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Article

Modelling Accessibility to Urban Green Areas Using Open Earth Observations Data: A Novel Approach to Support the Urban SDG in Four European Cities

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Abstract: Cities are recognised as key enablers for the world's sustainable future. Urban sprawl and inefficient use of land are important issues significantly impacting the provision and use of open green spaces. The United Nations Sustainable Development Goal (SDG) indicator 11.7.1 aims at globally monitoring the amount of land that is dedicated by cities for public space. In Europe, the indicator *"Share of urban population without green urban areas in their neighbourhood"* is supposed to correspond to the SDG11.7.1 but is currently on-hold due to methodological issues and lack of data. Moreover, to efficiently assess public space conditions, timely and spatially disaggregated information is essential but not yet widely adopted by urban practitioners. Hereafter, we use a combination of satellite and crowdsourced Earth Observations (EO) to model physical accessibility to urban green spaces in four European cities. Findings suggest that it is technically feasible to derive information on the share of urban population without green urban areas in their neighbourhood. Results demonstrate that the proposed methodology represents a consistent, valid, reliable, low-cost, timely and continuous source of information for sustainable urban development. Open and free EO data can be a good complement to enhance official and traditional statistics on urban areas facilitating EU reporting against the SDG indicator for better comparison between EU countries.

Keywords: urban green space; physical accessibility; sustainable development goals; earth observations; OpenStreetMap; Sentinel-2; AccessMod

1. Introduction

Over the last three decades, cities worldwide have altogether increased in size by an area equivalent to Ireland [1]. Currently, more than half of the world population live in cities and this number is likely to increase to 66% by 2050 [2,3]. In addition, 59% of cities have also observed a rise in land consumed per new resident [4]. Consequently, urban sprawl and inefficient use of land are important issues with many consequences [5,6]. Two important ones are the expansion of existing urban settlements and creation of new ones, and the increase of density and use of urban areas. These issues not only put pressure on urban infrastructures (e.g., road and water supply/sewage networks, transport infrastructures) but also have significant impacts on the use of open and green spaces such

as threat of their privatisation or loss of their original functions [4]. Therefore, there is a strong need to optimise the use of available space requiring efficient and effective land use management strategies to enhance inclusive and sustainable urbanisation [7,8].

Public space has an essential role to play in making cities liveable and is interlinked with various other development issues such as environment and climate change, economic development, urban poverty, security, community cohesion, social interaction, civic identity, entertainment, gender and social equality and quality of life [2,4,9]. Even if public space can be difficult to define (e.g., different features/elements, different geographical and cultural contexts) [10], one key element towards the sustainability of cities is when there is a good balance between private and public spaces. Public spaces can be regarded as symbols of equality because they are usually accessible, safe, open, inclusive (e.g., sex, age and disability) and available to everyone [2,3]. However, according to United Nations (UN)-Habitat, public spaces in cities have gradually diminished in recent years [3]. Such privatisation of public space increases exclusion and marginalisation, underlining the need for policies and strategies that ensure appropriate planning, design and management of public spaces [3].

Sustainable development cannot be achieved without significantly transforming the way urban spaces are built and managed [11]. The UN 2030 Agenda for Sustainable Development [12] recognises the importance of cities, including the Sustainable Development Goal (SDG) 11 to *"Make cities and human settlements inclusive, safe, resilient and sustainable"* that defines a specific target on public space (SDG 11.7) *"by 2030, provide universal access to safe, inclusive and accessible, green and public spaces, particularly for women and children, older persons and persons with disabilities"* [8,11]. This target is supported by two indicators, one of them (SDG 11.7.1) based on calculating the "*Average share of the built-up area of cities that is open space for public use for all, by sex, age and persons with disabilities*". According to the official UN Metadata Repository [13], the rationale for this indicator is that the value of public spaces is often overlooked or underestimated by policy makers, political leaders, citizens and urban developers. Consequently, this indicator aims at monitoring the proportion of land that cities dedicate to public space (e.g., open spaces and streets). Together with the *"New Urban Agenda"* (i.e., the key policy that drives urban resilience and sustainable urban development at local level [14]), the SDGs provide for the first time a platform where public space can be globally monitored [15], recognising cities as key enablers for the world's sustainable future [3], and acknowledging the increasing role of cities and local communities in the implementation of the SDGs [16].

In the latest classification for Global SDG Indicators (as of 17 July 2020), SDG 11.7.1 is classified as a Tier 2 indicator, meaning that it is conceptually clear, has an internationally established methodology, and standards are available. However, the related data are not regularly produced by countries [13]. UN-Habitat reported that data for this indicator is now available for only 289 cities in 94 countries [3]. This indicator is currently providing information on the share of land allocated to streets and public space in urban areas to support suitable and sustainable urban development. However, it should be ideally complemented with information on accessibility, use and safety, among other aspects [2]. While some cities have sufficient information about their public spaces, consistent global or regional datasets on open and green space in urban settlements are still lacking and jeopardising effective data exchange and comparisons between cities, regions, or nations [17].

In Europe, about 75% of the population already lives in urban areas, and recent projections estimate that the share of urban population in Europe will increase to 80% by 2050 [16]. The EU SDG indicator *"Share of urban population without green urban areas in their neighbourhood"* is one of the proposed indicators currently on-hold due to methodological issues and lack of data. It is supposed to correspond to the SDG11.7.1 of the UN SDG framework. This means that currently, no values are available at the EU level for this indicator. The proposed EU indicator emphasises the importance of the green portion of the public urban space because it is a significant contribution of nature to people (i.e., a nature-based

solution) providing valuable ecosystem services [18,19]. Green spaces contribute in various ways to climate change mitigation, e.g., by cooling through shade provision and moisture and therefore reducing impact of heatwaves, noise reduction and air filtration of pollutants through trees or the promotion of biodiversity (e.g., hosting birds and bees) [20,21]. They are important for social inclusiveness, human health, biodiversity, as well as offering an opportunity for social interaction and increasing people's quality of life [16,22].

The greenness of European cities has raised by 38% over the last two decades while globally increasing by 12% over the same period [23]. It is estimated that approximately 40% of total urban areas of European cities are covered by vegetation with a share of 18.2 m² of publicly accessible green space per inhabitant and 44% of population living within 300 m of a public park [4]. Nevertheless, there is a great variability, ranging from cities with forested areas in city centres to a lack of green areas, particularly in Eastern and Mediterranean regions [16,24,25].

Consequently, city planners should engage to deliver sufficient variety and quality of life by providing ample green public space for local inhabitants and visitors. They should not only supply enough space but also ensure its conditions so that it can deliver its full potential [4]. This raises the concern about not only the quality of the public space but also its accessibility to users in different neighbourhoods. To effectively deliver its services, a public area should be easily accessible by soft mobility (e.g., foot, bike, public transport) to all types of users as well as be safe and inclusive.

To answer this need of enhanced information on public space conditions, timely and spatially disaggregated information is essential [26], but currently its supply is lagging [8,11,27] and not widely adopted by urban planners. Earth Observations (EO), acquired remotely (e.g., satellite), in-situ (e.g., sensors) or by citizens (e.g., crowdsourcing), is considered to be a valid, reliable, timely and continuous source of information to support evidence-based decision-making for sustainable urban development [26,28]. EO data can therefore be a good complement or can enhance traditional data sources on urban areas [29–31].

Based on these considerations, the objectives of this paper are: (1) to review the current literature to identify existing limitations and to define possible ways to measure physical accessibility to urban green spaces, (2) to propose a new method for calculating the EU SDG indicator using the Open EO data and accessibility model and (3) to test the proposed method in four different European cities. This can ultimately help to provide consistent information on urban green areas and to contribute to move towards a harmonised indicator that can contribute to SDG 11.7.1 at the Pan-European level without necessitating additional data collection efforts for reporting from member countries.

2. Material and Methods

We first reviewed the current status in the field to identify existing limitations and possible technical solutions to generate a potential EU SDG indicator *"Share of urban population without green urban areas in their neighbourhood"*. Then, based on the identified limitations and potential solution, we developed a new methodology aiming at providing spatially disaggregated information on accessibility to urban green space. Note that we use here the concept of "accessibility" to mean physical (i.e., geographic or spatial) accessibility. Other types of accessibility (e.g., enabling access for people with disabilities, or special needs) are not considered.

In the frame of this study, we used the UN-Habitat definitions for (1) Urban extent: "the total area occupied by the built-up area and the urbanised open space. The built-up area is defined as the contiguous area occupied by buildings and other impervious surfaces" and for (2) Open public spaces: "those areas within the urban environment that are freely accessible to the public for use, regardless of ownership, and are intended primarily for outdoor recreation and informal activities irrespective of size, design or physical feature" [13].

2.1. Review of Current Research and Developments on Assessing Urban Green Spaces

We reviewed recent papers to study relevant literature, including the recent work on the use of satellite EO data and crowdsourcing for assessing green urban areas with specific emphasise on urban population, green urban areas, accessibility and neighbourhood. We followed the general methodology proposed for systematic reviews [32,33]. 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 and methods [34]. This is the case for urban green spaces as well as the Sustainable Development Goals.

