

TOWARDS AN AUTOMATED SPATIAL WORKFLOW FOR THE GLOBAL MONITORING OF PUBLIC URBAN GREEN ACCESSIBILITY IN THE LIGHT OF THE SUSTAINABLE DEVELOPMENT GOALS

Anna Kovács-Györi, Bernd Resch

Abstract: The 11th Sustainable Development Goal (SDG) by the UN sets the achievement of inclusive, safe, resilient and sustainable settlements as a goal by 2030. One of the sub-targets (11.7) within this goal addresses the safe and inclusive accessibility of public spaces considering also vulnerable social groups. This discussion paper reviews UN metadata reports and investigates the advantages of considering a spatial approach for SDG indicator 11.7.1 to be more informative. We argue that there are two crucial characteristics of this geospatial approach for global monitoring and assessment: transferability and automation. As a data source with high potential in global assessment, remote sensing is acknowledged to be useful and widely available but due to the lacking information extractable about ownership (public or private space), additional fieldwork is also necessary, which hinders automation and makes transferability time- and resource-consuming. Based on the review of the SDG goals and recent literature, we therefore propose a new, spatially explicit SDG indicator on urban green access and lay down the foundations of a potential workflow for transferable and automated analysis relying on remote sensing and geo-social media data.

Keywords: Sustainable Development Goals, public urban green access, remote sensing, geo-social media analysis

AUF DEM WEG ZU EINEM AUTOMATISIERTEN RÄUMLICHEN WORKFLOW FÜR DIE GLOBALE ÜBERWACHUNG DER ZUGÄNGLICHKEIT ÖFFENTLICHER STÄDTISCHER GRÜNFLÄCHEN IM HINBLICK AUF DIE ZIELE FÜR NACHHALTIGE ENTWICKLUNG

Zusammenfassung: Das 11. Ziel für nachhaltige Entwicklung (SDG) der Vereinten Nationen legt die Erreichung integrativer, sicherer, belastbarer und nachhaltiger Siedlungen als Ziel bis 2030 fest. Eines der Teilziele (11.7) innerhalb dieses Ziels betrifft die sichere und integrative Zugänglichkeit öffentlicher Räume, insbesondere für schutzbedürftige soziale Gruppen. In diesem Diskussionspapier werden UN-Metadatenberichte kondensiert dargestellt und die Potenziale eines explizit räumlichen Ansatzes für den SDG-Indikator 11.7.1 erörtert. Daraus schließen wir, dass es zwei Schlüsselmerkmale dieses räumlichen Ansatzes gibt, die für die globale Überwachung und Bewertung von entscheidender Bedeutung sind: Übertragbarkeit und Automatisierung. Fernerkundung wird hierbei als nützliche und weit verbreitete Datenquelle anerkannt. Aufgrund der fehlenden Informationen, die über den Besitz (öffentlicher oder privater Raum) extrahiert werden können, ist jedoch auch zusätzliche Feldarbeit erforderlich, welche die Automatisierung einschränkt und die Übertragbarkeit von Analysen zeit- und ressourcenintensiv macht. Basierend auf der Analyse der SDG-Ziele und aktueller Literatur diskutiert dieser Beitrag einen räumlich expliziten SDG-Indikator für die Bewertung des Zugangs zu städtischen Grünflächen und legt die Basis eines strukturierten Workflows für übertragbare und automatisierte Analysen fest, auf der Grundlage von Fernerkundungsdaten und Posts aus geosozialen Medien.

Schlüsselwörter: Nachhaltige Entwicklungsziele, öffentlicher Zugang zu urbanem Grün, Fernerkundung, Analyse geosozialer Medien

Authors

Dr. Anna Kovács-Györi
University of Salzburg
IDA Lab – Team Space & Mobility
Jakob-Haringer-Str. 6

A-5020 Salzburg
E: anna.gyori@sbg.ac.at
Assoc.-Prof. Dr. Bernd Resch
University of Salzburg

Z_GIS – Geo-social Analytics Lab
Schillerstr. 30
A-5020 Salzburg
E: bernd.resch@sbg.ac.at

1 SDG 11.7 – PROVIDING UNIVERSAL ACCESS TO SAFE, INCLUSIVE AND ACCESSIBLE, GREEN AND PUBLIC SPACES BY 2030

In 2015 the United Nations defined 17 global goals (Sustainable Development Goals – SDGs), which should be met by 2030 by humankind to provide a sustainable future for the next generations (United Nations General Assembly 2015). SDG 11 sets the goal of making human settlements safe, resilient and sustainable all over the world to provide better life circumstances for the increasing urban population (Jensen 2020). Beyond the 17 development goals, there are numerous targets and indicators also defined to facilitate decision-making and taking actions to achieve the main goals. This paper focuses on one of these targets (11.7) and its indicator (11.7.1) regarding the accessibility of public urban green by reviewing existing approaches and discussing the importance of a spatial approach in taking action to achieve the goal of inclusive, safe, and sustainable settlements.

