

Spatio-temporal analysis of land use/land cover dynamics in Sokoto Metropolis using multi-temporal satellite data and Land Change Modeller

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Received: 2019-10-19

Accepted: 2020-11-12

Keywords:

Urbanization;
LULC change;
Remote Sensing; GIS;
Landsat

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Abstract. Urbanization is currently one of the most pressing environmental issues which cuts across all countries at unprecedented rates and intensities, with far reaching consequences on ecosystems, biodiversity and human wellbeing. This paper assessed urban expansion and land use/land cover changes in Sokoto metropolis, North-western Nigeria using Remote Sensing and GIS. Landsat images of 1990, 1999 and 2015 were processed for LULC classification and change detection using the Maximum Likelihood Classification, Post Classification Comparison techniques and the Land Change Modeller. The classification revealed five broad land cover classes which include Built-up Area, Farmland, Green Area, Open Space and Wetland/Water. The Built-up and Green areas continuously increased while Farmland and Open space decreased throughout the study period. The metropolis expanded radially at a faster rate between 1999 and 2015 with the highest rate of increase (1890.5ha per annum) recorded in the Built-up Area. This implies a doubling time of approximately 30 years at the expense of Farmland and Open space which may be completely exhausted in 40 and 29 years respectively. Infrastructural provision should thus align with the rate and direction of growth and where the Green Area is converted, replacement should be made to ensure continued supply and stability of the numerous ecosystem services green areas provide.

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1. Introduction

Nigeria is the most populous country in Africa which was also poised to experience the highest increases in urban population (Farrell, 2018). The proportion of urban population in the country has continuously increased over the past 50 years, expediting the process of urbanization and urban expansion. Urbanization is one of the most pressing environmental issues of the present millennium. It is a natural phenomenon that involves changes in the physical and functional components of the built environment and presently cuts across all countries (Nkeki, 2016) at unprecedented rates and intensities (Bhat et al., 2017). Urban expansion occurs globally due to urban population growth and socioeconomic development in a particular area and represents the transformation of non-urban land to urban land (Jianguo, 2014). According to He et al. (2019), the global urban land increased at an annual rate of 3.5% between 1992 and 2016 which culminated into a total increase of 346.4 thousand km² (Bloch et al., 2015) and is expected to reach 58.3% and 67.1% by 2030 and 2050 respectively (United Nations, 2014). This translates to about 10-fold expansion of cities which has been largely, unplanned and uncontrolled (Aliyu and Amadu, 2017). As a result, urban areas in Nigeria face such problems as inadequate housing and infrastructure, slum proliferation, widespread poverty and unemployment (Jianzhu and Maduako, 2018) as well as alteration of natural land surface temperature, changes in urban drainage morphology and increased surface runoff and flood events (Mahmoud et al., 2016) among others.

Sokoto metropolis has in recent times witnessed significant increases in human population and thus, accelerated expansion from the urban core (Ogunjobi et al., 2018). According to Eniolorunda and Dankani (2012), rural-urban migration and proliferation of socio-economic activities brought about by the reintroduction of democracy in Nigeria in 1999, led to continuous growth of the city. These led to significant land use/land cover changes in the city, via conversion of adjacent farmlands and open spaces into residential, commercial and institutional structures as well as roads and other infrastructure (Dangulla, 2019).

Land use/land cover (LULC) changes are the most common phenomena associated with urbanization (Xiaowei et al., 2015). These are alterations in the manner and purposes underlying human exploitation of the earth's natural or human-engineered materials (Mekonnen et al., 2018). They result from the interaction between structural and behavioural factors in relation to the technological development, demand, and social realities of a particular environment (Rawat et al., 2013) and involve both changes to a different use or in the intensity of a particular use (Goodin et al., 2015). Rapid urbanization and land use/land cover (LULC) changes play significant roles in eco- environmental changes and deterioration (Wu et al., 2016). Analysing and understanding urban LULC changes is thus crucial for the assessment of human-environment interactions (Chowdhury et al., 2019), efficient use and management of resources (Lal et al., 2017), urban planning and sustainability (Ayele et al.,

2018) and monitoring of environmental problems (Bai et al., 2017).

LULC changes were traditionally assessed with the cumbersome, expensive and time consuming field studies, census data and/or aerial photographs (Fonji and Taff, 2014). In recent times, advances in Remote Sensing (RS) and Geographic Information Systems (GIS) have provided unique opportunities for generating dynamic and repeatable land-based information on wider spatial and temporal scales (Hermosilla et al., 2015). These tools have thus become increasingly reliable for studying and monitoring urban expansions and the resultant LULC changes (Sory et al., 2018) at lower costs and higher accuracies (Fenta et al., 2017). In many studies such as Eniolorunda and Dankani (2012) and Shamaki and Dankani (2012) however, land cover of the city was merely classified over given periods without modelling future trends of these changes. The aim of this paper is therefore to analyse the spatio-temporal trends and patterns of urban expansion and LULC dynamics in Sokoto

metropolis, North-western Nigeria over a 25year period using the Land Change Modeler (LCM) in RS and GIS environment. The LCM approach which is embedded in the Idrisi TerrSet software (Eastman, 2015), integrates the Multilayer-Perceptron (MLP) with the Markov Chain method to model land transition probabilities using historical LULC change data and other geospatial datasets (Iizuka et al., 2017; Mahmoud et al., 2016). Compared to many modelling approaches, the LCM is faster, more simplified and easily understandable (Eastman, 2015; Nor et al., 2017).

