

See discussions, stats, and author profiles for this publication at: <https://www.researchgate.net/publication/370632085>

Spatio-temporal change detection of built-up areas in ilorin metropolis and implications for green space conservation

Article in *Papers in Applied Geography* · April 2022

CITATIONS

0

READS

44

7 authors, including:



Maimuna Ore Abdulraheem
University of Ilorin

12 PUBLICATIONS 47 CITATIONS

[SEE PROFILE](#)



Oloyede Ismaila Ore
University of Ilorin Ilorin

11 PUBLICATIONS 22 CITATIONS

[SEE PROFILE](#)



Ayo Babalola
University of Ilorin

15 PUBLICATIONS 281 CITATIONS

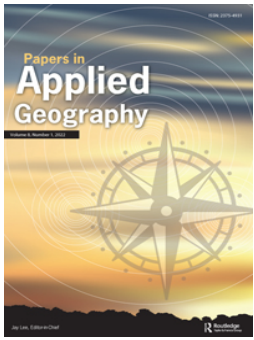
[SEE PROFILE](#)



Michaelmary Chukwu
University of Arkansas

9 PUBLICATIONS 6 CITATIONS

[SEE PROFILE](#)



Spatio-Temporal Change Detection of Built-up Areas in Ilorin Metropolis and Implications for Green Space Conservation

Abdulraheem Maimuna Orire, Xiao Huang, Orire Ismail Oloyede, Babalola Ayo, Wakeel Adeyemi Raheem & Michaelmary Chukwu

To cite this article: Abdulraheem Maimuna Orire, Xiao Huang, Orire Ismail Oloyede, Babalola Ayo, Wakeel Adeyemi Raheem & Michaelmary Chukwu (2022): Spatio-Temporal Change Detection of Built-up Areas in Ilorin Metropolis and Implications for Green Space Conservation, Papers in Applied Geography, DOI: [10.1080/23754931.2022.2062574](https://doi.org/10.1080/23754931.2022.2062574)

To link to this article: <https://doi.org/10.1080/23754931.2022.2062574>



Published online: 21 Apr 2022.



Submit your article to this journal [↗](#)



Article views: 15



View related articles [↗](#)



View Crossmark data [↗](#)



Spatio-Temporal Change Detection of Built-up Areas in Ilorin Metropolis and Implications for Green Space Conservation

Abdulraheem Maimuna Orire^a, Xiao Huang^b, Orire Ismail Oloyede^c, Babalola Ayo^d, Wakeel Adeyemi Raheem^a and Michaelmary Chukwu^a

^aDepartment of Urban and Regional Planning, University of Ilorin, Ilorin, Nigeria; ^bDepartment of Geosciences, University of Arkansas, Fayetteville, Arkansas, USA; ^cDepartment of Geography and Environmental Management, University of Ilorin, Ilorin, Nigeria; ^dDepartment of Surveying and Geoinformatics, University of Ilorin, Ilorin, Nigeria

ABSTRACT

Urbanization is a leading driver of green space depletion, and accurate land cover mapping is an essential, cost-effective technique for monitoring this phenomenon. In this study, we analyzed the spatio-temporal changes (1986 to 2020) of built-up areas in the city of Ilorin- Nigeria, and discussed the findings' implications for green spaces. A supervised pixel-based SVM algorithm was adopted for image classification to produce the land cover maps with multi-temporal Landsat images. The analyzed post-classification result yielded an overall accuracy (OA) of 99.87 percent and a Kappa coefficient (KA) of 0.998. The change metrics showed that built-up areas witnessed a decadal increase in spatial extent from 1986 to 2020. Whereas, vegetation land cover witnessed a decadal decline during these periods. The net-growth rate (%) for built-up areas and vegetation land cover between 1986 to 1996, 1996 to 2006 and 2016 to 2020 were +11.67, +5.04, +6.647, +0.06, and -14.1, -36.52, +25.81, -0.10 respectively. Meanwhile, the trend forecast predicted a decline in vegetation of 9510 hectares by the year 2030 if the current land use pattern continues unabated. The land consumption ratio (LCR) and land absorption coefficient (LAC) results were both positive, indicating a rise in the urban population correlating with larger consumption of new land areas over time.

KEYWORDS

Green space;
land consumption rate
and land absorption
coefficient;
land use and land cover;
supervised pixel-based
classification;
support vector machine

1. Introduction

Land has been modified and altered by humans since the beginning of time, either for agricultural purposes, construction of shelters, the building of dams, or the domestication of plants and animals. As the human population increased geometrically, there arose an increased need for modifications to accommodate these changes. These involved massive construction projects in the form of houses, roads, offices, hotels, schools, public utilities, and general infrastructure. Hence, small villages were transformed into large urbanized areas. In fact, in the year 2013, United Nations postulated that the proportion of people living in urban areas will increase from 50 percent in 2010 to nearly 70 percent by 2050. Schell and Ulijaszek (1999) opined that the world is increasingly transforming into an urban place, with some 65 percent of the world's population expected to be urban by the year 2025. This change in demographic distribution is caused by many factors and has many aftereffects, with major consequences being:

- i. the expansion of urban settlement or creation of newer ones
- ii. the increase in urban density

Invariably, this places stress on urban infrastructure such as road networks, transportation infrastructure. Most importantly, it threatens the survival of existing green space (Pafi et al. 2016).

Green space is of great significance. Notwithstanding the numerous meritorious advantages that accompany green space existence in cities such as sequestration of carbon emission, purification of air and water, regulation of micro-climate, soil conservation, protection of biodiversity and serves as recreational, cultural, and social values (Attwell 2000; Bolund and Hunhammar 1999; Costanza 1997; Feng et al. 2005; Jim 2001; Pauleit and Duhme 2000; Savard, Clergeau, and Mennechez 2000; Tarrant and Cordell 2002), available data reveal that these spaces are continuously declining across several cities of the world. More specific is the study on land-use change conducted across major European cities with the outcome showing that lands reserved for green spaces in over 25 major European cities have experienced significant loss (reduction) to other land uses, which accounted for nearly half a percent of land conversion (41 percent) (Mensah 2015). Similarly, studies carried out in the US on the same ground in 274 metropolitan areas revealed that about 1.4 million hectares of green spaces have been converted to different land developments (McDonald, Forman, and Kareiva 2010).

Coincidentally, the scenario is even more critical in developing countries, where existing study data show that urban green spaces in these cities have excessively been degraded and depleted to provide leeway for different human activities. Illustratively, Makworo and Mireri (2011), in their study of green spaces in different African cities, revealed a rather accelerating loss of green space with the wholesome effect being a disproportionately low coverage of green space in the geography of many African cities (in many instances less than 10% of the city land area). Other studies that focused on developing countries produced similar results with urban green space found to deplete in an accelerated manner (Gomes and Moretto 2011; Yusof 2012). Also, Fuwape and Onyekwelu (2011) asserted that rapid urbanization had caused many cities in West Africa to lose a significant amount of green space due to urban sprawl and infrastructure development. It has been established that the lack of vegetative covers in the urban areas make most African cities “environmentally unfriendly” with configurations that compromise their buoyancy to climate change (Mensah 2015).

Change detection (CD) in remote sensing aims to identify and map dissimilarity in bi-temporal and multi-temporal image datasets covering the same area. This practically is performed using low, medium, and high-resolution image datasets acquired from various earth observatory satellites sensors orbiting the earth (i.e., Landsat constellations, SPOT, and LISS). Besides, the advancement in earth observation science and technology, sensors with fine-grained resolutions have profoundly improved remote sensing applications via enriched image metadata (Chen et al. 2020; Pan, Zhang, and Zhang 2021; Ding et al. 2021a). However, compared to the low and high-resolution image, medium-resolution (30 m) image facilitates timely and efficient monitoring of large urban areas (Rokni et al. 2015; Ipadiola, et al. 2018; Ding et al. 2021b).

