THESIS

BUILDING ON SUSTAINABLE DEVELOPMENT GOAL INDICATOR 11.3.1. FOR IMPROVED UTILITY AND GUIDANCE

Submitted by

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ABSTRACT

BUILDING ON SUSTAINABLE DEVELOPMENT GOAL INDICATOR 11.3.1. FOR IMPROVED UTILITY AND GUIDANCE

The increased production of broad-coverage spatial datasets and investigation of these datasets by spatial analysis techniques allows for consistent examinations of urbanization patterns across the globe. Spatial data and analyses have proven valuable for sustainable urban development initiatives, including Sustainable Development Goal (SDG) 11 under the United Nation's 2030 Agenda for Sustainable Development. SDG Indicator 11.3.1 is a geospatially measured indicator implemented under SDG 11 for monitoring rates of urban expansion and population growth in a specific area over a period of time. Current methodological approaches and data inputs may hinder the application of SDG Indicator 11.3.1 at certain scales and extents. The overarching goal of this research is to build on the utility of SDG Indicator 11.3.1 by enhancing an existing urban delineation method for automated function, examining urban change at the urban agglomeration level across broad extents, highlighting hotspots of SDG Indicator 11.3.1, and evaluating the impacts of the spatial resolution of data inputs on SDG Indicator 11.3.1 and related outputs.

In Chapter 1, we advanced an existing urban delineation method for the automatic identification of individual urban agglomerations across broad extents. We accomplished this by integrating various open-source datasets and tools with spatial

analysis techniques. We used this methodology to examine SDG Indicator 11.3.1 and additional urban change metrics for urban agglomerations in Ethiopia, Nigeria, and South Africa over the 2016 to 2020 period. In Chapter 2, we applied our delineation methodology and examined the influence of spatial resolution of land use data on urban delineation, urban change metrics, and urban related land use change in Ethiopia over the 2016 to 2020 period. The results of Chapter 1 revealed trends of urban change and highlighted hotspots of SDG Indicator 11.3.1 at multiple levels across the three African countries. Chapter 2 revealed the implications of using varied spatial resolutions of land use maps when delineating urban areas, assessing SDG Indicator 11.3.1 and other urban change metrics, and examining urbanization-driven land use change.

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CHAPTER 1

AUTOMATED SPATIAL APPROACH FOR ASSESSING PATTERNS OF URBANIZATION AND IDENTIFYING HOTSPOTS OF URBAN CHANGE IN THREE AFRICAN COUNTRIES

Introduction

Africa is at the forefront of global urbanization, as many of its developing countries experience rapid urban population growth. United Nations 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 (UNDESA, 2019). Urbanization is being driven by various mechanisms in Africa, predominantly natural increase in the urban population but also by the reclassification of growing rural areas to urban and rural-to-urban migration (Awumbila, 2017; Heinrigs, 2020; Teye, 2018). An increasing urban population is leading to significant social, environmental, and economic changes across Africa's urban areas (African Policy Circle, 2020) and is expected to drastically transform Africa's landscapes, with urban land cover anticipated to expand 12-fold from 2000 to 2050 (Angel, 2012).

Moreover, the effects of urbanization in Africa will not be proportionate over the coming decades, with most urban population growth in Africa expected to be concentrated in smaller to intermediate-sized cities, otherwise referred to as secondary cities (UNDESA, 2019). 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 (Roberts, 2014). Secondary cities have remained essential for facilitating national development but are often limited in their resources and management capacity (Laituri et al., 2021; Roberts, 2014). These changes and limitations further stress the importance of consistent monitoring of urbanization-driven changes to guide sustainable development planning.

Various initiatives seek to aid Africa in managing rapid urban population growth and achieving sustainable development, including under the 2030 Agenda for Sustainable Development. The agenda was accepted by United Nations' State Members in 2015 and is comprised of 17 Sustainable Development Goals (SDG) and 169 targets, all aimed at improving various aspects of global welfare, with SDG 11 confronting challenges of urbanization (United Nations, 2015). SDG 11 specifically focuses on making cities and human settlements inclusive, safe, resilient, and sustainable, and Target 11.3 under it 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 urban population growth over time. Researchers have used spatial measures to examine SDG Indicator 11.3.1 at various scales and extents to examine rates of urban change across the globe (Mudau et al., 2020; Schiavina et al., 2019). Recent studies have revealed potential limitations associated with the implementation and interpretation of SDG Indicator 11.3.1 (Guo et al., 2022; Nicolau et al., 2018; Schiavina et al., 2019) and illuminated the need for additional works that enhance monitoring efforts for SDG 11.

One challenge of SDG Indicator 11.3.1 is defining the boundaries of the urban areas where change is to be assessed. Urban areas undertake a diversity of physical forms and can be defined by different characteristics, making the delineation of them nuanced or dissimilar depending on the techniques used (UN-Habitat, 2018b, 2021). To improve consistency in urban delineation for the assessment of SDG Indicator 11.3.1, the UN-Habitat (2018b) proposed the “functional” definition of a city, which can be accomplished using two methods: The Degree of Urbanisation method or the Urban Extent method. The former, endorsed by the United Nations Statistical Commission, reclassifies gridded population data into clusters based on population size and density thresholds (Dijkstra et al., 2021; UN-Habitat, 2018b). 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 (Angel et al., 2016; UN-Habitat, 2021). Both methods produce similar extents for larger cities but may vary in their delineation of smaller cities and urban centers (UN-Habitat, 2018b, 2021).

Current approaches are suitable for delineating boundaries and investigating urban change at a focal scale (e.g., a single city), which typically requires insight on local settlement interactions to accurately delineate boundaries, or a more generalized scale (e.g., administrative unit boundary), which may not capture the dynamic developed spatial form of an urban area. The available urban delineation approaches limit the scale and extent for assessments of SDG Indicator 11.3.1, and we highlight the need for a methodology that allows for the delineation of multiple, individual urban areas across a broad extent that is consistent over time. Detecting approximately the complete population of urban areas across an entire country would allow for relative comparisons to then highlight urban regions potentially experiencing the greatest change as indicated by SDG Indicator 11.3.1.

The aim of Chapter 1 was to advance the existing Urban Extent method defined in the Atlas of Urban Expansion and proposed for use in various SDG 11.3.1 related documents (UN-Habitat, 2018b, 2021) by integrating open-source datasets, open-source tools, and innovative spatial techniques to automate the identification of functional urban agglomerations across national extents. Using this automated methodology, we could then examine urban population changes, urban land use changes, and spatial patterns of development for functionally connected urban agglomerations by calculating SDG Indicator 11.3.1 and other relevant metrics. With this information, we could examine urban change trends at multiple levels and highlight hotspots of SDG Indicator 11.3.1.

Objectives

The specific objectives of Chapter 1 are to: 1) develop an automated urban delineation method to facilitate the application of SDG Indicator 11.3.1 at the functional urban agglomeration scale across the extents of our three study countries, Ethiopia, Nigeria, and South Africa, from 2016 to 2020; 2) quantify rates and spatial patterns of urban land use and population change, including SDG Indicator 11.3.1, within urban agglomerations to evaluate trends at multiple levels; and 3) use values of SDG Indicator 11.3.1 to identify hotspots of urban land use expansion across our focal countries for the 2016 to 2020 study period.

Methods

Study Regions

We selected Ethiopia, Nigeria, and South Africa as our case study countries as we believe they represent a diverse assortment of the political, economic, and societal dynamics that exist in Africa. We use open-source datasets and tools to delineate urban

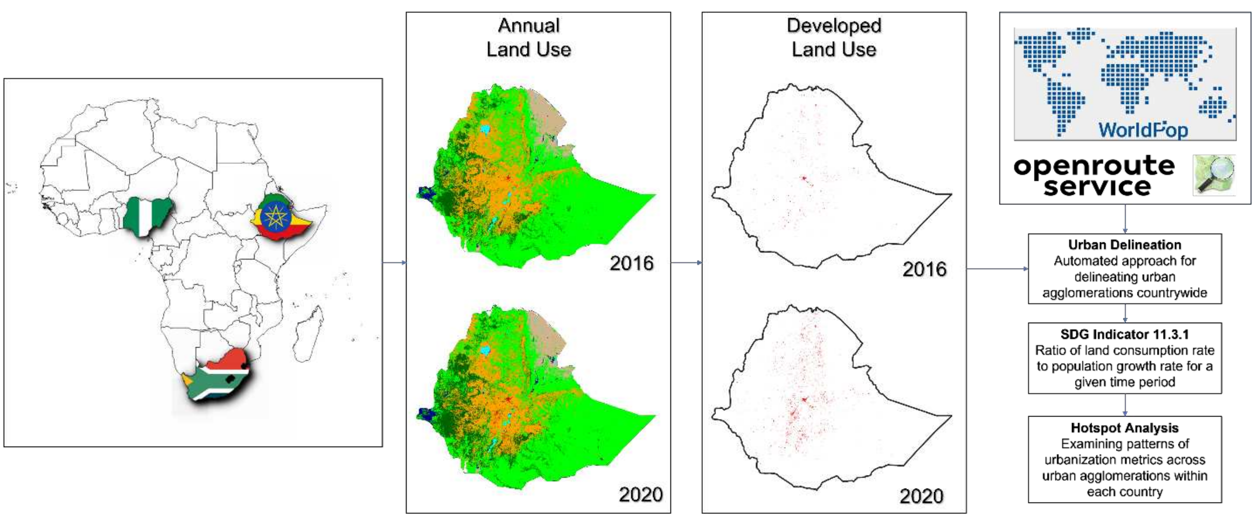

Figure 1.1: General workflow for delineating urban agglomerations, calculating SDG Indicator 11.3.1, and identifying hotspots of SDG Indicator 11.3.1. We examined SDG Indicator 11.3.1 and other metrics for Ethiopia, Nigeria, and South Africa for the 2016 to 2020 period using open-source datasets and tools that are integrated into the delineation approach we developed.

areas, calculate SDG Indicator 11.3.1 and related metrics, and identify trends and hotspots of change for the three study countries (Figure 1.1).

Nigeria

Nigeria, located in western Africa, is often recognized as Africa's natural leader due to its size and wealth (Foluke & Pius Olakunle, 2019). As of 2022, Nigeria is Africa's largest economy with a GDP of 477 billion and is the most populous African country at a population of 223 million (UNFPA, 2023b; World Bank, 2022a). Projections indicate an addition of 189 million people to Nigeria's urban population from the 2018 population estimate by 2050 (UNDESA, 2019). 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 (Aliyu & Amadu, 2017; Momoh et al., 2018).

Ethiopia

Ethiopia, located in the Horn of Africa, is one of the world's oldest settled countries known for its ancient history and culture. Ethiopia covers a total of 1.128 million square kilometers with a population of 126 million in 2023, making it the second most populous country in Africa behind Nigeria (UNFPA, 2023a). Ethiopia's population is predominantly rural, and it remains one of the least urbanized countries in Africa but 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 (OECD/Sahel and West Africa Club, 2020).

South Africa

South Africa, geographically located in the southernmost portion of Africa, is globally recognized for its mining of metals, rich culture, diverse topography, beautiful landscapes, and productive natural environments. South Africa covers a total of 1.22 million square kilometers, with over 2,850 kilometers of coastline, and elevations ranging from sea level to Mafadi Peak at 3,450 meters. The country comprises nine provinces containing 8 metropolitan municipalities and 44 district municipalities. In 2023, the South African population is estimated to be 60 million, with over two-thirds of the population estimated to be living in urban areas (UNFPA, 2023c; World Bank, 2022b). The population continues to rise, and it is forecasted that eight in ten South Africans will live in urban centers by 2030 (UN-Habitat, 2014).

Definitions and Overview of Methodology

We developed a methodology to automate the delineation of urban agglomerations and facilitate the assessment of SDG Indicator 11.3.1 at the urban agglomeration level across national extents (Figure 1.2). 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.

In regard to 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 is comprised of 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 the land use maps. Clusters, symbolized as polygons in spatial software, represent patches of urban areas and are primarily comprised of developed land use pixels that have certain urban characteristics. Urban agglomerations can be made up of one single cluster or numerous clusters and may represent a single contiguous urban settlement or multiple fragmented urban settlements that are functionally linked by a transportation network. Urban agglomerations, also referred to as agglomerations, are symbolized as polygons and SDG 11.3.1 and related urban calculations are carried out at the agglomeration level.

In the following sections, we are going to describe the methodology we developed for automating urban delineation, how we apply this methodology to our case study countries, and how we calculate urban change metrics and summarize spatial patterns of urban land use change for individual agglomerations. We then describe the multi-level analyses we conduct after completing these procedures, including examining change trends for all agglomerations and by population size class for each country, drawing hotspots from the largest size class within each country for focal investigation, and detailing how patterns of change are manifesting in one example hotspot city.

Automated Delineation Approach

Base Classification

Our automated delineation methodology builds off the Atlas of Urban Expansion method used in the SDG Indicator 11.3.1 training module (UN-Habitat, 2018a). The Atlas of Urban Expansion approach employs neighborhood spatial operations using GIS software (e.g., ArcGIS Pro) to reclassify developed land use pixels in a land use map into urban, suburban, rural, and open space classes (Angel et al., 2016). This pixelwise classification is completed by examining the share of developed land use pixels within the walking distance circle of a focal developed land use pixel. The walking distance circle is one kilometer in area and approximates a ten-minute walk from the focal pixel to circle's edge. The percentage of developed land use pixels within the walking