2. The Methods

The Study Area

Sokoto metropolis is located on latitudes 13° 03' 05"N and longitudes 05° 13'53"E and covers approximately 94km² (Figure 1). The city occupies high administrative and educational positions in the country being the headquarters of the Sokoto Caliphate (AD 1809) and later Sokoto State since 1976 (Wali, 2010). It has a projected population of 554,

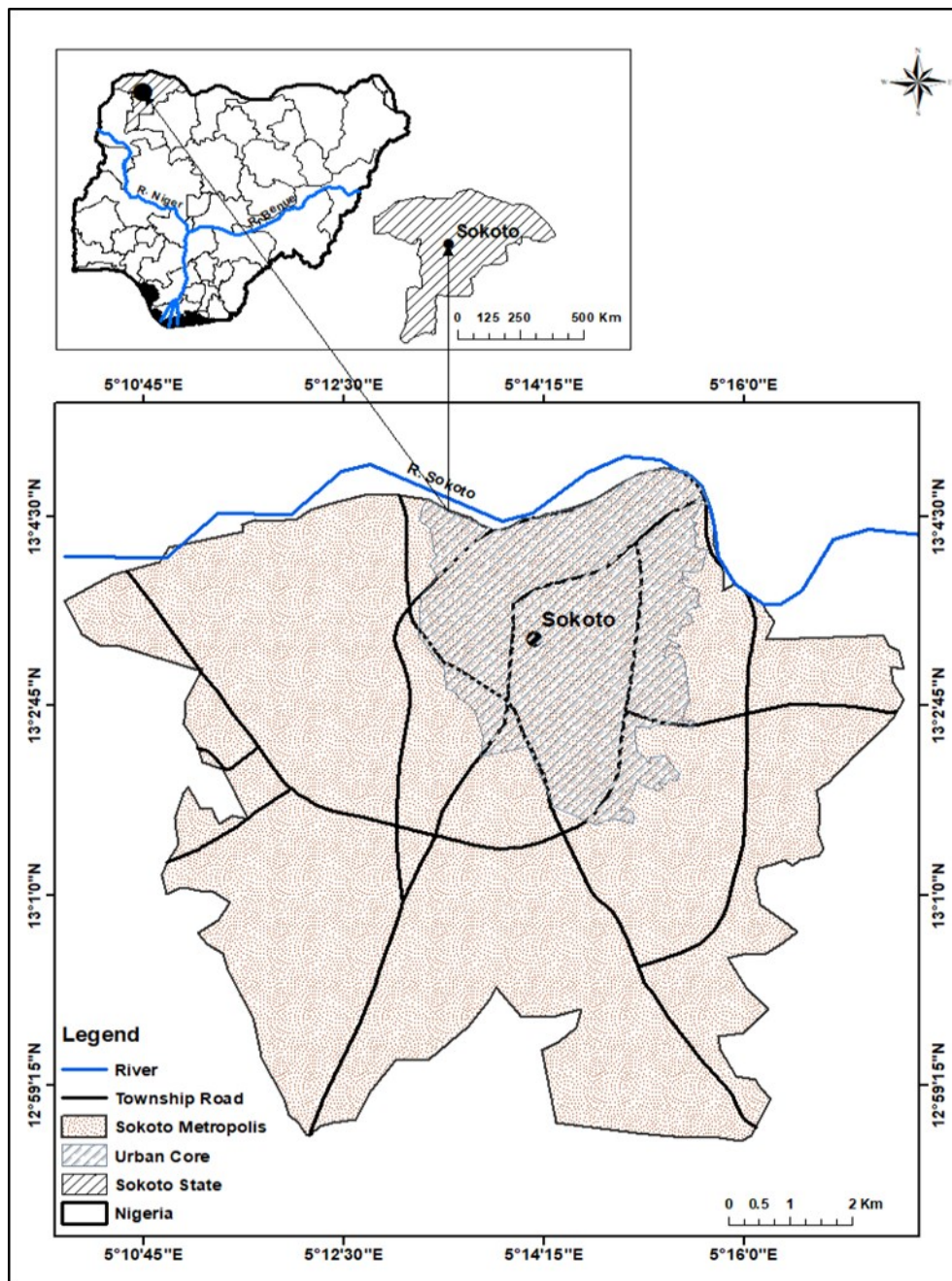


Figure 1. Sokoto metropolis and urban core (inset Nigeria and Sokoto State)

775 (National Bureau of Statistics, 2016).

The climate is semi-arid, coinciding with the Koppen’s tropical wet and dry (Aw) climate. Mean temperature ranges between 26°C and 28°C while rainfall ranges between 508mm and 1,016mm (Sanni et al., 2012). Vegetation is the Sudano-Sahelian type, composed of grasses and sparsely distributed, drought tolerant tree species (Karlson and Ostwald, 2016). The soils are generally ferruginous, light and of low nutrient value (Wezel and Lykke, 2006).