Conventionally, four classification approaches are frequently used in change detection studies; 1) supervised pixel-based CD, 2) unsupervised pixel-based CD, 3) supervised object-based CD, and 4) unsupervised object-based CD (Celik 2009; Li et al. 2021a; Li et al. 2021b; Hu et al. 2021a; Ding et al. 2021a). Although these classification methods are different- requiring basic input functions for machine learning to predict the outcome, they can be combined in a study for efficient analysis (Li et al. 2018). The pixel-based approach in CD relies on threshold segmentation and cluster analysis (Bovolo, Marchesi, and Bruzzone 2012). Here, the pixels are compared to corresponding bi-temporal and multi-temporal images-registering the spectral reflectances and then grouping them as either changed or unchanged classes (Bovolo, Marchesi, and Bruzzone 2012; Ding et al. 2021b). Impulse noises arising from disturbances in the image signal constitute a challenge in supervised pixel-based classification. In contrast, the object-based method relies on structural and geometric training. Whereby, clustering of neighboring pixels

generates information that reveals the statistical properties of features such as texture, size, shape, and orientation. Nevertheless, the ambiguity of object detachment, feature textural, and spectral refinement in high and medium-resolution images present new challenges to object-based CD.

In recent years, researchers have carried out studies using the supervised pixel-based method to map spatial expansion of built-up areas in Ilorin metropolis (Zubair 2006; Olaleye, Abiodun, and Asonibare 2012; Jibril and Liman 2014; Ipadiola, et al. 2018). Although, their studies did not establish the implications of the change trajectory on urban green space.

1.1. Aim and objectives

In this study, we conducted change detection with a focus on built-up areas and implications on greens pace in Ilorin. In the study, we 1) analyzed land use/land cover in Ilorin from 1986 to 2020, 2) conducted change detection analysis to ascertain the trend, nature, and rate of land use/and land cover change of the study area, and 3) determined the land consumption rate and land absorption coefficient for Ilorin.

2. Study area and materials

2.1. Study area

Ilorin, the capital of Kwara State in Nigeria has been considered one of the fastest-growing cities in Nigeria since it became the state capital in 1967. The city has grown from what can be described as a “foot city” with residential houses located around the Emir’s palace to an “auto-mobile city” (Ajadi et al. 2016). Ilorin is politically divided into three local Government areas, namely Ilorin West, Ilorin East, and Ilorin South Local Government Areas.

The geographical location of the study area covers the latitudes from 8°22’N to 8°33’59”N and longitudes from 4°28’E to 4°45’E, with a total area of about 278km² (Figure 1). The elevation of Ilorin measures 129m above the mean sea level (MSL). Geographically, it shares common boundaries with Asa, Moro, and Ifelodun Local Government Areas of Kwara State. The geology consists of a pre-Cambrian basement complex with an elevation of 273 m – 333 m in the West and 200 m –364 m in the East.

2.2. Materials

2.2.1. Data sources and types

Three different data sources were used, i.e., RS imagery, GIS layers, and population data (Table 1). The RS data were sourced from the U.S. Geological Survey (USGS) Earth Explorer website (2019) which includes Landsat 4-5 (MSS and T M), Landsat 7 (ET M), and Landsat 8 (OLI). The high-resolution Google Earth image dataset served as reference data for the accuracy assessment of image classification. The GIS layer was obtained from the Kwara State Ministry of Lands and Survey Bureau. The population data was extracted from the United Nations-World Population Prospects and verified against Nigerian census data obtained from the National Bureau of Statistics (NBS) (2011) remove the inconsistency.

2.2.2. Data preparation and processing

To map changes in Ilorin metropolis in an accurate manner, Landsat 4-5 (MSS and TM), Landsat 7 (ETM), and Landsat 8 (OLI) were preprocessed for data cleaning purposes, including image filtering (cloud and signal noise) and radiometric enhancement. The optical images were corrected and registered on the same reference system of Universal Transverse Mercator (UTM) zone 31 with the World Geodetic System 1984 (WGS 84) datum. Meanwhile, taking into account the existing conditions and resolution of the image datasets, the study area was classified into

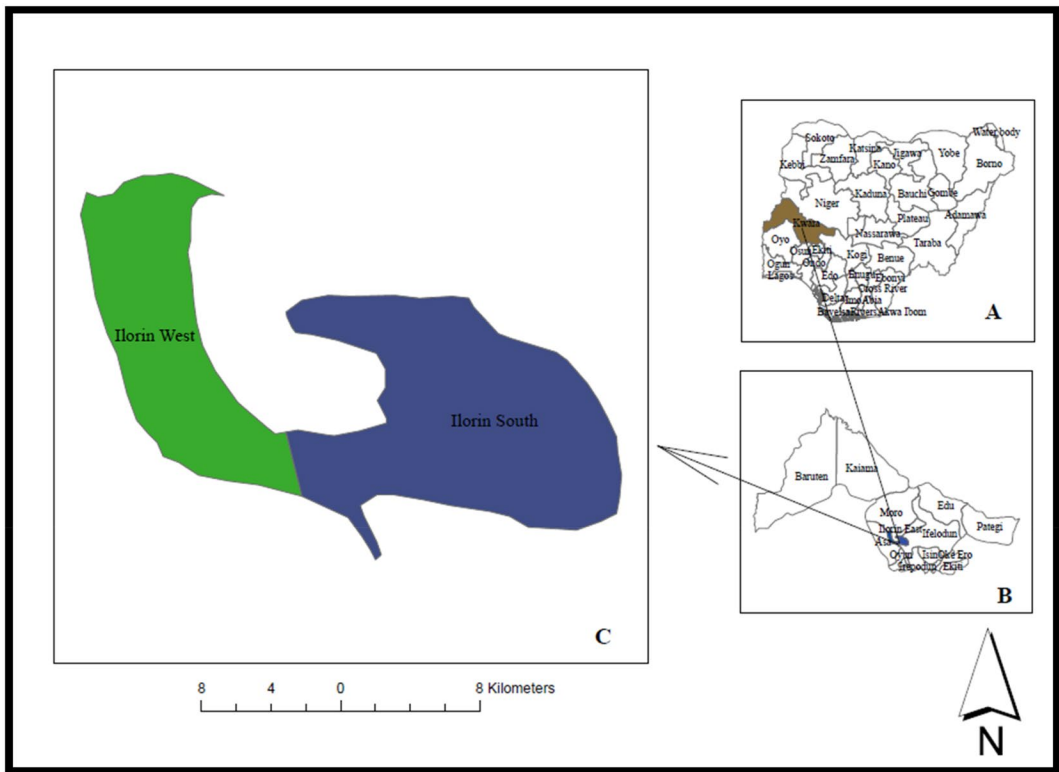


Figure 1. The geographical map of the study area (a) Map of Nigeria; (b) Map of Kwara State; (c) Study site.

Table 1. Data sources used in this study.

S/N	Data Type	Production Date	Resolution	Spectral Band	Source
1	Landsat 4-5	31-03-1986	30 m	5, 4, 1	USGS
2	Landsat 4-5	10-11-1996	30 m	5, 4, 1	
3	Landsat 7	13-11-2006	30 m	5, 4, 1	
4	Landsat 8	12-06-2016	30 m	5, 6, 4	Ministry of Land and Survey, Kwara State, Nigeria
5	Landsat 8	14-02-2020	30 m	5, 6, 4	
6	Study area boundary				
7	Population data				UN-World Population Prospects and NBS

four land use/land cover categories. Based on features spectral variability, size, shape, spatial distribution, and other metrics, a total of 48008 regions of interest (ROIs) were selected and used for support vector machine (SVM) training. This was synergized with the image classification scheme (level I) of Anderson et al. (1976), developed by the U.S. Geological Survey in 1976. We modified the scheme by reducing the categories into four main classes based on local conditions (Table 2).

3. Methodology

This study aims to map change detection in built-up areas and establish the implications on future green space development in the Ilorin metropolis. To meet this goal, we designed and followed a set analytical procedure listed below:

Table 2. Description of land use/land cover classification scheme.

S/N	Land use/cover categories	Description
1	Waterbody	River, permanent open water, lakes, ponds, canals, and reservoirs
2	Built-up area	All residential, commercial, and industrial areas, village settlement, and transportation infrastructure
3	Vegetation	Trees, shrubland and semi nature vegetation, deciduous, coniferous, and mixed forests, palms, orchids, herbs, gardens, and grasslands
4	Bare-soil	Fallow land, earth and sand land infillings, construction sites, excavation site, solid waste landfills, open space and exposed soil, rocky areas, dry grasses, etc.

- Deriving the yearly dynamics of land use/land cover and subsequently comparing the results;
- Implementing maximum likelihood classification;
- Performing accuracy assessment using a confusion matrix;
- Calculating land consumption rate and absorption coefficient;
- Conducting vegetation trend analysis.