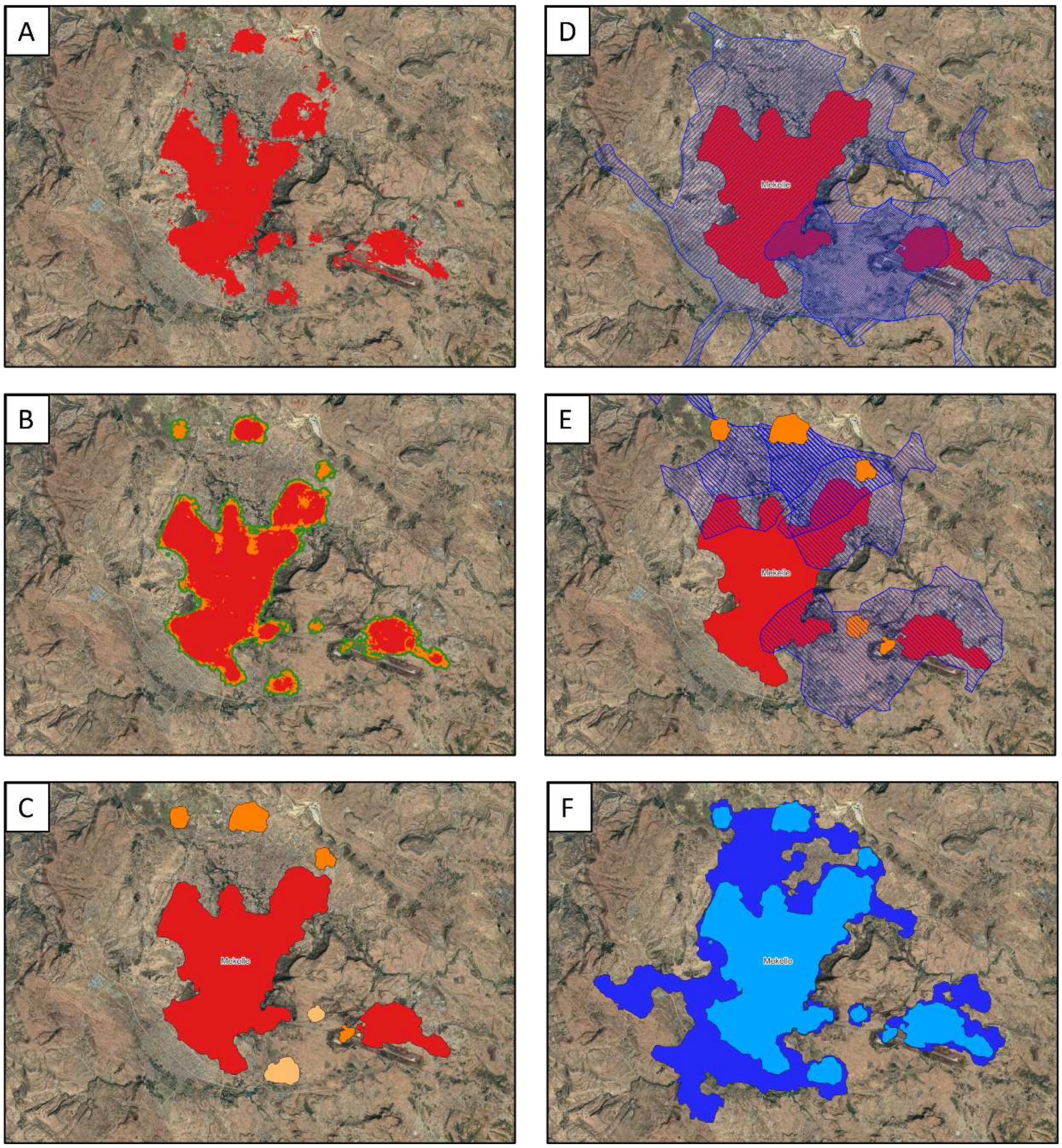

Figure 1.2: Automated workflow for delineating urban agglomerations. A: Developed land use raster. B: Developed land use raster pixels reclassified into urban (red), suburban (orange), and urbanized open space (green) pixels. C: Urban clusters comprised of urban, suburban, and urbanized open space pixels 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).

distance circle are examined, and the center focal pixel is classified as urban, suburban, or rural based on this percentage (Figure 1.2B). The walking distance circle and percentage thresholds for determining each class are explained in detail in the Atlas of Urban Expansion (Angel et al., 2016). 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. The urban cluster polygons are used as the main input for our automated approach and can be obtained by reaching step 18 of the SDG Indicator 11.3.1 training module (UN-Habitat, 2018a).

Determining Cluster Types

The identified urban clusters are then separated into three subgroups: core clusters, non-core clusters and clusters that do not meet relevant criteria (Figure 1.2C). Under our definition, core clusters are assumed to contain an urban center and could act as an urban agglomeration alone. In contrast, non-core clusters are assumed to not have an urban center and rely 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 including towns, suburbs, and other inhabited human developments. In our methodology, core clusters are differentiated from non-core clusters by two main criteria: satisfaction of a minimum population threshold and the presence of populated place data (i.e., a point location for a city or town) within or in proximity to the cluster. Additional criteria are applied to differentiate non-core clusters from clusters not meeting any of the relevant criteria (e.g., population size and density thresholds).

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/) or WorldPop (www.worldpop.org). We used WorldPop's top-down, 100-m² 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-km² and 100-m² spatial resolution gridded datasets (WorldPop, 2018). The WorldPop data is 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 (WorldPop, 2018). New maps are generated when new census or geospatial datasets are produced, indicating the likelihood of population count maps being available for years after 2020, 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 manipulated 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. Using Africa as an example, the 2015 African Urban Dynamics paper identified 5,000 as the minimum population size threshold for definitions of urban for 18 out of 34 African countries (Mo Ibrahim Foundation, 2015). 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’ (OECD/Sahel and West Africa Club, 2020). 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 threshold value of 5,000 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/) or OpenStreetMap (https://www.openstreetmap.org/). We utilized OpenStreetMap data (OpenStreetMap contributors, 2017) to determine the presence of city or town points within potential core clusters. OpenStreetMap is an open geographic database that is contributed to by a global community and consistently updated and validated by contributors with local knowledge (OpenStreetMap Wiki, 2022). 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 centre, between a village and city in size” (OpenStreetMap Wiki, 2023a). Although no population criteria exist for differentiating between these two places, as of 2019, 95% of city points had population values greater than 20,000 and 95% of town points had population values between 1,000 and 70,000 (OpenStreetMap Wiki, 2023c, 2023d). 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 (OpenStreetMap Wiki, 2023d, 2023c). Since OpenStreetMap is an openly contributed to geographic database, the user should be aware of limitations that exists, such as inconsistencies in naming, inaccuracies in placement of location points, and missing data (OpenStreetMap Wiki, 2023b). 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.

Once core clusters were determined, we identified non-core clusters using additional threshold criteria. The remaining clusters that were not classified as core clusters were considered potential non-core clusters. In preliminary analyses, numerous clusters formed as result of misclassified developed land use 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 from clusters that did not meet the relevant criteria. We conducted exploratory analyses to determine an approximate threshold that excluded misclassified clusters in our work in Ethiopia, Nigeria, and South Africa, which ended up ranging from 300 to 500 people per square kilometer of developed land use area. The remaining clusters that did not meet relevant criteria were saved for use in the latter end of the methods.

Associating Clusters

Categorizing clusters into core clusters and non-core clusters then allowed us to gauge connectivity between them to identify functional urban agglomerations. Particularly for Africa, we see that rural areas are strongly tied to urban cores (McHale et al., 2013) and significantly influences urban growth but may be disregarded or not included in urban change assessments. We wanted our approach to capture a more nuanced connected urban area than typically defined, and we aimed to include these often overlooked peripheral areas that interact with the urban core.

To accomplish this, we approximated connectivity using tools provided by Openrouteservice (Openrouteservice, 2023), 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. We wanted 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 as it is not a point. 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. This average travel distance from a center to the edge was added to the isochrone distance threshold we set for each cluster. This allowed us to better approximate connectivity between the edge of clusters versus approximating connectivity from the center of each cluster.

We then 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 a 5-kilometer base travel distance plus the value of the average travel distance derived from the travel distance matrices for each cluster. Any cluster overlapped by an isochrone was adjoined with the associated cluster. The adjoined clusters were now recognized as a new core area, and this was repeated until there were no non-core clusters left or 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 the urban region has multiple centers of activity (Anas et al., 1998; Kloosterman & Musterd, 2001). If the isochrone generated for a cluster overlaps or touches any portion of another cluster, those two clusters are associated. This rule applies to our assessment of connectivity between core clusters (e.g., two dense urban centers), and core clusters with non-core clusters (e.g., a core city and surrounding towns). Core clusters with overlap are associated and given the same unique identifier (Figure 1.2D). Isochrone maps are then generated for non-core clusters and those with isochrone maps that overlap with a core cluster or poly cores are associated (Figure 1.2E). 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.

Finalizing Agglomerations

The result of the presented operations should be a matching pair of unique agglomerations for the initial and final year, but that may not always be the case. The physical form and attributes of urban clusters are expected to change over the analysis period; therefore, we can expect to observe differences in the classification of agglomerations in the initial year versus the final year. For example, we observed instances where the classification for the initial year was missing less populated clusters that weren't identified as non-core clusters because they did not meet the set population size and density thresholds. These clusters grew in population by the final year and met non-core cluster thresholds, thereby changing their classification and inclusion. Clusters that did not meet thresholds that had a matching cluster in the initial or final year were reincorporated and joined with their relevant agglomeration. We also observed instances where the growth of clusters in the final year led to amalgamation of agglomerations that were separated and unique in the initial year. In this case, applicable agglomerations were combined into a new, single agglomeration to match the amalgamated agglomeration of the initial or final year to better facilitate change analyses. We used spatial join functions to investigate overlap and ensure the agglomerations contained the same relevant clusters in both years to improve comparability and accuracy of our change assessment. After this procedure, a matching pair of unique agglomerations should exist for the initial year and final year in the study period (Figure 1.2F).

Once agglomerations are finalized for both years, the place data associated with each agglomeration can be reestablished and all relevant urbanization metrics can be calculated. Place data is initially assigned to each cluster if applicable, but place data becomes construed as clusters are joined. Spatial join functions are repeated at this stage to assign proper place attribute data to each unique agglomeration. Our calculated urbanization metrics included land consumption rate, population growth rate, land consumption rate to population growth rate ratio, total developed land use area, developed land use area per capita, percent change in developed land use area, development by infill in areal units and development by extension and leapfrog in areal units. These metrics are discussed in detail in the Calculations section.

For our case study countries, we initially developed the geospatial processes presented above using ArcGIS Pro 3.0.1 (ESRI, 2022) and QGIS 3.22 (QGIS.org, 2023) to test applicability and appropriateness. We carried out the initial steps in ArcGIS Pro 3.0.1 as instructed in the SDG Indicator 11.3.1 training module (UN-Habitat, 2018a). The remaining developed geospatial workflow was conducted using QGIS 3.22 due to its vast library of tools and plug-ins. After determination of appropriate processes, we automated the approach using Python 3.9.16 (Van Rossum & Python Development Team, 2022) to facilitate the application of this methodology across each study region. The completed methods can then presumably be applied to any region of interest across any 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 in mind to ensure wide-ranging accessibility and robust performance.

Methodology Applied

To extract the extents of urban agglomerations across our three study regions, we applied the automated delineation method outlined in the previous section using a land use product developed by Shah Heydari et al. (n.d.). The land use product was generated using machine learning approaches, namely Random Forest classifier, with a set of optical, synthetic aperture radar, nightlight, and topographic remote sensing data inputs. The developed 30-m^2 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 use was mostly specified by impervious surfaces but may include other human development or surrounding context such as parks, lawn, cemeteries, mines, and connecting roads (either paved or wide dirt roads) (Shah Heydari et al., n.d.). The rules used in interpretation for the land use model training were mindful of the complex characteristics of developed land use, identifying human developments beyond just impervious surfaces.

Post-delineation, we revised all agglomerations and found lingering outliers containing misclassified developed land use areas and signified by lower cumulative population densities. We applied an additional density threshold to remove these areas. Once this was complete, the following calculations relevant to SDG Indicator 11.3.1 were integrated into our automated approach and calculated for each identified urban agglomeration in the three study regions using QGIS and Python.

Calculations

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 took the reclassified land use map with a single development class from our workflow above and calculated the total developed land use area within each agglomeration to then calculate land consumption rate. The Land Consumption Rate formula is as follows:

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

where $\boldsymbol{V_{present}}$ is the total developed land use area in the current year, $\boldsymbol{V_{past}}$ is the total developed land use area in the past year and $\boldsymbol{t}$ is the time period or number of years between $\boldsymbol{V_{present}}$ and $\boldsymbol{V_{past}}$ (UN-Habitat, 2021).

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^2 resolution gridded population datasets. 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 has transpired in an urban region over a period of time (UN-Habitat, 2021). We downloaded WorldPop Population Count data for each country (WorldPop, 2018), 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:

$$\boldsymbol{Population\ Growth\ Rate\ (PGR)}\ =\ \frac{\boldsymbol{LN\ (Pop_{t_{+n}}\ /\ Pop_t)}}{\boldsymbol{(y)}}$$

where ***LN*** is the natural log, $\boldsymbol{Pop_{t+n}}$ is the total population in the urban agglomeration in the last year of a given time period, $\boldsymbol{Pop_t}$ is the total population in the urban agglomeration in the initial year of the time period and $\boldsymbol{y}$ is the difference between the initial year and final year of the time period (UN-Habitat, 2021).

SDG Indicator 11.3.1 and Supporting Metrics

SDG 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 region over a specified period of time and is said to be a measure of land use efficiency (UN-Habitat, 2021). We argue that SDG Indicator 11.3.1 being referred to as a measure of land use efficiency may lead to a misconstrued interpretation, as it is difficult to determine if urban land development is being conducted in an efficient or inefficient manner under this indicator alone. Still, what the indicator can provide us with is information about how urban changes may be transpiring. An SDG Indicator 11.3.1 ratio greater than one likely indicates that land is being expended for urban use faster than the population is growing, and a ratio less than one may indicate that the population is growing faster than land is being expended for urban use. A ratio close to one reflects comparable rates of growth in both land consumption and population growth. SDG Indicator 11.3.1 may also be referred to as the Land Consumption Rate to Population Growth Rate Ratio (LCRPGR).

UN-Habitat (2021) suggests utilizing additional metrics, also referred to as secondary indicators, to support the interpretation of the SDG Indicator 11.3.1 ratio. The two suggested secondary indicators are total change in built-up area and built-up area per capita, and are formulated as follows:

$$\boldsymbol{Total\ change\ in\ built-up\ area}\ (\%) = \frac{(\boldsymbol{UrBU_{t+n}} - \boldsymbol{UrBU_t})}{\boldsymbol{UrBU_t}}$$

Total change in built up area is the percent change in built-up land within in an urban area over a period of time. In the above formula, $\boldsymbol{UrBU_{t+n}}$ is the urban built-up area in the final year of the time period and $\boldsymbol{UrBU_t}$ is the urban built-up area in the initial year of the time period (UN-Habitat, 2021).

$$\boldsymbol{Built-up\ area\ per\ capita}\ (\boldsymbol{m^2}/\ \boldsymbol{person}) = (\boldsymbol{UrBU_t}\ /\ \boldsymbol{Pop_t})$$

Built up area per capita is the built-up area available per person within the urban area. In the above formula, $\boldsymbol{UrBU_t}$ is the urban built-up area in time $\boldsymbol{t}$ and $\boldsymbol{Pop_t}$ is the population size within the urban area in time $\boldsymbol{t}$ (UN-Habitat, 2021). For our purposes, we substituted built-up area with developed land use area in all of the above formulas.

Spatial Patterns of Development

Understanding the spatial patterns of development taking place in and surrounding urban areas is crucial for informing future development plans and managing existing development. The spatial patterns of development we assessed at the agglomeration level are infill, and extension and leapfrog. We defined infill as new development that occurred within the boundaries of the urban agglomeration of the initial year. Extension and leapfrog included all new developments that occurred outside of the boundaries of the initial year but within the boundaries of the final year. The area for infill and extension and leapfrog were obtained by extracting the new developed land use pixels meeting the criteria described above for each agglomeration.

Analyses and Hotspots

We used an SDG 11.3.1 threshold value to identify hotspot agglomerations experiencing a rate of urban land consumption that was greater than the rate of urban population growth. Generally, an urban area with an SDG Indicator 11.3.1 value greater than 1 is thought to be indicative of potentially rapid urban land expansion that may warrant further focal investigation (UN-Habitat, 2021). We applied the threshold value of 1 to filter for hotspots of urban land expansion for all study countries. The agglomerations meeting this threshold were considered hotspots and summary metrics of urbanization for hotspots were compared between countries. Summaries were also initially completed for the entire sample of delineated urban agglomerations to obtain country level statistics.

