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Introducing PtAC – an open source tool to assess SDG 11.2 using open data

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ABSTRACT

This paper presents a novel approach for assessing and monitoring Sustainable Development Goal 11.2.1, which measures the proportion of an urban population having convenient access to public transport. Despite its global importance as the key indicator for urban mobility, many cities face significant barriers to implementation, including limited access to standardized input data and a lack of technical capacity. To address these challenges, we introduce PtAC, the Public Transport Access Calculator, an open-source Python library that combines remote sensing data from the World Settlement Footprint Population with crowdsourced geospatial data from OpenStreetMap. PtAC automates the calculation of SDG 11.2.1, offering a globally applicable, transparent, and reproducible methodology for consistent monitoring of urban transport accessibility. The tool was applied to 33 cities worldwide, and its outputs were validated against reference data provided by UN-Habitat. Validation results show a high correlation, underscoring the tool's potential to support scalable SDG monitoring. The study demonstrates how open and remote sensing data can be operationalized to bridge existing methodological gaps in urban sustainability assessments.

1. Introduction

In 2015, the United Nations adopted the 2030 Agenda for Sustainable Development—a global framework comprising 17 Sustainable Development Goals (SDGs) and 169 targets aimed at eradicating poverty, fostering peace, and ensuring environmental sustainability (UN, 2015). Progress toward these goals is tracked through a set of approximately 230 indicators (Assembly 2017). Among them, SDG 11—Sustainable Cities and Communities—addresses the pressing challenge of ensuring inclusive, safe, resilient, and sustainable urbanization in the face of rapid urban growth.

Transport is a cross-cutting theme in the SDGs, with relevance across several targets, including road safety (SDG 3.6), access to infrastructure and freight/passenger transport (SDG 9.1), and urban mobility (SDG 11.2). This paper focuses on SDG 11.2, which specifically aims to "provide access to safe, affordable, accessible and sustainable transport systems for all," with particular attention to the needs of vulnerable groups. Progress is monitored via Indicator 11.2.1, which measures the proportion of the urban population with convenient access to public transport, disaggregated by sex, age, and disability status (UN, 2015).

Conceptually, the indicator builds on the notion of accessibility (Hansen, 1959), which emphasizes the relationship between spatial residential location and access to (urban) opportunities. In the context of SDG 11.2.1, accessibility is operationalized through spatial proximity of a city's population to public transport services. Although this approach has drawn criticism for neglecting temporal and qualitative aspects of accessibility (Brussel et al., 2019), proximity-based indicators remain the standard within both policy and academic domains. For instance, (Alousi-Jones & El-Geneidy, 2025) show that time-based accessibility metrics play a crucial role in understanding transit use among older adults. Similarly, (Jahangir et al., 2024) conducted a scoping review on public transport access disparities among older adults and persons with disabilities in Bangladesh, highlighting how unequal access can lead to social exclusion. These findings underscore the importance of inclusive, data-driven methodologies such as the one proposed in this study.

Despite its centrality to urban sustainability, Indicator 11.2.1 remains difficult to implement consistently across different global contexts. Several challenges have been identified in the literature, including:

(1) the lack of standardized methodologies and input data (Koch & Ahmad, 2018; Simon et al., 2016);
(2) limited availability of open-source tools adapted to local planning needs (Hansson et al., 2019; Klopp & Petretta, 2017); and

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(3) inconsistencies in national definitions and data collection practices (Tiwari & Phillip, 2021)

UN-Habitat working groups continue to debate critical aspects of the indicator's definition, data requirements, and operationalization (Koch & Ahmad, 2018). Consequently, many cities—particularly in the Global South—struggle to monitor and report on this indicator effectively.

This methodological fragmentation presents a significant research gap: while several studies assess public transport access at the local level, there is no widely adopted, open-source, and scalable solution for calculating Indicator 11.2.1 using globally available data. In particular, tools that leverage open data (e.g., OpenStreetMap) and open methodologies are scarce, limiting reproducibility, comparability, and local usability.

To address this gap, we introduce PtAC (Public Transport Accessibility Calculator), an open-source Python tool designed to compute SDG Indicator 11.2.1 using two global, openly accessible datasets: OpenStreetMap (OSM) and the World Settlement Footprint Population (WSF2019-Pop) based on remote sensing (Marconcini et al., 2021). The use of remote sensing for transport applications is gaining momentum, as high-resolution data become increasingly accessible and effective in identifying land use and trip-generating areas (Soares Machado & Quintanilha, 2019). PtAC estimates the population within 500 m of low-capacity public transport stops and within 1000 m of high-capacity stops, following the UN definition of "convenient access" (Daniels & Mulley, 2013; UN, 2015).

Applied across 33 cities worldwide, PtAC enables direct comparison with results produced by UN-Habitat's closed-source workflows. Our findings demonstrate a strong correlation between PtAC outputs and those of the official reference approach, suggesting that PtAC can support scalable, transparent, and replicable measurement of urban transport access. In doing so, it offers a valuable tool for cities and researchers aiming to operationalize SDG 11.2.1 within local planning frameworks.

