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# Spatiotemporal Evolution of West Africa's Urban Landscape Characteristics Applying Harmonized DMSP-OLS and NPP-VIIRS Nighttime Light (NTL) Data

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**Abstract:** Investigating urban expansion patterns aids in the management of urbanization and in ameliorating the socioeconomic and environmental issues associated with economic transformation and sustainable development. Applying Harmonized Defense Meteorological Satellite Program-Operational Line-scan System (DMSP-OLS) and the Suomi National Polar-Orbiting Partnership-Visible Infrared Imagery Radiometer Suite (NPP-VIIRS) Nighttime Light (NTL) data, this paper investigated the characteristics of urban landscape in West Africa. Using the harmonized NTL data, spatial comparison and empirical threshold methods were employed to detect urban changes from 1993 to 2018. We examined the rate of urban change and calculated the direction of the urban expansion of West Africa using the center-of-gravity method for urban areas. In addition, we used the landscape expansion index method to assess the processes and stages of urban growth in West Africa. The accuracy of urban area extraction based on NTL data were $R^2$ = 0.8314 in 2000, $R^2$ = 0.8809 in 2006, $R^2$ = 0.9051 in 2012 for the DMSP-OLS and the simulated NPP-VIIRS was $R^2$ = 0.8426 in 2018, by using Google Earth images as validation. The results indicated that there was a high rate and acceleration of urban landscapes in West Africa, with rates of 0.016 0, 0.017 3, 0.018 9, and 0.068 6, and accelerations of 0.31, 0.42, 0.54, and 0.90 for the periods of 1998–2003, 2003–2008, 2008–2013, and 2013–2018, respectively. The expansion direction of urban agglomeration in West Africa during 1993–2018 was mainly from the coast to inland. However, cities located in the Sahel Region of Africa and in the middle zone expanded from north to south. Finally, the results showed that the urban landscape of West Africa was mainly in a scattered and disordered 'diffusion' process, whereas only a few cities located in coastal areas experiencing the process of 'coalescence' according to urban growth phase theory. This study provides urban planners with relevant insights for the urban expansion characteristics of West Africa.

**Keywords:** urban expansion; nighttime light remote sensing; DMSP-OLS (Defense Meteorological Satellite Program-Operational Line-scan System); NPP-VIIRS (Suomi National Polar-Orbiting Partnership-Visible Infrared Imagery Radiometer Suite); spatiotemporal evolution; West Africa

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## 1 Introduction

Rapid urbanization is defined by a significant amount of land being converted from agricultural to non-agricultural land and a shift in the demographic transition and distribution of the population from rural to urban areas

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(Imhoff et al., 2004; Cohen, 2006; Buyantuyev and Wu, 2012). The footprint of urban settlement, which includes all non-vegetation and human construction components, such as roads, houses, industries, and runaways, ultimately shapes the environmental landscape of a community, and West Africa is no exception (Schneider et al., 2009). West Africa has experienced rapid urbanization in the last decade, affecting the region's largest cities and urban agglomerations (Musah et al., 2021). As a result, there is a constant need to explore the trend in urban expansion, focusing on the significance of urban data in monitoring, measuring, and obtaining accurate and timely information about the dynamics of the spatial expansion of West African urban landscapes to aid in better governance and sustainable cities (Imhoff et al., 2004).

Socioeconomic data directly reflect the population and economic changes associated with urban expansion. However, such data are typically aggregated within coarse administrative divisions and lack adequate spatial information (Lu et al., 2018). Many researchers have employed location-based social network data to reflect human activities and delineate urban boundaries. Unfortunately, due to its short history, this type of data only covers a limited time and thus can not be applied to monitor long-term urban expansion characteristics and processes. Because of the advantages of rapid and periodic data collection and spatial coverage, remote sensing data provide useful information for characterizing and analyzing urban expansion and its dynamic changes (Liu et al., 2010; Li et al., 2016).

Remote sensing satellite imagery, such as IKONOS, Quick-bird, and Landsat TM (Thematic Mapper)/ETM + (Enhanced Thematic Mapper Plus), provides fine land cover and detailed information at small scales (Ma et al., 2019). However, the application of such data is limited by spatial coverage, requiring the application of time and financial resources to obtain results for large-scale areas, such as West Africa. To address this issue, nighttime light (NTL) time-series data have been used to assess the spatiotemporal characteristics of West Africa's urban landscape. NTL satellite imagery has evolved into a spatially explicit, global footprint, depicting human presence and activity on Earth's surface (Tuttle et al., 2013; Xiao et al., 2014). The Defense Meteorological Satellite Program (DMSP) Operational Line-scan System (OLS) and the Suomi National Polar-Orbiting Partnership (NPP) Visible Infrared Imagery Radiometer Suite (VIIRS) are the two most widely used series of nighttime lights data. The archived annual DMSP-OLS and NPP-VIIRS NTL data cover relatively long-time spans, between 1993–2013 and 2013–2018, respectively, and are easily and freely accessible. Data derived from NTL satellite imagery are used for an increasing number of applications, such as fishery detection, gas flares detection, impacts evaluation of sudden events (Gillespie et al., 2014; Zhao et al., 2022), urbanization monitoring (Xu et al., 2014; Gao et al., 2015; Xu et al., 2020), and measuring socioeconomic indicators (Wu et al., 2013; Chen et al., 2022). Although the DMSP-OLS NTL data have been extensively used in many studies due to their global coverage and long temporal span, the data became unavailable to the public after 2013, significantly limiting their use in many studies (Zheng et al., 2019). Although the new generation of NPP-VIIRS NTL data is advanced in terms of monitoring city lights at night (Ma et al., 2020), its available temporal span is only from 2012 to the present, resulting in a relatively short period for investigating human activity dynamics (Zheng et al., 2019). As a result, it is critical to harmonize NTL observations from DMSP and VIIRS NTL data. Scholars have made many efforts to integrate DMSP and the VIIRS data for assessing time-series urban expansion (Li et al., 2017; Zheng et al., 2019; Li et al., 2020; Ma et al., 2020). Due to its relatively new processing technology and higher precision we chose the harmonized DMSP-OLS and NPP-VIIRS NTL data published by Li et al. (2020) as a data source to investigate the evolution of the urban landscape of West Africa.