First, the process for computing the land cover statistics for change detection and the annual rate of change estimation were mathematically derived by defining the state equation. To achieve this, we built a table that shows the class areas in hectares and the percentage change for years 1986, 1996, 2006, 2016, and 2020 measured against each land use/land cover type. The extent change is expressed as:

$$\Delta Ex = (\text{Observed change}) / (\text{Total sum of change}) \times 100 \quad (1)$$

To obtain the annual rate of change quotient, the percentage change was divided by 100 and multiplied by the number of years 1986–1996 (10 years), 1996–2006 (10 years), 2006–2016 (10 years), and 2016–2020 (4 years).

3.1. Land use/land cover classification

Pixel-based supervised image classification was adopted for the study. The maximum likelihood classifier (MLC) examines the probability statistics of the training classes using cluster analysis. MLC approach is mostly used in quantitative analysis of remotely sensed image data (Richards and Jia 2006) and the application of SVM to define the Region of Interest (AOI). The trained samples were sufficiently large to support SVM training. The principle of component transformation was applied synergistically with the Landsat Images, Google Earth, and Google Map Satellite-View (Figure 2). This operation was carried out sequentially as follows:

Defining of training sites: As summarized before, the first step undertaken in supervised classification is to define training areas (sites) for the SVM algorithm. This is normally achieved using digitized on-screen features. The training samples selected were drawn from those image pixels mapped.

Extraction of signatures: After digitizing the training sites, statistical characters were created, called signatures (this process was completed in ArcMap 10.3). We created a signature (SIG) file for every period, which contains a variety of information on the land cover classes described. Further, we exported them to ENVI for the second SVM training to check the consistency in the model output, followed by the accuracy assessment.

Classification of image (maximum likelihood): The maximum likelihood classifier (MLC) in ArcMap 10.3 and ENVI were compared for consistency. The maximum likelihood classification window set to achieve better results was fed large training samples to calculate the probability statistics following the discriminant functional equation from Richards (1999) (Equation 2):

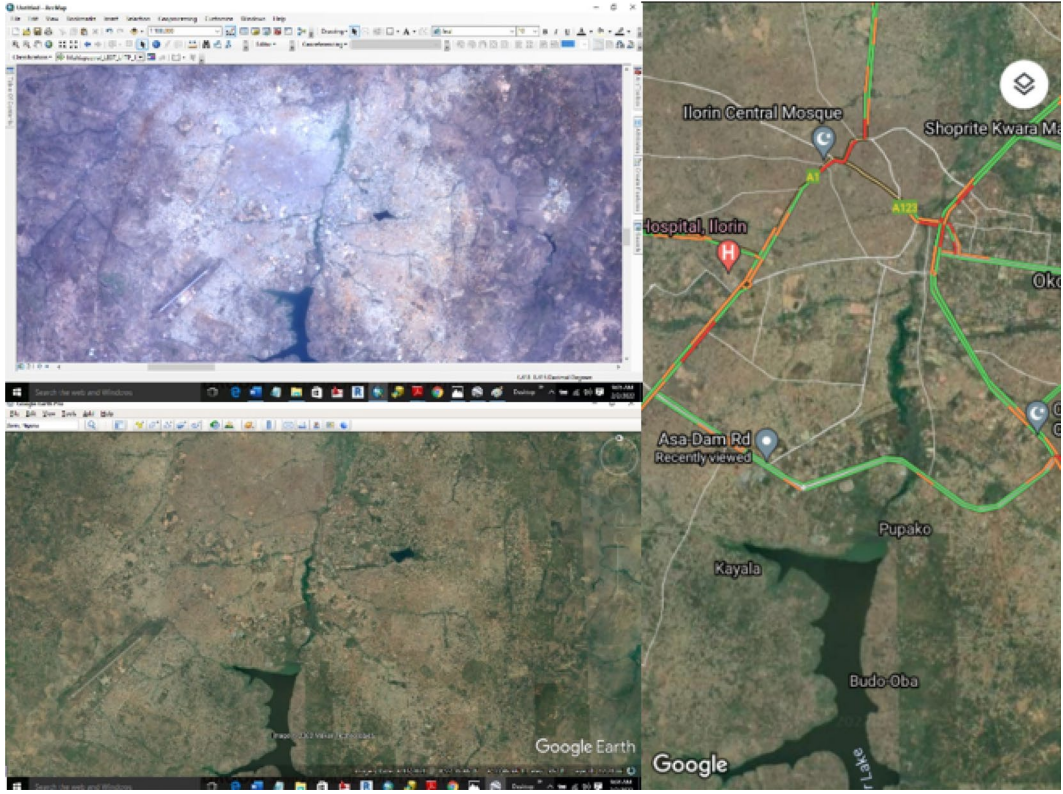


Figure 2. Identification of training sites using Landsat image, Google Earth, and Google Map.

$$g_i[x] = \ln P(\omega_i) - \frac{1}{2} \ln |\Sigma_i| - \frac{1}{2} (x - m_i)^T \Sigma_i^{-1} (x - m_i) \quad (2)$$

Where i denotes the class, x denotes the n -dimensional data (n is the number of bands), $P(\omega_i)$ denotes the probability that class ω_i occurs in the image and assumed the same for all classes, $|\Sigma_i|$ denotes the determinant of the covariance matrix of the data in class, Σ_i^{-1} denotes inverse matrix, and, m_i denotes mean vector.

3.1.1. Accuracy assessment

Remote sensing is widely used to generate land cover/land use maps. However, the uncertainties need to be quantified and reported (Sari et al. 2021). The popular evaluation method is to use a confusion matrix (i.e., error matrix). The thematic accuracy of a classification or change model is usually evaluated by computing the prediction efficiency for withheld or newly accumulated training data (Edwards, Moisen, and Cutler 1998; Foody 2002; Congalton and Green 2008). Therefore, in a simple classifier, observed locations can be mapped as: (1) truly changed, (2) falsely not changed, (3) falsely changed, and (4) truly not changed (Figure 3).

The diagonal elements represent the correctly classified observation, and the non-zero, off-diagonal counts represent the two classifier errors (i.e., commission and omission errors). The location labeled as falsely changed are the commission errors, while the falsely not changed are the omission errors. The task of the classifier is to minimize these errors (Hastie, Tibshirani, and Friedman 2009).

When a classifier correctly classifies a high percentage of observed changes, it is regarded as a model with high sensitivity (i.e., liberal classifier) (Fawcett 2006). When a classifier correctly

		Actual changed Status	
		Changed	No Changed
Modeled changed Status	Changed	Truly changed	Falsely Not changed
	No Changed	Falsely changed	Truly Not changed

Figure 3. Land use/land cover confusion matrix.

classifies high percentages of changes in non-changing observations, it is known to have a high specificity. Having noted that high sensitivity usually is accompanied by commission error (Type I error), while high specificity is accompanied more by omission errors (Type II error) (Pierce 2015). However, a compromise must be reached for optimizing between sensitivity and specificity in a classifier (Pierce 2015). This is achieved by changing the minimum accepted threshold used in labeling the analytical unit in a known class. Generally, the simple equations for the errors are expressed as:

$$E_{rr} = \frac{Fp + FN}{P + N} \quad (3)$$

$$s_N = \frac{TP}{TP + FN} \quad (4)$$

$$s_p = \frac{TN}{TN + FN} \quad (5)$$

where E_{rr} , s_N , s_p denote the error matrix, sensitivity error, and specificity error respectively. TP, TN, FP, FN denote the true positive, true negative, false positive, and false negative respectively.

The pixels of accuracy assessment cover areas that could be identified both on the Landsat medium-resolution image and fine-grained high-resolution Google Earth. The cell was computed according to the best guess using the reference points, where Google Earth and Google Map served as reference sources. The producer (PA) and user (UA) accuracies for built-up areas are 99.95% and 100%, respectively. The Kappa statistics test measures the extent of accuracy in the classification since it does not only take cognizance for diagonal elements but for all the elements within the confusion matrix (Rosenfield and Fitzpatrick-Lins 1986; Teshager and Abeje 2021). The Kappa rating is shown in Table 3.

Table 3. Kappa rating and its interpretation.