We searched peer-reviewed and non-peer-reviewed literature with a set of keywords targeting different repositories: three scientific libraries (Science Direct, Web of Knowledge, Google Scholar) and the Internet (e.g., Google searches). These searches were not limited by geographical extent or scale. The following keywords were used: 'urban green space', 'urban green areas', 'accessibility', 'private/public spaces', 'SDG 11.7.1', 'remote sensing', 'earth observations', producing a list of relevant articles. To refine results, three additional criteria were used: articles should address urban green space as the main or secondary subject, the keywords should be at least in the title, keywords or abstract, and articles should be written in English. Finally, following the recommendations for internet searches, the first 50 records were examined while the subsequent 50 were looked at for relevance [33]. The combined results of these various searches accounted for more than 6500 references over the last two decades. About two thirds were excluded because they were beyond the scope of this study (e.g., health issue, inequalities). The remaining articles were filtered manually to avoid duplications and screened to ensure that they were relevant to the topic. The final list of 74 papers was then used to identify the state-of-the-art solutions for measuring accessibility to urban green spaces.

Main Findings on State-of-the-Art Research and Development on Assessing Urban Green Space

Geographical Information Systems (GIS) can help deriving information on accessibility to urban green spaces [35,36]. This allows (1) the monitoring of the urban green space provision against quantitative and qualitative targets, (2) the comparison between cities and city parts, (3) the assessment of the effects of future policy scenarios and (4) the indication of locations where action is required [37,38].

Satellite EO data are an important component to identify urban green areas allowing to understand spatial–temporal dynamics of urban green space in response to rapid urbanisation and greening policies [39,40], effects of green space spatial pattern on land surface temperature [21] and quantifying the cool island effects of urban green spaces [41,42]. Most studies use the Normalised Difference Vegetation Index (NDVI) for identifying the vegetation using remotely sensed images [43].

Various indicators of urban green space availability or accessibility have been formulated [37,39,44,45] and recent studies [46,47] suggest to use urban green areas as a proxy for "public built-up areas". Using GIS and Remote Sensing techniques allows one to model urban expansion [48], accessibility [35], urban green space walkability [49], to assess the social benefits of urban green spaces [39], as well as to evaluate racial/ethnic and socioeconomic disparities in urban green space accessibility [50]. Most studies are modelling accessibility using Euclidean distance or simply applying a buffer. Network analysis appears a promising solution [51]. Accessibility is measured using rules for spatial proximity between objects, such as between people's permanent place of residence and public parks. In the metadata description, accessibility is measured at each identified individual public open space, such as a square. If no restrictions for the public to access the square are found, it is considered accessible open space. Approaches like the Urban Green Space Indicator [44] or Urban Neighbourhood Green Index [52] aim to provide quantifiable information regarding green structures and their amount and distribution for sustainable

planning. These indicators can be evaluated against the need to be comprehensible and practically applicable for cross-city comparisons, and for monitoring progress towards the goal of creating healthy and social-friendly urban environments.

Surprisingly, the literature is relatively poor concerning the SDG 11.7.1. Some studies concentrate on understanding how the concept of ecosystem services can contribute to the SDGs in building smart sustainable cities [53], identifying the data gaps for informing SDG 11 [54], the indicators, complexity and the politics of measuring cities, highlighting the poor data, lack of strong city data collection capacities and localisation are challenges for using the SDG as a tool to improve cities [8], how to monitor progress towards the SDG 11 in Germany and India [15], testing the SDG framework in cities [11], looking at nature-based solutions to support the SDG framework [55] and contextualising SDG 11 [15].

The most complete study at the EU level to assess access to green areas in European cities is from Poelman (2016) [56] using the Copernicus Urban Atlas. He determines an area of easy walking distance—around 10 minutes' walking time—around an inhabited Urban Atlas polygon, then calculates the median surface area of green areas that can be reached in this timeframe. This analysis also takes a closer look at the distribution of access to green areas within cities. Overall results highlight disparities in access between and within cities. The EU Joint Research Centre (JRC) also reported on measuring the accessibility of urban green areas [2] to tackle the issue of having consistent information on urban areas, allowing effective comparison of different cities and regions. It is based on the European Settlement Map (ESM) [57] available on the Copernicus Land Monitoring Service to extract relevant information on green areas in cities [58].

In summary, the identified challenges to overcome in order to obtain a consistent and robust methodology for generating this indicator are [17,26]:

1. Complexity and difficulty in calculating this indicator.
2. Definition and availability of data sources ensuring international data comparability.
3. Availability of data sources with ownership information (public vs. private).
4. Integration of the above geospatial data sources with typically very different properties, quality and uses.
5. Difficulty in delineating built-up areas and open space for public use.
6. Information on public vs private areas is a big challenge. Contributing countries have no figures for this indicator. Some countries may rely on a rich set of cadastral information and tax data, the complexity of urban land use prevents accurate classification of some areas in binary categories of public vs non-public space.
7. Identification of urban footprint.
8. Integration of satellite EO data with statistical information in production workflows is challenging.
9. Use of EO data for statistical production is evolving, but applications are mainly case-based and yet somewhat experimental.
10. Spatially disaggregated data are not widely adopted because the associated cost for generating data using traditional methods remains significant, technical capacity and skills on geospatial analysis is still lacking in many countries and due to difficulties to adopt new practices.

To overcome these identified limitations, we propose hereafter a methodology to assess urban green areas using open data, either from remotely sensed Earth Observations (EO) or alternative data sources (e.g., crowdsourcing). A first implementation of the methodology is done in four European cities in four different biogeographical contexts: Geneva (Switzerland), Barcelona (Spain), Goteborg (Sweden) and Bristol (UK).

2.2. Proposal for and Implementation of a New Method

The proposed methodology is based on distinguishing between public green areas and private green areas based on a model that combines available open and free Earth

Observation data, in-situ data such as Land Use and Coverage Area frame Survey (LU-CAS) [59] and national data including auxiliary information such as the cadastres. We suggest using EU resources such as Sentinel-2 data as well as derived products from the Copernicus Land Monitoring Service such as the Copernicus High-Resolution Layers. One clear novelty of our proposed approach is the compilation and use of various free and open data sources and tools.

The general workflow involved the following steps (Figure 1):

1.　Generate a maximum NDVI dataset (April–August) over the urban areas.
2.　Delimit built-up area of the city.
3.　Create a mask of public vs private areas using a mix of solutions (e.g., cadaster, Volunteered geographic information (VGI)).
4.　Overlay the mask with the NDVI dataset to identify only vegetated and public areas. This gives an estimation of the total public green space.
5.　Model the physical accessibility of the population to the nearest public green space, and compute accessibility coverage.
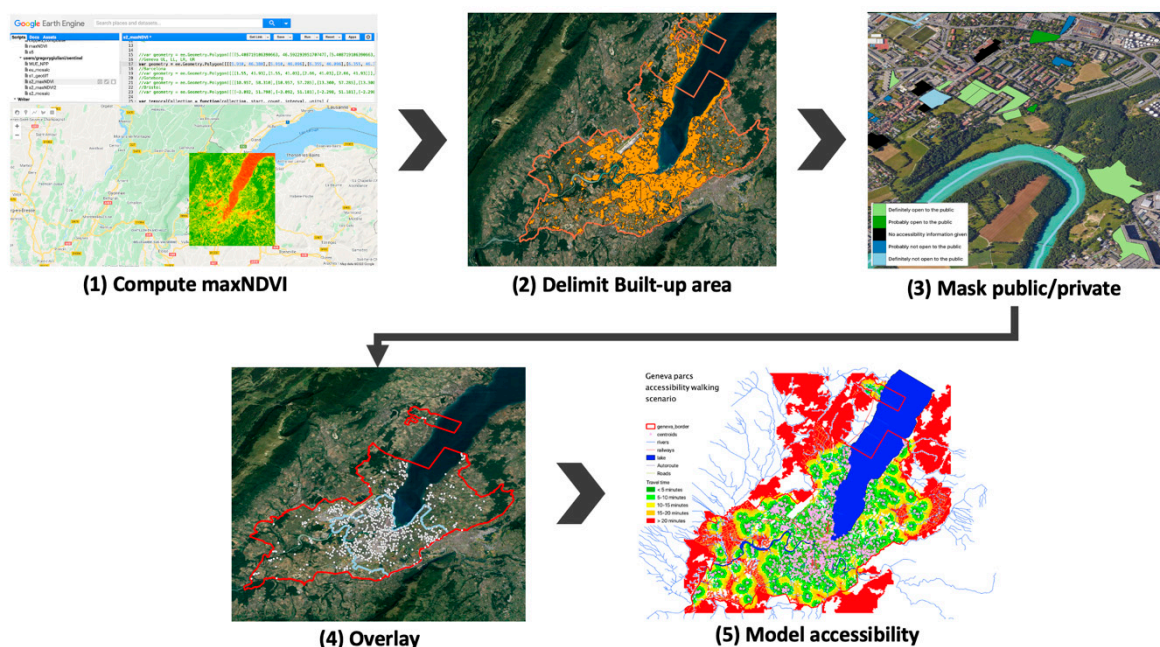
Figure 1. General workflow to model the physical accessibility to open green urban areas.

Implementation details for each step are provided in the next sub-sections. We used Geneva city as a benchmark for testing and comparison because most of the state data are available under an open data license. This allowed us to identify appropriate parameters/options (e.g., NDVI thresholds for vegetation identification, urban delimitation) and validate specific choices that are then replicated in the three other cities. Steps 1 and 4 of the workflow are not difficult, whereas steps 2, 3 and 5 require more work to properly select a suitable urban layer, define an effective public/private mask, and finally, model the accessibility.