In addition to the challenge of obtaining appropriate data sources, a challenge also exists in how to extract urban areas conveniently and accurately. Researchers have attempted various methods to extract urban areas from DMSP-OLS NTL imagery, among which the thresholding method is a widely accepted method (Wei et al., 2014; Zhou et al., 2014; Xie and Weng, 2016; Yao et al., 2018). For instance, Wei et al. (2014) proposed a pseudo-invariant features (PIFs) concept as local training data and built a regional linear model for temporal normalization. However, due to the renewal of urban space and changes in lighting technology, it is not easy to find ideal PIFs. Zhou et al. (2014) adopted a cluster-based model using watershed segmentation to map urban areas from NTL images. The use of the cluster-based urban thresholding method for NTL data provided a favorable result, however, the method is complex and inflexible. This is because a whole year's data need to be aggregated to create cluster masks to build normalized models of time-series NTL. In addition, when adding new NTL data, all clusters may change, and the model needs to be rebuilt. Some scholars have proposed using a mid-resolution image (such as Landsat TM) as a reference to determine the threshold, but there remains the problem that the accuracy of the mid-resolution image is insufficient, and that data acquisition is difficult. Using high-resolution images improves accuracy, but generally the acquisition cost is high and cannot guarantee coverage of all study areas. Due to their being an open source and with their high accessibility, Google Earth images may provide new answers to the problem (Mering et al., 2010; San-Emeterio and Mering, 2021). Therefore, this paper uses Google Earth as auxiliary data to extract urban areas from night light images.

The purpose of this study was to assess the characteristics of West African urban landscapes in order to assist in the management of rapid urbanization and the amelioration of socioeconomic and environmental issues associated with economic transformation and sustainable development. Furthermore, this study may provide urban planners with relevant insights into West African urban expansion characteristics.

## 2 Data and Methods

### 2.1 Study area

West Africa is the westernmost region of Africa, with 16 countries (Linard et al., 2012). The region's population is estimated at 416 million people as of 2020 (Toshiko et al., 2020). West Africa occupies an area about 6.14 million km$^2$, which is approximately one-fifth of the entire continent of Africa (Fig. 1). The region is divided into four broad geographical regions: the Saharan, Sahelian, Sudan, and Guinean regions. The Saharan Region is formed by the Sahara Desert, which stretches across the whole northern extent of West Africa; the Sahel Region is mostly a semiarid belt, extending from the Atlantic Ocean to the Red Sea and averaging about 350 km wide; the Sudan Region consists of a large Savanna belt that lies immediately south of the Sahel regions; and the Guinean Region lies south of the Sudan Savanna and is dominated by seasonal wet-and-dry deciduous and semi-deciduous forest. These regions' physiographies impact the demography and urbanization landscape of West Africa: Guinea and the Sudan Region, which are favorable for agricultural activities, are more densely populated that the desert regions of the Sahara and Sahel (ECOWAS-SWAC/OECD, 2008). The number of urban agglomerations in West Africa with a population of more than 300 000 reached 78 in 2018, with most of the cities located in Nigeria. Lagos is the biggest city in this region, with a population of about 14.5 million as of 2018 (Bloch et al., 2015).

### 2.2 Data source

In this study, harmonized DMSP-OLS and NPP-VIIRS nighttime light (NTL) data and Google Earth (GE) images were used to extract urban areas. The harmonized NTL observations from DMSP-OLS and NPP-VIIRS data were produced by Li et al. (2020), forming an integrated and consistent NTL dataset obtained by harmonizing the inter-calibrated NTL observations from the stable DMSP-OLS data and the simulated DMSP-like NTL observations from the NPP-VIIRS data. In this paper, the harmonized data from 1993 to 2018 were obtained from Li et al. (2020). Images extracted from a GE image have wide spatial coverage, making them suitable for assessing a large-scale urban landscape such as West Africa. Extracted GE images, comprising built-up polygons from 2000, 2006, 2012, and 2018, were utilized as ancillary data to assess the accuracy of the NTL data.

### 2.3 Methods

#### *2.3.1 Extraction method*

Google Earth (GE) images of 22 metropolitan areas of Nigeria, Ghana, Mali and other 10 countries from 2000, 2006, 2012, and 2018 were used as ancillary data, and a spatial comparison method was utilized to determine the threshold of the NTL data from 1993 to 2018. Fig. 2 shows the steps and methodologies used to obtain urban extents from the NTL data for this study. The GE built-up polygons accurately represent the characteristics of urban built-up areas in West Africa. Therefore, the NTL data threshold can be determined by comparing urban areas to the corresponding GE data. However, this fails to identify a single threshold for the large urban landscape of the study area, with variations in temperature