We then divided the hotspots into population size classes and compared results between the study countries. The population size classes were as follows: less than 50,000 people, 50,000 to 100,000 people, and more than 100,000 people. The population size breaks were strategically selected with the intent of maintaining decent sample sizes for each class and separating small urbanizing areas from secondary cities and larger metropolitans. The Degree of Urbanization cites various sources and uses a minimum population of 50,000 to classify a populated city (Dijkstra et al., 2021), so we used that threshold in our smallest class size to capture smaller urban areas. UN-Habitat and Roberts (2014) define and identify secondary cities as areas with a population greater than approximately 100,000 people. The largest size class with more than 100,000 people was meant to capture secondary cities and larger metropolitans. We divided the population size classes based on this information and created an intermediate size class between 50,000 and 100,000 people to capture potentially important and growing urban areas that may emerge as secondary cities in the future. Additional focal analyses were conducted for the top ranked SDG Indicator 11.3.1 hotspot agglomerations in the largest size class in each country and one example city was examined for detailed changes in development.

Results

Regional Summary Statistics

We summarized regional statistics relevant to urbanization for all delineated agglomerations in Ethiopia, Nigeria, and South Africa (Table 1.1). Agglomerations in Ethiopia endured the greatest relative increase, with approximately a 28% increase in the total population and 73% increase in the total developed land use area from 2016 to 2020. Nigeria's agglomerations displayed the greatest absolute increase in population, adding around 8 million people from 2016 to 2020, which was a 16% increase. Nigeria and Ethiopia's agglomerations had similar absolute increases in developed land use area, but Nigeria had a lower relative increase at 13%. Urban agglomerations in South Africa, however, experienced the smallest percentage increase in terms of both population and urban land expansion. Within South Africa's urban agglomerations, the total population only increased by 3% and the developed land use area only increased by 5% from 2016 to 2020.

We observed SDG Indicator 11.3.1 outliers 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 filtered out agglomerations that contained a land consumption rate or population growth rate with extremely small values close to 0, as these created disproportionately large SDG Indicator 11.3.1 values. After filtering the agglomeration dataset, Ethiopia had 192 total urban agglomerations, Nigeria had 323, and South Africa had 238.

Table 1.1: Total agglomerations, population, and developed land use area summary for all urban agglomerations identified under our approach in Ethiopia, Nigeria and South Africa. DA is the developed land use area.

	Total Agglomerations	2016 Population	2020 Population	2016 DA (km^2)	2020 DA (km^2)
Ethiopia	193	9,936,671	12,757,304	1,476	2,550
Nigeria	357	51,112,180	59,306,168	7,557	8,577
South Africa	369	43,728,813	45,321,001	8,107	8,514

SDG Indicator 11.3.1 Hotspot Trends at The Country Level

We identified hotspots of urban land expansion, which were agglomerations with an SDG Indicator 11.3.1 value greater than 1, across all three study countries (Figure 1.3). For the entire country of Ethiopia, we observed a consistently high proportion of agglomerations with SDG 11.3.1 values above 1 when compared to Nigeria and South Africa. Approximately 99% or 191 of the 192 agglomerations in Ethiopia had an SDG Indicator 11.3.1 value greater than 1. For agglomerations meeting the SDG Indicator 11.3.1 hotspot threshold in Ethiopia, the land consumption rate ranged from 0.024 to 1.019 and population growth rate ranged from 0.0016 and 0.2204. The average percent change in developed land use area in Ethiopia across all hotspot agglomerations was 104% from 2016 to 2020. Infill development accounted for 33% of the observed growth in developed land use area from 2016 to 2020, and extension and leapfrog development accounted for 67% of the observed growth in developed land use area from 2016 to 2020.

Nigeria displayed comparatively lower SDG Indicator 11.3.1 values than other countries, with the max value being 2.59. Approximately 33% of 323 agglomerations, or 105 agglomerations, in Nigeria had an SDG Indicator 11.3.1 value greater than 1. These hotspot agglomerations had land consumption rate values ranging from 0.012 to 0.361, and population growth rate values ranging from 0.009 to 0.163. The average percent change in developed land use area in Nigeria across all hotspot agglomerations was 48% from 2016 to 2020. Infill development accounted for 66% of the observed growth in the developed land use area of these agglomerations from 2016 to 2020, and extension and leapfrog development only accounted for 34% of the observed growth in developed land use area from 2016 to 2020.

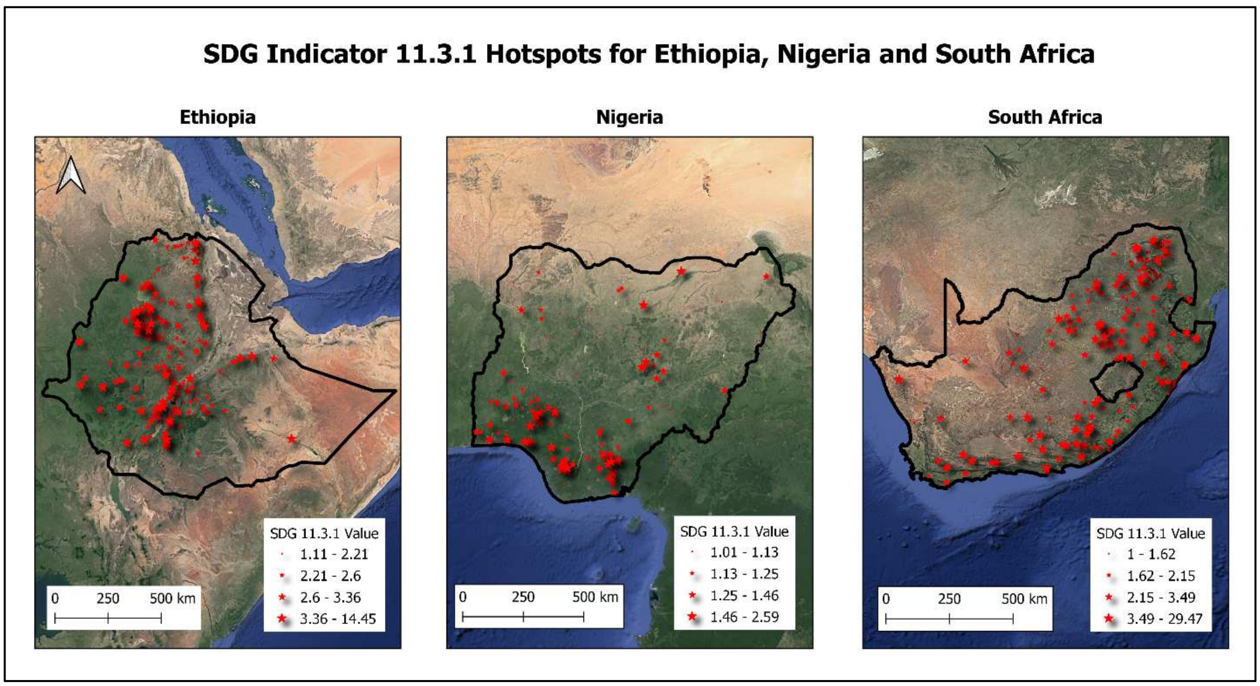

Figure 1.3: Map displaying range of SDG Indicator 11.3.1 values for urban agglomerations meeting the SDG Indicator 11.3.1 hotspot threshold value of 1 across Ethiopia, Nigeria, and South Africa.

South Africa displayed a wide range of SDG 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 SDG Indicator 11.3.1 threshold. The land consumption rate values ranged from 0.002 to 0.580, and the population growth rate ranged from 0.0005 to 1.564. Infill development accounted for 65% of the observed growth in the developed land use area of these agglomerations from 2016 to 2020, and extension development accounted for 35% of the observed growth in developed land use area from 2016 to 2020.

Results by Population Size Classes

All three countries displayed varied results when examined by population size class (Table 1.2). 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 hovering around a value of 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 use expansion was taking place in the smallest population size class in Nigeria.
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.

Table 1.2: Urban change metrics by population size class for Ethiopia, Nigeria and South Africa. DA is developed land use area, LCR is land consumption rate, PGR is population growth rate, and SDG 11.3.1 is the land consumption rate to population growth rate ratio. All metrics were calculated at the agglomeration level for the 2016 to 2020 period and summarized by population size class for each country.

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

Hotspot Agglomerations

Important areas of urban growth and development, particularly secondary cities, characteristically fell within the largest population size class of those that met the SDG Indicator 11.3.1 hotspot threshold. To narrow our findings, we extracted five focal hotspot agglomerations with the highest SDG Indicator 11.3.1 values from the largest population size class for each country (Table 1.3).

In Ethiopia, the five hotspot agglomerations displayed extremely large SDG 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 (Laituri et al., 2021; Maru & Worku, 2022). The SDG 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 were comprised of numerous clusters of smaller towns, aside from the Polokwane agglomeration. All South African agglomerations had SDG Indicator 11.3.1 values above 2, indicating considerable uptake of urban land over the 5-year period.

Table 1.3: Top-ranking hotspot agglomerations for SDG Indicator 11.3.1 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

Focal Hotspots in Each Country (Mekelle, Benin City, and Polokwane)

We selected a focal top-ranking hotspot agglomeration for each country to inspect urban change metrics and spatial patterns of development (Table A1- A3). Criteria for focal 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 focal 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 SDG Indicator 11.3.1 values above 2 for the 2016 to 2020 period (Table 1.4). Mekelle displayed a 51%

increase in the developed land use 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 use area per capita, 28% and 19%, respectively. Mekelle experienced the greatest total change in developed land use area, with a 98% increase from 2016 to 2020. Benin City's total change in developed land use area followed at 61% and Polokwane saw the smallest increase at 41%.

Table 1.4: Development metrics for three focal hotspot agglomerations. DA is developed land use 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 Extension and Leapfrog (%)
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 focal hotspot agglomeration displayed varied spatial patterns of development (Figure 1.4). Mekelle displayed excessive development outside of the initial urban extent over the 5-year period. 80% of Mekelle's new development was attributed to extension or leapfrog growth and 20% was by infill (Figure 1.4E). New development patterns in Benin City and Polokwane followed a similar split. New development by extension and leapfrog was slightly greater than new development by infill in Benin City, at 52% and 48% respectively (Figure 1.4D). Polokwane's new development by infill was slightly greater than new development by extension and leapfrog, at 56% and 44%, respectively (Figure 1.4F).

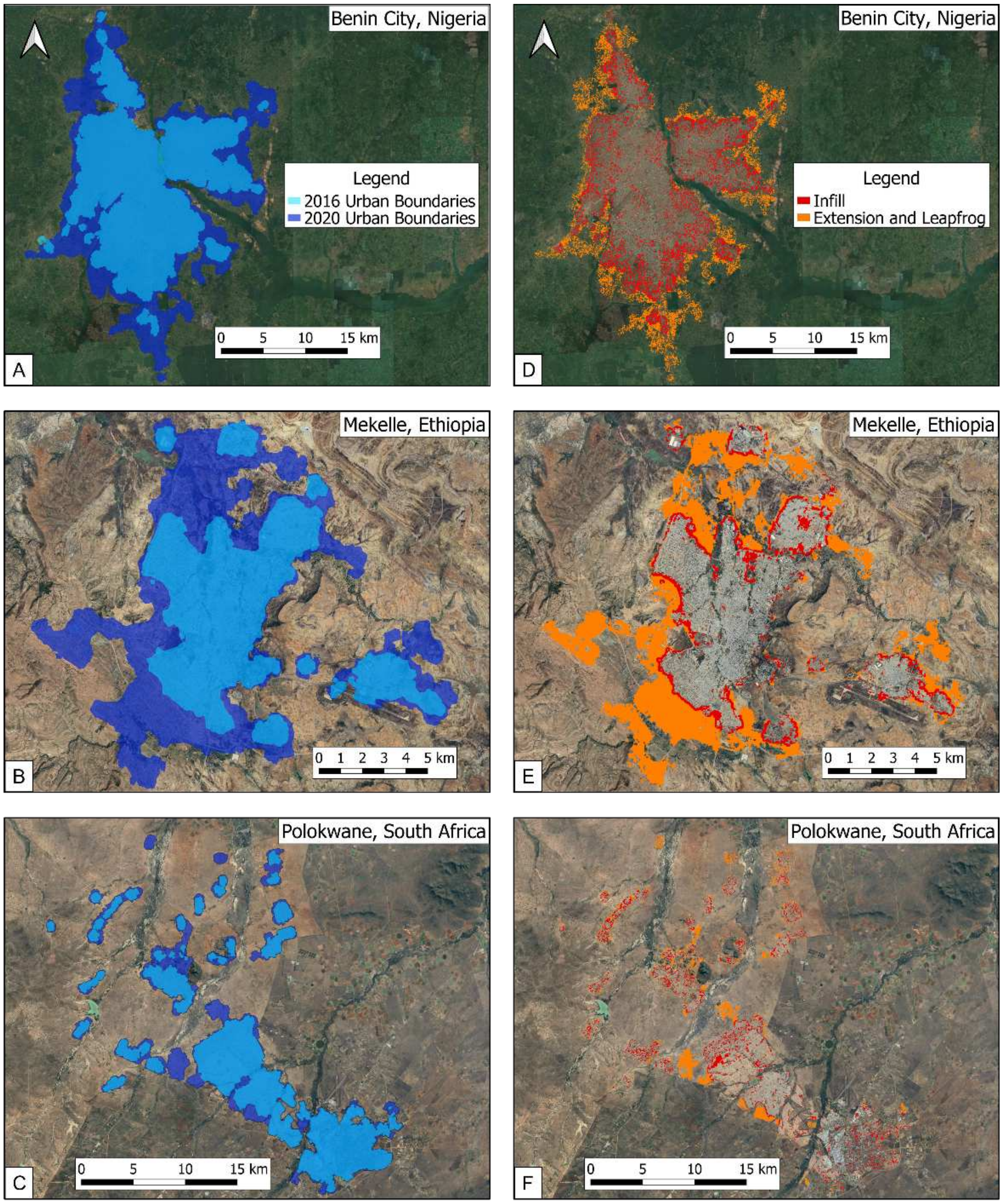

Figure 1.4: A-C show urban boundaries for 2016 and 2020 for each focal hotspot agglomeration. D-F show spatial patterns of development for each focal hotspot agglomeration.

Example Hotspot City (Mekelle)

We further dissected developmental changes within one of our focal hotspot cities to support the inferences drawn from the change metrics. We chose to further examine patterns within Mekelle since it exhibited the greatest relative change of the three focal hotspots (Figure 1.5). Mekelle's urban boundary grew drastically over the five-year period, connecting previously fragmented urban clusters and extending outwards to envelop new land for urban use. The majority of growth occurred in the northern and southwestern portions of Mekelle, but growth also occurred throughout denser areas of the city and around the airport. Our examination of the high-resolution imagery showed expansive residential development, densification of existing residential development, new transportation infrastructure such as roads, and new industrial developments across Mekelle.