SDG 11 sets the goal of resilient and sustainable cities and settlements. Within that, SDG 11.7 highlights the importance of public spaces for dwellers in many different ways (UN HABITAT 2018b). The SDG 11.7 advocates for “universal access to safe, inclusive and accessible, green and public spaces, particularly for women and children, older persons and persons with disabilities”. The emphasis is mainly put on public spaces as public goods and their relevance in organic city development, including open spaces and streets that are not privately owned. Interestingly, green areas are considered as one type (or quality) of public space, without detailing their vital impact (e.g. social, climatic or health aspects) on various scales for the dwellers (Hartig & Kahn 2016; UN HABITAT 2018b, 2018a). Although official metadata documents discuss used terms quite specifically, “green” is not even referenced in the formulation of the indicator (11.7.1), which only mentions open space (“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”). It is understandable that for such a complex objective, it is necessary to provide compact indicators to the highest possible degree, but in this specific case indicator 11.7.1 might be

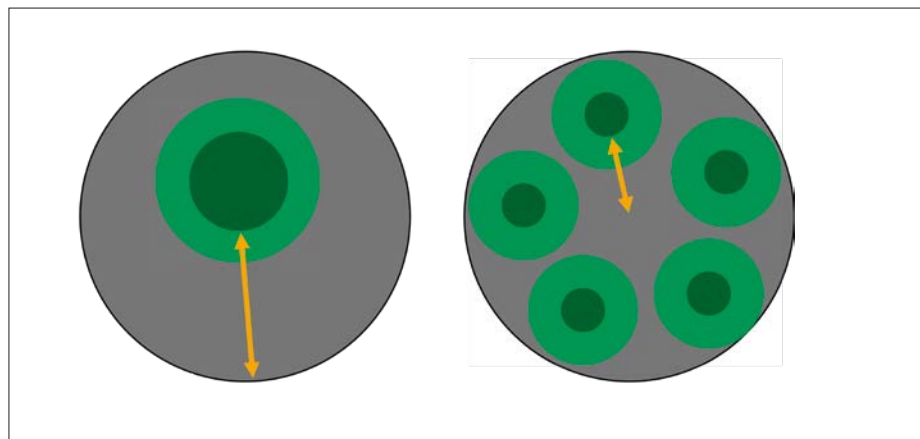


Figure 1: The role of proximity in urban green assessment analysis (Blaschke & Kovács-Györi 2020)

too simplistic. This leads to challenges for local actions taken by local stakeholders in favor of achieving the goal of sustainable cities, as the current formulation of the indicator provides no information about intra-urban differences or access in terms of distances.

The formulation of SDG indicator 11.7.1 “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” propose a clearly numerical way of assessment and lacks the spatial aspects completely. Even the same proportion may reflect highly different inequalities in the real access of public (or green) spaces, which is the core of SDG 11 target (“provide universal access”). For local action, there is a need for specific information about the real accessibility of green spaces, even considering walking distances, on an intra-urban level, using a spatial approach and statistical data on the different demographic groups referenced in the SDG 11.7 target.

Figure 1 illustrates the role of proximity in the case of urban green. Both circles contain the same amount of green, but without considering proximity such as the walking (or even Euclidean) distances, the most important aspect of accessibility is overlooked.

There are official guidelines and toolkits available to help planners and decision-makers in assessing and achieving SDG 11.7, however, these approaches often focus merely on policy-making (Garau 2016; UN HABITAT 2018b, 2018a). Although satellite imagery is listed and recommended as a potential source of data, a clear spatial approach is not included in these materials. As this target and the indicator focuses on access for various groups this lacking spatial view is critical. Official

sources point out that the whole assessment cannot be performed using only remotely sensed data, but this does not mean that geospatial analysis would not be beneficial in general. Section 2 provides further details about the official guidelines defining what open space is or how the indicator should be calculated.

