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Urban Development in West Africa—Monitoring and Intensity Analysis of Slum Growth in Lagos: Linking Pattern and Process

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Abstract: Upgrading all slums in Lagos by 2030 will an ambitious task, given that more than 70% of its residents resides in slums. Furthermore, there is no recent study identifying neither the slums nor their temporal growth/development pattern in Lagos that can backstop any slum management initiative. This study aims to contribute by applying object-based image analysis and intensity analysis to map and link patterns and processes of slum growth in Lagos. RapidEye imagery from 2009 and 2015 were used to create maps for each time point for six land use categories (water, vegetated area, open space, road, slum, and other urban). Intensity analysis was applied to quantify the annual intensity of changes at the category and transition level. An overall accuracy (and kappa coefficient) of 94% (0.9) and 89% (0.86) were achieved for the 2009 and 2015 land use and land cover maps, respectively. This study showed that slums in Lagos have increased spatially during the time interval studied, with a total net gain of 9.18 square kilometers, influenced by the increase in population, mainly due to in-migration to Lagos. However, this study also revealed that slums were actively losing and gaining land area between 2009 and 2015, with an annual gain and loss intensity of 10.08 and 6.41, respectively, compared to the uniform intensity of 3.15. The gain was due to poor maintenance of buildings and encroachment onto available spaces (water and open space), while the loss was attributed to gentrification and demolition processes. A systematic process of transition was observed between slums and other urban (and open space) areas in the interval studied, and this process was mainly influenced by the Lagos state government. This analysis is crucial for designing policy interventions to manage slum growth in Lagos.

Keywords: slum; object based image analysis; intensity analysis; Lagos

1. Introduction

Rapid urbanization with limited development has led to slum proliferation in many Sub-Saharan African cities [1–4]. Slums are part of the city where the housing and resulting social arrangements diverge from the general growth of the city [5]. Slums emerge due to the interaction of forces which give rise to communities with a devalued physical and social image [6]. Thus, slums are seen as a manifestation of urban decay, poverty, crime, and unemployment in developing countries [7–9]. Although the negativity attributed to slums is very high, nevertheless, they provide shelter at low cost for the poor, especially when the city government is unable to plan and provide affordable housing [10,11]. In addition, ([1], p. 28) refers to slums as "a solution to warehouse the twenty-first century surplus humanity, especially in the global south where housing is limited". Similarly, informal settlements arise due to the need for shelter by migrants, who migrate into the cities for better opportunities [12]. Therefore, slums have roles in cities [13] and may continue to grow if their functionality is not considered during urban planning process.

Slums are unique in terms of their history, growth and development, opportunities, and challenges, but often similar in their characteristics and physical manifestations [6,14]. Experts find it difficult to reach an agreement on what criteria to use in defining slums [15], resulting in many slums being invisible to the world [16]. Furthermore, understanding the intricacies of slum dynamics will require linking historical trends of slum patterns with their underlying process [17]. This starts by identifying and mapping existing slums and their temporal changes. Mapping/identifying slums is very important to assist governments in providing the necessary services, such as housing, health, infrastructural facilities, etc. [18]. However, slums are, in many cases, not recognized as an integral part of the city or in the overall growth of the urban economy, because many urban planners tend to overlook its growth during urban planning process [19–21]. In addition, many donors or non-governmental organizations interested in slum management are only interested in slum improvement and not in their mapping [22].

Like other land use types, slums have distinct spatial characteristics that can be identified and mapped with Earth observation technology [19,23,24]. While mapping of slums is important, their multi-temporal dimension is also necessary to understand their evolution and observe their general growth trends **[25]**. This would then be used to support planning policies, to improve the existing slums or prevent new ones from springing up. Although, Kuffer, M., et al. [26] showed that there are several studies that have utilized remote sensing to identify and map slums, studies on slum temporal dynamics are few [27–30]. This is due to the high cost of high-resolution temporal satellite imagery, and the imperfection of automated slum identification methods [30]. Additionally, most of the sensors with high-resolution imagery were established around the year 2000, the reason why identifying slums before that time proved to be a challenge due to the nonexistence or limited availability of spatial data, especially in Sub-Saharan Africa.

