Remote Sensing in support of Artisanal and Small-Scale Gold Mining policy development, implementation and evaluation - Technical guidance document

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Technical Guidance Document

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Terminology, concepts and acronyms

“Artisanal and Small-Scale Gold Mining” (ASGM) is defined in the Minamata Convention as gold mining conducted by individual miners or small enterprises with limited capital investment and production. “Artisanal mining” is understood as mining operations that use traditional or customary rudimentary methods and manual tools to access mineral ore, usually, on the surface or subsurface. ASGM is orchestrated with little or no mechanization, and the ore is largely processed with the use of mercury. ASGM practitioners, largely, operate informally; illegally or in legal “grey” areas. According to UNEP, ASGM contributes about 12-15% of global annual gold production and introduces about 1220 tones of mercury into the atmosphere, soils, and releases into water (UNEP a., 2021).

“Community-based indicators” refer to those pieces of information that are collected through every day’s experiences from ASGM practitioners themselves, children, health workers and community leaders.

“Community-based monitoring” is the involvement of communities to address resource development-related environmental issues in ways that can contribute to local sustainability.

“Ecological community-based monitoring” allows affected groups in a community to gather and provide relevant information to government agencies or organisational bodies on the extraction and use of natural resources. It allows collaboration between environmental activists, governmental agencies, industry, scientists, local institutions and groups for the monitoring, tracking, and management of environmental issues.

“Informal Artisanal and Small-Scale Mining” is mining activity performed by an individual or a group of people, company, or foundation, without a legal mining permit from regulatory government agencies. Minerals mined this way include gold, cassiterite, wolframite, colored gemstones, diamonds, cobalt, and even coal.

“Informal Artisanal and Small-Scale Gold Mining” refers to a mining activity conducted by a person, group of persons, a company, or a foundation, which does not hold a legal mining permit from regulatory government agencies for the extraction, marketing of gold.

“Indicators” are the primary sources of monitoring mercury pollution with the use of RS techniques. Indicators depend on several knowledge systems to determine the presence of ASGM and mercury pollution.

“Monitoring” is the process of taking regular observations over an activity or phenomenon using valid methods, tools and indicators for informed decision making. It is a tool that can be used to gather relevant information on mercury use in ASGM communities.

“Mercury inventory” is the process of gathering and documenting information on the extent of mercury pollution using reliable and scientific processes of investigation.

“Science-based indicators” are pieces of information identified through scientific process and analysis on the extent and presence of illegal ASGM activities and environmental pollution by mercury. Examples include the use of Remote Sensing (RS) and geographic information systems (GIS).

“Traditional knowledge indicators” pieces of information that are usually gathered from the perspectives of elders about how and when mercury use in ore processing started in the locality.

List of abbreviations

Acronym	Description
AfDB	African Development Bank
AI	Artificial Intelligence
ANN	Artificial Neural Networks
API	Application programming interface
ASGM	Artisanal and Small-Scale Gold Mining
ASM	Artisanal and Small-Scale Mining
ASTER	Advanced Spaceborne Thermal Emission and Reflection
AU	African Union
AusAID	Australian Agency for International Development
BS	Bare Soil
CASM	Communities and Small-scale Mining
CBERS	China-Brazil Earth Resources Satellite
CIDA	Canadian International Development Agency
CNN	Convolutional Neural Network
CPU	Central Processing Unit
CSV	Comma-separated values
DCoD	Data Cube on Demand
DDI	Diamond Development Initiative
DEM	Digital Elevation Model
DInSAR	Differential Interferometric Synthetic Aperture Radar
DL	Deep Learning
DRC	Democratic Republic of the Congo
DSM	Digital Surface Model
DT	Decision Tree
EEB	European Environmental Bureau

EMS	Electromagnetic spectrum
EMR	Electromagnetic radiation
EnGAGE	Enabling and Growing Artisanal Gold Enterprises
EPA	U.S. Environmental Protection Agency
ESA	European Space Agency
ESRI	Environmental System Research Institute
ESV	Ecosystem Service Value
EU	European Union
FAO	Food and Agriculture Organisation
GDEM	Global Digital Elevation Model
GEE	Google Earth Engine
GEF	Global Environment Facility
GEOBIA	Geographic Object-Based Image Analysis
GEOSS	Global Earth Observation System of Systems
GIS	Geographic Information System
GIZ	Deutsche Gesellschaft für Internationale Zusammenarbeit
GNASSM	Ghana National Association of Small-Scale Miners
GRID	Global Resource Information Database
HDD	Hard Disk Drive
HR	High Resolution
IIED	International Institute for Environment and Development
IK	Indigenous Knowledge
InSAR	Interferometric Synthetic Aperture Radar
IPIS	International Peace Information Service
ISBAS	Intermittent Small Baseline Subset
IUCN	International Union for Conservation of Nature
JAXA	Japanese Aeronautics Exploration Agency
LiDAR	Light Detection and Ranging
LST	Land Surface Temperature
LULC	Land Use / Land Cover
MinCom	Ministry of Lands and Natural Resources
ML	Machine Learning
MODIS	Moderate Resolution Imaging Spectroradiometer

MS	Microsoft
MSAVI	Modified Soil Adjusted Vegetation Index
MSF	Médecins Sans Frontières/Doctors Without Borders
NAP	National Action Plan
NASA	National Aeronautics and Space Administration
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
NEO	NASA Earth Observations
NGO	Non-Governmental Organisation
NISM	National Institute for Small Mines
NPV	Non-Photosynthetic Vegetation
OAU	Organisation of African Unity
OBCD	Object-Based Change Detection
OBIA	Object-Based Image Analysis
OECD	Organisation for Economic Co-operation and Development
OGC	Open Geospatial Consortium
PCA	Principal Component Analysis
PDF	Portable Document Format
PV	Photosynthetic Vegetation
RADAR	RAdio Detection And Ranging
RAM	Random Access Memory
REDD+	Reducing Emissions from Deforestation and forest Degradation project
RF	Random-Forest
RGB	Red/Green/Blue
RS	Remote Sensing
SADC	Southern African Development Community
SAICM	Strategic Approach for International Chemicals Management
SAM	Spectral Angle Mapper
SAR	Synthetic Aperture Radar
SAVI	Soil Adjusted Vegetation Index
SDG	Sustainable Development Goal
SEaTH	SEparability and THreshold
SEDAC	Socioeconomic Data and Applications Center

SEPAL	System for Earth Observation Data Access, Processing, and Analysis for Land Monitoring
SfM	Structure-from-Motion
SPOT	Satellite Pour l'Observation de la Terre
SVM	Support Vector Machine
TOA	Top of the atmosphere
TSAVI	Transformed Soil Adjusted Vegetation Index
TSS	Total suspended solids
UAS	Unmanned aerial system
UI	User Interface
UK	United Kingdom
UMaT	University of Mines and Technology
UN	United Nations
UNCCD	United Nations Convention to Combat Desertification
UNDP	United Nations Development Programme
UNECA	United Nations Economic Commission for Africa
UNEP	United Nations Environment Programme
UNIDO	United Nations Industrial Development Organisation
UNITAR	United Nations Institute for Training and Research
US-FDA	United States Food and Drug Agency
USDoS	United States Department of State
USGS	United States Geological Survey
UX	User Experience
VFC	Vegetation Fractional Cover
VHR	Very High-Resolution

Executive summary

This technical guidance document aims at showing the benefits and challenges of the use of Remote Sensing (RS) technologies to identify and monitor artisanal and small-scale gold mining (ASGM) activities and related environmental pollution, to support policy development, implementation and evaluation to address ASGM, with a special focus on the context of the Minamata Convention on Mercury. The document includes a comprehensive literature review on the various uses of RS for ASGM detection and monitoring, protocols and guidance on satellite image analysis, and final insights on benefits and challenges of such techniques. The document also includes recommendations targeting decision makers, providing them with evidence-based insights to support decision making and policy implementation. Finally, the document demonstrates two concrete case studies featuring ASGM activities in the Democratic Republic of the Congo and in Peru, illustrating how RS can support the identification and quantification of the impacts of mining activities occurring in remote areas.

These guidelines are designed as a supplement to the UNEP guidance document on *Developing a National Action Plan to Reduce, and Where Feasible, Eliminate Mercury Use in Artisanal and Small-Scale Gold Mining*, which offers overarching guidance to countries formulating ASGM National Action Plans (NAPs) for the Minamata Convention.

The document is structured in 5 chapters, as follows:

1. Background on Remote Sensing and Artisanal Small-Scale Gold Mining.
2. Literature review and main findings on the state-of-the-art use of RS applied to ASGM contexts.
3. Conceptual framework for ASGM monitoring for policy development, implementation and evaluation.
4. Summary of the potentials and challenges of using RS for ASGM monitoring.
5. Conclusions and recommendations.

This document aims at enabling users to understand how to use RS to detect and monitor ASGM activities; identify challenges and limitations in using RS technologies to monitor ASGM activities; raise awareness of decision makers of the potential for RS to be applied as a tool for monitoring ASGM; and provide tangible insights on the use of RS to inform decision making.

1. Background: Remote Sensing and Artisanal and Small-Scale Gold Mining

1.1. What is Artisanal and Small-Scale Gold Mining?

In the last three decades, there have been relevant discussions on Artisanal and Small-Scale Gold Mining (ASGM) at various international, regional, and national development platforms. The ASGM sub-sector is a global activity, which provides a critical longstanding livelihood for over 100 million people around the world (Eftimie et al., 2012). The practice of ASGM activities, as a means of economic livelihood, has been an intergenerational matter. In both historical, present, and future terms, the ASGM sub-sector has proven to have the potential to emancipate many rural folks out of poverty if properly structured, regulated, monitored, and organized responsibly (World Bank, 2009). Within the last decade, the sub-sector has received significant attention from international donor agencies due to its close relation to poverty. It is now in the agendas of many national governments and appreciably in Sub-Saharan Africa, Central and South America, and Southeast Asia, and other developing regions. It is ever more considered as a viable pathway for sustainable livelihood building and poverty alleviation. The sub-sector produces approximately 18% of Africa's gold export to the global market (O'Neill & Telmer, 2017; UN ECA, 2009). It is, therefore, essential to enhance public understanding of the ASGM sub-sector in perspective, to maximize its benefits and mitigate the associated costs.

There is no standardized definition of ASGM in literature. The proper definition of ASGM is location-based and country specific. In some countries, ASGM is defined as a sort of mineral extraction that is individual or group-based, highly labor-intensive, involving a limited capital investment, basic tools, manual devices, or simple portable machinery (Bryceson & Jønsson, 2014). This definition is in line with Sennett's work on artisanal craftsmanship and its impacts on human society (Sennett, 2009). That is, that class of workers who work primarily with their hands and with the use of hand-held tools. The government of Ghana for instance acknowledged the relevance of the ASGM sub-sector in gold production by enacting a Small-Scale Gold Mining Law (PNDCL 218) in 1989. This law defines small-scale gold mining as: *"The mining of gold by any method not involving substantial expenditure by an individual or group of persons not exceeding nine in number or by a cooperative society made up of ten or more persons"* (Ofei-Aboagye et al., 2004). Thus, ASGM refers to the mining of gold by individual miners or small enterprises with a limited capital investment and production (Coulter, 2016).

As to what form of mining operation constitutes ASGM or a method of operation showing ASGM is not clearly defined. This is so partly because the legal instruments that define ASGM vary from country to country. To this end, the scientific community, funding agencies and industry players use a combination of criteria to determine what constitutes ASGM. Currently, the United Nations (UN) uses the levels of mineral production to define ASGM as an extraction entity that operates between 50,000 tons a year for underground mines and 100,000 tons a year for open-pit mines. In terms of project financing, most ASGM operate under $5 million, with a limited labor force of less than 50 workers (UN ECA, 2011). However, some countries draw a boundary between artisanal and small-scale mining. For instance, in some Western African countries such as Mali, Niger, and Burkina Faso, while artisanal mining is an operation that is purely manual and involves the use of rudimentary tools, small-scale mining is an operation that is more mechanized with the presence of permanent, fixed installations (Hentschel et al., 2002). Anyhow, in Ghana and other West African Countries, there is no difference between artisanal mining and small-scale mining. What is common in the African context is that the ASGM operations are generally done either on private, public, or vested lands without any formal permission. Thus, ASGM operations are mostly uncontrolled, informal, and unauthorized.

A combination of criteria is used to determine whether a mining operation is ASGM or not. For instance, the laws in Brazil provide definitions for ASGM through its “Garimpo” or “Garimpogen” law (Hentschel et al., 2002). According to those authors, the criteria generally used to determine a mine operation as an ASGM are the following:

1. The volume of production,
2. Maximum number of workers,
3. Initial capital base,
4. Labor productivity,
5. Size of mine claim,
6. Quantity of reserves,
7. Sales volume,
8. Operational continuity,
9. Operational reliability,
10. Duration of the mining cycle.

However, the informal nature of ASGM sub-sector operations makes it difficult to appraise its total negative and positive impacts to the economies of African countries and their environment.

1.1.1. The impacts of Artisanal and Small-Scale Gold Mining

ASGM has become a basic livelihood activity and an agent of local economic development in the many local communities that it is practiced. Notwithstanding, ASGM operations bring a complex array of positive and negative socioeconomic and environmental impacts, which are discussed in the succeeding paragraphs.

1.1.1.1. Positive

The World Bank estimates that about 44.75 million people across 80 countries worldwide are employed by ASGM (World Bank, 2020). In Ghana, the ASM sector alone directly employs about 1 million people and indirectly supports about 4.5 million more. Despite the dearth of reliable statistics, it is universally acknowledged that the ASGM sub-sector contributes a significant amount of gold to global production and consumption. The estimate is at 330 tones a year (Hentschel et al., 2002) and at least 134 million people work in related industries (World Bank, 2020). An estimated 3.7 million people directly engage in the ASGM operations, and support about 30 million households in Africa (UN ECA, 2009). For instance, in Sierra Leone, it is estimated that the ASGM sub-sector alone employs over 80,000 youth, which represents over 3% of the total rural workforce in the country (Environment Protection Agency Sierra Leone, 2019). The ASGM sub-sector catalyzes economic multipliers through enhancing local purchasing power with mining returns and the growth of small and medium scale businesses (Franks et al., 2020). These arrays of positive impacts of the ASGM sub-sector notwithstanding, the sub-sector has sustainability challenges, with negative impacts outweighing the positives.

1.1.1.2. Negative

It is noted that both private and public initiatives on managing and mitigating the negative impacts of ASGM activities often focus on land, water, vegetation and society. That is, ASGM activities may lead to the contamination of water bodies (see Figure 1); which further serve as breeding grounds for mosquitos and malaria, and heavy metal contamination of soils; making land unavailable for crop farming. The operators of ASGM often use mercury, a highly toxic chemical, in ore processing. As little as 19 million ASGM operators in the world use mercury in ore processing, which makes the use of mercury in the sub-sector a global issue (Esdaile & Chalker, 2018). Currently, it is estimated that ASGM operations alone release over 1,000 tones of mercury per annum (UNEP, 2019). A study conducted in Tanzania found that about 98% of all ASGM sites in the country use mercury in ore processing. Out of this, about 71% of the sites are found near residential areas and associated vulnerable groups (Merket, 2019).

Figure 1. The negative impacts of informal ASGM on river networks in Ghana. Left: pollution of the Pra River. Right: pollution of the Ankobra River.

There are relevant health concerns as the toxic chemical is transported along both surface and underground waterways surrounding the mining sites (see (Basu et al., 2015)). The health effects on both miners and host local communities include neurological damage, physical and mental disabilities, and compromised development. In most of the ASGM endemic areas in Ghana, water quality has been significantly affected by turbidity, resulting in a water quality index of at least 500% higher than the upper limit of the WHO water potability index (Bansah et al., 2018). A study conducted by the United Nations Industrial Development Organisation (UNIDO) to determine the environmental impacts of mercury found widespread contamination of groundwater, rivers, and soil systems in Dumasi, a village in the Bono Region of Ghana, found that mercury losses mainly occurred during amalgamation and have resulted in widespread pollution of soils and sediments throughout the village. Many fish fillets in the river channels were found to have mercury contents exceeding the United States Food and Drug Agency (US-FDA) action level (Babut et al., 2003).

Three studies were independently conducted in different Ghanaian ASGM localities (Paruchuri et al., 2010; Basu et al., 2015; Rajaee et al., 2015). They compared the urine mercury concentration levels between miners and non-miners of the same locality but who reside outside 10 km from the mine site on one hand, and between non-miners of a mining locality and residents of non-mining localities on the other hand. One of the studies found that the mean urine mercury concentration in small-scale miners in Dunkwa and Tarkwa (e.g., mining localities) is higher than that found in farmers of the same locality. Another study found the difference between the results found in non-miners living in the same area and non-mining Accra residents was quite small. Overall, many means exceeded the average mercury concentration in urine for the U.S. population (Basu et al., 2015). At Talensi Nabdam in the Upper East Region of Ghana, it was certified that ASGM workers who handle mercury most often have significantly higher urine mercury concentration levels than those who have little contact with mercury in their routine businesses on site (Paruchuri et al., 2010). It was found that 5% of such workers had urine mercury concentration levels that exceeded the World Health Organisation (WHO) guideline value of 50 µg/L. Furthermore, a significant positive correlation was found between fish consumption and hair mercury levels. Whereas sediment mercury concentrations exceeded WHO guideline values in 64% of the study samples, arsenic, cadmium, and lead also exceeded the WHO guideline values of water samples.