Data Acquisition and Processing

Landsat imageries for the years 1990, 1999 and 2015 for the metropolis (Path/Row 191/051) were obtained from the United States Geological Survey (www.earthexplorer.usgs.gov) and primarily used for the study. Landsat data has been extensively used in LULC change analyses due to its consistent, global coverage and archive since 1972 and free availability since 2008 (Wulder et al., 2012). The images were acquired in the dry season to minimize cloud cover and at near-anniversary to limit the effects of seasonal variations on the classification (Lal et al., 2017). The various images used in this study are presented in Table 1.

Image Pre-processing

Image pre-processing involves removal or minimization of distortions introduced to satellite images due to sensor, solar, atmospheric and topographic effects. This is to enhance the quality and interpretability of the image components for remote sensing analysis (Sowmya et al., 2017). The study area was first clipped from the respective images and then orthorectified to the UTM 31N projection and WGS 84 datum so that each point of the image matches each corresponding point on the ground. The image digital numbers (DNs) were converted to At-sensor radiance and to Top of Atmosphere (TOA) reflectance while the COST model (Chavez, 1996) was employed for atmospheric correction. Due to sensor difference, geometric correction was also carried out. The 1990 and 1999 images were co-registered to the 2015 image which was taken as the reference image. The operation revealed an RMSE of 0.134 (≈4m).

Image Classification

We adopted the widely used Maximum Likelihood Classification (MLC) (Al-doski et al., 2013; Jawak et al., 2015) and the modified Anderson’s Level 1 classification. MLC classifies image pixels based on the highest probability of belonging to a particular class (Shi and Xue, 2017) and minimises misclassification errors by allowing variable weight specifications during the classification process (Abudu et al., 2019). This approach was preferred for its enhanced accuracy (Hasmadi et al., 2009), operational simplicity, easy applicability and performance (Lillesand and Kiefer, 2015).

It is given as:

$$g_i(x) = \ln p(\omega_i) - \frac{1}{2} \ln |C_i| - \frac{1}{2} (x - m_i)^t C_i^{-1} (x - m_i) \tag{1}$$

where:

- $g_i(x)$ = likelihood that x belongs to class ω_i
- c_i and m_i = sample estimates of covariance and mean in class ω_i and
- $p(\omega_i)$ = class probability

A total of 200 pixels were selected across the metropolis using the stratified sampling module of Idrisi TerrSet software and their coordinates imputed into the waypoint list of a Garmin GPS. These were used as sample points for ground data collection and training sites for supervised classification.

Accuracy Assessment

To ensure the accuracy of remote sensing image classification, accuracy assessment is traditionally carried out to quantitatively assess how effectively the pixels were sampled into the correct land cover classes (Rwanga and Ndambuki, 2017). In this study, this was achieved by assessing the overall, producer and user accuracies of the maps using the confusion matrix and Kappa coefficient (Foody, 2015). An additional 150 pixels (Chowdhury et al., 2019) were selected for assessing the accuracy of 2015 image while the 1990 and 1999 images were assessed with the historical images of Google Earth as obtained from Pellikka et al. (2018). The matrix table was then developed for each year. The confusion matrix and Kappa coefficient were calculated as:

$$\text{User accuracy} = \frac{\text{Number of Correctly Classified Pixles in a class}}{\text{Total Number of Pixles in a class}} \tag{2}$$

$$\text{Producer’s accuracy} = \frac{\text{Number of Correctly Classified Pixles in a class}}{\text{Total Number of Pixles in all classes}} \tag{3}$$

$$\text{Overall accuracy} = \frac{\text{Total Number of all Correctly Classified Pixles}}{\text{Total Number of Pixles in all classes}} \tag{4}$$

$$\text{Kappa Index of Agreement (KIA)} = \frac{N \sum_{i=1}^n m_{i,i} - \sum_{i=1}^n (G_i C_i)}{N^2 - \sum_{i=1}^n (G_i C_i)} \tag{5}$$

where:

- i = class number
- N = total number of classified values compared to truth values
- $m_{i,i}$ = number of values belonging to the truth class i (also classified as class i)
- C_i = total number of predicted values belonging to class i and
- G_i = total number of truth values belonging to class I

Table 1. Landsat data for Sokoto metropolis (Path 191/Row 051) used in the study

S/N	Landsat Image	Sensor	Spatial Resolution	Date of Acquisition
1.	Landsat 5	TM	30m	27/12/1990
2.	Landsat 7	ETM+	30m	18/11/1999
3.	Landsat 8	OLI TIRS	30m	22/11/2015

Change Detection

Change detection was carried out using the Post Classification Comparison (PCC) which is the most popular and most accurate change detection approach (Mallupattu et al., 2013). PCC describes the nature of changes between study epochs while minimizing the problem of radiometric calibration between images of different dates (Wang, 2012). The proportion of each LULC class was calculated for each year and the changes between the respective years were determined.

Rate and pattern of LULC Change

The rate of LULC change in the metropolis during the study period (1990 – 2015) was determined using the formula obtained from Pham et al. (2015) as follows:

$$r = \frac{\ln\left(\frac{A2}{A1}\right)}{t} \tag{6}$$

where:

- r = rate of change
- A1 = area extent of LULC the initial time (t1)
- A2 = area extent of LULC at later time (t2)
- ln = natural log
- t = t2 – t1

The pattern of LULC changes as well as the matrix of change between the LULC classes, were assessed using the Land Change Modeler (LCM) embedded in the Idrisi TerrSet software (Areendran et al., 2017). The Cubic trend analysis

was used to show the pattern of land use conversion from the city center while the interchange between individual land use/cover classes was derived from the transition matrix generated with the software.