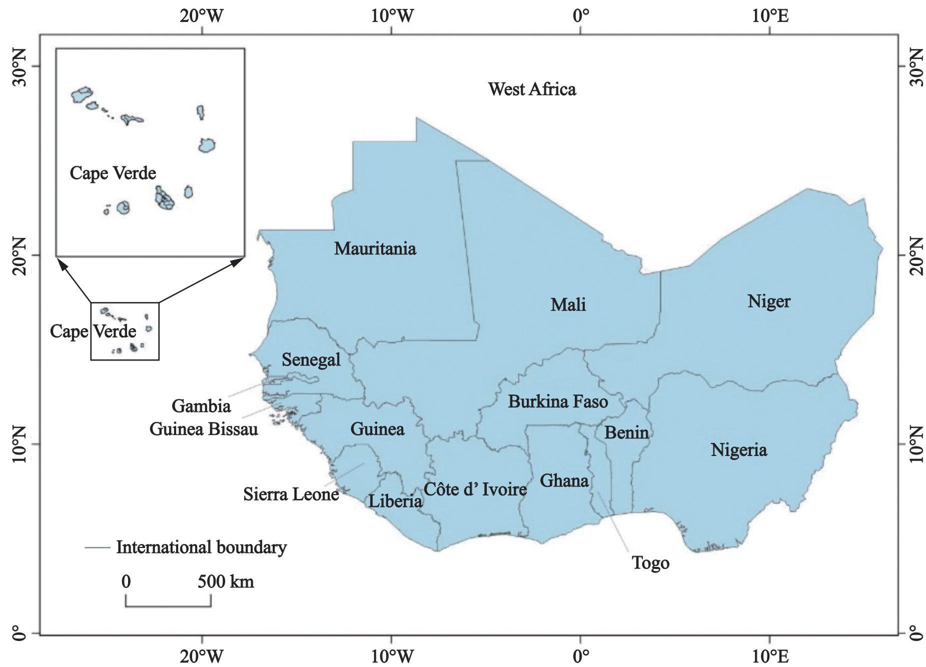


**Fig. 1** Location and spatial scope of West Africa

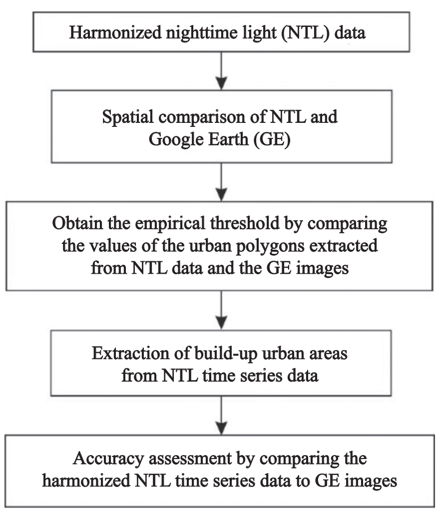


**Fig. 2** Flowchart for extracting urban extents from the nighttime light (NTL) data

and geomorphology, as well as different levels of socioeconomic development. As a result, we calculated various thresholds for the 22 metropolitan areas and then extracted urban lit areas from NTL data for 2000, 2006, 2012, and 2018.

The following procedures were used to determine the NTL data thresholds for each city using spatial comparison methods (Fig. 2). Firstly, we manually digitized 22 metropolitan areas on GE as a set of polygons for the study area and calculated each of the total built-up areas within each of the 22 metropolitan areas created in 2000, 2006, 2012, and 2018. We grouped the 22 metropolitan areas based on their location, climatic conditions, and socioeconomic status. For instance, cities such as Monrovia in Liberia, Freetown in Sierra Leone, and Aba in Nigeria located in a highly dense tropical rainforest were grouped and given the same empirical threshold. Also, large metropolitan cities with a large population, such as Lagos and Abuja in Nigeria, Accra in Ghana, Abidjan in Côte d'Ivoire, and Dakar in Senegal, were grouped with the same empirical threshold. Secondly, after thresholding, the lighted areas of NTL data were obtained. The total light patch areas of each city in the West African regions were then compared to the corresponding built-up polygons obtained from GE for the years 2000, 2006, 2012, and 2018. Lastly, we determined the optimal urban threshold for the NTL image so that the extracted lights of each urban area at that threshold value matched the urban polygons within the metropolitan areas obtained from the GE data in the total area the closest (Ghosh, 2017; Lu et al., 2018).

### *2.3.2 Examining urban extents*

The urban extents extracted from NTL data were used to investigate the rate of increase and acceleration of urban sprawl in West Africa. To examine the change in urban extents between years, we used the ratio of change in urban extent, *R*, which is calculated by Yao et al. (2018):

$$R_t = \frac{A_t - A_{1993}}{A_{1993}} \tag{1}$$

where $R_t$ is the ratio of urban extent change, $A$ is the area contained within the urban extent, and $t$ is the year. To analyze an urban cluster, the ratio $R$ of the urban extent is derived at year $t$, and 1993 is the base year for comparison. We employed the finite difference methods used by Yao et al. (2018) to examine the rate of increase in urban extension and acceleration. The finite difference method is based on a Taylor series expansion, which can be used as a function to replace the derivatives of the differential equation. Therefore, the first derivative can be utilized to examine the rate of increase of urban sprawl:

$$\frac{\partial R}{\partial t} = \frac{R_{t+1} - R_{t-1}}{2} \tag{2}$$

When the value remains steady at 0, the urban area is considered stable. Therefore, values greater than 0 indicate growth in an urban area, and the higher the value, the higher the rate of urban growth. $R_{t+1}$ stands for the change ratio of the year after investigated year $t$, and $R_{t-1}$ stands for the change ratio of the year before investigated year $t$. The acceleration of urban sprawl is measured by the second derivative, which is (Yao et al., 2018):

$$\frac{\partial^2 R}{\partial t^2} = \frac{(R_{t+1} + R_{t-1}) - 2 \times (R_t)}{4} \tag{3}$$

The growth in urban extent is determined using the rate and acceleration of urban extension; hence positive values indicate an increase in size at an increasing rate of urban extent, while the value 0 indicates a constant level. The meanings of $R$ and $t$ are as above.

#### *2.3.3 Urban expansion directions*

To elucidate the spatial and temporal characteristics of urban development in West Africa, this study used centroid-of-urban-area-over-time method to examine the direction of urban expansion. The centroid of the urban area is calculated as in Zou et al. (2017).

$$C = \begin{cases} \left(\sum_{i=1}^{n} (GV_i \times x_i)\right) \Big/ \left(\sum_{i=1}^{n} GV_i\right) = X \\ \left(\sum_{i=1}^{n} (GV_i \times y_i)\right) \Big/ \left(\sum_{i=1}^{n} GV_i\right) = Y \end{cases} \tag{4}$$

where $X$ and $Y$ are the longitude and latitude of centroid $C$, respectively; $GV_i$ is the grey value of the $i$th grid; and $x_i$ and $y_i$ are the coordinates of the $i$th grid. The gravity center of the urban area was used to determine the trajectory of the urban extents in the Accra (Ghana), Abuja (Nigeria), Lagos (Nigeria), Bamako (Mali), Dakar (Senegal), and Abidjan (Côte d'Ivoire) urban agglomerations in West Africa.