Resulting from the considerations above, this paper discusses and proposes a new approach to analyze accessibility of public urban green space in the light of SDG monitoring. The novelty in this approach is 1.) in its spatially explicit nature, leveraging spatial data and analysis in the assessment; 2.) in the combination of remotely sensed data and geo-social media data to account for the various requirements as defined by the SDG; 3.) in the inherently combined view of urban green space accessibility through external environmental factors (green space derived from remote sensing imagery) and social factors (derived from geo-social media data); 4.) in its world-wide applicability through global data availability; and 5.) in its potential for full automation across all steps of the workflow.

2 UN METADATA REPORTS ON URBANIZED OPEN SPACE

The UN metadata reports provide details about the definitions and measures used in SDG targets and indicators. Regarding SDG 11.7.1 reports define what urban extent, built-up area, or urbanized open space is. Urbanized open space can be classified into three main categories, and mainly interpreted as unbuilt areas including open countryside, forests, crop fields, parks, cleared land. The three categories are the followings (UN HABITAT 2018b):

- *Fringe open space*: open space pixels within 100 meters of urban or suburban pixels;
- *Captured open space*: open space clusters fully surrounded by urban and suburban built-up pixels (and fringe open space around them), also they are less than 200 hectares in area;
- *Rural open space*: all open space that are not falling into the first two categories.

Reports also detail elements that can be considered as open public space (UN HABITAT 2018b):

- *Parks*: open space inside an urban territory, providing free air recreation, and contact with nature;
- *Recreational areas*: public areas contributing to environmental preservation – for example playgrounds, riverfronts, waterfronts, public beaches among others;
- *Squares and plazas*: significant architectural elements and interaction between buildings and the open area, they often have strong cultural importance.

UN Habitat also provides a relatively simple workflow for the basic computation of SDG 11.7.1 indicator (UN HABITAT 2018a). The method consists of three main steps:

1. Spatial analysis to delimit the built-up area;
2. Computation of total area of open public space;
3. Computation of land allocated to streets.

The final formula to calculate the “share of the built-up area of the city that is open space in public use (%)” (n) is presented in Equation 1.

$$n = \frac{(A_o + A_s)}{A_b} \cdot 100$$

A_o = Total surface of open public space,
 A_s = Total surface of land allocated to streets, A_b = Total surface of built up area of the urban agglomeration

Equation 1: Formula of SDG 11.7.1 indicator

According to the guidelines, the first step includes the classification of satellite imagery and cluster analysis based on the

categories described above for open spaces and built-up area. The second step considers which open spaces are actually available for the public. The identification can happen based on an existing inventory or deriving an inventory using satellite imagery, which is then verified by field-work due to the lack of information on the ownership. However, using open data sources such as OpenStreet Map or the Urban Atlas for some cities in Europe can help to provide the necessary information. Having a focus on urban green as a sub-category of SDG 11.7, the usage of remote sensing can clearly have advantages and can provide a baseline especially for developing areas where official spatial datasets on urban green might not be available. In this regard, extracting information can indeed not satisfy the information needed for SDG 11.7.1 target but can provide a core part and a starting point for further in-situ evaluation. Nevertheless, the report does not detail what happens if an existing inventory is used but it is not matching the classification for open spaces from the first step, which might be a significant issue when calculating proportions at the end.

In the third step the area of streets is calculated, using either direct data on streets or manual digitization within sampling areas. OpenStreetMap (OSM) could be a viable option also in this case, especially when a quick solution is needed, or global comparison is important. It is not included in the report but classification (e.g. object-based image analysis) directly from satellite imagery can also provide the necessary information about the approximate extent of roads, moreover it would fit much better the workflow including the other two steps in the assessment process.

Disaggregation into intra-urban metrics is also mentioned in the report, however there are no details on how it should be performed or why it would provide more benefits for local actions.

3 EVALUATION OF THE OFFICIAL ASSESSMENT APPROACHES DEVELOPED BY THE UN

Overall, there is a large gap between the intended focus (“access”) of the target and the proposed indicator (“proportions”) to measure progress. The aggregated nature to the whole extent of a given urbanized

area is also problematic because it is not able to uncover the real situation about the accessibility of given public spaces. These are the two key points where a spatial approach would be clearly beneficial: what should be actually assessed (interpretation) and on what scale this assessment is performed (disaggregation). By applying a spatial approach, it is possible to consider “real” access for example in the form of walking distance and at the same time it would provide details at much finer spatial scales than an aggregated measure for the whole city.