Kappa	Interpretation
0	No agreement
0.10–0.20	Slight agreement
0.21–0.40	Fair agreement
0.41–0.60	Moderate agreement
0.61–0.80	Substantial agreement
0.81–0.99	Near-perfect agreement
1	Perfect agreement

The Kappa coefficient rating in Table 2 shows the level of agreement in an inter-rater assessment, where the coefficient must fall between 0 and 1, where the value of 0 indicates the absence of any agreement between the raters evaluated, while the value of 1 indicates a perfect agreement between raters.

3.2. Land consumption ratio (LCR) and land absorption coefficient (Lac)

Both land consumption ratio (LCR) and land absorption coefficient (LAC) are quantitative measures of change dynamics in the urban population. LCR measures the progressive urbanization of a place while the LAC measures urban change given a unit increase in population (Yeates and Garner 1976). LCR metric index accounts for the compactness and texturization in the built-up feature class achieved from the SVM training algorithm. LCR and LAC can be calculated as:

$$\text{Land Consumption Ratio (LCR)} = \frac{A}{P} \quad (6)$$

where A denotes the area extent of the city in hectares and P denotes the population.

LAC index measures the consumption rate of new urban land—a function of unit increment in the population. Mathematically, LAC is a derivative function, where an increment (∂) in population affects urban land, supposing the conditions $y_{(urb)} = f(x_{La})$. The equation is expressed as:

$$\text{Land absorption coefficient (LAC)} = \frac{A2 - A1}{P2 - P1} \quad (7)$$

where $A1$ and $A2$ are the areal extents (in hectares) for the early and later years, respectively; $P1$ and $P2$ are the populations' counts for the early and later years, respectively

4. Results

4.1. Land-use changing dynamics

The classified four different land cover types in the years 1986, 1996, 2006, 2016, and 2020 are presented in Table 4. From the classified image of 1986, vegetation land cover recorded the highest: a spatial extent of 23090 hectares (83.08 percent). In 1986, Ilorin had fewer settlements, and those were largely agrarian. Whereas built-up areas covered a spatial extent of 3850 hectares (13.85 percent). This is very much connected to the earlier reasons that Ilorin at this time was largely an agrarian society. Waterbody covered 240 hectares (0.86 percent), and bare-soil covered 610 hectares (2.19 percent) (Figure 4A).

Table 4. Land use/land cover change matrix.

S/N	Land use/ cover category	1986		1996		2006		2016		2020	
		Area (Ha)	Area (%)	Area (Ha)	Area (%)	Area (Ha)	Area (%)	Area (Ha)	Area (%)	Area (Ha)	Area (%)
1	Water	240	0.86	243.09	0.87	359.28	1.29	270.18	0.97	219.06	0.79
2	Built Up	3850	13.85	7092.9	25.52	8495.11	30.56	10292.94	37.03	11843.28	42.61
3	Bare-soil	610	2.19	1287	4.63	9918.15	35.68	1035.27	3.72	2413.26	8.68
4	Vegetation	23090	83.08	19171.08	68.98	9021.18	32.46	16195.68	58.27	13318.47	47.92
TOTAL		27790	100	27794.07	100	27794.07	100	27794.07	100	27794.07	100

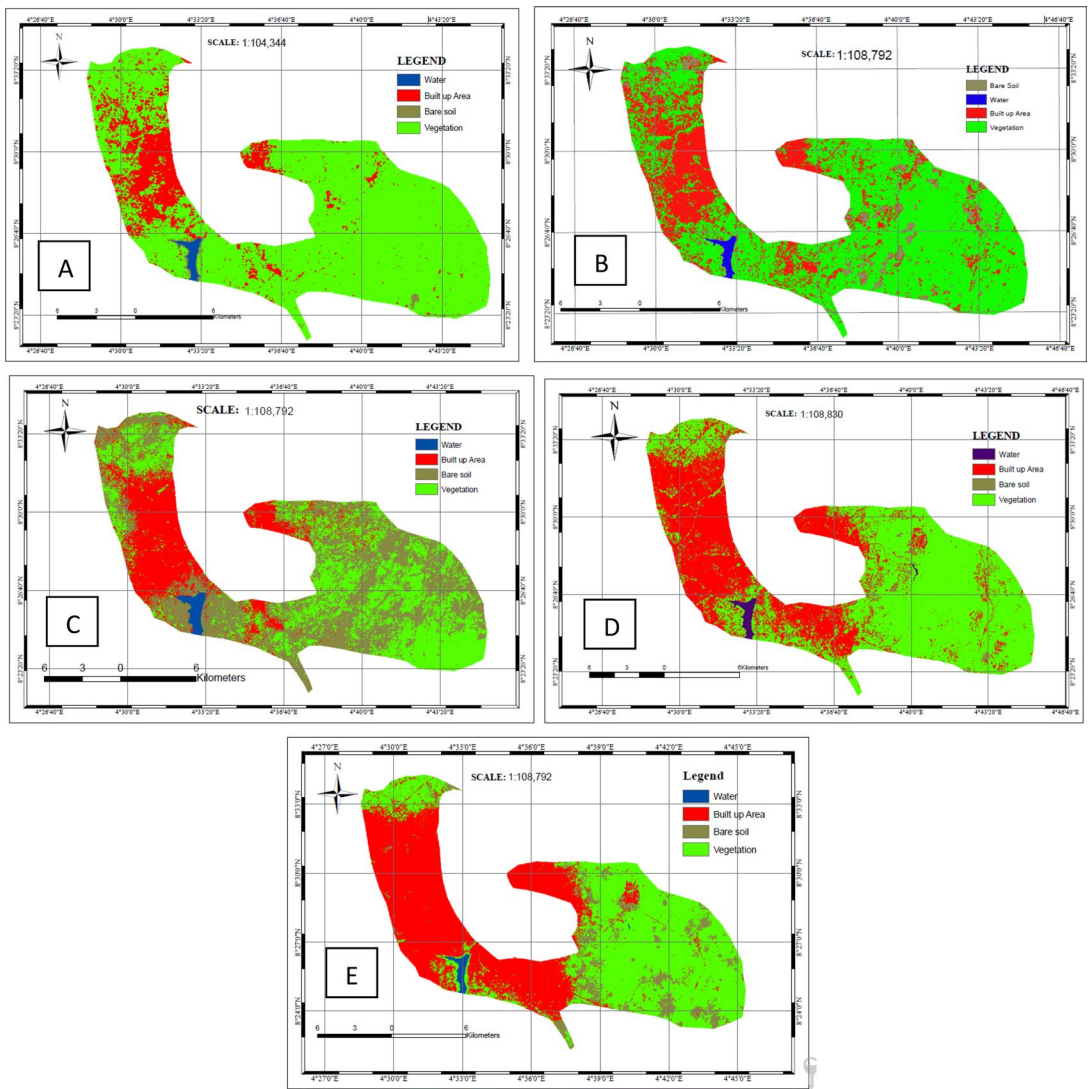


Figure 4. Classified images- 4A) 1986 land cover map; 4B) 1996 land cover map; 4C) 2006 land cover map; 4D) 2016 land cover map; 4E) 2020 land cover map.

In addition, the built-up areas increased in spatial extent while vegetation land cover declined in 1996. The built-up areas increased to 7092.9 hectares (25.52 percent), while vegetation land cover declined to 19171.08 hectares (68.98 percent) (Figure 4B). This is due to the growing commercial activities taking shape in the city, such as the implementation of the Rolling Plan by the Nigerian government and several other projects. Moreover, other land covers witnessed

notable changes too. Waterbody increased to 243.09 hectares (0.87 percent) and Bare-soil increased to 1287 hectares (4.63 percent).

In 2006, a shift in the pattern was observed among the land use categories: bare-soil cover increased to 9918.15 hectares (35.68 percent) away from 1287 hectares in 1996 (Figure 4C). Meanwhile, vegetation land cover declined to 9021.18 hectares (32.46 percent). Other land use covers like waterbody increased in the spatial extent to 359.28 hectares (1.29 percent). The built-up areas also increased in spatial extent to 8495.11 hectares (30.56 percent).

In 2016, both built-up area and vegetation land cover witnessed a sharp increase. Though, vegetation recorded a higher increase value. It increased to 16195.68 hectares (58.27 percent). The built-up areas increased in the spatial extent to 10292.94 hectares (37.03 percent). This is connected to the teak plantation in the University of Ilorin and the general presence of vegetation in the city's south area. However, it is different from the city's western area with high urbanization. Further, the increase in vegetation land cover is directly connected to the time of imaging by the sensor. The image was captured in June, during the rainy season (period of intense precipitation) in Nigeria, when most of the unoccupied bare lands regained their natural green cover (Figure 4D).