3. Results and Discussion

LULC classification

Based on the Anderson Level I classification scheme, the Maximum Likelihood Classification employed in this study revealed five broad LULC classes in the metropolis which include the Built-up Area (BUA), Farmland (FL), Green Area (GA), Open Space (OS) and Wetland/Water (WWT). Wetland and water bodies were merged into one LULC class because it was difficult to differentiate these bodies in view of their relatively small proportion in the metropolis. The respective LULC classes are described in Table 2.

Classification Accuracy Assessment

The overall classification accuracy of the final maps was 91.7%, 92.1% and 90.3% for 1990, 1999 and 2015 respectively. The user and producer accuracies however varied between the LULC classes and study years. In 1990, higher producer accuracy of 95.9% and lower user accuracy of 45.3% were achieved in the Wetland/water area. The higher producer accuracy obtained in this LULC class could be due to their very low spectral confusion while the lower user accuracy could be attributable to the relatively poor quality of the 1990 image (Landsat 5) used in the classification. In 1999, both user and producer accuracies were highest in the Farmland area while in 2015, the highest user accuracy was obtained in the Built-up area and the highest producer accuracy was

Table 2. Description of LULC classes in Sokoto metropolis

LULC	Description
Built-up Area	Residential, institutional, commercial, industrial, transportation and other built areas.
Farmland	Rainfed crop area, irrigated and fallow lands
Green Area	Planted and artificial trees, shrubs and grasses
Open Space	Open spaces, bare surfaces, exposed soils and rocks, undeveloped plots and playing grounds
Wetland/Water	Rivers, ponds, reservoirs and marshy areas

Table 3. Classification accuracy assessment (%) of final land cover maps for 1990, 1999 and 2015 in Sokoto Metropolis

LULC	1990		1999		2015	
	UA	PA	UA	PA	UA	PA
Built-up Area	94.7	93.4	94.3	93.4	95.9	89.6
Farmland	95.8	91.8	97.3	93.9	87.7	92.8
Open Space	82.9	89.4	82.7	90.6	75.4	87.7
Green Area	93.9	90.8	88.2	86.4	93.5	92.5
Wetland/Water	45.3	97.5	68.4	87.8	74.4	100.0
Overall Accuracy	91.7		92.1		90.3	
Kappa Coefficient	0.93		0.93		0.91	

UA = User Accuracy; PA = Producer Accuracy

obtained in the Wetland/water area. The Landsat 8 (OLI TIR) image used for LULC classification in 2015 has a better spectral quality which allowed the identification of built-up areas and water bodies (Table 3).

According to Anderson et al. (1976), an overall classification accuracy of 85% is recommended which implies that the overall accuracy achieved for this study is acceptable since this has been achieved in all the final classified maps. The study also achieved overall Kappa coefficient of 0.93 in both 1990 and 1999 and 0.91 in 2015 which shows that there is a strong agreement between the classified maps and the

ground reality (John et al., 2020; Rwanga and Ndambuki, 2017). The final classified maps of the metropolis for 1990, 1999 and 2015 are shown in figure 2 (a, b and c).

LULC Changes

Using the Post Classification Comparison, changes in LULC between 1990 and 1999 and between 1999 and 2015 in the metropolis were detected. In 1990 which is the base year, FL occupied the largest percentage (38.2%) of the total area (3608ha), followed by the BUA which occupied 25.4% (2400ha) and OS which occupied 21% (1972.5ha). The GA