The interaction between humans and the biophysical environment has been pointed out as the main driver of land use and land cover changes [31–33], nevertheless, it is important to link the patterns of land use and land cover changes (LULCC) with their underlying processes, and bridging the gap between social science and remote sensing [34]. Further, quantification of land use and land cover changes (LULCC) entails computation of a land cover/use transition matrix. However, this matrix does not provide sufficient information on the quantitative and systematic signals of land use and land cover changes [35]. In many cases, the transition matrix is analyzed at a broad level and may fail to reveal the total change on the landscape; for instance, zero net change due to simultaneous gain and loss within the landscape [36]. Additionally, discriminating significant signals during land use shifts is important in LULCC [37] and it is difficult to establish from a transition matrix. Purposefully, Aldwaik, S.Z., et al. [38] developed the intensity analysis, a type of change detection, to quantitatively analyze changes in different land use categories from time to time for a single site, by utilizing cross-tabulation matrices to summarize changes for each time interval. Although intensity analysis is sensitive to domain selection and the size of land use categories [39], it has been successfully utilized to integrate patterns with processes of land use and land cover changes [33,40,41].

Lagos developed from a small farming and fishing village in the fifteenth century to become one of the fastest growing cities in the world [42]. Lagos Bureau of Statistics [43] projected the population of Lagos metropolitan area as 21,324,114 in 2015. Lagos is projected to be the ninth most populous city by 2030 [44], and its population is expected to double by 2050 [45]. Amidst these projections is a city where more than 70% of its resident resides in slums [46–48]. Furthermore, Benjamin, M., et al. [49] observed that slum growth accounts for most of the urban growth experienced in Nigerian cities. In the past, scant attention was paid to urban planning in Lagos, but change in the government in 1999 led to the development of new reforms, including new policies to curb slum growth in Lagos through slum upgrading and redevelopment [42]. Yet, there is still need for improvement if the city hopes to be "free of slums by 2030", such as utilizing remote sensing techniques to improve our understanding on the spatial and temporal dynamics of slum in Lagos; this can then be used to create knowledge repositories of these slums. These repositories can provide important information on the existing situation and also assist to devise a tailored slum management approach (either proactive or adaptive) for the city of Lagos. Presently, there is no study identifying slums or their growth patterns in Lagos. Hence, this study aims to contribute by applying remote sensing techniques and intensity analysis, to map and link patterns and processes of slum growth in Lagos from 2009 to 2015. The objectives of this study are:

- To delineate slums from other land use types in Lagos;
- To determine how slums in Lagos developed over time;
- To quantify the patterns of change observed between 2009 and 2015; and
- To identify the underlying processes leading to the observed change.

This paper is structured as follows: Section 1 gives the rationale and objective of this study; Section 2 discusses the study area and data utilized for this study; Section 3 gives the methodology utilized; Section 4 gives the result; Section 5 gives the discussion; while Section 6 gives the conclusion.

2. Study Area and Data

2.1. Study Area

The study was conducted in six local government areas (Apapa, Ajeromi-Ifelodun, Amuwo-odofin, Surulere, Lagos Island, and Lagos Mainland) of Lagos metropolis, constituting a section of the older part of the city. The population densities per square kilometer of Apapa, Ajeromi-Ifelodun, Amuwo-odofin, Surulere, Lagos Island, and Lagos Mainland was projected to be 18,016; 137,102; 3892; 62,552; 123,290; and 42,598, respectively in 2015 [43] (Figure 1). Most of the unplanned settlements (slums and squatters) are located within this area because of its proximity to Lagos lagoon and the central business district [47].