2.2.1. Compute Maximum NDVI Time-Series Using Sentinel-2 Data to Get Vegetated Areas

To identify vegetated areas, we computed a maximum NDVI from a 5-month time-series of Sentinel-2 data over the summer months for the year 2018. The maximum value composite image is calculated as follows:

$$maxNDVI = MAX_{t0,tx} ((NIR - Red)/(NIR + Red)) \tag{1}$$

where NIR is the Near-InfraRed band, and Red is the red band. This allows extracting for each pixel the maximal NDVI value over the time period t0–tX and therefore facilitates vegetation identification.

The Copernicus Sentinel-2 is a twin satellites polar-orbiting mission that acquires multi-spectral optical images (e.g., 13 bands in visible, near infrared and short-wave infrared) at high spatial (e.g., 10 to 60 m) and temporal (e.g., 5 days) resolutions [60,61]. To process data, we used the JavaScript Application Programming Interface (API) Google Earth Engine (GEE) [62], a cloud-based processing platform for processing planetary-scale data from various sources such as Landsat, Moderate Resolution Imaging Spectrometer (MODIS) and other types of geospatial data [63].

Finally, the computed NDVI map is clipped to the desired geographical extent and reclassified to extract all vegetated areas using the threshold value of 0.5 that is a widely accepted limit for identifying vegetation in temperate areas [64]. The final result is shown in Figure 2.
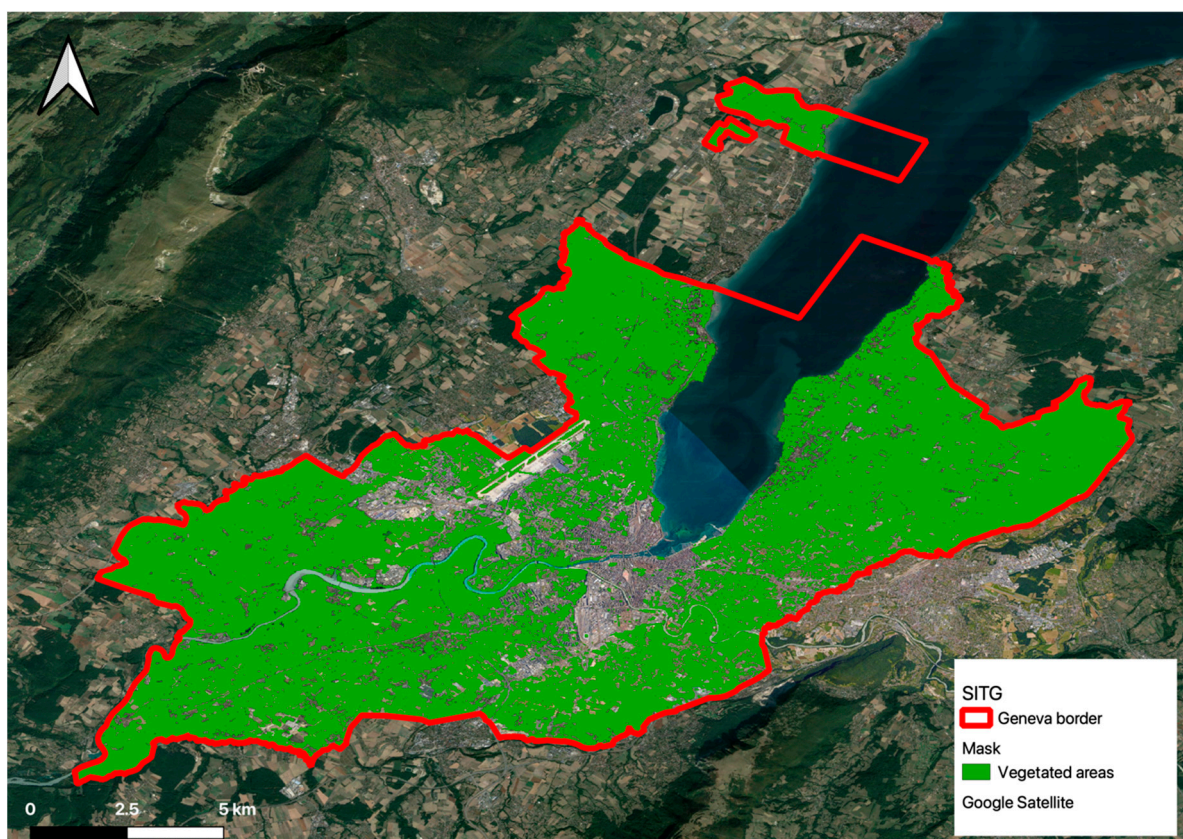
Figure 2. Vegetated areas over the Geneva canton for the year 2019, computed with Sentinel-2 data.

A visual comparison with high-resolution imagery from Google Earth allowed us to visually verify that the vegetation is correctly identified and mapped (Supplementary Figure S1). Using Sentinel-2 data with a 10 m resolution, we may miss very small green areas, but we are assuming this will not significantly impact the results.

2.2.2. Delimitation of the Built-Up Area/City

To identify urban areas, there are various data sources of value for this analysis. Based on surveys undertaken by UN-Habitat in 2018, it was concluded that major variations exist in many countries between what is statistically identified as urban (e.g., the separation of enumeration areas into urban and rural as implemented by national statistical offices, for census purposes), and what is officially defined as urban (e.g., as per existing municipal or city boundaries in the country). In almost all the surveyed countries, the classification of enumeration areas as either urban or rural changes over time, with rural units meeting certain population or density thresholds getting reclassified as urban units from one census cycle to the other. However, in most countries, these revisions barely inform the revision of municipal or city boundaries. In many cases, what is statistically urban is much larger than what is officially (administratively) urban. Matching the dynamic statistical classifications at the country level to the proposed global city definition approaches can offer good insights into the identification of functional city boundaries. UN-Habitat has proposed a methodology to identify built-up areas using satellite EO data based on the use of dynamic and functional city boundaries (UN-Habitat, 2019).

Two recent products are interesting for mapping built-up areas: the Urban Atlas (UA) [65], which is part of the Copernicus Land Monitoring Service [66], and the Global Human Settlement Layer (GHSL) [10,67,68]. UA is provided in vector format whereas GHSL is a raster-based map. The EU Urban Atlas, compiled by the European Environment Agency (EEA), is a harmonised dataset across Member states. The European Settlement Map (ESM) produced by the JRC is providing urban data at 2.5 m spatial resolution that can be interesting for detailed and harmonised calculations on urban areas [57].

To identify which one is more suitable for the purpose of this work, we compared them with a reference dataset from Geneva that has a precise map of the built-up area (https://ge.ch/sitg/fiche/6172). This dataset is freely accessible on the "Système d'Information du Territoire Genevois" (SITG) [69].

As exemplified in Figure 3, both GHSL and UA give good results compared to SITG data. GHSL even detects separate buildings. Compared to SITG, UA and GHSL give 96% and 97.5% overlap, respectively.
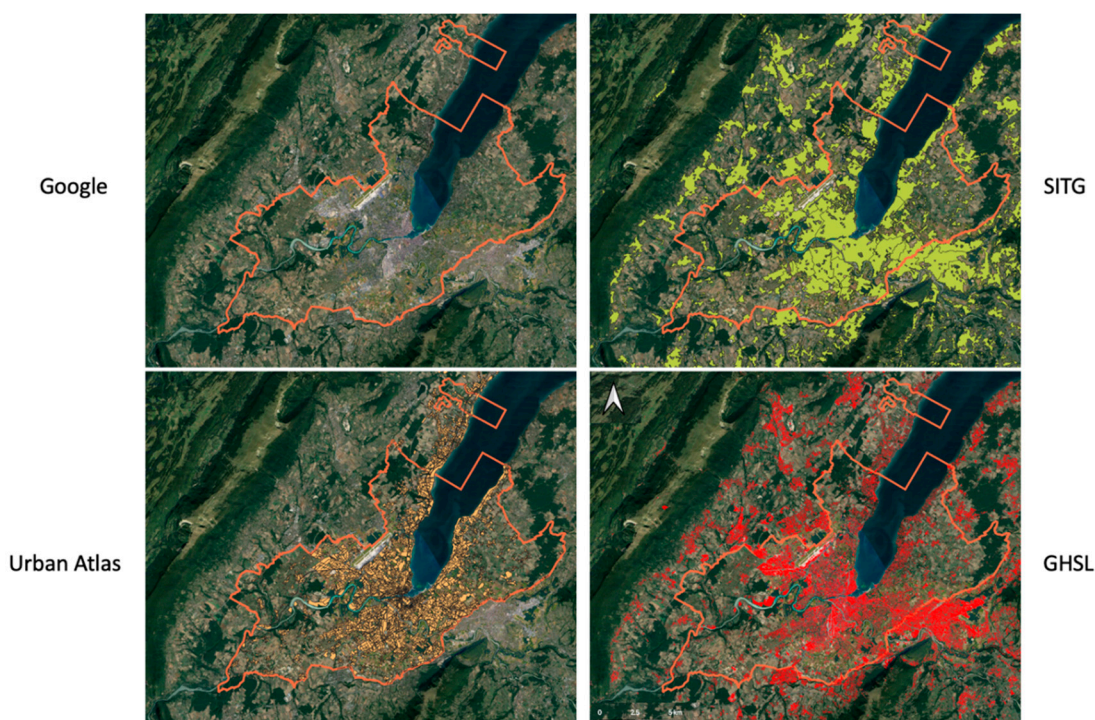
Figure 3. Comparison between Google Earth imagery, SITG, Urban Atlas 2018 and GHSL for delimiting urban areas.