Additional ASGM-related negative impacts include deforestation, biodiversity loss, social issues (e.g., armed conflicts, socio-environmental struggles over control of space, mineral resources and development opportunities, defense of human rights and citizenship, and dissatisfaction with the distribution of mineral rents, see (Bebbington, 2007; Bebbington et al., 2008; Collier & Hoeffler, 2005; Peluso et al., 2001; Ross, 2008)) and potential linkages to climate change (Rajaee et al., 2015). Between 2014 and 2017, it was found that approximately 47’000 ha ($\pm$2,218 ha) of vegetation were destructed in Ghana by the ASGM activities at an average rate of ~2,600 ha yr^{-1}. It is further found that about 700 ha of protected areas have been disturbed by the ASGM as mapped by the World Database of Protected Areas (Barenblitt et al., 2021). According to the Global Mercury Assessment report 2018 (UNEP, 2019), ASGM activities are estimated to account for 38% of the global anthropogenic atmospheric mercury emissions to the environment. The sub-sector’s negative impacts on social issues include labor migration, human trafficking, and conflicts in Latin America and Africa (Franks et al., 2020). It is also sometimes observed to promote truancy, child labor, teenage pregnancy, and sexually transmitted diseases. The ASGM sector can be tax evasive and non-compliant if the government is unable to detect their presence in space and in places. Especially in case the extracted mineral is converted to non-local money (generally the case for gold), the benefits that the ASGM sector brings to the local market may disappear fast, while the negative consequences at social and environmental scales may last for a long time (IIED, 2002).

Despite the global concerted efforts aimed at addressing all the identifiable negative impacts of the ASGM sub-sector, there has been limited overall progress and success in evidence. The critical challenge towards addressing the ASGM sub-sector issues is how to transform its negative impacts into enhanced positive impacts, maximise its contribution to poverty reduction and the creation of resilient communities. To this end, there is the need to improve the understanding of ASGM issues on the policy, and regulatory domains. Thus, efforts are required to encourage the adoption of advanced technologies such as Remote Sensing (RS) to give consistent and effective data based on which discussions on the environmental protection, sustainability and livelihood security of the ASGM sub-sector can be built.

1.1.2. The links between Remote Sensing and Artisanal and Small-Scale Gold Mining Monitoring

According to (White, 1977) and (Lillesand et al., 2015), RS comprises of the set of methods scientists and practitioners use to obtain images or record electromagnetic footprints of Earth's surface materials from a distance, process and interpret these images and footprints of the Earth's surface. According to the perspectives of (Campbell, 1996), RS is the method of acquiring information about the features or activities on the surface of the Earth including water and land using a source of energy and sensors. RS, thus, is the detection and recording of the electromagnetic radiation (EMR) of the electromagnetic spectrum (EMS) from target areas in the field of view of a sensor instrument. The EMR could originate directly from separate components of the target area or activity, or the reflection of solar energy from them. EMR may also be the reflections of energy transmitted to the target area from the sensor itself. To acquire information about the Earth's surface, the sensors are placed on a holder called platform. Examples of platforms include the stationary tripod for field observations, stationary balloon or mobile aircrafts and spacecrafts. Generally, these examples are grouped into (1) ground borne, (2) air borne and (3) space borne sensors. The platform is determined by the objective, resources, and constraints of the observation mission. According to the United Nations (95th Plenary meeting, 3rd December 1986), the general purpose of RS is towards improving natural resource management, land use and environmental protection.

Importantly, remote sensors are classified based on the source of energy used by the sensors in data acquisition. These are active sensors and passive sensors. Active RS methods provide their own source of EMR to illuminate the terrain. A photographic camera using its flashlight to acquire images acts as an active sensor. Radar and laser altimeter are examples of active sensors, which mostly work in microwave regions of the EMS, penetrate clouds and are not affected by rain. This allows an accurate mapping of ASGM activities in rainforest areas, which are otherwise too obscured by clouds and rain. Active remote sensors systems are versatile providing images in both day and night and under all-weather conditions, mapping landforms, water, soil, vegetation, and crop health around ASGM sites. Passive RS methods do not have their own source of energy but detect energy naturally reflected or radiated energy from the area being observed. Passive remote sensors include film photography usually employed during fieldwork, infrared, and radiometers. The methods of analysing RS data include spectral analysis, spatial analysis, contextual analysis, knowledge-based analysis, pixel-based and object-based analysis. A detailed discussion on these methods is provided in the succeeding subsections.

1.2. Challenges of Governments' actions on the monitoring of the Artisanal and Small-Scale Gold Mining sub-sector

1.2.1. Background

At the end of the last century, UN agencies and NGOs started to raise awareness on the consequences related to the use of mercury in the ASGM sector. A typical example is the UNIDO's Global Mercury Project that started in 1994 with some individual projects in the

Philippines, Ghana and Tanzania (Spiegel et al., 2015). However, it is only in the last two decades that more countries began to embrace more comprehensive actions on reducing the use of mercury, thanks to the growing evidence associated with the risks for both the populations living near local emission sources as well as more dispersed transboundary pollution. This eventually led to the agreed regulation on the use of mercury that is expressed in the text of the Minamata Convention on Mercury by Parties to the Convention in 2013. The convention regulates the use of mercury in multiple forms and sectors from trade to waste's disposal and focuses on the ASGM sector in its Article 7 by mandating that countries where ASGM takes place "shall take steps to reduce, and where feasible eliminate, the use of mercury and mercury compounds in, and the releases to the environment of mercury from such mining and processing" (Article 7, Paragraph 2). In addition to this, in Paragraph 3, it also demands that parties who have notified the Secretariat that they have more than insignificant ASGM activity in their territory should develop and implement NAPs for reducing mercury use and pollution risks in ASGM within three years. The Minamata convention on Mercury entered into force in 2017 and, at the time of writing, it has been signed by 128 countries. By 4th October 2021, only 16 parties have submitted their NAP out of the 31 Parties who have notified the Secretariat of recording more than insignificant ASGM activity in their territory.

To create effective NAPs, countries need to have a comprehensive approach that includes policy, regulatory, institutional, technical, environmental, health and socio-economic aspects and to propose tailored solutions that are context-specific rather than using a common strategy. To facilitate countries' implementation of Article 7 of the Convention, international organisations have created a series of tools such as the planetGOLD Project (led by UNEP and Conservation International with specific international programmes in 23 developing countries), the Socio-economic ASGM Research Methodology (United Nations Institute for Training and Research - UNITAR) and the UNEP Global Mercury Partnership (stakeholders include governments, industry, NGOs, and academia).

According to UNEP (UNEP, 2019), ASGM activities are most common in tropical and subtropical countries. Examples of areas of occurrence include East and Southeast Asia, South America, and Sub-Saharan Africa (Tsang et al., 2019). From the mid-1990s, most Sub-Saharan African countries started developing and implementing policy initiatives and legislative instruments that would support the development of the ASGM sub-sector. Central issues addressed in these policy frameworks include lack of strong governmental initiatives to support ASGM operators, and insufficient attention to ASGM associated environmental issues. As proposed in the Socio-economic ASGM Research Methodology (UNITAR), countries should harvest information on several aspects such as social dynamics, role of women in the mining population, health, environment, and many others, to have a clear understanding of the ASGM phenomenon in their country. Many member countries have started this process amidst several challenges as is discussed in the next section and illustrated in Table 1.

Table 1. Examples of actions at national level on the ASGM sub-sector

Country	Period	Objective	Partners	Reference
Brazil	1988	Establish control over the ASGM sector by making it	_	(Telmer et al., 2006)

		legal		
Colombia	2015	Detect and characterize the activity of alluvial gold mining artisanal sites	The Ministry of Justice and Law of Colombia and UNODC	(UNODC, 2016)
Colombia	2016	Characterize the socio-economic aspects of the ASGM sector and develop policies	The Ministry of Justice and Law of Colombia and UNODC	(UNODC, 2020)
Colombia	2018	Law 1658 of 2013 established a ban on the use of mercury in mining in Colombia, granting a period of five years for miners to make the transition to the use of clean technologies to obtain responsible gold. On July 16, 2018, and after this deadline, the country officially banned the use of mercury in gold mining	_	(Ibrahim et al., 2020)
French Guiana	2004	Governmental decision: control and regularize the ASM sector	Region Guiana, Forest Department of the French Agricultural Research Centre for International Development (CIRAD), ONF	(Brognoli, 2004; Linarès et al., 2008)
Ghana	1989	ASM formalization	_	(Gallwey et al., 2020)
Ghana	2013	Stop all ASM operations	_	(Gallwey et al., 2020)
Ghana	2015	Train GNASSM members on various technical, management, health and safety aspects of ASM	University of Mines and Technology (UMaT), Ghana National Association of Small-Scale Miners (GNASSM)	(Hilson & Mcquilken, 2016)
Ghana	2015	Review the categorization of ASM mining licenses to account for changes in characteristics and enable foreign investment	Ministry of Lands and Natural Resources (MinCom)	(Hilson & Mcquilken, 2016)
Ghana	2017	Stop all ASM operations	_	(Gallwey et al., 2020; Nyamekye et al., 2021)
Ghana	2017	Sanitize illicit mining activities	Ministry of Lands	(MLNR, 2017)

	- 2022	in Ghana	and Natural Resources	
Ghana	2021	Sanitize illicit mining activities in Ghana	Ministry of Lands and Natural Resources	National Dialogue on Small-scale mining
Peru	2002, 2004	Combat illegal mining	_	(Malca & Ruesta, 2019)
Peru	2011, 2013, 2014	Combat illegal mining	_	(Malca & Ruesta, 2019)
Peru	from early 2019	Combat environmental crimes in the Amazon	USAID	(MAAP, 2020)
Sierra Leone	_	Evaluate the location and activity of ASGM sites for the development of their NAP	Government, UNs	(Environment Protection Agency Sierra Leone, 2019)
South Africa	1994	Legal recognition of the ASM sector	_	(Mhangara et al., 2020)
South Africa	2008	Mineral and Petroleum Resources Development Amendment Act (MPRDA), No. 49 of 2008 (Ledwaba and Nhlengetwa, 2016)	_	(Mhangara et al., 2020)
Suriname, Guyana, French Guiana and the Brazilian state of Amapá	2014	(1) Monitor the impact of gold mining on forest cover and freshwater in the Guiana Shield (2) Develop a robust, reliable and transparent regional methodology (3) Encourage regional cooperation, dialogue and knowledge sharing	Forestry and environmental services of Suriname (SBB), Guyana (GFC), Amapá (SEMA) and French Guiana (ONF). Co-funded by WWF Guianas, it was conducted under the supervision of ONF International in the framework of the REDD+ for the Guiana Shield project	(Rahm et al., 2015)
Tanzania	1989 - 1997	Combat illegal mining	_	(Dreschler, 2001)
Zimbabwe	2006 - 2009	Combat illegal mining	_	(Kamete, 2008; Spiegel, 2009, 2014, 2015; Spiegel et al., 2015)

1.2.2. Challenges of national initiatives

In the last decades, countries have tried to contrast the health, environmental and socio-economic consequences issued by the ASGM practices with a policy approach often oriented towards the criminalization of artisanal miners. Unfortunately, these actions have generally led to negative consequences such as generating conflicts between the local population and the competing large companies, decreasing the trust towards governments, favoring infiltrations of criminal groups into the socio-economic layers of the local populations, and so far not succeeding in reducing the health and environmental issues caused by the ASGM practices (Gallwey et al., 2020; Kamete, 2008; MAAP, 2020; Nyamekye et al., 2021; Spiegel, 2009, 2014, 2015; Spiegel et al., 2015).

Although the regularisation process of artisanal miners might seem an additional cost to governments, this approach would not only benefit human health and environment but it would also benefit governments in terms of budget by (1) moving in the money generated from the sale of minerals extracted in the artisanal mines that are generally sold internationally and (2) favoring foreign investments given a more stable social and political context (IIED, 2002). For instance, Tanzania's liberal politics 1989 to 1997 resulted in mining licenses passing from 17 to 2000 and money gained from minerals exportation by the country from 16 to 184 million US Dollars (Dreschler, 2001). Unfortunately, most regularization processes promoted by governments in the past decades (e.g., Brazil (1988), Ghana (1989), South Africa (1994), Peru (2002, 2004, 2011, 2013, 2014)) did not succeed as artisanal miners found the regularization process unappealing or disfavored by complex bureaucratic processes (IIED, 2002).

Based on the collected evidence, national and international policies of ASGM are still weak, and regulation of this mining sector remains problematic. Studies suggest that national policies of ASGM would benefit (1) a collaborative writing process of governments with local populations and mining associations (IISD, 2019; Kamete, 2008; MAAP, 2020; planetGOLD, 2021 ; Rahm et al., 2015; Spiegel, 2009, 2014, 2015; Spiegel et al., 2015); (2) the regularization of artisanal miners rather than their criminalization (Clifford, 2010; Dreschler, 2001; Kamete, 2008; Spiegel, 2009, 2014, 2015; Tschakert & Singha, 2007) even by proposing fiscal advantages and making an effort to buy them minerals at an equal price to that of the black market (IIED, 2002) and by decreasing the bureaucratic process to get the licenses (Mhangara et al., 2020); (3) the recognition of the property rights of local (especially indigenous) populations (Hook, 2019); and (4) the inclusion of post-mining land-reconversion processes (Asamoah et al., 2017).

1.3. Goal and scope of this document

1.3.1. Scope and boundaries

This guidance document aims to show the benefits and challenges of using RS technologies to support ASGM policy development, implementation and evaluation. It provides insights on monitoring ASGM activities and related pollution, and reports on the evolution of ASGM activities. It identifies RS techniques to detect ASGM sites, to characterize the evolution of

ASGM activities, and to monitor mercury pollution to inform decision makers. It also highlights the national measures taken to address ASGM challenges.

More specifically, the guidance document provided in this report can help countries to implement the Minamata Convention in ASGM environments. The Minamata Convention on Mercury addresses ASGM in which mercury amalgamation is used (Article 7) and requires that any party with more than insignificant ASGM develop and implement "a national action plan in accordance with Annex C" (Article 7.3(a)). The formulation of the NAP should be based on Convention's obligations and current technical and scientific understanding of the ASGM sector, including the use of mercury and processing of gold amalgam, including its health and environmental effects, as well as social and economic analysis of the ASGM sector. This guidance document provides detailed information on RS possible contributions to elaborate and implement NAPs.

The approaches described in this document rely on analyzing the scientific literature on the use of geographic information systems (GIS) and RS technologies in assessing ASGM activities and its impacts, as well as "grey" literature produced by organisations and institutions specialized in environmental management. This guidance document aims at providing clear guidance on what is feasible with such technologies and how to implement them and for which objective. It also includes recommendations targeting decision makers, providing them with evidence-based insights to support decision making and policy implementation. Finally, it features two concrete case studies in ASGM activities in the Democratic Republic of the Congo and in Peru, illustrating how RS can support the identification and quantification of mining activities impacts occurring in remote areas.

In summary this guidance document can enable users to:

- Understand how to use RS to detect and monitor ASGM activities.
- Identify challenges and limitations in using RS technologies to monitor ASGM activities.
- Raise awareness of decision makers of the potential for RS to be applied as a tool for monitoring ASGM.
- Provide tangible insights on the use of RS to support decision making.

1.3.2. Who is this guidance for?

This guidance document has been designed in priority to assist governments and policymakers in ASGM countries. It provides them with insights on RS technologies to better prepare and implement the NAPs for reducing, and where feasible eliminating, mercury use in ASGM as required by the Minamata Convention. Researchers, international and civil society organisations, as well as the private sector, may also find in these guidelines relevant insights to investigate and document their activities in the ASGM sector. This document is designed as a supplement to the UNEP guidelines on *Developing a National Action Plan to Reduce, and Where Feasible, Eliminate Mercury Use in Artisanal and Small-Scale Gold Mining*, which offers overarching guidance to countries formulating ASGM NAPs for the Minamata Convention.

This document was developed under the assumption that users have limited but existing knowledge of GIS and RS. However, if some aspects remain too technical, users are encouraged to review additional sources of information provided further in the document.

1.3.3. Challenges

Unlike large-scale mining activities, it can be challenging to obtain reliable information about the location and spatial extent of ASGM activities. Artisanal mining is often informal, and sometimes illegal, with little government oversight and few reliable statistics on location and production. Most often, finding reliable information on ASGM sites, mercury use, gold production, and tailings disposal requires extensive site visits, multiple interviews with miners, gold buyers, local government officials, and other categories of stakeholders, plus additional observations and physical measurements on ASGM sites. For this reason, a successful and accurate understanding of the ASGM activities will likely rely on a variety of direct and indirect types of information, provided by a diverse sample of practices. Satellite images offer a powerful tool for monitoring the territory, especially areas that are remote, difficult to access, and hidden by the forest canopy, such as those where ASGM occurs. The regular analysis of satellite images provides decision-makers with a tool to intervene, if feasible, in a short time, and the immediacy of the information produced opens the door to an efficient monitoring system of the territory. It is a relevant tool for collecting geographic information about artisanal mining sites, such as the surface extent, distribution, accessibility, land use, and tailing waste. RS is particularly useful when collecting information in environments where low accessibility makes it difficult to collect field information.

Specifically, RS technologies are relevant for observing ASGM activities at various spatial scales and contribute real-time and historical data and information for monitoring associated environmental impacts. For example, RS tools can sense and determine land use change, soil and water contamination and associate biodiversity degradations due to ASGM.

1.4. Structure of the document

In the first section of this guidance document, a general background on ASGM, its positive and negative impacts as well as key terminology concepts on RS are provided. Challenges of governments' actions on ASGM monitoring are discussed and examples of actions at national level are listed. The intended audience of the document is specified as well as its goals and scope and the structure of the document is introduced.

The second section of the guidance document starts from the extensive literature review that was achieved and draws the main findings on the state-of-the-art use of RS applied to ASGM contexts in application projects and in research. An overview of the literature review is provided, describing its scope and the methodology that was used to conduct it. An overview of the main RS methods is provided as well as a list of case studies using RS applied to ASGM, associated results and possible indicators in the context of ASGM monitoring.