Moreover, conceptually it is also problematic that the distinction between urban green and other public spaces is vague. Accessibility or proportion of urban green is not even considered at the indicator scale, while many advantages of urban green related to SDG 11 such as sustainability or resilience is not detailed in the target, which focuses more on the benefit of public spaces rather from the community and civic aspects.

A further point to highlight is that GIS can provide benefits also in terms of input data for the analysis or calculation of the indicators. Satellite imagery, their classification, or existing spatial databases and their analyses are clearly necessary even for a basic calculation, especially for global monitoring and comparisons, but their potential is not considered to full depth in official guidelines and reports.

As a follow-up, Section 4 discusses the requirements for an assessment workflow aiming to support SDG target 11.7. while using a spatial approach and considering intra-urban scales.

4 THE NEED FOR A TRANSFERABLE AND AUTOMATED GIS-BASED URBAN GREEN ACCESSIBILITY ASSESSMENT FRAMEWORK

To provide an effective assessment workflow for global analysis and monitoring purposes, it is not enough if we apply a pure spatial approach instead of proportions aggregated to city-level, as it is proposed in the official indicator. We should also facilitate transferability, and automation to the best possible degree when we use this assessment workflow. Both characteristics are important and crucial for several reasons as it is discussed below. Beyond that, to promote also local actions,

the findings acquired by using this workflow, should be interpreted in a way that is compact and clear for decision-makers or planners also outside the GIS or spatial domain.

4.1 TRANSFERABILITY

Transferability makes it possible that the analysis and the workflow can be applied for any given area or city. This means that the only limitation to perform the required analysis is whether there are adequate data sources available.

There are many existing approaches to analyze urban green accessibility (e.g. Bardhan et al. 2016, Comber et al. 2008, Kolcsár & Szilassi 2018, Rahman & Zhang 2018) where analysis is performed in a very detailed and sophisticated manner but focuses only on one study area or case study. The transferability of these approaches often comes with inherent limitations. Either already from the conceptualization (what phenomenon they investigate) or the used data sources, that are only available locally. To avoid these issues to the best possible degree, we rely on input data for the assessment that have a global coverage and develop metrics that can be universally applied. Similarly to SDG targets and indicators, transferability would also require balancing between the details and depth we can consider for the analysis and the desired outcome.

4.2 AUTOMATION

Automation in this context means that the same workflow (that is also transferable) can be executed several times as one sequence without any external action beyond changing the required parameters or input data. It can be either useful to monitor the situation for the same location from time to time or to perform the analysis for a new area. It saves resources, as the details and steps of the analysis should not be defined and specified each time over and over again. Moreover, through automation and providing open access, transferability in terms of knowledge transfer is also achieved. This is particularly important for international agreements and to achieve global goals, so any interested researcher, decision-maker, institute etc. has access to this knowledge and can utilize it much easier for their purposes.

4.3 INTERPRETATION OF THE RESULTS FOR PLANNERS AND DECISION-MAKERS

In the case of urban planning decisions are often made at different levels (e.g. city administration, council) than who is actually taking action (planners). Also, GIS and a spatial approach might be not evident for these stakeholders. Therefore to utilize the findings on the availability of urban green and where improvement might be necessary should be summarized in a way that it is helpful and clear for people outside the spatial domains. This includes how visualization in maps is performed and also what information is highlighted and how.

5 THE USE OF GEO-SOCIAL MEDIA TO ANALYZE URBAN GREEN SPACES

In the recent past, there have been numerous approaches that geospatially analyzed various aspects of urban green spaces using social media data. These social media data are usually georeferenced (either through an attached GNSS position, a tagged location, or a location mentioned in the textual content of a post). This is why we use the term "geo-social media" in this article.

First of all, a larger number of research efforts investigated urban green space from a health, recreation and well-being viewpoint. Gosal et al. (2019) used natural language processing (NLP) and image analysis algorithms on Flickr posts to extract information on green space use and associated recreational benefits for the Camargue delta. The authors discovered six distinct user groups: people interested in nature, ornithologists, religious pilgrims, general tourists and aviation enthusiasts. Although the results matched known recreational attractions in the area and managers of the Camargue regional park validated the information, the process itself is hardly automatable. Similarly, Zhang & Zhou (2018) used social media posts to investigate how park attributes, park location, park context and public transportation affected the number of park check-in visits. The authors state that the number of visits was significantly different among different types of parks. This is in line with Brindley et al. (2019), who found that urban green spaces with lower quality, in terms of cleanliness, were associated with

higher prevalence of self-reported poor health. This leads to the conclusion that different spatial configurations and intra-urban mobility affect green space users and park visitors. This, in turn, means that better accessibility to green spaces can be reached through improved public transportation and planning small, accessible green spaces in residential areas.