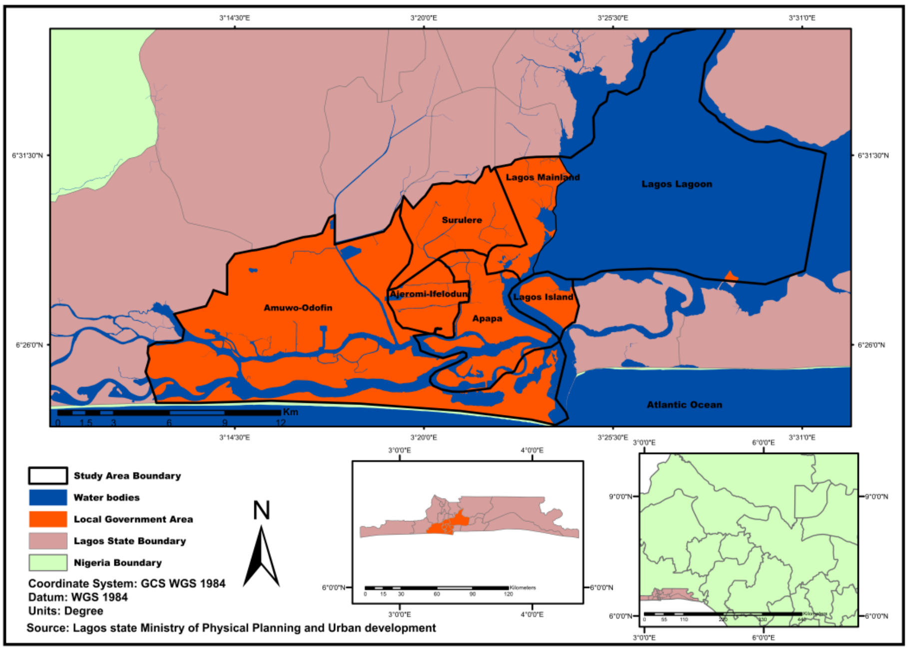


Figure 1. Study area in Lagos State, Nigeria.

The study area covers approximately 395 square kilometers. It lies approximately between 3°12′E and 3°24′E longitude and 6°24′N and 6°31′N latitude. The elevation of the study area ranged from 38 m below sea level to 52 m above sea level. Four dominant land cover classes were identified in the study area using the RapidEye image (20/12/2015) which includes: vegetated area (20.1%), water (47.9%), bare land (8.5%), and built up area (23.5%) (Figure 2).

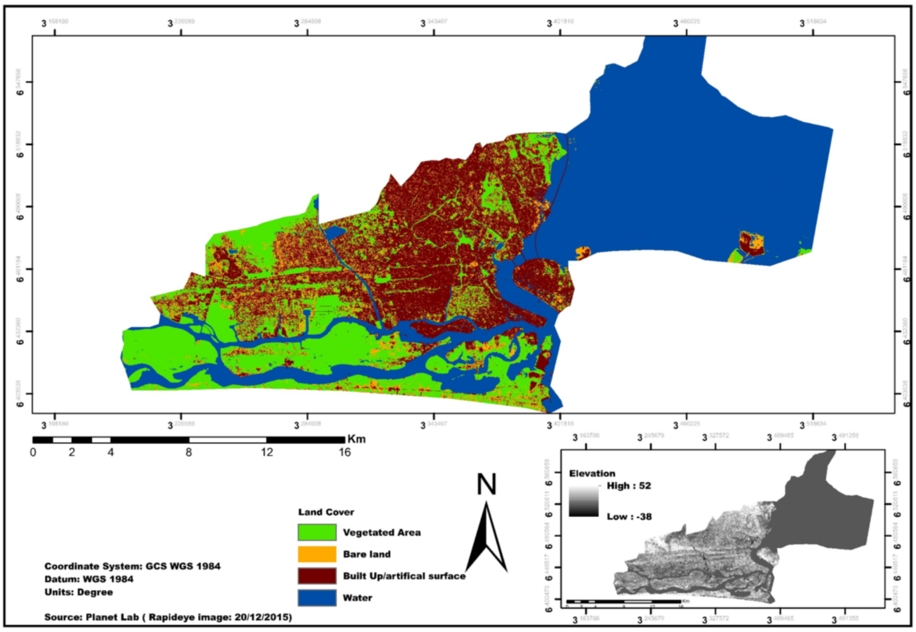


Figure 2. Landcover map and DEM of the study area in the city of Lagos. The landcover map is based on classified RapidEye data acquired on 20 December 2015.

According to [50], there are two types of deprived urban areas in Nigeria: squatters and slums. Squatters are uncontrolled or temporary dwellings inhabited by migrants from within and outside the city, while slums are old residential areas built long ago, in line with the then-prevailing urban planning, zoning, and construction standards, but now dilapidated and overcrowded. The research conducted by [51] shows that Lagos has the two identified deprived areas (Figure 3). Further, the Lagos state government sometimes include squatters under the category of slums, due to their similar physical characteristics, as observed in the Lagos Metropolitan Development and Governance Project (2006), where water, road, and electricity were provided to nine blighted communities (Agege, Ajegunle, Amukoko, Badia, Iwaya, Makoko, Ilaje, Bariga, Ijeshatedo/Itire), without considering if it was a squatter or slum. In this study, squatters and slums were equally considered to prevent bias as they all need to be monitored and improved.

Figure 3. Squatter (**A**) and slum (**B**) communities in Lagos (author's photo, 2017).