The third section presents the proposed conceptual framework for ASGM policy development, implementation, and evaluation. This section is at the heart of the technical guidance document. After having presented the vision and objectives of the proposed conceptual framework and discussed the definition of a reference period for monitoring, a methodology for ASGM monitoring is provided, including precise guidelines. The section ends with the presentation of two case studies that were developed in 2021 by UNEP/GRID-Geneva in Eastern Democratic Republic of the Congo and in the region of Madre de Dios, Peru, to showcase how it is possible to monitor land cover changes using RS open-source technologies.

The fourth section of the document gives as summary of the potentials and challenges of using RS for ASGM monitoring.

The last section provides conclusions and recommendations for different typologies of end users: government officials and policymakers in ASGM countries; researchers; International Organisations and funders; and data and software providers.

2. Literature review and main findings on the state-of-the-art use of Remote Sensing applied to Artisanal and Small-Scale Gold Mining contexts

2.1. Overview of the literature review

2.1.1. Scope

A review of scientific and grey literature on the use of satellite and aerial RS analysis, and GIS technologies as the primary means of monitoring ASGM activities was carried out. The reviewed publications refer to the use of RS techniques for very specific purposes (e.g., to monitor the extent of mining areas) or explore the potentials of RS technologies applied to ASGM contexts. This literature review also includes publications referring to numerous initiatives on ASGM and containing insights and recommendations on suitable methods and technologies to address ASGM pollution, including –but not limited to— the use of RS methods.

In this review, we consider artisanal mining activities, licensed or unlicensed, but excluding large scale mining activities. Regarding the type of minerals, although this document focuses on gold mining, some work on other types of minerals (such as emeralds) provides interesting insights and has been included in our search. However, they remain a minority as the vast majority of the work reviewed is concerned with gold mining activities.

A large number of papers report on the use of RS technologies and GIS for mining purposes, including exploration, mineral prospecting, applied geological purposes and pre-mining risk assessment. We chose to not consider this work in our literature review. Therefore, this review focuses only on works that use RS as a core component of their analysis, that is to say for which spatial analysis is an essential element of the study. Works referring to spatial analysis in general as a secondary technique or input have been excluded.

The literature shows a long history between the use of RS technologies and mining activity. To limit the scope of the literature review, we have chosen to focus on relatively recent literature (mostly from the last decade) whose technical developments allow us to address our concerns. Our literature review encompasses different types of works, mainly from the scientific literature, but also works that have not been peer-reviewed, such as technical reports from various UN agencies, or policy guidelines. The search was not limited by geographical extent or scale and includes inputs coming from contributions not focusing on any country.

2.1.2. Methodology

The review presented in this section follows the general methodology proposed for systematic reviews. This type of review is particularly useful when a subject is the focus of considerable research in recent years and where a comprehensive view can be useful for orienting future research methods. This is the case for ASGM.

The approach taken for searching relevant peer-reviewed and non-peer-reviewed literature consisted of a set of keywords used to query different repositories such as scientific libraries (e.g., Science Direct, Web of Knowledge, Google Scholar), personal databases of the researchers and their research groups, and the Internet (such as Google searches). The following list of keywords were used individually and combined with each other for each query: "Remote sensing", “Satellite”, “Detection”, “Imagery”, “Mines”, “Mining”, “Gold”, “Extractive”, “Extraction”, “Artisanal”, “Minamata”, and produced a comprehensive list of articles. To refine results three additional criteria were used: articles should address artisanal types of mining activities, the keywords should be at least in the title, keywords or abstract; and articles should be written in English, French or Spanish. Following the recommendations for systematic literature reviews on the internet, the first 50 records were screened within online scientific libraries to identify the most relevant publications addressing applications of RS and/or GIS for the monitoring and assessment of ASGM activities. Additional 100 publications, whose main objectives focus on the applications of RS and or GIS for the monitoring of formal or informal, small- or large-scale mining activities, were also looked at for relevance. A general consideration for publications and other published records that seek the applications of RS and GIS for the monitoring, evaluation and decision-making with respect to formal or informal, small- or large-scale mining in Latin America, Asia and Africa were also considered for the review.

The combined results of these various searches account for more than 200 references over the last three decades. About half were excluded because they were beyond the scope of this study. The remaining articles were filtered manually to avoid duplications and screened to ensure that they are relevant to the topic. A final list of 81 publications was used.

Aside from the state-of-the art literature search, about 50 other publications were used to illustrate the concepts, arguments, examples and case studies presented in this technical guidance document.

2.2. Use of Remote Sensing for the monitoring of Artisanal and Small-Scale Gold Mining

Since the entry into force of the Minamata Convention on Mercury in 2017, many governments must develop and implement an effective NAP capable of reducing or eliminating the use of mercury in ASGM. To facilitate governments in this process, UN agencies and NGOs are contributing to the development of capacity and frameworks for governments on the assessment of the status of the ASGM sector by implementing projects at national and sub-national levels (planetGOLD, 2021 ; UNEP b., 2021 ; Brognoli 2004; Linarès, Joubert, and Gond 2008; Rahm et al. 2015; UNITAR 2016; UNODC 2016; IISD 2019). In these projects, the monitoring of the environment in relation with the ASGM sector is often central and it is generally based on integrated approaches that include field work, interviews with locals, analysis of mercury concentration in water samples and, especially, RS data. This is the case in Colombia, (UNODC, 2016), French Guiana (Brognoli, 2004; Linarès et al., 2008; Rahm et al., 2015), Indonesia (UNEP b., 2021 ; UNITAR, 2016), Sierra Leone (Environment Protection Agency Sierra Leone, 2019), Guyana (Rahm et al., 2015), Suriname (Rahm et al., 2015) and Brazil (Rahm et al., 2015).

The importance of using RS data to identify and follow the evolution of artisanal mines has been largely demonstrated by research (Baghdadi et al., 2004; Barenblitt et al., 2021; Bruno et al., 2020; Caballero Espejo et al., 2018; Ibrahim et al., 2020; Lobo et al., 2016; MAAP, 2020; Malca & Ruesta, 2019; Nyamekye et al., 2021; Telmer et al., 2006) and it is crucial for monitoring the ASGM sector where mines are often found in the most remote and inaccessible sectors of the countries. Furthermore, one of the most peculiar characteristics of the use of RS data is the possibility to analyze situations back in time - given the availability of RS data for at least 4 decades - and reconstruct the evolution of artisanal mining sites through time.

RS data are mostly applied to the ASGM sector on two main topics:

(1) The evaluation of the deforestation or land cover change caused by the mining process (generally related to alluvial mines and open hard rock mines), and the effects of soil contamination on plant growth due to the presence of mercury.

(2) The evaluation of water pollution caused by the mining activity in proximity to rivers by detecting turbidity changes of river streams.

The identification of mining sites using RS data generally relies on a land cover analysis approach, which means applying image-classification algorithms to the pre-processed multispectral imagery to identify mining-related land cover classes (Baghdadi et al., 2004; Barenblitt et al., 2021; Caballero Espejo et al., 2018; Gallwey et al., 2020; Nyamekye et al., 2021; Song et al., 2020; UNODC, 2016). The evaluation of water pollution relies, instead, on the quantification of water turbidity which is usually derived using specific multi-band indexes (Brognoli, 2004; Linarès et al., 2008; Lobo et al., 2016; Rahm et al., 2015; Telmer et al., 2006; UNODC, 2016) and can be analysed with image-classification techniques (UNODC, 2016).

RS data can be integrated with environmental data to generate more accurate results and better analyze the influence of the mining process on the biota / mercury content in the environment. For instance, the location of mining sites from existing datasets or from field work can be utilized to create label data that can be used to train the supervised classification models or to refine the results of the model with the assumption that a non-existing mine in recent high-resolution [1]images implies the mine was not present in the past (Brognoli 2004; Le Tourneau and Albert 2005; Linarès, Joubert, and Gond 2008; Gallwey et al. 2020; Nyamekye et al. 2021). Similarly, the turbidity of water could be used as a proxy for mercury content in water if the RS data are combined with in-situ water sample data taken on specific dates that correspond with the available RS data (Telmer et al. 2006; Lobo et al. 2016). In a project run in Colombia (UNODC, 2016), additional data were derived from the results of the RS study such as (1) the direction of expansion of the mining sites through time, (2) the amount of people being affected by the polluted waters resulting from the mining activity, and (3) the

[1] Resolution refers to the smallest unit area an object or detail can be represented in an image. Spatial resolution refers to the size of the smallest possible Earth surface feature that can be detected by a sensor. That is the size of one pixel on the ground. A pixel is that smallest 'dot' that makes up an optical satellite image and basically determines how detailed a picture is. High resolution means that pixel sizes are smaller, providing more detail. With high resolution images, small objects can be detected. For example, 30cm resolution satellite imagery can capture details on the ground that are greater than or equal to 30cm by 30cm

coexistence of illegal cultivations and ASGM sites. This could be done by (1) analyzing time-series data on mines size and location, and (2) integrating external GIS data such as the delimitation of watersheds, the gridded population data, and the location of illegal cultivation spots. The information obtained could be used to orient government policies and actions towards specific directions that deserve the highest priority.

Among the countries that have run assessment projects on the status of the ASGM sites in their territory (e.g., Colombia, Peru, Indonesia, Mongolia, Philippines, Suriname, Guyana, French Guiana, Brazil), Colombia and those part of the "REDD+ for the Guiana Shield" project have developed frameworks to facilitate governments carrying on the monitoring plan in the future using RS techniques (Rahm et al. 2015; UNODC 2016).

The identification of mining sites using RS data can involve manual inputs, especially in the data preparation and in the post-classification steps. Manual editing of the results of classification models is generally more present in government and UN-managed projects compared with research studies (Brognoli 2004; Le Tourneau and Albert 2005; Linarès, Joubert, and Gond 2008; UNODC 2016). This is generally present in the post-classification part of the workflow in order to best differentiate bare soil land cover type from mines as the two have a similar spectral composition of the signal (UNODC 2016; Caballero Espejo et al. 2018; Malca and Ruesta 2019). In some cases, the process of identification of mining sites is completely based on visual identification on aerial photos and satellite imagery from Google Maps and similar providers, or on bands-compositions from multispectral data (Rahm et al. 2015; Lobo et al. 2016).

The involvement of non-automated steps in monitoring projects can be explained (1) by the fact that not all steps involving the use of algorithms for multispectral image-classification techniques are automated, and (2) the difficulty of application scientists in dealing with the those algorithms. Image classification techniques, but also GIS in general, are, in fact, scientific methods that require knowledge and capacity that might be lacking in the local population and the local mining associations that are, in theory, required to collaborate in the policy development process and the environmental monitoring using a "collaborative mapping process" (Spiegel et al., 2012). Probably due to these difficulties, only Sierra Leone has yet included the RS methodology in its NAP: "Remote sensing was not originally planned to be that important, but it emerged as a crucial methodology to better understand the scale of the scattered artisanal mining sector in Sierra Leone." (Environment Protection Agency Sierra Leone, 2019).

2.3. Overview of Remote Sensing methods and indicators in the Artisanal and Small-Scale Gold Mining sub-sector

2.3.1. Remote Sensing techniques

Optical remote sensing considers the range of the electromagnetic spectrum that covers the visible, near infrared and short-wave infrared parts. It is based on sensor systems mounted on platforms, such as satellites, to detect solar radiation that is reflected from targets on the Earth's surface. As various materials are characterized by their specific reflectance spectra, target can be thus differentiated depending on their reaction to certain wavelengths. Optical remote sensing systems are classified into various types such as multispectral and hyperspectral systems, and this characterization depends on the number of spectral bands and their spectral properties. Most current spaceborne systems are multispectral (such as ASTER, Landsat 8 OLI and Sentinel-2 MSI) while hyperspectral missions are currently being tested (such as PRISMA) or are planned (such as ESA's CHIME and NASA's SBG).

Available data for optical image processing are commonly available as top of the atmosphere (TOA) level or as surface reflectance after considering atmospheric influences. The availability of surface reflectance data can vary depending on location and date. If not available, the end-user could need to carry out atmospheric correction. Depending on the methodology for image analysis, certain levels might be required where certain indices have been designed for specific level or have been known to perform best at certain levels of processing (Soudani et al., 2006; Du et al., 2016) When utilizing optical spaceborne data, cloud coverage can be a hindering factor, and thus cloud and cloud-shadow detection is essential prior to using the imagery. In various cases, the footprints of bare excavated areas are of relatively high reflectance while when coupled with water ponds for certain cases of ASGM activities, cloud and cloud-shadow detection can become challenging (Ibrahim et al., 2021).

Once the imagery is analysis-ready, various techniques can be utilized to extract information. The approaches are very diverse and include image classification (e.g., supervised and unsupervised approaches), image transformation using indices, and feature targeting approaches. Image processing can be pixel or object-based techniques, by means of artificial intelligence algorithms such as simulated, and annealing classifiers, machine/deep learning, artificial neural networks, and fuzzy logic classification systems.

Numerous software and tools abound for the processing of spaceborne imagery and spectral geo-spatial data. These include ArcGIS, ERDAS IMAGIN, ENVI, ILWIS, IDRISI, Orfeo ToolBox (OTB), SNAP, Multispec, and QGIS. Among these, OTB, SNAP, Multispec, and QGIS are open-source software for image processing. Furthermore, open-source packages in R programming (Bivand, 2020) and Python are available (Ibrahim et al., 2021). As the datasets can be large, especially in the case of time-series analysis, cloud computing has become essential. Various solutions using Python, R programming, and Javascript APIs are available and include Google Earth Engine, the Open Data Cube, OpenEO, and SentinelHub with all having their benefits and constraints (Gomes et al., 2020).

2.3.1.1. Pixel-based Image Analysis Technique

In the past, the most common approach to land cover mapping was through a pixel-based image-classification model using machine-learning algorithms (Gallwey et al., 2020). Classical examples of pixel-based algorithms are minimum-distance/nearest neighbour, parallelepiped and maximum likelihood classifiers (MLC). Detailed description of these algorithms can be found in Lillesand et al., 2015. A subset of these methods, used primarily in deforestation studies, are capable of detecting sub-pixel changes, which eventually reduces the problems caused by spectral mixture analysis (Asner et al. 2013; Asner and Tupayachi 2017; Caballero Espejo et al. 2018). The major challenges with pixel-based image classification include misclassification of features with similar spectral properties such as open mines with bare soil and mine ponds with isolated water bodies (Myint et al., 2011). This can be improved using an object-based classification approach as this takes spatial context into account (Gallwey et al., 2020).

2.3.1.2. Object-based Image Analysis Technique

Object-based image classification comprises of two procedures, namely: (1) segmentation and (2) classification, usually done on high resolution images. In image segmentation, image objects are delineated based on homogeneity of pixels and spatial contingencies; continuous and contiguous objects (Blaschke et al., 2014). Image objects are then classified using visual techniques such as colour, texture, form, and context properties. The classification is done using two classifiers algorithms: a (standard) nearest neighbour (NN) classifier, and fuzzy membership functions. It is also possible to combine both algorithms depending on the level of accuracy required in the classification. A detailed description of image segmentation and classification is provided in (Hofmann, 2001) and (Yan et al., 2006). The object-based approach is very promising and generally increases the performances of the classification algorithms when applied to the detection of features with a unique shape and topography (Isidro et al., 2017; Myint et al., 2011; Gallwey et al., 2020). The choice of the parameters to be used for the initial segmentation is, however, crucial and can dramatically affect the results of the classification algorithm (Liu & Xia, 2010; Nuijten et al., 2019). The major challenge of the object-based image classification technique is that it only produces high accuracy in case of (1) availability of a near perfect segmentation and (2) availability of a high spatial resolution image. It works well on images with pre-defined boundaries. Thus, it is not a suitable method for classifying areas with no clear boundaries readily available, such as semi-natural areas.

2.3.1.3. Image-classification algorithms

Machine-learning (ML) algorithms are generally chosen for image-classification models in RS applications as they are able to model complex class signatures, can accept a variety of input predictor data, and do not necessarily require knowing the data distribution (i.e., are nonparametric) (Maxwell et al., 2018). ML algorithms can operate supervised and unsupervised learning with the first ones requiring labelled training data while the second ones operate through clustering and association techniques (Alloghani et al., 2020). On supervised learning the user must feed the model with interpreted (i.e., labelled) training data. These can be retrieved from existing land cover datasets if they are available with resolution compatible with that of RS data but can also be created by manually picking spots on satellite imagery that belongs to a given land cover class with a certain confidence. This process can be run by integrating field work with local knowledge (“collaborative mapping”) and the visual interpretation of very high-resolution imagery. On unsupervised learning, the model can be trained with unlabeled data using a smaller portion of the area that should be classified as the model is allowed to act on that data without any supervision (Alloghani et al., 2020). The machine-learning algorithms that are most used in multispectral image-classification are Random-Forest (RF) Classifier, Support Vector Machines (SVMs) (supervised), Decision Trees (DT) and Artificial Neural Networks (ANN) (Mhangara et al., 2020). Recent studies on Deep Learning (DL) techniques (i.e., neural networks algorithms involving a higher number of hidden layers) suggest that the Convolutional Neural Network (CNN) is a valid candidate for land cover classification purposes and can outperform the aforementioned ones having omission and commission errors as low as 8% (Gallwey et al., 2020). Unfortunately, the literature showing how the CNN should be applied for land cover tasks is still limited (Gallwey et al., 2020).

Although the accuracy of ML algorithms is generally higher than that of traditional parametric classifiers, the latter are still commonly used especially in application articles and remain one of the major standards for benchmarking classification experiments (Maxwell et al., 2018). For instance, the parametric maximum likelihood classifier was the most used method in RS studies until 2014 (Yu et al., 2014). This has been found to be related to the uncertainties regarding how to use and implement machine-learning techniques by many application scientists and the wide availability of traditional classifiers in conventional RS image-processing software packages (Maxwell et al., 2018).

It is, therefore, important to note that there is no stand alone, one-size-fit-all methodology for image classification. The choice of techniques is contingent upon but not limited to: (1) the objective of the study, (2) image data accessibility for the area of interest and objectives and, (3) availability of and access to relevant image processing software.