Furthermore, several research efforts have examined spatial emotion patterns related to urban green space. Roberts et al. (2018) analyzed Twitter data and extracted positive and negative sentiments towards urban green spaces. The authors found that positive responses were more common than negative ones across all seasons. Furthermore, happiness and appreciation of beauty were the most common positive emotions identified. Similarly, Kovacs-Györi et al. (2018) aimed to identify spatio-temporal and sentiment patterns for urban green space use in Twitter data. The authors concluded that people tweeted mostly in parks 3 – 4 km away from their center of activity (an approximation for their home location) and they were more positive in parks. Additionally, Roberts et al. (2018) mentions that the results of urban green space related emotion research may significantly expand urban planners' views and decision bases in terms of the choices available to identify and analyze the sentiment present in tweets. Thus enabling the creation of evidence-based spaces which enhance positive outdoor experience, where the choice of the most appropriate analysis method is crucial.

Some recent research efforts have tried to combine social media and remote sensing approaches for analyzing urban green space. For instance, Chen et al. (2018) mentions the inability of remote sensing data and methods to identify social features. In their presented approach, the authors combined the Hyperplanes for Plant Extraction Methodology (HPEM) and considered parcels segmented from crowdsourced OpenStreetMap (OSM) road network data as the basic analytical units. Like this, they were able to extract social functions of urban green spaces. Shao et al. (2020) combined remote sensing data and Twitter posts to analyze urban sprawl and its impact on sustainable urban development. The results indicate

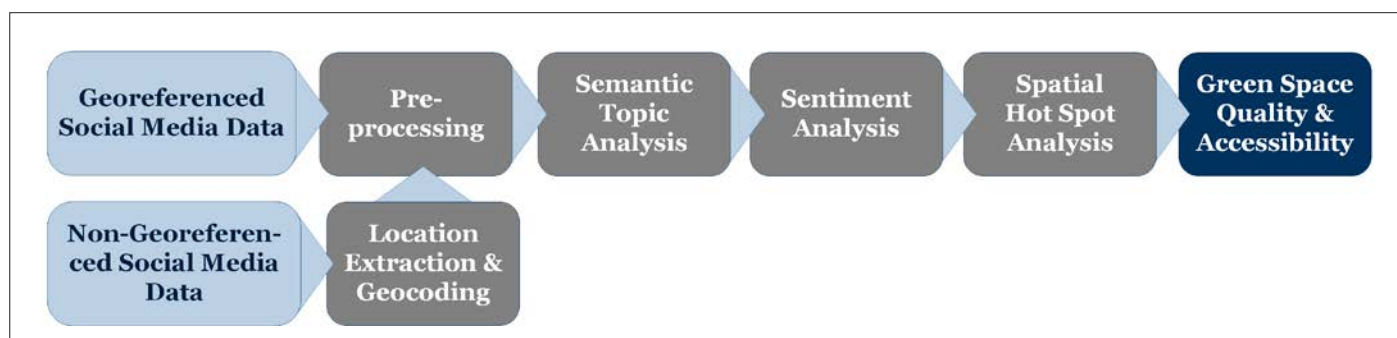


Figure 2: Key analysis steps for an automated workflow to identify public access to green spaces through geo-social media analysis

that urban expansion – being mainly driven by population growth – has negative impacts on ecosystem services like urban green spaces.

6 PROPOSED ENRICHMENT OF THE OFFICIAL CALCULATIONS FOR A SPATIALLY EXPLICIT AND AUTOMATED SDG INDICATOR ASSESSING URBAN GREEN ACCESSIBILITY

As discussed in Section 2, the official guidelines suggest a remote sensing-based assessment if an inventory of public open spaces is lacking for a given area. Texier et al. (2018) compared remote sensing, OSM and official data sources to see the impact of the data source on the analysis of urban green. The authors acknowledged the limitation of remote sensing considering the ownership of urban green (publicly or privately owned), however, they found that the interpretation of intra-urban spatial variations are not much affected by changes in data source.