The final choice has been made on the UA dataset for the following reasons: (1) there are several years available (2006-2012-2018), (2) it has different classes that are useful to map the built-up area, (3) it is an EU product and (4) it provides the delimitation of cities and countryside. Consequently, we extracted the following UA classes to get the best possible fitting with the reference layer from the SITG: 'Continuous urban fabric (Sealing Level (S.L.): >80%)', 'Discontinuous dense urban fabric (S.L.: 50–80%)', 'Discontinuous low-density urban fabric (S.L.: 10–30%)', 'Discontinuous medium-density urban fabric (S.L.: 30–50%)', 'Discontinuous very low-density urban fabric (S.L.: <10%)', 'Industrial, commercial, public, military and private units', 'Isolated structures', 'Open spaces with little or no vegetation (beaches, dunes, bare rocks, glaciers)', 'Railways and associated land'. The extracted data were then dissolved to produce the final footprint of built-up areas in the entire selected region. We also extracted city centre (_UrbanCore) and region (_Boundary) delimitations that are provided with the Urban Atlas 2018 (Supplementary Figure S2).

To compare UA2012 and 2018, we computed the differences between the two selected datasets. These differences were small, accounting for approximately 1.5% of the total urban area. Most of the changes occurred in the rural area where new neighbourhoods are in construction. These changes may affect accessibility to urban green areas in the rural part and not in the city centre in the future. We can make the reasonable hypothesis that more significant changes in accessibility coverage are caused by the increase in population density between 2012 and 2018 than through the construction of new buildings, that remains somewhat limited.

2.2.3. Creation of a Public/Private Mask

Distinguishing between public green space and private green space in cities is challenging as it usually requires the use of national official information and statistics, such as cadaster data, that is unfortunately not always publicly available from each Member State. Also, in larger housing areas, green space between buildings might be private but can still be accessible to the public. Therefore, potential alternatives need to be identified to distinguish between public and private land in the absence of suitable land management information.

To tackle this issue, we adapted the methodology proposed by Le Texier et al. [51] and adopted the green space classification from ITO (https://wiki.openstreetmap.org/wiki/Green_space_access_ITO_map). We used crowdsourced data from OpenStreetMap (OSM), a collaborative project to create a global free and editable map of land features. Currently, more than two million users are contributing to it, collecting data from manual survey, Global Positioning System (GPS) devices, aerial photography and other open resources. We used the QuickOSM plugin in Quantum Geographical Information System (QGIS) to extract categories that are listed in the OSM Wiki, assuming they are representative of green space access [70]. This approach has been tested in Brussels, where a comparison between cadaster and OSM data has been evaluated [51]. Authors concluded that OSM can adequately capture public green space, with the caveat of being less precise for private green space where it tends to underestimate results. The extracted categories are shown in Table 1.

Table 1. OpenStreetMap (OSM) extracted categories and associated tags representative of green space.

Access Rights	
Category	**Tags**
Non-public areas	Access = no/private/official/military/agricultural/forestry/destination/restricted/delivery
Public areas	Access = yes/permissive/public

Unknown access status	Access = unknown
Fee	
Free access	Fee = no
Access available on payment of a fee	Fee = yes
Access is sometime free and sometimes for a fee	Fee = interval, unknown
Greenspace	
Tourism	'Tourism' = camp_site
Amenity	'Amenity' = grave_yard
Leisure	'Leisure' = garden, nature_reserve, park, pitch, golf_course, common, dog_park
Land use	'Landuse' = forest, grass, meadow, orchard, greenfield, vineyard, recreation_ground, village_green, cemetery
Natural	'Natural' = scrub, fell, grassland, heath, wood, moor

These layers are then intersected together with the NDVI map to identify areas that are:

1. Definitely open to the public although a fee may be required (Light green).
2. Probably open to the public (Dark green).
3. No accessibility information given or implied (Black).
4. Probably not open to the public (Dark blue).
5. Definitely not open to the public (Light blue).
6. The tag combination is illegal or discouraged (land use = wood or a village green area that is tagged as being private, for example) (Red).

The final output is a map of the public/private areas according to their degree of openness (Figure 4).
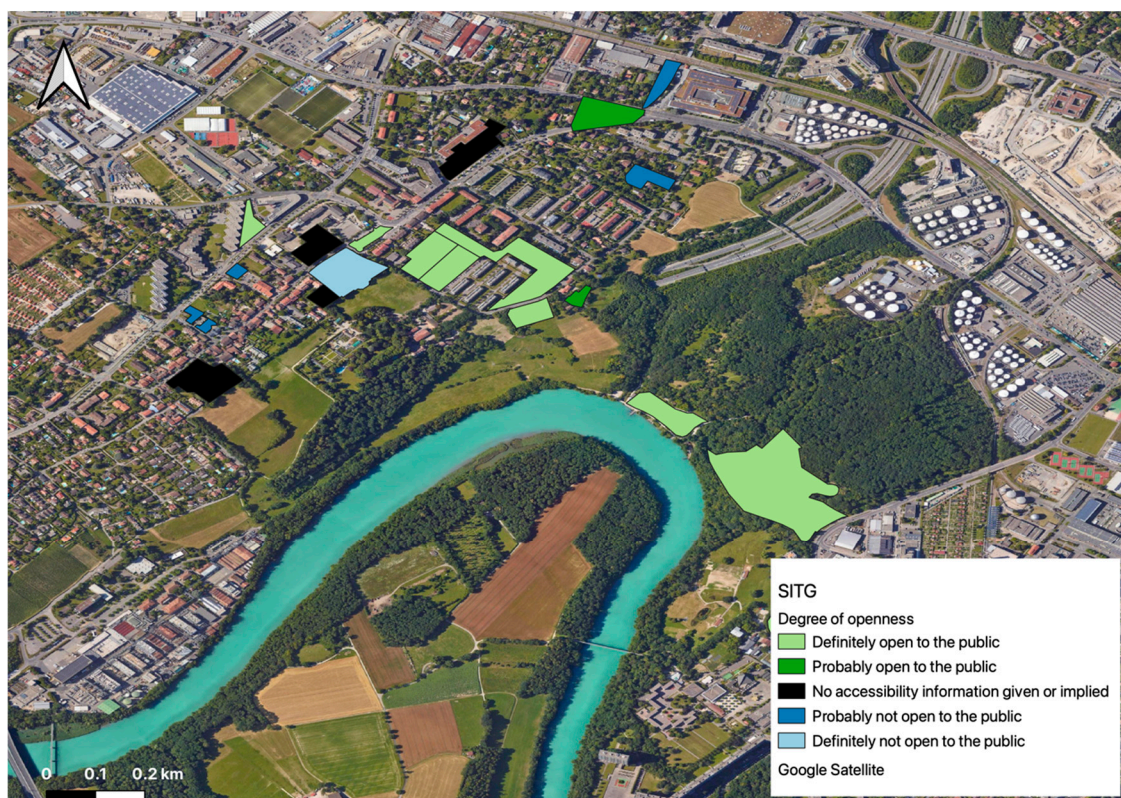

Figure 4. Public/private mask and their degree of openness.

2.2.4. Overlay and Clip Mask with NDVI

The fourth step is aiming to identify only vegetated spaces in urban and public areas (i.e., categories 1 and 2 defined in Section 2.2.3). This gives an estimation of the total public green space. For this step, we intersected outputs from three previous steps and then computed the centroids (in QGIS) to get a localisation of each identified urban green area (Figure 5). This will serve as inputs for modelling the physical accessibility in the next step.
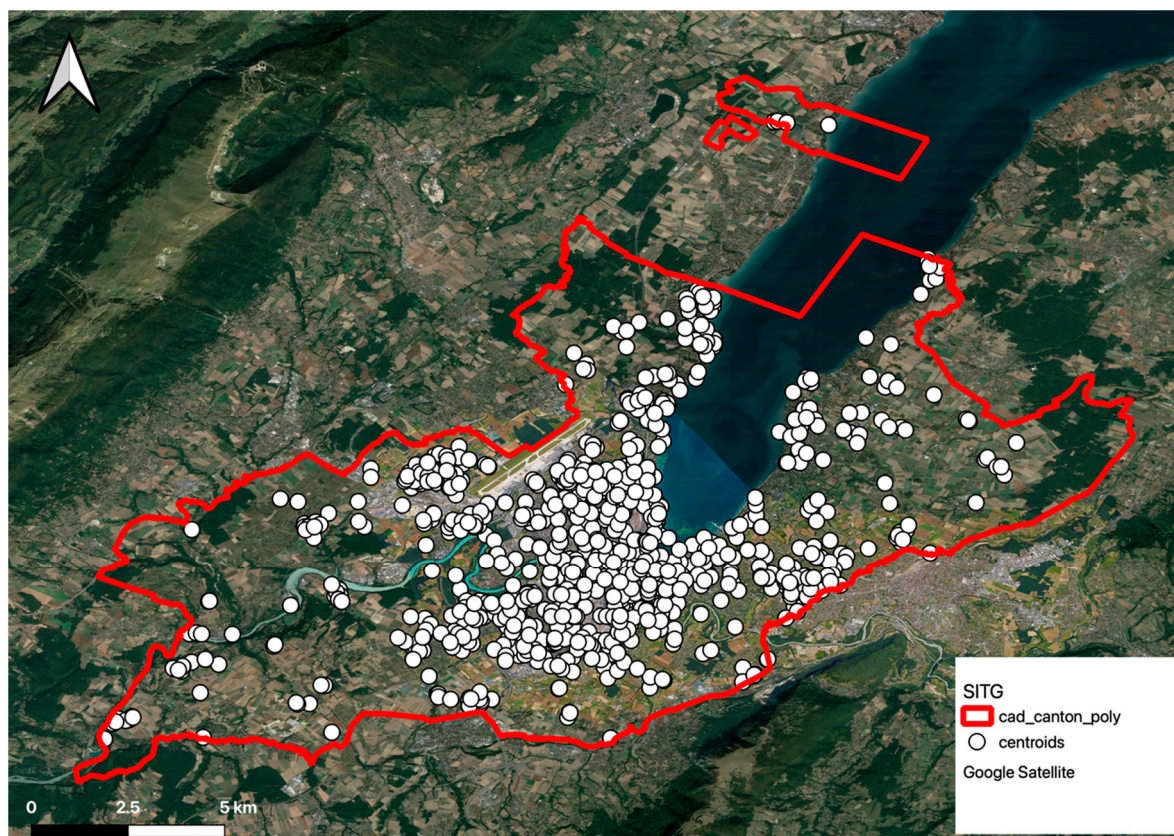
Figure 5. Identified centroids of green areas (white points) in the Geneva canton. The many points identified as open public green areas outside the city correspond to small parks and other types of publicly accessible green areas (e.g., vineyards).

