International Journal of Geo-Information

MDPI

Article

Automated Geospatial Approach for Assessing SDG Indicator 11.3.1: A Multi-Level Evaluation of Urban Land Use Expansion across Africa

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Abstract: Geospatial data has proven useful for monitoring urbanization and guiding sustainable development in rapidly urbanizing regions. The United Nations' (UN) Sustainable Development Goal (SDG) Indicator 11.3.1 leverages geospatial data to estimate rates of urban land and population change, providing insight on urban land use expansion patterns and thereby informing sustainable urbanization initiatives (i.e., SDG 11). Our work enhances a UN proposed delineation method by integrating various open-source datasets and tools (e.g., OpenStreetMap and openrouteservice) and advanced geospatial analysis techniques to automate the delineation of individual functional urban agglomerations across a country and, subsequently, calculate SDG Indicator 11.3.1 and related metrics for each. We applied our automated geospatial approach to three rapidly urbanizing countries in Africa: Ethiopia, Nigeria, and South Africa, to conduct multi-level examinations of urban land use expansion, including identifying hotspots of SDG Indicator 11.3.1 where the percentage growth of urban land was greater than that of the urban population. The urban agglomerations of Ethiopia, Nigeria, and South Africa displayed a 73%, 14%, and 5% increase in developed land area from 2016 to 2020, respectively, with new urban development being of an outward type in Ethiopia and an infill type in Nigeria and South Africa. On average, Ethiopia's urban agglomerations displayed the highest SDG Indicator 11.3.1 values across urban agglomerations, followed by those of South Africa and Nigeria, and secondary cities of interest coinciding as SDG Indicator 11.3.1 hotspots included Mekelle, Ethiopia; Benin City, Nigeria; and Polokwane, South Africa. The work presented in this study contributes to knowledge of urban land use expansion patterns in Ethiopia, Nigeria, and South Africa, and our approach demonstrates effectiveness for multi-level evaluations of urban land expansion according to SDG Indicator 11.3.1 across urbanizing countries.

Keywords: sustainable development goals; urban Africa; land use change; isochrone; OpenStreetMap; openrouteservice

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Citation: Cardenas-Ritzert, O.S.E.; Vogeler, J.C.; Shah Heydari, S.; Fekety, P.A.; Laituri, M.; McHale, M. Automated Geospatial Approach for Assessing SDG Indicator 11.3.1: A Multi-Level Evaluation of Urban Land Use Expansion across Africa. *ISPRS Int. J. Geo-Inf.* **2024**, *13*, 226. https://doi.org/10.3390/ijgi13070226

Academic Editors: Godwin Yeboah and Wolfgang Kainz

Received: 16 April 2024
Revised: 7 June 2024
Accepted: 21 June 2024
Published: 28 June 2024

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1. Introduction

Africa is at the forefront of global urbanization, as many of its developing countries experience rapid urban population growth and endure multi-dimensional transformations. United Nations (UN) projections estimate more than half of the global urban population growth from 2019 to 2050 will occur in Africa, and 22 percent of the total global urban population will be concentrated in the continent by 2050 [1]. Drivers of urbanization vary across Africa and are a function of increasing birth rates in urban areas, reclassification of

growing rural areas to urban, as well as some rural-to-urban migration [2–4]. An increasing urban population is leading to significant social, environmental, and economic changes across Africa's urban areas [5] and is expected to drastically transform Africa's landscapes, with urban land cover anticipated to expand 12-fold from 2000 to 2050 [6].

Moreover, the effects of rapid urbanization in Africa will likely not be proportionate over the coming decades, with most urban population growth expected to be concentrated in smaller- to intermediate-sized cities, otherwise referred to as secondary cities [1]. Although secondary cities lack a single, universal definition, they are often identified based on population, size, function, economic status, and other characteristics. Roberts (2014) defines secondary cities by functional traits and broadly categorizes them into the following three classes: (1) urban centers that are hubs for economic, industrial, agricultural, and governmental activities; (2) peripheral cities connected to a larger metropolitan area that functionally support the growth and development of the metropolitan area; or (3) cities located in economic corridors of trade and transportation [7]. Secondary cities have remained essential for harboring growing urban populations and facilitating national development but are often limited in their resources and management capacity [7,8], further highlighting the importance of consistent monitoring of urbanization-driven changes to guide sustainable development planning.

Various initiatives seek to aid Africa and other rapidly urbanizing regions across the globe in managing urban growth and accelerating sustainable development practices, including Sustainable Development Goal (SDG) 11 under the UN's 2030 Agenda for Sustainable Development [9]. SDG 11 focuses on making cities and human settlements inclusive, safe, resilient, and sustainable, and Target 11.3 aims to enhance inclusive and sustainable urbanization and capacity for participatory, integrated, and sustainable human settlement planning and management in all countries by 2030. SDG Indicator 11.3.1, a ratio of the Land Consumption Rate (LCR) and Population Growth Rate (PGR), was developed under Target 11.3 as a measure for monitoring rates of urban land development and population growth over time in an allocated urban area. Spatial demographic data and land cover and land use (LCLU) data have been analyzed to assess SDG Indicator 11.3.1 at various scales and extents [10,11], but numerous limitations for implementing and interpreting SDG Indicator 11.3.1 have been realized [11–13] and emphasize the need for further development to improve its applications.

In the initial stages of SDG Indicator development, the absence of a universal definition of urban areas was highlighted as a challenge for achieving global and prospective comparisons [14–17]. Urban areas undertake a diversity of spatial forms and can be defined by different criteria (e.g., population measures, built-up characteristics, non-agricultural economy), making the spatial identification of their boundaries nuanced or dissimilar depending on the definition and method used [14,17]. A vast library of works exist that have developed and tested methods for the spatial identification of urban boundaries, largely based on characteristic scales (e.g., population density distribution) or scaling laws (e.g., fractal approaches) [18–23]. These often complex methodologies have proven effective at identifying urban agglomerations across large extents, but the UN-Habitat and their partners tested various concepts and agreed upon two methods for the practical application of SDG Indicators [14].

The UN-Habitat proposed the "functional" definition of a city, which can be derived using The Degree of Urbanization method or the Urban Extent method [14,24,25]. The former, endorsed by the United Nations Statistical Commission, reclassifies gridded population data into clusters based on population size and density thresholds [14,25]. The Urban Extent method, developed by New York University in conjunction with UN-Habitat, explicitly utilizes built-up land cover characteristics as input to identify the urban, suburban, and open space areas that comprise the extent of an urban area [15,17]. Both methods have shown to produce similar extents for larger cities but may vary in their delineation of smaller cities [14,17].

The two current approaches are suitable for delineating boundaries and investigating urban change at either a finer scale (e.g., a single city), which typically requires insight on local settlement interactions to accurately delineate boundaries, or a more coarse or generalized scale (e.g., administrative unit boundary), which may not capture the dynamic and developing spatial form of an urban area. The recommended urban delineation approaches limit the scale and extent for assessments of SDG Indicator 11.3.1, hereafter referred to as Indicator 11.3.1, highlighting the need enhancements in these methodologies that allow for the automated delineation of all urban areas in a country consistently through time. Delineating and characterizing all urban areas within a national extent can allow for relative comparisons to identify hotspots of urbanization as indicated by Indicator 11.3.1.

The aim of our work was to advance the existing non-automated Urban Extent method defined in the Atlas of Urban Expansion and proposed for use in various SDG 11.3.1-related documents [14,17] by integrating public datasets, open-source tools, and innovative spatial techniques to automate the identification of functional urban agglomerations spanning national extents. Using this automated methodology, we examined urban population changes, urban land changes, and spatial patterns of urban development for the identified urban agglomerations of the three study countries. We evaluated urban change by calculating Indicator 11.3.1 and other applicable metrics for all identified functional urban agglomerations. We defined functional urban agglomerations as a core urban area that may also include functionally connected hinterland areas as informed by examinations of developed land use characteristics, population thresholds, locality data, and transportation connectivity measures. The functional urban agglomeration is the unit under which all spatial analytical calculations were carried out and, for ease of reading, is hereafter referred to as urban agglomeration or agglomeration. Our study focuses on urban agglomerations with values of Indicator 11.3.1 greater than one, as they reflect situations where both the population and urban land are growing, but the rate at which urban land is developed is greater than that of the change in urban population.

The objectives of this work were the following: (1) to develop an automated urban delineation method to facilitate the application of Indicator 11.3.1 at the urban agglomeration scale across the extents of our three study countries, Ethiopia, Nigeria, and South Africa, for the 2016 to 2020 period; (2) to utilize values of Indicator 11.3.1 to identify hotspots of urban land expansion across our focal countries for the study period; and (3) to quantify rates and patterns of urban land and population change, including Indicator 11.3.1, and investigate spatial patterns of urban development to evaluate trends and characteristics countrywide, by population size class, and at the level of individual urban agglomerations.

2. Materials and Methods

2.1. Study Countries

We selected Ethiopia, Nigeria, and South Africa as our case study countries as they represent a diverse range of the political, economic, and societal dynamics in Africa. We use open-source datasets, tools, and spatial techniques in our automated methodology to delineate urban agglomerations, calculate Indicator 11.3.1 and related metrics, and identify hotspots to examine trends of change for the three study countries (Figure 1).