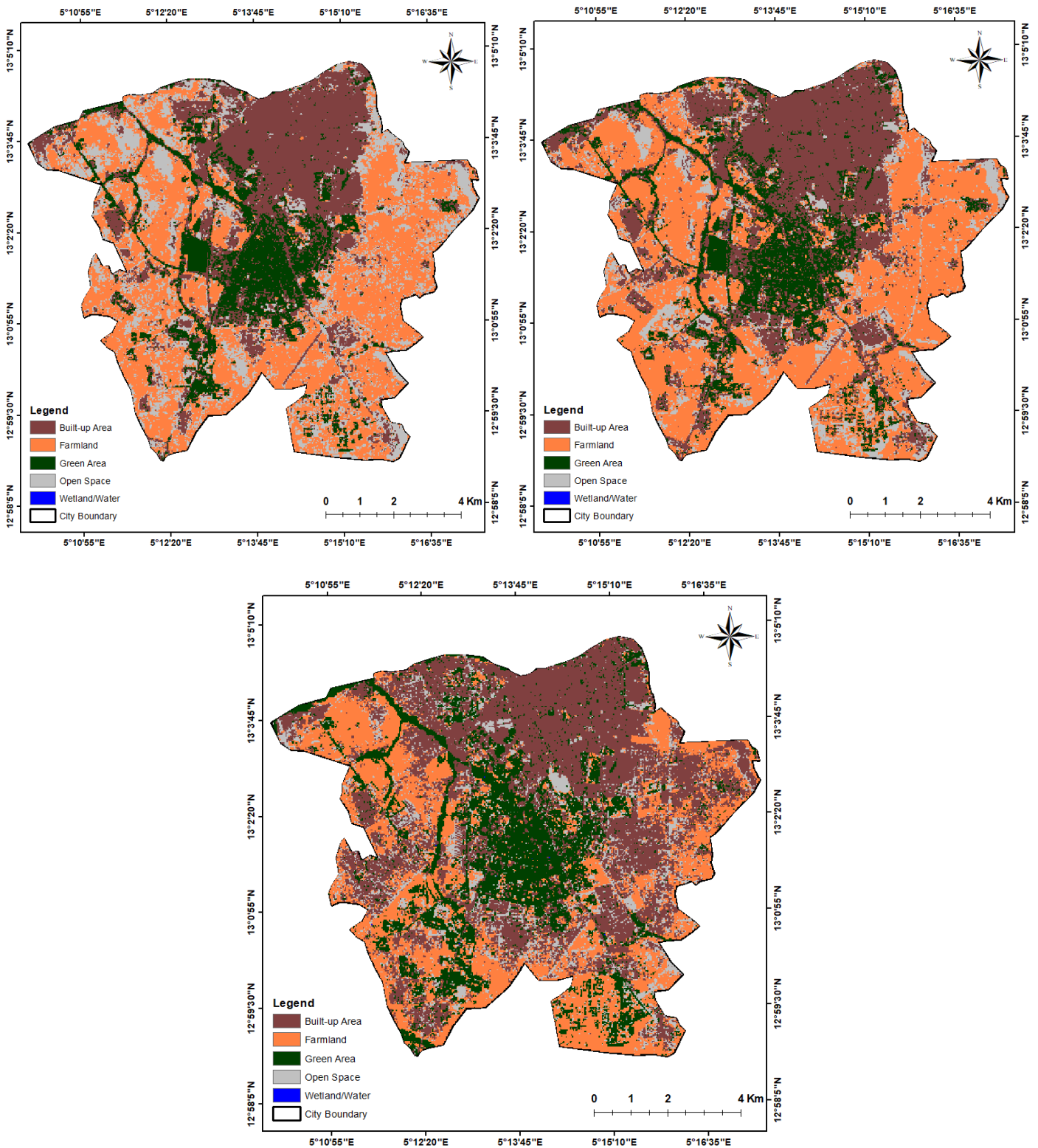


Figure 2. Final classified LULC maps for 1990 (a), 1999 (b) and 2015 (c)

and WWT on the other hand occupied 13.7 and 1.8% of the total area (1290.5 and 172 hectares) respectively. By the year 1999, the pattern of LULC changed with noticeable increases in all the LULC classes except the OS. FL expanded a little to occupy 39% of the total area while the BUA expanded by 382.5ha to occupy 39%. The GA increased by 18.5ha to occupy 13.9% of the area while WWT increased by 123.5ha to occupy 3.1%. Conversely, OS decreased by approximately 600ha and thus, decreased to 14.5% of the total area. Between 1999 and 2015, the BUA further expanded by 1508ha into the neighbouring farmlands and open spaces to occupy 45.4% of the total urban area while the GA appreciated by 116ha to occupy 15.1% of the area. On the other hand, FL, OS and WWT decreased by 1300, 287.6 and 36.5 hectares respectively. Correspondingly, these land cover classes occupied 25.2, 11.5 and 2.7% of the total urban land respectively by the year 2015 (Table 4).

Overall LULC gains and losses during the study period (1990-2015) showed that approximately 2100ha have been transformed from one LULC to another. The gains were recorded in the BUA, WWT and GA while losses were recorded in the FL and OS. The highest net gain of 1890.5ha was recorded in the BUA while the GA and WWT gained

134.4 and 87 hectares respectively. On the other hand, FL lost a cumulative 1225.3ha while OS lost 886.7ha (Figure 3).

Rate and Pattern of LULC Change

The annual rate of LULC change was generally slow between 1990 and 1999 with the exception of WWT which increased at 6.01% (10.3ha) per annum. During this period, the BUA increased at 1.64% (39.4ha), the FL increased at 0.23% (8.2ha) while the GA increased at 0.16% (2.0ha) per annum. Conversely, the OS decreased at 4.02% (79.3ha) per annum. Between 1999 and 2015, the rate of LULC change in the metropolis increased considerably. The BUA increased at 2.71% (65.0ha) and the GA increased at 0.53% (6.8ha) per annum. On the contrary, the FL, OS and WWT decreased at 2.72 (98.2ha), 1.47 (29.0ha) and 0.82% (1.4ha) respectively.

The overall average rate of change (1990-2015) was 2.3% (59ha) increase in the BUA and 1.7% decrease (60ha) in the FL per annum. The OS decreased rapidly at 4% (79.3ha) between 1990 and 1999 but slowed down to 1.5% (29ha) between 1999 and 2015. Interestingly, GA and WWT increased throughout the study period with the overall rate of increase at 0.4% and 1.6% (5.1 and 2.8 hectares) respectively (Table 5).