In 2020 (Figure 4E), vegetation land cover continued to decline in the spatial extent to the built-up areas. It declined to 13318.47 hectares (47.92 percent). Contrastingly, the built-up areas- a major land-use competitor, increased in the spatial extent to 11843.28 hectares (42.61 percent). Although, bare-soil mostly accounted for the gains in the built areas. Bare-soil decreased to 2413.26 (8.68 percent). Waterbody also declined in the spatial extent to 219.06 hectares (0.79 percent).

4.2. Annual rate of change (ARC) matrix

The annual rate of change (ARC) suggests the net change statistics of the land cover classes (Table 5). Our results suggest that vegetation land cover steadily declined in 1986, 1996, 2006, with a break in 2020. The reason is not far-fetched from the several development projects undertaken by the Nigerian government between 1988 to 1990, 1991 to 1992, and 1993 to 1996 (i.e., the Rolling Plan).

In this study, we focused on built-up areas and vegetation land cover. Nevertheless, other land cover classes are worth mentioning. Vegetation land cover declined by -3918.9 hectares to -10149.9 hectares between 1996 and 2006. Built-up areas and bare-soil experienced a significant increase in their ARC by 1402.21 and 8631.15 hectares, respectively. Bare-soil changed more significantly than built-up areas, largely because of project abandonment, logging of trees for commercial purposes, and civil engineering construction works which exposed the topsoils to intense solar radiation.

In the following decade, vegetation land cover witnessed a differential increase between 2006 and 2016. Vegetation land cover recorded an increase of 7174.5 hectares, possibly due to the imaging time. The image in 2016 was captured during the rainy season, and it is believed that unoccupied bare lands regained substantial green cover. In addition, the deliberate policy for the teak plantation within the University of Ilorin campus is another reason for the vegetation land cover increase.

The trend continues with vegetation land cover further declining by -2877.21 between 2016 and 2020, calling for action to mitigate the trend with a focus on the city's western area. The ARC exposes the inefficiencies and absence of urban planning measures to control unrestrained development in the city. The built-up areas increased by 1550.34 hectares. If this urbanization pattern continues without careful planning, many problems can emerge, including traffic congestions, environmental disturbances (e.g., flooding and heat island effect), housing (e.g., blighted homes and urban decay), and waste management (e.g., indiscriminate solid waste disposal, large generation of solid and liquid wastes).

The producer accuracy (PA) and user accuracy (UA) for the built-up area are 99.95% and 100%, respectively. Table 6 displays the land cover change confusion matrix for the combined

Table 5. Land use change: annual rate of change.

Land use categories	1986–1996			1996–2006			2006–2016			2016–2020			Annual rate of change		
	Area (Ha)	%Δ	Area (Ha)	Area (Ha)	%Δ	Area (Ha)	Area (Ha)	%Δ	Area (Ha)	Area (Ha)	%Δ	Area (Ha)	1986/1996	1996/2006	2016/2020
Waterbody	309	0.01	116.19	0.42	–89.1	–0.32	–51.12	–0.00	0.309	11.619	–0.00	–8.91			–12.79
Built-up Area	3242.9	11.67	1402.21	5.04	1797.83	6.47	1550.34	0.06	324.29	140.221	0.06	179.783			387.58
Bare-soil	677	0.44	8631.15	31.05	–8882.88	–31.96	1377.99	0.05	67.7	863.115	0.05	–888.288			344.50
Vegetation	–3918.92	–14.1	–10149.9	–36.52	7174.5	25.81	–2877.21	–0.10	–391.89	–1014.99	–0.10	717.45			–719.30

Table 6. Land use/land cover confusion matrix.

Classified	Waterbody	Built-up	Bare soil	Vegetation	Total	Correct sample
Water body	12371	7	7	3	12388	12371
Built-up	0	15321	0	0	15321	15321
Bare soil	0	0	9388	12	9400	9388
Vegetation	28	0	0	10871	10899	10871
Total	12399	15328	9395	10886	48008	47951

*Note: Accuracy of land use/land cover classification;
Overall user accuracy: 99.8696;
Overall producer accuracy: 99.8791;
Kappa: 0.9984;
Overall accuracy: 99.8813.

Table 7. Population changes of Ilorin in years 1986, 1996, 2006, 2016, and 2020.

Year	Population	Growth rate (%)	
1986	468000	1986–1996	24.79
1996	584000	1996–2006	22.26
2006	714000	2006–2016	22.27
2016	873000	2016–2020	8.82
2020	950000		

Note *United Nations- World population prospects.

Website: www.macrotrends.net/cities/21998/ilorin/population

Table 8. Juxtaposing built-up area and vegetation from 1986 to 2020.

Land use/land cover	1986		1996		2006		2016		2020	
	Ha	(%)	Ha	(%)	Ha	(%)	Ha	(%)	Ha	(%)
Built-up	3850	13.85	7092.9	25.52	8495.11	30.56	10292.94	37.03	11843.28	42.61
Vegetation	23090	83.08	19171.08	68.98	9021.18	32.46	16195.68	58.27	13318.47	47.92

Table 9. Land consumption rate and land absorption coefficient.

Year	LCR	Year	LAC
1986	0.0082	1986–1996	0.0280
1996	0.0121	1996–2006	0.0108
2006	0.0119	2006–2016	0.0113
2016	0.0118	2016–2020	0.0201
2020	0.0125		

1986, 1996, 2006, 2016, and 2020. The column axes of the confusion matrix contain the classes of pixels in the validation set (ground-truth), and the row axes show the classes that the pixels have been assigned to. The diagonals show the pixels classified correctly by the classifier. The overall accuracy (OA) for the classification is 99.88 percent, the overall producer accuracy (OPA) is 99.88 percent, the overall user accuracy (OUA) is 99.87 percent, and the Kappa coefficient is 0.998.

4.3. LRC and LAC computation

The population statistics of the study area are presented in Table 7. In 1986, the population of Ilorin was 468000, and this number increased steadily on a decadal basis to 584000, 714000, 873000, and 950000 for 1996, 2006, 2016, and 2020 respectively. The growth rate between 1986–1996 was 24.79 percent, while it was 22.26 percent between 1996–2006. Between 2006–2016 and 2016–2020, the growth rates were 22.27 percent and 8.82 percent, respectively.

Since our study focuses on two land covers, i.e., built-up area and vegetation, we juxtaposed these two land cover classes for comparison (Table 8). The results suggest that the built-up areas occupied about 3850 hectares in 1986 and this number increased steadily to 11843.28 hectares in 2020. Studies have shown that built-up areas increases in spatial extent due to induced migration (push and pull factors) and rising birthrate, especially in the developing world (Ipadiola, et al. 2018; Naikoo et al. 2020; Xie et al. 2020).

The LCR and LAC are summarized in Table 9. The LCR measures the spatially progressive change due to urbanization. The LCR in 1986 was low, compared to the progressive years (0.0082). However, from 1996 to 2020, i.e., years 1996, 2006, 2016, and 2020, the LCR were 0.0121, 0.0119, 0.0118, and 0.0125, respectively. We assume that this urban expansion is attributed to the rise in developmental projects and economic development (Sharma, Pandey, and Nathawat 2012). The LAC measures the rate of consumption of new urban land. The result revealed the fact that urgent actions are needed. Between the LAC between 1986–1996 was 0.0280, and the

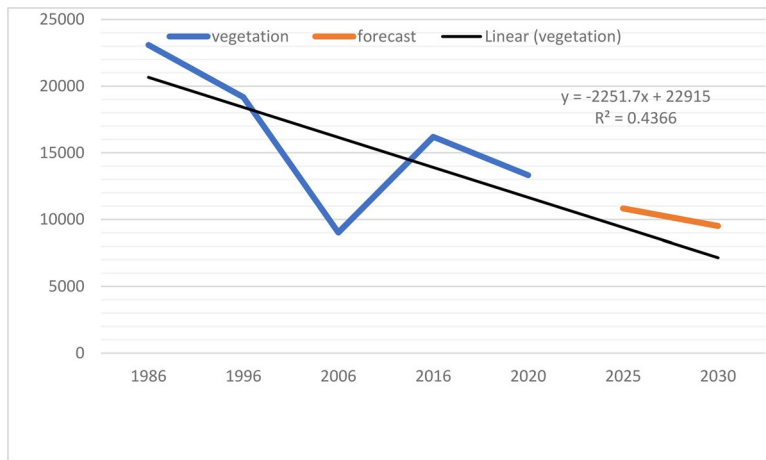


Figure 5. Trend analysis and forecast for 2030.

