2011.

Peduzzi, P., Deichmann, U., Maskrey, A., Nadim, F., Dao, H., Chatenoux, B., Herold, C., Debono, A., Giuliani, G., Kluser, S., *et al.*, Global disaster risk: patterns, trends and drivers, *ISDR (2009) Global Assessment Report on Disaster Risk Reduction*, United Nations, Geneva, Switzerland, chapter 2, pp. 17-57, 2009.

Peduzzi, P., Chatenoux, B., Dao, H., De Bono, A., Herold, C., Kossin, J., Mouton, F., Nordbeck, O., Tropical cyclones: global trends in human exposure, vulnerability and risk, *Nature Climate Change*, (in press).

Peduzzi, P., Velegrakis, A., Chatenoux, B., Estrella, M., Kluser, S., Karambas, Th., Quantifying the role of marine ecosystems in reducing coastal erosion: the RiVAMP study in Negril Jamaica, in prep.

Pozdnoukhov A.and Kanevski M., Multi-scale support vector algorithms for hot spot detection and modelling. *Stochastic Environmental Research and Risk Assessment*. **22**(5), 647-660, 2008.

Raftery, AE., Alkema, L., Gerland, P., Clark, SJ., Pelletier, F., Buettner,T., Heilig, G., Li, N., Sevcikova, H., White Paper: probabilistic projections of the total fertility rate for all countries for the 2010 World population prospects, 2009. http://esa.un.org/unpd/wpp/Documentation/EGM-RFTF_P16_Raftery.pdf, last consulted June 2011.

Robinson, D., Jamaican minister of foreign affairs, personal communication during the launch of RiVAMP, March 2010.

Ross, A. (director of seascape, specialist on coral restoration), private discussion at the high level policy-makers event, Kingston, Jamaica, 9 December 2011.

Schmidtlein, M.C., Deutsch, R.C., Piegorsch, W.W., Cutter, S.L., A Sensitivity Analysis of the Social Vulnerability Index, *Risk Analysis*, **28**(4), 1099–1114, 2008.

SRTM: The Shuttle Radar Topography Mission Global. 90m Digital Elevation Database v4.1 http://www.cgiar-csi.org/data/elevation/item/45-srtm-90m-digital-elevation-database-v41, last checked October 2011.

StatSoft Electronic Statistics Textbooks: http://www.statsoft.com/textbook/statistics-glossary/, access date: 27 October 2011.

Stow, C.A., Reckhow, K.H., Qian, S.S., A Bayesian approach to retransformation bias in transformed regression, *Ecology*, **87**(6), 1472-1477, 2006.

Stynes, D.J., Peterson, G.L., Rosenthal, D.H., Log transformation bias in estimating travel cost models, *Land Economics*, **62**(1), 94-103, 1986.

Thywissen, K., Core terminology ofisater reduction: a comparative glossary, *Measuring vulnerability to promote disaster-resilient societies*, 448-4496, United Nations University, United Nations University Press, Tokyo, New York, Paris, 524 pp., 2006.

Turner II, B.L, Roger E. Kasperson, William B. Meyer, Kirstin M. Dow, Dominic Golding, Jeanne X. Kasperson, Robert C. Mitchell, Samuel J. Ratick, Two types of global environmental change: Definitional and spatial-scale issues in their human dimensions , *Global Environmental Change*, **1**(1), 14-22, 1990.

Turner II, B.L., Kasperson, R.E., Matson, P.A., McCarthy, J.J., Corell, R.W., Christensen, L., Eckley, N., Kasperson, J.X, Luers, A., Martello, M.L., Polsky, C., Pulsipher, A., Schiller, A., A framework for vulnerability analysis in sustainability science, *PNAS*, **100**(14), 8074-8079, 2003.

UN, *Risk and poverty in the context of climate change, the 2009 Global Assessment report on disaster risk reduction*, United Nations International Strategy for Disaster Reduction, United Nations, Geneva, Swizerland, 2009.

UNDP, *Reducing Disaster Risk: a challenge for development*, United Nations Development Programme, Bureau for Crisis Prevention and Recovery, 146 p., New York, NY 10017, USA, 2004.

United Nations Disasters Relief Co-Ordinator (UNDRO), Natural Disasters and Vulnerability Analysis, Report of Expert Group Meeting, 9-12 July 1979, Geneva, Switzerland

UNEP and ISDR, 2000-2011 : The PREVIEW Global Risk Data Plateform, http://preview.grid.unep.ch, last accessed : September 2011.

UNEP, PIOJ, *Risk and Vulnerability Assessment Methodology Development Project (RiVAMP), Linking Ecosystems to Risk and Vulnerability Reduction: The Case of Jamaica. Results of the Pilot Assessment*, United Nations Environment Programme, Planning Institute of Jamaica, 130 pp., 2010.

UNEP, the Global Environment Outlook geodata portal, UNEP/GRID-Geneva, 2000-

2011, http://geodata.grid.unep.ch/, last access: December 2011.

UNEP, 21 Issues for the 21st Century: Results of the UNEP 2011 Foresight Process on Emerging Global Environmental Issues, United Nations Environment Programme, in prep.

UNISDR, *Hyogo Framework for Action 2005-2015: building the Resilience of Nations and Communities to Disasters*, United Nations International Strategy for Disaster Reduction, 25 pp., 2005. http://www.unisdr.org/eng/hfa/docs/Hyogo-framework-for-action-english.pdf, last accessed: 29 April 2011.

UNISDR, terminology, Preventionweb, http://www.preventionweb.net/english/professional/terminology/?pid:6&pih:2, last checked: 27 April 2011.

UNPD, Population Projection, United Nations Population Division in *Geodata portal*, UNEP, 2010. http://geodata.grid.unep.ch, last consulted 25 April 2010.

Urban Population - Percent of Total Population, United Nations Population Division in *Geodata portal*, UNEP, 2010. http://geodata.grid.unep.ch, last consulted 25 April 2010.

Vanacker, V., Vanderschaeghe, M., Govers, G., Willems, E., Poesen, J., Deckers, J., and De Bievre, B.: Linking hydrological, infinite slope stability and land-use change models through GIS for assessing the impact of deforestation on slope stability in high Andean watersheds, *Geomorphology*, **52**, 299–315, 2003.

Verelst, L., Recommendations for georeferencing EM-DAT database: Consultancy Report prepared for the Asia FIVIMS Project and the CRED, Rome, Italy, 1999.

Wald, D. J., Earle, P.S., Porter, K., Jaiswal, K. and Allen, T. I., Development of the U.S. Geological Survey's Prompt Assessment of Global Earthquakes for Response (PAGER) System. Proceedings of the 14th World Conference on Earthquake Engineering, October 12–17, 2008. Beijing, China, 2008.

Webster, P. J., 2008: Myanmar's deadly daffodil. *Nature Geoscience*, **1**, 488-490.

Webb, A.P, Kench, P.S., The dynamic response of reef islands to sea-level rise: Evidence from multi-decadal analysis of island change in the Central Pacific, *Global and Planetary Change* **72**(3), 234-246, 2010.

White, G.F., *Natural Hazards*, Oxford, New York, 1974.

Wisner, B., Disaster vulnerability: scale, power and daily life, *GeoJournal*, **30**(2), 127-40, 1993.

Worrell, J., personal communication, March 2004.

World Bank, Development Actions and the Rising Incidence of Disasters, Evaluation Brief #4, Independent Evaluation Group, the World Bank, Washington, DC, 34 pp. (2007).