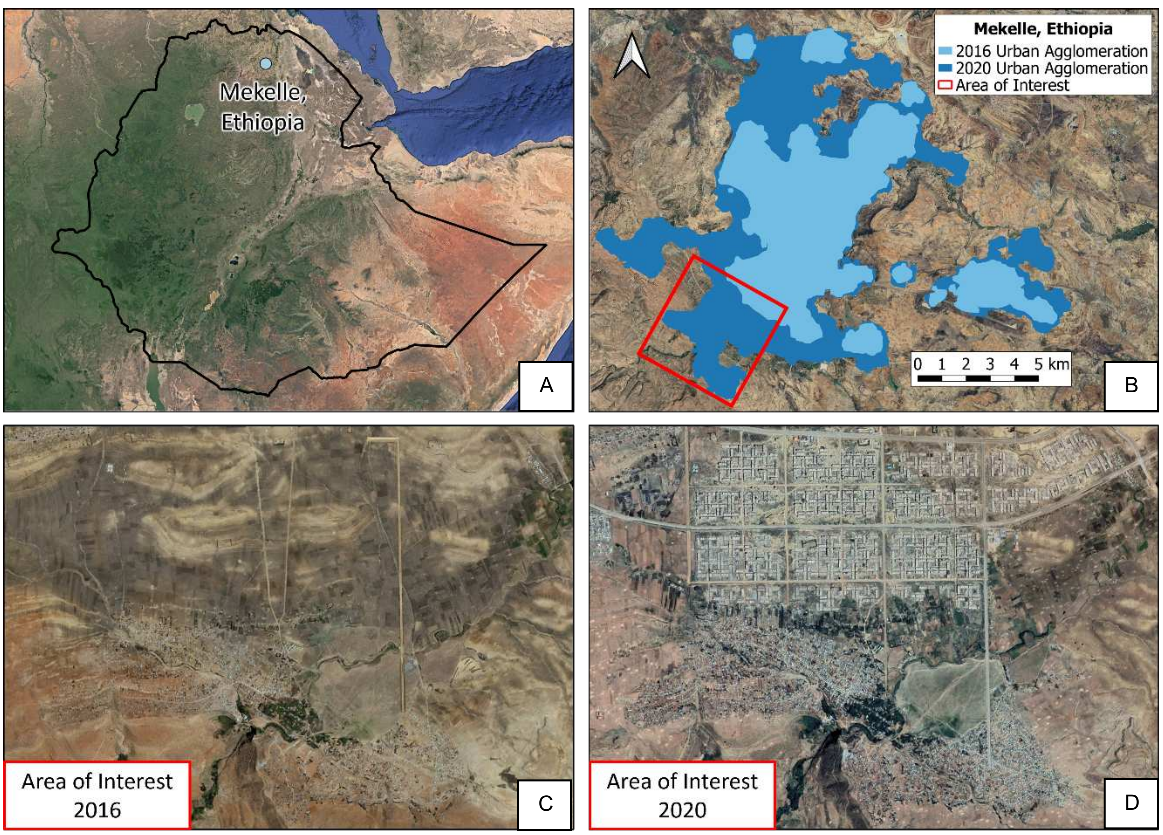

Figure 1.5: Highlighting new development in southwestern Mekelle. A: Mekelle is located in northern Ethiopia B: Urban agglomeration boundaries including Mekelle, Ethiopia in 2016 and 2020. Red box highlights area of interest. C: High-resolution imagery showing area of interest in 2016 composed of agricultural lands and sparse development D: High-resolution imagery showing area of interest in 2020 composed of dense development.

Discussion

Our approach leveraged openly accessible tools and datasets to automate the delineation of functional urban agglomerations across national extents to support the assessment of SDG Indicator 11.3.1. By facilitating broad extent assessments of urban change within individual urbanizing environments, we anticipate our approach will fulfill an array of objectives for urban monitoring initiatives. We illustrated the value of our methodology by summarizing rates of change and spatial patterns of development for all agglomerations at the country level and when disaggregated by population size class. We then highlighted hotspots of urban land expansion through SDG Indicator 11.3.1 and further investigated focal urban changes through added calculations and analyses. This multi-step approach, moving from broad comprehensive urban change trends to fine scale examinations of SDG 11.3.1 hotspots, 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 SDG 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 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 large extent monitoring efforts. In the absence of local knowledge, the 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 (Angel et al., 2016). 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 and was based on an “as the crow flies” Euclidean distance buffer. It particularly became difficult to interpret what urban settlements are 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 centres, 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 (Dijkstra et al., 2021). 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). The issue with assessing SDG Indicator 11.3.1 at the administrative unit level is that administrative boundaries are static. We acknowledge that this population-based approach was developed for an array of SDG Indicators and not developed to identify urban boundaries from built-up or developed land cover characteristics alone, but these characteristics are essential for accurate assessments of urban land use change. Failure to account for built-up or developed characteristics of the land in the delineation of urban boundaries will assume differences in boundaries and, therefore, differences in outcomes of the land consumption rate value included in the SDG Indicator 11.3.1 calculation and spatial patterns of development. Additionally, the grid cells under this method are at 1km resolution, which is fairly coarse and may not be appropriate for small 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). 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 issue of static spatial units persists as it uses administrative units, and the classification requires commuting data which is not regularly produced or readily available in many countries (Bédécarrats et al., 2016; European Union/FAO/UN-Habitat/OECD/World Bank, 2020). 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, we included testing our methodologies on publicly available datasets, such as the Copernicus annual 100-m^2 spatial resolution global land cover maps (as a proof of concept, not included in our presented results) and used the opensource

Openrouteservice API to generate isochrone maps, which can act as a proxy for commuting data (Buchhorn et al., 2020; Openrouteservice, 2023).

We assume the discussed limitations are reasons for SDG Indicator 11.3.1 studies often being conducted at a focal city scale (Laituri et al., 2021; Mudau et al., 2020)or a more generalized scale (e.g., administrative unit level, country level) (Schiavina et al., 2019; Wang et al., 2020). Our automated approach expands the spatial scale at which SDG 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 SDG Indicator 11.3.1 proved valuable, additional urban change calculations provided important insight on spatial patterns of development not illuminated by SDG Indicator 11.3.1. The top-ranking SDG Indicator 11.3.1 hotspots all exhibited high rates of inefficient land use, but supplementary calculations revealed inter and intra-country variability in spatial patterns of development among hotspots with similar SDG Indicator 11.3.1 values. For example, new development in Benin City in Nigeria was largely caused by extensive and leapfrog development, while new development in Akure in Nigeria was by infill development, although both agglomerations had similar SDG Indicator 11.3.1 values and the majority of agglomerations in Nigeria displayed development by infill. Furthermore, Mekelle in

Ethiopia had an SDG 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 SDG 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 SDG Indicator 11.3.1 may expose information imperative for guiding focal analyses and on ground planning efforts (Johnson, 2001; Nguyen, 2010; Paull, 2008; US EPA, 2014; Yiran et al., 2020). Future work may consider using a combination of metrics including SDG Indicator 11.3.1 to extract hotspots of urban change.

Secondary cities are known to facilitate and harbor considerable urban growth in developing countries (Donaldson et al., 2020; Marais & Cloete, 2017) and our findings corroborate this as numerous secondary cities, such as Mekelle and Polokwane, exhibited drastic change over the short 5-year period. Secondary cities often face numerous challenges associated with rapid urbanization due to waning governance, economic, and social systems, consequently resulting in poor land management, low economic productivity, insufficient provision of basic services, and environmental challenges (Pozhidaev, 2020; Roberts, 2014). Secondary cities can play a vital role in the development of a nation but are often limited in their capacity, resources, and data (Roberts, 2014), making strategic analyses and informed development plans crucial for improving existing secondary cities (Al-Jawari et al., 2020; Mokoele, 2023; Tahir & Hussain, 2013; US Department of State, 2023) and new secondary cities that are emerging (Chan, 202). Our work and approach can support organizations and initiatives, such as the Cities Alliance (https://www.citiesalliance.org/) and Secondary Cities Initiative (https://secondarycities.state.gov/), by identifying hotspots of inefficient land use 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. In regard to resolution, globally available land cover and land use (LCLU) datasets and gridded population datasets are typically produced at more coarse resolutions which may influence delineations and calculations. In terms of accuracy, different LCLU maps may capture varied degrees of development or built-up areas. The implications of the map classifications should be considered when selecting a LCLU product as it will determine what characteristics of an urban area are captured by the methodology. False classifications are also an inherent characteristic of LCLU maps and may impact outcomes of the automated delineation approach. Lastly, gridded population datasets are modeled on census data. 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 (Glassman & Ezeh, 2014; Ntozi, 201), so we can expect some degree of inaccuracy in the gridded population estimates. These limitations emphasize the importance of incorporating local information and data whenever possible and understanding what can and can’t be accomplished with spatial work.

Regardless, continued efforts are needed to build upon our work and improve spatial strategies for monitoring urban growth in Africa and other developing regions.

Our presumed next steps are to conduct finer scale spatial assessments within hotspots to examine the type of developments occurring (residential, commercial, industrial, etc.), and availability of social, health and ecosystem services. We also anticipate applying this methodology to countries outside of Africa to examine its flexibility in identifying functional urban agglomerations. We hope we can continue building on the methodology by integrating additional datasets and spatial techniques to improve its performance and utility.

Conclusions

This work was conducted with optimism of further building on SDG Indicator 11.3.1 as an indicator for monitoring urban land use expansion. We developed an automated method for delineating functional urban agglomerations to facilitate the calculation of SDG Indicator 11.3.1 across national extents. We expect that automating delineation efforts will increase the accessibility, utility, and convenience of delineating urban areas across larger extents, thereby enabling more continuous, consistent monitoring of urbanization patterns and associated land use changes, globally.

Our work quantified regional trends of urban change and identified hotspots of SDG Indicator 11.3.1 in Ethiopia, Nigeria, and South Africa. 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 (Gizelis et al., 2021; Lone & Ahmad, 2020; Yang et al., 202). We propose future monitoring be carried out for the coming years, as well as in hotspot locations 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 SDG Indicator 11.3.1 and urban monitoring efforts.

CHAPTER 2

IMPACTS OF SPATIAL RESOLUTION ON AUTOMATED URBAN DELINEATION AND CHARACTERIZING URBAN CHANGE

Introduction

Urbanization continues to be a leading driver of global land use change (Nuissl Henning & Siedentop, 202) and various global and national sustainable development initiatives have been established to monitor and address urbanization impacts (UN-Habitat, 2017; United Nations, 201). The most prominent global initiative, the 2030 Agenda for Sustainable Development, was adopted in 2015 by United Nations State Members with the purpose of tackling the globe's most pressing issues, including urbanization-driven land use transformations. Drawn from the Millennium Development Goals and their shortcomings, 17 Sustainable Development Goals (SDG) and 169 targets shape the 2030 Agenda for Sustainable Development and synergistically confront the social, economic, and environmental needs for global sustainable development (United Nations, 201). The SDGs and their targets aim to achieve broad objectives including eradicating poverty, increasing access to essential resources, reducing inequalities, promoting peace, and stimulating sustainable development (United Nations, 2015). The SDGs and targets alone are objectives; thus, the United Nations Statistical Commission formed and tasked the Inter-Agency and Expert Group on Sustainable Development Goal (IAEG-SDG) indicators with developing the Global Indicator Framework (United Nations, 202). The indicator framework contains 231 unique indicators intended to monitor and measure progress towards the achievement of the SDGs and associated targets, but most need more examination to progress their operation and utility.

Finding consistent data sources across global extents to fulfill SDG Indicator measurements is challenging (Avendano et al., 2021; Nilashi et al., 2023), but the availability of earth observation and other geospatial data allows for practicable, consistent, and timely implementation of numerous Sustainable Development Goal (SDG) Indicators (Estoque, 2020; United Nations, 201). The IAEG-SDG's Working Group on Geospatial Information emphasizes the importance of geospatial data for obtaining pertinent SDG Indicators provided the infrequent production of official census statistics (UN-GGIM, 202). A multitude of studies have displayed the viability and value of using spatial approaches to examine SDG Indicators, for instance, monitoring SDG 11.7.1 (share of open urban space) in Greece, SDG 6.4.1 (change in water use efficiency) in South and South-East Asia, and SDG 15.3.1 (identification of degraded lands) in Ukraine (Giupponi et al., 2018; Kussul et al., 2019; Verde et al., 202). Limitations still exist in the spatial assessment of suitable indicators, specifically due to data production, resolution and accuracy constraints, and differences in methods for their implementation (Giuliani et al., 2021; Han et al., 2022; Qiu et al., 202). Global organizations, such as the World Bank and United Nations, are working to improve spatial data infrastructures, facilitate improved data production, and develop innovative data approaches (UN Global Pulse, 2022; World Bank, 202), but continued work is needed to understand the impacts of spatial data inputs on the functionality and interpretations of geospatially compatible indicators.

Sustainable Development Goal Indicator 11.3.1 is one of the geospatially compatible indicators related to urbanization and was developed to monitor urban land use expansion and population change under Goal 11 and Target 11.3 (Table 2.1). The indicator is a ratio of the land consumption rate to population growth rate and can be measured by spatial analysis of earth observation and integrated population data within a region of interest (UN-Habitat, 2018a, 2021. SDG Indicator 11.3.1 evaluates whether land is being transitioned to urban use at a lesser, greater, or similar rate to which the population in the same area is growing. SDG Indicator 11.3.1 is currently classified as a Tier 2 indicator, meaning it is a conceptually clear indicator and methods exist for its computation, but data is not regularly produced for some regions (UN-Habitat, 2021). Global spatial datasets can be used in place of absent local data, but the resolution at which global spatial data is available may affect fine scale estimations.

Table 2.1: Description of Sustainable Development Goal 11, Target 11.3, and SDG Indicator 11.3.1

Sustainable Development Goal 11
Make cities and human settlements inclusive, safe, resilient, and sustainable.
Target 11.3
Enhance inclusive and sustainable urbanization and capacities for participatory, integrated, and sustainable human settlement planning and management in all countries by 2030.
SDG Indicator 11.3.1
Ratio of land consumption rate to population growth rate

SDG Indicator 11.3.1 has displayed its utility for monitoring urban growth and informing sustainable development at varying scales and expanses using geospatial analyses (Calka et al., 2022; Mudau et al., 2020; Philip, 2021). Although these works have proven valuable, various limitations regarding the implementation and interpretation of SDG Indicator 11.3.1 are known. Nuanced approaches for delineating urban areas and limited availability of timely and high-resolution data are a few of the limitations for executing SDG Indicator 11.3.1 (Simon et al., 2016; UN-Habitat, 2021).