2.2.5. Model Physical Accessibility and Coverage of Urban Green Areas

Most studies are trying to measure remoteness and proximity to urban green spaces using simple Euclidean distances or buffers to model accessibility. However, such methods tend to overestimate general access, and network approaches are better to model the effective accessibility [2]. Currently, the most used physical accessibility model is Access-Mod [71], that allows one to model travel time from any location to a set of predefined target locations and can compute accessibility coverage (i.e., the percentage of the population within a given maximum travel time to a set of target locations) [72]. We used the following AccessMod modules for our analysis:

1. Accessibility analysis: Compute the traveling time surface, informing the time needed to reach the nearest urban green space.
2. Zonal Statistics: Obtain the accessibility coverage for each geographical division.

To model the accessibility, AccessMod requires a set of input data, as listed below (Table 2) with their respective data source. We used the European grid system ETRS89/ETRS-LAEA (EPSG: 3035). It is based on the ETRS89 Lambert Azimuthal Equal-Area projection coordinate reference system.

Table 2. Input data required for modelling physical accessibility and computing statistics.

Raster Data	URL
Digital Elevation Model (Shuttle Radar Topography Mission (SRTM))	https://srtm.csi.cgiar.org/srtmdata/
Population grid (WorldPop or Center for International Earth Science Information Network (CIESIN)/Facebook)	https://data.humdata.org/organization/facebook?groups=che&q=&ext_page_size=25 https://www.worldpop.org/project/categories?id=3
Land cover (CORINE)	https://land.copernicus.eu
Vector Data	**URL or OSM tag(s)**
Roads (OpenStreetMap)	Highway = motorway, trunk, primary, secondary, tertiary, residential, unclassified
Rivers (OpenStreetMap)	Waterway = river
Lakes (OpenStreetMap)	Natural = water
Other barriers (airport, railways) (OpenStreetMap)	Railway = rail; aeroway = aerodrome
Centroids (urban green areas)	Provided by step 2.2.4
Administrative boundaries (Urban Atlas)	https://land.copernicus.eu/local/urban-atlas
Additional Data	**Description**
Travel scenario file	Used to inform the model on the modes and speeds of travel for the population willing to reach the nearest green public space. In this study, we only consider walking as the means of transport, and therefore do not consider other means such as car, bike, or public transportation.

The above-mentioned layers are merged into one single raster file (called land cover merged) to represent friction surfaces. This layer is used to produce the accessibility map and the accessibility coverage statistics (when combined with administrative boundaries and population density datasets).

2.3. A Short Comparison of OSM and Cadaster Data

An important aspect of the proposed methodology is to understand if OpenStreetMap (OSM) data can be an appropriate source of data to overcome the potential lack of official cadaster data in cities. To that aim, we compared OSM data with official Geneva data provided by the SITG. In Geneva, approximately 70% of territorial data are available under an Open Data license and are therefore easily accessible.

In the proposed workflow, OSM data are used in two ways. Firstly, for identifying the public/private areas of interest and, secondly, in the accessibility model, where vector data (e.g., roads, river, lakes, other barriers) are downloaded from OSM. In terms of network data (roads, rivers), we found a good fit between official data and OSM, the latter being even more complete in some places. This is exemplified by Supplementary Figure S3 comparing the two sources of road network in Geneva city centre.

The final comparison to understand if the proposed approach is efficient for identifying public/private areas relates to step 4 of the workflow, where we output the centroids of identified public urban green areas. We compared these centroids with the official SITG layer Public Green Space, as exemplified in Figure 6. We see in this figure that almost all official public green areas (in green) have been correctly identified with the proposed methodology (red dots), with 94% of the parks identified. Errors are mostly from areas that are not correctly tagged in OSM and consequently, lead to an inaccurate identification of public/private areas. The methodology even detects some smaller green areas, that after verification on the ground correspond to real parks. However, some of them can also be false-positive as they may correspond to paved areas with dense tree coverage and should

then be removed (accounting for approximately 2% of errors). We conclude that the OSM green spaces dataset is sufficiently good to be a valid source of data.

Figure 6. Identified centroids (red dots) compared to official Public Green Space of Geneva city (green polygons).

3. Results

To validate the technical feasibility, identify the possible issues and determine the potential of our methodology to determine the accessibility coverage to urban green space as well as to contribute to the measurement of the EU SDG indicator, we tested it in four different cities. For each city, the outputs are a set of maps and statistics representing (1) vegetated areas, (2) delimitation of built-up areas, (3) a mask of public/private spaces and (4) the accessibility coverage of public green spaces. The resolution of output raster is 100 m and statistics are provided according to two scenarios. We considered that people walk to go to a park, but distinguishing between a fast scenario (e.g., adults alone) and a slow scenario (e.g., people walking with children or strollers, or elderly people with reduced mobility). Details are as follows:

- Scenario "Fast":
  - 5 km/h walking in town and on roads/footpaths.
  - 2 km/h walking in rural areas off-road.
- Scenario "slow":
  - 3 km/h walking in town and on roads/footpaths.
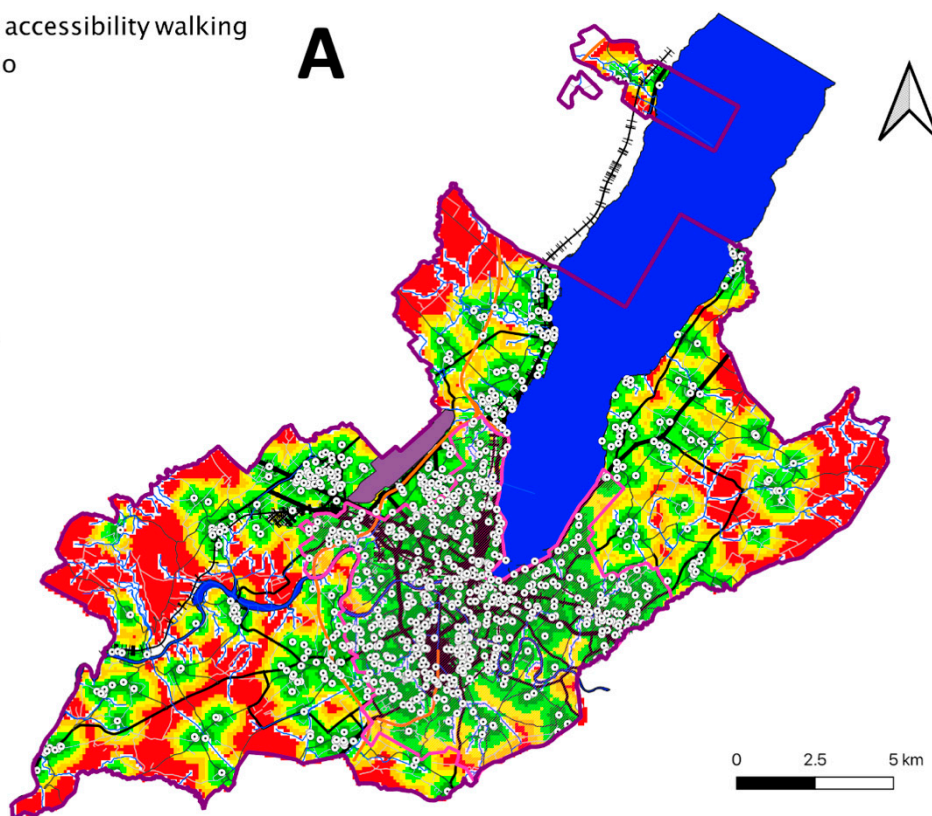 - 2 km/h walking in rural areas off-road.

3.1. Accessibility Maps

Below, we provide the accessibility maps of each city centre according to the two defined scenarios (Figures 7–10).