2. Approach & method

This section delineates the methodology that we employed in the calculation of SDG 11.2, utilizing remote sensing-based population data and freely available datasets. It introduces PtAC,[1] a Python library that automatically downloads and stores road networks, computes routes from the population to public transport and calculates the actual indicator. The section also provides a comprehensive overview of the methodology employed to derive population information from remote sensing imagery on a global scale. The proposed approach involves the utilization of freely available data sources and open data standards to automate and efficiently calculate the input variables. We not only intend to showcase the ability of the tool here, but also the general application of such a workflow-related tool to systematically guide the homogenous assessment of the SDG goals.

Fig. 1 gives an overview on the functionality and workflow of PtAC. The calculation of this indicator for a specific region requires the following data sources: 1) disaggregated population information (see section 2.2); 2) a routable road network (see section 2.3); 3) the city boundary (see section 2.4); and 4) a spatial allocation of public transport stops (see section 2.5). The SDG 11.2.1 indicator is then computed by calculating the walking distance to the next public transport stop for each of the population points along the street network, and then determining the share of the population that can walk to public transport within 500 m or 1 km distance. The intention is that the approach should be transferable and applicable almost everywhere and by everyone. To this end, we aim to rely on open and globally available data wherever possible, and to utilize open source software for the calculation. Details about the functionality[2] and installation instructions[3] are provided within the project and working examples of the application are provide using Jupyter notebooks including necessary data and illustration the results.[4] The subsequent chapter provides an overview of the approach and the data sources utilized. Starting with an introduction of the study sites (2.1), we subsequently introduce the steps, based on the required input data as introduced in the beginning of this section. However, it should be noted that alternative data sources that meet the criteria outlined in points 1), 2), 3) and 4) can also be employed.

2.1. Study sites

In order to demonstrate the applicability and evaluate the quality of the outcomes, we employed PtAC to calculate SDG 11.2.1 for 33 example cities. The selection of these cities was based on criteria such as data availability and geographic location, with the objective of ensuring representation from all continents, excluding Antarctica due to the absence of substantial urban areas. The population size of the cities ranged from under 500.000 to over 5 million inhabitants (see Table 1).

2.2. Deriving population information from remote sensing

Gridded population datasets for 33 cities located around the world (see Table 1) were produced for this research, following the methodology employed in the production of the WSF2019-Pop dataset (Palacios-Lopez et al., 2021). In particular, a weighted, dasymetric modelling approach was used to disaggregate 2019 population estimates from administrative units (i.e. highest level of administrative boundaries for each city) into grids of 10 m spatial resolution, using as proxy layer the novel World Settlement Footprint 2019 Imperviousness layer (WSF2019-Imp) (Marconcini et al., 2020) produced by the German Aerospace Center (DLR). Accordingly, the population estimates for 2019 and corresponding administrative boundaries (i.e. vector data) were downloaded from the open archive of the WorldPop Global project (Lloyd et al., 2019).

The WSF2019-Imp layer is a global dataset that describes the percent of impervious surface (0 < PIS<=100 %) within areas categorized as settlement in the WSF2019 layer (Marconcini et al., 2020). Concisely, for each pixel within a given administrative unit, the estimated population is defined as follows:

$$Pop_p = Pop_{AU}\frac{PIS_p}{\sum_{(p\in AU)}PIS_p} \tag{1}$$

where each pixel in a given administrative unit (AU) is assigned a proportion of the total population (Pop_{AU}), relative to their percent of impervious value (PIS_p).

UN-Habitat utilizes WorldPop population count data (2020) with a resolution of 100 m that assumes all buildings within the service area are habitable and the population is equally distributed across built settlements (constrained). Moreover, the dasymetric mapping technique they utilize allows them to map relative homogeneity of population in each service area.

Fig. 2-a shows an example of the final gridded population dataset for the district of Friedrichshain (Berlin). All datasets have been produced at a spatial resolution of 0.3 arc-sec (~10 m at the Equator), and represent the number of people per pixel. Once the population grid was produced, these were converted into point (vector) data using the pixel centroids as shown in Fig. 2-b.

[1] https://github.com/DLR-VF/PtAC.

[2] https://ptac.readthedocs.io.

[3] https://github.com/DLR-VF/PtAC/blob/master/docs/source/user-guide.rst.

[4] https://github.com/DLR-VF/PtAC-examples.