#### *2.3.4 Temporal evolution of West Africa urban expansion*

To extensively study the landscape pattern and temporal dynamics of urbanization in West Africa, we used the landscape expansion index method proposed by Liu et al. (2010). Liu et al. (2010) employed ArcGIS and FRAGSTATS programs to calculate the Landscape Expansion Index (LEI) and its variants from 1993 to 2018. Firstly, the NTL imagery used for the study were extracted into urban patches by setting up an optimal threshold for the entire study area. Then buffer zones for all new patches were generated by setting a constant distance of 1m from the old patches. According to Liu et al. (2010), the smaller the buffer distance the more stable the value of the LEI. After obtaining all the buffer zones for all growth patches, the old urban patches were overlaid with new urban patches. For instance, the initial urban patches of (1993) were overlaid by the new urban patches of 1998. Consequently, the LEI was calculated for each new patch by using Eq. (5). Then, based on the values obtained after LEI calculations, the expanding urban patches were classified as edge expansion, outlying expansion, and infilling expansion. The values of the mean expansion index and Area-Weighted Mean expansion index (AWMEI) of newly grown urban patches were also calculated using Eqs. (6) and (7). In this research, the LEI was adopted to examine the urban expansion of West Africa in two stages, from 2004 to 2008 and from 2009 to 2013. The LEI is defined by using buffer analysis, and can be used to determine which urban expansion type occurs. Thus, the LEI can be calculated by examining the characteristics of its buffer zones. Mathematically, the $LEI$ is expressed as follows (Liu et al., 2010):

$$LEI = \frac{A_o}{A_o + A_v} \times 100 \tag{5}$$

where $LEI$ is the landscape expansion index for a newly grown patch, $A_o$ is the intersection between the buffer zone and the occupied category, and $A_v$ is the intersection between the buffer zone and the vacant category.

Using this definition, the range of LEI values varies between $0 \leq LEI \leq 100$. Hence, the *LEI* can be used to interpret the three major types of urban expansion: infilling, edge-expansion and outlying. In this study, a buffer zone that is occupied by an old patch $A_o \geq 50\%$ constitutes infill growth; a change from vacant land to a newly grown patch occurring beyond the existing old patch constitutes outlying growth; and an area of buffer zone occupied by an old patch $A_o \leq 50\%$ constitutes edge expansion growth.

(1) Mean expansion index (MEI)

In this study, one of our interests is in the pattern of the entire landscape mosaic (Moser et al., 2002). Consequently, we employed a variant of the patch area index at the landscape level, called the mean expansion index (*MEI*). The *MEI* is integrated into the landscape indicators of all patches by means of basic averaging. *MEI* is computed by dividing the total landscape area by the number of patches. *MEI* is defined by (Liu et al., 2010):

$$MEI = \sum_{i=1}^{n} \frac{LEI_i}{n} \tag{6}$$

where $LEI_i$ is the *LEI* for a new patch in year *i*, and *n* is the total number of newly grown patches. A larger *MEI* value signals a more substantial compacting trend along with the landscape expansion.

(2) Area-weighted mean expansion index (AWMEI)

To consider the weight of the area for each patch for the entire landscape of West Africa, we utilized the area-weighted mean expansion index method for the study. *AWMEI* is computed as area-weighted mean at the landscape level. The area-weighted mean equals the sum, across all patches in the landscape, of the corresponding patch metric values multiplied by the proportional abundance of the patch. The formula to calculate *AWMEI* is as follows (Liu et al., 2010):

$$AWMEI = \sum_{i=1}^{n} \left( LEI_i \left( \frac{A_i}{n} \right) \right) \tag{7}$$

where $A_i$ is the area of new patch. The trend of landscape expansion is said to be compact when *AWMEI* is large and in a diffusion process when the value of the *AWMEI* is small.

## 3 Results

### 3.1 Urban area extraction and accuracy assessment

The 22 metropolitan areas extracted from the GE were georeferenced and classified with RGB (red, blue, green) spectral bands and used as a validation to evaluate the accuracy of the corresponding lighted areas from the harmonized NTL. Fig. 3 delineates a random sample of GE images of five cities (Abidjan, Accra, Lagos, Kumasi, and Monrovia) used as ancillary data to validate the accuracy of the DMSP-OLS NTL images.

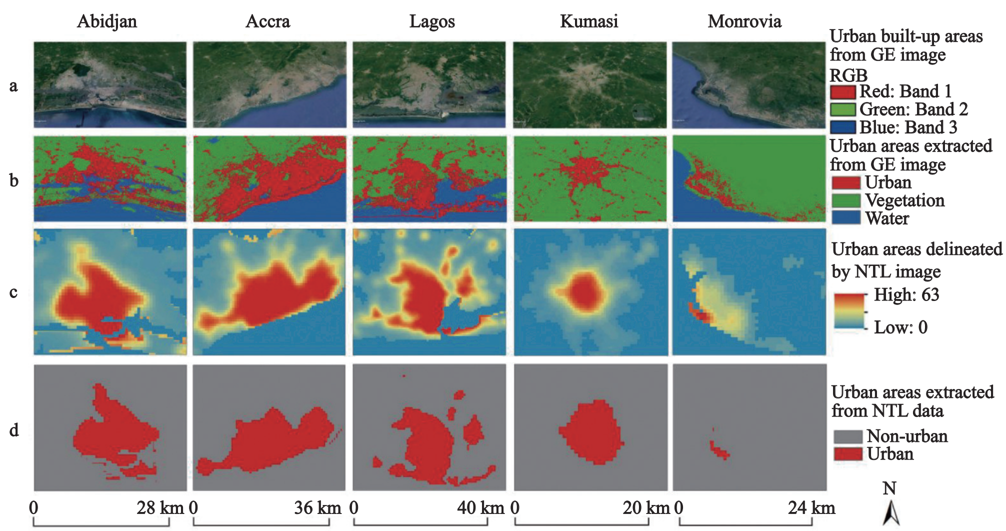


**Fig. 3** Boundary comparison for five urban areas from Google Earth (GE) and DMSP-OLS NTL (The Defense Meteorological Satellite Program-Operational Line-scan System nighttime light) for five cities in 2012. (a) Urban built-up area of GE (Google Earth) image; (b) Maximum likelihood supervised classification of urban areas extracted from GE image; (c) Urban areas delineated by NTL image; (d) Urban areas extracted from NTL data