Figure 7. Urban green areas accessibility maps for the slow (**A**)-fast (**B**) scenarios for Geneva.
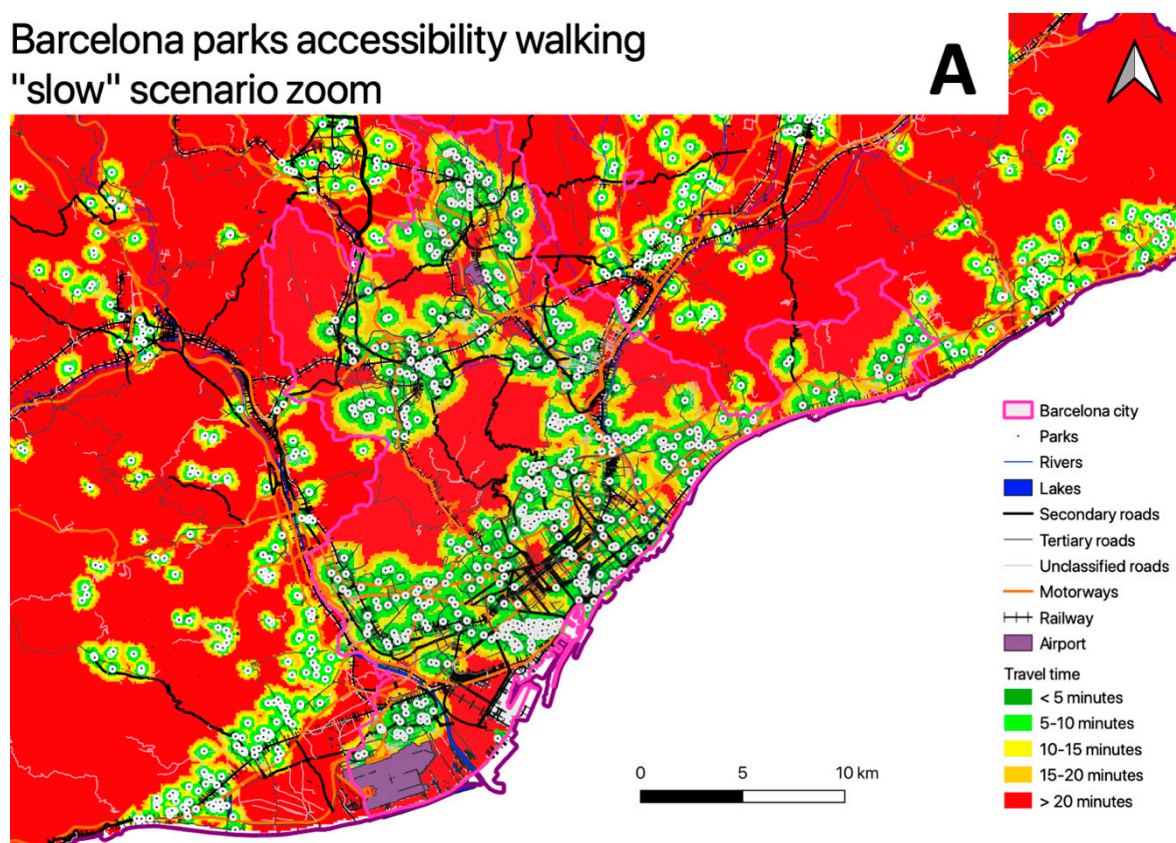
Figure 8. Urban green areas accessibility maps for the slow (**A**)-fast (**B**) scenarios for Barcelona.

Figure 9. Urban green areas accessibility maps for the slow (**A**)-fast (**B**) scenarios for Goteborg.

3.2. Accessibility Statistics

The output statistics allow us (1) to estimate the percentage of the population that has access to the nearest public green space (accessibility coverage, thereafter) within a given m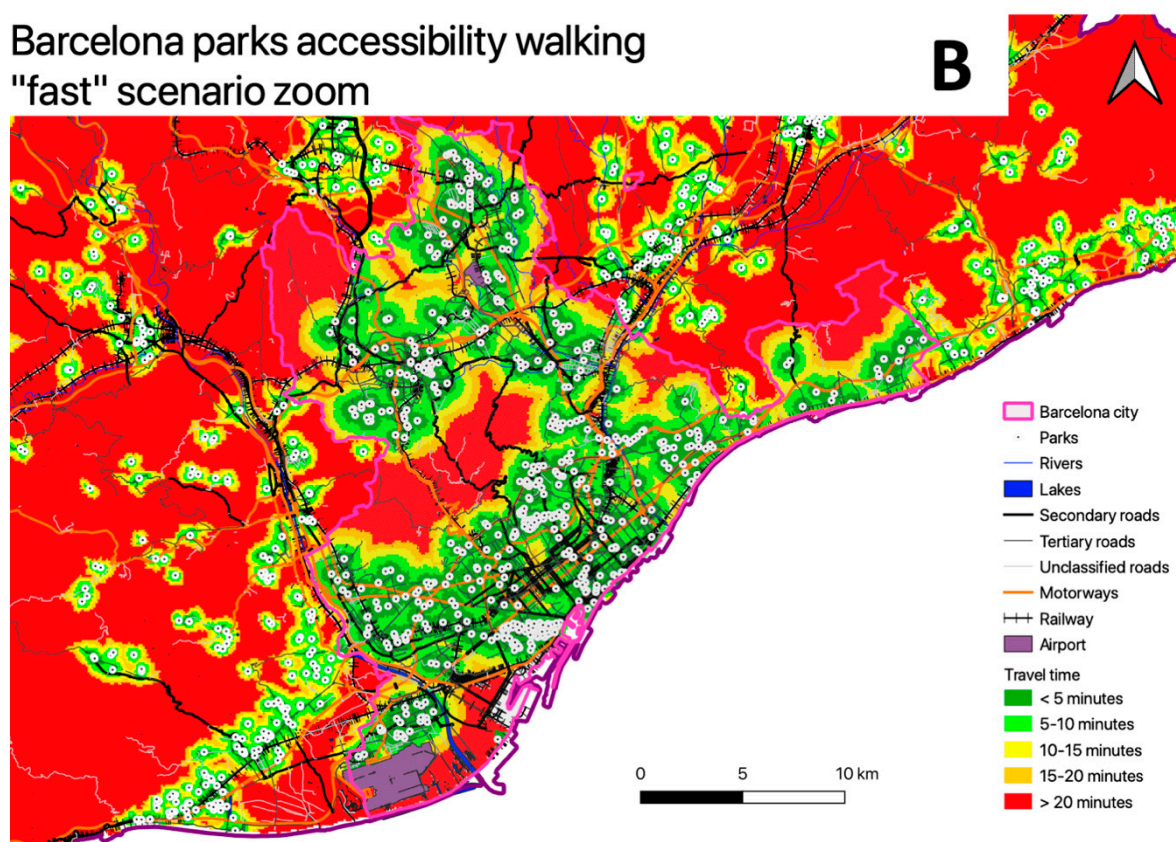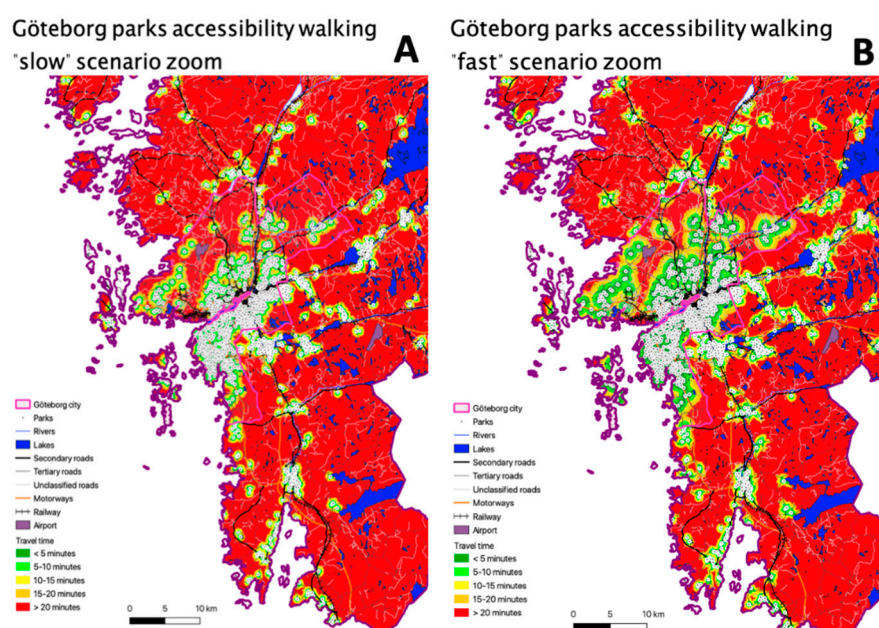aximum walking time, and (2) to compare results between two different years (assuming that the difference in accessibility is correlated with changes in population density) and the two different walking scenarios, "slow" and "fast". Based on these results, we are able to evaluate the EU SDG indicator "*Share of urban population without green urban areas in their neighbourhood*" that is obtained by subtracting the accessibility coverage values from 100% (Tables 3 and 4).

Table 3. Share of urban population without green urban areas in their neighbourhood, with two walking scenarios (slow and fast), and computed with 2018 population density estimates.