Xu, J., Grumbine, R.E., Shrestha, A., Eriksson, M., Yang, X., Wang, Y., Wilkes, A., The melting Himalayas: cascading effects of climate change on water, biodiversity, and livelihoods. *Conservation Biology*, **23**, 520–530, 2009.

Xu. Z.W., GIS and ANN model for landslide susceptibility mapping. *Journal of Geographical Sciences*, 11, 374-381, 2001.

Zemp, M., Roer, I., K¨a¨ab, A., Hoelzle, M., Paul, F., and Haeberli, W.: *Global Glacier Changes: facts and figures*, UNEP, World Glacier Monitoring Service, Zurich, Switzerland, 88 pp., available at: http://www.grid.unep.ch/glaciers/, (last access: August 2010), 2008.

Zong, Y., Chen, Z., Innes, J.B., Chen, C., Wang, Z. & Wang, H., Fire and flood management of coastal swamp enabled first rice paddy cultivation in east China. *Nature* **449**, 459-463, 2007.

Chapter 6 Conclusions, achievements, perspective and author's point of view

In the context of this thesis, I wanted to study and identify the role of underlying risk factors related to global change, such as demographic growth, climate change and the impacts from the decline of ecosystems. Many other subjects could have been chosen. These choices were made based on opportunities and mandates as well as time availability.

At the global level, the method exposed in this thesis tries to understand what are the roles of the different components of risk, through an attempt at modelling past impacts (mortality). Past losses as reported from inventory are compared with models attempting to simulate equivalent losses using physically measured data (e.g. from satellite, meteorological stations), population distribution models (based on census and GIS processing) and vulnerability contextual parameters (from global datasets). The reported losses and the datasets for modelling losses being independent from each other, the comparison between reported losses (or observed impacts) and GIS models trying to approach similar levels of losses, enabled the identification of some underlying factors of risk and helped to quantify the respective role of some risk components (hazard, exposure and vulnerability). This did certainly not solve everything. Risk was mapped (at a global scale), but not at a level of precision that can be used for local land planning. These studies are to be taken for what they were designed for, i.e. a support to DRR awareness, to identify the underlying risk factors, and thus were not intended for evaluation of future risk, which would require the development of a probabilistic approach.

At the local level, case studies used observed impacts from satellites (areas of landslides or areas and thickness of ice in glaciers) to highlight possible links between either ecosystems decline or climate change and risk. The improved understanding gained from these studies was used to raise awareness on some selected impacts of global change on risk.

Results from this thesis show that the joint use of Geographical Information System, Remote sensing, mathematical models and statistical analysis can be used to help addressing some of the HFA priorities (i.e. part of priority 2 and part of priority 4, see box 1).

GIS is an efficient tool for extracting information and generating the necessary material for statistical analysis. Multiple regression analysis can identify and quantify the role of individual factors and related weight, thus allowing spatial modelling in GIS and visual representations (such as maps and graphs). The same techniques were successfully adapted and applied at different scales. At the global scale it was applied to risk to different hazards (floods, tropical cyclones, landslides,...). At the local level it was applied to evaluate glacier retreat, links between deforestation and landslides; links between coastal ecosystems and beach erosion – the latter is not presented in this thesis – but can be found in the UNEP report on RiVAMP (UNEP and PIOJ, 2010).

From this research, several original datasets were generated, which are, in some cases, the first such attempt at the global level (e.g. for flood and for tropical cyclones). The results of these studies were used for raising awareness on the need for action or for advocating the consideration of underlying factors such as poverty, governance, deforestation, climate change impacts on water supply and the need for restoring / maintaining natural ecosystems for DRR. It is in no way claimed that this work has resolved these issues - the task is still immense - however, it constitutes one of the pioneer works in this field and has already triggered interest from governments and even actions (at least in one case) at the local level.

This work engaged in a holistic thinking process, although much more work is needed to achieve fully comprehensive assessments. Tools and methodology provided here aim to advance such integrated assessments, looking first at global issues and then zooming down to more regional/local issues. At the local level, the method should be further developed to integrate an entire watershed, from the highland to the coast. It should also include collaboration with an economist to setup a risk assessment including monetary terms (Hallegatte, 2007).

Contributions to the first steps towards this aim were presented here.

6.1.1. Global level researches

At a global level, as compared with previous global studies (Dilley *et al.*, 2005) significant improvements were achieved in the characterisation of disaster risk as well as a finer identification of spatial distribution. Innovative methods for modelling hazards, exposure and identifying the underlying factors of vulnerability were developed. In the models, vulnerability had a higher share in low intensity events, whereas the role of exposure was more preponderant at higher intensities. This finding has significant consequences should the intensity of hazards increase, e.g. due to climate change. It means that more developed countries might be more affected than in the past. It confirms that poverty is the main underlying factor of vulnerability, especially when associated with poor governance.

The multiple Mortality Risk Index provided UN development agencies and DRR stakeholders with a tool for comparing countries at risk allowing for prioritisation of DRR measures and projects. Within countries, the distribution of risk for individual hazard, allows the identification of areas where disaster risk reduction should be carried out in priority. The methodology allows comparison between countries despite differences in population and type of hazards affecting the countries. Derivative products were developed such as country profiles. We saw that these techniques due to the margin of error and the use of logarithmic regressions, may require the correction of the statistical bias induced by such processes. However, this depends whether the median or the mean is the most relevant indicators when translating the values from logarithm to original metrics (Manning, 2001; Stow, 2006), more researches are needed to test whether the median or the mean should be used (Stynes, 1986; Hanemann, 1984). Both options might be suitable estimators (Stynes, 1986; Miller, 1984). We used the median for the MRI, but in the case of tropical cyclones, the final choice was to use a QMLE. This was evidence based (improved total estimates). Both approaches can be justified, but the impacts on the predicted being significant, a formal mathematical study should be conducted. This should be carried out on tropical cyclones, but also on floods and earthquakes as the conditions to use log-normal distribution in science varies from one subject to another (Limpert *et al.*, 2001).

It is fair to say that this global approach was the key component of the GAR 2009 and had a significant impact for local stakeholders. The 2009 GAR report is the most downloaded report of UNISDR at all time. Each of its seven chapters can be downloaded and, as of 31 December 2010, there were more than 480,900 chapters downloaded, chapter 2 (Peduzzi *et al.*, 2009) was by far the most downloaded chapter representing 26% of the downloads (125,180).

The GAR 2009 report also obtained high visibility as it was launched in Bahrain by the UN Secretary General, Mr Ban Ki-Moon. It was then officially presented in multiple regions: Bali (Indonesia), Tokyo (Japan), Bangkok (Thailand), New York and Washington (USA), Geneva (Switzerland), London (UK), Oslo (Norway), Paris (France), Teheran (Iran), Cusco (Peru), Buenos Aires (Argentina), Christ Church (Barbados) and Dushanbe (Tajikistan). Results were also presented at the Global Risk Data Platform 2009 (Geneva, May 2009) in front of a majority of the governments. This ensured high visibility of the results.

6.1.2. The PREVIEW Global Risk Data Platform

All the global datasets generated were made available for visualisation, query and download through the PREVIEW Global Risk Data Platform (http://preview.grid.unep.ch). This provides free access to the data for scientific research and non-profit organisations (see Figure 123). This interactive internet mapping application was initially developed by UNEP/GRID-Geneva in 2000 (Peduzzi, 2000), since 2009, the Global Risk Data Platform has been drastically improved and turned into a full Spatial Data infrastructure (SDI) providing all web services (Giuliani and Peduzzi, 2011).