In 2000, 2006, and 2012, the accuracy of the relationship between the NTL image and GE image was, respectively, $R^2$ = 0.8314, $R^2$ = 0.8809, $R^2$ = 0.9051, for DMSP-OLS, and $R^2$ = 0.8426 in 2018 for the simulated NPP-VIIRS. The data point (Port Harcourt) was deleted because higher resolution images from GE in 2006 were unavailable or the images were blurred by cloud cover, making it difficult to delineate and extract the urban polygon for accurate comparison with the NTL image from the same year.

Table 1 shows the urban extents of cities in West Africa in 1993, 1998, 2003, 2013 and 2018. The characteristics of west African urbanization show that almost all the countries expanded from 1993 to 2018. Furthermore, the trend in urban sprawl was consistent with the increase in the intensity of the NLT imagery, as a result of rapid development and increasing urban population in West African cities, particularly the capital cities and other cities, such as Kumasi, Port Harcourt, and Ibadan. In 1993, the majority of West African urban areas were concentrated in Nigeria (45%), Cape Verde (33%), and Guinea Bissau (11%). In addition, during this period, urban areas were concentrated along West Africa's coast. Between 2003 and 2008, the expansion of urban agglomeration in these three countries, as well as in many small cities and towns, began, particularly in West Africa's middle zone. Capital cities in Mali, Senegal, Burkina Faso, and Togo also grew. Furthermore, the period of 2013 to 2018 saw a marked increase in West African urbanization. The number of small towns and cities grew at an exponential rate. In 2018, urban areas in Senegal, Mali, and Burkina Faso increased by 25%, 50%, and 7%, respectively. The expansion of urban extent from 1993 to 2018 can be attributed to the delegation of administrative functions and decentralization of decision making, which raised the status and development of infrastructure, such as transportation networks and electricity, in many small towns and cities in various West African countries. And most countries experienced a high rate of urban expansion and displayed a trend of continuous growth from 1993 to 2018. For example, Ghana's urban areas increased at a rate of about 700%. However, Nigeria's urban areas experienced a ups and downs growth and urban areas increased at a rate of about 35% from 1993 to 2018.

### 3.2 Urban expansion trends of majors cities

In this section, we employed the finite difference method to calculate the rate and acceleration of urban sprawl for the entire region of West Africa. Table 2 shows the expansion of urban area in West Africa based on rate and acceleration. Using the period from 1993 to1998 as

**Table 1** Urban areas of West Africa's countries from the harmonized NTL (nighttime light) images using optimal threshold values / km$^2$

| Countries | 1993 | 1998 | 2003 | 2008 | 2013 | 2018 |
|---|---|---|---|---|---|---|
| Benin | 21.0003 | 47.4482 | 95.1442 | 86.6308 | 206.2574 | 211.3774 |
| Burkina Faso | 38.8843 | 126.9334 | 175.3939 | 208.5147 | 297.3543 | 319.0300 |
| Cape Verde | 4688.5493 | 4685.9438 | 4686.5258 | 4686.5258 | 4685.9417 | 4685.3881 |
| Gambia | 0.1401 | 10.3860 | 12.4126 | 42.6544 | 46.3222 | 27.5682 |
| Ghana | 292.3111 | 435.4000 | 776.6365 | 817.5317 | 1310.7623 | 2388.2321 |
| Guinea | 4.4626 | 58.9176 | 44.7287 | 58.4337 | 65.4576 | 214.1577 |
| Guinea Bissau | 1517.1883 | 1517.1883 | 1517.1883 | 1517.1883 | 1517.8724 | 1517.1883 |
| Côte d'Ivoire | 223.8042 | 384.0423 | 445.8122 | 488.1783 | 760.9053 | 1279.1815 |
| Liberia | 1.3654 | 1.3654 | 1.3654 | 1.3654 | 1.3654 | 1.3654 |
| Mali | 33.3706 | 84.0574 | 185.7750 | 191.5680 | 262.9564 | 394.2040 |
| Mauritania | 241.5256 | 351.6106 | 369.6792 | 398.2844 | 429.7888 | 646.2792 |
| Niger | 29.7178 | 55.7226 | 71.3075 | 71.4652 | 175.9391 | 216.8275 |
| Nigeria | 6537.6536 | 6583.6357 | 8077.8402 | 5123.9515 | 5958.2889 | 8808.8345 |
| Senegal | 74.5337 | 171.2761 | 244.9766 | 255.1234 | 385.8076 | 484.1209 |
| Sierra Leone | 646.7717 | 646.7717 | 653.3979 | 656.8305 | 656.8159 | 651.0818 |
| Togo | 31.1235 | 51.3707 | 80.5798 | 97.8881 | 167.9154 | 205.7092 |

**Table 2** Information of urban expansion in West Africa from 1993 to 2018

| Period | Area / $km^2$ | Ratio | Rate | Acceleration |
|---|---|---|---|---|
| 1993–1998 | 1.0322 | 0.1345 | 0.0000 | 0.0000 |
| 1998–2003 | 1.1058 | 0.2155 | 0.0160 | 0.3069 |
| 2003–2008 | 1.1442 | 0.2576 | 0.0173 | 0.4216 |
| 2008–2013 | 1.2288 | 0.3506 | 0.0189 | 0.5381 |
| 2013–2018 | 1.5383 | 0.6909 | 0.0686 | 0.9033 |

an initial urban area, the rate and acceleration of West Africa's urbanization indicate that there is steady growth in the urban areas. The rates and accelerations during the periods 1998 to 2003, 2003 to 2008, 2008 to 2013, and 2013 to 2018 are 0.0160, 0.0173, 0.0189, 0.0686, and 0.3069, 0.4216, 0.5381, and 0.9033, respectively. The last stage (2013 to 2018) has the fastest rate and acceleration in the entire study period.