	Geneva		Barcelona		Goteborg		Bristol	
Walking Time	**Slow**	**Fast**	**Slow**	**Fast**	**Slow**	**Fast**	**Slow**	**Fast**
5 min	29.39	16.54	78.72	58.74	52.91	33.86	73.66	47.53
10 min	14.35	11.43	50.29	26.61	29.09	19.32	36.94	14.62
15 min	11.79	10.74	31.21	15.05	20.94	14.08	17.32	11.3

Table 4. Share of urban population without green urban areas in their neighbourhood, with two walking scenarios (slow and fast), and computed with 2012 population density estimates.

	Geneva		Barcelona		Goteborg		Bristol	
Walking Time	**Slow**	**Fast**	**Slow**	**Fast**	**Slow**	**Fast**	**Slow**	**Fast**
5 min	29.24	16.28	78.59	58.55	52.66	33.48	73.76	47.54
10 min	14.12	11.3	50.12	26.45	28.73	19.09	36.94	14.64
15 min	11.66	10.67	31.06	14.92	20.67	13.92	17.3	11.31
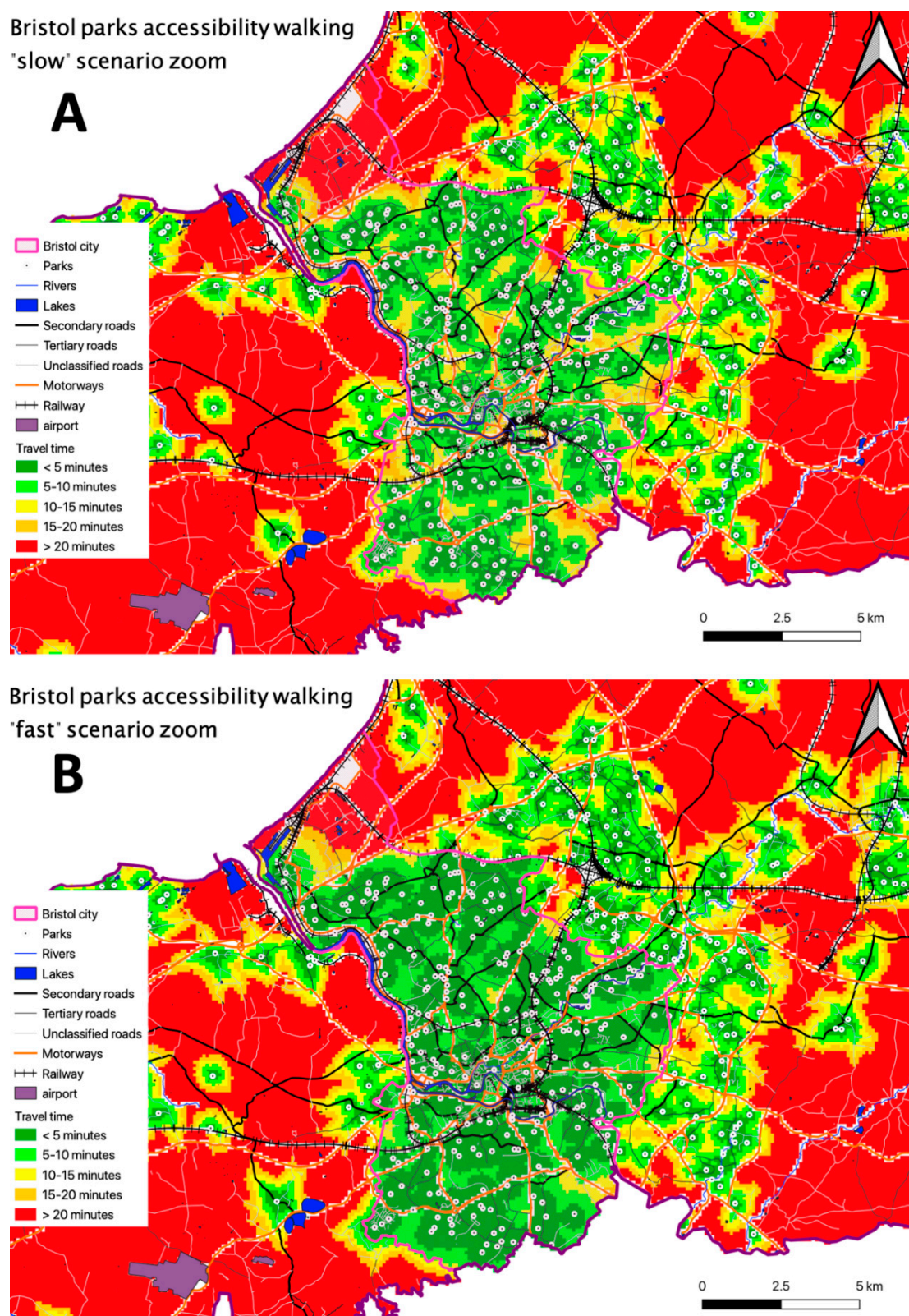
Figure 10. Urban green areas accessibility maps for the slow (**A**)-fast (**B**) scenarios for Bristol.

3.3. Comparing the Centroid-Based Approach with Large Park Entrance

The tested methodology relies on the identification of green areas. Their position is currently estimated using centroids, which is probably sufficient for small urban green areas but for the large parks could translate into different values of population accessibil-

ity depending on actual park entry points. Therefore, to test the sensitivity of this param-
eter, we focused on the 13 largest parks of Geneva and manually shifted the centroids to
the main entrance of the parks. The results have not significantly changed, except for the
5 min slow scenario that shows an increase in terms of accessibility (Table 5). This may
indicate that centroids are a valuable approximation, but this should be further confirmed
in larger parks in Europe.

Table 5. Geneva accessibility coverage computed with 2018 population density estimates on the 13
largest parks of Geneva.

	Geneva Original		Geneva Shifted	
Walking Time	**Slow**	**Fast**	**Slow**	**Fast**
5 min	5.06	14.14	5.77	13.83
10 min	19.1	37.67	18.89	36.74
15 min	34.38	48.34	33.36	47.85

3.4. Testing the New Worldpop "Constrained" Data

The population dataset used for the accessibility modelling comes from the
Worldpop database [73], a global dataset of population distribution [74]. One of the ad-
vantages of this dataset is to allow for comparable multi-temporal analysis. Recently,
Worldpop provided a new dataset for 2020 where estimation of population density is con-
strained within areas mapped as containing building settlements. For the detailed meth-
odology, more information is available in Reference [75].

Although this dataset provides a more realistic representation of where people live,
it is currently only available for 2020, which precludes exploring comparable evolution of
accessibility through time. Comparisons of estimates between Worldpop 2020 constrained
and unconstrained in the four cities are provided in Supplementary Tables S1 and S2 and
show very similar results at the 100 m spatial resolution. A comparison has also been
made with the CIESIN/Facebook dataset of population distribution that relies on another
source for built-up areas: the accessibility coverages for Barcelona, Bristol and Geneva are
in the same order of magnitude as for Worldpop (both constrained and unconstrained).

4. Discussion

These results show that the proposed methodology can help in providing detailed
information on physical accessibility to urban green spaces and generate the EU SDG in-
dicator that corresponds to the SDG11.7.1 of the UN SDG framework. Additionally, it can
also help in disaggregating the indicator at the pixel level at high-resolution (10 m), by
capturing both spatial (e.g., maps) and temporal (e.g., graphs) dynamics of accessibility of
urban green spaces.

The population accessibility to public green space according to different walking
times in the four cities show important differences, with Geneva having the highest fig-
ures considering the 5 min walking time (i.e., time suggested in the UN SDG framework).
This is not a surprise because it is also the smallest region of the four investigated, with a
high population density (12,000 people per km² in Geneva, 16,000 for Barcelona, 1300 for
Goetborg, 10,000 for Bristol) and a high number of parks that can quickly be reached
thanks to a good access network. With the 10 and 15 min scenarios, differences are becom-
ing less important, with most of the population in the four cities being within 15 min travel
time to the nearest public green space.

In all cases, estimates for the rural area are lower than in the city centres. This indi-
cates that accessibility to rural green spaces is different and alternative transport means
(e.g., bike, public transport) should be considered in refining accessibility models as they
may facilitate the access to these locations and improve our accessibility indicators. More-
over, in rural areas, we only looked at what we identified as park but not as forest, farm-
land, etc. These public green areas should be ideally also taken into account to obtain a

valid representation of the indicator in rural context as these areas can be accessed relatively quickly with alternative means of transport.

By comparing 2018 with 2012 results, we found the accessibility figures to be nearly identical. We are assuming the small changes in accessibility are more related to population growth than newly created green spaces. However, this could be further investigated in regions where the historical series of the creation of public green spaces would be available.

4.1. Benefits

Our methodology has confirmed that it can contribute to consistently measure the EU SDG indicator *"Share of urban population without green urban areas in their neighbourhood"*. Moreover, the resulting accessibility maps are provided at the pixel level, which can better capture both spatial and temporal dynamics of accessibility to urban green spaces.

Expanding this methodology to other EU cities could facilitate EU reporting against the SDG indicator, enabling a better comparison between EU countries. Moreover, EU resources, such as Urban Atlas and Sentinel-2 data for data provision and the Coperniucs Data and Information Access Services (DIAS) platforms for data processing, could be used for that purpose [76].