Recent SDG Indicator 11.3.1 research has attempted to address limitations through innovative, explorative methodologies and analyses. Nicolau et al. (2018) compared the performance of two formulations for examining SDG Indicator 11.3.1, the UN-Habitat's proposed land consumption rate to population growth rate and the change rate of the built-up area per capita, as well as investigating the influence of thematic map resolution on indicator 11.3.1 in mainland Portugal. They found that the change rate of the built-up area per capita was more informative than SDG Indicator 11.3.1 for monitoring urban change as it was easier to interpret, and higher thematic resolution was favored. Schiavina et al. (2019) assessed SDG Indicator 11.3.1 at the global, regional and settlement level, revealing the benefit of multi-scale comparisons for capturing dynamics of urban change. Guo et al. (2022) proposed an additional indicator, the ratio of economic growth rate to land consumption rate, to be applied alongside SDG Indicator 11.3.1 to evaluate the relationship between urban economic growth and urban land use efficiency.

To build on this, in Chapter 1, we developed an approach to automate the delineation of functional urban agglomerations across national extents to facilitate the calculation of SDG Indicator 11.3.1 and other urban change metrics at the agglomeration scale across national extents. Our delineation approach is built on the Urban Extent method outlined in the SDG Indicator 11.3.1 training module (UN-Habitat, 2018a) and utilizes transportation analyses and geolocation data to link urban cores with peri-urban areas. Conceptually, our method borrows from the concept of the Functional Urban Area, a city and its commuting zone as defined by the Organization for Co-Operation and Economic Development (OCED) (Dijkstra et al., 2019). It also follows principles outlined in the SDG 11 Monitoring Framework, where urban agglomeration delineation accounts for towns and cities functionally dependent on the main city (UN-Habitat, 2016). Automating this task permits a user to capture urban agglomerations composed of multiple non-contiguous but interacting settlements and examine urban change within them, thereby increasing the efficiency of monitoring agglomeration level change across large extents.

Nevertheless, geospatial assessments of SDG Indicator 11.3.1 may be influenced by the spatial resolution of input land cover and land use data and understanding the implications of this connection may help guide future applications of SDG Indicator 11.3.1. The work of Chapter 2 aims to evaluate this notion by assessing the impacts of input land use data spatial resolution on the delineation of urban areas, SDG Indicator 11.3.1 estimates, urban change metrics, and urbanization-driven land use change patterns using our methodology. A higher spatial resolution captures finer features and increases mapping precision of land cover and land use data (Murtaza & Romshoo, 2014), so we hypothesize that details of urban land use and urban boundary edges are changed or lost when spatial resolution changes. We postulate that a changing urban boundary would greatly influence the delineation of physically smaller urban units, change urban metrics and spatial patterns of development values within urban units, and influence urbanization-driven land use change assessments.

Objectives

The aim of this chapter is to assess the influence of land use data at two spatial resolutions, 30-m^2 and 90-m^2, on the delineation of functional urban agglomerations and their associated characteristics of urban change. This includes observed variations in SDG Indicator 11.3.1, urban change metrics, spatial patterns of development, and urbanization-driven land use changes. We examine this relationship across urban agglomerations likely experiencing rapid urban land use expansion according to SDG Indicator 11.3.1 in Ethiopia for the 2016 to 2020 period.

The main objectives for this study are to: 1) examine the influence of developed land use data spatial resolution on the extent of urban agglomeration boundaries when using our automated methodology; 2) compare SDG Indicator 11.3.1, supporting metrics, and spatial patterns of development across urban agglomerations derived from land use data with differing spatial resolutions; and 3) evaluate the influence of land use data spatial resolution on urbanization-driven land use change patterns within and around urban agglomerations.

Methods

Study Region

Although predominantly rural, Ethiopia is one of Africa's fastest urbanizing countries. Ethiopia's urban population is anticipated to increase from 22 million people in 2018 to 74 million by 2050, thereafter accounting for 39% of the Ethiopia's total population (UNDESA, 2019). Recent estimates show Ethiopia's urban population comprising 22% of the total Ethiopian population in 2022 and the country was estimated to be urbanizing at an annual rate of around 4%-5% in 2015 (World Bank, 2015, 2023b).

Natural population growth, rural to urban migration, and reclassification of rural settlements to urban settlements are driving urbanization in Ethiopia. Although drivers of urbanization vary and are contextual, rural to urban migration is expected to account for a significant proportion of Ethiopia's future urban population growth as rural dwellers leave rural areas in search of greater livelihood security and opportunity in larger cities (Awumbila, 2017; Benti et al., 2022; Jenberu & Admasu, 2020; Mezgebo, 2021). Rapid urban population growth in Ethiopia has generated various challenges (Abraha et al., 2022; Kebbede, 2017; UNICEF, 2022; World Bank, 2015) and underlines the need for ongoing monitoring and planning for urban change.

Although our analysis took place prior to the peak of recent issues, major tribulations such as the COVID-19 pandemic, Tigray conflict, and drought situation (Abbink, 2021; Harris et al., 2020; UNOCHA, 2023), have likely impacted the process of urbanization in Ethiopia and exacerbated the challenges of it. Global and national organizations continue to support Ethiopia to address these issues and aid in its journey towards sustainable, resilient, and productive urbanization (USAID, 2020; World Bank, 2020, 2023a).

Automated Approach for Identifying Urban Agglomerations

In Chapter 1, we developed and presented a methodology to automatically delineate functional urban agglomerations across national extents to facilitate the assessment of SDG Indicator 11.3.1. The methodology incorporates various spatial datasets, tools, and techniques to detect functionally connected urban areas. The approach builds on the delineation method outlined in the Atlas of Urban Expansion by Angel et al. (2016) with a GIS workflow of that method provided in the UN-Habitat's

SDG Indicator 11.3.1 training module (UN-Habitat, 2018a). In our adapted approach, the data inputs and tools used for delineation of urban areas include a land use dataset, gridded population dataset, OpenStreetMap (OpenStreetMap contributors, 2017), and Openrouteservice API (Openrouteservice, 2023). The approach employs various spatial analysis techniques, thresholds of population characteristics, and transportation analyses from the Openrouteservice API to identify clusters of urban character, differentiate urban clusters into classes, assess connectivity between these cluster classes, and produce functionally connected urban agglomerations. The automated approach was written in the Python (Van Rossum & Python Development Team, 2022) language, and primarily utilized the ArcPy (ESRI, 2022) and PyQGIS (QGIS.org, 2023; Van Rossum & Python Development Team, 2022) libraries to conduct the spatial analysis work. Within Chapter 1, our approach only used 30-m^2 resolution land use spatial maps, while in Chapter 2, we will compare the outputs of this approach utilizing two different spatial resolutions common to land cover and land use products, 30-m^2 and 90-m^2.

Data

Two data inputs are selected by the user for the automated approach for urban delineation and calculation of SDG Indicator 11.3.1 and related metrics: a land use and land cover (LCLU) dataset and gridded population dataset. For this work, we selected WorldPop's top-down unconstrained 100-m^2 spatial resolution gridded population counts and a base 30-m^2 gridded land use product developed by Shah Heydari et al. (n.d.), which we summarized at two spatial resolutions. WorldPop takes administrative censuses and projections and applies modeling approaches with geospatial datasets to disaggregate population count data into 100-meter by 100-meter cells (WorldPop, 2018). Gridded population counts are available for numerous developing countries from 2000 to 2020 as of early 2023 and new WorldPop datasets become available as new census or geospatial datasets arise (WorldPop, 2018), permitting comprehensive and ongoing assessments of SDG Indicator 11.3.1 and other population dynamics. We downloaded the WorldPop 100-m^2 resolution population count dataset for Ethiopia for 2016 and 2020 from the WorldPop website (www.worldpop.org/) and the 30-m^2 land use maps were obtained for Ethiopia for 2016 and 2020 directly from Shah Heydari et al. (n.d.)

The 30-m^2 gridded land use map product developed by Shah Heydari et al. (n.d.) is central to the delineation of urban agglomerations in the automated approach and is the focus of the work in this study. Using machine learning approaches, mainly Random Forest modeling, and a variety of remote sensing data inputs, Shah Heydari et al. (n.d.) produced 30-m^2 spatial resolution land use maps for Ethiopia, Nigeria, and South Africa for each year in the 2016 to 2020 period. The product is comprised of seven land use classes: Agriculture, Developed, Forest, Rangeland, Bare, Wetland, and Water. For urban delineations and calculation of SDG Indicator 11.3.1 and relevant metrics, only the Developed land use class is needed.

To examine the influence of spatial resolution, we resampled the 30-m^2 spatial resolution developed land use raster to 90-m^2 spatial resolution using a majority rule. Our goal was to assess the influence of spatial resolution alone, and resampling the developed land use raster allowed us to maintain consistency in map production and classification methods. The 30-m^2 spatial resolution and 90-m^2 spatial resolution versions of the land use product were incorporated into the automated urban delineation approach using the associated Python scripts written in Chapter 1.

After delineation, overlap analyses were carried out manually in QGIS to ensure the occurrence of corresponding urban agglomerations for both resolution inputs. Agglomerations present under one resolution input and not the other were documented for discussion and then removed from the dataset undergoing additional analyses. The agglomerations present under both resolutions were examined for differences in urban delineations, urban change metrics, spatial patterns of development, and urbanization-driven land use changes.

SDG Indicator 11.3.1 and Related Metrics

After we delineated urban boundaries for the 2016 to 2020 period, SDG Indicator 11.3.1 and all related metrics were calculated for both resolution land use maps. Individual metrics were calculated within the boundaries of each unique agglomeration and included land consumption rate, population growth rate, SDG Indicator 11.3.1, percent change in developed land use area, developed land use area per capita in 2016, developed land use area per capita in 2020, development by infill, and development by extension and leapfrog. The metrics and corresponding formulas are explained in the following section.

The Land Consumption Rate examines the change in the developed land use area within a unit from the initial year in a period to the final year. The Land Consumption Rate formula is:

$$\boldsymbol{Land\ Consumption\ Rate\ (LCR)} = \frac{\left(\boldsymbol{V_{present}} - \boldsymbol{V_{past}}\right)}{\left(\boldsymbol{V_{past}}\right)} * \frac{\mathbf{1}}{(\boldsymbol{t})}$$

$\boldsymbol{V_{present}}$ is the total developed land use area in the final year, $\boldsymbol{V_{past}}$ is the total developed land use area in the initial year and $\boldsymbol{t}$ is the time period or number of years between $\boldsymbol{V_{present}}$ and $\boldsymbol{V_{past}}$ (UN-Habitat, 2021).

The Population Growth Rate evaluates the change in population within a unit from the initial year in a period to the final year. The Population Growth Rate formula is:

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

$\boldsymbol{LN}$ is the natural log, $\boldsymbol{Pop_{t+n}}$ is the total population in the urban agglomeration in the final year of a given period, $\boldsymbol{Pop_t}$ is the total population in the urban agglomeration in the initial year of the given period and $\boldsymbol{y}$ is the difference between the initial year and final year of the time period (UN-Habitat, 2021).

SDG Indicator 11.3.1 is the ratio between the land consumption rate and the population growth rate. SDG Indicator 11.3.1 may also be referenced to as LCRPGR and the formula is:

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

where LCR is land consumption rate and PGR is population growth rate (UN-Habitat, 2021).

Metrics are suggested for supporting the interpretation of SDG Indicator 11.3.1 and include the total change in built-up area and built-up area per capita (UN-Habitat, 2021). The first metric inspects the percent change in built-up land within a unit over a period. We used developed land use area from our land use product in place of built-up area in the total change in built-up area formula. The formula is:

$$\boldsymbol{Total\ change\ in\ built-up\ area}\ (\%) = \frac{\boldsymbol{(UrBU_{t+n} - UrBU_t)}}{\boldsymbol{UrBU_t}}$$

where ***$UrBU_{t+n}$*** is the urban built-up area in the final year of the period and ***$UrBU_t$*** is the urban built-up area in the initial year of the period (UN-Habitat, 2021).

We also used developed land use area in place of built-up area in calculating built-up area per capita. The formula for this metric is:

$$\boldsymbol{Built-up\ area\ per\ capita}\ (\boldsymbol{m^2}/\ \boldsymbol{person}) = (\boldsymbol{UrBU_t}\ /\ \boldsymbol{Pop_t})$$

where ***$UrBU_t$*** is the urban built-up area in time ***t*** and ***Pop_t*** is the population size within the urban area in time ***t*** (UN-Habitat, 2021).

Lastly, urban development by infill, extension and leapfrog were calculated for each urban agglomeration under both resolution inputs. Infill was defined as the new developed land that occurred after the initial year and existed only within the urban boundaries of the initial year. Extension and leapfrog were defined as new developed land that occurred after the initial year and only existed in the boundaries of the final year and not the initial year. Extension and leapfrog were not examined individually, but instead included all expansive spatial patterns of development. The value of this metric indicates the percentage of new development that was by infill or extension and leapfrog. The formulas for the percent development by infill and percent development by extension and leapfrog were as follows:

$$\boldsymbol{Development\ by\ infill}\ (\%) = \left(\frac{\boldsymbol{IF}}{\boldsymbol{NDL}}\right) * \mathbf{100}$$

$\boldsymbol{IF}$ is the infill developed land use area and $\boldsymbol{NDL}$ is the new developed land use area.

$$\boldsymbol{Development\ by\ extension\ and\ leapfrog}\ (\%) = \left(\frac{\boldsymbol{EXTLF}}{\boldsymbol{NDL}}\right) * \mathbf{100}$$

$\boldsymbol{EXTLF}$ is the extension and leapfrog developed land use area and $\boldsymbol{NDL}$ is the new developed land use area.

Summary and Statistical Analyses

We used descriptive statistics and statistical tests to evaluate the differences in metrics derived under differing spatial resolutions. We began by converting the attribute table containing metrics for the 30-m^2 spatial resolution outputs and 90- m^2 spatial resolution outputs into a CSV. We used R Version 4.2.1 for summary and statistical analyses, including the tidyverse library within R to manipulate and prepare the data for summarization and use in statistical tests (Wickham et al., 2019). We used the Wilcoxon signed rank test to examine the differences using the wilcox.test function in R (R Core Team, 2021).

We tested significant differences between the outputs of the 30-m^2 and the 90-m^2 spatial resolution land use data for the entire agglomeration sample and for the agglomerations when categorized by population size class. We divided the agglomerations into three population size classes: population less than 50,000, population between 50,000 to 100,000, and population greater than 100,000. The population size classes were intended to separate relatively small urban areas, such as less dense towns with less than 50,000 people, from larger urban areas with more than 100,000 people, such as megacities, larger metropolitans, and secondary cities (Dijkstra et al., 2021; Roberts, 2014). The intermediate population size class between 50,000 and 100,000 people was created to capture emerging urbanizing areas and potential future secondary cities. The population size class divisions we selected also yielded a more equal distribution of the agglomerations in our sample to allow for more appropriate comparison of urban changes between urban agglomeration size classes.

Land Use Change Under Different Spatial Resolutions

We summarized urbanization-driven land use changes between 2016 and 2020 within and around focal urban agglomerations at both input resolutions. The initial intent of the land use change analysis was to focus on defined hotspot agglomerations, which had an SDG Indicator 11.3.1 value above 1, suggesting that urban land is being consumed at a greater rate than the population is growing (UN-Habitat, 2021). Incidentally, all agglomerations identified under both resolution inputs had SDG Indicator 11.3.1 values above 1. We used the land cover change tool from the Semi-Automatic Classification Plugin in QGIS to examine land use change (Congedo, 2021). The tool required two raster inputs to measure change. We used the 2016 seven class land use map and the raster containing only new developed land use that occurred by 2020 as inputs. The output of the tool was a change map with a file explaining the land use type that existed in 2016 and was converted to developed land use by 2020.