It allows users to visualise, interrogate and access data (either by downloading them or by direct connection). Its technology is based on Open Source Software and it is the first application of UNEP/GRID-Europe based on our newly-emerging Spatial Data Infrastructure (SDI)[1], allowing us to share all the data available through the Global Risk Data Platform (Giuliani and Peduzzi, 2011).

Several web services are proposed in order to be fully interoperable with other applications, to support the different GIS standards developed by the Open Geospatial Consortium (OGC) and to fulfil the requirements of the main SDI initiatives such as GEOSS (at the global level), UNSDI (for the United Nations) and INSPIRE (at the European level). Since its launch in May 2009, the PREVIEW Global Risk Data Platform has been visited by nearly 130,000 visitors (as of 30 November 2011), of these more than 87,500 were unique visitors, there were more than 4 million hits and more than 120 Gb of zipped data were downloaded. A Google search provides 8570 citations.

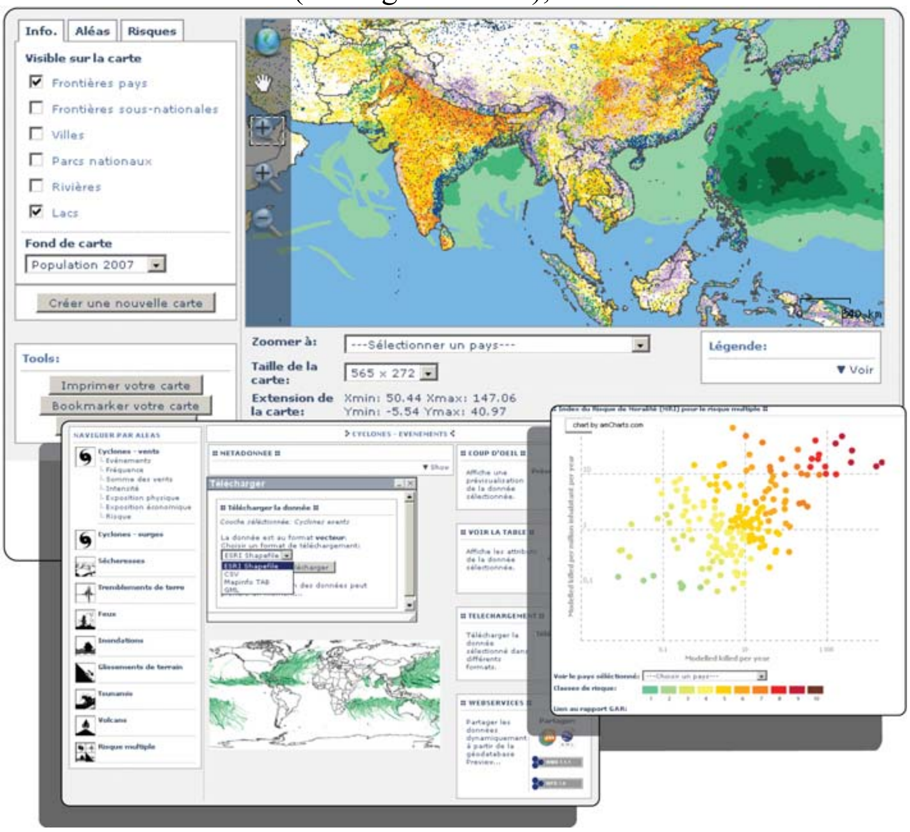


Figure 123 The PREVIEW Global Risk Data Platform see http://preview.grid.unep.ch

The mandate received from the UNISDR in improving the DRI as published by the UNDP (UNDP, 2004) and bridging the gaps in the World Bank Hotspot research (Dilley *et al.*, 2005) was achieved. On the hazards side, the resolution for mapping distribution was significantly improved, especially for floods where a model was computed at 90 m for the entire world. Landslide hazards were characterised with much higher resolution thanks to the use of SRTM data (90 m). Differentiation between landslides triggered by earthquakes and triggered by precipitation was also provided.

The improvement in mapping hazards distribution has a direct impact on the quality of estimation of human and economic exposure. In the methodology, the event by event approach allowed the association of the contextual parameters at the time of the event and permitted the inclusion of individual event intensity and duration. It opens the door to other analyses; for example crossing sea surface temperatures and individual tropical cyclone events or including the time gap between two events as a variable. We could also modify the inputs to run scenarios on climate change, e.g. by changing the severity of tropical cyclones. It could be used for developing hazard calendars for different regions.

Nevertheless, improvements are needed. Drought hazards, which are probably the hazard with the largest extent and which affects food supply in vulnerable populations, was not characterised successfully. This leads to an underestimation of the risk faced by some African and central Asian countries and should be corrected in future research.

Earthquake and drought models need further development. It was not possible to improve these models within the time at disposal for this study. For earthquakes, the Global Earthquake Model (GEM, 2011) initiative will soon provide new earthquake hazard and risk maps. Drought is a difficult hazard. The same amount or percentage of rainfall decrease for an extended period does not necessarily lead to a similar degree of agricultural drought. However, it is certainly an area where more efforts will be required.

On the vulnerability side, new research should be based on sub-national information. This would drastically reduce the number of factors available for the analysis. If the reduced number of factors available should prove too limiting for most countries, sub-national information should, at the very least, be analysed, for large countries such as e.g. China, India, Russia or USA.

The transposition of the approach used on mortality risk to risk of economic losses is not straight forward. The choice to concentrate on mortality risk was based on two main reasons. Firstly, the mandate to study economic risk for the GAR 2009 was provided to the World Bank. Secondly, the economic data are much less reliable and require extensive standardisation in order to take into account the inflation through time, the difference in purchasing power parity and the exchange rate to US$ at the time of the impact The best way found to normalise economic losses, was to express them as a share of national GDP expressed in purchasing power parity. Despite such transformations, comparisons are not always possible. In our globalized world, indirect losses can extend beyond the border of the affected country. Comparison of losses through time is also difficult.

Given all the difficulties in generating the hazards, exposure and vulnerability datasets, concentrating on mortality risk was already a major endeavour. It avoided having to deal with the complexity of indirect losses and capacity to bounce back (irrelevant for mortality risk) which is complex and requires high expertise in macro-economics.

Small islands also require more attention. The size of the territory often prevents accurate automatic extraction of exposure. This is also a key priority given the vulnerability of these territories. To a certain extent, islands, given their small territories, remoteness and low elevation, might need their own specific study. This is also becoming urgent due to the prospect of accelerated sea level rise and potential intensification of tropical cyclones under warmer climatic conditions.

Also for small islands floods were not computed for watersheds smaller than 1000 km^2. This threshold was chosen in order to reduce the number of watersheds computed, given that floods were modelled by watersheds and computation already took more than 6000 hours. As a result, identification of flood prone-areas on small islands is missing in most cases.

A specific study on small islands might also reveal another specific threat to islands, that being isolation. Distance from one island to another or to mainland, might be another vulnerability factor. The small size of island territories and distance reduces the possibilities of shelter and evacuation. Threat from sea level rise and intensification of storms are also bringing another dimension to small territories, with their – usually – low average altitude.

These studies show that identifying the underlying factors of risk from natural hazard can be complex and no single model presented here can claim to describe it fully. However, it is fair to say that the proposed quantitative approach - with model of events footprints, hazards frequency, population exposure using GIS and statistical modelling and connecting them with socio-economic parameters - greatly helps global risk assessments. Using satellite records, geological, meteorological, topographical and environmental data, a hazard’s frequency, intensity and individual event footprints were modelled to provide a first estimate of population exposure, with a global coverage. Contextual parameters were associated with more than 8760 available individual events from 1970 to 2010.