2.2. Data

The satellite images utilized in this study were from RapidEye (through the RapidEye science archive), acquired on 29 November 2009 and 20 December 2015 (Table 1). Other data utilized were vector data (road, water, land use maps, etc.) obtained from the Lagos State Ministry of Physical Planning and Urban Development. The imagery was not radiometrically calibrated because it was a Level 3A product (radiometric, sensor, and geometrically corrected). However, atmospheric correction and haze removal was done using ATCOR 2 on all the scenes. The corrected scenes were mosaicked and the study area subset was derived using its shapefile.

Table 1. Satellite imagery description.

Data Source/Type	Acquired Scene	Spatial Resolution	Acquisition Date
RapidEye/Level 3A	3142015_2009-11-29_RE2_3A_412557	5	29 November 2009
RapidEye/Level 3A	3142016_2009-11-29_RE2_3A_412557	5	29 November 2009
RapidEye/Level 3A	3142017_2009-11-29_RE2_3A_412557	5	29 November 2009
RapidEye/Level 3A	3142116_2009-11-29_RE2_3A_412557	5	29 November 2009
RapidEye/Level 3A	3142117_2009-11-29_RE2_3A_412557	5	29 November 2009
RapidEye/Level 3A	3142015_2015-12-20_RE4_3A_412557	5	20 December 2015
RapidEye/Level 3A	3142016_2015-12-20_RE4_3A_412557	5	20 December 2015
RapidEye/Level 3A	3142017_2015-12-20_RE4_3A_412557	5	20 December 2015
RapidEye/Level 3A	3142116_2015-12-20_RE4_3A_412557	5	20 December 2015
RapidEye/Level 3A	3142117_2015-12-20_RE4_3A_412557	5	20 December 2015

3. Overview of Methodology

This section discusses the methodology utilized in this study. The flowchart represents the successive steps taken in this study (Figure 4).

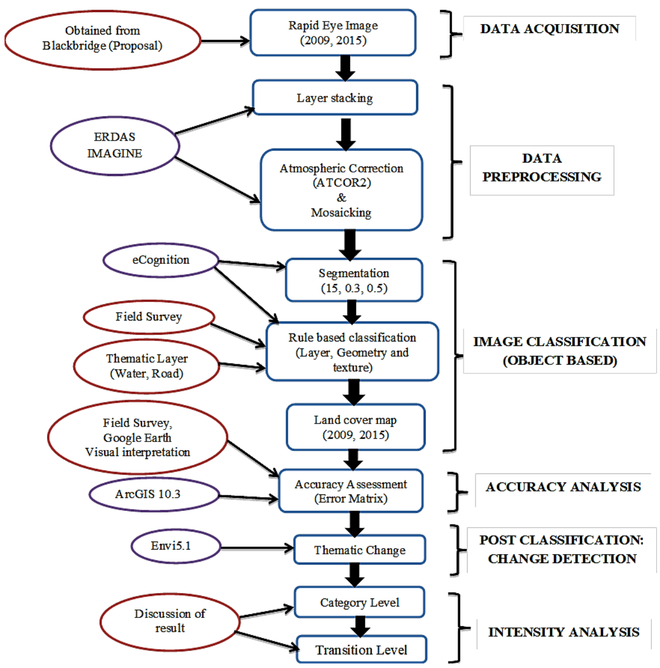


Figure 4. Work flow of the study.

3.1. Data Processing

Change detection from satellite imageries could be from pre-classification or post-classification. This study utilized the post-classification techniques to detect changes in the land use maps developed from the satellite imageries acquired at different dates. This technique includes: data pre-processing, image classification, accuracy assessment, and change detection [35]. The post classification is widely utilized because it provides a matrix of land transition among different categories [32], which serves as the input data for the intensity analysis. The thematic change workflow in the ENVI software package [52] was utilized to detect spatial changes in the extent of slums and other identified LULC in the maps produced for 2009 and 2015.

3.2. Classification of Imagery

The images were analyzed using the object-based image analysis (OBIA). OBIA is conducted in two stages: segmentation of the image into homogenous objects based on their spectral and spatial/contextual properties, and classification of identified objects into different land use or land cover categories [53,54] The subset images were segmented using the multi-resolution segmentation algorithm in the eCognition Developer software [55], using scale factor, shape, and compactness values of 15, 0.3, and 0.5, respectively. Additionally, a weight of 2 was assigned to band 3 (red) of the image, because the reflectance of built-up areas is high in this band. Existing road and water layers were used as predefined boundaries for the segmentation process. The classification of the segmented image was carried out using the rule set classification method, which allows the combination of OBIA with expert knowledge and integration with geographic information systems data to produce a better result, especially in the extraction of slums from other land use types in urban areas [56].