To assess the urbanization-driven land use changes around agglomerations identified at both resolutions, we needed to first define a shared focal boundary for consistency in the spatial analysis area. Focusing on a set of shared urban agglomerations, we used the Convex Hull tool to create a boundary geometry around each unique set of urban areas for each resolution. We then combined the boundaries by dissolving to create one shared analysis area for each focal agglomeration. Each boundary was manually validated to ensure the bounding geometries contained the correct agglomerations for each resolution. We conducted zonal statistics to summarize the area of each land use conversion type under both resolutions within the shared focal boundaries.

Results

We observed differences in agglomeration boundaries, metrics of urban change, and land use change patterns between the 30-m^2 and 90-m^2 spatial resolution inputs. The 30-m^2 spatial resolution land use data and 90-m^2 spatial resolution land use data both identified a similar number of agglomerations when using the automated delineation approach. Although both resolutions of land use data inputs captured a similar number of agglomerations, there were agglomerations captured under one resolution input that were absent in the other. We examined the agglomeration outputs and identified 183 agglomerations that were captured under both resolution inputs.

Differences in Delineation Boundaries

Agglomerations smaller in area and, correspondingly, smaller in population size were better identified by the 30-m^2 spatial resolution land use input data than the 90-m^2 spatial resolution land use input data. We observed eight instances where an agglomeration was identified under the 30-m^2 input and not under the 90-m^2 input. These agglomerations were exceptionally small with populations ranging from approximately 5,000 people to 10,000 people in 2020 and urban extents ranging from an approximated 1 square kilometer to 5 square kilometers in area in 2020 (Table 2.2).

The 30-m^2 spatial resolution land use data input also incorporated smaller peripheral urban areas better than the 90-m^2 resolution land use data input. There were several instances where a peripheral urban area was included in an agglomeration under the 30-m^2 resolution but did not exist under the 90-m^2 resolution. These clusters or extensions representing smaller peripheral urban areas typically were comprised of sparse development, only containing a few developed land use pixels under the 90-m^2 spatial resolution version or were linked to the core urban areas by linear developments, such as roads, which were scarcely captured under the 90-m^2 resolution land use data (Figure 2.1). Clusters with these characteristics typically differed in size or contiguity and were typically not dense enough in developed land or population to be retained within our automated delineation approach.

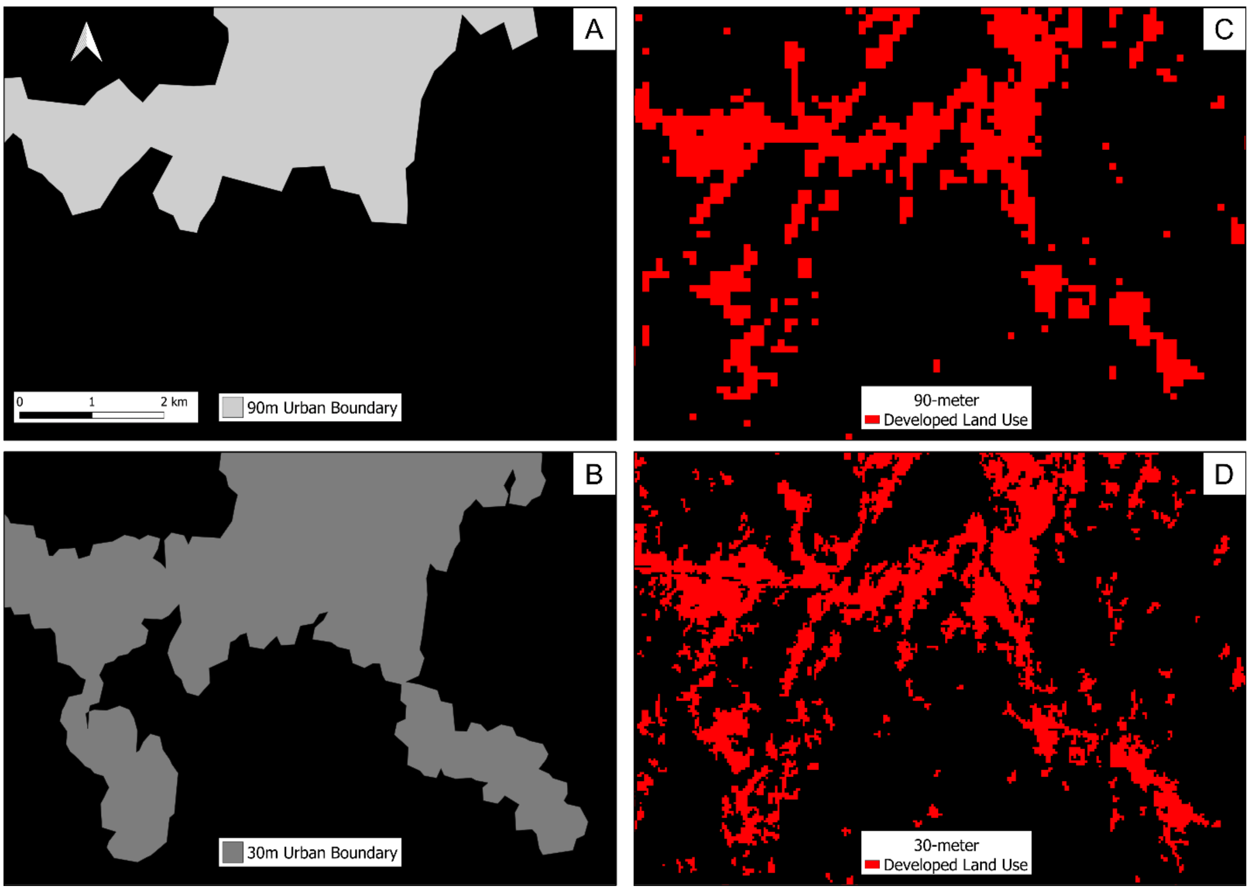

Figure 2.1: Influence of spatial resolution of the land use data on the delineation of the southern portion of the Durame agglomeration. Contiguity of developed land use pixels present under the 30-m^2 resolution developed land use raster but absent in the 90-m^2 developed land use raster led the southern peripheral areas to be omitted under the 90-m^2 input A: Urban boundary in 2020 derived from 90-m^2 spatial resolution land use data B: Urban boundary in 2020 derived from 30-m^{2}spatial resolution land use data C: 90-m^2 spatial resolution developed land use raster D: 30-m^{2}spatial resolution developed land use raster

Table 2.2: Agglomerations present under 30-m^2 spatial resolution inputs but not under 90-m^2 spatial resolution inputs. The table includes the associated name of the agglomeration, the population of the agglomeration in 2020, and the area of the urban boundaries in 2020.

Agglomeration	2020 Population	2020 Urban Boundaries Area (km²)
Kobo	7,014	1.17
Chwahit	9,196	2.51
Kumbabe	9,339	4.81
Tis Abay	7,428	1.36
Wukro Maray	6,373	1.76
Elias	8,201	5.32
Deksis	7,841	3.25
Karamile	5,468	1.60

Summary and Statistical Results

We observed variability in the differences of urban change metrics produced for all agglomerations under both resolutions (Table 2.3). The differences in LCR between the 30-m^2 and 90-m^2 ranged from -0.13 to 0.30. The differences in PGR between the 30-m^2 and 90-m^2 spatial resolution land use data were minor, with the differences ranging from -0.03 to 0.06. SDG Indicator 11.3.1 did convey a substantial difference between resolutions, with a minimum difference of -69.9 and max difference of 0.80. The developed land use area per capita for 2020 and total change in developed land use area for 2020 displayed substantial differences across resolutions. A shift also appeared under both metrics measuring the spatial patterns of development.

Table 2.3: Summary statistics for differences in outputs between the 30-m^2 spatial resolution land use data input and 90-m^2 spatial resolution land use data input. Min is the minimum difference observed and Max is the maximum difference observed from the 30-m^2 input to the 90-m^2 input. LCR is Land Consumption Rate, PGR is Population Growth Rate, and DA is the developed land use area.

Differences between 30-m^2 and 90-m^2 resolution data outputs								
	All		**Less Than 50k**		**50k to 100k**		**More than 100k**	
Metrics	*Min*	*Max*	*Min*	*Max*	*Min*	*Max*	*Min*	*Max*
LCR	-0.13	0.30	-0.13	0.07	-0.02	0.01	-0.01	0.30
PGR	-0.03	0.06	-0.03	0.02	< -0.01	< 0.01	< -0.01	0.06
SDG Indicator 11.3.1	-69.9	0.80	-69.9	0.69	-0.14	0.46	-0.24	0.80
2020 DA Per Capita	-58.0	52.0	-58.0	52.0	-10.0	8.0	-10.0	13.0
Total Change in DA (%)	-65.0	150.0	-65.0	34.0	-11.0	8.0	-7.0	150.0
Infill (%)	-0.17	0.24	-0.17	0.24	< 0.00	0.04	< -0.01	0.06
Extension and Leapfrog (%)	-0.24	0.17	-0.24	0.17	-0.04	< 0.00	-0.06	< 0.01

Our examination of summary statistics for agglomerations divided by population size class revealed variations from the differences we observed across summary statistics for all agglomerations (Table 2.3). The agglomerations with less than 50,000 people appeared to dominate the minimum differences across all metrics as it had the same minimum values observed for all agglomerations. Differences in other metrics were also quite considerable for this class, with SDG Indicator 11.3.1 values displaying a substantial range in differences from -69.9 to 0.69. For agglomerations with 50k to 100k, the largest differences were also detected for SDG Indicator 11.3.1, with a range of -0.14 to 0.46. Larger agglomerations with more than 100,000 people had the greatest max difference of 0.30 for LCR and a range of -0.24 to 0.80 for SDG Indicator 11.3.1. The minimum and maximum values may not be fully representative of changes as the values could be the result of outliers, but our examination of the distributions of the differences showed that individual differences for each metric appeared profound (Figure B1-B7), thereby motivating statistical testing.

Under the Wilcoxon Signed Rank Test, we recorded statistically significant differences for SDG Indicator 11.3.1, developed land use area per capita in 2020, infill, and extension and leapfrog values between the differing resolution inputs (Table 2.4). We detected statistically significant differences in 2020 developed land use area (DA) per capita, infill, and extension and leapfrog for agglomerations with less than 50,000 people between resolution inputs. This was also the case for the agglomerations with 50,000 to 100,000 people. The largest size class of agglomerations with more than 100,000 people displayed statistically significant differences for SDG Indicator 11.3.1, 2020 DA per capita, infill, and extension and leapfrog. While there was statistical evidence of a difference, the estimated average magnitude of differences across all of the significant results were relatively small.

Table 2.4: Results of the Wilcoxon Signed Rank Test for the differences between the 30-m^2 and 90-m^2 outputs.

	Wilcoxon Signed Rank Test of the Differences							
	SDG Indicator 11.3.1		**2020 DA Per Capita**		**Infill**		**Extension and Leapfrog**	
	Median	*p-value*	*Median*	*p-value*	*Median*	*p-value*	*Median*	*p-value*
All	0.02	*0.02	-5.00	*< 0.01	0.03	* <0.01	-0.03	* <0.01
Less Than 50k	0.02	0.14	-7.00	*<0.01	0.03	* <0.01	-0.03	* <0.01
50k to 100k	<0.01	0.27	-4.50	*0.01	0.03	* <0.01	-0.03	* <0.01
More than 100k	0.05	*0.03	-2.00	*0.01	0.03	* <0.01	-0.03	* <0.01

Land Use Change Analysis Results

We summarized developed land use conversions that occurred in the 2016 to 2020 period within our identified urban agglomerations and their surrounding areas with both 30-m^2 and 90-m^2 spatial resolution land use data (Table 2.5). We first summarize the land use conversions observed under the 30-m^2 spatial resolution land use data to then conduct comparisons in differences. Firstly, agricultural land experienced the greatest conversion to developed land use at approximately 1,044 km^2 according to the 30-m^2 spatial resolution land use data. Rangeland was the second most converted land use in these areas, with 160 km^2 of land transformed to developed land use. Forest was the next most converted land at 17 km^2, followed by wetland at 2 km^2. Less than 2 km^2 of barren land and water was transitioned to developed land within the focal areas from 2016 to 2020.

The land use change analysis conducted under both resolution inputs yielded different outcomes. The main types of conversions remained the same between the 30-m^2 and 90-m^2 inputs with agricultural land, rangeland, and forest experiencing the greatest urbanization-driven changes. Although the main types of conversions remained the same, the resulting areas for each conversion type did change between the differing resolution inputs. From the 30-m^2 input to the 90-m^2 input, agricultural conversions decreased by 15 km^2, rangeland conversions decreased by 15 km^2, and forest conversions decreased by 2 km^2. There was less than a 1 km^2 difference between both resolution inputs for barren, water, and wetland conversions. Although the difference was small, water conversions were the only conversion type to increase in total area from the 30-m^2 resolution input to the 90-m^2 resolution input.

Table 2.5: Summary of land use conversion area within identified urban boundaries and their immediate surroundings under 30-m^2 spatial resolution land use data and 90-m^2 resolution land use data.

Land Use Change Type	30-m^2 spatial resolution land use data area (m^2)	90-m^2 spatial resolution land use data area (m^2)
Agriculture to Developed	1,044,825,779	1,029,453,382
Barren to Developed	708,924	554,452
Forest to Developed	17,039,378	15,493,416
Rangeland to Developed	160,122,435	145,383,560
Water to Developed	311,280	429,506
Wetland to Developed	2,752,031	1,967,914

The following statements reference differences from the 30-m^2 spatial resolution to the 90-m^2 spatial resolution across size classes. Urban areas with less than 50,000 people and urban areas with a population from 50,000 to 100,000 showed a substantial positive difference in agricultural to developed land conversions, whereas urban areas with more than 100,000 people displayed an immense negative difference (Table 2.6). The difference in rangeland conversions was negative across all population size classes. The difference in forest to developed conversions was negative for all population size classes and was very similar between the smallest population size class. The remaining classes displayed differences, but differences were rather small.

Table 2.6: Differences in land use change conversion area between 30-m^2 spatial resolution land use data and 90-m^2 resolution land use data for each conversion type across each population size class.