LAC between 1996–2006 was slowed by 0.0108. However, between 2006–2016 and 2016–2020, LAC increased marginally by 0.0113 and 0.0201, respectively. These importance indicators provide important references for future urban green space and city infrastructure planning in Ilorin.

4.4. Vegetation trend analysis

Figure 5 shows the dynamics of vegetation land cover from 1986 to 2020. We noticed that 2006 saw the highest vegetation land cover decline. In 2016, vegetation coverage increased in a significant manner, followed by a decrease in 2020. The trend line for vegetation is expressed as a linear regression function as $Y = -2251.7x + 22915$, $R^2 = 0.4366$ (coefficient of determination). The -2251.7 value indicates a continuous decline in vegetation land cover throughout the periods of 1986 to 2020. Further, the 43.66 percent coefficient of determination explains the threshold variance.

The trend analysis was also used to forecast vegetation land cover change for a period of 10 years (2020–2030). The result is still presented in Figure 5. The result for 2025 revealed a continuous decline in vegetation land cover by 10829.62 hectares. The trend line traces the scattered plots and the result for 2030 predicts a further future decline in this land cover class by 9510.345 hectares. Given this result, drastic measures must be taken by the authorities to curb the menace. Legislation should be passed to establish and conserve a certain number of green fields such as arboretum, nature reserves, and sanctuaries.

4. Discussion

4.1. Classification performance

The performance of the SVM-based land cover classification achieved satisfactory accuracy. The medium-resolution Landsat images offered better results for the change detection analysis- periods between 1986 to 2020. Meanwhile, this was possible via image validation testing, comparing the predicted outcome with known reference data from fine-grained high-resolution Google Earth images (Li et al. 2018; Hu et al. 2021b; Ding et al. 2021a; Ding et al. 2021b) (OUA = 99.86 percent while OPA= 99.88 percent). Our results demonstrated that the well-trained SVM classifier performed greatly in classifying land cover, successfully avoiding overestimation. Nevertheless, randomly selected training data were fed to the SVM algorithm, possibly leading to data overfitting (Hu et al. 2021a). In our study, built-up areas recorded the highest PA and OA (99.95 percent and 100 percent, respectively).

Importantly, monitoring and mapping changes in built-up class can be difficult due to the multiplex distribution of geographical land cover features and their spatial mixed-matrix (Ding et al. 2021a). There are many instances of different features with similar spectral reflectance and the same features with different spectral reflectance. This, therefore, brings about validation testing assessment using a high-resolution Google Earth image to support the SVM training and to increase prediction accuracy. However, there exist other techniques to improve the classification results, including fusing multifold RS datasets with SAR and developing deeply supervised-guided SVM models (Ding et al. 2021a; Ding et al. 2021b; Hu et al. 2021b).

Our study suggested that the LCR and LAC for the study were both positive. This is indicative of progressive expansion in the built-up areas, leading to compactness and densification. The LCR was lowest in 1986 (0.0082), followed by 2016 (0.0118), and 2006 (0.0119). It was highest in 2020 (0.0125), followed by 1996 (0.0121). Meanwhile, we observed a slowing down in population growth in 2006 and 2016. This demonstrated the possibility of obtaining a negative LCR if we continue to observe the situation. For that reason, LCR can be negative where the urban population experiences negative growth (Cal 2020). The LAC is often under-reported in change detection studies of built-up areas, partly because LCR is a better explainer of urban change (Babu, Padma, and Suneetha 2014; Fenta et al. 2017; Hu et al. 2021a; Hu et al. 2021b). LAC measures unit change by comparing two intervening periods. In our study, the periods between 1986 to 1996 and 2016 to 2020 saw a high LAC (0.0280 and 0.0201).

5.2. Implications for green space conservation

The study demonstrated the manner built-up areas propelled over the years in Ilorin, owing to the population growth, land consumption rate, and absorption patterns. This phenomenal growth in built-up areas implies a steady loss in green space. Operationally, greenspace in this context loosely means the natural and man-made vegetation land cover (Akmar et al. 2011; Almanza et al. 2012; White et al. 2013; Taylor and Hochuli 2017). These may include green parks (neighborhood, district, and regional), gardens, forest areas, riparian greens, coastal promenades, green streetscapes, to list a few. Interestingly, built-up land class is considered a dominant competitor for land use as observed in our study, and it is continuously on the rise spatially. The results from the net-growth change in built-up class between 1986 to 2020 increased by 13.855, 25.52, 30.56, 37.03, and 42.61 percent, respectively. The drastic increase in the built-up areas is believed to be responsible for green space, as evidenced by various studies (Zhou and Wang 2011; Byomkesh, Nakagoshi, and Dewan 2012; Naikoo et al. 2020; Puplampu and Bofo 2021).

Green space has benefits linked to human health, the social, and the economic (Willis and Crabtree 2011; Zoest and Hopman 2014; Cole et al. 2019). Our study suggests that green space witnessed a decadal decline except for 2016, presumably due to imaging time during the wet season when most unoccupied bare soil changed back to green. Additionally, rainfall pattern in Nigeria continues to show greater variation in different parts of the country due to climate change. The Nigerian Meteorological Agency (NiMet) reported that Akwa-Ibom State recorded the highest precipitation in 2015. Consequently, this change in rainfall pattern has a significant impact on green space survival in the Ilorin metropolis. Although built-up areas will continue to expand over time, more attention should be paid to vegetation distribution. The idea of vertical city growth (Al-Kodmany 2018) can be implemented to allocate more spaces for agriculture, parks, arboretum, promenades, forest, and other types of green spaces. Although there is clear evidence that growth in built-up areas is not slowing down, attention must be shifted to the sustainability of such growth. Besides, migration and increased birthrate are the two main drivers of urbanization in Sub-Saharan Africa. The growth of the urban population contributes to the spatial expansion in built-up areas observed in the study. Green space monitoring can be achieved by calculating the Normalized Difference in Vegetation Index (NDVI), as NDVI is

able to reveal the health of green land cover (Beck et al. 2006; Martinez and Gilabert 2009; Zewdie, Csaplovics, and Inostroza 2017). Our future study is to incorporate NDVI in our analytical workflow.

5. Conclusion

This study investigated changes in built-up areas in Ilorin and the implications on green space conservation using Landsat images acquired for different years (1986–2020). The acquired images were processed and analyzed in a GIS environment and ENVI. Accuracy assessment was performed on the images to compare ground-truth data using a confusion matrix. We performed spatio-temporal analysis of land use/land cover change, trend analysis, land consumption ratio, and land absorption coefficient. The results of the land use/land cover change demonstrated that built-up areas witnessed a steady increase, an increase of 13.85 percent in 1986 to 42.61 percent in 2020, demonstrating the rapid urbanization of Ilorin during the investigated 34 years (from a small agrarian settlement into a large urbanized city). These changes in built-up areas implied a concurrent decline in green space. In 1986, vegetation land cover accounted for 83.08 percent of land area but steadily declined to 47.92 percent by 2020. Finally, the trend analysis demonstrated that green space experienced a clear downward trend from 1986 to 2020. We predicted that green space is likely to lose 9510.345 hectares by 2030 if actions are not taken to control urbanization. Indeed, this study has shown that geospatial techniques offer the best method in change detection of built-up areas and vegetation land cover.