2.1.1. Nigeria

Nigeria, located in western Africa, is recognized as one of Africa's significant powers due to its size, wealth, influence, and historical significance [26]. As of 2022, Nigeria was Africa's most populous country at a population of 223 million [27]. Projections indicate Nigeria's urban population will increase by 189 million people from 2018 to 2050 [1]. Urbanization in Nigeria is expected to raise a myriad of challenges, making long-term planning, diverse stakeholder cooperation, and consistent management essential for achieving desired sustainability outcomes [28,29].

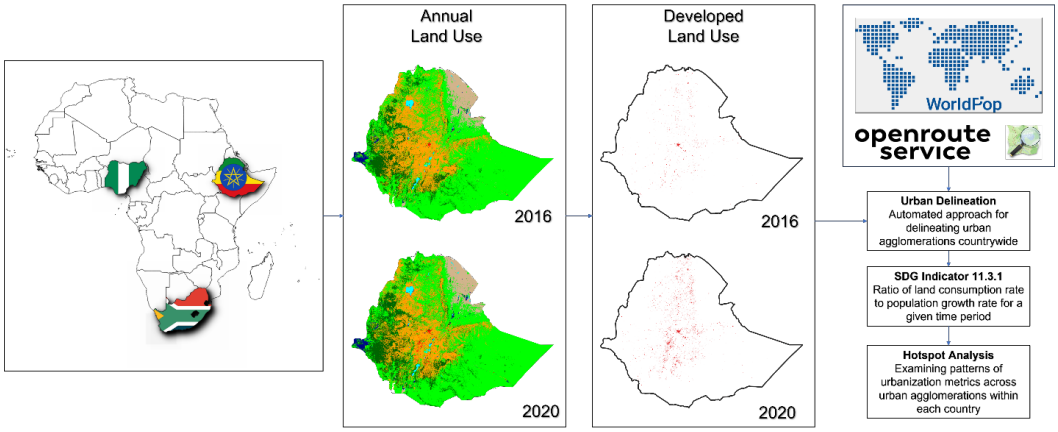


Figure 1. General workflow for delineating urban agglomerations, calculating Indicator 11.3.1, and identifying hotspots of Indicator 11.3.1. We integrated developed land use data with open-source data and tools to examine Indicator 11.3.1 and supporting urban change metrics for Ethiopia, Nigeria, and South Africa for the 2016 to 2020 period.

2.1.2. Ethiopia

Ethiopia, located in the Horn of Africa, is one of the world's oldest settled countries and is known for its ancient history and culture. Ethiopia has an estimated population of 126 million in 2023, making it the second most populous country in Africa behind Nigeria [30]. Ethiopia's population is predominantly rural, and it remains one of the least urbanized countries in Africa, although it is experiencing rapid urban population growth. Ethiopia's annual compound growth rate of the urban population ranged from 4.5% to 5.9% over the 1950–2010 period and jumped to 17% during the 2010 to 2015 period [31].

2.1.3. South Africa

South Africa, geographically located in the southernmost portion of Africa, is globally recognized for its mining of metals, rich culture, diverse topography, and productive natural environments. In 2023, the South African population was estimated to be 60 million, with over two-thirds of the population estimated to be living in urban areas [32,33]. The population continues to rise, and it is forecasted that eight in ten South Africans will live in cities or urbanized areas by 2030 [34].

2.2. Data Sources

We integrated various open-source spatial datasets and tools to develop an urban delineation methodology that supports the calculation of Indicator 11.3.1. Our data sources and tools included land use maps, gridded population count data from WorldPop, geographic data from OpenStreetMap, and tools from openrouteservice.

We developed 30 m spatial resolution, annually available land use maps for Ethiopia, Nigeria, and South Africa from 2016 to 2020 (see Supplementary Materials). The main optical input for our land use modeling efforts was 30 m resolution imagery from the Landsat Collection-2 Surface Reflectance product. From the Landsat imagery, we derived a variety of informative indices including Tasseled Cap brightness (TCB), wetness (TCW), greenness (TCG), and angle (TCA) [35], the Normalized Difference Vegetation Index (NDVI) [36], the Urban Composition Index (UCI) [37], the Modified Normalized Difference Water Index (MNDWI) [38], and a custom Wetness Index (WI). A range of other datasets were included to improve predictive information in our land use modeling. Sentinel Synthetic Aperture Radar products were included, with Gray Level Co-Occurrence Matrix metrics calculated and used in modeling. Additionally, we incorporated night-light information from the Visible Infrared Imaging Radiometer Suite [39], as well as climatic and topographic data from WordClim [40], Continuous Heat-Insolation Load Index [41], iSDA [42], and World Ecoregion (RESOLVE) [43]. We selected training and validation pixels across our study

countries to train our models and examine model performance for national-level, annual LU classifications. The LU classes that we included were agriculture, bare, developed, forest, rangeland, water, and wetland. In our training, we used photointerpretation of high-resolution imagery available on Google Earth Pro and spectral information to verify the LU class for each pixel. We visually examined the land cover within a pixel and used spatial and temporal contextual information to determine the land use of an individual pixel in a given year. We considered land cover and land use characteristics of pixels surrounding the individual training pixel to inform our interpretations, as well as considered spatial and spectral information across a 3-year epoch, one year prior to the focal year, during the focal year, and one year after the focal year, to determine LU class and LU change. Our initial modeling procedure consisted of obtaining important training features, running correlation tests to reduce our feature set, and training a Random Forest classifier. We then quantitatively and qualitatively examined the performance of our models and selected the most optimal models for each country. For our final map models, we conducted accuracy assessments and found similar results across all years. For illustration of performance, the overall accuracies were 74.6% for Ethiopia, 65.9% for Nigeria, and 73.6% for South Africa for the 2020 maps.

Land use maps aided in the identification of land that was urban in character (i.e., developed). Population count data maps are provided by WorldPop and are available for most countries in the world from 2000 to 2020 at 100 m spatial resolution [44]. We used population count data to examine population characteristics of urban areas. Point location and attribute data were extracted from the OpenStreetMap geographic database [45]. We used point location and attribute data to identify the names of cities or towns comprising the urban agglomerations. Transportation tools were obtained from openrouteservice which utilizes OpenStreetMap and other underlying global datasets to conduct transportation analyses and obtain related outputs [46]. We used openrouteservice tools to examine connectivity between clusters of urban areas which are described in the following section.

2.3. Definitions and Overview of Methodology

We developed a methodology to automate the delineation of urban agglomerations and facilitate the assessment of Indicator 11.3.1 at the urban agglomeration level across national extents (Figure 2). We dissect this methodology in the following sections, but first define important terminology and provide a general overview to clarify the spatial procedures we discuss.

Regarding terminology, three spatial units are consistently referred to in our methods: pixels, clusters, and urban agglomerations. The base of our methodology relies on a land cover and/or land use map which comprises pixels. Pixels are the gridded unit of the map and represent a class of features. In our work, we focus on "developed" land use pixels which represent areas of human development as identified in land use maps. Built-up land cover data is also commonly accessible and may be used in place of developed land use data. Although not synonymous, the purpose of utilizing developed land use and built-up land cover data is to first identify the presumed physical urban features on the ground that characterize the spatial form of the urban area. Hereafter, we will only mention developed land use pixels as that is what was used in our work and, for ease of reading, will refer to developed land use as developed land. Clusters, symbolized as polygons in spatial software, represent patches of urban areas, and primarily comprise developed land pixels that satisfy certain developed pixel density requirements, meet population size measures, and/or contain place data (e.g., a city point in OpenStreetMap). Urban agglomerations can be made up of a single cluster or numerous clusters and may represent a single contiguous urban settlement or multiple fragmented urban settlements that are functionally connected by a transportation network. Urban agglomerations are symbolized as polygons, and related urban calculations, including SDG 11.3.1, are carried out at the agglomeration level.