Before classifying the image, a reconnaissance survey and review of the literature were used to develop a slum ontology [57] to serve as a comprehensive basis for the image based classification of slum in the study area. This includes:

At the environs level:

- Nearness to water bodies could not be used as some of the planned communities were also located close to the water bodies;
- Some of the slums were located close to employment opportunities in Lagos (markets, central business district, industrial sites etc.);
- Need to combine the slums and squatter settlement as they have similar manifestations in Lagos;
- Most of the squatter settlements along the expressway have been demolished by precedent governments; and
- In some parts of the city, there were no distinct boundaries between the planned and the slum communities.

At the settlement level:

- Most of the slums were highly compacted; and
- The shape of the slums were irregular.

At the object level:

- Roof type could be used to determine the use of some buildings in the study area; and
- Although some of the slum communities have paved roads, unpaved roads and footpath were important observations to identify slums in Lagos.

The implication of these observations was that some of the rules utilized in the extraction of slums from satellite imagery, e.g., closeness to rivers or roads, were not entirely applicable in Lagos. Hence, extractions of most of the slum buildings in the study area were based on the textural properties of objects at the settlement level. Table 2 presents the categorization and analysis of the observations listed above based on the ontological framework and its OBIA parameterization.

Table 2. Adaptation of generic slum ontology concepts to an ontology for Lagos, with OBIA parameterization at environs, settlement, and objects.

Level	Indicators	Observation (Lagos)	OBIA Parameterization
Environs	Location	Located on river banks and marshy areas	Vector layer water: Min overlap on water bodies
	Neighbourhood characteristics	Close to employment opportunities (central business district, industries etc.)	Not used due to absence of spatial data on economic opportunities
		No defined boundaries between planned and slum communities.	Not used due to absence of spatial data on different types of residential land use in the city
		There are some public buildings that that were poorly maintained and need to be extracted to prevent misclassification	Vector layer of public buildings to extract those buildings
Settlement	Density	Denser than the planned communities	Texture—GLCM
	Shape	Irregular	Not used
Object Level	Building	Roof materials: corrugated iron sheets, concrete and plastic.	Spectral—Layer mean values
	Access network	Unpaved road and foot path	Not used

Using trial and error techniques and studies [24,58–60], rule sets were developed to classify the images into classes, i.e., background, water bodies, slum, road, open space, vegetated area, and other urban areas. The 2015 image was classified first and the rule set transferred to the 2009 image with minor changes in some of the values. Tables 3 and 4 describe the parameters used for the classification, and summarize what each class represents and the rule set utilized for their extraction from other land use types in the study area, respectively.

Table 3. Description of parameters used in the classification of the study area.

Parameter	Description
Normalized difference vegetation index NDVI	Index used to measure vegetation
Mean Blue	Mean intensity of all pixels forming an image in Blue band
Mean NIR	Mean intensity of all pixels forming an image in NIR band
Density	Distribution in space of the pixels of an image object
Brightness	Mean intensity of all pixels forming an image object
Relative Border to road	The ratio of the shared border length of an image object (with a neighboring image object assigned to Road) to the total border length
Minimum overlap with a thematic polygon	Computes the maximum value of the overlap between an image object and a selected vector layer in percent
$GLCM_{BLUE\_CONTRAST}$	Measure of the amount of local variation in the image in Blue Band
$GLCM_{RED\_CONTRAST}$	Measure of the amount of local variation in the image in Red Band
Red Ratio	Enhancement of red band

Source: [55].

Table 4. Description of land use classes and a summary of rule set used for the classification in eCognition.