This database offers multiple opportunities for future researches.

6.1.3. Quantifying the role of ecosystems

These studies were aimed at quantifying their influence on disaster risk. Although we hope that good ecosystem management reduces disaster risk, we have to admit that although sometimes it does (e.g. Pakistan landslides (Peduzzi, 2010), coral and sea grass for mitigating beach erosion (Peduzzi *et al.*, in prep.; UNEP, 2010), sometimes it does not e.g. in tsunami wave reduction (Chatenoux and Peduzzi, 2007).

This thesis also looked at the influence of ecosystems decline. For many developing countries, there is little they can do to mitigate climate change. However, local change in ecosystems may have much more rapid influence. In north Pakistan, rapid land cover changes, such as deforestation, led to slopes devoid of vegetation which were more susceptible to landslides (IUCN, 2005).

These results can be used in two ways. Firstly to blame deforestation practices, but also, in a more positive way, to support the use of ecosystems for DRR actions.

More research is needed to support the use of ecosystems for DRR. It should be emphasized that ecosystems (as opposed to engineering structures) offer co-benefits. For examples when comparing the building of a wall or the planting of vegetation to stabilize a slope (assuming both are feasible), the ecosystem based approach offers multiple benefits:

- It is often cost effective
- It is natural and environmental friendly
- Easier: it can be done with the help of the local population.
- Requires low (if any) maintenance
- Has esthetical, recreational value
- Can store carbon
- It supports biodiversity
- May provide food (hunting, fruits)

This is not to say that ecosystems can be used in all situations, but the ecosystems alternative should be at least studied. This was highlighted by IPCC special report (IPCC, 2011) for climate change adaptation: "*Successful strategies include a combination of hard infrastructure-based responses and soft solutions such as individual and institutional capacity building and ecosystem-based responses.*" (IPCC, 2011).

A study performed on 27 atoll islands in the central Pacific over a 19 to 61 year period (Webb and Kench, 2010), showed that despite accelerated sea level rise, 86% of these islands have remained either stable (43%) or have increased in area (43%). This provides hope on the capacity of healthy ecosystems to adapt to climate change. It should also be further studied to better understand how it functions, thus providing insight on how to use ecosystems for climate change adaptation.

The signal of the role of ecosystem decline on hazard susceptibility can be detected. This requires, however, local scale type of studies. The role of deforestation on landslides susceptibility was significant in the case of the North Pakistan landslides. Other studies have revealed the strong role of coral and sea grass in mitigating beach erosion (Peduzzi *et al.*, in prep; UNEP and PIOJ, 2010).

6.1.4. Local level research

In Pakistan, the link established between deforestation and landslide susceptibility adds elements for protection of natural vegetation on slopes and even reforestation projects. The partnership on Environment for Disaster Risk Reduction (PEDRR) which includes UNEP, UNDP, UNISDR, IUCN, UNU, ProAct, WWF and other agencies, expressed interest in the study.

The methodology was successfully replicated for a similar study on the role of marine ecosystems for mitigating beach erosion in Jamaica (UNEP and PIOJ, 2010; Peduzzi *et al.*, in prep.). It opens the way to developing such studies in different ecosystems. The more the scientific evidence collected, the more it will support the recognition of the role of ecosystems. It will help to raise awareness on the role of ecosystems and may thus support actions for their protection and their restoration.

The research conducted in high altitude areas (Peduzzi *et al.*, 2010), in mountainous areas (Peduzzi, 2010), on marine and coastal ecosystems for both the Indian Ocean tsunami (Chatenoux and Peduzzi, 2007) and on beach erosion in Jamaica (Peduzzi *et al.*, in prep.), shows that the method is easily adaptable and can be applied to a wide range of ecosystems and issues. Issues in dry land and in flood prone areas should be addressed in the future.

The process of the various studies followed mostly the same path. The use of remote sensing and/or GIS modelling allowed for the identification of events' or features' footprints. These were used for spatial extraction of associated parameters. These were then incorporated into a database for preparation of tables. Such tables were then entered into statistical software for multiple regression analysis. Once the variables were identified (after transformations, if needed), the related weights are used for GIS modelling. This process appears to be robust and provided reliable results despite the variety of issues to which it was applied.

Adaptations were necessary, as each project was different. For example the research in Peru required extensive ground collection of data. The remaining depth of ice could not be measured by means of remote sensing techniques.

The requirement in computing power was substantial. The team reached the limits of PC work stations and of software on several occasions, the processing of 1.7 Tb of data kept the computer busy during several thousand hours. Computation of the entire world at 1 x 1 km resolution was only possible for integer values. Innovative solutions had to be found for data including digits. Such research would benefit from cloud computing (especially for tropical cyclones and flood modelling) which is currently under development. Also, the methodology has now being adapted to run on free Open Source software to avoid creating dependencies, when this method is transferred to developing countries. Training was provided to 21 practitioners for identifying and quantifying the role of ecosystems (Kingston, Jamaica, from 5 to 8 December 2011). This module will soon be provided on-line with a step by step training manual, sample data and links to Open Source software. It is hoped that such efforts will contribute to facilitate the generalisation of such studies.

Also, for reproducing the research on the role of ecosystems, it might be interesting to test the same methodology on open source GIS and remote sensing software for the transfer of the methodology to developing countries.

Quantifying the role of the different risk components provided factual credibility. It is one thing to say that poverty kills, but providing statistical evidences that this is the case has a much stronger power of advocacy. Highlighting the role of governance gives a strong signal to leaders, reminding them of their responsibilities when they accepted their position. The results were presented to many different audiences; for example in front of leaders from 160 countries at the global platform on disaster risk reduction in Geneva (May 2009), as well as officially in 14 other major cities for the regional launch of the GAR 2009.

Although the mapping of distribution of natural hazards at the global scale was performed at an unprecedented resolution and precision, it remains a global analysis which should not be used for local land planning.

By weighting the role of the different components of risk, this study flags governance, population growth, poverty and other contextual parameters as important components of risk. This helps to achieve the transition from a hazard-based/random events perspective to a perception of a level of risk resulting from inappropriate choices (or lack of choices due to poverty) in development, where urban and land planning, quality of building, level of prevention and preparedness play the main role. It is not surprising that poverty is highlighted in all models as the main vulnerability parameter. Poverty *de facto* reduces the possibility of choice. However, poor countries such as Bangladesh or Cuba, have demonstrated that actions can be undertaken for reducing disaster risk. The comparison of the outcomes from the tropical cyclones Sidr (Bangladesh, 2007) and Nargis (Myanmar, 2008) shows the importance of the role of governance. Even a poor country such as Bangladesh can drastically reduce disaster risk with appropriate DRR actions (see Box 7).

Studies at the local level also demonstrated that the slow but continuous processes which lead to climate change or to the decline of ecosystems are exacerbating risk.

6.1.5. Broader context

With an average of 75,000 to 100,000 (depending on the period of references) of deaths per year, losses from natural hazards might not be the main threat to human population (EM-DAT, 2011). Globally, 7.6 million people die from cancers (1.3 million from lungs cancer), AIDS is responsible for 2.1 million deaths per year, car and other traffic accidents claim yearly 1.2 million lives and according to the World Health Organisation (WHO), malaria kills a child every 30 seconds and accounts for one millions killed per year (see Figure 124).