	Differences between 30-m^2 spatial resolution land use data and 90-m^2 spatial resolution land use data area (m²)		
Land Use Change Type	*Less than 50k*	*50k to 100k*	*Greater than 100k*
Agriculture to Developed	3,873,626	2,150,645	-21,396,668
Barren to Developed	-39,255	-1,475	-113,742
Forest to Developed	-696,325	-155,762	-693,875
Rangeland to Developed	-2,796,725	-950,391	-10,991,759
Water to Developed	73	-9,285	127,438
Wetland to Developed	-218,245	-89,242	-476,630

Discussion

We found the spatial resolution of land use data to be influential on the delineation of urban agglomerations, calculations highlighting urban change, metrics for spatial patterns of development, and urban related land use change patterns. In our analysis, the 30-m^2 spatial resolution land use map identified smaller urban areas, including individual urban agglomerations and smaller peripheral urban areas associated with a denser urban core, better than the 90-m^2 spatial resolution land use map. Urbanization metrics derived from the 30-m^{2,} and 90-m^2 land use maps displayed a range of differences. Statistical testing highlighted significant differences, particularly differences in SDG Indicator 11.3.1, 2020 developed land use area per capita, and spatial patterns of development between the differing resolution maps. The land use change analysis conducted within urban agglomerations and their surroundings revealed differences in the areas of conversion types under each resolution. All conversion types experienced a decrease in area from the 30-m^2 to 90-m^2 land use maps, except Water to Developed experienced a slight increase. Differences were anticipated given the principles of spatial resolution, but a quantification of the differences further emphasized the importance of proper data selection when conducting these analyses for multiple urban areas diverse in size and across large extents, as well as in the interpretation of urbanization-driven land use change patterns.

Under the automated delineation approach, the 90-m^2 spatial resolution data ineffectively captured standalone, smaller urban areas, as well as smaller settlements on the peripheries of denser urban cores. For example, the town of Kumbabe agglomeration was not captured as a standalone urban area under the 90-m^2 resolution but was under the 30-m^2 resolution (Table 2.2). In 2016, the developed land use summarized under the 90-m^2 land use product for this area was very small. Due to this, we assume it was not big enough to be captured in the first year of the 90-m^2 resolution input. The automated approach does not retain agglomerations that do not have a pair in both years, so was likely removed at this step. These smaller urban areas play an important role in the progression and development of urban Africa (Agergaard et al., 2019; Zimmer et al., 2020) but global land products that are often of coarser resolutions (e.g., 100-m^2) (Buchhorn et al., 2020) may not be sufficient for accurately identifying and spatially analyzing change for them.

Current global products may also produce biased estimates of SDG Indicator 11.3.1 for very small urban areas, as we highlighted major differences in LCR and SDG Indicator 11.3.1 between the 30-m^2 and 90-m^2 spatial resolution land use inputs. For example, the town of Gore agglomeration's SDG Indicator 11.3.1 value jumped from 6 under the 30-m^2 resolution input to 38 under the 90-m^2 input. Under both resolutions, SDG Indicator 11.3.1 indicated extreme expansion of urban land use, but the magnitude of that change varied between. In our examination of the high-resolution imagery, we could see that the extent of this town comprised a small area and did not contain a large amount of developed land use pixels and did not change significantly over the 5-year period. For this small urban agglomeration, the addition of only a few developed land use pixels created a rather large LCR value under both resolutions and thereby inflated the SDG Indicator 11.3.1 value. Furthermore, we observed inflation of SDG Indicator 11.3.1 values for larger agglomerations that incorporated peripheral areas under one resolution and not the other. Based on these results, we support other works suggesting a stronger reliance on metrics outside of SDG Indicator 11.3.1, such as change in built-up area per capita or change in total built-up area, for evaluating urban change (Nicolau et al., 2018), as those metrics appeared more robust to the effects of spatial resolution and still illuminate similar urbanization patterns.

Land use change analyses provide important information for sustainable urban development and conservation of priority land use types (Briassoulis, 2020), and our findings show that summaries of land use change analyses vary under different spatial resolutions and for urban areas of different population sizes. These changes may be negligible across broad scale summaries, but finer scale assessments may exhibit differences in spatial patterns of land use conversions or shifts in the proportion of land use conversions. Our findings are not novel (Momeni et al., 2016; Toure et al., 2018), but they further corroborate the importance of considering the influence of spatial resolution on land use change assessments, including calculations of SDG Indicator 11.3.1, and future work should further test these finer scale effects.

Studies examining SDG Indicator 11.3.1 and urban characteristics have been conducted on small and large urban areas, using spatial products of varying resolutions (Calka et al., 2022; Mudau et al., 2020; Philip, 2021; Tuholske et al., 2019; Zimmer et al., 2020), but few have evaluated the influence of spatial resolution data inputs on SDG Indicator 11.3.1 related assessments. Discrepancies may exist in the results of studies like these as the ability to capture specific changes under coarse or moderate resolution data varies. Future assessments should be cognizant of the potential effects of spatial resolution on delineation, SDG Indicator 11.3.1, and other related metrics and acknowledge this limitation.

Our findings underline an important aspect of geospatial work that may be overlooked in SDG Indicator applications: the significance of input spatial data characteristics and its implications on outputs and interpretations. Assessments such as the one presented in this chapter are important for identifying and better understanding the limitations of available data and methods for monitoring urban change, especially for data poor areas reliant on geospatial evaluations (e.g., developing countries, particularly smaller urban areas within them) (Satterthwaite, 2017). Our findings show that spatial assessments using varied resolutions will lead to discrepancies in outputs. Generally, the magnitude of the differences we observed between outputs was minor, meaning that even coarser resolution datasets, such as 100-m^2, may still be valid for conducting urbanization-related geospatial assessments across urban areas of all sizes, but users should be cautious when interpreting results, especially SDG Indicator 11.3.1.

Our work only examined the influence of moderate and coarse resolutions on SDG 11.3.1 and related outputs. Land use and land cover datasets at higher resolutions, such as 10-m^2, would likely be more effective at capturing the true spatial form of an urban area and identify developed or built-up land with a higher degree of accuracy, leading to more detailed SDG 11 and 11.3.1 related assessments. The limitations of spatial data we highlight in our work emphasize the importance of continued ground-based efforts and incorporation of higher resolution spatial datasets when possible. Future work should evaluate the performance of higher spatial resolution datasets (e.g., 10-m^2) and the influence of other characteristics of data inputs in the assessments of urban change to continue improving urban monitoring efforts for SDG 11.

Conclusions

The purpose of this work was to assess the influence of spatial resolution when employing urban delineation methods relying primarily on land use data, such as the Urban Extent method or our automated method proposed in Chapter 1, on urban agglomeration extents, SDG Indicator 11.3.1, metrics of urban change, spatial development patterns, and urbanization-driven land use changes. Our findings revealed that the spatial resolution of land use data was indeed influential on urban delineations, calculated metrics, and patterns of land use change. We expect that this work will help guide more appropriate data selection when addressing SDG Indicator 11.3.1 and quantification of appropriate spatial urban change metrics. Consideration of spatial data characteristics when conducting geospatial assessments is not only important when assessing SDG Indicator 11.3.1 but is applicable to all geospatially compatible indicators. Further work is needed to identify the influences of higher spatial resolutions and other characteristics of data inputs to aid monitoring efforts for SDG 11 across urban areas of all sizes.

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APPENDICES

Table A1. Metrics for top 5 ranking SDG 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	3.63
Infill (%)	23	12	27	9	20
Extension and Leapfrog (%)	77	88	73	91	80

Table A2. Metrics for top 5 ranking SDG Indicator 11.3.1 urban agglomerations with populations greater than 100,000 in Nigeria.

	Urban Agglomerations				
	Benin City	**Akure**	**Ikeja**	**Ondo**	**Ughelli**
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
Extension and Leapfrog (%)	52	31	25	33	36

Table A3. Metrics for top 5 ranking SDG 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	3.402	2.576	2.449	2.065
Infill (%)	83	62	65	56	52
Extension and Leapfrog (%)	17	38	35	44	48

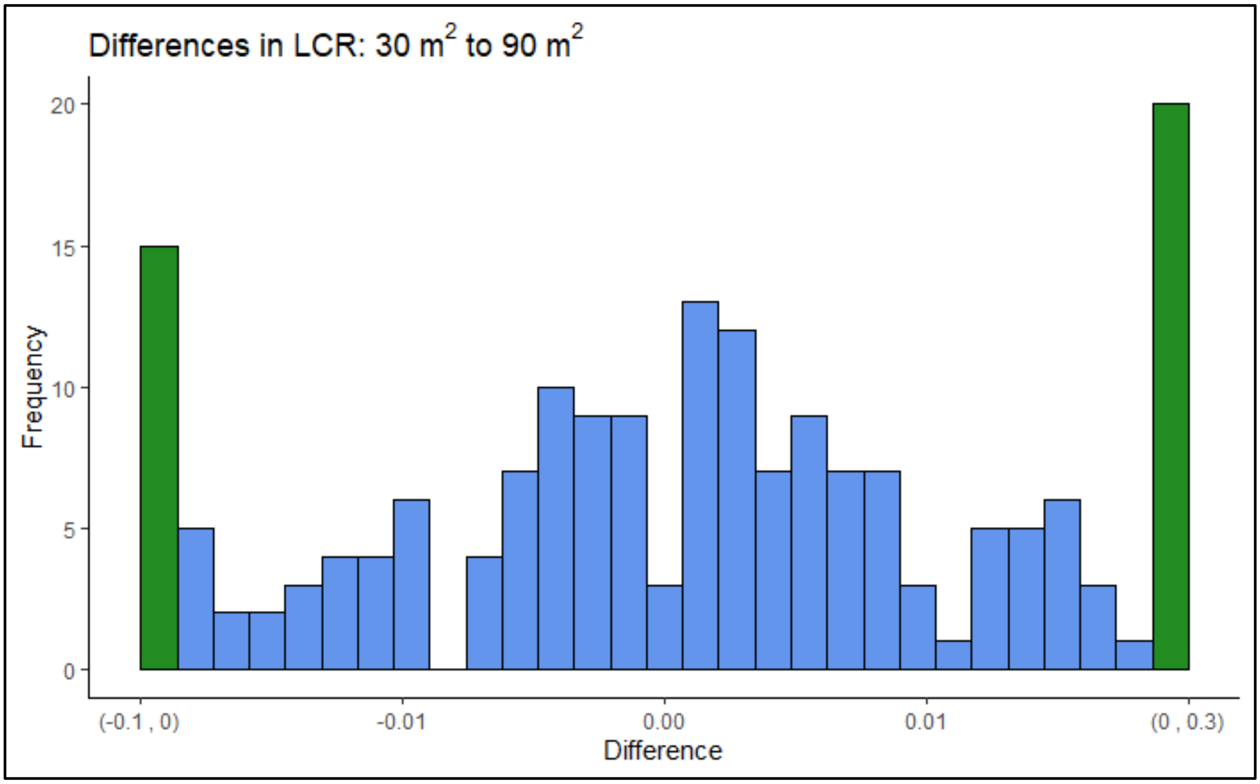

Figure B1. Distribution of land consumption rate differences between 30-m^2 resolution and 90-m^2 resolution for all urban agglomerations in Ethiopia.

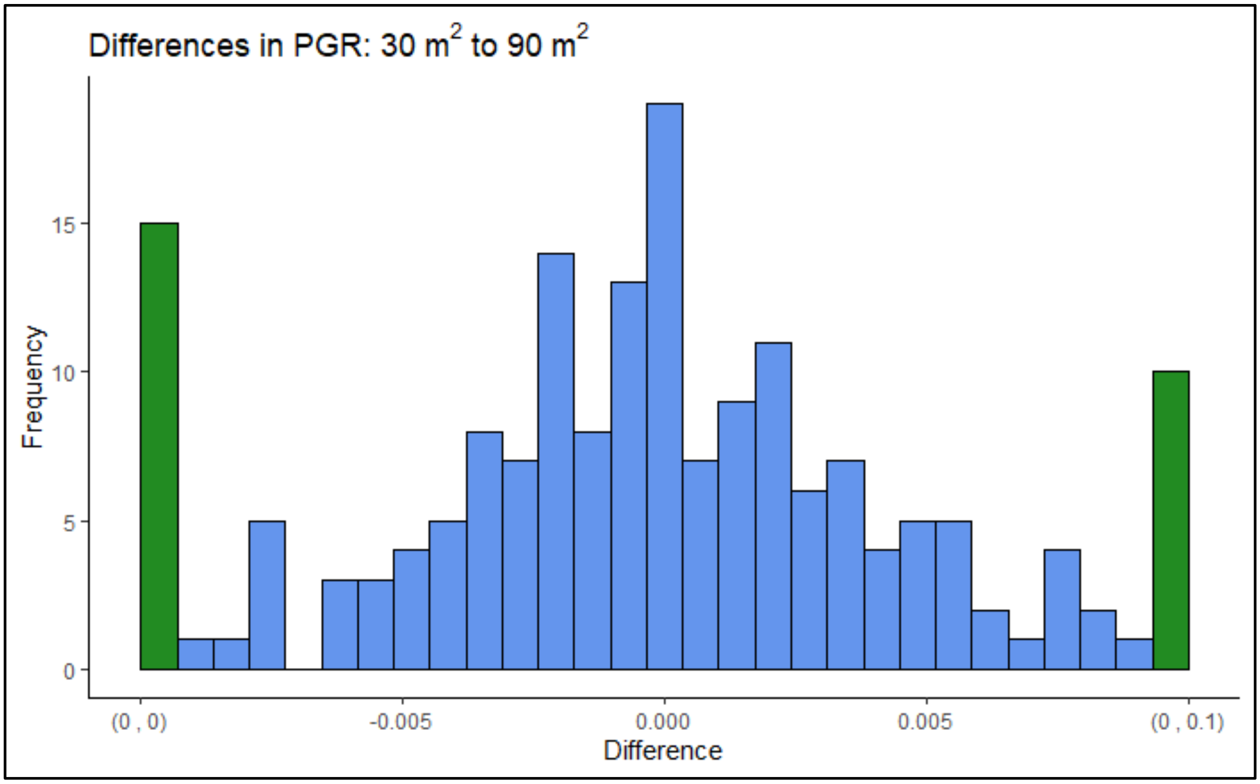

Figure B2. Distribution of population growth rate differences between 30-m^2 resolution and 90-m^2 resolution for all urban agglomerations in Ethiopia.