	Land Types	Description	Rule Set for 2009	Rule Set for 2015
1	Background	Black Background	Mean Blue = 0	Mean Blue = 0
2	Water	Lagoon, rivers, ponds, reservoirs, swamps, water way	Mean NIR $\leq$ 840	Mean NIR $\leq$ 1075
3	Vegetated area	Sparse and dense vegetation, forest, grassland	NDVI $\geq$ 0.34	NDVI $\geq$ 0.34
4	Road	Roads (Primary and secondary), tarred road	Road layer map Density $\leq$ 1 and Relative border to road $\geq$ 0.5	Road layer map Density $\leq$ 1 and Relative border to road $\geq$ 0.5
5	Other urban areas	Other built up (residential, public, commercial, industrial etc.) except slum	Brightness $\geq$ 1700 $GLCM_{BLUE\_CONTRAST} \geq 400$ $Ratio_{RED} \geq 0.207$ Min Overlap (old industrial and public space) $\geq$ 20	Brightness $\geq$ 1700 $GLCM_{BLUE\_CONTRAST} \geq 400$ $Ratio_{RED} \geq 0.219$ Min Overlap (old industrial and public space) $\geq$ 20 $GLCM_{RED\_CONTRAST} \geq 420$
6	Slum	Slum and squatters settlements	Min Overlap Water $\geq$ 95% $210 \geq GLCM_{BLUE\_CONTRAST} \geq 65$ $GLCM_{RED\_CONTRAST} \leq 200$ 1050 $\geq$ Mean Red $\geq$ 900	Min Overlap Water $\geq$ 95% $210 \geq GLCM_{BLUE\_CONTRAST} \geq 65$ $GLCM_{RED\_CONTRAST} \leq 200$ 1050 $\geq$ Mean Red $\geq$ 900
7	Open space	Exposed soil, concrete floor, dump sites etc.	$0.34 \geq NDVI \geq 0.245$ $GLCM_{BLUE\_CONTRAST} \leq 65$	$0.34 \geq NDVI \geq 0.23$ $GLCM_{BLUE\_CONTRAST} \leq 65$

The first step taken was the classification of the non-built up area, which includes background, water, vegetated area, open space, and road. The *background* was classified as anything with a mean blue value of zero. The existing water polygon could not be utilized because of the encroachment of other land use categories on the water bodies, hence, a mean NIR value of less than 1075 for 2015 and 840 for 2009 was used to classify *water*. The thematic layer of road available was a line vector map, it was only able to classify the object under it and, to classify the exempted part, the density and relative border to the already-classified road was utilized. Normalized difference vegetation index (NDVI) values above 0.34 were used to classify *vegetated area*. *Open space* was classified using an NDVI value less than 0.34, but greater than 0.23. Additionally $GLCM_{BLUE\_CONTRAST}$ below 65 was classified as *open space*.

Brightness, $GLCM_{BLUE\_CONTRAST}$, $GLCM_{RED\_CONTRAST}$, and $Ratio_{RED}$ values greater than 1700, 400, 420, and 0.219, respectively, were used to classify *other urban areas*. The available thematic layer for the public and industrial old buildings was also utilized to classify *other urban areas* in the study area. *Slums* were classified using the Min overlap of the water layer on the remaining unclassified objects; $GLCM_{BLUE\_CONTRAST}$ between 210 and 65; GLCM $_{RED\_CONTRAST}$ above 200, and mean red between 1050 and 900. The rest of the unclassified objects were assigned to the *other urban area* class. The classified objects were exported from eCognition to ArcGIS [61] for accuracy assessment.

3.3. Accuracy Assessment

A thematic map derived from a classification is considered accurate if it provides an unbiased representation of the land cover it portrays [62]. An extensive field survey was conducted in the study area for verification of the developed LULC maps. Although 600 points (100 from each local government) were randomly selected using ArcGIS Random points, only 449 and 455 reference points were utilized for the 2009 and 2015 images, respectively (Table 5). This was due to inaccessibility to some of the sites and the unstable nature of some of the reference points. The assessment was complemented with the support of the *historical view* tool in Google Earth for 2009 and 2015, especially for the 2009 classification of *water* and *vegetated area*. Using these reference points, an error matrix was generated in ArcGis 10.3 to calculate the producer, user, and overall accuracy of the LULC maps [61]. Finally, a concordance analysis was implemented, and the Cohen kappa statistic computed [63].

Table 5. Sample sizes allotted to the targeted land use class in 2009 and 2015.

Land Use	Verified Reference Points	
	2009	2015
Vegetated area	129	117
Open space	54	59
Other urban area	69	71
Road	42	49
Slum	77	80
Water	78	78
Total	449	455

3.4. Intensity Analysis

Since slums have distinctive spatial characteristics [19], intensity analysis can help to understand the underlying processes leading to their observed growth pattern. Intensity analysis compares the predicted annual uniform rate of change, the rate that will exist if the annual changes were distributed uniformly across the entire time extent, against the observed annual rate of change among categories [39]. The intensity analysis is based on the availability of maps of different time periods for the same sites containing the same land use categories. The application and limitations of intensity analysis have been discussed in several studies (see [35,38–41]).