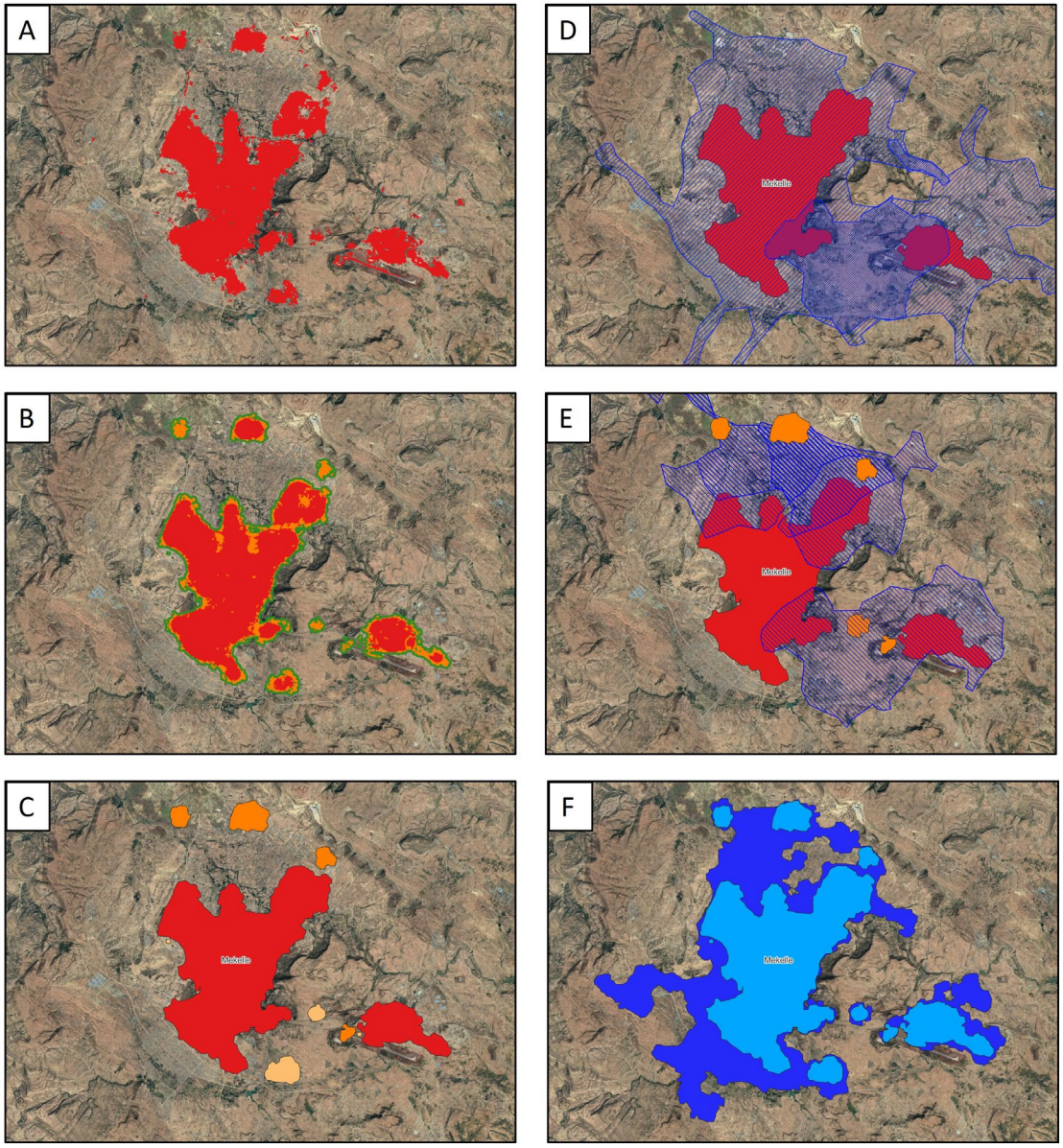


Figure 2. An example of the automated workflow for delineating urban agglomerations for Mekelle, Ethiopia. (**A**) Developed land raster. (**B**) Developed land raster pixels reclassified into urban (red), suburban (orange), and urbanized open space (green) pixels. (**C**) Urban clusters comprising urban, suburban, and urbanized open space pixels are reclassified as core (red), non-core (orange), and clusters not meeting relevant criteria (tan) using population thresholds. (**D**) Isochrone maps linking core clusters. (**E**) Isochrone maps linking non-core clusters to core clusters. (**F**) Final agglomeration boundaries incorporating all relevant clusters for initial year (light blue) and final year (dark blue).

In the following sections, we describe the methodology developed for automating urban delineation, and how we apply this methodology to our case study countries, calculate urban change metrics, and summarize spatial patterns of urban land change for individual agglomerations. We describe the multi-level analyses we conduct, first examining change trends for all agglomerations, then by population size class for each country, drawing hotspots from the largest size class within each country for more detailed investigations, and detailing how patterns of change are manifesting in example secondary cities.

2.4. Automated Delineation Approach

2.4.1. Base Classification

Our automated delineation methodology builds off the Atlas of Urban Expansion method used in the Indicator 11.3.1 training module [47]. The Atlas of Urban Expansion approach employs neighborhood spatial operations using GIS software (e.g., ArcGIS Pro) to reclassify developed land pixels into urban, suburban, rural, and open space classes [15]. This pixelwise classification is completed by examining the share of developed land pixels within the walking distance circle of each pixel classified as developed land. The walking distance circle is 1 km in area and has a 584 m radius, approximating a ten-minute walk from the pixel under analysis to the edge of its corresponding walking distance circle. Each pixel representing developed land was classified as urban, suburban, or rural, based on the percentage of similar pixels found in its 1 km circular neighborhood (Figure 2B). The walking distance circle and percentage thresholds for determining each class are explained in detail in the Atlas of Urban Expansion [15]. The method also accounts for open spaces within and on the edges of an urban area, referred to as urbanized open space. Urbanized open space pixels are non-developed pixels that are on the fringe of, or fully encapsulated by, the identified urban and suburban pixels. The contiguous urban and suburban pixels, as well as urbanized open space pixels, create urban clusters and rural pixels are discarded. The urban cluster polygons derived from the Urban Extent method are used as the base input for our automated approach and can be obtained by reaching step 18 of the Indicator 11.3.1 training module [47].

2.4.2. Determining Cluster Types

Our methodology begins building on the Urban Extent method by first separating clusters into three subgroups: core clusters, non-core clusters, and clusters that do not meet relevant criteria (Figure 2C). Under our definition, core clusters are identified by meeting a population size threshold. Additionally, core clusters are assumed to contain an important urban center, identified by an OpenStreetMap (OSM) place point which is typically marked at the center of a city or town. Meeting these criteria allows a cluster to proceed to status as an urban agglomeration even if no additional linkages are found. In contrast, non-core clusters are assumed to not have an identifiable urban center and are smaller in population, thus relying on the linkage to a core cluster for access to the urban services and resources of the core cluster. Non-core clusters are meant to represent peripheral urban areas or hinterlands including smaller towns, suburbs, and other inhabited human developments which do not contain important locality data, such as a city point in OSM. Additional population size and density thresholds are applied to differentiate non-core clusters from clusters not meeting any of the relevant criteria. Some clusters may arise as a result of misclassifications in developed land pixels in the underlying maps, so as mentioned, population size and density measures are used to filter out these "noise" clusters. These clusters may first be deemed non-relevant but are marked as so and are re-evaluated for incorporation in final urban agglomerations towards the end of the analysis.

To begin differentiating cluster types, urban clusters are overlaid with a gridded population map and population values are extracted within the urban clusters. Any gridded population dataset can be used at this step, such as the Global Human Settlement Layer https://ghsl.jrc.ec.europa.eu/ (accessed on 10 June 2024) or WorldPop www.worldpop.org (accessed on 10 June 2024). We used WorldPop's top-down, 100 m gridded population datasets to gauge population count estimates for urban clusters. WorldPop's top-down models use administrative census and projection counts with geospatial datasets to create 1 km and 100 m spatial resolution gridded datasets [48]. The WorldPop data are produced for Central and South America, Africa, and Asia, the most rapidly urbanizing regions in the world, and the unconstrained WorldPop Population Count maps are currently available annually for African countries from 2000 to 2020 [48]. New maps are generated when new census or geospatial datasets are produced, permitting continued analyses of population dynamics using our proposed methodology.

Once the clusters have associated population values, a population threshold can be applied to separate cluster types. The population threshold to differentiate core from non-core clusters should be calibrated to match the context of urbanization in the region of interest or to identify specific urban areas of interest. Users can determine core cluster thresholds based on expert opinion, past information, or other logical reasoning. For example, African Urban Dynamics identified 5000 as the minimum population size threshold for definitions of urban for 18 out of 34 African countries [49]. Africapolis, a recent urban agglomeration mapping initiative carried out across Africa, utilized a minimum threshold of 10,000 people to identify an urban agglomeration, as they cited authors signifying that 10,000 inhabitants are the 'scale above which new activities and services become possible' [31]. Additional criteria can be set to identify cores such as a population density threshold. We used a cumulation of sources and exploratory analyses to determine our core population size threshold of 5000 for our work in South Africa, Ethiopia, and Nigeria.

The last step in identifying core clusters is examining the presence of place data within, or in proximity to, clusters meeting the minimum population threshold. Various global datasets exist that can be used at this step, including geographical databases such as GeoNames https://www.geonames.org/ (accessed on 10 June 2024) or OpenStreetMap https://www.openstreetmap.org/ (accessed on 10 June 2024). We utilized OpenStreetMap data to determine the presence of city or town points within core clusters [50]. OpenStreetMap is an open geographic database that is contributed to by a global community and consistently updated and validated by contributors with local knowledge [45]. OpenStreetMap uses tags to describe map elements, with each tag containing a key and a value. The "place" key is used to indicate locations known by a particular name. For populated settlements, values exist under this key such as city, borough, suburb, town, village, hamlet, and more. OpenStreetMap defines a city as a place that is "the largest urban settlement or settlements within the territory" and a town as a place that is "an important urban center, between a village and city in size" [51]. Although no population criteria exist for differentiating between these two places in OpenStreetMap, as of 2019, 95% of city points had population values greater than 20,000 and 95% of town points had population values between 1000 and 70,000 [52,53]. Contributors are instructed to map city or town nodes, which are point features, at the center of the place such as at a central square, central administrative or religious building, or a central road junction [52,53]. Since OpenStreetMap is an openly contributed to geographic database, the user should be aware of limitations that exist, such as inconsistencies in naming, inaccuracies in placement of location points, and missing data [54]. The user should use best judgement when deciding what geographic data to include from OpenStreetMap. We identified core areas by extracting information from place point locations within the extent of, or near, clusters meeting the core population threshold.

A core may contain multiple place tags or no tag. In the case of the existence of multiple place tags within a single core, the core is identified by the place tag with the most overlap, therefore the most central point. The user also has the option to identify all place tags that exist in the core. We used iterative joining operations in GIS software to first assess the presence of place tag data within the cores, identifying the possible presence of a city point, and then examining for the presence of a town point if a city point was not found. It also should be noted that in rare cases, place point locations did not occur exactly within the extent of clusters, so we added a 1 km buffer to associate place point locations with clusters that were cores. Multiple buffer distances were tested, with 1 km distance performing best, and manual validation was carried out to ensure 1 km was an adequate buffer to associate place point locations. In the cases of clusters meeting the 5000-population size threshold but not having a place tag, the cluster was evaluated to determine if it should be considered a core in the analysis in the automated methods outlined below.