Modern journalistic practices tend to overemphasis the most spectacular deaths. The space dedicated in the media to mortality is not proportional to the number of deaths (Bomlitz and Brezis, 2008). Illicit drugs, motor vehicles, toxic agents and homicide are overrepresented (Frost *et al.*, 1997). In fact, rarer factors (e.g. SARS, bioterrorism) are inversely proportionally overrepresented as compared with the related losses, while the main causes of mortality, AIDS, physical inactivity and smoking) are inversely misrepresented (Bomlitz and Brezis, 2008).

Figure 124 shows that natural hazards are not the main threat to human life. So, why concentrate our efforts on natural hazards? Are we participating to the inversely misrepresentation of threat?

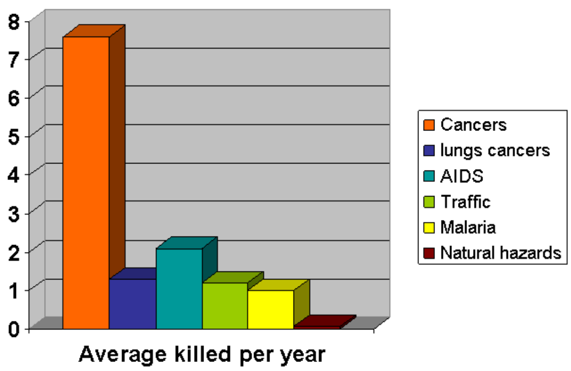


Figure 124 Comparison with impacts from other hazards

The main reason was that this was our mandate. However, despite the modelling of mortality from natural hazard, the angle taken is more led by the inequality of risk introduced by poverty, governance, climate change and ecosystems decline. Not that the question of risk from natural hazards is not important. Disasters from natural hazards can be highly disruptive and might even cause the collapse of society. Cardona *et al.* (2005) demonstrated that savings for coping with future hazards can significant reduce development. Small economies (such as SIDS) may never recover from a shock (Fellipe Barito in GAR 2009, ch.2). As opposed to death caused by lungs cancer or by car accident, disasters from natural hazard may kill large number of people and destroys infrastructures, leading societies to significant threats and placing them in a difficult position to recover, depending on the magnitude of the disaster. The question of recovery, however, does not apply to mortality. Threat to societies is probably best approached by modelling economic losses rather than mortality. In the case of earthquakes, mortality is induced by the collapse of buildings, hence it can be a good proxy for economic losses, this is very different for floods however.

The interest in studying mortality, is to point out the weaknesses of societies in protecting the most vulnerable people. The level of mortality is not only a question of exposure and poverty, in countries with similar levels of development, large discrepancy in the number of people killed can be observed this largely comes from differences in governance. This is a good indicator of how governments care for the poor population (see box 7).

Can we build similar tools for raising awareness on creeping issues, which are threatening humans as a whole?

- The accelerating trends of unsustainable urbanisation and the consequences of unplanned development of megacities,
- the consequences of climate change,
- the freshwater crisis and its consequences for food security and the environment,
- the unsustainable exploitation and depletion of natural resources,
- desertification and soil erosion,
- the uncontrolled deforestation and consequences on biodiversity, climate and soils,

- the risk to human health and the environment from hazardous chemicals, and land-based sources of pollution.
- the rapid on-set of the end of cheap petrol and its consequences on our dependency for energy and food production.
- The potential collapse of ocean ecosystems.

Common sense dictates that we treat these issues as top priorities. But to stand a chance of being re-elected politicians must focus on what can be achieved in a four to five-year mandate. Long term issues tend to be side-lined. Similarly, for the media, it is difficult to make the headlines with continuous degradation and in their uphill struggle to keep readers' and viewers' attention, issues related to global change are often relegated to scientific pages. But such topics are more complex than such simple statements (Neto *et al.*, 2006).

To overcome this, identifying links between global change and disaster risk is one strategy amongst others. It helps to raise awareness outside the usual environmental circle.

However, if the environment can exacerbate disaster risk, the reverse is also true. With an increase of dangerous infrastructures, we may see an increase of environmental consequences from natural hazardous events.

The emergence of complex hazards such as the earthquake and related tsunami, triggering a nuclear accident in Fukushima (Japan) raises several questions. Firstly, the comparison of the aftermaths of the 2004 Indian Ocean and the 2011 Japanese tsunamis reveals significant differences. The Indian Ocean Tsunami was the third largest disaster in terms of mortality since 1975, while the 2011 Japanese tsunami triggered the highest economic losses. However the main point of distinction is the difference in the duration of the impacts. One of the differences between a nuclear accident and a natural hazard is the possibility of intervention. Radioactivity precludes direct intervention to mitigate the impacts. Another consequence of a nuclear accident is to remove large areas of land from human use for an extended time period.

It may be interesting in future studies on natural hazards to include potentially dangerous assets such as Nuclear Power Plants (NPP), chemical plants, dams,… . The tragic accident in Fukushima illustrates that not all developments are reducing human vulnerability.

6.1.6. The need for a global change

This research underlines the usefulness of quantitative studies for a better identification of populations at risk. Maps are a powerful tool for making the invisible visible. However, quantitative analysis cannot depict all the dimensions of disasters. As Albert Einstein said: "*Not everything that can be counted counts, and not everything that counts can be counted.*" The level of despair of survivors who have lost their partner, children, friends or relatives or their houses, falls in the latter category. A farmer, who loses his crop production due to a tropical cyclone, might not have enough money to start cultivating the following year, let alone have enough food for the next month. If he loses his cows because of severe drought, he might borrow some funds to buy one or two new cows, but if he loses them again in a flood, nobody will lend him money again (Chambers, 1983; Adger, 1999).

Through these recovery mechanisms the poor are losing all their assets and even their capacity to obtain future loans (Mustafa, 1998). The rapid recurrence of hazardous events can prevent vulnerable communities from recovering and then set them further back. Mortality as an indicator does not show the reality of survivors experience and the possibilities for a society to bounce back.

This research was intended at supporting Disaster Risk Reduction actions, by providing elements to convince policy makers. This kind of study is far from the work conducted at a community level. One approach should not preclude the other. Studies at the local and community levels are providing different information from GIS studies: both address different needs and different levels of complexity. Tools are needed to raise awareness and flag areas where more research and support are needed, including at the local level.

6.2. Future researches

The lack of concern, let alone action, regarding depletion of natural resources, the increasing poverty and poor spatial planning, is a recipe for disaster. We saw that most disasters are not random events without underlying causes. They are the sudden manifestation of slow but continuous degradation processes.

Risk is a human construct and fatalities are not a fatality. True one cannot prevent the earth from shaking, but one can avoid building a city on a fault line; one cannot prevent tropical cyclones, triggering heavy precipitations and high winds, but one can introduce efficient early warning systems, evacuate populations and build resistant shelters for inhabitants as well as for cattle, as in Bangladesh, where nearly 4000 such shelters were built (Paul, 2009).

In this thesis, both global and local scales have highlighted that while the hazard may be rapid all the other underlying factors of risk are mostly slow onset fators, such as level of development, governance, urban growth, deforestation, climate change. Humans are poorly equipped to deal with slow onset processes. Researchers (Glantz, 1999) call this category of environmental change ‘creeping changes’. These incremental changes are unnoticed until they pass a threshold and quickly lead to changes in the environment, or get revealed by a sudden onset hazard (Maskrey, 1999). Biodiversity loss, climate change, desertification, stratospheric ozone depletion, tropical deforestation, mangrove and coral destruction, soil erosion, soil and water pollution, overfishing, invasive species, all fall into this category of slow on-set processes which are continuously destabilizing the Earth system on which we depend and are leading to increased risk. Locally the study on Coropuna glacier retreat (Peru) and the deforestation increasing landslides susceptibility unveiled the role of these creeping processes in exacerbating disaster risk.