### 3.3 Urban expansion directions of major cities

We used the gravity centers of six metropolitan areas in the Sudan and Sahel regions, namely Dakar, Bamako, and Abuja, as well as coastal cities in the south of West Africa, namely Accra, Lagos, and Abidjan, to study the direction of urban expansion in the region from 1993 to 2018. Fig. 4 shows how the centroid of coastal cities appears to expand inward from the coast. Between 1993 and 1998, Accra's center of gravity shifted from west to east. There was a minor shift from East to West from 1998 to 2003, and another minor shift from West to East from 2003 to 2008. There was also a shift from East to West from 2008 to 2013. Accra's gravity center shifted to the northwest in the last period 2013 to 2018. From 1993 to 1998, 1998 to 2003, and 2003 to 2018, the centroid of Lagos shifted from east to northwest. Lagos' gravity center shifted from east to west from 2008 to 2013, and from north to southeast from 2013 to 2018; however, the period 2013 to 2018 showed an inverse expansion as the city's centroid shifted from north to south. From 1998, the expansion directions of the Abidjan centroids moved from south to north, with a slight east-west shift from 2003 to 2008.

For comparison, the period from 1993 to 2018 showed that the gravity center of cities in West Africa's middle belt moved from north to south. For instance, the centroid of the Bamako shifted from east to west by small margins from 1993 to 1998, and the shift changed from east to west toward the south for the rest 1993–1998 and 1998–2003. It further shifted from West to East in period 2003–2013 and significantly shifted to the South in the period 2013–2018. The centroid of the Abuja urban agglomeration shifted from west to east in the periods 1993–1998 and 1998–2003, remained nearly stable in 2003–2008, and began to shift from north to south from 2008 to 2018. In the case of the Dakar agglomeration, which is located on West Africa's eastern coast, the centroid moved from east to west throughout the entire period from 1993 to 2018. As a result, West Africa's urban expansion is shifting from the coast in the south and north of the Sahel region to the middle belt.

### 3.4 Spatiotemporal evolution of urban expansion

Table 3 shows the results for the three urban patch growth types in the spatial distribution of the region during the entire study period. Between 1993 and 2018, the urban landscape in West Africa showed many similar growth patterns with only a few exceptions. In the first period (1993–1998), an edge-expansion-type pattern (i.e., 61 patches) dominated urban expansion patterns, accounting for 43% of urban expansion patterns in West Africa's landscape. During this period, the number of patches for outlying expansion was significant (69), accounting for approximately 48% of all patches. This indicates that many metropolitan cities, particularly the coastal cities Accra (Ghana), Abidjan (Côte d'Ivoire), Lagos (Nigeria), Port Harcourt (Nigeria), Conakry (Guinea), Freetown (Sierra Leone), and Dakar (Senegal), were expanding. An infilling type pattern (13) of urban expansion in the landscape occurred primarily in the capital cities and some other cities, with Nigeria accounting for 9% of the total.

During the second stage (1998–2003), the number of patches in the outlying expansion 78 (47%) was significantly higher than that of edged expansion (72), representing 43%, and the infilling type of expansion 16, representing 10%. During this stage, major cities grew in strength, and many smaller cities sprouted up. The third stage (2003–2008) saw a slight increase in all three types of expansion, with edge expansion 76 representing 43%, outlying 80 representing 46%, and infilling 19 representing 11%. Furthermore, the previous stage of