Clusters that were not classified as core clusters were separated and considered potential non-core clusters. We identified non-core clusters using additional threshold criteria. In preliminary analyses, numerous clusters formed as result of misclassified

developed land pixels in the underlying land use map. To minimize the inclusion of these areas in analyses, we implemented an additional population size and density criterion to differentiate non-core clusters (i.e., surrounding settlements that may be functionally linked to the central urban area) from clusters that did not truly represent an urban-related area (i.e., clusters of barren land that had been misclassified as developed land). We conducted exploratory analyses to determine an approximate threshold that excluded misclassified clusters in our study countries, which ended up ranging from 300 to 500 people per square kilometer of developed land area. The clusters that did not meet the population criteria were set aside and analyzed by subsequent procedures, as the population density thresholds were intended to account for misclassifications in the underlying land use maps but may have resulted in the removal of relevant clusters. We discuss the potential reincorporation of these clusters not meeting relevant criteria in Section 2.4.4.

2.4.3. Associating Clusters

Categorizing clusters into core clusters and non-core clusters allowed us to gauge potential connectivity between a central, largely populated urban core and surrounding, less populated settlements to identify functional urban agglomerations. In Africa, rural areas are tied to urban cores [55] and significantly influence urban growth but may be disregarded or not included in urban change assessments. Our approach was designed to capture urban areas linked to the often-overlooked peripheral zones interacting with the urban cores.

To accomplish this, we used connectivity tools provided by openrouteservice [46], including travel distance matrices and isochrone mapping. Isochrone mapping uses information such as shortest routes, transportation type, and speed limit to determine the reachability of surrounding areas from a specific location provided a threshold travel time or distance. Our goal was to examine connectivity from the edge of clusters to the edge of other clusters using isochrone maps. Isochrone mapping from the openrouteservice tool is conducted using a start point location and end point location; therefore, the tool is unable to determine the reachability of an area from the edge of a cluster (i.e., polygon) as it is not a point feature. To work around this, we used the travel distance matrix tool from openrouteservice to calculate the average travel distance from the population-weighted center of a cluster to numerous edge points on the cluster boundary to estimate an average distance to the edge of the cluster. We combined the average travel distance from the center to the edge of the cluster with an additional distance value to approximate connections between different clusters, which is explained in detail in the following paragraph.

We generated isochrone maps and used an incremental joining approach to determine the connectivity between clusters and define our final agglomerations. Under our methodology, the user can specify a threshold travel distance for which they want to assess connectivity between clusters. We examined the datasets and tested the best distance thresholds for our purposes in Ethiopia, Nigeria, and South Africa. We used the value of the average travel distance derived from the travel distance matrices for each cluster and added a 5 km travel distance. Based on preliminary analyses, a distance of 5 km under the incremental joining approach provided the most realistic connections between clusters. Clusters with overlapping isochrone polygons were adjoined. Adjoined clusters were then recognized as a new core area, and this process was repeated until there were no non-core clusters within the threshold distance of a core area.

Our methodology uses a combination of spatial analysis techniques to determine how urban clusters are connected. Connectivity is first examined between core clusters to capture potentially polycentric agglomerations, as some urban areas follow a polycentric structure in which one urban agglomeration has multiple cores of activity [56,57]. If the isochrone generated for a cluster overlaps or touches any portion of another cluster, those two clusters are associated. This rule applies to the connectivity between core clusters (e.g., areas containing two dense urban cores) and between core and non-core clusters (e.g., a core city and surrounding towns, suburbs, or less populated settlements). Core

clusters with overlap are associated and given the same unique identifier (Figure 2D). Isochrone maps are generated for non-core clusters and those with isochrone maps that overlap with a core cluster or polycores are associated (Figure 2E). If the isochrone polygon of a non-core cluster overlaps with multiple cores, it is associated with the core in which it has the greatest overlap area.

2.4.4. Finalizing Agglomerations

All of the above spatial operations should be conducted twice, once for the initial year and once for the final year of the analysis period. The user should then have a pair of delineated urban agglomerations, one for the initial year and one for the final year in the analysis period. The spatial form and population attributes of urban clusters are expected to change over the analysis period as a result of urban growth; therefore, we can expect to observe differences in the classification of agglomerations between the first and last year. For example, we observed where an agglomeration in the initial year did not include peripheral areas that were part of its delineation in the final year. This was because the clusters representing the peripheral areas did not meet the set population size and density thresholds in the initial year but grew to meet them in the final year. To ameliorate this, we carried out an additional spatial overlay analysis to match clusters that may have been removed incorrectly during the initial analyses. We also observed instances where the growth of clusters in the final year led to the merging of agglomerations that were separated and unique in the initial year. In this case, the agglomerations of the initial year were overlaid on that of the final year and reclassified as a matching urban area to facilitate the analysis of changes. We used spatial join and overlay functions to investigate overlap and ensure the agglomerations contained the same relevant clusters in both years to improve the comparability and accuracy of our change assessment. After these procedures, a matching pair of agglomerations should exist for the initial year and final year of the study period (Figure 2F). All agglomerations and their attributes were inspected to ensure our dataset reasonably represented the urban areas existing within each country. We used data sources such as high-resolution imagery and Africapolis data to validate the accuracy of the delineated agglomerations [4].

Once agglomerations are finalized for both years, gridded population data is extracted within urban agglomeration boundaries of each year and all relevant urbanization metrics can be calculated. Calculated metrics included the land consumption rate, the population growth rate, the ratio of land consumption rate to population growth rate, the developed land area, the developed land area per capita, the percent change in the area of developed land, and the areas of infill development and external growth development. These metrics are discussed in detail in Section 2.6.

For our case study countries, we initially developed the geospatial processes presented above using ArcGIS Pro 3.0.1 [58] and QGIS 3.22 [59] to test applicability and appropriateness. We carried out the initial steps in ArcGIS Pro 3.0.1 as instructed in the Indicator 11.3.1 training module [47]. The remaining developed geospatial workflow was conducted using QGIS 3.22 due to its vast library of tools and plug-ins and being free and open-source software. After the determination of appropriate processes, we automated the approach using Python 3.9.16 [60] to facilitate the application of this methodology across each study region. The completed methods can be applied to any region of interest across any specified time period, as long as relevant data and tools are available for the given spatial extent and temporal range. We developed this methodology with the relevant publicly available datasets to ensure wide-ranging accessibility across datasets of varying characteristics.

2.5. Land Use Mapping and Delimitation of Developed Land across Africa

To extract the extents of urban agglomerations across our three study regions, we developed a land use product and applied the automated delineation method outlined in the previous section. The land use product was generated using a Random Forest classifier with a set of optical, synthetic aperture radar, nightlight, and topographic remote sensing

data inputs (see Supplementary Materials). The developed 30 m resolution annual land use classification maps followed a classification scheme similar to other publicly available land use datasets and were the main input of our analyses. The definition of developed land adopted refers mainly to impervious surfaces but may include other human development or surrounding contexts such as parks, lawns, cemeteries, mines, and connecting roads (either paved or wide dirt roads). The rules used in the interpretation for the land use model training were mindful of the complex characteristics of developed land, identifying human developments beyond just impervious surfaces.

Following the development of land use maps and delineation of urban areas for each country, Indicator 11.3.1 and relevant urban calculations were integrated into our automated approach and calculated for each identified urban agglomeration in the three study regions using QGIS and Python.

2.6. Calculations of Metrics Associated with Indicator 11.3.1

2.6.1. Land Consumption Rate

We calculated the Land Consumption Rate (LCR) for each urban agglomeration in all study countries for the 2016 to 2020 analysis period. We used a single development class of the reclassified land use map to calculate each agglomeration's total developed land surface area. The Land Consumption Rate formula is as follows:

$$\text{Land Consumption Rate (LCR)} = \frac{(V_{present} - V_{past})}{(V_{past})} * \frac{1}{(t)}$$

where $V_{present}$ is the total developed land area in the last year of the period under evaluation, V_{past} is the total developed land area in the initial year of the same period, and t is the number of years between $V_{present}$ and V_{past} [17].

2.6.2. Population Growth Rate

We calculated the Population Growth Rate (PGR) for each urban agglomeration in all study countries for the 2016 to 2020 analysis period leveraging information from the WorldPop 100 m resolution gridded population datasets (https://www.worldpop.org) (accessed on 10 June 2024). The PGR is the change in total population over a given period within a defined urban agglomeration. It can be viewed as a reflection of the births, deaths, emigration, and migration that have transpired in an urban region over the same period [17]. We downloaded WorldPop Population Count data for each country [48], which was reprojected into Africa Albers Equal Area Conic and population values were extracted within each agglomeration. This gave us the total population for 2016 and 2020 for each agglomeration. We were then able to calculate the Population Growth Rate using the following formula:

$$\text{Population Growth Rate (PGR)} = \frac{\text{LN}\,(Pop_{t+n}/Pop_t)}{(y)}$$

where LN is the natural log, Pop_{t+n} is the total population in the urban agglomeration in the last year of a given time period, Pop_t is the total population in the urban agglomeration in the initial year of the same period, and y is the number of years between t and t + n [17].