Creeping changes are often overlooked, because we think we can deal with them later on. Hence, showing the link between these slow onset processes and disaster risk from sudden onset hazards is relevant to policymakers.

One way to decrease our vulnerability is to deal rapidly with these creeping changes. In their early stages, they are usually cheaper to fix and easier to deal with. Should we wait too long (e.g. Haiti), the costs may become prohibitive and even technically not feasible anymore (Glantz, 1999, Harremoës *et al.* 2001; Biggs, *et al.*, 2009, Lenton *et al.*, 2008, Lenton, 2011). They can even build up over time and lead to global impacts or reach tipping points after which, the no return situation has been reached. This may be the case for irreversible melt of the Greenland ice sheet, dieback of the Amazon rainforest and shift of the West African monsoon (Lenton, 2011, Nobre and Borma, 2009).

The studies clearly highlighted the role of poverty, poor governance and, at the local level, the impacts of ecosystems decline. Climate change having an impact at both global and local levels. All these factors reveal the responsibility of human choices (or lack of choices in the case of poverty).

The report "Late lessons from early warnings: the precautionary principle 1896–2000" (Harremoës et al, 2001) reviews several cases of historical warning on issues such as over-fishing, radiation effects, Benzene toxicity, asbestos, PCBs, chemical contamination of the Great Lakes, Mad cow disease, and other environmental and health issues. This report shows that the transmission of scientific evidence to decisions makers and governments is not enough to trigger action. Warnings from scientists were largely ignored. Is this because slow processes are not sufficiently striking or showing urgency to be dealt with?

Past collapses of societies might give us some hints on why this is so (see box 8).

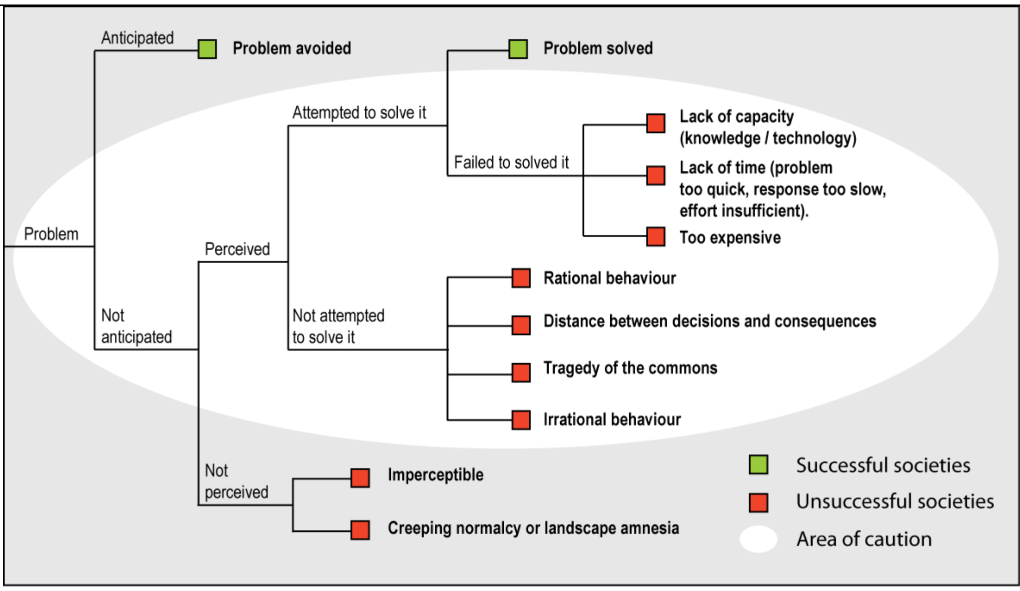


Figure 125 Pathway for successful problem solving in past societies. Climate change shares many aspects with unsolved issues (white area). Graph: Pascal Peduzzi, 2010, based on J. Diamonds (2005)

In his popular book "Collapse", Jared Diamonds (2005) discussed several examples of past collapses of societies. He showed how a careless use of natural resources led to the collapse of several societies in the past. Climate change and failing to adapt to it, led to the collapse of the Greenland Norse. The need for wood to transport, build and erect the gigantic statues of Easter Island may have contributed to the collapse of the Rapa Nui society.

Some of the examples chosen have been debated by the scientific community. The Mayan civilisation may not have collapsed from careless deforestation (McNeil *et al.*, 2010), but from severe drought (Gill *et al.*, 2007) which might have been triggered by a large volcanic eruption (Gill and Keating, 2002). The removal of all trees for building statues was said to be the cause of the Rapa Nui collapse, however there are other alternative explanations. It may have resulted from invasive animal species: an invasion of rats brought in with boats (Hunt, 2007). It seems coherent, though, that the main trigger for the collapse of the Anasasi society was a prolonged drought (Benson *et al.*, 2006). Other authors proposed - using mathematical models - that the only options in order not to collapse in the cases of the Anasasi, Rapa Nui, Maya or the Sumerians was population control (Good and Reuveny, 2009). Although scientists may disagree on the causes, nobody disputes the fact that these societies have collapsed. In some cases we might never know why. Interesting as it might be, these findings cannot necessarily be transposed to our globalised world. All the societies which are described in Diamonds book, were isolated societies (Good and Reuveny, 2009). However this is not the main point. Beyond the truth about reasons for past collapse, the most interesting aspects are the paths taken either to successful or collapsing societies.

It provides examples of processes which lead to successful societies or to collapse. Successful paths require that the threat was anticipated or that it was perceived, that decisions were taken to take action and that the capacities and time available were sufficient to solve the issue.

Collapse may result from threats which were not perceived (because they were imperceptible at least with the technology available) or because the process is so slow that it remains unnoticed before it is too late (creeping normalcy or landscape amnesia). In this case, decision makers cannot be blamed as they did not realise until it was too late.

Depletion of natural resources or climate change is not part of these two paths. Clearly these issues were not anticipated when the industrial revolution started. At that time natural resources were thought to be so abundant that they could never be all used and no one could guess that GHG might lead to climate change. However, now these issues are perceived. The pathways to solving these problems are:

1) to attempt to solve it (meaning having the political and individual will to do so), and;

2) to succeed in solving it (meaning having the know-how, the time and the resources to do so).

Aside from the questions about having enough time, capacities and funds to solve this challenging threat;

the issue is: "are we attempting to solve it? And if not why?".

In his book Jared Diamond (2005) named four reasons for which a society may collapse. This is deduced from past collapses where decisions makers failed even to attempt solving the issue. These reasons share much in common with contemporary issues with regards to ecosystems decline, demographical growth and climate change.

Rational behaviour: Decision makers employ correct reasoning, but perpetrators know that they will get away either because there are no laws or that the laws are not enforced. They feel safe because they are few in number, while the losses are spread over a large number of individuals.

Distance between decisions and consequences: Decision makers are not in contact with the consequences. The distance can be spatial (e.g. distance between GHG emissions and impacts from climate change), or temporal (e.g. future generations).