To our knowledge, this study represents the first attempt to model physical accessibility to urban green spaces within the framework of the SDGs using a least-cost path approach. Our approach is more realistic for estimating accessibility than methods using Euclidean distance or buffers from remoteness and proximity measurements. Moreover, our approach also captures the particular landscape of the considered cities. Barcelona and Bristol are relatively hilly and results clearly show that hills act as barriers, resulting in slower accessibility to parks in these regions.

Traditional environmental data has long suffered from data breaks, due to changes in reporting methods, and from data gaps. With satellite data, the same measurements are conducted globally at regular intervals, which provides a timely source of data that is commensurable across countries, regions and cities, and enables consistent and comparable time-series analyses that can be automatically updated. In addition, earth observation data can be combined with other geo-referenced socio-demographic, economic and public administration data to make indicators and analyses more relevant and targeted. This can help in harmonising international reporting on natural resources and ecosystems, offering a cost-effective approach without the need to require additional data collection efforts for reporting from countries.

4.2. Limitations

Our proposed methodology has also shown some limitations:

(1) For a potential scaling-up of the methodology at the global level, and specifically for the identification of built-up areas, the GHSL dataset should be considered instead of Urban Atlas, which covers only Europe. This is important for having a consistent approach to extract built-up areas and to allow comparison between countries/regions.

(2) A key element for measuring this indicator is the identification of private/public spaces. Alternative data sources such as OSM have proved to be a valuable resource in cases where an official land cadaster is not freely available (or at least at an acceptable cost). Purchasing cadaster data from the cities whose green space accessibility needs to be modelled can be expensive and become a major barrier to an effective monitoring of this indicator. Yet, cadaster data would still be required in cases where information of the private/public nature of the parks in OSM is very incomplete.

(3) Working with the centroids of green spaces can be a valid approach for a first approximation, but it can have an impact on the estimation of accessibility, especially if

we consider short traveling time (e.g., 5 min) towards large urban green areas. In that case, it would be interesting to have information on the location(s) of parks' entrances to provide an enhanced view on accessibility but noting that dedicated entrances may imply fences around the park that should also be considered. For the large parks that can be entered from everywhere, with no restrictive entry point, a least-cost path algorithm considering polygons instead of points for the target areas may be preferred. More work is needed to better understand the impacts of alternative accessibility algorithms given various park configurations.

(4) Our accessibility modelling requires various input raster datasets. We used mostly global datasets whose resolution is typically 100 m or more, which could be considered too coarse to adequately model barriers to movement in some cities. To get more accurate physical accessibility estimates at higher spatial resolution, national datasets should be considered.

(5) The travel scenario (modes and speeds on various roads and off-road), as well as barriers to movements, can have specificities in the different cities considered, depending on country-specific and city-specific policies (e.g., soft mobility). More work is needed to understand to which extent a single baseline travel model could be used for sets of cities (e.g., European cities), or if city-specific constraints should always be considered.

(6) An assumption of the least-cost path approach is that the population always reaches the closest area in terms of travel time. But, by-passing the nearest area to reach one further away could be a reality for a subset of the population. For example, where kid-friendly and playground infrastructures are needed, this target population may have a limited choice of green areas to access. Stratifying the analyses by considering alternative target populations could be possible if sufficient information on the park infrastructures is available.

(7) Our presented methodology that aims to be in line with the SDG indicators framework only considered cities. A valuable addition in the future would be to also consider rural areas and take into consideration objects such as forests, vineyards, riverbanks, etc., that are also vegetated areas in or around which people like to walk. For these particular areas, the population is generally willing to travel for a longer time and distance (by car, bike or public transport), and then walk. Such behaviours/cases can also be adequately modelled using AccessMod, that can combine several modes of transport in a single analysis.

4.3. Perspectives

These results are encouraging but further work is required to strengthen the results. Hereafter, we provide some ideas:

1. The methodology could be tested on other cities/countries in different socio-economic-environmental contexts (e.g., megacities, developing countries) and in cities that have existing data we can validate results against.

2. We only considered walking in the travel scenarios. Other types of scenarios of movement, such as bike, public transport or car, could be considered to inform about additional accessibility patterns.

3. Comparisons could be done with alternative scenarios such as the one provided by UN-Habitat that proposes to use 400 m walking distance along the road network as delineation of the catchment area. In that specific case, 400 m at a walking speed of 5 km/h corresponds to a travel time of 4.8 min, which more or less corresponds to the computed 5 min distance we used. However, results could be different depending on how one treats off-road movements, and the configuration of barriers to movements in the cities considered.

4. Explore the use of freely and openly available cadaster to identify public/private space.

5. With the current implementation, green areas smaller than 10 by ✳ 10 m could not be identified. A possible solution is to use satellites that can provide higher spatial resolution images such as WorldView or Pleiades sensors.

6. The current methodology used the Urban Core layer (from the Urban Atlas 2018) to delimit cities. This was selected for replicability concerns, ensuring that the methodology can be replicated in any European city. However, local data can be even more precise and/or have a different city delimitation. Such data could be easily used to re-compute the zonal statistics on the share of the population that has access to urban green areas.

7. For the potential scaling-up of the methodology at a global level, the GHSL dataset should be considered instead of Urban Atlas (that only covers Europe) for the identification of built-up areas. This is important in order to have a consistent approach to extract built-up area and to allow comparison between countries/regions.

8. We used the GEE platform to process Sentinel-2 data. However, in the EU context, it would have been preferable to use EU resources such as the Copernicus DIAS platforms. Nevertheless, there is an associated cost for using DIAS and currently, the business model is not yet entirely clear and processing costs should be carefully assessed. To ensure reliable estimations, the use of Sentinel-2 is recommended to reduce biases and uncertainties.

9. The validation process is an important step that should be properly handled. Citizen science approaches complemented with the use of aerial and/or on-the-ground imagery can be used to validate the identification of green areas as well as identifying private and public space from LUCAS database pictures [77,78]. It could help to build a tool able to efficiently and accurately classify and differentiate private green space from public green space. This can be a valuable addition, when land parcel data is not available (thus, without ownership information). Validation should also ideally be performed on travel behaviour and travel speeds through population surveys and citizen science approaches, which are yet to be developed and made available at the appropriate scale.

10. To complement the private/public mask and further identify public green areas, valuable alternatives exist such as using patterns of mobile phone data (e.g., number and pattern over time of mobile phone users in green spaces) to detect if space is accessible to the public or not. Alternatively, pictures from public databases with geo coordinates (Flickr, Mapillary) [79] or public information on green spaces (e.g., in Hamburg, Germany) [80] are also additional useful sources of information when available. This can help to estimate visitation rates and can potentially help to understand which elements of urban green areas attract people.

11. Artificial intelligence, and particularly Machine Learning (ML) techniques, can also be a valuable option to complement the differentiation of private green space from public green space [81,82], if land parcel data (without ownership information) is not available. Such an approach has been tested in the UK to map urban green spaces (such as residential gardens, steps, patios and paths) [83]. In this regard, it would be interesting to test this against the LUCAS database to understand if it can be a reliable source of information for classifying/identifying private green areas.

12. Automatising our full workflow could be possible, especially if OSM data are used. Workflow using R could automatically download the appropriate dataset, prepare the data for ingestion in AccessMod (or other libraries), run it and output the appropriate maps and statistics.

13. Considering the use of the WorldPop "constrained" dataset may improve the realism of the spatial distribution of the population.

14. An issue that warrants further consideration is how to deal with forest areas/cropland/grassland in the periphery of urban areas. Indeed, rural parts might have large, vegetated areas that can be publicly accessible and therefore represent important areas for leisure.

This work can be a contribution to the Group on Earth Observations (GEO) Work Programme that is advocating for the use of EO data for sustainable development, with activities such as the Earth Observations for the Sustainable Development Goals (EO4SDG), the GEO Human Planet or the Global Urban Observation and Information activities [84]. In particular, it can contribute to the emerging EO toolkit, an online knowledge resource that is aiming to support countries and cities in using EO data for their SDG monitoring needs and urban policy priorities [85]. It can facilitate engagement, capacity development, knowledge sharing and collaboration on the use of EO for urban issues [26].

5. Conclusions

Public space in urban context can provide a multitude of benefits to the population: improving air quality, providing microclimate regulation and enhancing safety, social integration and public health. Consequently, urban planners and policy/decision-makers should ensure sufficient variety and quality of public spaces, while enabling the conditions for these spaces to deliver their full potential. To reach this objective, timely and spatially disaggregated information are crucial but are not widely adopted, and supply of such information is underdeveloped.

Our proposed methodology combines satellite and crowdsourced (e.g., OSM) EO data to model physical accessibility to urban green spaces in four European cities (Geneva, Barcelona, Goteborg, Bristol). Our initial results indicate that it is technically feasible, with results from modelling the physical accessibility to urban green spaces that provided consistent and useful information. Such an approach can be a potential contribution from Europe to the global UN SDG framework, providing a consistent methodology to measure this indicator. It can also complement current official Eurostat statistics, facilitating EU reporting against the SDG indicator, and allows better comparison between EU countries, having the same methodology applied at the Pan-European level without necessitating additional reporting from member countries. It offers a simple, reliable, timely, replicable, cost-effective, synoptic, scalable and rapid alternative to derive information on the share of urban population without green urban areas in their neighbourhood. Finally, our proposed workflow can be further combined with other geospatial and socio-economic data to help contextualise the generated information and support evidence-based decision-making for sustainable urban development.

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