Table 4. Composition of LULC types and their percentage changes between 1990 and 2015 (ha)

LULC	1990	%	1999	%	2015	%	Change	%
Built-up Area	2400.0	25.4	2782.5	29.5	4290.6	45.4	1890.5	78.8%
Farmland	3607.9	38.2	3682.5	39.0	2382.7	25.2	-1225.3	-34.0%
Open Space	1972.5	20.9	1373.5	14.5	1085.9	11.5	-886.7	-45.0%
Green Area	1290.5	13.7	1309.0	13.9	1424.9	15.1	134.4	10.4%
Wetland/Water	171.9	1.8	295.4	3.1	258.9	2.7	87.0	50.6%
	9442.9	100	9442.9	100	9442.9	100		

Figure 3. Net gains and losses in land use/cover in Sokoto metropolis between 1990 and 2015 (hectares)

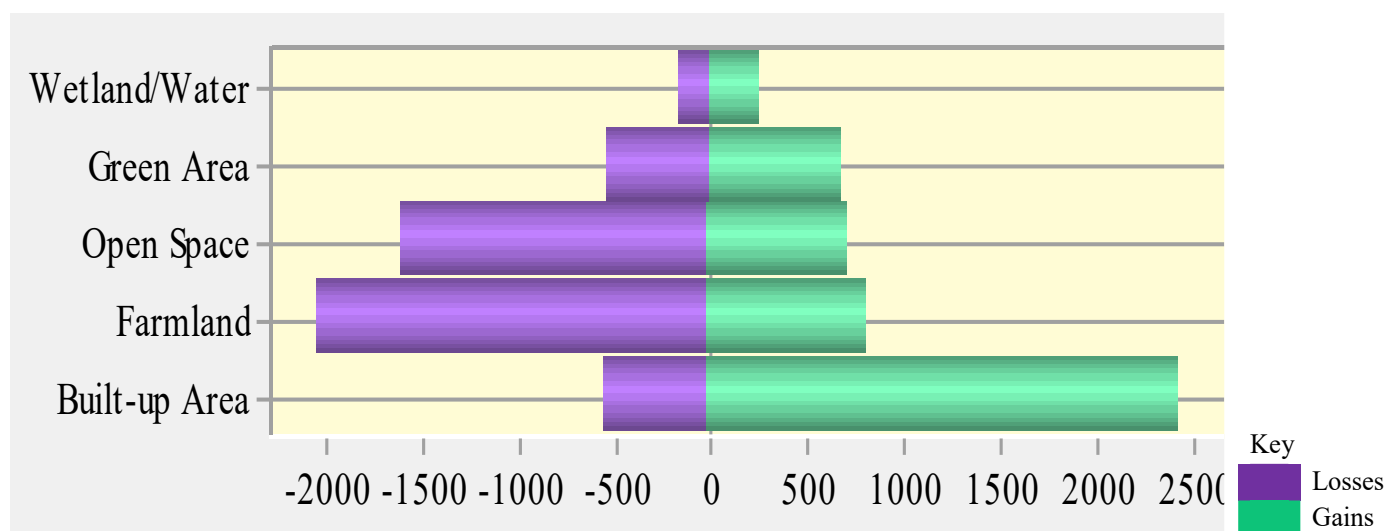


Table 5. Average annual rate of LULC change in Sokoto Metropolis – 1990 to 2015 (Hectare)

LULC	1990 - 1999		1999 - 2015		Overall (1990 – 2015)	
	Ha	%	Ha	%	Ha	%
Built-up Area	39.4	1.64	65.0	2.71	55.8	2.3
Farmland	8.2	0.23	-98.2	-2.72	-59.9	-1.7
Open Space	-79.3	-4.02	-29.0	-1.47	-47.1	-2.4
Green Area	2.0	0.16	6.8	0.53	5.1	0.4
Wetland/Water	10.3	6.01	-1.4	-0.82	2.8	1.6

4. Discussion

The spatial pattern of LULC conversion in the metropolis was radial as it occurred in all directions. This is however more pronounced to the North-western and South-western sides where development lands were supposedly more accessible. The OS and FL were the most vulnerable LULC classes as the metropolis expanded. While conversion of OS inclined to the Eastern and Southern sides, conversion of FL areas was more to the North-west and South-west. Farmlands in the first three concentric zones around the urban core were severely converted during the study period while conversions continued towards the fourth and fifth concentric zones. This followed the natural urban development process where cities expand along ring roads from city center to the fringe, as obtained in Changchun (Zhang et al., 2016) and Chengdu cities of China (Peng et al., 2015). The pattern and trend of land cover conversions in the metropolis is shown by the cubic trend analysis (Figure 4a and b).

Rapid population growth and land use/cover changes are some of the major challenges of urban areas in developing countries with profound negative impacts on agricultural lands, vegetation and other valuable habitats (Abudu et al., 2019; Jianzhu and Maduako, 2018). On a spatial scale, our study revealed that Sokoto metropolis expanded radially but

more to the north-western, southern and eastern parts, eating into the available farmlands and open spaces. On a temporal scale, the metropolis expanded faster between 1999 and 2015. The BUA expanded at the rate of 1.6% between 1990 and 1999 but at 2.71% between 1999 and 2015. This implied that, the metropolis will double its present size by 2045 (≈ 30 years). As observed by McGovern and Pasher (2016) and Wang and Maduako (2018) among others, most LULC conversions affect agricultural lands, vegetation and other natural land cover. In this study, OS and FL which decreased at 2.4 and 1.7% respectively, were largely converted to BUA and a large vegetation patch was converted for a residential project. Based on the “Rule of 70” (Donnermeyer, 2015), OS may be totally converted in approximately 29 years while adjacent farmlands may be totally absorbed in ≈ 40 years (Figure 5).