Tragedy of the commons: Consider a situation in which many consumers are harvesting a communally owned resource, e.g. timber: "if I do not cut that tree, someone else will anyway, so it makes no sense for me to refrain from deforesting". One solution comes from governments or outside forces to step in and to enforce quotas and rules.

Irrational behaviour: Reluctance to abandon a policy (or sell a stock) in which we have already invested heavily: "Persistence in error, wooden-headedness, refusal to draw inference from negative signs; mental standstill, or stagnation”. This also occurs with religious and/or societal values (e.g. Easter island, Greenland Norse).

The successful pathways, when anticipation is not an option anymore, are to perceive new threats (meaning capacity in monitoring), the willingness to take action and attempt to solve the issues and finally to have the necessary funds, capacities (technologies, know-how) to adapt.

Successful coping with disaster, is the result of a society having a good understanding of its exposure to hazards and of its vulnerability toward them. This is usually achieved by learning from past experiences. Nevertheless, due to the dynamics of risk, what worked well in the past might not be appropriate in future situations. Higher population density and shifts in local climate conditions or environmental degradation can also lead to new exposure or higher vulnerability, unknown in the past. Hence successful traditional modes of coping, based on past trends, might not be valid in the mid / long term. Examples of failing past societies can be as follows:

- The hazard is totally new, unexpected and sudden, so that there was no way for the concerned population to take any preventive action.
- The hazard could have been identified, but the local population was unaware of the threat, hence people did not even think about taking action to alleviate such risk.
- They knew about their risk, but did not have the capacity (know how, means, technology,…) to take preventive actions.
- They knew about the risk and they had the capacity to do something but they did not take any action because this was not perceived as a priority.

In the latest case, several reasons can lead to inaction: lack of political leadership, lack of concerns by decision makers for people at risk. The poorest populations have less access to decision making. Their voices might not have the same influence when matters are brought to decision makers.

Box 8 looking at past collapse

It is important to highlight the role of creeping change in risk to human societies (and not only risk from natural hazard). Possible tipping points also need to be studied (Russill and Nissa, 2009) as we are not sure that these creeping changes will continue to have slow onset effects. Some scientists are already not excluding a global collapse in the 21st century (Randers, 2008; Turner, 2008).

Animal populations during the phase between decline to collapse show increasing fluctuations in their populations (Drake and Griffen, 2010). This might be transferable to other fields of study and has large implications on the detection of tipping points (Scheffer, 2010).

There is a need to build arguments, and design tools that can be used to convince decision makers. Glantz (1999) and other researchers believe this would require a rapid shift in the focus of environmental policy, the inclusion of new early monitoring followed by quick actions. Lenton and others (2008) highlight the need for systems with improved capacity for real-time monitoring, e.g., effective signal detection and precision predictions. They also emphasized the need for backward extrapolation of existing monitoring data to develop better predictive models and for anticipating creeping changes.

Studies focussing only on impacts were shown to be less effective in influencing changes in policy (Barnett, 2001). The use of ecosystems for adaptation to climate change and DRR, may provide the "no regret" option because of the co-benefits provided by ecosystems (Barnett, 2001). Understanding how ecosystems may mitigate impacts from climate change such as on beach erosion (Peduzzi *et al.*, in prep., UNEP and PIOJ, 2010) or on atoll resilience to sea level rise (Webb and Kench, 2010) are important contributions towards proposing solutions.

Action is not likely to be taken unless scientists can make a clear connection between a particular creeping change and an important consequence of this change. This was the purpose of this thesis in choosing, deliberately, disaster risk from natural hazards as a high visibility subject to shed the light on these slow but continuous creeping changes. These changes have now, due to long lasting negligence from decisions makers, reached a level of global impacts and high capacity of nuisance.

If decisions and policy makers continue to focus on crisis management rather than trying to anticipate these creeping changes, we will continue to jump from one emergency to the next one, without solving the underlying factors.

This study is a call for better consideration of these creeping changes. It aims not only at providing such warning through the providing of statistical evidences, but also at providing methods for building more evidences. We live in a world where the generation of data and its access is increasing. The capacity to handle large data is also increasing. All these conditions are facilitating quantitative approaches. The number of studies on the threats posed by ecosystems decline and climate change should be multiplied and presented at all levels (from local communities to the international arena) providing good advocacy tools for supporting those who are pushing these issues at the policy levels, until the message become so loud that it can no longer be ignored.

6.3. References

Adger, W.N., Social vulnerability to climate change and extremes in coastal Vietnam, World Development, 27(2), 249-269, 1999.

Barnett, J., Adapting to climate change in pacific island countries: the problem of uncertainty, *World Development*, **29**(6), 977-993, 2001.

Benson, L., K., Petersen, J. Stein, 2007: Anasazi (Pre-Columbian Native-American) migrations during the middle-12th and late-13th centuries - were they drought induced?, *Climatic change*, 83:187-213.

Biggs, R., Carpenter, S.R., Brocks, W.A. 2009. Turning back from the brink: detecting an impending regime shift in time to avert it. *Proceedings of the National Academy Sciences of the United States of America*, **106**, 826–831.

Bomlitz, L.J. and Brezis M., Misrepresentation of health risks by mass media. *Journal of Public Health*, **30**, 202-4, 2008.

Cardona, O.D., Hurtado, J.E., Chardon, A.C., Moreno, A.M., Prieto, S.D., Velásquez, L.S., Duque, G., *Indicators of disaster risk and risk management*. Program for Latin America and the Caribbean, summary report for the world conference on disaser reduction. IDB/IDEA program of indictors for disaster risk management, national university of Columbia, Interamerican Development Bank, 2005.

Chambers, R., Rural Development: Putting the Last First. Longman, London, 1983.

Chatenoux, B., Peduzzi, P., Impacts from the 2004 Indian Ocean Tsunami: analysing the potential protecting role of environmental features, *Nat. Hazards*, **40**, 289-304, 2007.

Diamond, J., *Collapse: How Societies Choose to Fail or Succeed*. Viking, New York, 356 pp., 2005.

Dilley, M., Chen, R.S., Deichmann, U.Lerner-Lam, A.L., Arnold, M., Agwe, J., Buys, P., Kjekstad, O., Lyon, B., Yetman, G., *Natural disaster hotspots: a global risk analysis*, World Bank Publications, 2005.

Drake, J.M., Griffen, B.D., Early warning signals of extinction in deteriorating environments, *Nature*, **467**, 456–459, 2010.

EM-DAT: The OFDA/CRED International Disaster Database, Université Catholique de Louvain, Brussels (Belgium). http://www.emdat.be, last consulted September 2011.

GEM, Global Earthquake Model, 2011. http://www.globalquakemodel.org/ Last checked December 2011.

Gil, R.B., Mayewski, P.A., Nyberg, J., Haug, G.H., and Peterson, L.C., Drought and the Maya collapse, *Ancient Mesoamerica*, **18**, 283-302, 2007.

Gill, R.B., Keating, J.P., Volcanism and Mesoamerican archaeology, *Ancient Mesoamerica*, **13**, 125–140, 2002.

Giuliani, G., Peduzzi, P., The PREVIEW Global Risk Data Platform: a geoportal to serve and share global data on risk to natural hazards. *Nat. Haz. Earth Syst. Sci*, **11**(1):53-66, 2011.

Glantz M. H., editor. *Creeping environmental problems and sustainable development in the Aral Sea basin.* Cambridge University Press, Cambridge, UK, 1999.

Good, D.H., Reuveny, R., On the collapse of Historical civilizations, *Amer. J. Agr. Econ.* **91(4)**, 863-879, 2009.