2.6.3. Indicator 11.3.1 and Supporting Metrics

Indicator 11.3.1 is calculated as a ratio between the rate of consumption of land for urban use and the rate of urban population growth in an urban agglomeration over a specified period of time and is said to be a measure of land use efficiency [17].

$$\text{Indicator 11.3.1 (LCRPGR)} = \text{LCR/PGR}$$

Indicator 11.3.1 may also be referred to as the Land Consumption Rate to Population Growth Rate Ratio (LCRPGR). We disagree that Indicator 11.3.1 is referred to as a measure of land use efficiency, as it alone does not allow us to determine if urban land development has been conducted efficiently or inefficiently. Still, what the indicator can provide us with is information about how urban changes transpired. An Indicator 11.3.1 ratio greater than one indicates that the urban land is growing faster than the urban population, and a ratio less than one may indicate that the urban population is growing faster than the urban land. A ratio close to one reflects comparable rates of growth in both land consumption and population growth.

UN-Habitat suggests utilizing additional metrics, also referred to as secondary indicators, to support the interpretation of the Indicator 11.3.1 ratio [17]. The two suggested secondary indicators are total change in built-up area and built-up area per capita, which are formulated as follows.

Total change in built-up area is the percent change in built-up land within an urban area over a period of time. In the formula below, $UrBU_{t+n}$ is the urban built-up area in the final year of the time period and $UrBU_t$ is the urban built-up area in the initial year of the same period [17]:

$$\text{Total change in built-up area } (\%) = \frac{(\text{UrB U}_{t+n} - \text{ UrBU}_t)}{\text{UrBU}_t} * 100$$

Built-up area per capita is the built-up area available per person within the urban area. In the formula below, $UrBU_t$ is the urban built-up area in time t and Pop_t is the population size within the urban area in time t [17]:

$$\text{Built-up area per capita}\left(\text{m}^2/\text{person}\right) = (\text{UrBU}_t/\text{Pop}_t)$$

In this study, we substituted built-up area with developed land area in all of the above formulas.

2.6.4. Spatial Patterns of Development

Understanding the spatial arrangement of new urban development is crucial for informing future planning and managing existing development. The spatial patterns of urban development we assessed included infill, extension, leapfrog, and inclusion. We follow the definitions specified in the UN Indicator 11.3.1 Training Module, where infill represents the new development occurring within the boundaries of the initial urban agglomerations, extension, and leapfrog concern, respectively, the new development adjoining and not adjoining to the initial agglomeration boundaries, and inclusion comprises the existing development that becomes engulfed within the final year urban agglomerations [47]. Using the delineated urban boundaries and the developed class from the land use data in both years, we applied spatial analyses techniques to obtain infill development and extensive, leapfrog, and inclusive forms of development, grouped as outward development, for each urban agglomeration.

2.7. Hotspot Identification and Analysis

The agglomerations with Indicator 11.3.1 values above one were classified as hotspots, and summary metrics of urbanization for hotspots were compared between countries. Summaries were also initially completed for the entire sample of urban agglomerations to obtain country-level statistics.

Additionally, we divided the hotspots into population size classes (<50,000 people, 50,000 to 100,000 people, >100,000 people) and compared results between the study countries. The chosen population classes enable the differentiation between small urban areas with less than 50,000 inhabitants and secondary cities and large metropolises with more than 50,000 inhabitants. The Degree of Urbanization cites various sources and uses a minimum population of 50,000 to identify a populated city [25], so our lowest class captured the

smallest urban areas. UN-Habitat and Roberts (2014) define and identify secondary cities using a population above 100,000, approximately [7,17]; therefore, our upper class captures secondary cities and larger metropolitans. Our intermediate class (50,000–100,000 inhabitants) captures potentially important and growing urban areas that may later emerge as secondary cities. In addition, the agglomerations with the highest values for Indicator 11.3.1 were analyzed by country, and a visual inspection of the results obtained for the city of Mekelle, Ethiopia was undertaken.

3. Results

3.1. Regional Summary Statistics

The three countries showed different trends in urban population growth and changes in developed land area (Table 1). In absolute terms, Nigeria's urban agglomerations experienced the greatest overall population growth, adding almost 8 million people from 2016 to 2020. Although Nigeria and Ethiopia displayed similar growth in overall developed land area, Ethiopia endured the greatest relative increase in population growth and total developed land area. Ethiopia had an approximately 28% increase in the total population within urban agglomerations and a 73% increase in the total developed land area. On the other end of the spectrum, urban growth in South Africa was slower than the two other countries; the total population only increased by 3% over the five-year period and was associated with a 5% increase in developed land area.

Table 1. Agglomerations, urban population, and developed land area identified in the 2016 to 2020 period in Ethiopia, Nigeria, and South Africa (DA is developed land area).

Country	Total Agglomerations	2016 Urban Population	2020 Urban Population	5-Year Population Change (%)	2016 DA (km^2)	2020 DA (km^2)	5-Year DA Change (%)
Ethiopia	193	9,936,671	12,757,304	28.4	1476	2550	72.8
Nigeria	357	51,112,180	59,306,168	16.0	7557	8577	13.5
South Africa	369	43,728,813	45,321,001	3.6	8107	8514	5.0

We observed outliers of Indicator 11.3.1 across the urban agglomerations of all three study countries. Major outliers typically manifested negative growth values. We filtered outliers by removing agglomerations with negative land consumption rate values or negative population growth rate values, as these patterns of change were not the focus of our study. Additionally, we did not include agglomerations that contained a land consumption rate or population growth rate with extremely small values close to zero, as these created disproportionately large Indicator 11.3.1 values. These agglomerations were often extremely small in area and had inflated Indicator 11.3.1 values which we believed were not representative of actual changes. After filtering the agglomeration dataset, Ethiopia had 192 total urban agglomerations, Nigeria had 323, and South Africa had 238.

3.2. Indicator 11.3.1 Hotspot Trends at The Country Level

We identified hotspots of urban land expansion, which were agglomerations with an Indicator 11.3.1 value greater than one, across all three study countries (Table 2; Figure 3). For Ethiopia, we observed a consistently high proportion of agglomerations with SDG 11.3.1 values above one when compared to Nigeria and South Africa. Approximately 191 of the 192 agglomerations in Ethiopia had an Indicator 11.3.1 value greater than one. The majority of growth in developed land area from 2016 to 2020 occurred in the form of outward development. Nigeria displayed comparatively lower Indicator 11.3.1 values than the other study countries, with the max value being 2.59. Approximately 33% of 323 agglomerations, or 105 agglomerations, in Nigeria had an Indicator 11.3.1 value greater than one. Infill development accounted for the majority of the observed growth in the developed land area in both Nigeria and South Africa. South Africa did display a wide

range of Indicator 11.3.1 values, ranging as low as 0.05 and as high as 20. A total of 173, or about 73%, of 238 agglomerations in South Africa met the Indicator 11.3.1 hotspot threshold.

Table 2. Agglomerations identified as hotspots, Land Consumption Rate (LCR) range, Population Growth Rate (PGR) range, infill development, and outward development for Ethiopia, Nigeria, and South Africa for 2016 to 2020.

Country	Proportion of Agglomerations Identified as Hotspots (%)	LCR Range	PGR Range	Infill Development	Outward Development
Ethiopia	99	0.024–1.019	0.002–0.220	33%	67%
Nigeria	33	0.012–0.361	0.009–0.163	66%	34%
South Africa	73	0.002–0.580	0.001–1.564	65%	35%