2.3.2. Input data for the models

Classification models do not necessarily need the totality of the spectral information. An effective band selection process would result in enhanced performances of the model in terms of costs and accuracy of the results (Torres et al., 2020). The performance of bands can be evaluated in a subset region before the model is run. For instance, it has been shown in a case study in Ghana that the Sentinel-2 Band 5 (band center 705 nm) was the highest contributor to the overall accuracies of the land cover classification and, more importantly, it contributed most to delineating mines sites (Nyamekye et al., 2021). Classification models can also use multi-band indexes as input data such as the Normalized Difference Vegetation Index (NDVI) (MAAP 2020; Mhangara, Tsoeleng, and Mapurisa 2020; Barenblitt et al. 2021; Nyamekye et al. 2021) but attention should be paid when using NDVI as it is very influenced by many environmental factors such as topography, bare soil conditions, atmospheric conditions, vegetation association, rainfall, and non-photosynthetic materials (Qi et al. 1994; Bannari et al. 1996; Huete 2012; Verrelst et al. 2015). Other indexes such as the Soil Adjusted Vegetation Index (SAVI), the Modified Soil Adjusted Vegetation Index (MSAVI) and the Transformed Soil Adjusted Vegetation Index (TSAVI) can be used instead to feed the classification models with enhanced performances especially in low vegetation areas (Mhangara et al., 2020).

Other bands and indexes have been shown useful in detecting water turbidity and should be prioritized to identify mining hotspots along rivers (e.g., the Modified Normalized Difference Water Index (MNDWI) (UNODC, 2016), the Band 8A - VRE 4 and the Band 3 (Green) in Sentinel-2-A data (Nyamekye et al., 2021), combination of Landsat 8 bands to distinguish deep water from shallow water (4,3,2), water from ground (5,6,4) and bare ground from ponds (6,5,2) (UNODC, 2016)). The effects of precipitations on water turbidity, and on the values of the index that is used to infer it, can be minimized by determining the threshold between naturally and human induced turbidity (UNODC, 2016). In this case, the MNDWI values were collected at different times, within the dry season, at specific locations along a river in proximity to a known artisanal mine in order to identify the effects of the mining activity. The collected values were analyzed statistically using the K-means algorithm to group values into classes and the results were eventually analyzed on the basis of an unsupervised image classification process.

2.3.3. Post-classification methods to refine the models' results

Features with similar spectral properties that are potentially misinterpreted by the classification model can be corrected in the post-classification stage with different methods handling manual to automated operations. Some studies use manual decisions based on visual identification of critical features located next to the misinterpreted features based on a defined framework (e.g., Colombia in UNODC 2016).

Another approach is to define an automated process that can analyse the land cover classes of features and convert them to another class based on the defined conditions. For instance, another study in Colombia revealed the utility of performing an automated proximity analysis on the output data of the model to refine the interpretation of feature classes that were difficult to interpret (Ibrahim et al., 2020). In particular, "isolated water bodies" that were in proximity to pixels classified as "open mines" were converted to the class "mine-pond" and, similarly, "open mines" that did not fall near "isolated water bodies" were converted to the class "bare-soil". Features/pixels that experienced land cover variation due to seasonal change can be grouped if the typical seasonal change effects on time-series data is known/determined. This can be done by performing a sequential pattern analysis on time-series data to discard the high frequency land cover change and associate them to the seasonal effect rather than the mine's activity (Ibrahim et al., 2020).

As the multispectral signature of bare-soil and open mines is relatively similar, in very dry environments the presence of mines can be very difficult to detect (Mhangara et al., 2020). For this reason, a morphological profiling that is run on the output of the classification model can better differentiate mining sites from bare-soil due to its ability to delineate edges effectively on high spatial resolution imagery. The success of the morphological profile could be attributed to its ability to isolate bright and dark structures in images, by exploring a range of different spatial domains as well as brightness and darkness contrast (Mhangara et al., 2020). This approach allows to properly distinguish non-vegetated areas that could have been identified quite simply with a classifier that is relatively insensitive to the illumination and albedo effects common in rugged terrains such as the Spectral Angle Mapper (SAM) (Mhangara et al., 2020).

Finally, NDVI could also be used in post-classification steps to reduce the uncertainty over land cover changes after the determination of a threshold that separates seasonal change influence from artificial influence on the land cover change (Malca & Ruesta, 2019).

2.3.4. Change detection

The images produced using classification methods can eventually be used to determine where land cover has changed through time and calculate areas that evolved into artisanal mining sites. This can be achieved performing a change detection process over pairs of images and determine the evolution of land cover between two times.

The detection of the activities of the ASGM sector is not a monopoly of optical RS methods. The feasibility of the Intermittent Small Baseline Subset (ISBAS) interferometric synthetic aperture radar (InSAR) method together with Sentinel-1 imagery for monitoring ASGM activities has been done by (Ji et al., 2011). The study found a high level of subsidence based on surface motion values, which is a clear indicator of mining activity. Several simulation results show that the European Space Agency Copernicus Sentinel-1A/B constellation is capable of mapping rapid ASGM activities in the landscape. For instance, Forkuor et al. (2020) used annual time-series Sentinel-1 data to map and monitor ASGM activities along major rivers in South-Western Ghana. A change detection approach based on three time-series features was used to compute a backscatter threshold value suitable for detecting mining-induced land cover changes and water pollution in the study area. Thus, Radarsat-2 and Sentinel-1 C-band data can detect water contamination over dry surface with sparse vegetation. However, ground survey data must be integrated with synthetic aperture radar data for detecting mining locations and monitoring activities.

2.3.5. List of Remote Sensing methods and possible indicators

A list of RS methods illustrated with use cases, associated results and possible indicators is presented in Table 2. Most studies relate to ASGM, a few of them to ASM.

Table 2. List of RS methods and possible indicators

Paper	Methods	Results/indicators	No. ASGM sites
(Manu et al., 2004)	RS and GIS	Time series analysis indicated the study area was a healthy ecosystem in 1986. By 2001, over 60% of the land in the study area was degraded beyond use for other activities such as farming. An additional 35,000 ha of land/soil has been polluted within the same period	–
(Schueler et al., 2011)	Landsat satellite images from 1986–2002 to map land cover change due to surface mining	Surface mining resulted in about 58% deforestation, about 45% of farmland losses within mining concessions, and widespread spill-over effects due to the expansion of farmlands into forests	One Block
(Asner et al., 2013)	Combined field surveys, airborne mapping, and high-resolution satellite imaging to assess road and river-based mining	The geographic extent of gold mining increased by 400% between 1999-2012; the average annual rate of forest loss tripled in 2008. ASGM operations were identified to be more than half of all gold mining activities throughout the region.	One

		These rates of ASGM activities are far higher than previous estimates that were based on traditional satellite mapping techniques. The results prove that ASGM is growing more rapidly than previously thought, and that high-resolution monitoring approaches are required to accurately quantify the impacts	
(Abood et al., 2014)	250 m spatial resolution land cover classification maps	Four industries accounted for ~44.7% (~6.6 Mha) of forest loss in Kalimantan, Sumatra, Papua, Sulawesi, and Moluccas between 2000 and 2010. Fiber plantation and logging concessions accounted for the largest forest loss (~1.9 Mha and ~1.8 Mha, respectively). The contribution of ASGM to forest loss is negligible	Regional Block
(Bao et al., 2014)	Object-based image analysis (OBIA) methods and high-spatial resolution SPOT-5 imagery, spatial autocorrelation, and normalized difference vegetation index (NDVI)	A relatively high-classification accuracy shows the potential of SPOT-5 imagery for monitoring mine rehabilitation. The complete spatial coverage associated with RS data at fine spatial scales has the potential to complement field-based approaches commonly used in rehabilitation monitoring. SPOT-5 data along with OBIA can characterize vegetation spatial patterns at spatial scales appropriate for monitoring rehabilitated landscapes, providing an important tool for landscape function analysis	One block
(Cuba et al., 2014)	Polygon areas of exploration and of active resource exploitation	High portions of agricultural land use in both countries are located within areas that are subject to mineral or hydrocarbon concessions (38% in Peru, 39% in Ghana), predominantly within leases (36% in Peru, 35% in Ghana); overlaps between concessions and protected areas (10% for Perú, 2% for Ghana), concessions overlap with titled indigenous communities in Peru (35%)	Regional Block

(Elmes et al., 2014)	Landsat 5 imagery via decision tree classification; Spectral mixture analysis; WorldView and QuickBird I imagery	A large proportion of illicit ASM activity (~65% of all ASM in the study area) occurring outside the permitted concessions	Regional Block
(Lüthje et al., 2014)	A multi-scale analysis; multi-temporal analyses of very high-resolution (VHR) satellite data; Geographic Object-Based Image Analysis (GEOBIA) techniques to identify hot-spots of mining activities	Detailed multi-temporal analyses of very high-resolution (VHR) satellite data demonstrates the capabilities of GEOBIA techniques for providing information about the activities of illicit ASGM between September 2010 and March 2011. Land cover change between two or more satellite images does not in itself produce evidence of ASGM activities. A combination of field observations and image data, provides enough evidence that ASGM activities exist in an area	Regional Block
(Alvarez-Berríos & Aide, 2015)	Land Mapper web application and images from the MODIS satellite, MOD13Q1 vegetation indices 250 m product. Annual maps of forest cover used to model incremental change in forest in ~1600 potential gold mining sites between 2001–2006 and 2007–2013	1680 km^2 of tropical moist forest was lost in these mining sites between 2001 and 2013; More than 90% of the deforestation occurred in four major hotspots; active zones of gold mining deforestation occurred inside or within 10 km of ~32 PAs	Four major hotspots
(Lobo, 2015)	Total suspended solids (TSS), in situ data and historical Landsat-MSS/TM/OLI data, Measurements of radiometric data to calibrate satellite atmospheric correction and establish an empirical relationship with TSS	The role of the temporal changes of ASGM area in the water siltation; ASGM increased from 15.4 km2 in 1973, to 166.3 and 261.7 km2 in 1993 and 2012, respectively	Four sub-basins

(DeWitt, 2016)	Land Use / Land Cover (LULC) classified from Landsat between 1984 and 2014; Corona imagery extends LULC analysis; ASGM interpreted from Very High-Resolution (VHR) satellite imagery and integrated into regional analysis	Regional land cover trends: cashew orchards, uncultivated forest, urban space, mining/ bare, and mixed vegetation, were produced; the locations of ASM activity in the study area	One Block
(Patel et al., 2016)	Mapping spatial overlaps between large and small-scale miners; Classification tree analysis of 2013 and 2015 Landsat 7 and 8 imagery to identify small-scale mine sites	52% of identified small-scale mining activity occurs within large-scale concessions. The northwest corner of the study area contains 50% of the identified overlaps; the southwest corner contains 40%; and the northeast corner contains 10%; land use conflicts	Four blocks
(Weisse & Naughton-Treves, 2016)	Examines the efficacy of buffer zones in the Peruvian Amazon to (a) prevent deforestation and (b) limit the extent of mining concessions from 2007 to 2012. Employed covariate matching to determine the impact of 13 buffer zones on deforestation and mining concessions	Despite variation between sites, the 13 buffer zones have prevented ~320 km^2 of forest loss within their borders during the study period and ~1739 km^2 of mining concessions. A closer look at the buffer zone around the Tambopata National Reserve reveals the difficulties of controlling illegal and informal activities	13 buffer zones
(Amadi et al., 2017)	Geological mapping, soil analyses	High concentrations of mercury, cadmium, lead and arsenic, a westward groundwater flow direction; area was dominated by schist and granite	Regional Block

(Asamoah et al., 2017)	Classified and analyzed high-quality Landsat image data (1986–2016) to monitor processes and changes in the river basin and adopted the Ecosystem Service Value (ESV) model to quantify the forgone value in monetary term	The initial ESV of 17.69 million US$ in 1986 was shown to have increased to 18.40 million US$ in 2002 for the study landscape. The ASGM accounted for 8.4% of trade-off costs. In 2016, out of the total ESV of 14.63 million US$ obtained, ASGM activities accounted for 36.8% of the trade-off costs	Regional Block
(Dewitt et al., 2017)	Unmanned aerial system (UAS); structure-from-motion (SfM) photogrammetric techniques; very high-resolution imagery and digital surface models (DSMs); wide-angle and narrow field of view camera systems	Moderate-scale categories of LULC, including cashew orchards, uncultivated forest, urban space, ASM, and mixed vegetation, were produced through supervised classification of Landsat multispectral imagery from 1984, 1991, 2000, 2007, and 2014. The fine-scale ASM land use was identified through manual interpretation of high-resolution satellite imagery. The mining/ bare class in the integrated analysis exhibits a substantially different spatial distribution than in the original classifications. This information regarding the locations of ASM activity in the Tortiya area is important from a policy and planning perspective	Regional Blocks
(Kranz et al., 2017)	Very high-resolution (VHR) optical stereo satellite data analysis; a combination of object-based change detection (OBCD) based on optical VHR data and generated digital surface models (DSM)	Land cover changes as analysed by OBCD reveal an increase in bare soil area by a rate of 47% between April 2010 and September 2010, followed by a significant decrease of 47.5% of bare soil area October 2010 and March 2015; DSM characterization of pits and excavations	Regional Block
(Markham, 2017)	Random forest classification and Multicriteria evaluation	Models pollutant transport from ASGM sites to predict locations and species assemblages at risk; determines how flow accumulation, distance from mining area, total suspended sediment load, and soil porosity influence the vulnerability of regions to mercury	Regional Block

		pollution. The resulting risk map identifies areas of greatest risk of mercury pollution	
(Snapir et al., 2017)	Multi-date UK-DMC2 satellite images to map the extent and expansion of illegal artisanal and small-scale gold mining (galamsey) from 2011 to 2015	Area of illegal ASGM (galamsey) has more than tripled from 2011 to 2015, from 10,907 to 36,696 ha; River network with downstream pollution affecting both land and water; In 2013, an estimated area of 551,496 ha was affected; In 2015, galamsey encroached into at least 603 ha of protected forest reserve	Multiple
(Wyatt et al., 2017)	Analysis of time series satellite imagery for ASGM site identification and exposures to mercury contaminations	ASGM has increased 4–6 fold over a decade, communities located hundreds of kilometers from ASGM are vulnerable to chronically elevated mercury exposure	Regional Block
(Caballero Espejo et al., 2018)	A fusion of CLASlite and the Global Forest Change dataset, two Landsat-based deforestation detection tools, in 1984–2017 period	Nearly 100,000 ha of deforestation due to ASGM in a 34-year study period, an increase of 21%; 10% of deforestation occurred in 2017, 53% occurred since 2011	One block
(Hausermann et al., 2018)	Combining geospatial, ethnographic, and quantitative methodological approaches	The total extent of mining increased by 2,772.6% to cover 998.23 Ha between 2008 and 2013; "mine water" increased by 13,000% to cover 200 Ha within the same period	Regional Block
(Lobo et al., 2018)	Multi-satellite data	ASGM attributes revealed and varied from region to region. Mining areas derived from validated S2A classification totals 1084.7 km^2 in the regions analyzed. ASGM (617.8 km^2) comprises up to 64% of total mining area detected. The large extension of ASGM areas detected raises a concern regarding its socio-environmental impacts for the	Regional Block

		Amazonian ecosystems and for local communities	
(Markham & Sangermano, 2018)	Geographic information science; a spatial model of pollution risk from mining sites; Multicriteria evaluation; flow accumulation	RS data used to create a spatial model of pollution risk from mining sites, predict locations and species assemblages at risk, highlights the need for future ASGM research to consider more than deforestation risk alone while protecting biodiversity	Regional Block
(Kyba et al., 2019)	Detecting known artisanal and small-scale mining sites via Artificial night light emissions by Visible Infrared Imaging Radiometer Suite Day/Night Band (DNB)	Known ASGM sites in the Democratic Republic of the Congo (DRC) are associated with observations of night light emissions by the Visible Infrared Imaging Radiometer Suite Day/Night Band (DNB). Light emissions from the mining sites were not observed. DNB night lights' products provide useful data in other resource extraction contexts, but they could not identify ASGM sites in the DRC probably due to thick forests cover	Regional Block
(Mensah et al., 2019)	Sentinel-1 and Sentinel-2 data;	The illicit mining area increased from 13,456 hectares to 29,275 hectares between 2015 and 2018. In 2016 and 2017 the extent of illegal mining was 29,026 and 24,323 hectares respectively; As of 2018, the total extent of forest degradation in these reserves was about 10 hectares	Regional Block
(Obodai et al., 2019)	Multi-spectral Landsat images of 30 m resolution; spectral angle mapping algorithm	Closed forest which occupied 40.4% of the total basin area in 1991 reduced drastically to 22.8% in 2016 due to ASGM activities in area.	Regional Block
(Rodrigue, 2019)	A combination of spatial analysis, questionnaires administration and	Destruction of habitats; decrease in quantity of forested area; and high turbidity	One site

	Leopold's grid of impact assessment		
(Usman et al., 2019)	Landsat image (Landsat ETM 1998, Landsat ETM 2008, Landsat ETM 2018) of the study location was utilized to determine the trend of the land use and land cover in the study area	Vegetation land decreases from 486.324 (Km^2) (42.96 %) in 2008 to 367.6473 (Km^2) (32.47%) in 2018 which may be attribute to the influx of people for ASGM activities, leading to increased deforestation activities as well as pressure on other available vegetation resources. Agricultural land on the other hand has increased further to 362.8728 (Km^2) (32.05%) in 2018, from 311.7456 (Km^2) (27.54 %) in 2008, which can be attribute to the conversion of vegetation, open surface as well as other land uses to agricultural land to meet the increase demand for food supply in the area as a result of increasing ASGM activities and associated influx. Water turbidities increased from 8.8956 (Km^2) (0.79%) in 2008 to 15.5025 (Km^2) (1.37%) by spatial extents due to various mining activities going in the study area	Regional Block
(Ammirati et al., 2020)	Sentinel-1 data, the differential interferometric synthetic aperture radar (DInSAR) technique has been used to study terrain deformation related to ASGM in Ecuador	Detected surface deformations that occurred in the ASGM area from 2015 to 2019. Deformations of the order of five centimeters were revealed both in correspondence of known exploitation tunnels, but also in areas where the presence of tunnels had not been verified	Regional Block
(Brown et al., 2020)	Intermittent Small Baseline Subset (ISBAS) interferometric synthetic aperture radar (InSAR), teamed with Sentinel-1 imagery,	A high level of subsidence (i.e., negative ISBAS pixel value) is a clear indicator of ASGM activity	Regional Block
(Bruno et al., 2020)	RS techniques	The documented spatial extent of ASGM is ~9175 km^2 along the Marupa River and ~30,427 km^2 along the Kahayan	Two sites