To provide information about the ownership, either official data sources are required, which is challenging in the case of global calculations or the outcome of the remote sensing-based analysis should then be validated by fieldwork. This can also result in a reliable outcome for one particular area but both monitoring or global comparisons are challenging to perform on a regular basis. The benefits of a spatial approach were already described above, in this section we provide further suggestions how this GIS-based assessment might work for reporting on urban green access within cities. The proposed workflow design serves as a basis that can provide transferable and automated analysis steps, mainly for global monitoring (and comparison) purposes. To the best of our knowledge, there is no

available workflow for global analysis using a spatial approach on the current progress of cities regarding the SDG 11.7.1 indicator. The UN Habitat's initiative for city prosperity covers 450 cities worldwide, also focusing on national reporting, but their monitoring interval is 5 years, and availability for smaller cities is not provided. Beyond global monitoring and comparisons, the workflow can also be used and further specified to facilitate local planning actions. In that regard, adding information about different social groups might be beneficial to investigate inequalities of the access even better, which can help prioritization in planning decisions.

6.1 EXTRACTING URBAN GREEN SPACES FROM REMOTE SENSING IMAGERY

The first step of the workflow aligns with the official metadata reports, using remote sensing coupled with analysis techniques to identify urban green. After the required preprocessing steps of the images (e.g. atmospheric correction if required), extracting urban green areas is performed most often by Normalized Vegetation Index (NDVI) calculations (Ekkel & de Vries 2017, Texier et al. 2018, UN HABITAT 2018a). Following the approach of Texier et al. (2018) the outcome of the NDVI layer can be converted into polygons to perform further statistical analysis. In our suggested approach, this layer serves as an input for geo-social media analysis to identify ownership before calculating further metrics (Figure 2).

6.2 EXTRACTING PUBLIC ACCESS FROM GEO-SOCIAL MEDIA DATA

Identifying public access indirectly from social media data is typically done through

three distinct methods. First, social media users often attach their current location to the post, where the location is obtained through a GNSS receiver, for instance, on a user's smartphone. Second, most social media platforms allow their users to tag posts with a location or point of interest. These spatial references strongly vary in size, referring to countries, cities, or single addresses, including recreational areas and parks. Third, social media users frequently mention locations or places in the textual content of their posts. By applying semantic analysis like, for instance, Named Entity Recognition (NER) and grammatical analysis, and subsequently geocoding posts, dedicated locations can be extracted. These explicit (e.g., GNSS positions) or implicit (e.g., tags and mentions of locations or places) spatial references can then be used to assess the quality of urban green spaces including accessibility, quality or visiting frequencies (see Section 5).

Furthermore, as it was detailed in Section 5, social media analysis can also provide information about the quality of the green space or the experience of the visitors. To a certain degree, demographic information can also be extracted, however, this will always have inherent limitations due to the lacking representativeness of social media data. Therefore, we do not suggest to derive information directly from social media data about the social groups as it can lead to false interpretation. But in general, extracting information on whether a green space was visited by the public, can substitute fieldwork in the case of global monitoring or comparisons.

6.3 OVERVIEW OF THE WHOLE WORKFLOW

Figure 3 summarizes the key steps of the enriched spatial approach to automatically ex-