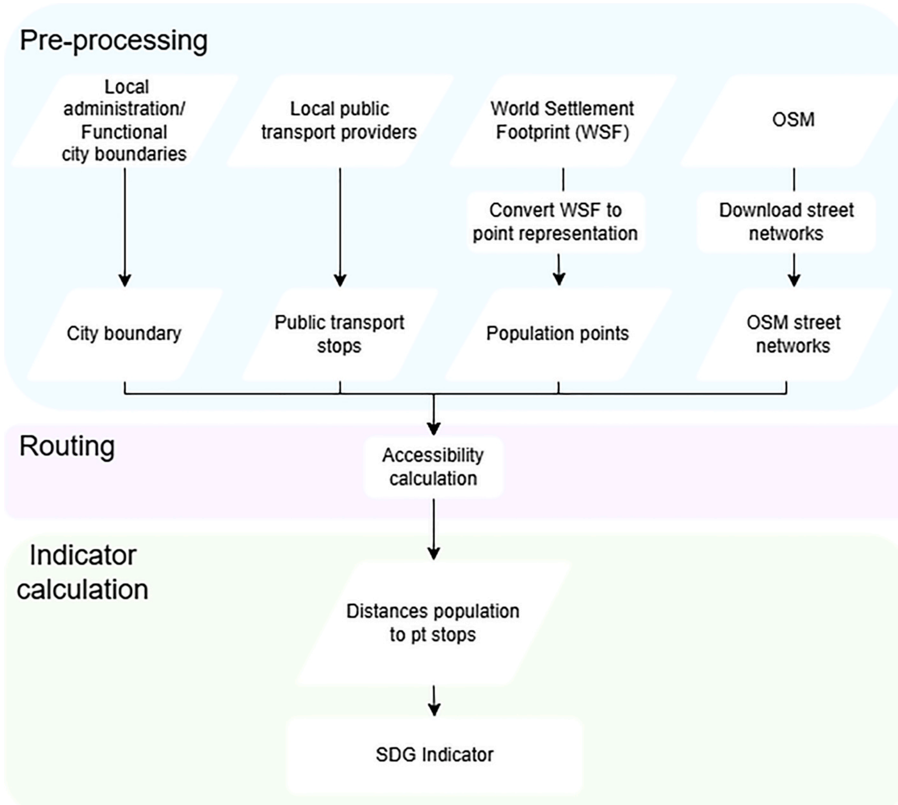

Fig. 1. PtAC workflow.

2.3. Retrieve and process street networks from OpenStreetMap

To assess the distance the population of a city must walk to access public transportation, a routable street network is essential. In our approach, we utilize OpenStreetMap (OSM) because it is open-source, globally available, and can be seamlessly integrated into PtAC (see Fig. 3). OSM (OpenStreetMap contributors, 2017) is a collaborative initiative that collects geographic data to create a free and editable global map. While the quality of OSM networks is generally high, it varies across different regions. According to (Barrington-Leigh & Millard-Ball, 2017), 42 % of countries worldwide have networks that are over 95 % complete, and the global road network coverage is approximately 83 %. As the number of contributors continues to grow, the OSM database is rapidly expanding, making it increasingly reliable for researchers and policymakers in many parts of the world, particularly in densely populated urban areas which are often well-mapped.

In this study, we download and preprocess OSM road networks using the methodology described by (Boeing, 2017). This involves obtaining the walkable sections of city networks via the Overpass API and preparing them to create consistent and routable network graphs. "Walkable" refers to all publicly accessible streets or paths where walking is permitted. This excludes roads such as motorways or cycle paths. Non-connected segments are removed from the largest network component to ensure continuous and accurate routing. All edges in the network are bidirectional, supporting routing in both directions.

2.4. City boundaries

For each analyzed city, a spatial area is defined. This task is not straightforward, as administrative boundaries do not commonly cover the urban extent sufficiently and the delineation of city boundaries has a large impact on the calculation results (Openshaw, 1981). Cities and agglomerations may span farther than their administrative boundaries, mostly as a result of urban growth. In many cases, city boundaries that are designed for statistical purposes are much larger than the settlement areas of an urban agglomeration (UN-Habitat, 2018). Therefore, the analysis area (city/urban area) must be carefully defined by adopting the degree of urbanization for computation of the SDG 11.2. indicator. For this study, we used the urban extents as defined and calculated by UN-Habitat (ibd.) (see Fig. 3). These so-called functional city boundaries rely on an assumption which takes the presence of buildings into account, thereby defining an indicator of how urban an area is. This is done in the following way: An area which is densely built up is accounted as urban, whereas a sparse area is ranked as rural settlement. The urban extent is then generated based on these area classifications.

In order to define functional urban areas, each small administrative area is classified as urban or rural by undertaking supervised image classification including classes for built-up, water, open spaces such as forests and green areas, etc. After defining hypothetical city boundaries, the outcome of the supervised classification is reclassified to extract only built-up pixels using GIS software. Then, focal statistics are computed to determine the density of built-up areas per square kilometer. The focal statistics output is then reclassified to determine the urbanness of each zone based on the built-up area density per square kilometer. The total urbanized area is the entire spatial extent that meets the defined threshold of "urban" which is a minimum of 50 % of pixels around each gridded population cell. The built-up area that has pixel density between 25 and 50 % is defined as "sub-urban area" whereas the built-up area with pixel density less than 25 % is classified as "rural-area".