		River. It was established these activities change rapidly (2–3 years) in space	
(Csillik & Asner, 2020)	Satellite RS, airborne LiDAR, and deep learning models to create high-resolution, spatially explicit estimates of aboveground carbon stocks and emissions from gold mining	For an area of ~750 000 ha, it is found to have high variations in aboveground carbon density (ACD) with mean ACD of 84.6 (±36.4 standard deviation) Mg C ha−1 and 83.9 (±36.0) Mg C ha^{-1} for 2017 and 2018, respectively. Alarming 1.12 Tg C of emissions occurred in a single year affecting 23,613 hectares. The tested methods and findings are preparatory steps for the creation of an automated, high-resolution forest carbon emission monitoring system that will track near real-time changes and will support actions to reduce the environmental impacts of gold mining and other destructive forest activities	Regional Block
(Feemster et al., 2020)	Omnibus Q-test Change Point Detection Algorithm to identify changes in Synthetic Aperture Radar (SAR) monthly-aggregated temporal data from the Sentinel-1 satellite; PlanetScope and Landsat 8 OLI through Collect Earth Online	ASGM-related deforestation detection; 19% of change detected were due to mining activity.	One Block
(Forkuor et al., 2020)	Time-series Sentinel-1 data	A backscatter threshold value of +1.65 dB found suitable for detecting illegal mining activities; illegal mining area extents of 102 km^2, 60 km^2 and 33 km^2 for periods 2015/2016–2016/2017, 2016/2017–2017/2018 and 2017/2018–2018/2019, respectively	Regional Block
(Gallwey et al., 2020)	Multispectral U-Net convolutional neural network to detect artisanal scale mining; open-source Sentinel-2	Mining related deforestation increased by 15,000 ha over the study period; mining and urban land use changes	6 million hectares

	MSI imagery; traditional machine learning methods		
(Mhangara et al., 2020)	SPOT 6 satellite imagery; Spectral Angle Mapper; Morphological classification	Changes in vegetation cover, bare soil, and mined open pits; continuous decrease of vegetated areas and expansion of bare soil surfaces	Regional Block
(Ngom et al., 2020)	Sentinel-2 data and the Google Earth Engine; Principal component analysis (PCA); Separability and threshold (SEaTH), automatic classification and mapping of scenes with support vector machine (SVM) classifier	Spectral signatures for ASGM sites against other types of land use; categories of land use	Two artisanal mining sites
(Barenblitt et al., 2021)	Landsat image archive via Google Earth Engine	Vegetation loss due to artisanal gold mines; New mining extent dominated by ASM (~89%); Over 700 ha of ASM detected in protected areas	Regional Block
(Ibrahim et al., 2021)	Two-step machine-learning approach using freely available tools to detect clouds and shadows in mapping small-scale mining areas; supervised support-vector-machine classification; geometry-based improvement of cloud-shadow detection; Sentinel-2 (S2A and S2B) data	50% more detection of clouds and shadows than Sen2Cor; detection of water ponds; and small-scale mining sites	Regional Block
(Nyamekye et al., 2021)	Sentinel-2 data, four ML and DL models (Artificial Neural Network –ANN, Random Forest – RF,	Changes in LULC; ASM increased by 59.17 km^2 within the period of the study	Regional Block

	Support Vector Machines –SVM, a pixel-based Convolutional Neural Network-CNN) and image segmentation		
(Owolabi et al., 2021)	Normalized difference vegetation index (NDVI); normalized difference water index (NDWI); and land surface temperature (LST) were used to assess the impacts of ASGM operations on environmental degradation	A gradual decrease in the NDVI values was observed across two sampled areas with a corresponding change in the highest NDVI values while one area witnessed a higher NDVI value in 2017 relative to the previous years. NDWI values for 2017 were above 0 in all host communities. Mean LST values are in the order 24.63 °C (1986) < 25.26 °C (2002) < 26.32 °C (2017) for one study area; while mean LST values are in the order 24.30 °C (1986) < 24.46 °C (2002) < 25.82 °C (2017) in another study area. Modified Normalized Difference Water Index (MNDWI) seemed a more reliable indicator as the index was able to enhance the water surfaces more clearly	Regional Block
(Ibrahim et al., 2020)	Image classification, post-processing using field knowledge, time series (2016 to 2019) and NDVI	The finds a slight reduction in the detected mining areas from 2016 to 2019. More mining activities detected in the dry season than in the wet season. The finds about 35% loss of vegetative cover due to ASGM. Only 7% of vegetative recovery was observed at the ASGM areas in June 2019. An analysis of abandoned sites using NDVI shows that it takes a much longer period than the one considered in this paper for potential natural recovery of vegetation	Regional Block

3. Conceptual framework for Artisanal and Small-Scale Gold Mining monitoring for policy development, implementation and evaluation

3.1. Framework vision and objectives

RS techniques have unique capabilities and resources for addressing some ASGM-related issues. RS techniques allow a comprehensive understanding of resource potential and extraction, and the environmental impacts of legal and informal ASGM operations at various geographical scales, especially at the local scale. Integrating RS tools when monitoring ASGM activities can alert governments and communities of the need to increase security, to create a path towards socially and environmentally responsible resource extraction and management, and to move towards safe and environmentally sustainable mining practices. According to Mutemeri et al. (2016), the current regulatory and policy frameworks for monitoring activities of the ASGM sub-sector in Africa needs reform and there is a need for information for inclusive policymaking and implementation. This includes appropriate extraction of the ore body, and the sustainable use and management of natural resources, such as water, soils, food and wood. Mainstreaming policy development and implementation across relevant sectors is also required. For example, policies that create economic incentives and disincentives for the industrial sector (e.g., manufacturing of electronics) that rely on gold have an important role to play in the regularization of ASGM activities. As a good knowledge base is the backbone to formulate and implement appropriate policy decisions to address the problems associated with mercury and ASGM; using RS systems can be a good starting point.

The following framework defines a methodology that can be suitably applied to monitoring ASGM sites to support policymaking and implementation. It describes analytical and non-analytical monitoring techniques that integrate RS data, field work/measurements, and the knowledge of the local population. In particular, the framework starts with an excursus on the most suitable time period for monitoring. This, being dependent on the external variables, is covered with a case-by-case approach with the most important scenarios being highlighted. It then proposes a brief description of techniques that should be employed for ASGM monitoring projects; and it continues with a list of relevant data sources and processing platforms for RS data. The framework finally provides an overview of the most suitable processing techniques for RS data that can be employed by governments or implementing agencies. Two case studies focusing on the identification/quantification of land cover change due to mining activities in the Democratic Republic of the Congo and in Peru are also reported as examples of monitoring techniques.

3.2. Defining a reference period for monitoring

A reference period for the monitoring of ASGM that fits all cases does not exist and cannot be defined *a priori*. The most suitable monitoring period depends on factors such as the objective of the study, the type of mining activity (e.g., alluvial vs bedrock mines), the climate of the area (e.g., the frequency of cloud coverage of the area and the rate of vegetation growth) to name only a few. Nevertheless, a few suggestions can be given and must be considered when planning a monitoring study of the ASGM sector.

First, the use of RS data allows one to analyze the situation retroactively using one of the available datasets that cover the area on a given period of time.

To monitor the effects of a government action over time, a before/after comparison of the status of ASGM sites can be suitable. This can be performed by selecting a dataset immediately before the action (this might be difficult to know exactly - one can refer to the legislation date to which the action is based on) and another one at a time when the consequences of the law can be evaluated. This is generally done across a relatively short time period (e.g., 2 years in (MAAP, 2020)).

ASGM sites are created and abandoned within a period of months (Isidro et al., 2017), especially if they are located along rivers (e.g., alluvial type). In addition to this, depending on the climate of the area, vegetation can grow quite rapidly in abandoned mining areas, so far making the detection of abandoned mines difficult after some time (Le Tourneau & Albert, 2005). Therefore, the monitoring would benefit a selection of datasets at a high frequency (e.g., one every year or even more frequently) rather than simply comparing two datasets far from each other in time if the main objective of the study is to monitor ASGM activity through time.

As seasonal change plays a role in the vegetation status, the spectral signature of vegetated land can change in datasets that are taken at different periods of the years depending on the region. Therefore, datasets across years should ideally be selected from the same season. This is sometimes obliged in very humid areas where cloud cover is very often present and so far, reduces the time window for land cover analysis to the dry season (Gallwey et al., 2020).

Finally, depending on the selected source of satellite data, the available period for monitoring can be constrained by the availability of data. For instance, the first Landsat satellite was launched in 1972 while Sentinel data are only available since 2015. In terms of frequency of availability of images in a given place, Landsat 1–3 cover the Earth every 18 days, Landsat 4, 5, 7 and 8 have a coverage cycle of 16 days, and Sentinel-2 images the globe every 5 days.

3.3. Methodology for Artisanal and Small-Scale Gold Mining monitoring

3.3.1. Methodology

To monitor the use of mercury in ASGM, two methods are available: the technical and non-technical methods.

- Technical methods require the use of RS technologies, sometimes combined with laboratory-based mercury analyzers to detect the presence of mercury, for example, in fish, sediments, and water. These methods are more resource intensive and, for this reason, may not be appropriate in all contexts.

- Non-technical methods include participatory community-based monitoring of the applications of mercury by ASGM practitioners in ore processing. These methods are typically more sustainable as they have knowledge transfer to, and higher buy-in of local communities through the active engagement of ASGM practitioners.

Scientists who conduct field mapping, use geomorphological and RS techniques to map, monitor, and evaluate mineral deposits, ASGM activities and mercury pollution. These methods require transferable expertise to acquire meaningful knowledge in developing areas. In particular RS techniques allow a detailed mapping and monitoring of ASGM activities and the development of high-resolution geomorphic models for identifying host resource deposits. High-resolution satellite imagery enables scientists to identify active informal or illegal alluvial ASGM pits, estimate production, and monitor changes over time. Satellite image analysis is integrated with ground-truthing data. The use of Unmanned Aerial System (UAS) imagery (such as drones) to map alluvial deposits in ASGM regions has also been explored in recent scientific studies (Martin et al., 2015). A combination of these technologies enhances a rapid assessment and mapping of environmental, social, and economic impacts of the ASGM activities. Important variables could be added to the analysis, such as protected areas, critical ecosystems and populations vulnerability.

3.3.1.1. Data sources and collection

Given the nature of ASGM, governments require extensive data resources and analysis to monitor and enforce applicable laws and policies. There are two principal sources of primary data collection for ASGM monitoring. These are: (1) image-based and (2) field-based sources.

Image-based primary sources of data include but not limited to: multi-spectral satellites such as the United States Geological Survey (USGS) Landsat sensors, ASTER-Derived Global Digital Elevation Model (GDEM) Versions, Light Detection and Ranging (LiDAR), Google Earth interface, SPOT-2, CBERS-2, QuickBird, the Japanese Aeronautics Exploration Agency (JAXA), European Space Agency (ESA), Africa Regional Data Cube, the Global Earth Observation System of Systems (GEOSS), Conservation X Laboratory, regional governments' databases, and International bodies like UNEP, UNDP, and UNIDO. Most of data sources require subscriptions for free download of data. Examples include the USGS Earth Explorer, ESA Copernicus Sentinel Satellite Data, ESRI Open Data Hub, NASA's Socioeconomic Data and Applications Center (SEDAC), Open Topography, Open Street Map, UNEP Environmental Data Explorer, Natural Earth Data, and NASA Earth Observations (NEO), Terra Populus, FAO GeoNetwork, and Global Map GitHub. Some of these data sources are listed in Table 3, with key characteristics.

Table 3. Relevant characteristics of RS data sources

Database / Provider	Cost per tile / Km^2	Type of imagery	Website of Provider	Spacecraft / Data Frequency	Scope
Google Earth	Free access	High-resolution	https://earth.google.com/web/	Largely from airplanes and satellite.	Global

				Available 3-4 years.	
ESA Sentinel Hub Copernicus Open Access Hub	Free Sentinel-1/2 images.	High/medium resolution	https://www.sentinel-hub.com/ https://scihub.copernicus.eu/	Satellite. Every 5 days	Global
NASA/USGS	Free access Licensing for commercial use required	High/medium resolution - Landsat, MODIS, and ASTER data Hyperspectral	https://earthexplorer.usgs.gov/	Satellite. Every 7 days. Aerial, and UAV	Global
NOAA	Free access	GEOS-R and NOAA-20 data. Very low resolution (250m and above)	https://www.nesdis.noaa.gov/content/imagery-and-data	Real-time satellite data. Every 15 minutes	America
Earth on AWS	Free access	Medium resolution. Sentinel-2, Landsat-8, GEOS, NOAA, Sentinel-1 and China-Brazil Earth Resources Satellite (CBERS)	https://aws.amazon.com/earth/	Satellite. Every 7 days	Global
Zoom.Earth	Free access for non-commercial applications	Near real-time satellite data and high-resolution archival data	https://zoom.earth/	Every 10 minutes from NOAA GOES and JMA Himawari-8 satellites, and every 15 minutes via EUMETSAT Meteosat satellites	Global
NASA Worldview	Free access	Low resolution, open data only	https://worldview.earthdata.nasa.gov/	Near real-time satellite data	Global
NASA EarthData GIBS	Free access	Low resolution, open data only	https://earthdata.nasa.gov/eosdis/science-system-description/eosdis-components/gibs	Available within a few hours after satellite observation	Global
Remote Pixel	Free access	Landsat 8	https://search.remotepixel.ca/	Satellite. 5-7 days.	Global
INPE Image Catalog	Free access	CBERS-4, alongside U.S., UK, and India's Earth-observing missions: Aqua, Terra, Landsat-8, ResourceSat, Suomi-NPP, DEIMOS, and UK-DMC 2	http://www.dgi.inpe.br/catalogo/	Satellite. 5-7 days	S. and C. America, Africa

JAXA's Global ALOS 3D World	Free access	30 m horizontal resolution; DSM, SRTM HGT	https://www.eorc.jaxa.jp/ALOS/aw3d30/l_map_v2003.htm	Satellite. Every 7 days	Global
VITO Vision	Free access	Proba-V, Spot-vegetation, Sentinel-2, Metor-AVHRR, Envisat-Meris). Resolution: 100m to 1km	https://vito.be/en	Satellite. 5-7 days	Global
DigitalGlobe Open Data Program	Free access	High-resolution satellite imagery	https://www.digitalglobe.com/company/about-us/	Satellite. Daily image capacity of more than three million km^2	Global
Geo-Airbus Defense	$30-40	Very High-resolution, SPOT, Pleiades, RapidEye, TerraSAR-X, 12-meter WorldDEM	https://www.airbus.com/space/earth-observation.html	Satellite. Daily and on demand	Global
SPOT 6/7	$5-8	High-resolution	https://eos.com/find-satellite/spot-6-and-7/	Satellite. Daily. On demand	Global
KOMPSAT-3A	$15-48	Very high-resolution	https://www.satimagingcorp.com/satellite-sensors/kompsat-3a/	Satellite. Daily. On demand	Global
WorldView	$18-52	Very high-resolution	https://www.satimagingcorp.com/satellite-sensors/worldview-3/	Satellite. Daily. On demand	Global
QuickBird	$10-50	Very high-resolution	https://www.satimagingcorp.com/satellite-sensors/quickbird/	Satellite. Daily. On demand	Global
IKONOS	$25-50	Very high-resolution	https://www.satimagingcorp.com/satellite-sensors/ikonos/ikonos-stereo-satellite-images/	Satellite. Daily. On demand	Global

Since the last decade, most studies have used Landsat data to analyze land cover changes through time given their availability since the 70s (Hemati et al., 2021; Wulder et al., 2019). Recently, the availability of satellite imagery is growing in number, frequency of available images per region, and resolution (Li & Roy, 2017). Among the freely available data, the Copernicus Sentinel-2 multispectral datasets offer a reasonably high-resolution for the ASGM sector: 10 to 60m depending on bands but interpolations can be run to increase the resolution of the 20m resolution bands to 10m (Gallwey et al., 2020; Nyamekye et al., 2021). Several platforms offer pre-processed satellite data that is analysis-ready with the possibility to combine multiple images into mosaics. This includes Google Earth Engine (GEE), Microsoft Planetary Computer, Food Agriculture Organisation (FAO) and SEPAL. This can help obtain cloud-free images made from multiple times data falling in an acceptable interval length. A detailed presentation of such platforms is provided in Table 4.

The field-based primary sources of data include ground truthing, reconnaissance, and citizen science techniques. These consist of the use of simple tools such as focus group discussions, indigenous knowledge, community surveys, key informant interviews, field observations, site surveys, and public participatory mapping. When conducting interviews as part of field data collection, stakeholders who represent various interests of the locality are selected. If possible, groups or individuals who are objective about the issues of ASGM may be selected. Questionnaires and interviews are the most useful tools for detailed data collection on people's opinion on the use of mercury ASGM operations in a locality. The interview questions may be structured or open ended and should be simple, and comprehensible. Another quick way to collect relevant data on the situation is a simple observation of what is visible in the ASGM host locality. During fieldwork, a site characterization may be conducted. This entails the collection of geologic and geomorphic data through measurement, sampling, and observation. Photograph taking is recommended. Sources of field-based secondary data include miners (both large and small-scale), central government agencies, local government, local people, the private sector, and the general public.