Disclosure statement

The authors report there is no competing interest to declare.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

References

- Ajadi, B. S., M. A. Adaramola, A. Adeniyi, and M. I. Abubakar. 2016. Effect of effluents discharges on Public Health in Ilorin Metropolis. *Ethiopian Journal of Environmental Studies and Management* 9 (4):389–404. doi: 10.4314/ejesm.v9i4.1.
- Akmar, A. A., C. C. Konijnendijk, M. Sreetheran, and K. Nilsson. 2011. Greenspace planning and management in Klang Valley, Peninsular Malaysia. *Arboriculture & Urban Forestry* 37 (3):99–107. doi: 10.48044/jauf.2011.014.
- Al-Kodmany, K. 2018. *The vertical city: A sustainable development model*. Ashurst, England: WIT Press.
- Almanza, E., M. Jerrett, G. Dunton, E. Seto, and M. A. Pentz. 2012. A study of community design, greenness, and physical activity in children using satellite, GPS and accelerometer data. *Health & Place* 18 (1):46–54. doi: 10.1016/j.healthplace.2011.09.003.
- Anderson, J. R., E. E. Hardy, J. T. Roach, and R. E. Witmer. 1976. *A Land use and land cover classification system for use with remote sensor data*. Washington, DC: U. S. Geological Survey Professional Paper 964. Government Printing Office.
- Attwell, K. 2000. Urban land resource and urban planting—case studies from Denmark. *Landscape and Urban Planning* 52 (2–3):145–63. doi: 10.1016/S0169-2046(00)00129-8.
- Babu, T., V. Padma, and P. Suneetha. 2014. Impact of urban sprawl and land use pattern in and around Vizianagaram City, using remote sensing and GIS. *American Journal of Sustainable Cities and Society* 3 (1):728–741.
- Beck, P. S., C. Atzberger, K. A. Hogda, B. Johansen, and A. K. Skidmore. 2006. Improved monitoring of vegetation dynamics at very high latitudes: A new method using MODIS NDVI. *Remote Sensing of Environment* 100 (3):728–741. doi: 10.1016/j.rse.2005.10.021.
- Bolund, P., and S. Hunhammar. 1999. Ecosystem services in urban areas. *Ecological Economics* 29 (2):293–301. doi: 10.1016/S0921-8009(99)00013-0.

- Bovolo, F., S. Marchesi, and L. Bruzzone. 2012. A framework for automatic and unsupervised detection of multiple changes in multitemporal images. *IEEE Transactions on Geoscience and Remote Sensing* 50 (6):2196–212. doi: [10.1109/TGRS.2011.2171493](https://doi.org/10.1109/TGRS.2011.2171493).
- Byomkesh, T., N. Nakagoshi, and A. M. Dewan. 2012. Urbanization and green space dynamics in Greater Dhaka, Bangladesh. *Landscape and Ecological Engineering* 8 (1):45–58. doi: [10.1007/s11355-010-0147-7](https://doi.org/10.1007/s11355-010-0147-7).
- Cal, G. 2020. Identification of urban land use efficiency by indicator- SDG 11.3.1. *PLoS One* 15 (12).
- Celik, T. 2009. Unsupervised change detection in satellite images using principal component analysis and k-means clustering. *IEEE Journal of Geoscience and Remote Sensing Letters* 6 (4):772–6.
- Chen, H., C. Wu, B. Du, L. Zhang, and L. Wang. 2020. Change detection in multisource VHR images via deep siamese convolutional multiple-layers recurrent neural network. *IEEE Transactions on Geoscience and Remote Sensing* 58 (4):2848–64. doi: [10.1109/TGRS.2019.2956756](https://doi.org/10.1109/TGRS.2019.2956756).
- Cole, H. V., M. Triguero-Mas, J. J. Connolly, and I. Anguelovski. 2019. Determining the health benefits of green space: Does gentrification matter? *Health & Place* 57:1–11. volumedoi: [10.1016/j.healthplace.2019.02.001](https://doi.org/10.1016/j.healthplace.2019.02.001).
- Congalton, R. G., and K. Green. 2008. *Assessing the accuracy of remotely sensed data: principles and practices*. 2nd ed., Mapping Science ed. Boca Raton, FL: CRC Press.
- Costanza, R. 1997. The value of the world's ecosystem services and natural capital. *Nature* 387 (15):253–60.
- Ding, Q., Z. Shao, X. Huang, and O. Altan. 2021b. DSA-Net: A novel deeply supervised attention-guided network for building change detection in high-resolution remote sensing images. *International Journal of Applied Earth Observations and Geoinformation* 105.
- Ding, Q., Z. Shao, X. Huang, O. Altan, and Y. Fan. 2021a. Improving urban land cover mapping with fusion of optical SAR data based on feature selection strategy. *Photogrammetric Engineering & Remote Sensing* 88 (1):17–28. doi: [10.14358/PERS.21-00030R2](https://doi.org/10.14358/PERS.21-00030R2).
- Edwards, T., G. Moisen, and D. Cutler. 1998. Assessing map accuracy in a remotely sensed, ecoregion-scale cover map. *Remote Sensing of Environment* 63 (1):73–83. doi: [10.1016/S0034-4257\(96\)00246-5](https://doi.org/10.1016/S0034-4257(96)00246-5).
- Fawcett, T. 2006. An introduction to ROC analysis. *Pattern Recognition Letters* 27 (8):861–74. doi: [10.1016/j.patrec.2005.10.010](https://doi.org/10.1016/j.patrec.2005.10.010).
- Feng, L., W. Rusong, P. Juergen, and L. Xusheng. 2005. Comprehensive concept planning of urban greening based on ecological principles: A case study in Beijing, China. *Landscape and Urban Planning* 72:325–36.
- Fenta, A. A., H. Yasuda, N. Haregeweyn, A. S. Belay, Z. Hadush, M. A. Gebremedhin, and G. Mekonnen. 2017. The dynamics of urban expansion and land use/land cover changes using remote sensing, spatial metrics: The case of Mekelle City of northern Ethiopia. *International Journal of Remote Sensing* 38 (14):4107–29. doi: [10.1080/01431161.2017.1317936](https://doi.org/10.1080/01431161.2017.1317936).
- Foody, G. M. 2002. Status of land cover classification accuracy assessment. *Remote Sensing of Environment* 80 (1):185–201. doi: [10.1016/S0034-4257\(01\)00295-4](https://doi.org/10.1016/S0034-4257(01)00295-4).
- Fuwape, J. P., and J. C. Onyekwelu. 2011. Urban forest development in West Africa: benefits and challenges. *Journal of Biodiversity and Ecological Sciences* 1 (1):78–94.
- Gomes, C. S., and E. M. Moretto. 2011. A framework of indicators to support urban green area planning: A Brazilian case study. *Proceedings of the International Academy of Ecology and Environmental Sciences* 1 (1):47–56.
- Hastie, T., R. Tibshirani, and J. Friedman. 2009. *The elements of statistical learning: Data mining, inference, and prediction*. 2nd ed., Springer Series in Statistics ed. New York, NY: Springer.
- Hu, J., Y. Wang, H. Taubenbock, and X. X. Zhu. 2021b. Land consumption in cities: A comparative study across the globe. *Cities* 113:103163. doi: [10.1016/j.cities.2021.103163](https://doi.org/10.1016/j.cities.2021.103163).
- Hu, B., Y. Xu, X. Huang, Q. Cheng, Q. Ding, L. Bai, and Y. Li. 2021a. Improving urban land cover classification with combined use of Sentinel-2 and Sentinel-1 data. *ISPRS International Journal of Geo-Information* 10 (8):533. doi: [10.3390/ijgi10080533](https://doi.org/10.3390/ijgi10080533).
- Ipadiola, A. O., et al. 2018. Geospatial analysis of the land use and land cover changes of Ilorin Metropolis between 2000 and 2017 using remote sensing and GIS techniques. *Journal of Geomatics and Environmental Research* 1 (1):15–28.
- Jibril, M. S., and H. M. Liman. 2014. Land use and land cover change detection in Ilorin, Nigeria, using satellite remote sensing. *Journal of Natural Science Research* 4 (8):123–129.
- Jim, C. Y. 2001. Managing urban trees and their soil envelopes in a contiguously developed city environment. *Environmental Management* 28 (6):819–32. doi: [10.1007/s002670010264](https://doi.org/10.1007/s002670010264).
- Li, M., L. Hong, J. Guo, and A. Zhu. 2021b. Automated extraction of lake water bodies in complex geographical environments by fusing sentinel-1/2 data. *Water* 14 (1):30. doi: [10.3390/w14010030](https://doi.org/10.3390/w14010030).
- Li, C., Z. Shao, L. Zhang, X. Huang, and M. Zhang. 2021a. A comparative analysis of index-based methods for impervious surface extraction using multi-seasonal Sentinel-2 Satellite data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 14:3682–94. volumedoi: [10.1109/JSTARS.2021.3067325](https://doi.org/10.1109/JSTARS.2021.3067325).
- Li, H., C. Wang, X. Huang, and A. Hug. 2018. Spatial assessment of water quality with urbanization in 2007–2015, Shanghai, China. *Remote Sensing* 10 (7):1024. doi: [10.3390/rs10071024](https://doi.org/10.3390/rs10071024).
- Makworo, M., and C. Mireri. 2011. Public open spaces in Nairobi City, Kenya, under threat. *Journal of Environmental Planning and Management* 54 (8):1107–23. doi: [10.1080/09640568.2010.549631](https://doi.org/10.1080/09640568.2010.549631).