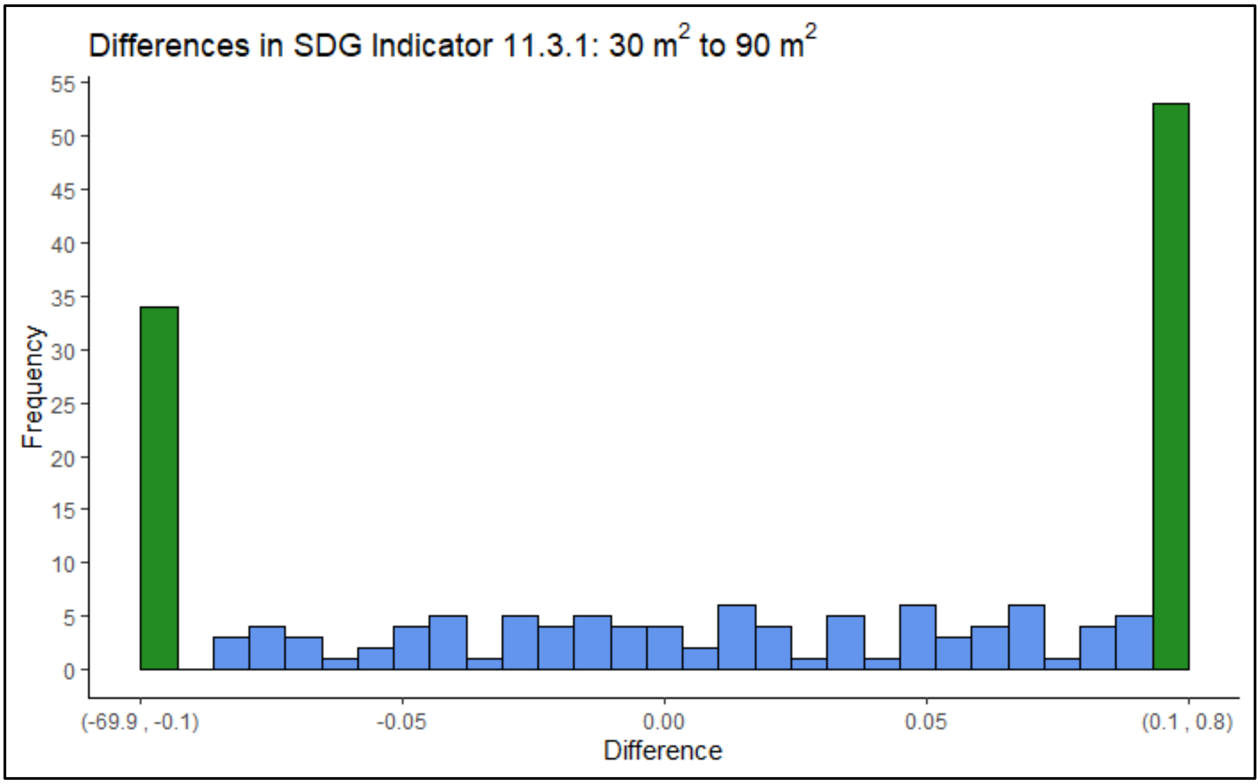

Figure B3. Distribution of Sustainable Development Goal Indicator 11.3.1. differences between 30-m² resolution and 90-m² resolution for all urban agglomerations in Ethiopia.

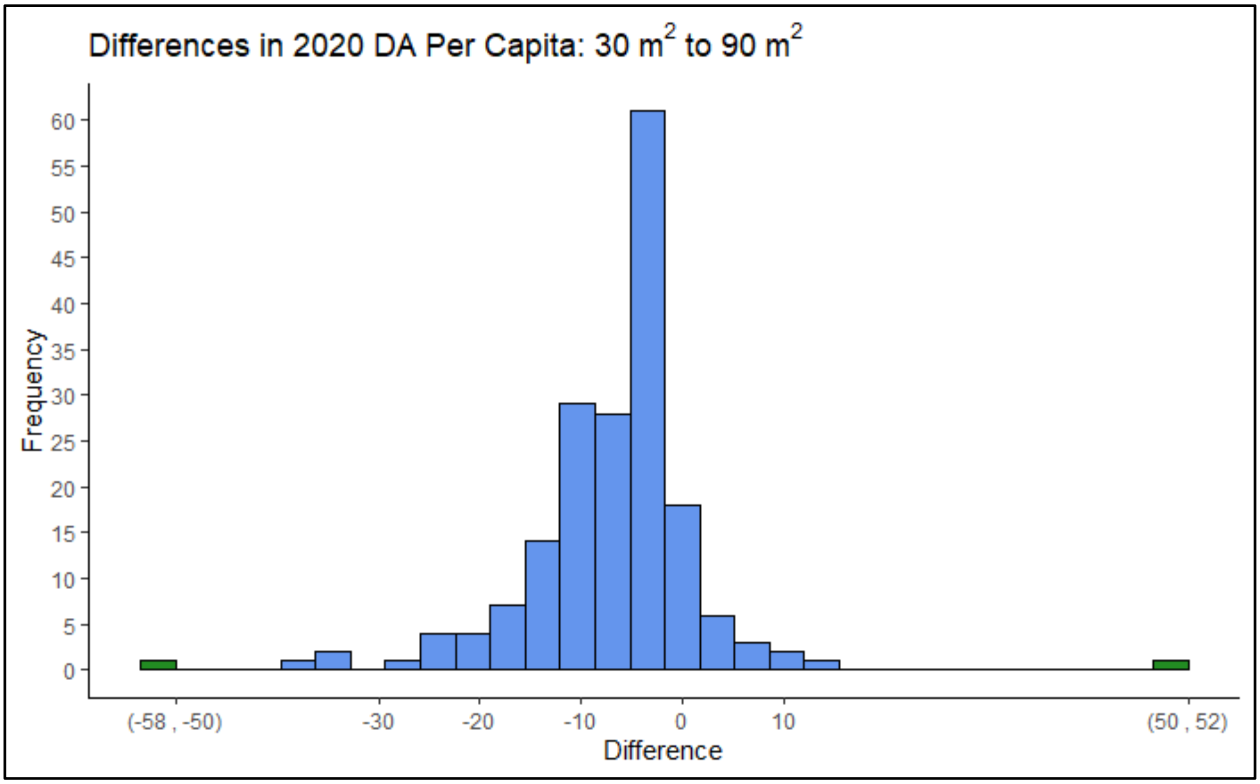

Figure B4. Distribution of 2020 developed land use area per capita differences between 30-m² resolution and 90-m² resolution for all urban agglomerations in Ethiopia.

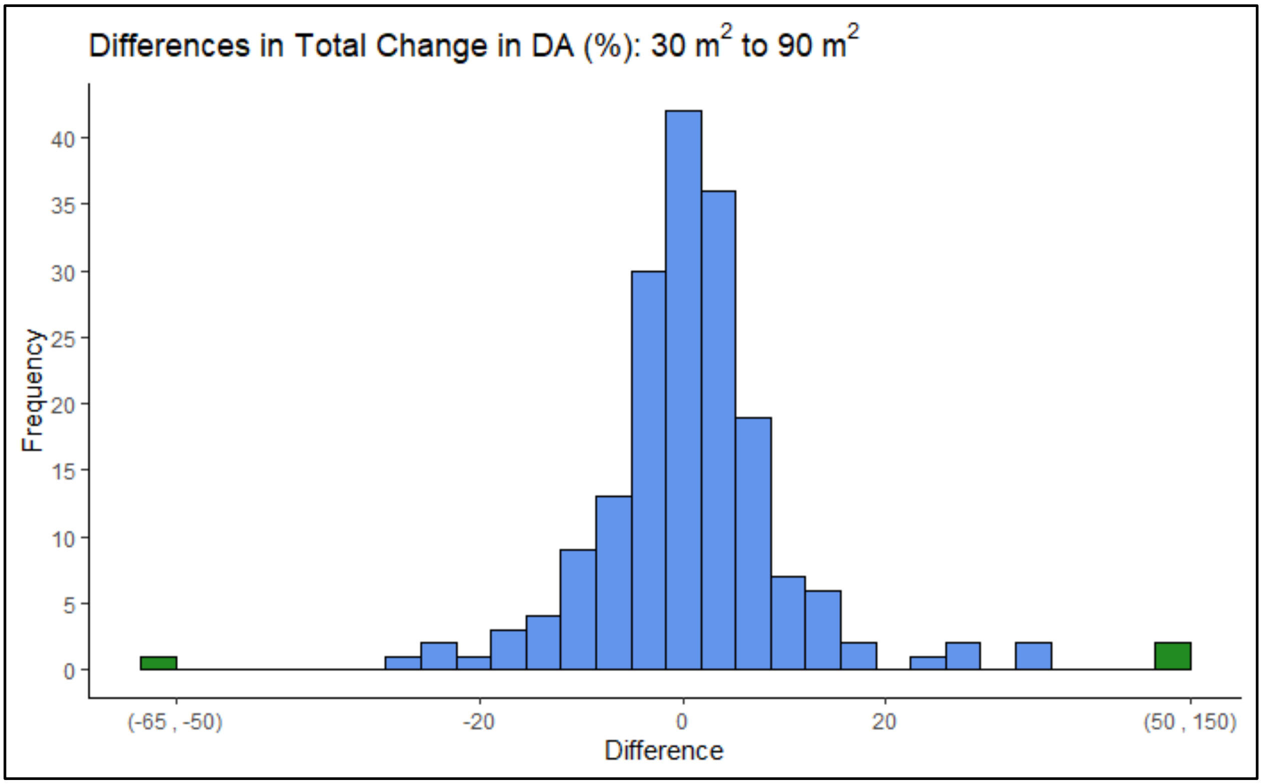

Figure B5. Distribution of total change in developed land use area differences between 30-m² resolution and 90-m² resolution for all urban agglomerations in Ethiopia.

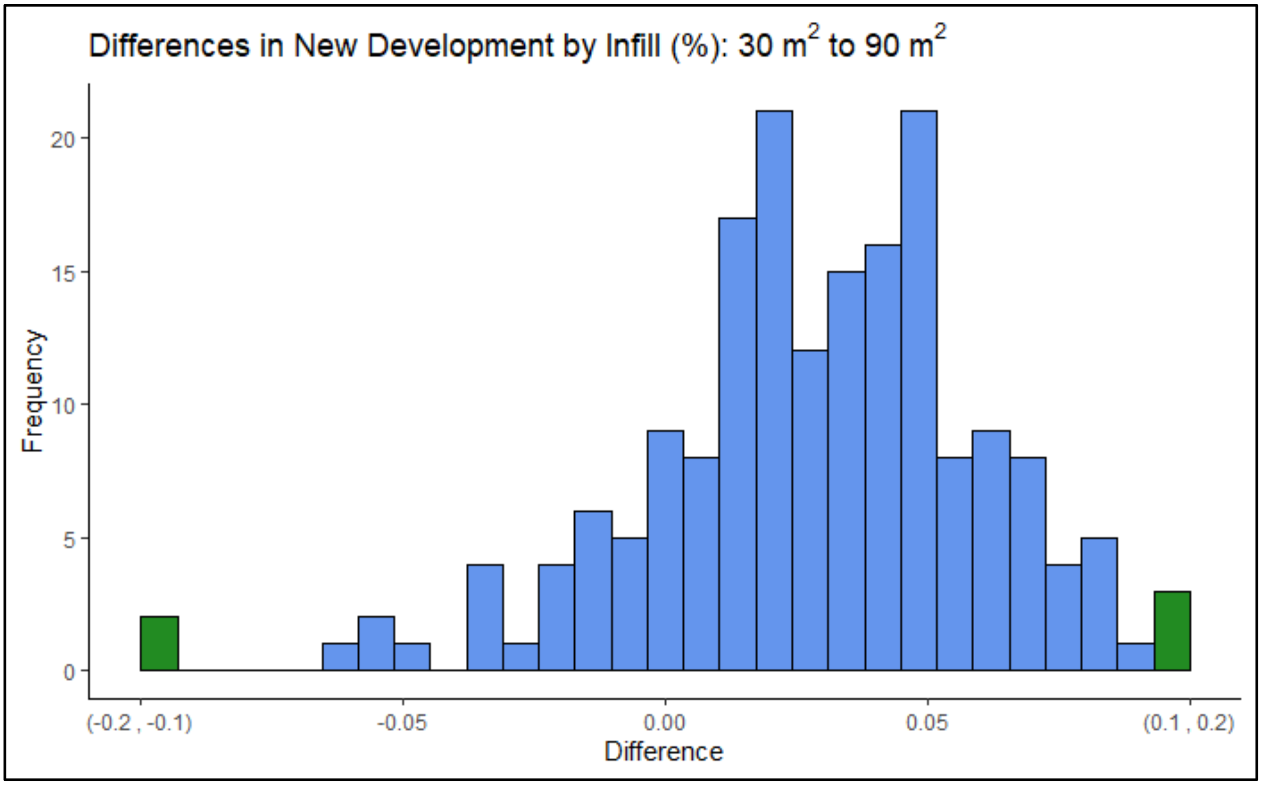

Figure B6. Distribution of 2020 new development by infill differences between 30-m² resolution and 90-m² resolution for all urban agglomerations in Ethiopia.

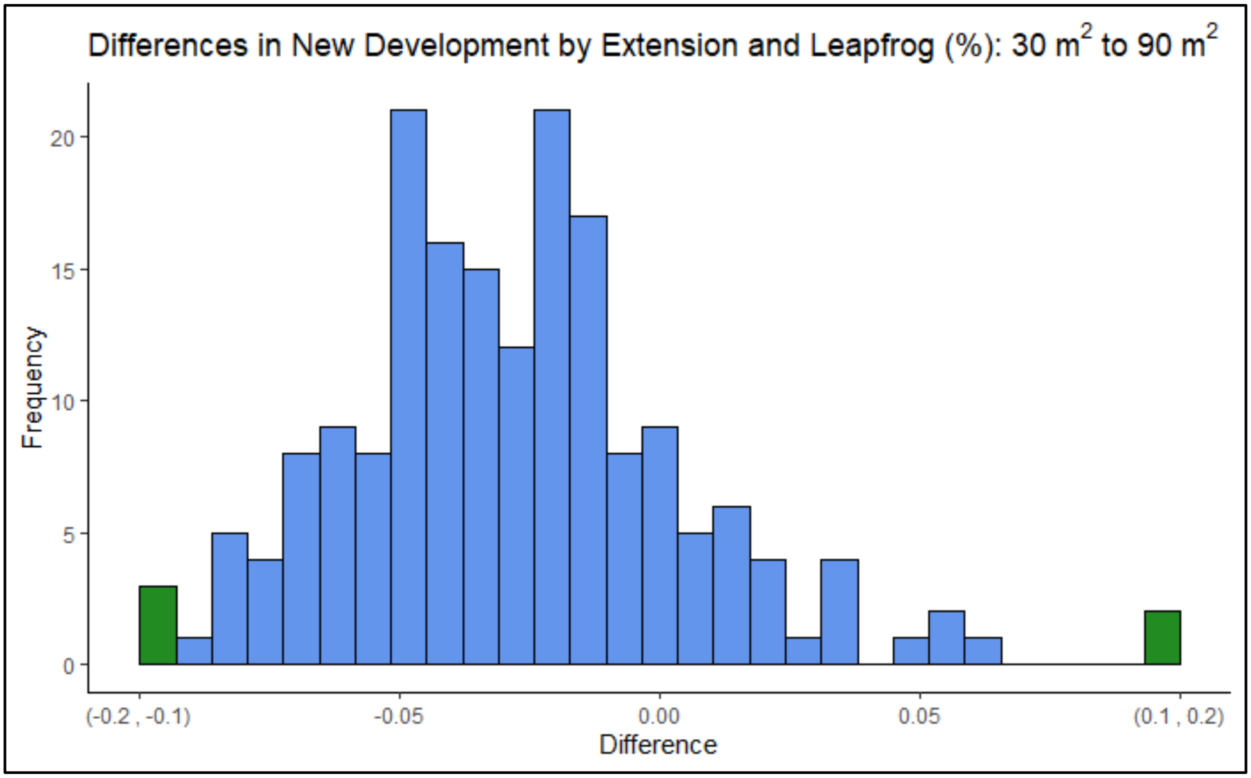

Figure B7. Distribution of 2020 new development by extension and leapfrog differences between 30-m² resolution and 90-m² resolution for all urban agglomerations in Ethiopia.