However, a combination of fieldwork with imagery will build a database that would span spatial and temporal scales greater than possibly through field-based data alone.

3.3.1.2. Database development and monitoring of Artisanal and Small-Scale Gold Mining using Remote Sensing

Time-series multiple-scenes satellite imagery are essential to document the transformation of a landscape from ASGM. Image classification techniques can be employed to delineate distinctive land-cover classes in mine sites. These classes may include affected waters (ponds and filled pits), exposed sands (mining sites) and exposed soils (from mining and forest clearcutting and burning). With reference to the different kinds of methods presented already, variables that can be detected through image classification include: (1) spatial dynamics (everything that is mappable in the Earth's surface), (2) biogeochemical parameters like turbidity and mercury concentrations in biotic and abiotic matrixes and (3) aspatial and population/community-based information. Each of these variable groups are associated with one of the earlier discussed methodologies. If data collection using these three methods is planned and performed in a coordinated manner, the ability to establish connections between the three parameter classes becomes easier. Field techniques such as aerial photography, interviews with ASGM miners, and sediment samples can be used additionally to model and develop statistics on the use of mercury and gold production in a locality. However, high-resolution imagery is recommended for detecting ASGM operations. Examples of high-resolution satellite imagery include QuickBird and PLANET data.

Satellite images can reveal the existence and emergence of tailings, which can be a sign of ASGM. Historical images show the host region and its existing conditions before the emergence of ASGM, while current scenes reveal the growth of ASGM and its related effects. The Australian Data Cube, the Swiss Data Cube and the Africa Regional Data Cube are a strong promise in this perspective. However, atmospheric conditions (cloud cover and seasonal burning) disturb the use of even high-resolution satellite imagery in mine pits and environmental effects observations. Thus, the use of radar can overcome the challenges of optical satellite imagery in monitoring ASGM. Radar is able to penetrate cloud-cover to retrieve ground data in terms of pit subsidence and land use and land cover changes. However, attention must be paid as high precipitations have been proven to affect the accuracy of the data (Forkuor et al., 2020).

Radar Interferometry uses multiple radar images of the same area, which have been taken on different dates and times for change detection. In this regard, two general approaches can be used. These are: (1) InSAR, which typically uses succeeding Radar images to increase the information in a scene or to develop a Digital Elevation Model (DEM) data and, (2) Repeat Pass Interferometry, which also uses Radar scenes of the same area but on different passes of the satellite. It is possible to identify changes in topography caused by ASGM with the use of geometrically corrected repeat-pass scenes taken on different dates. Change detection indicators include deforestation as well as water and soil pollution. Changes detected from Radar images can be used to quickly understand the extent and movements of ASGM operations in near real time (time scales of weeks, months, or years, depending on the objectives of a study).

Table 4. RS data processing platforms, their benefits and limitations

Platform	Link	Benefits	Limitations
ASM Spotter	https://business.esa.int/projects/asmspotter	- Relies on Planet Labs imagery - Localisation of ASM sites, their spatial extent and shape - Full-service solution, including support to the client in analysis and interpretation of results	- Images are provided manually by the user - Currently focused on Suriname - Not free
Google Earth Engine	https://earthengine.google.com	- Rich data catalog: https://developers.google.com/earth-engine/datasets/ - Computing power of Google - AI component (TensorFlow) - Free - Ease of use - User community - Python and JavaScript APIs	- Dependent on what they offer - Future pricing plans (Google Maps Story)
Open Data Cube	https://www.opendatacube.org	- Ease of use - User community - Widely adopted solution - Flexibility of ingestion of different raster data types - Python API and Open Geospatial Consortium (OGC) services - Variety of out-of-the-box algorithms	- Installation can be complex - Many dependencies with other open-source packages

Planetary Computer	https://planetarycomputer.microsoft.com	- AI component - Computing power of Microsoft - Free	Restricted data catalog (as of 2021) > not all Landsat archive is there
Remap	https://remap-app.org Publication: https://www.biorxiv.org/content/10.1101/212464v2	- Computing power of Google Earth Engine - Free	- Limited datasets (mostly Landsat) - Focuses on Ecosystems, IUCN Red List - Dependency to Google Earth Engine
SentinelHub	https://www.sentinel-hub.com	- Rich data catalog - Mature solution - APIs - Not dependent to Google or Microsoft	Commercial service (but not super costly)
SEPAL	https://sepal.io	- Ease of use - User community - Computing power of Google Earth Engine - R integration - Recipe system	Dependency to Google Earth Engine

3.3.2. Proposed guidelines

The guidelines proposed in this document focus on the use of RS for monitoring the applications of mercury for ore processing at ASGM activity areas and close neighbourhood. Maximizing the development benefits of ASGM while improving the social and environmental responsiveness of the sector was first addressed in the Johannesburg Plan of Implementation (JPOI) of the World Summit on Sustainable Development in 2002. The following three priority areas were identified in the JPOI:

1. The environmental, economic, health and social impacts and benefits of mining throughout their life cycle.
2. Enhancing the participation and beneficiation of local and indigenous communities and women in the mining sector policymaking.
3. Fostering sustainable mining practices through the provision of financial, technical and capacity-building support to developing countries and communities.

The guidelines herein proposed, therefore, suggest that first, local practitioners of ASGM, their associations and host communities should be involved in the policymaking process. Note that to properly enhance the participation of the local participants in ASGM sub-sector policymaking, they must first understand the implications of the different effects of mercury on both environmental and human health. This may be backed by scientific evidence that can be used to develop measures for improving the ASGM sub-sector towards enhancing endogenous growth and achieving the sustainable development of indigenous communities. Secondly, they may be introduced to the RS protocols for monitoring the use of mercury at the ASGM sites. The RS protocols introduced here, basically, start with environmental monitoring.

The principal environmental variables considered in the context of the widespread applications of mercury in ore processing by the ASGM practitioners and local communities are: (1) vegetation, (2) soil and (3) water. Using RS for environmental monitoring can be a complex activity. However, the following protocols provided in this proposed guide for regulatory policymaking would make the process easier.

1. Identify source of pollution. That is, track the specific location where the ASGM is taking place. Depending on the objective of the monitoring (water contamination, air pollution or soil contamination) and depending on the availability of resources in terms of money and accessibility of the area of interest, the most appropriate RS data source should be selected. An integrated use of high-resolution optical imagery, current and historical aerial photographs, SAR images and DSMs could be helpful in situations where mines are not easily distinguishable from the surrounding areas.

   Embark on fieldwork and sampling trips by first undertaking reconnaissance to the site. During reconnaissance and subsequent fieldworks, take notes and select sites for sampling. It also works utilising indigenous knowledge (IK) during fieldwork. Take soil, vegetative, and water samples using appropriate containers and safety equipment. That is in-situ data. These samples must be safely stored and well protected. It is also advisable to take photographs and videos during field visits to sites. These would serve as training data for RS image classification, calibration, and validation.

   The model should ideally be fed with training data consisting of a large set of labelled data. The higher the number of training data, the higher the performance of the model. The attribution of labels is a process that can be based on (1) existing and historical geographical datasets of mine extents at a given time, (2) existing and historical water, air, soil and vegetative cover data, (3) collaborative mapping of artisanal mine sites on high resolution true-color images by local people and, (4) evidence from fieldwork.

   Post-classification processing (automated where possible) should be defined in order to improve the distinction between ASGM sites and bare soil. Here, the location association technique can be employed. This is a spatial analysis technique which can determine the levels of water or soil mercury contamination with respect to the distance from an identified ASGM site. This technique can be executed in a GIS platform for passive monitoring. It is based on the hypothesis that the existence of ASGM activities in a particular place is an indicator of the presence of mercury in nearby waterbodies, soils, food crops and plants, ASGM activities being closely associated with the use of mercury.

   If seasonality has a role in land cover changes in the area throughout the selected series of images, its role could be quantified with statistical methods using the RS data after the classification. In case of dry environments, a morphological analysis could be helpful in further separating bare soil from mining sites. This might be useful in case of bed-rock mines as they are likely to feature a depressed morphology compared to the surroundings, but it would not make a huge difference when looking for alluvial mining sites which are generally located along rivers.

2. Identify the potential contaminant; in this case, mercury, from the RS data you have obtained. This requires a basic knowledge of the physical and chemical properties of the geology of the area (rocks and soils). It also requires an understanding of the chemical and physical properties of mercury to differentiate between, for example, acidic soils and water on one hand, and mercury contaminated soils and water on the other hand. That is, understanding the spectral signature of mercury, healthy vegetation, healthy soils and clear water. Indices such as NDVI, NDWI, MNDWI, and SAVI are mostly used to aid analysis and understanding. For instance, the presence of iron minerals in soils is an indicator for soil fertility and a potential for food crop farming in the area. The physical and chemical properties of mercury will help to determine: (1) its spectral reflectance and signatures in a given geological area, (2) the extents of surface, subsurface, and structural contamination in the environment, (3) an estimate of the associated potential health and/or environmental impacts, and (4) decisions on mitigation, remediation, and reclamation action measures needed at ASGM sites.

   Take samples to an approved laboratory for test and analysis. Compare the laboratory results with standard indices and guidelines for robust decision making. For a proper understanding of the laboratory results, seek expert opinion or IK. Expert opinion and IK are good sources for RS data and results validation. These protocols are suitable for both passive and real-time ASGM site monitoring of mercury contaminations.

3. Identify the "age" of mining activities to map hotspots of mercury contamination. This leverages on the temporal archives of RS data. Using historical data, it is possible to identify areas which have been mined for a long time or previously mined and abandoned. Such places with long history of ASGM operations can be mapped as hotspot areas due to the accumulation of mercury in the soils and both underground and surface water reservoirs. This is an important mechanism for detecting hotspots and building mitigation protocols.

4. Assess mercury pollution through linking it to turbidity and suspended matter in the rivers. That is to simply link with field samples as in objectives two and three above. A reverse analysis of historical RS data baseline conditions of existing and previous sites would facilitate linking the spectral signatures of samples from trees and shrubs to satellite data as mercury contamination produces a unique colouration in the spectra.

5. Establish real-time Satellite monitoring station. This presents a unique opportunity for regulatory agencies to directly collaborate with RS data providers. Further establish sub-stations across ASGM zones to transmit 24/7 high resolution satellite data to main receiver station. These data should be processed on the spot for (1) mercury hazard identification, (2) monitoring the emergence of new activities and/or expansions of existing activities and spillage beyond standard thresholds, and (3) real-time feedback mechanism to regulators, host communities, and miners.

6. With respect to real-time monitoring of ASGM activities and the presence of mercury contamination using RS methods, identify enclaves and delineate these into zones. Train local regulatory operations and supervisory teams in the zones on the use of GPS and mechanised mobile phones for prompt reporting to sub-stations and onward

transmission to the main station. Deploy quick response team to sites to address intrusion and observed changes in plants, soils and waterbodies. These are indicators of mercury presence in unknown sites. This model is demonstrated in Figure 2.

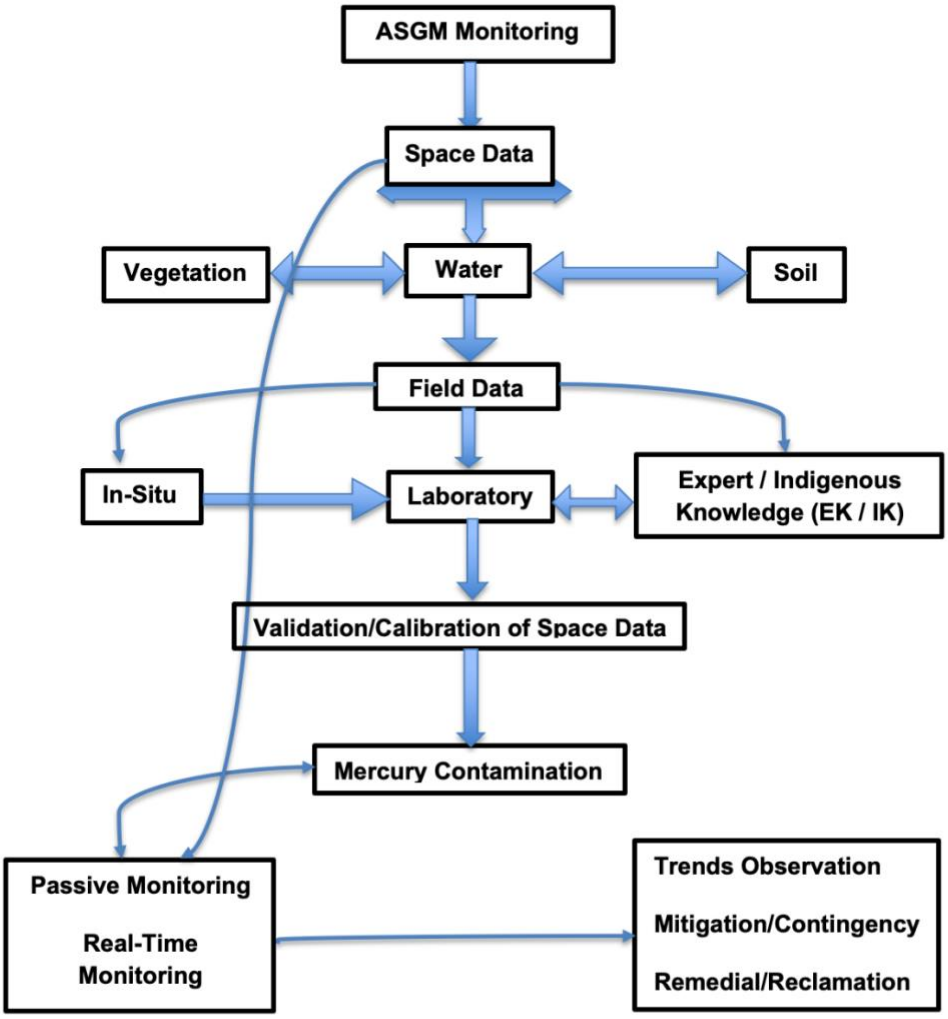

Figure 2. Proposed Guide for Monitoring Mercury Contamination in ASGM sites

3.3.3. Providing relevant information through science-policy interfaces

RS has an important role to play in terms of providing trusted, scientific-based, multi-scale (both spatial and temporal) and open data to decision makers.

Importantly, this supposes that we transform raw data into information and knowledge to inform decisions, investments, consumers and citizens. One challenge is to update this transformation process frequently, because environmental issues (hence related decisions) may change rapidly.

Another challenge is to include stakeholders in the design and implementation of the entire science-policy process. This is particularly important in the case of ASGM for building trust between the different stakeholders.

An additional challenge is the need to understand the uncertainties involved. Good policy decisions can only be made with an understanding of the underlying complexity and probabilistic nature of the presented conclusions and recommendations. This is relevant particularly to remedy certain limitations like accuracy of RS techniques and crime mapping, as presented in the next Section. Not all data, information and knowledge need to be certain or even high quality (even if it is certainly preferable) to be useful, as long as the level of confidence is understood by whomever is making a decision based on it. Ultimately a good decision will be based on multiple lines of evidence, some of which are stronger, some weaker – and all of which are useful.

In addition to providing actionable information, one of the key challenges related to the science-policy gap is for scientists to develop smart interfaces for those end users. If they want to facilitate the navigation into those interfaces, it is critical to understand the typology of the end users and to collect their requirements. A good practice can consist in consulting various types of end users of the future interface, including local communities and local mining associations. This can be done for instance through stakeholder workshops, webinars, or questionnaires, to determine their typology and to inventory their technical capacity.

When developing an end user interface that has a geospatial component, as this is the case with RS, user friendliness and simplicity of the navigation are often strong requests from users, as many of them are not experts in GIS, especially local communities and local mining associations. An interface must then be visually attractive; thus, user experience and user interface (UX/UI) testing can be conducted by early adopters of the interface at different steps of its development.

Furthermore, some of the technological choices in the development of the interface can be guided by the need to have specific functions in place for efficient and smart visualization and use of ASGM related information. In many cases, the capacity to provide dashboards for monitoring environmental information over time in a smart way, to support multiple languages and to tell stories are perceived by the user community as key functionalities of the interface.

Data quality is also a key challenge that needs to be addressed by providing the necessary tools to the end users through the interface. This can include tools for documenting the data (metadata) and for informing about their degree of reliability, openness, technical accessibility, and accuracy –the latter being important to communicate to end users in the case of RS.

From a technical perspective the development of the interface must consider the low Internet connectivity that can be encountered in the targeted end users' countries (which is often the case in areas where ASGM occurs).

3.4. Case studies

3.4.1. Introduction

UNEP/GRID-Geneva has implemented two case studies to show concretely how RS tools and methods can be used to generate key indicators on mining activity. The first case study is focused on the Kamituga region in the Democratic Republic of the Congo and for RS analysis, UNEP/GRID-Geneva used an in-house implementation of the Open Data Cube[2]. The second one focuses on the Madre de Dios region in Peru and is based on the use of GEE.

3.4.2. Case study using the Open Data Cube

This first case study aims to show how RS analysis can support policymakers to monitor mining activities at the local and / or regional level and to design interventions to reduce negative impacts of mining by quantifying the extent of land cover/land use changes over time.

Kamituga is a mining town located in the province of South Kivu in Eastern Democratic Republic of the Congo. Its mining history dates to the 1920s when gold deposits were first discovered with industrial gold production starting in the 1930s (Buraye et al., 2017). Since the 1960s, Kamituga has seen the development of artisanal mining and informal trade networks. During the two Congo wars, artisanal mining activities expanded and Kamituga's population more than doubled (Buraye et al., 2017). In 2002 the gold concession of Kamituga was acquired by Banro and exploration activities started in 2011 (Stoop & Verpoorten, 2021). Nowadays, artisanal mining is the main source of income for the inhabitants of Kamituga (Geenen, 2011). According to the 2015 population census, the population of Kamituga is around 130,000 inhabitants (187,000 counting neighboring villages) and between 13,000 and 15,000 artisanal miners operate on Banro's concession (Stoop & Verpoorten, 2021).