2.5. Public transport stops

In order to calculate SDG 11.2.1, public transport (PT) stops are used as destination points for the accessibility calculation. Getting such information is challenging as there is no global, open data set available that provides this information. Collecting it therefore requires manual

Table 1
Overview of cities that have been selected for the study.

City	Population (Mio)	City area (km^2)	Number of high-capacity public transport stops	Number of low-capacity public transport stops
Africa				
Addis Ababa	3,5	296,69	40	183
Casablanca	4	268,42	43	1237
Johannesburg	9,5	2638,28	162	1479
Lagos	12,3	830,09	6	1092
Nairobi	5,6	720,40	11	2636
America				
Chicago	9,1	8297,28	497	12,846
Medellin	3,2	147,94	40	306
Montreal	3,6	1133,64	243	16,153
Santiago	6,7	761,41	437	10,695
Asia				
Dubai	4,0	792,37	101	2189
Makassar	2,2	285,26	–	326
Manila	12,6	1110,27	90	1194
Mashhad	2,8	315,50	106	783
Mumbai	26,4	711,67	139	4392
Seoul	24,3	3174,05	3325	11,818
Singapore	5,9	422,33	402	4813
Tehran	9,8	784,70	258	1927
Australia				
Brisbane	2,0	1054,23	124	9319
Melbourne	4,4	2207,35	214	19,014
Sydney	4,5	1628,28	281	7801
Europe				
Ankara	4,9	537,07	64	1032
Berlin	3,8	977,50	2004	7461
Budapest	2,2	730,34	1055	5681
Izmir	2,8	292,88	84	1454
London	12,3	2524,91	89	28,555
Madrid	5,4	845,46	911	8877
Milan	6,5	2780,94	1564	10,046
Moscow	17,3	3595,39	2444	15,128
Paris	11,4	2862,43	2292	25,580
Strasbourg	0,4	127,45	178	993
Vienna	2,3	537,67	1521	4206
Warsaw	2,7	746,78	931	5264
Zurich	0,8	215,72	638	1829

research and analysis. A common data format that includes information on public transport stops is the General Transit Feed Specification (GTFS), but any other datasets containing the location of stops can also be used. GTFS is a data format which is developed for trip planning and visualization of public transport network by Google Maps and TriMet (McHugh, 2013). PtAC supports reading of PT stops directly from GTFS sources (in text file format) or any geodata point source that can be read by GDAL/OGR (see Fig. 3).

Since the goal of this study is to compare outcomes of the classical (closed-source) approach used by UN-HABITAT to calculate the indicator to the output of PtAC, we used the same public transport stops in both approaches. They were gathered from OSM and from open data platforms like OpenMobilityData and Transitland, and were extended by manual localization using very high-resolution optical imagery.

2.6. Routing and indicator calculation

PtAC was developed to ease the calculation of SDG 11.2.1 by simplifying the data processing steps and handling of the Open Source accessibility tool UrMoAC (Krajzewicz et al., 2017) (https://github.com/DLR-VF/UrMoAC). PtAC provides wrapper functionalities for UrMoAC including: downloading a street network from OSM (see section 2.2), reading of public transport stops and population information (see section 2.1 and 2.4), and doing the actual calculation and visualization of the SDG 11.2.1 indicator. Based on current definitions, SDG 11.2.1 represents the accessibility within 500 m walking distance to low-capacity public transit system and 1 km to high-capacity system. Low-capacity public transport systems include bus, tram and Bus Rapid Transit (BRT) stops while high-capacity systems cover train, metro and ferry stops.

PtAC calculates shortest distances on the street network from the centroid of any pixel of the population dataset to the next public transport stop. The routing starts at the pixel's centroid, searches for the nearest edge of the street network and performs routing until the nearest edge of the closest public transport stop is reached. In this process, access and egress distances from population points to the street network and from the street network to the public transport stops are omitted. In order to calculate the SDG 11.2.1 indicator pixel centroids within a distance of 500 m for low capacity transit and respectively 1000 m for high capacity transit are summed up and divided through the overall population of the city (see equation (1).