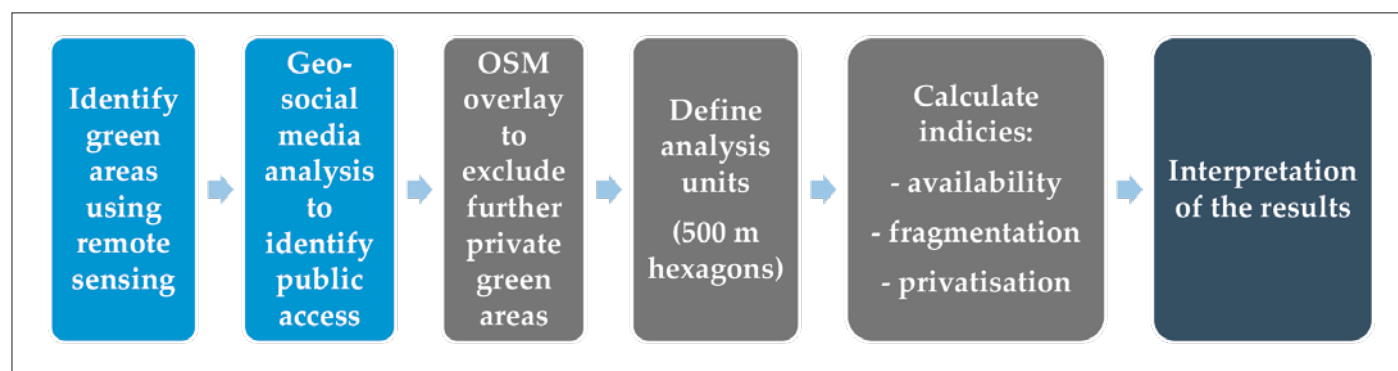


Figure 3: Overview of the suggested enriched and automated workflow for global monitoring of public urban green access using a spatial approach supporting SDG target 11.7

tract information about the accessibility of public urban green worldwide. Similar to the official UN metadata reports and guidelines, remote sensing is used in the first step to extract potential green spaces all over the world using the same principles in the analysis. This step is followed then by the analysis of geo-social media to identify areas with public access to the extracted green spaces in the first step. Unlike remote sensing, geo-social media will have different coverage in different parts of the world and it might work better for cities with higher population, particularly because spatial scale and density of social media posts strongly determine the granularity and reliability of the analysis results (Resch et al. 2017). Nevertheless, once being aware of the limitations, applying it for global comparisons and monitoring, especially on a regular basis, makes it a powerful tool, which would be impossible with manual work. The methodology can even be used to prepare local planning actions, but in that case, complementary fieldwork is required to validate the data, ideally also complemented with further data on demographics and the location of vulnerable groups within the city. For one city or an even smaller area, this validation is completely feasible, yet, social media data and automated processes can bring useful information also in this case. Moreover, in developing areas where official data sets might not be available, up-to-date or fine scale enough, the automated approach can bring useful information, which again in this case, can save work and resources compared to fieldwork with no input data.

After completing the analysis of geo-social media data, the polygons of those urban green areas that were not considered

public, can be overlaid with data from OSM. OSM has specific tags for green areas, such as "park", "garden" or "forest", and an access tag is also available, where it might be detailed whether the area is accessible to the public (access = yes or public) (Kovacs-Györi et al. 2018, Texier et al. 2018). All the remaining green areas will be considered private for the rest of the analysis (Figure 3).

In the next step, analysis units are defined to serve as a basis for further metrics calculations. To minimize edge effect and provide the best possible area to perimeter ratio, we suggest to use hexagons. The diameter of these hexagons can represent shorter walking distances to be informative on the available green spaces also without more sophisticated metrics as well. Although Modifiable Areal Unit Problem (MAUP) cannot be neglected, using 500 m wide hexagons, areas with no or limited amount of urban green available in 5-min walking distance can be easily identified by overlaying the analysis units with the output of the urban green layer from the previous step. This means if there is no polygon representing public urban green falling into a hexagon, people living or staying in that area have to walk more likely longer distances to the nearest public green space. A simple overlay function in this regard can facilitate automation and transferability, as no extra data about the street network or the definition of entry points for distance measurements is required. To minimize MAUP, the surrounding of these empty hexagons should also be analyzed in terms of the amount of public urban green.

In the last analysis step before interpreting the results, various metrics can be calculated to further characterize the available

urban green based on their distribution, size, and ownership status. Based on the approach from Texier et al. (2018) we suggest to use the following calculations for each analysis units:

1. *Availability index*: share of space in % occupied by public urban green;
2. *Fragmentation index*: perimeter divided by the area of public urban green – the higher the fragmentation is, the more likely that the green spaces are dispersed within the analysis units, but at the same time, their size might be also smaller;
3. *Privatization index*: ratio of public to total urban green.

The privatization index is important if we consider the advantages of urban green that are not strictly related to whether it is public or not, such as the effect on the microclimate, or aesthetic. Often, areas towards the outskirts of a city has less public green but people tend to have their own garden, which may influence their perception and there is no high demand for increasing the amount of public urban green in general. By using these metrics, it is possible to identify intra-urban differences in both the public urban green distribution and access.

The target 11.7 and indicator 11.7.1. specify also vulnerable social groups for whom access to public green spaces should be provided. Acquiring this demographic information for global analysis seems even more challenging than ownership aspects. As an intermediate solution, the "Gridded Population of the World" (<https://sedac.ciesin.columbia.edu/data/collection/gpw-v4>) data set can be used to estimate population densities for each square kilometer. This at least can serve as a basis to as-

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