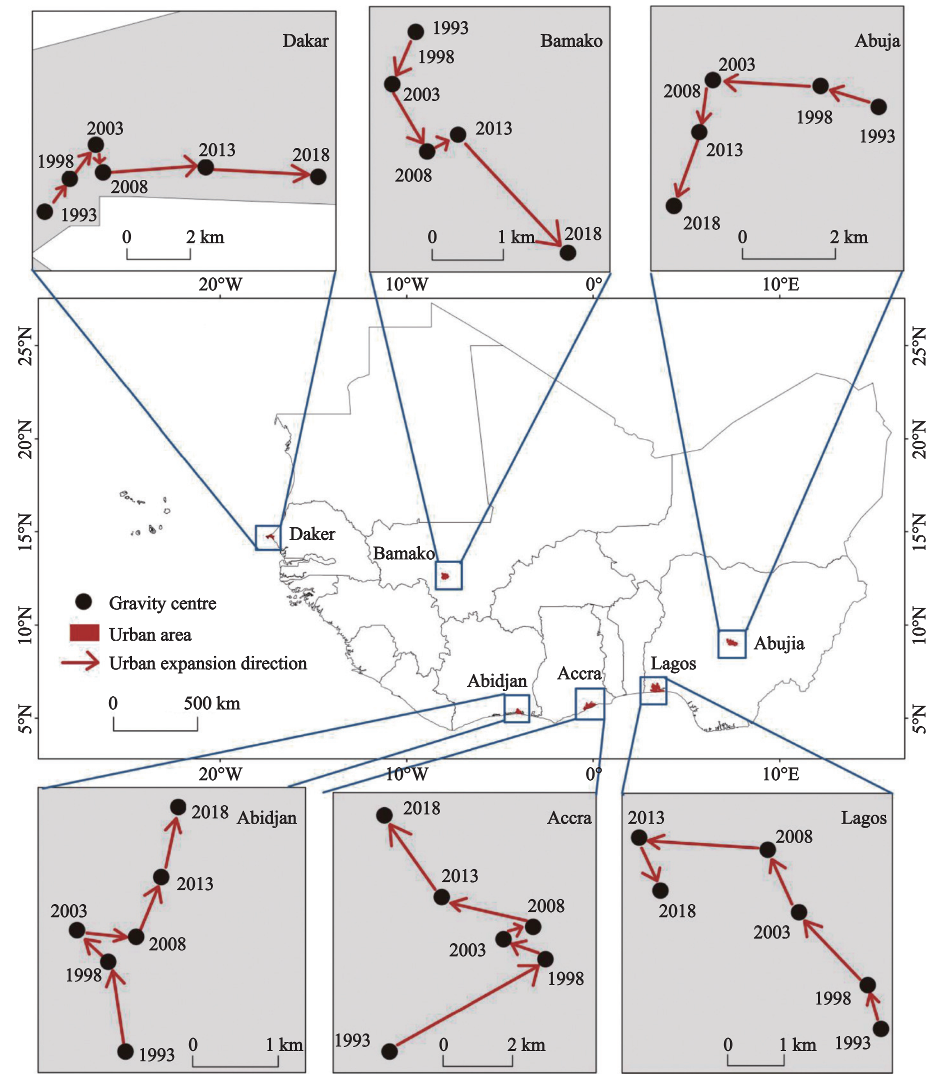


**Fig. 4** Trajectory of the gravity center of urban agglomeration expansion in six metropolitan areas, namely Accra, Abidjan, Abuja, Bamako, Dakar, and Lagos in West Africa from 1993 to 2018

**Table 3** Urban expansion characteristics delineated by urban patch growth types and landscape indexes during 1993–2008 in West Africa

| Period | No. of patches in edge-expansion | No. of patches in infilling | No. of patches in outlying | Total no. of patches | Mean expansion index | Area-weighted mean expansion index |
|---|---|---|---|---|---|---|
| 1993–1998 | 61 | 13 | 69 | 143 | 2.82 | 0.59 |
| 1998–2003 | 72 | 16 | 78 | 166 | 2.33 | 0.76 |
| 2003–2008 | 76 | 19 | 80 | 175 | 2.39 | 0.47 |
| 2008–2013 | 83 | 31 | 98 | 212 | 2.18 | 0.61 |
| 2013–2018 | 86 | 34 | 113 | 233 | 1.89 | 0.89 |

urban landscape expansion in West Africa increased, with 18 patches of outlying expansion, 11 patches of infilling expansion, and 7 patches of edge-expansion. The final stage (2013 to 2018) showed an increase in outlying expansion (15) and slight increase in both edge-expansion (3) and infilling type expansion (3). West Africa had a high level of urban agglomeration in the last two stages. Although major cities, such as Niamey, Bamako, and Ouagadougou, were sparser in the landlocked Sahel region, a new cluster of lighted cities emerged. Many towns developed into cities along major rivers, which served as an important agricultural resource for regional markets in countries such as Mali, Burkina Faso, Niger, Chad, and Senegal, as well as other countries in the Sahel region. The results obtained for the five periods indicate that the characteristics of West Africa's urban expansion landscape are young and in the process of diffusion.

According to Table 3, the MEI values for the five stages, 1993 to 1998, 1998 to 2003, 2003 to 2008, 2008 to 2013, and 2013 to 2018, were 2.82, 2.33, 2.39, 2.18, and 1.89, and the AWMEI values for the five stages, were 0.59, 0.76, 0.47, 0.6, 0.89. The values obtained for MEI and AWMEI are relatively small which confirmed that the West African urban expansion landscape is in the process of diffusion during the study period. This explains why the outlying expansion and edge expansion patterns have continued to grow throughout all of the periods from 1993 to 2018.

### 3.5 Urban sprawl in Accra and Lagos metropolitan areas

Fig. 5 shows the urban development patterns of Accra and Lagos metropolitan areas from 1993 to 2018. The rate and pattern of growth in Lagos have been alarming; the Lagos metropolitan area is expanding in an amalgamated form. From 1993 to 2018, the city experienced rapid amalgamation expansion, which resulted in an enlargement of the metropolitan area and a reduction in the distance between the urban peripheries.

The conversion of coastal wetlands into urbanized communities has resulted in urban sprawl, which has contributed to the spatial expansion of the Lagos metropolitan area (Wang and Maduako, 2018). According to the Lagos State Government, the state's population growth rate of 8.0% in 2009 resulted in the state capturing 36.8% of Nigeria's urban population, which was estimated to be 49.8 million people (Robert, 2019). Population growth in the Lagos Metropolitan areas is primarily due to rural-urban migration, which has resulted in urban land expansion (Robert, 2019). Lagos, with a population of about 16 million people, is the seventh fastest-growing city in the world and the second-largest in Africa. The city has a long history of socioeconomic growth and transformation. The city is well-known for its industrial and commercial activities, with an $80 billion GDP in 2010 (Wang and Maduako, 2018; Robert, 2019). Lagos has emerged as a major hub for national and global corporate headquarters, bolstered by complex businesses and professional services (Güneralp et al., 2017).

Accra, Ghana's largest metropolitan city and capital city, has seen a significant change in the trends and patterns of its urban landscape Otiso and Owusu, 2008; (Appiah et al., 2014). Rapid urbanization has resulted in ongoing changes in urban form of Accra. Similar to the case for most cities, its suburban towns have merged with metropolitan areas, resulting in a significant increase in urban agglomeration. Accra's rapid spatial expansion can be attributed to an increase in urban migration into the city (Appiah et al., 2014). Lagos and Accra have a large population, which gives them the scale that other cities in West Africa's economies lack, making them potential regional powerhouses (Wang and Maduako, 2018).