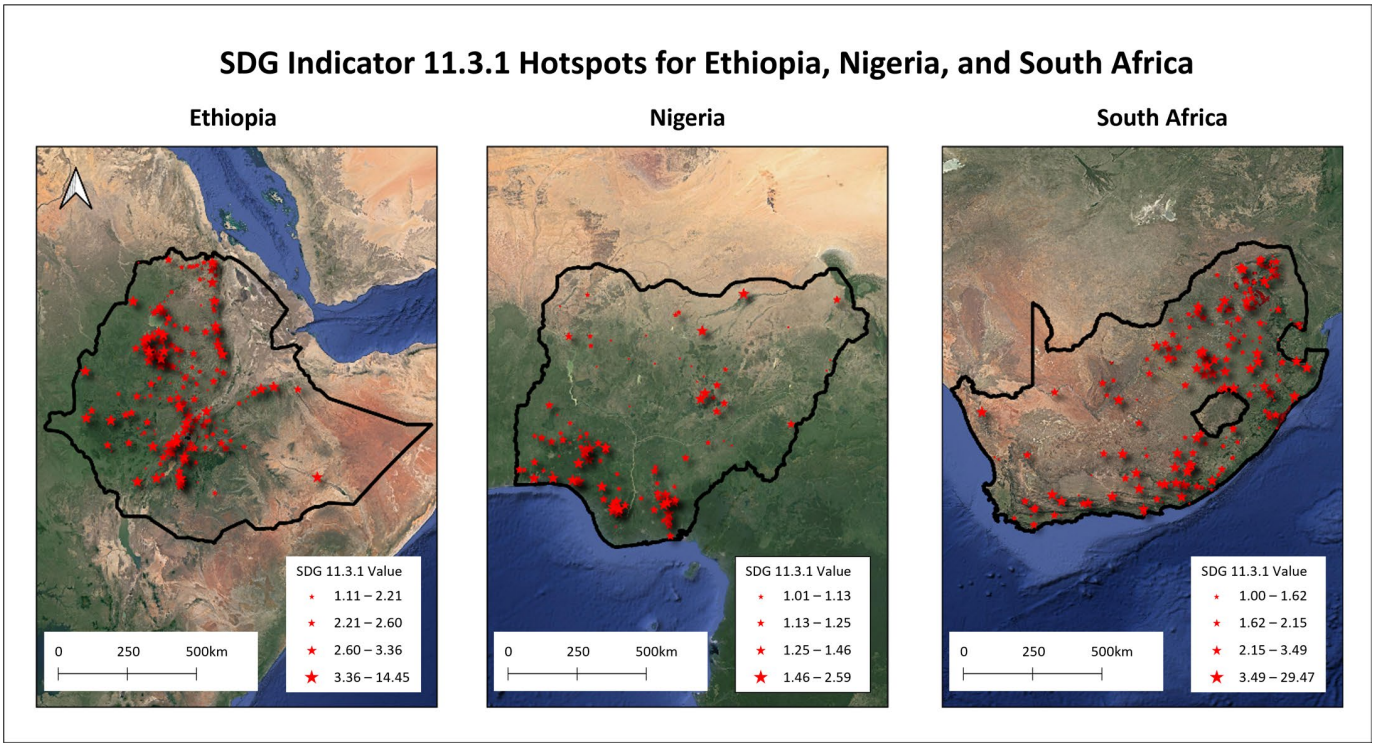


Figure 3. Urban agglomerations in Ethiopia, Nigeria, and South Africa classified as hotspots (presenting Indicator 11.3.1 values greater than one) in the 2016 to 2020 period.

3.3. Results by Population Size Classes

All three countries displayed varied results when examined by 2020 population size class (Table 3). Ethiopia's hotspot agglomerations displayed high average SDG 11.3.1 values in each population size class. Ethiopia's hotspots with a population greater than 100,000 had the highest average LCR, lowest average PGR, and highest average SDG 11.3.1 value among the three population size classes. The hotspot agglomerations in Nigeria displayed negligible differences in average SDG 11.3.1 value across population size classes, all with values around 1.3. Although the magnitude of the differences was small, the average LCR, PGR, and SDG 11.3.1 values all decreased as the population size class increased, indicating that the greatest urban land expansion was taking place in the smallest population size class in Nigeria.

Table 3. Urban change metrics for agglomerations with Indicator 11.3.1 values greater than one in the 2016–2020 period, by population size class in 2020 and country (DA is the developed land area, LCR is the Land Consumption Rate, PGR is the Population Growth Rate, and SDG 11.3.1 is the Land Consumption Rate to Population Growth Rate Ratio. Light gray corresponds to population size classes less than 50 k, gray corresponds to population size classes 50 k to 100 k, and dark gray corresponds to population greater than 100 k.

	Population Size Class (Based on 2020 data)	Mean Change in DA (%)	Mean LCR	Mean PGR	Mean SDG 11.3.1
Ethiopia	*Population < 50* k	104	0.208	0.076	2.940
	Population 50 k *to 100* k	93	0.186	0.065	2.890
	Population > 100 k	110	0.219	0.060	3.308
Nigeria	*Population < 50* k	55	0.110	0.078	1.366
	Population 50 k *to 100* k	45	0.091	0.065	1.360
	Population > 100 k	33	0.066	0.049	1.343
South Africa	*Population < 50* k	39	0.078	0.032	3.308
	Population 50 k *to 100* k	31	0.063	0.033	2.407
	Population > 100 k	41	0.083	0.039	2.054

Similar to Nigeria, South Africa's average SDG 11.3.1 value for hotspot agglomerations decreased as the population size increased, and agglomerations in the smallest size class had the highest average SDG 11.3.1 value. South Africa's agglomerations displayed no direct trend in the average LCR values across population size classes, but the intermediate size class had the lowest average LCR value, and the largest size class had the highest average LCR value. There was a direct positive trend between the population size class and average PGR value, indicating faster population growth in more populous urban areas over the 2016 to 2020 period.

3.4. Highest Ranking Agglomerations by Indicator 11.3.1

Important areas of urban growth and development, particularly secondary cities, characteristically fell within the largest population size class of agglomerations that had an Indicator 11.3.1 value above one. To narrow our findings, we extracted five agglomerations with the highest Indicator 11.3.1 values from the largest 2020 population size class for each country (Table 4).

Table 4. Agglomerations with more than 100,000 inhabitants in 2020, which showed the five highest values for Indicator 11.3.1 from 2016–2020 in Ethiopia, Nigeria, and South Africa.

Ethiopia		Nigeria		South Africa	
Agglomeration	*SDG 11.3.1 Value*	*Agglomeration*	*SDG 11.3.1 Value*	*Agglomeration*	*SDG 11.3.1 Value*
Bahir Dar	7.33	Benin City	2.60	Witsieshoek	3.69
Durame	6.71	Akure	2.01	Siyabuswa	3.40
Kombolcha	5.20	Ikeja	1.56	Kwamhlanga	2.58
Sodo	4.04	Ondo	1.56	Polokwane	2.45
Mekelle	3.63	Ughelli	1.55	Jeppe's Reef	2.07

In Ethiopia, the five hotspot agglomerations displayed extremely large Indicator 11.3.1 values, ranging from 3.63 to 7.33. These agglomerations were associated with rapidly growing secondary cities, including Bahir Dar, Mekelle, and Kombolcha [8,61]. The Indicator 11.3.1 values for Nigeria's hotspot agglomerations were low in comparison

to Ethiopia and South Africa, with Benin City having the highest value of 2.6. Unique to Nigeria's top five hotspot agglomerations was the range in population size. The Ikeja agglomeration included major cities such as Lagos and Ikorodu and had a total population greater than 13 million. Intermediately, Benin City had a population of around 1.3 million and Akura had a population of around 500,000. Ondo and Ughelli were much smaller in population at around 150,000 people each. South Africa's top five agglomerations were relatively small, with populations ranging from around 225,000 to 560,000. All five South African agglomerations differed from the five agglomerations in Ethiopia and Nigeria, as they comprised numerous clusters of smaller towns, aside from the Polokwane agglomeration. All South African agglomerations had Indicator 11.3.1 values above two, indicating uptake of urban land occurring at twice the rate of population growth over the 5-year period.

3.5. Analysis of Hotspots in Each Country (Mekelle, Benin City, and Polokwane)

We selected a top-ranking hotspot agglomeration for each country to inspect urban change metrics and spatial patterns of development (Tables A1–A3 of Appendix A). Criteria for hotspot selection included falling within the top-five-ranked hotspot agglomerations and being identified as a secondary city in the literature or having basic characteristics of a secondary city. The three agglomerations we selected were associated with Mekelle, Ethiopia, Benin City, Nigeria, and Polokwane, South Africa. All three hotspot agglomerations, hereafter referred to by their associated city name, had Indicator 11.3.1 values above two, indicating the rate of urban land expansion being double the rate of population growth for the 2016 to 2020 period (Table 5). Mekelle displayed a 51% increase in the developed land area per capita over the study period, the largest increase of the three cities. Benin City and Polokwane displayed comparable increases in their developed land area per capita, 28% and 19%, respectively. Mekelle experienced the greatest total change in developed land area, with a 98% increase from 2016 to 2020. Benin City's total change in developed land area followed at 61% and Polokwane saw the smallest increase at 41%.

Table 5. Urban development metrics for agglomerations in Ethiopia, Nigeria, and South Africa, selected based on the size of their population in 2020 and Indicator 11.3.1 values greater than one in the period 2016 to 2020 (DA is the developed area).

City	SDG 11.3.1 Value	2016 DA Per Capita (m^2/person)	2020 DA Per Capita (m^2/person)	Total Change in DA (%)	New Development by Infill (%)	New Development by Outward Growth (%)
Mekelle	3.63	184	278	98	20	80
Benin City	2.60	185	237	63	48	52
Polokwane	2.45	257	306	41	56	44

Each hotspot agglomeration displayed varied spatial patterns of development (Figure 4). Mekelle displayed excessive outward development outside of the initial urban extent over the 5-year period. A total of 80% of Mekelle's new development was attributed to outward growth and 20% was by infill (Figure 4E). New development patterns in Benin City and Polokwane followed a similar split between the development types, infill and outward development. New development by outward growth was slightly greater than new development by infill in Benin City, at 52% and 48%, respectively (Figure 4D). Polokwane's new development by infill was slightly greater than new development by outward growth, at 56% and 44%, respectively (Figure 4F).