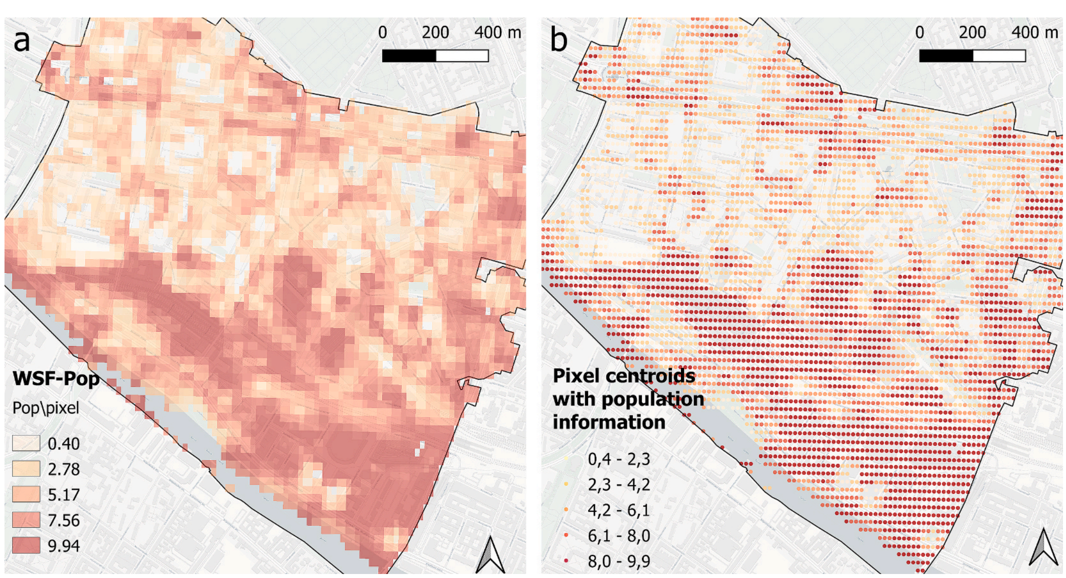

Fig. 2. a) Population information from WSF-Pop in raster format (left) and b) pixel centroids (right) for the district of Friedrichshain (Berlin).

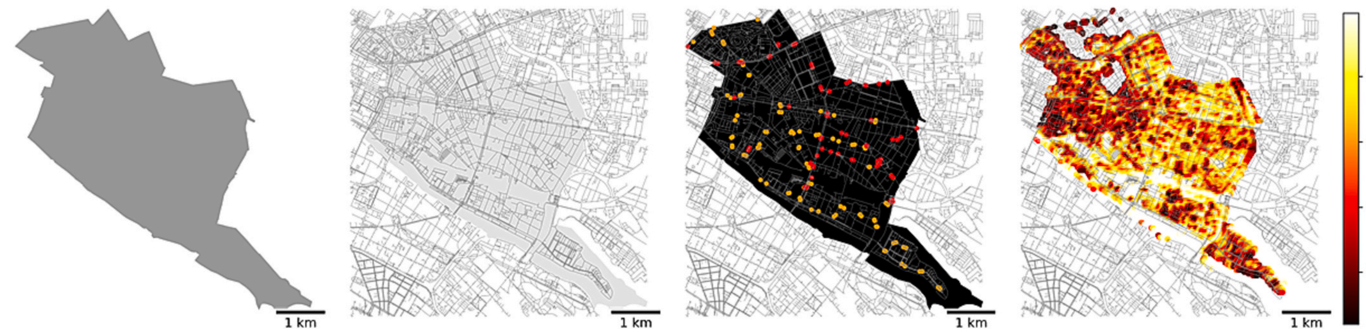

Fig. 3. Example of input data for Berlin's district Friedrichshain. a.) illustrates the district/city boundaries, b.) shows the routable street network downloaded from OSM, c.) depicts the public transport stops where the red points indicate high-capacity and the yellow points low-capacity transport stops and d.) shows the remote sensing-based population estimation where the colors indicate the population per pixel. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

$$\text{SDG }11.2.1\text{ Indicator} = \frac{\sum_{i=1}^{n} p_i}{p_a}$$

where p_i is the population of a single pixel within 500 m/1000 m distance to the next station and p_a is the overall population of the city area.

2.7. Evaluation

For validation purposes, SDG 11.2.1 indicators were calculated for each case study city using the PtAC approach, and the results were systematically compared to the reference values published by UN-Habitat. The latter were derived using a proprietary methodology based proprietary tools and data that are not publicly accessible or available to local stakeholders. UN-Habitat employs the High-Resolution Settlement Layer (HRSL, 2015), developed by the Facebook Connectivity Lab, to estimate population distribution. This dataset offers global coverage at a spatial resolution of 30 m and is freely available for use. In contrast, PtAC calculations are based on the World Settlement Footprint (WSF) population dataset from 2019, which provides more recent population estimates and a significantly higher spatial resolution of 10 m. When interpreting the comparative analysis, two major distinctions in data sources must be considered: (1) the PtAC approach utilizes more temporally current population data (2019 vs. 2015), and (2) the spatial resolution of the WSF dataset is three times finer than that of the HRSL, allowing for a more detailed and accurate representation of population distribution.

3. Results

This section presents the results of the study, including exemplary outputs and a comparative analysis of the SDG 11.2.1 indicator calculated using the PtAC methodology across 33 global cities. These results are benchmarked against reference values published by UN-Habitat.

Fig. 4 illustrates the results of the PtAC calculations for the metropolitan area of Manila. The left panel displays the distribution of population points and their respective distances to the nearest public transport stop. The right panel shows the cumulative share of the population by distance to the nearest stop. As expected, central urban areas exhibit high accessibility to public transport, with the majority of the population residing within 500 m of a transit stop. In contrast, peripheral and suburban areas show markedly reduced procimity.