Hallegatte, S., Hourcade, J.C.. Dumas, P., Why economic dynamics matter in assessing climate change damages: Illustration on extreme events. *Ecological Economics*, **62**(2) 330-340, 2007.

Hanemann, W.M., Welfare evaluations in contingent valuation experiments with discrete responses, *American Journal of Agriculture Economics*, **66**(3), 332-341, 1984.

Harremoës. P., Gee, D., MacGarvin, M., Stirling, A., Keys, J., Wynne B., Guedes Vaz, S., *Late lessons from early warnings: the precautionary principle 1896–2000*, European Environment Agency, Copenhagen, 211 pp., 2001. http://www.eea.europa.eu/publications/ environmental_issue_report_2001_22/Issue_Report_No_22.pdf, last accessed : 30 April 2011.

Hunt, T.L., Rethinking Easter Island's ecological catastrophe, *Journal of Archaeological Science*, **34** (3), 485-502, 2007.

IUCN, *Rapid Environmental Appraisal of Developments in and Around Murree Hills*, International Union for Conservation of Nature, 16 pp., 2005.

Lenton, T.M., Early warning of climate tipping points. *Nature Climate Change*, **1**, 201-209, 2011.

Lenton, T.M., Held, H., Kriegler, E.,. Hall, J.W., Lucht, W., Rahmstorf, S.,Schellnhuber, H.J., Tipping elements in the Earth's climate system. *Proceedings of the National Academy of Sciences of the United States of America*, **105**, 1786-1793, 2008.

Limpert, E., Stahel, W.A., Abbt, M., Log-normal Distributions across the Sciences: Keys and Clues, *BioScience*, **51**(5), 341-352. 2001.

McNeil, C.L., Burney, D.A., Pigott Burney, L., Evidence disputing deforestation as the cause for the collapse of the ancient Maya polity of Copan, Honduras, *PNAS*, **107**, 1017-1022, 2010.

Manning, G.W., The logged dependent variable, heteroscedasticity, and the retransformation problem, *Journal of Health Economics*, **17**, 283-295, 1998.

Manning, G.W., Mullahy, J., Estimating log models: to transform or not to transform?, Journal of health *Economics*, **20**, 461-494, 2001.

Miller, D.M., Reducing transformation bias in curve fitting, *The American Statistician*, **38**(2), 124-126, 1984.

Mustafa, D., Structural causes of vulnerability to flood hazard in Pakistan, *Economic Geography*, **74**(3), 289-305, 1998.

Neto F., Lazerg C. and Muillet E., Perception des risques et couverture médiatique, 85-97. In: Kouabenan D.R. , Cadet B., Hermand D. et Muñoz Sastre M.-T. (Ed) *Psychologie du risque : Identifier, évaluer, prévenir*. DeBoek, 346 p., 2006.

Nobre, C. A., and Borma, L.D.S., ‘Tipping points’ for the Amazon forest. Current Opinion in Environmental Sustainability, **1**, 28-36, 2009.

Paul, B. K., 2009: Why relatively fewer people died? The case of Bangladesh's Cyclone Sidr. *Natural Hazards*, **50**, 289-304.

Peduzzi, P., Project for Risk Evaluation, Vulnerability, Information and Early Warning (PREVIEW), http://www.grid.unep.ch/preview, 2000.

Peduzzi, P., 2005b; Asking for disaster, *Environment & Poverty Times, **3***, 6, Special Edition for the World Conference on Disaster Reduction January 18-22, United Nations Environment Programme, Kobe, Japan.

Peduzzi, P., Herold, C., and Silverio, W.: Assessing high altitude glacier thickness, volume and area changes using field, GIS and remote sensing techniques: the case of Nevado Coropuna (Peru), *The Cryosphere*, **4**, 313-323, 2010.

Peduzzi, P., Velegrakis, A., Chatenoux, B., Estrella, M., Kluser, S., Karambas, Th., Quantifying the role of marine ecosystems in reducing coastal erosion: the RiVAMP study in Negril Jamaica, in prep.

Peduzzi, P., Deichmann, U., Maskrey, A., Nadim, F., Dao, H., Chatenoux, B., Herold, C., Debono, A., Giuliani, G., Kluser, S., *et al.*, Global disaster risk: patterns, trends and drivers, ISDR (2009) *Global Assessment Report on Disaster Risk Reduction*, United Nations, Geneva, Switzerland, chapter 2, pp. 17-57, 2009.

Peduzzi, P.: Landslides and vegetation cover in the 2005 North Pakistan earthquake: a GIS and statistical quantitative approach, *Nat. Hazards Earth Syst. Sci*., **10**, 623-640, 2010.

Randers, J., Global collapse—Fact or fiction? *Futures*, **40**, 853–864, 2008.

Russill, C., and Z. Nyssa. The tipping point trend in climate change communication. *Global Environmental Change*, **19**, 336-344, 2009.

Scheffer, M., Complex systems: Foreseeing tipping points. *Nature*, **467**, 411-412, 2010.

Stynes, D.J., Peterson, G.L., Rosenthal, D.H., Log transformation bias in estimating travel cost models, *Land Economics*, **62**(1), 94-103, 1986.

Stow, C.A., Reckhow, K.H., Qian, S.S., A Bayesian approach to retransformation bias in transformed regression, *Ecology*, **87**(6), 1472-1477, 2006.

Turner, G.M., A comparison of the limits to growth with thirty years of reality, *Global Environmental Change*, **18** (3), 397-411, 2008. http://www.csiro.au/files/files/plje.pdf, last checked: 26 April 2011.

UNDP, *Reducing Disaster Risk: a challenge for development*, United Nations Development Programme, Bureau for Crisis Prevention and Recovery, 146 p., New York, NY 10017, USA, 2004.

UNEP and ISDR, 2000-2011 : The PREVIEW Global Risk Data Plateform, http://preview.grid.unep.ch, last accessed : September 2011.

UNEP, PIOJ, *Risk and Vulnerability Assessment Methodology Development Project (RiVAMP), Linking Ecosystems to Risk and Vulnerability Reduction: The Case of Jamaica. Results of the Pilot Assessment*, United Nations Environment Programme, Planning Institute of Jamaica, 130 pp., 2010.

Webb, A.P, Kench, P.S., The dynamic response of reef islands to sea-level rise: Evidence from multi-decadal analysis of island change in the Central Pacific, *Global and Planetary Change* **72**(3), 234-246, 2010.

Acknowledgments

I would like to thanks my wife Corinne Sirusas-Peduzzi and my two suns, Antoine and Gaétan Peduzzi, my family and friends for their support during the production of this thesis. I'm grateful to my team Christian Herold, Bruno Chatenoux, Gregory Giuliani, my colleagues Hy Dao, Andrea De Bono, and other co-authors: Frédéric Mouton, Ola Nordbeck, Walter Silverio, James Kossin, Uwe Deichmann, for their contributions in the researches undertaken. I would like to thanks Ron Witt, Andrew Maskrey, Joseph Heider, for their trust in mandating me on the coordination of these interesting projects. Thank you to all the administrative assistants and my colleagues for providing administrative support and fun working environment. I would like to thanks the United Nations Environment Programme, the United Nations International Strategy for Disaster Reduction, the University of Lausanne, the University of Geneva, as well as the Swiss Federal Office for the Environment for funds, logistics and other support. Thank you to Ruth Harding for reviewing my English. A special thanks to Jean-Michel Jaquet for inspiring my interest for remote sensing and GIS.