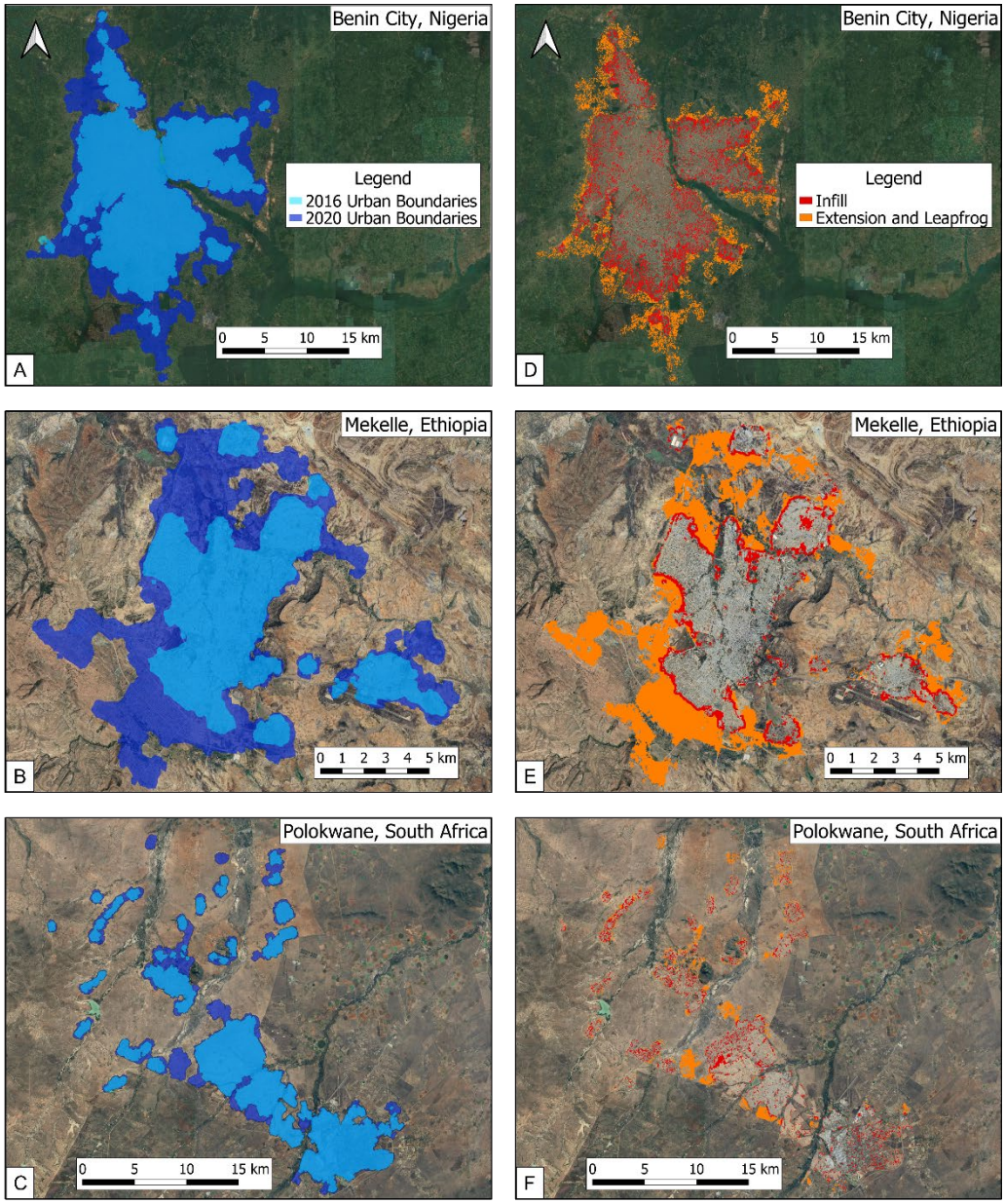


Figure 4. (**A**–**C**) show urban boundaries for 2016 and 2020 for specific hotspot agglomerations, and (**D**–**F**) show spatial patterns of development for the same agglomerations.

4. Discussion

We leveraged openly accessible tools and datasets to automate the delineation of functional urban agglomerations across national extents to support the assessment of Indicator 11.3.1. Metrics of urban change, including Indicator 11.3.1, and spatial patterns of development were evaluated across urban agglomerations in Ethiopia, Nigeria, and South Africa from 2016 to 2020, providing new insight on urban land expansion patterns. At the national level, Ethiopia, Nigeria, and South Africa exhibited increases in developed land area at 73%, 14%, and 5%, respectively. Urban agglomerations experiencing rates of land consumption higher than the rate of population growth included 99% of agglomerations identified in Ethiopia, 33% in Nigeria, and 73% in South Africa, highlighting the need for continued national level monitoring. Important secondary cities coinciding as hotspots of urban land expansion included Mekelle, Ethiopia; Benin City, Nigeria; and Polokwane, South Africa. In previous studies, Mekelle displayed an Indicator 11.3.1 value of 4.48 from 2000 to 2015 and Polokwane a value of 0.92 from 2000 to 2011 [8,10]. Our findings show

that Polokwane is now experiencing significant urban land expansion with an Indicator 11.3.1 value of 2.45 and Mekelle at 3.63. The multi-step approach we utilized, moving from broad comprehensive urban change trends to fine-scale examinations of SDG 11.3.1 hotspots and change patterns, illuminated urbanization and associated land use impacts at multiple levels and, most importantly, highlighted urbanizing areas likely in need of developmental support.

Our approach attempts to address the limitations of the suggested delineation methods for calculating Indicator 11.3.1: the Atlas of Urban Expansion method and Degree of Urbanization method. The Atlas of Urban Expansion method requires local knowledge for accurate delineation of the urban area which limits the ability to assess SDG 11.3.1 rapidly for more than one urban area. Attempts to delineate various urban areas would require assembly of a significant amount of local information, arguably making a widespread delineation effort time-consuming and knowledge-intensive, and potentially unfeasible for consistent large-extent monitoring efforts. In the absence of access to local knowledge, the Atlas of Urban Expansion method applies a proximity inclusion rule to a main city to determine what surrounding clusters are associated with it, which is a buffer equal to 25% the area of the main city cluster [15]. The proximity inclusion rule appeared unsuitable under a minimally supervised or automated delineation approach as it did not capture the true connectivity of urban centers and associated settlements comprising an urban agglomeration based on a straight-line distance buffer. It particularly became difficult to interpret what urban clusters were connected under this rule as buffers had overlapped across multiple larger urban areas or eliminated supporting smaller cities or towns that were likely connected to the main urban area. Our approach attempts to ameliorate these issues by substituting the proximity inclusion rule with travel analyses to determine connectivity and uses a hierarchical assembly approach to identify polycentric urban agglomerations and peri-urban areas functionally connected to the main urban core.

Similarly, we observed limitations in the application of the Degree of Urbanization method for our intended purposes. This method can be applied automatically and identifies three settlement types based on population characteristics: urban centers, urban clusters, and rural grid cells. The method can also be applied across large extents but currently does not include an urban agglomeration equivalent under their definitions [25]. Although no urban agglomeration definition exists under this method, the initial settlement types can be further classified into cities, towns, suburban areas, villages, and more at a local unit level (e.g., administrative units). Nonetheless, the suggested pixel resolution for this method is 1 km, which is fairly coarse and does not appear appropriate for delineating and calculating change in smaller urban areas.

The Degree of Urbanization does offer an extension to the initial classification where a user can define and extract the Functional Urban Area (FUA) [24,62]. The FUA consists of a city and the surrounding less dense spatial units which are within the city's commuting zone and labor market. This classification is practically similar to our approach, but the classification requires commuting data which is not regularly produced or readily available in many countries [16,63]. Other sources are mentioned for estimating commuting flows such as mobile phone data or employment registers, but we argue that these data may be just as difficult to attain or dissect. We attempted to fill these gaps by developing an approach that could capture the dynamic boundaries of functional urban agglomerations using globally-available and accessible datasets and tools, for example, using the open-source openrouteservice API to generate isochrone maps, which can act as a proxy for commuting data [46].

We assume the discussed limitations are reasons for Indicator 11.3.1 studies often being conducted at a finer city scale [8,10] or a more generalized scale (e.g., administrative unit level, country level) [11,64]. Our automated approach expands the spatial scale at which Indicator 11.3.1 is evaluated by examining urban change for individual urbanizing environments across national extents. This allows for comprehensive analyses, from comparisons among urban agglomerations within a country to detection of individual

areas displaying suboptimal patterns of development. It also enhances the flexibility of the urban areas being delineated by giving the user the ability to manipulate thresholds defining the characteristics of urban areas and the measures associating the settlements forming an urban agglomeration.

Although highlighting hotspots of Indicator 11.3.1 proved valuable, additional urban change calculations provided important insight on spatial patterns of development not illuminated by Indicator 11.3.1 alone. The top-ranking Indicator 11.3.1 hotspots all exhibited high rates of Indicator 11.3.1 but supplementary calculations revealed inter- and intra-country variability in spatial patterns of development among hotspots with similar Indicator 11.3.1 values. For example, new development in Benin City in Nigeria was largely caused by outward development, while new development in Akure in Nigeria was primarily by infill development, although both agglomerations had similar Indicator 11.3.1 values, and the majority of agglomerations in Nigeria displayed development by infill. Furthermore, Mekelle in Ethiopia had an Indicator 11.3.1 value of 3.63 with expansive forms of development accounting for 80% of new development. The Witsieshoek agglomeration in South Africa had a similar Indicator 11.3.1 value of 3.69 but, conversely, 83% of new development was by infill. Densifying and sprawling development patterns have varying benefits, as well as negative environmental, economic, and social impacts; therefore, examining the spatial patterns of development displayed by hotspots of Indicator 11.3.1 may expose information imperative for guiding future analyses and on ground planning efforts [65–69].

Secondary cities are known to facilitate and harbor considerable urban growth in developing countries [70,71] and our findings corroborate this as numerous secondary cities, such as Mekelle and Polokwane, exhibited notable change over the short 5-year period. Secondary cities often face numerous challenges associated with rapid urbanization in relation to governance abilities, economic productivity, and social systems [7,72]. Secondary cities can play a vital role in the development of a nation but are often limited in their capacity, resources, and data [7], making strategic analyses and informed development plans crucial for improving existing secondary cities [73–76] and for new secondary cities that are emerging [77]. Our work and approach can support organizations and initiatives, such as the Cities Alliance https://www.citiesalliance.org/ (accessed on 10 June 2024) and Secondary Cities Initiative https://secondarycities.state.gov/ (accessed on 10 June 2024), by identifying hotspots of Indicator 11.3.1 and prioritizing the allocation of investment resources for advancing sustainable urban development in secondary cities.