The cumulative distribution indicates that 24.8 % of the population lives within 500 m, 56.6 % within 1,000 m, and 97.5 % within 3,000 m of a stop.

Based on these distance thresholds and following the SDG 11.2.1 methodology (see Section 2.5), the final SDG indicator value—defined by the population share within 500 m of low-capacity and 1,000 m of high-capacity public transport—is computed to be 29 %. This result deviates by 3.5 percentage points from the corresponding UN-Habitat reference value.

The distribution of results reveals three distinct clusters, each corresponding to a different range of urban accessibility levels, as highlighted in Fig. 5:

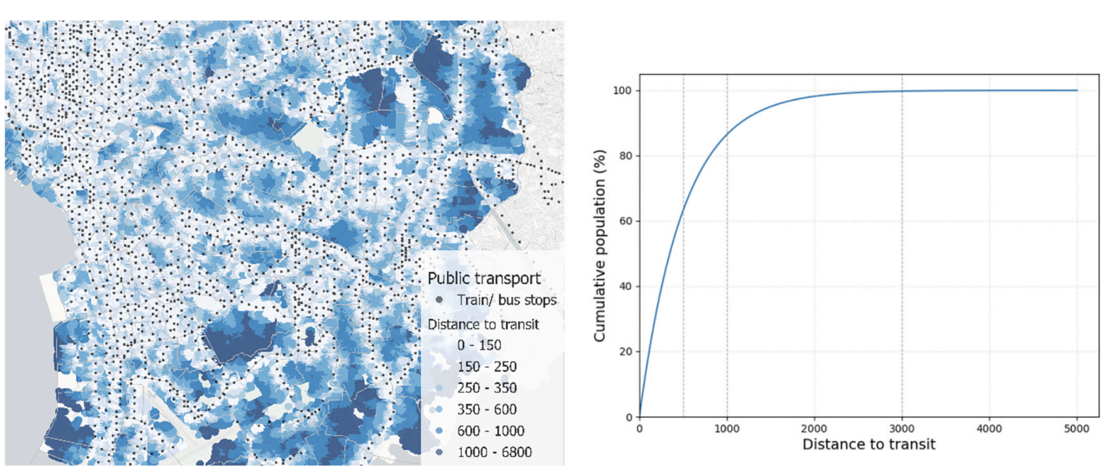

Fig. 4. Exemplary results of PtAC calculations for the city of Manila. Spatial distribution of population points and computed distances to the nearest public transport stop. Right: Cumulative population share by distance to public transport.

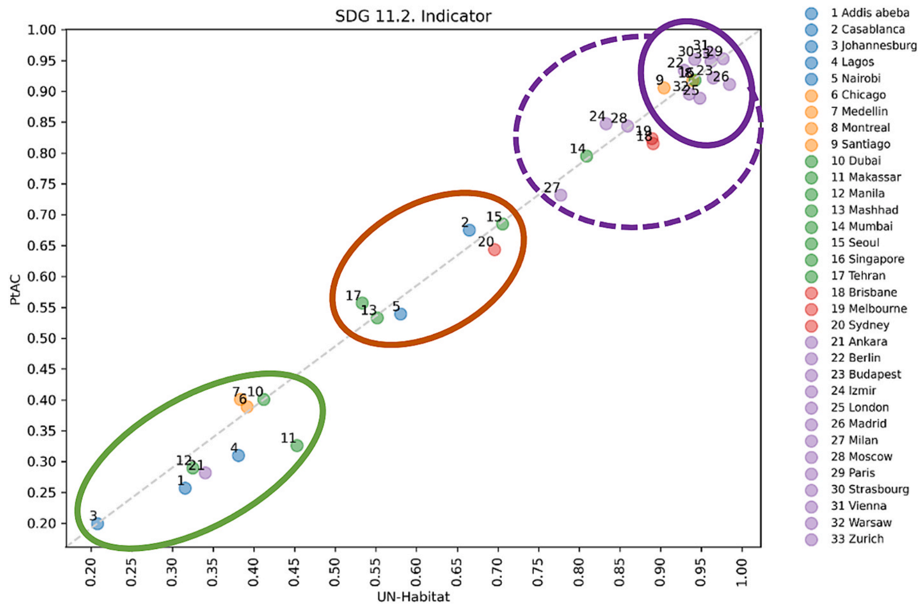

Fig. 5. Comparison of PtAC and UN-Habitat SDG 11.2.1 values across 33 cities. Each dot represents one city, color-coded by continent. The dashed and solid lines highlight three main clusters—low (<50 %, green), medium (50–75 %, orange), and high (>75 %, purple)— and illustrate varying levels of public transport access and correspond to different urban development patterns. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