- Martinez, B., and M. A. Gilabert. 2009. Vegetation dynamics from NDVI time series analysis using the wavelet transform. *Remote Sensing of Environment* 113 (9):1823–42. doi: [10.1016/j.rse.2009.04.016](https://doi.org/10.1016/j.rse.2009.04.016).
- McDonald, R. I., R. T. Forman, and P. Kareiva. 2010. Open space loss and land inequality in United States' cities. *Polson* 5 (3):1990–2000.
- Mensah, C. A. 2015. Sustaining urban green spaces in Africa: A case study of Kumasi Metropolis, Ghana. A. Ph.D. thesis., submitted to the University of Birmingham. Birmingham: University of Birmingham e-repository.
- Naikoo, M. W., M. Rihan, M. Ishtiaque, and Shahfahad. 2020. Analyses of land use land cover (LULC) change and built-up expansion in the suburb of a metropolitan city: Spatio-temporal analysis of Delhi NCR using Landsat datasets. *Journal of Urban Management* 9 (3):347–59. doi: [10.1016/j.jum.2020.05.004](https://doi.org/10.1016/j.jum.2020.05.004).
- National Bureau of Statistics. 2011. Annual abstract of statistics. [Online] Available at: www.nigeranstat.gov.ng
- Olaleye, J. B., O. E. Abiodun, and R. O. Asonibare. 2012. Land-use and land-cover analysis of Ilorin Emirate between 1986 and 2006 using Landsat imageries. *African Journal of Environmental Science and Technology* 6 (4):189–98.
- Pafi, M., A. Siragusa, S. Ferril, and M. Halkia. 2016. *Measuring the accessibility of urban green areas: A comparison of the green ESM with other datasets in four European cities*, Luxembourg: Publications Office of the European Union.
- Pan, D., M. Zhang, and B. Zhang. 2021. A generic FCN-based approach for the road- network extraction from VHR remote sensing images – using openstreetmap as benchmarks. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 14:2662–73. volumedoi: [10.1109/JSTARS.2021.3058347](https://doi.org/10.1109/JSTARS.2021.3058347).
- Pauleit, S., and F. Duhme. 2000. Assessing the environmental performance of land cover types for urban planning. *Landscape and Urban Planning* 52 (1):1–20. doi: [10.1016/S0169-2046\(00\)00109-2](https://doi.org/10.1016/S0169-2046(00)00109-2).
- Pierce, K. B.Jr. 2015. Accuracy optimization for high-resolution object-based change detection: an example mapping regional urbanization with 1-m aerial imagery. *Remote Sensing* 7 (10):12654–79. doi: [10.3390/rs71012654](https://doi.org/10.3390/rs71012654).
- Puplampu, D. A., and Y. A. Boafo. 2021. Exploring the impacts of urban expansion on green spaces availability and delivery of ecosystem services in the Accra metropolis. *Environmental Challenges* 5:100283. doi: [10.1016/j.envc.2021.100283](https://doi.org/10.1016/j.envc.2021.100283).
- Richards, J. 1999. *Remote sensing digital image analysis*. 1st ed. Berlin: Springer-Verlag.
- Richards, J., and X. Jia. 2006. *Remote sensing digital image analysis: An introduction*. Berlin: Springer.
- Rokni, K., A. Ahmad, K. Solaimani, and S. Hazini. 2015. A new approach for surface water change detection: Integration of pixel-level image fusion and image classification technique. *International Journal of Applied Earth Observation and Geoinformation* 34:226–34. doi: [10.1016/j.jag.2014.08.014](https://doi.org/10.1016/j.jag.2014.08.014).
- Rosenfield, G. H., and K. Fitzpatrick-Lins. 1986. A coefficient of agreement as a measure of thematic classification accuracy. *Photogrammetry Engineering Remote Sensing* 52:223–7.
- Sari, I. L., C. J. Weston, G. J. Newnham, and L. Volkova. 2021. Estimating land cover map accuracy and area uncertainty using a confusion matrix: A case study in Kalimantan Indonesia. *Earth and Environmental Science* 914:1–11.
- Savard, J. P. L., P. Clergeau, and G. Mennechez. 2000. Biodiversity concepts and urban ecosystem. *Landscape and Urban Planning* 48 (3-4):131–42. doi: [10.1016/S0169-2046\(00\)00037-2](https://doi.org/10.1016/S0169-2046(00)00037-2).
- Schell, L. M., and S. J. Ulijaszek. 1999. *Urbanism, health and human biology in industrialized countries*. Cambridge: Cambridge University Press.
- Sharma, L., P. C. Pandey, and M. S. Nathawat. 2012. Assessment of land consumption rate with urban dynamics change using geospatial techniques. *Journal of Land Use Science* 7 (2):135–48. doi: [10.1080/1747423X.2010.537790](https://doi.org/10.1080/1747423X.2010.537790).
- Tarrant, M. C., and H. K. Cordell. 2002. Amenity values of public and private forests: Examining the value-at-titude relationship. *Environmental Management* 30 (5):692–703.
- Taylor, L., and D. F. Hochuli. 2017. Defining greenspace: Multiple uses across multiple disciplines. *Landscape and Urban Planning* 158:25–38. doi: [10.1016/j.landurbplan.2016.09.024](https://doi.org/10.1016/j.landurbplan.2016.09.024).
- Teshager, Z., and K. Abeje. 2021. GIS and Remote Sensing based Land Use/Land Cover Change Detection. *Journal of Remote Sensing & GIS* 10 (3)
- U.S. Geological Survey. 2019. USGS Science for a changing world. [Online]. Available at: www.usgs.gov/core-science-systems/nli/landsat/landsat-collections
- White, M. P., I. Alcock, B. W. Wheeler, and M. H. Depledge. 2013. Coastal proximity, health and well-being: results from a longitudinal panel survey. *Health & Place* 23:97–103. doi: [10.1016/j.healthplace.2013.05.006](https://doi.org/10.1016/j.healthplace.2013.05.006).
- Willis, K., and B. Crabtree. 2011. Measuring health benefits of green space in economic terms. *Forests, Trees and Human Health* :375–402.
- Xie, Z., Y. Han, L. Sun, and J. Ping. 2020. Analysis of land cover evolution within the built-up areas of provincial capital cities in northeastern China based on nighttime light data and Landsat data. *Plos ONE* 15 (10):e0239371. doi: [10.1371/journal.pone.0239371](https://doi.org/10.1371/journal.pone.0239371).
- Yeates, M., and B. Garner. 1976. *The North American City*. New York: Harper and Row Publisher.
- Yusof, M. J. 2012. The true colors of urban green spaces: Identifying and assessing the qualities of green spaces in Kuala Lumpur, Malaysia. Edinburgh. Ph.D. thesis., submitted at the Institute of Geography, School of Geosciences, University of Edinburgh.
- Zewdie, W., E. Csaplovics, and L. Inostroza. 2017. Monitoring ecosystem dynamics in northwestern Ethiopia using NDVI and climate variables to assess long-term trends in dryland vegetation variability. *Applied Geography* 79:167–78. doi: [10.1016/j.apgeog.2016.12.019](https://doi.org/10.1016/j.apgeog.2016.12.019).

- Zhou, X., and Y.-C. Wang. 2011. Spatio-temporal dynamics of urban green space in response to rapid urbanization and greening policies. *Landscape and Urban Planning* 100 (3):268–77. doi: [10.1016/j.landurbplan.2010.12.013](https://doi.org/10.1016/j.landurbplan.2010.12.013).
- Zoest, J. V., and M. Hopman. 2014. Taking the economic benefits of green space into account: The story of the Dutch TEEB for cities project. *Urban Climate* 7:107–14. doi: [10.1016/j.uclim.2014.01.005](https://doi.org/10.1016/j.uclim.2014.01.005).
- Zubair, O. A. 2006. Change detection in land use and land cover using remote sensing data and gis (a case study of Ilorin and its environs in Kwara state). (unpublished master thesis), Ibadan.