As this study focused on one time interval (2009–2015), the category and transition levels of the intensity analysis were employed. The category level examines the size and speed of loss and gain for each land use category within a time interval, implying the gain (Gtj) or loss (Lti). It also gives information on which land use category is dormant or active during that time interval (Equations (1) and (2)). The transition level gives information if a land use category is being targeted or ignored during a time interval. It is calculated in two parts: transition "to" and transition "from". (i) The transition "to" examines other categories transition to a land use category "n" during a time interval (Equation (3)), and the expected uniform intensity of transition to (Equation (4)).; and (ii) the transition "from", which examines how other land use categories transit from category "m" (Equation (5)); similarly, the uniform intensity of transition "from" is also calculated (Equation (6)).

Category level:

$$G_{tj} = \frac{\left[\left(\sum_{i=1}^{J} C_{tij}\right) - C_{tjj}\right] / Y_{t+1} - Y_t}{\sum_{i=1}^{J} C_{tij}} \times 100\% \tag{1}$$

$$L_{ti} = \frac{\left[\left(\sum_{j=1}^{J} C_{tij}\right) - C_{tii}\right] / Y_{t+1} - Y_t}{\sum_{j=1}^{J} C_{tij}} \times 100\% \tag{2}$$

Transition level:

$$R_{tin} = \frac{C_{tin} / (Y_{t+1} - Y_t)}{\sum_{j=1}^{J} C_{tij}} \times 100\% \tag{3}$$

$$W_{tn} == \frac{\left[\left(\sum_{i=1}^{J} C_{tin}\right) - C_{tnn}\right] / (Y_{t+1} - Y_t)}{\sum_{j=1}^{J}\left[\left(\sum_{i=1}^{J} C_{tij}\right) - C_{tnj}\right]} \times 100\% \tag{4}$$

$$Q_{tmj} = \frac{C_{tmj} / (Y_{t+1} - Y_t)}{\sum_{i=1}^{J} C_{tij}} \times 100\% \tag{5}$$

$$W_{tn} = \frac{\left[\left(\sum_{j=1}^{J} C_{tmj}\right) - C_{tmm}\right] / (Y_{t+1} - Y_t)}{\sum_{i=1}^{J}\left[\left(\sum_{j=1}^{J} C_{tij}\right) - C_{tim}\right]} \times 100\% \tag{6}$$

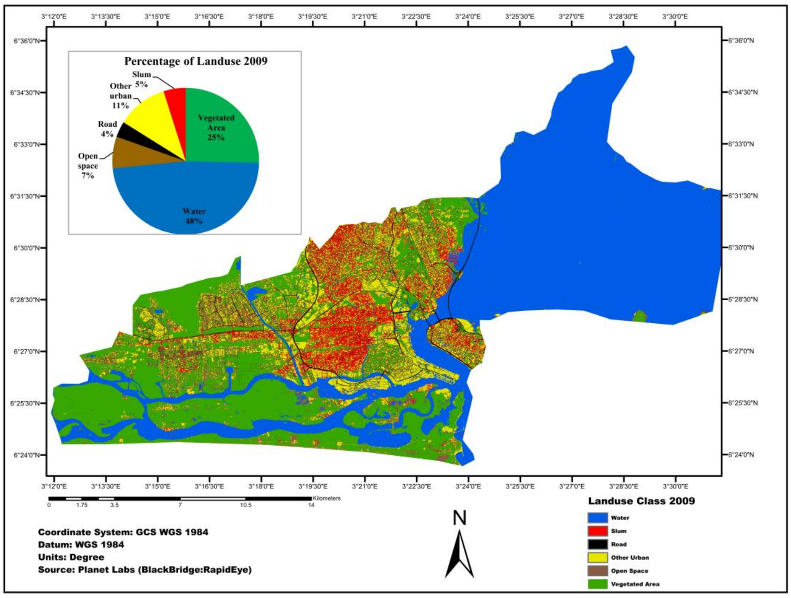
Symbol	Meaning
J	Number of categories
i	Index for a category at the initial time point for a particular time interval;
j	Index for a category at the final time point for a particular time interval;
m	Index for the losing category in the transition of interest;
n	Index for the gaining category in the transition of interest;
T	Number of time points
t	Index for the initial time point of interval $[Y_t, Y_{t+1}]$, where t ranges from 1 to $\mathrm{T} - 1$;
$\mathrm{Y_t}$	Year at time point t
Cij	Number of pixels that transition from category i at time Y_t to category j at time Y_{t+1};
G_{tj}	Annual intensity of gross gain of category j for time interval $[Y_t, Y_{t+1}]$;
L_{ti}	Annual intensity of gross loss of category i for time interval $[Y_t, Y_{t+1}]$;
R_{tin}	Annual intensity of transition from category i to category n during time interval $[Y_t, Y_{t+1}]$ where $i \neq n$;
W_{tn}	Value of uniform intensity of transition to category n from all non-n categories at time Y_t during time interval $[Y_t, Y_{t+1}]$
Q_{tmj}	Annual intensity of transition from category m to category j during time interval $[Y_t, Y_{t+1}]$ where $j \neq m$
V_{tm}	Value of uniform intensity of transition from category m to all non-m categories at time $[Y_{t+1}]$;during time interval $[Y_t, Y_{t+1}]$;