It was also observed that some parcels of the BUA and GA were converted to OS while many others were converted to GA. The former trend was accounted for by some of the construction projects executed in the metropolis such as dualization of township roads which led to the clearance of many street trees and shops. In the latter case, peoples’ efforts at planting trees or introductions of non-native species

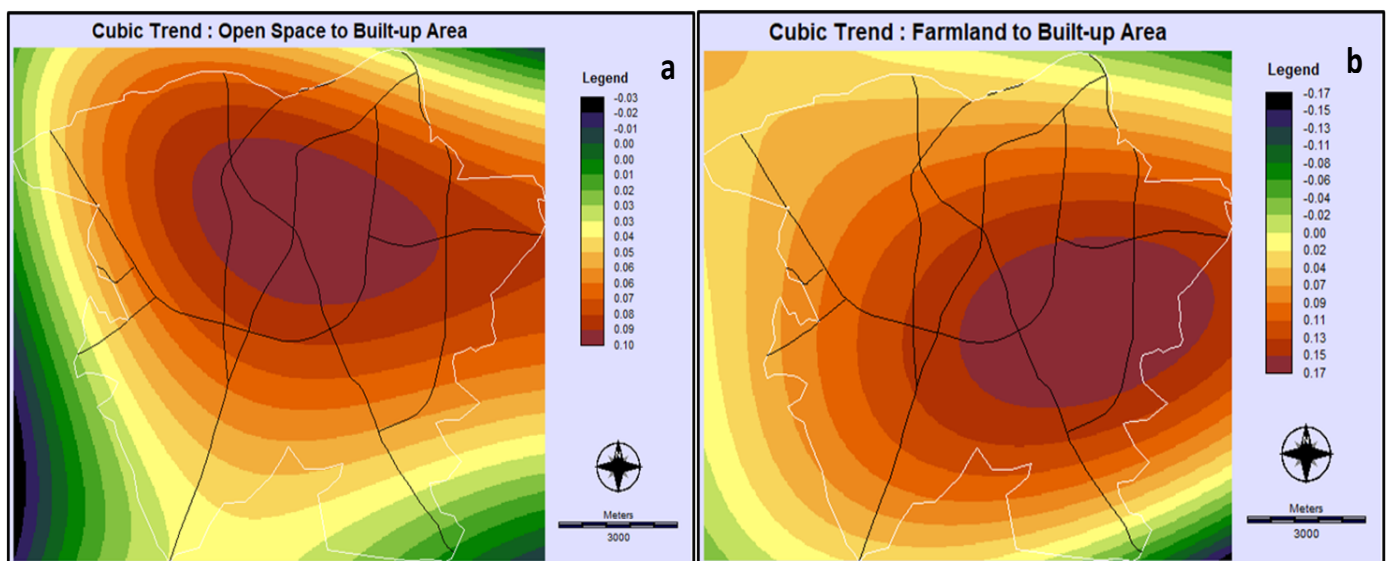


Figure 4. Pattern and trend of land cover conversions from (a) OS to BUA and (b) FL to BUA