- **Cluster 1 (Green ellipse)** includes cities with low public transport accessibility (SDG 11.2.1 values below 50 %), such as Johannesburg, Manila, and Nairobi. These cities are predominantly located in Africa, Asia, or Latin America and are often shaped by automobile-centric development patterns or high reliance on informal transport systems (Behrens et al., 2015), which due to data scarcity are not captured by the SDG 11.2 indicator. As such, the relatively low accessibility values may reflect the methodological limitations of the indicator rather than the actual availability of mobility options.
- **Cluster 2 (Orange ellipse)** represents cities with medium accessibility levels (between 50 % and 75 %), including Seoul, Tehran, and Sydney. These cities are typically in a transitional phase, expanding their public transport infrastructure and working toward broader integration of suburban and peripheral areas. They can be interpreted as cities that are "picking up" in terms of public transport development.
- **Cluster 3 (Purple ellipse)** contains cities with high accessibility (above 75 %), such as Zurich, Paris, and Warsaw. These are primarily located in Europe or other highly developed regions and are characterized by mature, dense, and well-integrated public transport systems. Within this group, a dashed line marks the 75 % threshold, and a solid line highlights cities exceeding 90 %, emphasizing their ability to meet and surpass the accessibility targets defined in SDG 11.2.1. The consistently high values in both PtAC and UN-Habitat data highlight the reliability of these systems in providing widespread, convenient access to transit.

A continental breakdown reveals that the highest mean deviation occurs in Australia (6.4 %), while the lowest is found in the Americas (1.1 %), as detailed in Table 2. The consistently high R^2 value substantiates the reliability and robustness of the PtAC method in replicating SDG 11.2.1 values across diverse urban contexts.Table 3.

Table 2
Results of comparison based on continents.

Continent	R^2-Score	Median difference (%)	Mean difference (%)	Standard deviation of difference (%)
Africa		4.1	3.8	2.8
America		1.0	1.1	1.0
Asia		2.2	3.4	3.8
Australia		6.5	6.4	1.1
Europe		2.3	3.1	2.3
All	0.97	2.3	3.3	2.8

Table 3
Comparison of the ease of implementation.

	PtAc	Manual Calculation
Data acquisition		
City boundaries	Manual input	Manual input
Population Data	Automatic (WSF)	Manual attention
Transportation Network	Automatic (OSM)	Manual attention
Public transit stops	GTFS	
Data Processing		
Routing	Automatic (Wrapper for UrMoAc)	Manual, using accessibility tools (e.g. R5, ArcGIS)
Analysis		
Indicator assessment	Automatic	Manual

4. Discussion

In this study, we present a methodology for computing the SDG 11.2.1 indicator using remote sensing data products, open-access datasets, and open-source software. While SDG 11.2.1 has been evaluated across a wide range of cities globally, the novelty of our approach lies in its operational simplicity, high transferability, and negligible data acquisition costs, all while delivering robust and accurate indicator estimates. These characteristics make the method particularly relevant for contexts with limited technical and financial resources. Accordingly, this paper provides a critical evaluation of the methodology, focusing on two key aspects: (a) the extent to which the approach fulfills the objective of ease of implementation, and (b) the quality and reliability of the resulting indicator values compared to established reference data.

To assess ease of implementation, we outline the PtAC methodology, which organizes the computation process into three core phases: data acquisition and preprocessing, routing, and indicator assessment. Unlike conventional manual workflows that often require extensive technical expertise, PtAC automates most procedures and significantly reduces user input. Users are required only to define the city boundaries and, when GTFS data are unavailable, to specify public transport stop locations. If GTFS data are available, even this step can be automated. Key input datasets—namely population data from the World Settlement Footprint (WSF2019-Pop) and transport network data from OpenStreetMap (OSM)—are retrieved and processed automatically. Routing is performed using a wrapper for UrMoAc, and the final calculation of the SDG indicator is fully automated. Of the seven total process steps, only two require manual input, representing a substantial reduction in technical workload. As a result, PtAC offers a scalable and accessible tool for local governments to independently and consistently monitor progress toward SDG 11.2.1, even in the absence of specialized GIS capacities.

To evaluate the quality of the results, we compare our outputs with official reference values calculated by UN-Habitat. The results demonstrate a high overall correlation, with an R^2 value of 0.97, indicating strong agreement between the two approaches. Despite this, certain deviations are observed, particularly in Australian cities and in Makassar. These discrepancies are most likely attributable to differences in the underlying population datasets. PtAC employs WSF2019-Pop, which offers higher spatial resolution (10 m versus 30 m) and more recent data (2019 as opposed to 2015). Furthermore, UN-Habitat's methodology assumes a uniform distribution of population across built-up areas, which can result in a more homogeneous density and may potentially overestimate accessibility in low-density regions. Such differences become especially relevant in peripheral or semi-urban areas, where PtAC's more granular data may yield more conservative—but arguably more accurate—estimates. Nevertheless, given the relatively small sample size of 33 cities, statistical results should be interpreted cautiously, and further applications of the tool are necessary to verify robustness across diverse geographic and socio-economic contexts.