Spatial products covering large extents often have tradeoffs in resolution and accuracy which should be considered when employing this methodology and interpreting the presented results. Concerning spatial resolution, we observed numerous instances where delineation and calculations for smaller urban regions were not accurate. Under the 100 m WorldPop data and 30 m land use data, the addition or subtraction of pixels within the boundaries of a smaller urban area drastically changed the Land Consumption Rates and Population Growth Rates. Large changes in these measurements then inflated the Indicator 11.3.1 value. We discuss in Section 3.1 that we used filtering methods to remove small urban areas strongly impacted by resolution, but other small urban areas not exhibiting largely inflated calculations were likely impacted and included in analyses. Additionally, implications of the map classifications should be considered when selecting an LCLU product as it will determine what characteristics of an urban area are captured by the methodology. The classification of developed area in the 30 m land use data included human developments in addition to built-up area, which may capture more area as urban than a dataset that only considers built-up area. False classifications are also an inherent characteristic of LCLU maps and may impact outcomes of the automated delineation approach. Under the 30 m land use data, larger plots of bare land were often misclassified as developed land. We used population size and density measures to remove clusters impacted by this misclassification, but our filtering methods were imperfect and misclassified clusters were likely included in the analyses. Lastly, gridded population datasets are modeled on census

data. We observed instances where the population appeared to be underestimated for multiple urban areas. Regions like Africa have been impacted by infrequent and inadequate population censuses, as a result of civil conflict, poor organization or capacity, and inadequate participation [78,79], so we can expect some degree of inaccuracy in the gridded population estimates.

Our multi-level approach for assessing Indicator 11.3.1 and urban change is the first to be conducted across the three African countries for the 2016 to 2020 period; therefore, we are unable to directly compare our findings with those of other Indicator 11.3.1 studies. Mudau et al. and Laituri et al. assessed Indicator 11.3.1 for cities we examined (i.e., Mekelle, Ethiopia and Polokwane, South Africa) over different time periods [8,10] and we discussed changes in values, but Indicator 11.3.1 has yet to be assessed in other urban areas we identified. We anticipate our work can serve as a baseline for future comparisons of Indicator 11.3.1. Additionally, this study only focused on analyzing agglomerations with Indicator 11.3.1 values greater than one, thereby impacting the summarized values of urban change metrics across each country. Future efforts should evaluate Indicator 11.3.1 for the entirety of agglomerations in the study countries for all Indicator 11.3.1 values and continue building on the presented methodology by integrating additional open geographic, demographic, and Earth Observation datasets and spatial techniques to improve its performance and utility.

5. Conclusions

This paper introduces an automated methodology for delineating functional urban agglomerations across national extents to assess Indicator 11.3.1 and demonstrates its application across Ethiopia, Nigeria, and South Africa for the 2016 to 2020 period. The automated methodology expands upon the United Nations' proposed delineation methods to allow for the delineation of individual functional urban agglomerations across entire countries using openly available and wide coverage data and tools, including WorldPop, OpenStreetMap, and openrouteservice. We successfully delineated functional urban agglomerations across three African countries and calculated urban change metrics to reveal varying patterns of urban land expansion, with Ethiopia's urban agglomerations displaying the greatest absolute change in urban land and population and, on average, exhibiting the highest Indicator 11.3.1 values, followed by Nigeria and South Africa, respectively. Additional analyses highlighted hotspots of Indicator 11.3.1, notably Mekelle, Ethiopia; Benin City, Nigeria; and Polokwane, South Africa, and included detailed patterns of urban land change that occurred within them. The multi-level approach presented in this work illustrates a new pathway for evaluating urban change using Indicator 11.3.1, revealing insightful information for national level urban monitoring, highlighting hotspots of change under Indicator 11.3.1, and unveiling changes in urban form and spatial patterns of new development in Indicator 11.3.1 hotspots. The findings of this work contribute to the existing knowledge of urban land expansion patterns in Ethiopia, Nigeria, and South Africa, and the automated delineation methodology constructed for use with widely available data can increase the accessibility and convenience of delineating urban areas and assessing Indicator 11.3.1 across larger extents, thereby enabling more continuous, consistent monitoring of urban land use expansion at multiple levels.

We acknowledge that the outcomes of this work are representative of change only occurring within agglomerations of each country over the 2016 to 2020 period and as informed by the datasets used. The rise of social unrest, the COVID-19 pandemic, and other pressing issues in the countries we have examined have likely altered various aspects of the urbanization process [80–82]. We propose future monitoring be carried out for the coming years in Ethiopia, Nigeria, and South Africa, as well as in hotspot cities we identified to examine fine-scale urbanization effects and better guide local management and sustainability planning. We also suggest building upon delineation methodologies, hotspot identification, and supporting spatial metrics as improved datasets, techniques, and services arise to progress the utility of Indicator 11.3.1 and urban monitoring efforts.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/ijgi13070226/s1. We produced 30 m spatial resolution annual land use maps for the 2016 to 2020 period for Ethiopia, Nigeria, and South Africa (Figure S1).

Author Contributions: Conceptualization, Jody C. Vogeler, Melissa McHale, Melinda Laituri, and Orion S. E. Cardenas-Ritzert; methodology, Orion S. E. Cardenas-Ritzert and Jody C. Vogeler; software, Orion S. E. Cardenas-Ritzert and Patrick A. Fekety; validation, Orion S. E. Cardenas-Ritzert and Shahriar Shah Heydari; formal analysis, Orion S. E. Cardenas-Ritzert; investigation, Orion S. E. Cardenas-Ritzert; resources, Jody C. Vogeler; data curation, Orion S. E. Cardenas-Ritzert and Jody C. Vogeler; writing—original draft preparation, Orion S. E. Cardenas-Ritzert; writing—review and editing, Orion S. E. Cardenas-Ritzert, Jody C. Vogeler, Melissa McHale, Melinda Laituri, Shahriar Shah Heydari, and Patrick A. Fekety; visualization, Orion S. E. Cardenas-Ritzert; supervision, Jody C. Vogeler; project administration, Jody C. Vogeler; funding acquisition, Jody C. Vogeler. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the NASA Land Cover and Land Use Change Program, grant number 80NSSC21K0313.

Data Availability Statement: The code for the presented methodology can be accessed at the following repository: https://github.com/VogelerLab/SDG-11.3.1-Automated-Urban-Delineation-Code.git (accessed on 10 June 2024). The original land use data in this study is pending data archiving on ORNL DAAC under the title: Annual Land Use and Urban Land Cover maps: Ethiopia, Nigeria, and South Africa 2016–2020. The population, geographic, and network data and tools presented in this study are available at the following URLs: [https://www.worldpop.org; https://www.openstreetmap.org/; https;//openrouteservice.org] (accessed on 10 June 2024).

Acknowledgments: We would like to acknowledge Steven Filippelli and other members of the Vogeler Research Lab at Colorado State University for constructive methodological conversations during the development of this work. We would also like to acknowledge Joshua Reyling of the Colorado State University Geospatial Centroid for his help in code development.

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Appendix A

Table A1. Metrics for top-five-ranking Indicator 11.3.1 urban agglomerations with populations greater than 100,000 in Ethiopia.

	Urban Agglomerations				
	Bahir Dar	**Durame**	**Kombolcha**	**Sodo**	**Mekelle**
2016 DA Per Capita	83	56	96	172	184
2020 DA Per Capita	144	160	150	312	278
Total Change in DA (%)	98	510	83	445	98
LCR	0.200	1.020	0.165	0.889	0.196
PGR	0.027	0.152	0.032	0.220	0.054
SDG 11.3.1	7.329	6.707	5.190	4.035	3.630
Infill (%)	23	12	27	9	20
Outward (%)	77	88	73	91	80

Table A2. Metrics for top-five-ranking Indicator 11.3.1 urban agglomerations with populations greater than 100,000 in Nigeria.

	Urban Agglomerations				
	Benin City	**Akure**	**Ikeja**	**Ondo**	**Ugheli**
2016 DA Per Capita	185	206	76	197	236
2020 DA Per Capita	237	238	80	213	256
Total Change in DA (%)	63	42	24	39	51
LCR	0.127	0.084	0.047	0.079	0.101
PGR	0.049	0.042	0.030	0.050	0.066
SDG 11.3.1	2.593	2.012	1.564	1.557	1.548
Infill (%)	48	69	75	67	64
Outward (%)	52	31	25	33	36

Table A3. Metrics for top-five-ranking Indicator 11.3.1 urban agglomerations with populations greater than 100,000 in South Africa.

	Urban Agglomerations				
	Witsieshoek	**Siyabuswa**	**Kwamhlanga**	**Polokwane**	**Jeppe's Reef**
2016 DA Per Capita	205	293	229	257	208
2020 DA Per Capita	229	396	314	306	256
Total Change in DA (%)	18	62	111	41	99
LCR	0.035	0.124	0.222	0.082	0.197
PGR	0.009	0.037	0.086	0.033	0.096
SDG 11.3.1	18.00	3.402	2.576	2.449	2.065
Infill (%)	83	62	65	56	52
Outward (%)	17	38	35	44	48

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