3.4.2.1. Methodology

Study area

A first selection of artisanal gold mines that could be good candidates for the study case was made from the catalog of “Artisanal mining site visits in Eastern DRC”[3] published by The International Peace Information Service (IPIS). This dataset contains the locations of several hundred mines as well as information collected in the field. To keep the best candidates, only gold mines visited since 2016 with a number of workers greater than 1,000 were selected. Then, each site was studied using Google Earth satellite imagery to ensure that its extent and its environment (e.g., proximity to dense vegetation, rivers, water bodies, urban area) allow RS analysis. One region stood out, the city of Kamituga with no less than five eligible gold mines in its surroundings, i.e., mines with more than 1,000 artisanal miners.

A first study area was defined in the Western part of Kamituga where the Bipasi and Kazibe mines are located (Figure 3.). The map on the bottom-left corner (Geenen et al., 2021) allows locating this study area within the country. A first set of results was produced by applying the vegetation fractional cover algorithm to this area and was presented by UNEP/GRID-Geneva to the IPIS team that provided the ASGM data for Eastern Democratic Republic of the Congo. The relevance of the use of Kamituga as a study case was confirmed during this interview with IPIS as the city is a major place for mining and trading activities in South Kivu. In addition, the IPIS team recommended using a larger study area for the analysis to cover the entire city as

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[2] https://www.opendatacube.org/

[3] http://geo.ipisresearch.be/geoserver/web/wicket/bookmarkable/org.geoserver.web.demo.MapPreviewPage?

well as the region to the South. The reason is that a larger study area would allow better analysis in land cover changes, provided there are several dozen artisanal gold mines located in the South of the city –most of their ore being sold at Kamituga-- and that the mining activity in the region is very fluctuating over time. Therefore, a second study area was defined according to IPIS recommendations (see Figure 3.).

Figure 3. Study areas. In red, the study area covering the Bipasi and Kazibe mines. In green, the study area covering Kamituga and the region South of the city.

Infrastructure

To perform RS analysis, a Data Cube on Demand (DCoD) (Giuliani et al., 2020) was deployed in a virtual machine (4 CPU, 32GB RAM, 250GB HDD) on the infrastructure of the University of Geneva. GeoServer and the online, open-source cartographic platform MapX[4] (Lacroix et al., 2019) are used to publish and visualize the results generated by the DCoD. The complete architecture of the system used for the case study is as follows (Figure 4):

[4] https://www.mapx.org/

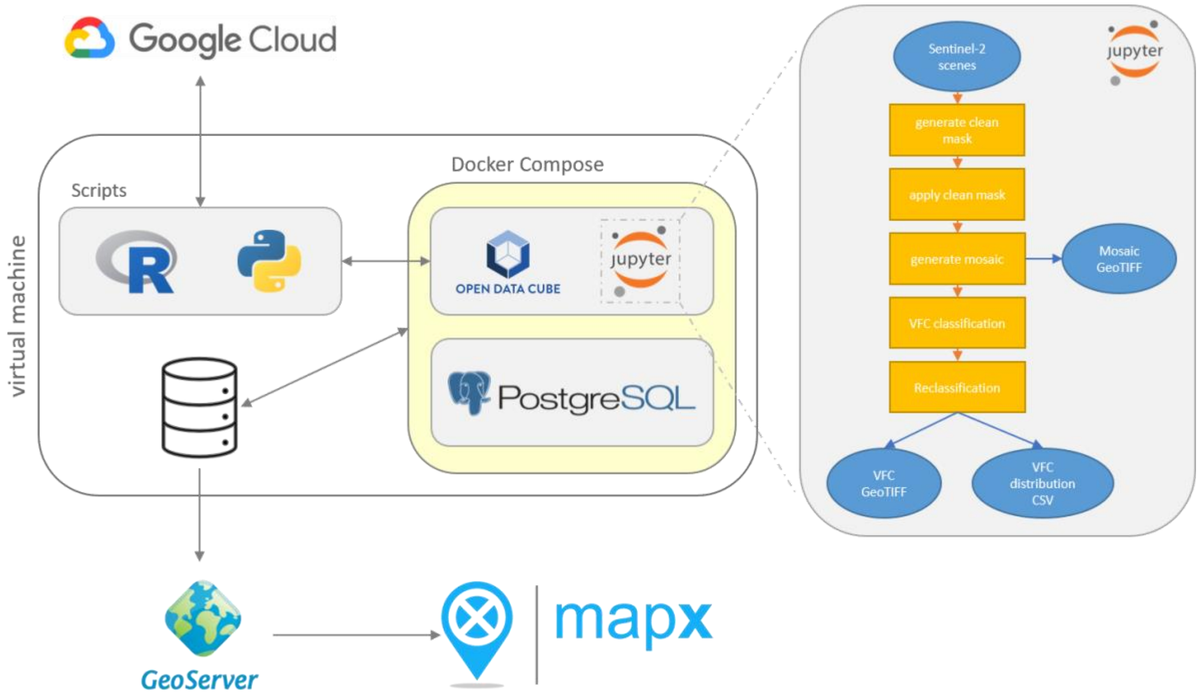


Figure 4. Technical components of the infrastructure set up for the case study and data processing workflow.

- Python and R scripts to index Sentinel-2 scenes from Google Cloud[5].
- Data Cube on Demand (DCoD) for RS analysis.
- GeoServer to publish results in compliance with Open Geospatial Consortium (OGC) services.
- MapX frontend to visualize the results.

Algorithm and data

Land cover changes across large areas can be monitored over time using Vegetation Fractional Cover (VFC) that estimates the fractions of Photosynthetic Vegetation (PV), Non-Photosynthetic Vegetation (NPV) and Bare Soil (BS) for each pixel. The sum of the three fractions should be 100% and VFC is shown in Red/Green/Blue (RGB) colors. Although originally developed for Landsat 5/Landsat 7 products, the vegetation fractional algorithm (Guerschman et al., 2015) was implemented by UNEP/GRID-Geneva and tested on Sentinel-2 products as they have a 10m resolution, which is more suitable for monitoring artisanal mining activities than Landsat products (30m resolution). These tests being conclusive, Sentinel-2 products covering the study areas were downloaded from Google Cloud and indexed in the DCoD using R and Python scripts developed by UNEP/GRID-Geneva. According to research carried out, the dry period in eastern Democratic Republic of the Congo usually runs from early June and late August leading to less cloud cover. Therefore, the indexation was carried out for these three months specifically from 2016 (1st year available)

[5] https://cloud.google.com/storage/docs/public-datasets/sentinel-2

to 2021. Jupyter notebook was used to interact with the DCoD and process Sentinel-2 products as follows:

1. Data was cleaned by creating a clean mask for clear land and water pixels. Shadow, snow, cloud, and 'No Data' pixels were masked out.
2. As the region is quite cloudy, generation of an image mosaic using all the indexed scenes for a year (3-month period: June 1 to August 31).
3. VFC calculation (at this stage, the output is in RGB colors).
4. To facilitate the interpretation of VFC, each pixel of the output produced in Step 3 was assigned the most represented fraction as a value. The final VFC output is therefore a raster[6] composed of three classes: BS = 1, PV = 2 and NPV = 3.
5. VFC transitions from one year to the next were calculated using rasters produced in Step 4:

   transition = VFC_{year} + (VFC_{year+1} x 10)

In the end, the following outputs were generated by the notebooks: one image mosaic per year; VFC (per year) including one raster (3 classes) and a CSV compiling the pixel count by class; VFC transition (per couple of successive years) including one raster (9 classes) and a CSV compiling the pixel count by class.

3.4.2.2. Results

First, the VFC products generated using the DCoD were compared with the location of the mines visited by IPIS using satellite images to ensure that the classification fits what was observed in the field. This verification showed a good correspondence between the model and the observations. VFC products can be used to monitor mining activity by making the following hypothesis on the three classes:

- Photosynthetic vegetation = green vegetation (e.g., leaves, grass, and growing crops).
- Non-photosynthetic vegetation = mining area.
- Bare soil = urban area.

The classification made with the VFC algorithm allows monitoring of mining activities with better confidence when the study area is defined at site level. Indeed, by comparing the two study areas, the land cover is more homogeneous at the site level (Bipasi and Kazibe mines) and the hypothesis that the NPV class represents mining areas is more accurate. For VFC calculated at the larger scale, the land cover is more heterogeneous. Some fields and river sections rich in alluvium are classified 'NPV', making the results less accurate.

[6] This type of data shows an image made up of a matrix of pixels, each pixel having its own values

The VFC and VFC transition rasters from both study areas were published in GeoServer[7] as this technology allows visualization in cartographic platforms such as MapX. For each of the study areas, a layer was developed in MapX to visualize land cover changes in an interactive and comprehensive way. The delimitation of the study area is displayed in the map, and VFC and VFC transition results are displayed in a dashboard composed of 5 features (Figure 5):

1. Interactive map that allows to swipe between two rasters and so to compare VFC between two years.
2. Bar chart showing the distribution of the vegetation cover fractions over time.
3. Line chart showing the trends of the vegetation cover fractions since 2016 (change in percent).
4. Table summarizing the VFC transitions from one year to the next.
5. Interactive map that allows to swipe between two rasters and so to compare image mosaics between two years.

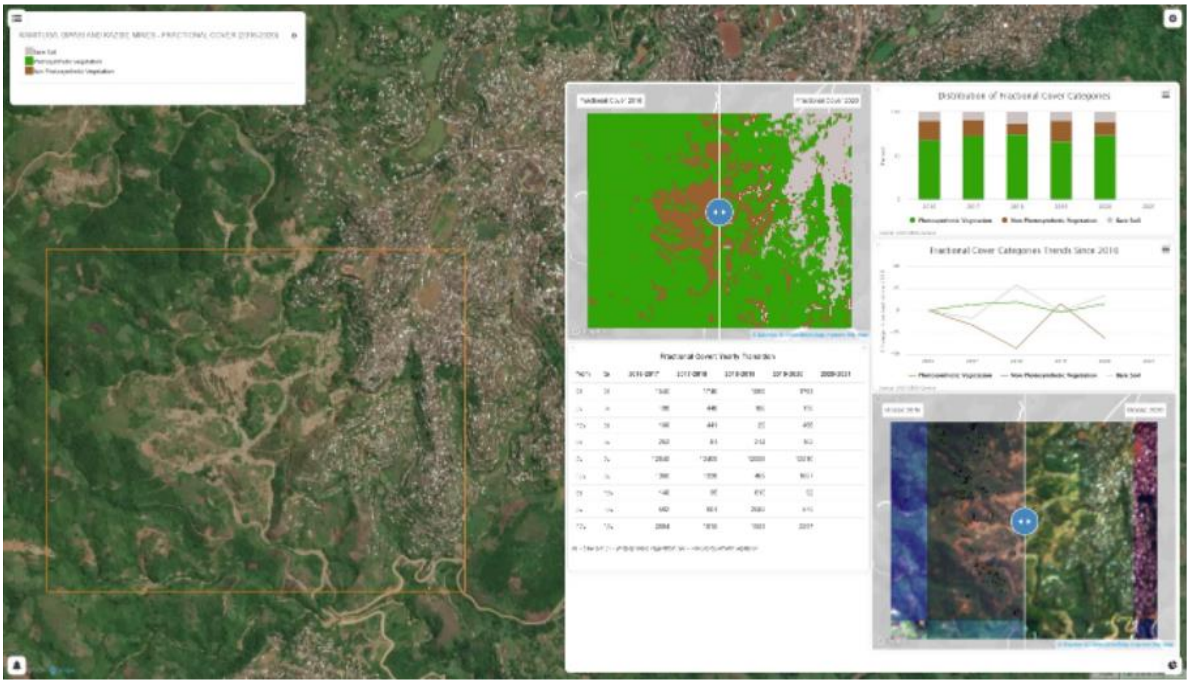


Figure 5. Screenshot of the layer developed for the study area covering the Bipasi and Kazibe mines.

The “Artisanal mining site visits in Eastern DRC” dataset (IPIS, 2021) was also published in the project as it is sometimes difficult to identify mines on the MapX aerial base map. These field observations can also be used to verify the VFC classification for a specific mining area. It should be noted that the IPIS dataset does not list all the mines in the region.

The three geospatial layers developed in the frame of the case study can be accessed using the following link:

7 https://datacore.unepgrid.ch/geoserver/rs_for_asgm/wms?service=WMS&version=1.1.0&request=GetCapabilities&format=text/xml

https://app.mapx.org?project=MX-IY9-QCF-ILZ-UVO-07Y&views=MX-BD2ZB-CPRZ6-ISSWP,MX-QSNYV-VWM4T-1T4NT,MX-RQ6YP-SP29M-Z01X6&lat=-3.899&lng=20.376&z=5.256&viewsListFlatMode=true&language=en

In MapX, the products derived from the VFC classification show a significant decrease in the area assigned to the NPV class for both study areas. Assuming that this class mainly represents mining area, this can be interpreted as a decrease in the impact of ASGM activity on the land use / land cover. However, it should be noted that the BS class, interpreted as urban area, has been increasing since 2016. This shows that the urban growth observed in the region since the end of the 1990s has not stopped.

3.4.3. Case study using Google Earth Engine

To showcase the benefits of the GEE platform here are two basic examples showing how processing of RS images can be done with this cloud-based platform.

The targeted area is near Huaypetue in the Madre de Dios region of Peru. It is an area with well-known ASGM activities.

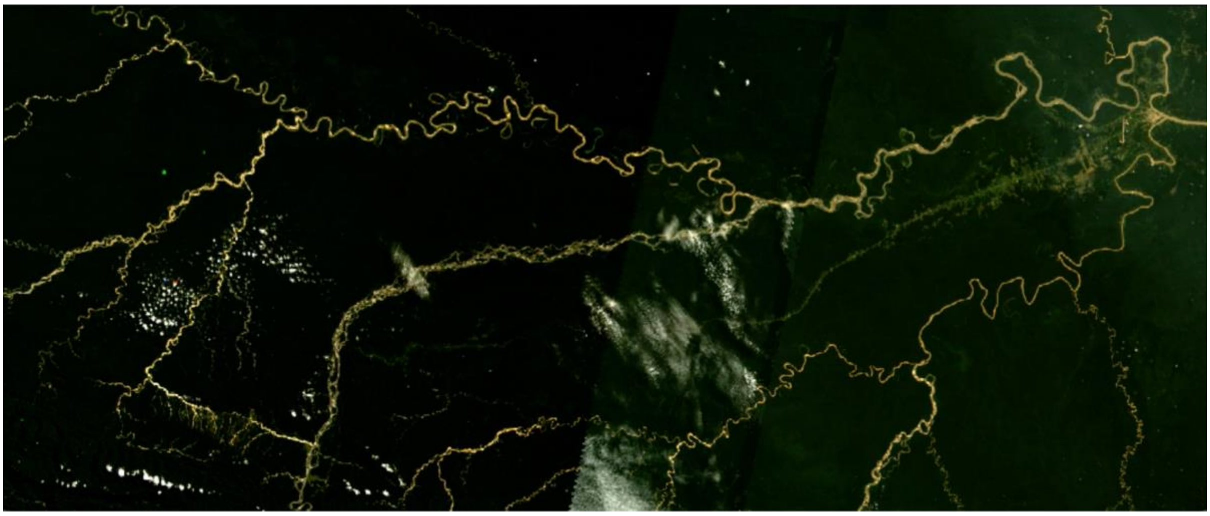
UNEP/GRID-Geneva created a time-series movie using yearly Landsat true-color composites from 1984 to 2020 (see Figure 6**Error! Reference source not found.**).

The video can be downloaded at:

https://drive.google.com/file/d/1WldWQ8zHVTgvIvDZ_sCoaV4r9PM0fdis/view?usp=sharing

The code is available at:

https://code.earthengine.google.com/6e3dffa0d85c542e54065eded3f5d77e



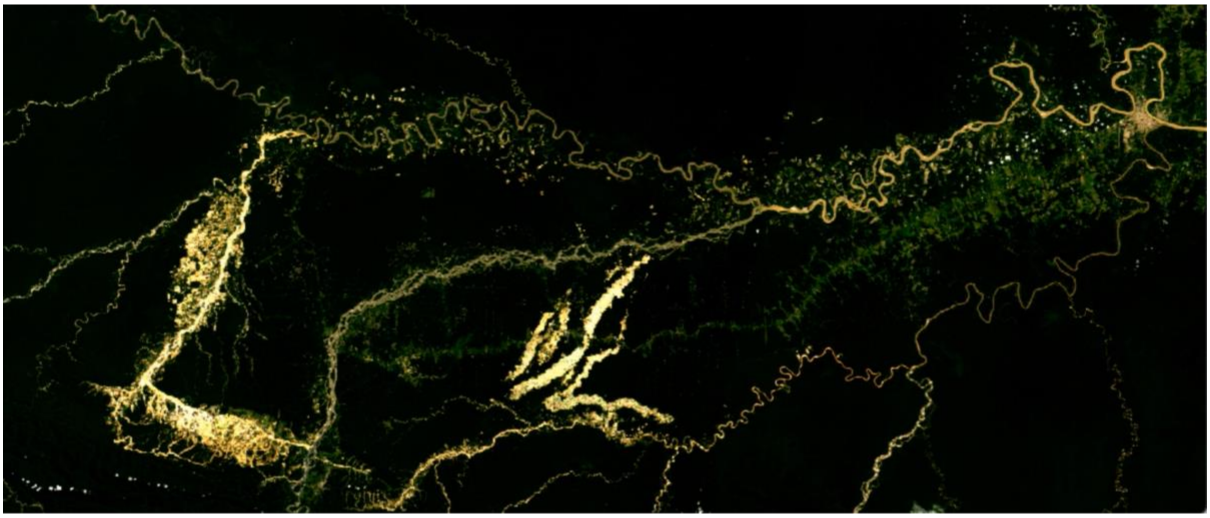


Figure 6. 1984 (above) and 2020 (below) Landsat yearly true-color composite over the Madre de Dios region (Peru)

One can see that beginning in the late 1990s, large areas around rivers turn from green (rain forest), to brown (cleared areas for mining). The trend seems to accelerate in the last 10-15 years.