The three empirically derived clusters correspond closely to Kenworthy's typology of urban transport systems (Kenworthy & Laube, 1999). Cities in Cluster 1 reflect the characteristics of "automobile cities" or "informal transport cities," where public transport access is structurally limited and not fully captured by formal indicators such as SDG 11.2.1. Cluster 2 represents hybrid cities in transition toward more integrated systems, while Cluster 3 includes mature "transit cities" with long-standing investments in public transport infrastructure and land-use integration. This clustering not only validates the PtAC methodology but also reveals broader regional patterns and development stages of public transport infrastructure. Moreover, it highlights a structural bias in SDG 11.2.1 toward formalized systems, potentially underrepresenting mobility access in cities where informal transport plays a central role.

Beyond technical validation, this study contributes to both urban policy and transportation research. For urban policy-makers, PtAC offers a scalable, transparent, and cost-effective instrument for integrating transport accessibility indicators into planning routines. The tool's reliance on openly available data and automated workflows lowers the barrier for implementation, particularly in cities with limited resources. It supports data-driven decision-making by identifying underserved areas and monitoring progress toward sustainable urban mobility in alignment with international frameworks such as the 2030 Agenda. For transportation researchers, PtAC provides an open and reproducible framework that facilitates large-scale comparative studies of urban accessibility. It enables testing of alternative accessibility models, integration of additional data sources such as land use or transport quality metrics, and the exploration of urban mobility inequalities through standardized global assessments.

The PtAC methodology offers substantial long-term benefits, both in terms of resource efficiency and urban governance. Its reliance on open data (e.g., WSF2019-Pop, OpenStreetMap, GTFS) and open-source software ensures minimal to no financial cost for data acquisition and software licensing. This dramatically reduces recurring expenses compared to traditional, proprietary GIS workflows—particularly relevant for low- and middle-income cities facing fiscal constraints.

Moreover, from a policy impact perspective, the return on investment is amplified through improved decision-making and spatial targeting. By accurately identifying underserved areas using high-resolution and recent population datasets, PtAC supports the prioritization of infrastructure investments where they are most needed. This alignment with international goals—such as the 2030 Agenda for Sustainable Development—not only enhances accountability but may also open access to global funding mechanisms tied to SDG performance.

Finally, the reproducibility and transparency of the PtAC methodology offer significant long-term value for transportation research. The method facilitates longitudinal monitoring, comparative studies, and the integration of additional layers (e.g., land use, socio-economic indicators), all of which contribute to more holistic and inclusive urban mobility planning. In this sense, PtAC functions not only as a tool but as an enabler of systemic, cost-efficient improvements in sustainable urban transport monitoring and policy formulation.

5. Conclusion

In this study we introduced a workflow for the calculation of SDG 11.2.1. The study is founded on the utilization of open data and open-source tools, thereby allowing the easier applicability on a global scale. We introduced the python library PtAC which has been developed and made available as open source by the authors/DLR. We compared the outcomes of PtAC to a conventional methodology previously applied by UN Habitat for 33 cities worldwide. Our results turned out to be very similar on a city aggregate level for most places, indicating that our methodology delivers equally good results.

For the future, we expect that open data will become increasingly available, with enhanced quality in terms of spatial resolution and timeliness. Furthermore, we expect that with increasing computational power, automatic or semi-automatic calculations like the one introduced by us will become even more relevant to generate topical findings and to monitor ongoing developments. We also expect that the SDG 11.2.1. Indicator will be refined, for instance by including more variables and a more complex calculation method. Beyond incorporating distance-to-transit, refinements could include aspects such as proximity-centred accessibility and route-based accessibility measures (Lucas Albuquerque-Oliveira et al., 2024; Silva et al., 2023).

Another, more general limitation of the procedure pertains to informal transport, which is frequently excluded from GTFS datasets and other public transport stop data. Consequently, it cannot be incorporated in the calculation. Informal transport is a form of public transport that is privately developed and run and mainly operates outside the wider official regulatory framework (Oviedo Hernandez et al., 2021). It is widely common in the developing world, often constituting the sole publicly available transport option in numerous cities. The absence of any formal transport planning for informal transport means that knowledge about its extent is frequently limited. Regarding the appraisal of SDG 11.2, omitting informal transport where available would mean to systematically underrate the indicator value of this *de-facto* public mode of transportation. In recent years, however, mapping informal transport has become more common, for instance in Nairobi (Digital Matatu) or by companies and NGOs. Nevertheless, further research and manual effort are required to improve the quality of accessibility assessments where informal transport is available, and also how other public modes of transport such as electric scooters can be included (Hasselwander et al., 2023).

CRediT authorship contribution statement

Simon Nieland: Writing – review & editing, Writing – original draft, Supervision, Software, Methodology, Investigation, Conceptualization. **Mirko Goletz:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Data curation, Conceptualization. **Daniel Krajzewicz:** Writing – review & editing. **Daniela Palacios Lopez:** Writing – original draft, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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