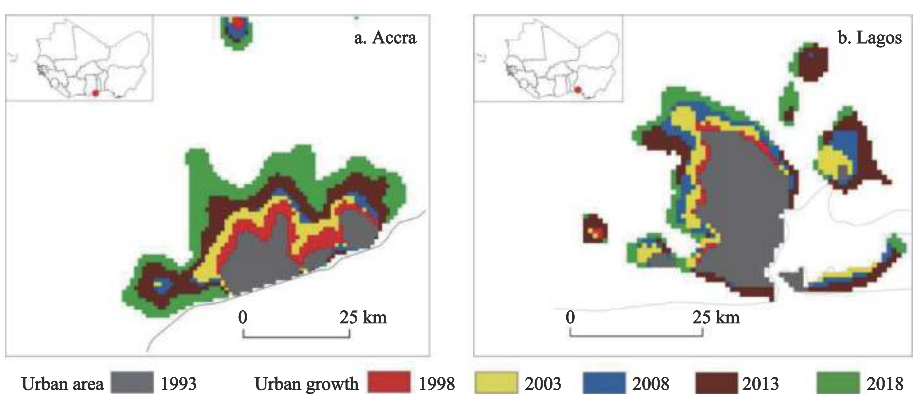


**Fig. 5** Expansion of urban areas in Accra (Ghana) and Lagos (Nigeria) metropolitan areas from 1993 to 2018

## 4 Discussions

### 4.1 Urban sprawl features in West Africa

Over the years, there has been much discussion on how urban expansion manifests itself in the form of a wave (Liu et al., 2010). Individual urban centers form as a result of an oscillatory growth between two processes: diffusion and coalescence. Expansion of the town or core area occurs in the early stages. The core area disperses as it grows, and new urban patches emerge. This is diffusion. Following that, the development of urban patches gradually reduces the distance between the new urban patches by filling in the gaps between existing urban patches. This is coalescence (Wei et al., 2014). The values obtained from LEI, MEI, and AWMEI over the entire period imply that the West African urban landscape is in a scattered and disordered diffusion phase rather than a coalescence phase.

Results indicate that there was a significant expansion during the study period, as the distance between agglomerations decreased and the number of new urban patches increased. The urban expansion analysis reveals how major urban agglomerations were shifting from the coast in the south and north of the Sahel region to the middle belt of West Africa. Many major cities in West Africa were built during the colonial era as trading centers and colonial administrative centers (Denis and Moriconi-Ebrard, 2009). Cities along the coast, such as Lagos, Accra, Lomé, Port Harcourt, Abidjan, Monrovia, Conakry, and Freetown, were the first urban centers in the 1950s and 1960s. Initially, urban patches were mostly concentrated along the coast. As urban development continues, more and more new urban patches form in landlocked regions, increasing the number of outlying expansions and edged expansions. The small values obtained from both MEI and AWMEI during the study period indicate that urban development in the region was in the process of diffusion, and that the majority of newly grown urban patches were of the outlying type. However, many cities, especially the capitals, are experiencing a high rate of edge-expansion urban development; while a few cities, particularly the capitals, are in the process of coalescence, marking the beginning of an infilling type of urban expansion.

### 4.2 Advantages and limitations of NLT data in urban expansion studies

The harmonized DMSP-OLS and NPP-VIIRS NTL data provide an effective method for analyzing and monitoring the dynamics of a large-scale urban landscape. Because urban extent can be directly related to spatiotemporal lighted areas from NTL images, time-sensitive NTL image data can be used as an objective and consistent measure of urban landscape, in contrast with conventional population data and other statistical data (Zou et al., 2017).

During the urban extraction process, we discovered that NTL images may contain errors. Firstly, cities in the Guinea region with dense forests, such as Monrovia, Freetown, and Conakry, had very low light intensity, resulting in a reduction in the threshold value of 40 to 25 for city extraction. Secondly, many studies have argued that the use of satellite imagery to evaluate urban extents generates uncertainty that arises from coarse spatial resolution, saturation, and blooming effects, as well as from a lack of an onboard calibration system in the DMSP-OLS and NPP-VIIRS NTL data (Liu et al., 2010; Ghosh, 2017; Zou et al., 2017). A reflected light wave detected by satellite sensors coming from urban areas, particularly West Africa in the tropical region, can be altered and blocked by phenomena such as clouds in GE and NTL images.

## 5 Conclusions and Recommendations

### 5.1 Conclusions

To effectively identify urban areas in West Africa from 1993 to 2018, this paper explored optimal threshold and spatial comparison methods. Unlike many West African urbanization studies, our study provides a comprehensive evaluation of the characteristics and processes of the urban landscape using the urban expansion rate, acceleration, direction, LEI, and spatio-temporal dynamics of the West African urban system using harmonized DMSP-OLS and NPP-VIIRS NTL images from 1993 to 2018.

Our findings revealed that urban growth in most West African countries and regions increased significantly during the study period, particularly in coastal areas and metropolitan areas. The growth of major cities and small urban centers in coastal countries, such as Ghana, Nigeria, Côte d'Ivoire, and Senegal, was quite dramatic, whereas cities in the Sahel region experienced a more stable expansion trend.

From LEI analysis, all the three types of urban expansion have been found in West Africa. But in terms of the number of urban patches, outlying expansion type appear most, while the edge expansion and filling expansion appear less. Combined with the expansion pattern dominated by outlying expansion and the small MEI and AWMEI value, we judge that the urban landscape of West Africa was mainly in a scattered and disordered 'diffusion' process, with only a few cities located in coastal areas experiencing the process of 'coalescence'.

Finally, the rapid urban growth in West Africa was attributed to the delegation of administrative functions, decentralization, and development of infrastructure, such as road transport systems. Therefore, mapping and monitoring the expansion of West Africa's urban landscape with NTL data is critical for providing accurate urban footprints, and for anticipating the socioeconomic development of West African urban centers.

### 5.2 Policy recommendations

According to the findings of this study, many cities in West Africa are expanding towards large rivers or fertile agricultural lands, which may have a negative impact on primary production. As a result, the infill development pattern, which involves the redevelopment, improvement, and renovation of old urban districts and worn-out textures, as well as the reuse of abandoned land for new urban development, should be considered as a method for simulating future urban development.

Many large and small cities in a region are expanding and increasing urban agglomeration; thus, there should be a planning approach in which urban expansion is acknowledged and embraced by securing a grid of arterial roads on the urban periphery before development takes place. This enables a city to plan ahead and ensures that vital infrastructure corridors and orderly road networks are in place as it expands beyond its urban core.

The rapid acceleration of the urban landscape of West Africa requires the (re-)demarcation of urban and peri-urban areas. Determining the boundaries of these areas is essential for developing appropriate and effective policies for managing and preserving cities in a region.

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