The second example uses Sentinel-1 imagery to detect land changes from polarized channels (see Figure 7).

The code is available at:

https://code.earthengine.google.com/d9581816bb0ef6e8b758747898be2d81 (Earth Engine registration needed).

It shows important differences between 2016 and 2021 that can be attributed to deforestation related to ASGM activities in the region. All the newly bare areas appear in black.

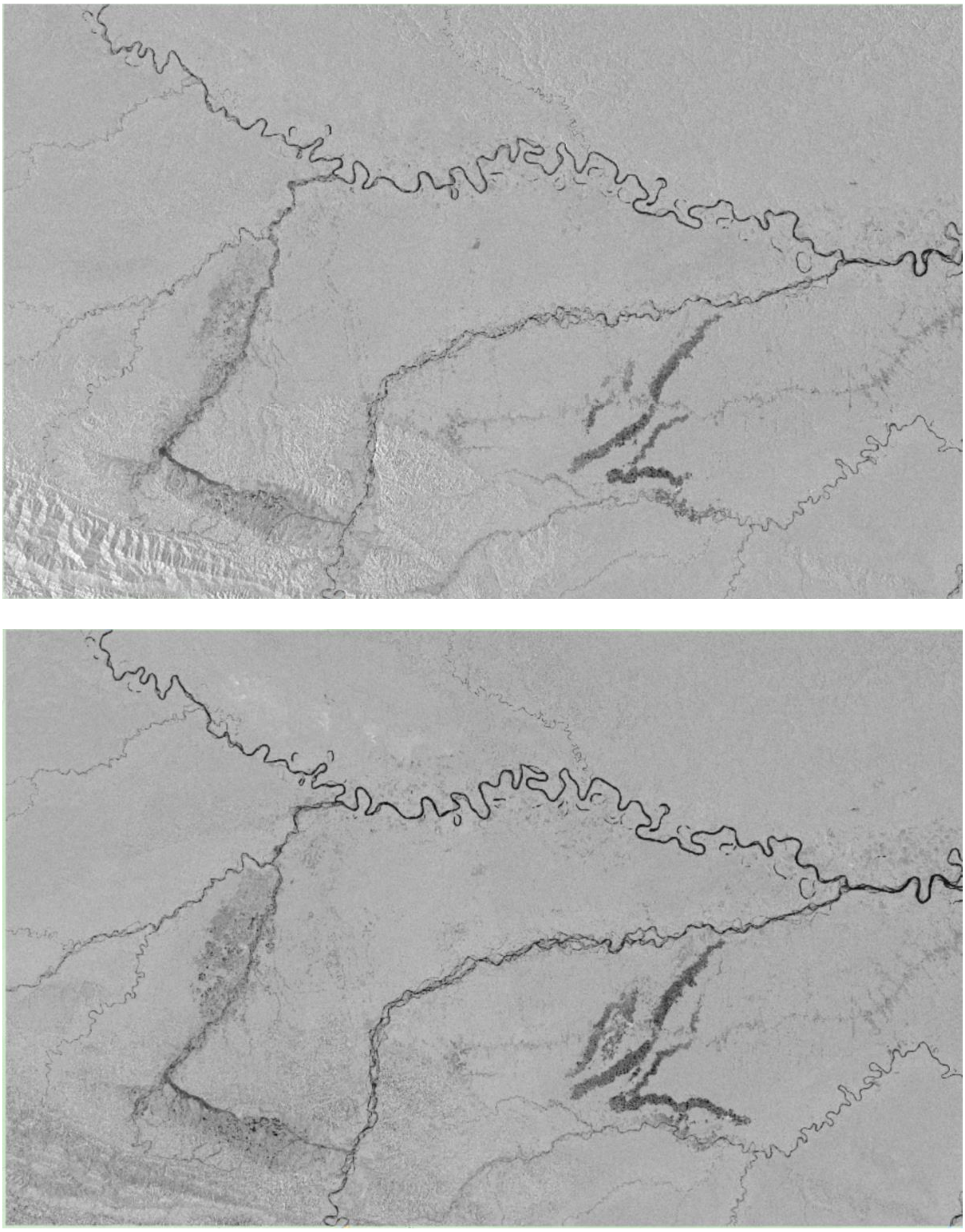


Figure 7. 2016 (above) and 2021 (below) Sentinel-1 VV weekly composite over the Madre de Dios region (Peru)

3.4.4. Conclusion and recommendations

These case studies demonstrate that RS methods and tools can be used to monitor the impact of mining activities on land cover. The development of cartographic and statistical products allows disseminating results in a form understandable by a non-technical/non-expert audience and therefore, it facilitates the management of artisanal mining policies.

For what concerns the first case study, although the VFC algorithm was not developed specifically to monitor artisanal mining activities, it produced results allowing to quantify (within a certain margin of error) the evolution of the surface exploited by the mines, the gain or loss of vegetation and urban development. The accuracy of the VFC classification has been assessed using visual inspection. UNEP/GRID-Geneva recommends implementing a quantitative accuracy assessment that would allow to identify and quantify classification errors (Congalton, 2001) for better informed decision-making. UNEP/GRID-Geneva also recommends using the VFC algorithm on an area focused on a single mine to ensure a more accurate classification. Other implementations of VFC or even other land cover classification methods may be more suitable for monitoring artisanal mining activities. Although going beyond the scope of this case study, it would be relevant to identify and to implement these methods in the DCoD to compare their results and thus find the most suitable method available.

The second case study shows the ease of use of the GEE platform to quickly monitor (potential) impacts of ASGM activities in a given region. The analyses performed under this case study can be further refined to get more detailed information such as the percentage of changes but still from a decision maker perspective this can already be powerful communication means to understand the issue at stake.

4. A summary of the potentials and challenges of using Remote Sensing for Artisanal and Small-Scale Gold Mining monitoring

The use of RS data in ASGM monitoring has several benefits but also some limitations, mostly related to the technical competences that are required to properly employ RS techniques and obtain the most accurate results out of them.

Benefits can be summarized as:

- Analyze large geographical areas at the same time.
- Analyze back in time (e.g., time-series analysis).
- Study inaccessible/remote areas.
- Multispectral information (optical and radar) can be combined to extract different information on a given area.
- Integrate the results of ASGM monitoring with field data in order to calculate proxy data at past times or in large space (e.g., mercury concentration in water can be calculated using a correlation function between mercury concentration at times and RS index values from satellite imagery).
- Integrate the results of ASGM monitoring with other geographical data in GIS software in order to understand cause/consequence relations between different factors.
- Collaborative mapping can help define the labelled training data for supervised image classifications of RS data.
- Large and increasing availability of processing platforms, pre-processed data and available tools can facilitate the workflow compared to previous times.
- LULC methods applied to ASGM are being studied in research and will likely increase their accuracy and ease of use through time.
- RS data of higher resolution and frequency of coverage on a given area has increased considerably in the last decade.
- The use of medium-resolution satellite images such as Landsat (30m), Sentinel-2 (10m) SPOT (5m), and CBERS-2 (260m), are capable of revealing ASGM operations at a large-scale with a single scene than high-resolution sensors.

Limitations can instead be summarized as:

- RS techniques require technical competences that are present in scientific communities but can instead be absent or not high enough in policy agencies and governmental agencies.
- Technical competences can be rarely present in local mining associations and local communities, so far decreasing the involvement of the latter in the monitoring project and the policy development. This can often undermine local trust, inflame tensions, and render alternative “grassroots GIS” strategies impracticable.
- Accuracy of RS techniques depend largely on human choices and should, therefore, be proof checked before policies are designed based on its results.

- RS technology used for environmental surveillance purposes may lead to “crime mapping”, which prioritized enforcement over engagement with communities and can enhance socio environmental disputes.
- Not all types of satellite sources perform the same way. For instance, single band radar data (e.g. RADARSAT sensor) seem to have lower accuracy than multi-band radar data (e.g. SIR-C) in detecting gold mining washing sites.
- Use of optical imagery can be hampered by clouds. Consequently, the use of radar and/or dense time-series analysis techniques are relevant choices to overcome this issue.
- RS data cannot easily distinguish mining areas from bare soil due to similar spectral signatures.
- Low vegetated areas might require a more complex approach compared to the vegetation change monitoring workflow that can be applied in most tropical places where ASGM occurs.
- The medium-resolution sensors do not fully capture activities in smaller areas such as along the shores of rivers. Such resolutions fail to separate linear features along river edges from natural river shorelines.
- The exposure of natural river shorelines depends on water depth and season.
- Medium-resolution images do not account for ASGM river dredging.
- Medium-resolution satellite images are available on a longer time span compared to high-resolution imagery, but their limited frequency does not easily allow following the rapid evolution of ASGM activity in a given area.
- The limited size of single scenes of high-resolution satellite images could result in expensive prices for projects that require several scenes to cover a large area.
- Large forest canopy cover can affect the visibility of satellite sensors.
- Comparability of a hotspot from one season to another is difficult. Seasonality limits the use of remotely sensed satellite data on ASGM monitoring.
- ASGM activities are not always detectable by night light emissions.
- ASGM is an activity, which can quickly move from one area to the next one since artisanal mining communities often consist of migrants without any roots in local villages next to the ASGM active spots. This dynamic nature should be carefully considered, mostly depending on local circumstances, to get a realistic sense of the reactivity of ASGM tracking by RS to allow government officials to act/intervene rapidly (often in remote areas), while ASGM is still going on, instead of just taking note of long gone ASGM activities.

5. Conclusions and recommendations

5.1. Conclusions

This guidance document is based on an extensive review of scientific and grey literature that use satellite and aerial RS analysis, and GIS technologies as the primary means of monitoring ASGM activities. It served as an input to develop this technical guidance document aiming at showing the benefits and limitations of using RS technologies to support ASGM monitoring, policy development, implementation and evaluation, with a special focus on the context of the Minamata Convention on Mercury.

This guidance provides insights on benefits and challenges of RS techniques based on a comprehensive literature review on the various uses of RS for ASGM detection and monitoring, protocols and guidance on satellite image analysis. This document also includes recommendations targeting decision makers providing them with evidence-based insights to support decision making and policy implementation. Finally, this document demonstrated two concrete case studies featuring ASGM activities in Peru and in the Democratic Republic of the Congo, illustrating how RS can support the identification and quantification of mining activities occurring in remote areas.

This document aims at enabling users to:

- Understand how to use RS to detect and monitor ASGM activities.
- Identify challenges and limitations of RS technologies applied to ASGM activities.
- Raise awareness of decision makers of the potential for RS to be applied as a tool for monitoring ASGM.
- Provide tangible insights on the use of RS to inform decision making.

RS and GIS techniques are valuable means to provide consistent information on ASGM activities and contribute to get complementary information from field data/measurements to support official/national statistics. It also helps to have harmonized information/indicators at different geographical scales. These techniques offer, simple, replicable, cost-effective, synoptic, scalable and rapid alternative to derive information on ASGM activities. It can be combined with other geospatial and socio-economic data to help contextualize the generated information.

5.2. Recommendations

5.2.1. For government officials and policymakers in Artisanal and Small-Scale Gold Mining countries

Government officials and policymakers are encouraged to include GIS and RS tools in programmes that aim to monitor ASGM activities and/or to define related policy.

RS can be used to identify and monitor ASGM activities, and that information is useful in establishing baseline of mercury use in ASGM, and plan/evaluate policies to address it. RS tools are capable of providing reliable and up-to-date data on the environmental impacts of areas surrounding ASGM activities. The dissemination of RS outputs in the form of cartographic and statistical products and information makes them understandable by a non-technical audience and therefore, it facilitates the design of artisanal mining policies.

Since RS techniques require technical competences that are usually present in scientific communities but not necessarily in governmental agencies or policy agencies, government officials and policymakers are encouraged (1) to develop capacity building among mining administrations lacking technical knowledge and (2) to solicit the know-how of researchers from local universities.

More widely, multidisciplinarity is highly recommended. From a very practical perspective, combining RS data/information with survey/interview results on the one hand and with other geographical data (e.g., social, health, conflict, demography etc.) in GIS software on the other hand is relevant to understand cause/consequence relations between different factors. Another source of useful data to consider is locally obtained biogeochemical parameters collected in-situ. Those can indeed help understanding the effects of mining-induced pollution over biota using RS-derived proxies. Such approach requires the different techniques to be tuned in order to reduce the errors induced in the deriving process.

Technical competences are not always present in local communities and local mining associations. This can decrease or compromise their involvement in the monitoring programmes and in the policy development. Sometimes this can undermine local trust and exacerbate tensions. Government officials and policymakers are therefore encouraged to pay extra attention to include local communities and artisanal miners in the elaboration of ASGM policies and programmes based on RS analyses and outputs.

Finally, it is recommended that government bodies keep in mind that using RS techniques can have unintended consequences as they can favor crime mapping and lead to prioritizing enforcement over engaging with local communities. This is mostly associated with investigative (e.g., to understand what has happened once a crime has been committed) and evidentiary processes (e.g., the collection of evidence to be used in court). If a law enforcement agency has adopted intelligence based policing strategies, utilising RS data to better understand the ASGM phenomenon on a general level would be similar to the needs of general ASGM policy development.

5.2.2. For researchers

Concerning scientific research efforts should be directed towards improving LULC methodologies applied to ASGM. In particular, the use of ML/DL techniques together with data fusion techniques (e.g., optical, radar, UAV, lidar, in-situ, crowded-sourced), time-series analysis and stack of analysis ready data organized in Data Cubes are relevant means to reliable and consistent LULC information.

Additionally, the development of models integrating satellite data with in-situ measurements can help, first, to provide better estimates of pollutant contents, and second, training and validating outputs of ML/DL algorithms.

Further research is also needed to build models based on data from intensively in-situ monitored sites where relationships between mercury concentrations found in different environmental matrixes and parameters detectable by RS can be made. These relationships could be used to predict mercury concentrations in remote areas with similar site-characteristics based on RS data alone.

Finally, great advantage could bring the development of a methodology able to identify different types of ASGM activities by the recognition of their characteristic geographical shape, dimension and distribution.

5.2.3. For International Organisations and funders

International organisations and funders are encouraged to build on RS methods in projects and monitoring programmes for policy development, implementation and evaluation in the ASGM sector. This approach is recognized to be particularly useful especially in remote or difficult-to-access areas. International Organisations are therefore encouraged to foster collaborations with RS scientists while conducting ASGM monitoring projects, but also to develop a broader reflection on its usages and consequences.

While RS has proven to be highly relevant for land cover changes and pollution monitoring, it is crucial to be cautious when using such technologies and its outputs in policies and programmes. The use of RS by International Organisations can be perceived as explicitly supporting a top-down approach for decision making and measures enforcement. International Organisations and funding programmes are therefore encouraged to engage discussions on the consequences of RS, especially in terms of surveillance and crime mapping, to dissociate direct law enforcement from application of RS produced knowledge.

Additionally, International Organisations are encouraged to develop a reflection on the role of RS in emphasizing ASGM as a source of dispute. Evidence from the literature shows that the outputs of GIS and RS tend to bring a focus on one or several particular dimensions of an object or a situation. In the case of the ASGM sector, RS analysis points out the negative effects of such activities on the environment. However, by doing so, RS contributes to highlight some aspects of the sector but obscures others, acting as a source of friction between various dimensions of the ASGM activities. This can be detrimental to local populations as it contributes to undermining trust in both ASGM monitoring programmes and in the very institutions themselves. To mitigate those effects, International Organisations and donor programmes are encouraged to include other ASGM dimensions in their RS analysis where possible, and to include other stakeholders (researchers, government officials, local communities' representatives, artisanal miners) in the elaboration of RS-based funding programs and projects to allow equitable ASGM monitoring policies.

5.2.4. For data and software providers

One of the largest barriers against wide use of RS data for ASGM monitoring is the data collection process, which involves the choice of the most suitable data source, the download of several scenes that cover the area of analysis and the pre-processing of the images to be able to start the image-classification process. This whole process has fortunately been greatly improved in the last decade with the creation of platforms that propose pre-processed "ready-to-use" satellite imagery from different sources such as GEE and technologies that facilitate the whole process such as the Data Cube. This is the direction to go as it considerably reduces the time required to perform RS analysis in ASGM monitoring projects. The large availability of free-satellite data should also be seen as an incentive for software developers to offer pre-processed data and tools to facilitate the data pre-processing given the likely increasing data availability in the future and the increasing problems for users to navigate through the vast amount of different types of RS data that will be available. The same can be said for the processing capabilities that are offered by some platforms such as GEE, which externalize the data processing so far allowing everyone to perform RS image classification no matter what their hardware capabilities are.

Although the research focusing on RS techniques applied to ASGM monitoring encourages the use of machine-learning algorithms with its positive results, application articles and reports on monitoring projects generally do not fully exploit the potential of machine-learning algorithms in image-classification of RS data but rather use less performant image-classification algorithms and/or involve manual decisions in the process. It has been recognized that the uncertainty on how to use and implement machine-learning techniques is a blocking factor for their use with RS data and that this is influenced by algorithms' availability in software that allow image-classification processing of RS data. Therefore, platforms and software allowing image-classification processing should keep up with the advancement in research on ML algorithms and facilitate, where possible, the parameterization of those algorithms to users.

Finally, one of the key challenges towards efficient the science-policy gap is for scientists to develop smart interfaces for those end users. If they want to facilitate the use of software, it is critical to understand the typology of the end users and to collect their requirements. When developing an end user interface that has a geospatial component, as this is the case with RS, user friendliness and simplicity of the navigation are often strong requests from users, as many of them are not experts in GIS, especially local communities and local mining associations.

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