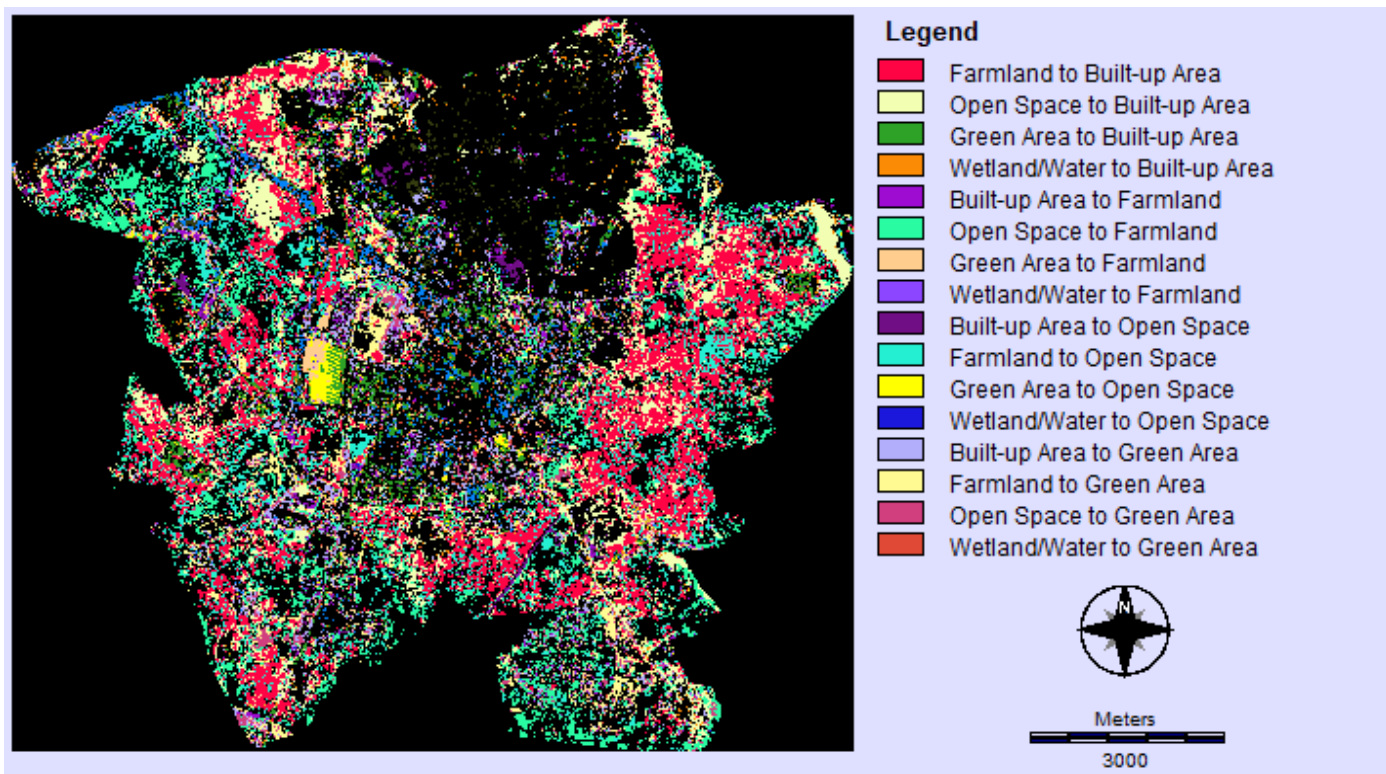


Figure 5. Transition matrix of LULC in Sokoto metropolis between 1990 and 2015

especially in new residential areas and other private lands for shade and beautification as also opined by Blood et al. (2016), greatly increased tree species richness and density in the metropolis. In addition, the natural growth of existing trees invariably increases the percentage of tree canopy cover (McGovern and Pasher, 2016) which was captured by the satellite sensor during the 25year study period. Similar results were obtained by Sinha et al. (2016) in Adama Municipal Area, Ethiopia.

The rate of urban expansion recorded in this study is however, slower than what was reported in other cities. In Kaduna for instance, Akpu and Tanko (2017) reported an annual increase of 5.72%. Mahmoud et al (2016) reported that the Federal Capital Territory (FCT) Abuja expanded at 6.31% between 2001 and 2014 while Jos expanded at 6.7% (Akintunde et al., 2016). Higher annual growth rates of 5.6% and 4.2% were also reported in Rustenburg, South Africa (Mudau et al., 2014) and Fez, Morocco (El Garouani et al., 2017). This may however not be surprising as these cities are larger and perform higher socio-economic functions than Sokoto metropolis.

The predominance of agriculture as the main source of employment and livelihood for about 80% of the people in Northern Nigeria (Macaulay, 2014) implied that FL was the dominant LULC around Sokoto metropolis. With growing human population however, there was increased need for shelter, infrastructure and other commercial facilities which accounted for the expansion of the city and loss of adjacent farmlands. The total population was 2, 418, 585 in 1991 but rose to 3, 702, 676 in 2006 and to 4,998,090 in 2016, implying an increase of about 48.4% in 25 years (Nigeria Population Council, 2007). Conversion of farmlands recorded in this study tallied with what was reported in many cities such as Lagos and Abidjan (Nlend et al., 2018), Hyderabad (Gumma

et al., 2017), Riyadh (Alqurashi and Kumar, 2017) and Hanoi (Pham et al., 2015) among others, where loss of valuable agricultural lands was related to population increase and urban expansion.

Expansions of urban areas are variously shown to adversely affect ecosystems and biodiversity through fragmentation and habitat loss (Delphin et al., 2016), vegetation degradation (Li et al., 2015) and alteration in the distribution and pattern of surrounding energy cycles leading to urban heat island phenomenon (Schneider et al., 2012). In Nigeria, urban expansions were attributable to accelerated rural-urban migrations and higher fertility rates which brought about health crises among city dwellers especially the urban poor (Aliyu and Amadu, 2017). Similarly, vegetation degradation due to continued urban expansion may potentially trigger flash flood events especially in areas with deficient drainage systems (Mahmoud et al., 2016).

5. Conclusion

This study highlighted the usefulness of RS and GIS in mapping and detecting urban LULC dynamics at both spatial and temporal scales. Multi-temporal Landsat data has also been shown to accurately detect urban LULC changes despite their moderate spatial resolutions. Although the MLC is a widely used LULC classification technique, it has been shown to perform better when combined with the LCM. Farmland was the dominant LULC class around the metropolis but was extensively converted to serve the increasing demands of residential, institutional and commercial spaces of the people. Analysis with the Land Change Modeler also showed that the metropolis expanded radially but more to the north-western, southern and eastern parts. At the present rate, the metropolis will double its size in approximately 30 years at the expense of FL and OS which were generally more

vulnerable as the city expanded. This will have profound implications for urban planning and sustainability. Infrastructural provision should thus align with this pattern and, where GA is converted, measures should be taken to ensure replacement so that the numerous ecosystem services that urban vegetation provide are guaranteed.

Acknowledgements

This research was supported by Universiti Putra Malaysia (Grant No. GCS15-4002). We also acknowledge the United States Geological Survey (USGS) for freely providing the Landsat data used in the study.

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