The mathematical notation for intensity analysis. Source: ([38], p. 107).

4. Results

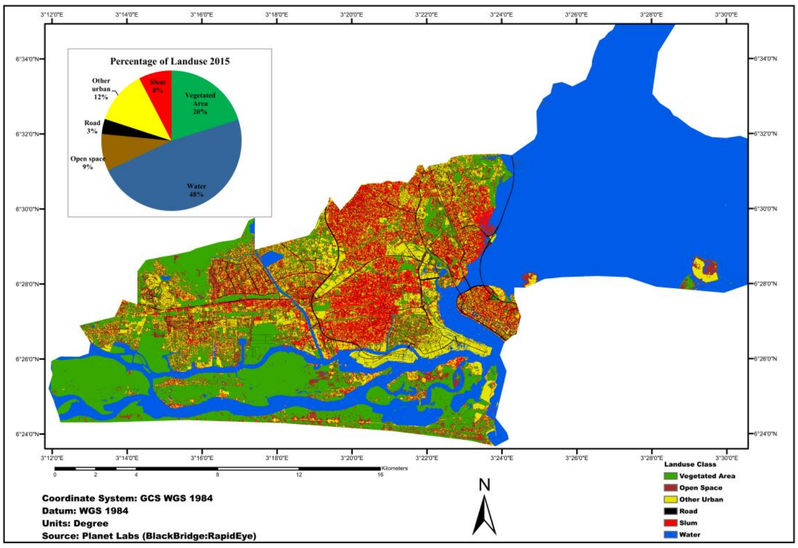
4.1. Production of Land Use and Landcover Maps and Accuracy Assessment

Based on the integration of OBIA with expert knowledge and GIS data, a LULC map of the study area was developed for 2009 and 2015. Six LULC (water, vegetated area, open space, other urban areas, roads, and slums) were derived from the RapidEye images (Figure 5a,b). Overall accuracies of 94% and 89% were estimated for the produced LULC maps of 2009 and 2015, respectively. Kappa coefficients of 0.9 and 0.86 were achieved for the 2009 and 2015 classified map, respectively. Furthermore, user and producer accuracies for each land use category were above 75% for the two maps, except for open space, which reached 66.1%, and which could be attributed to the heterogeneous nature of the land use class (Table 6).



(**a**)

Figure 5. *Cont.*



(**b**)

Figure 5. (**a**) Land use/cover map of study area in 2009; and (**b**) land use/cover map of the study area in 2015.

Table 6. Summary of LULC map accuracies (%) for 2009 and 2015.

	2009		**2015**	
Land Use	**User's Accuracy (%)**	**Producer's Accuracy (%)**	**User's Accuracy (%)**	**Producer's Accuracy (%)**
Water	98.7	100.0	100.0	100.0
Vegetated Area	100.0	100.0	100.0	100.0
Open	88.0	77.0	78.0	66.1
Slum	88.0	86.0	76.7	85.0
Other urban	83.0	91.0	77.5	87.3
Road	100.0	98.0	98.0	79.6
Overall Accuracy	94.0		89.0	
kappa coefficient:	0.9		0.86	

4.2. Observed Patterns of Land Use and Land Cover Change Dynamics

4.2.1. Visual Interpretation

Figure 6 presents a map showing the detected changes in the land use pattern in the study area during the time interval studied. The map gives information on the final state of the use of the land area. Transitions in all land use categories were observed during this time interval. Changes were observed in the proportion of areas covered by each land categories, except water, though small changes may have occurred. Furthermore, the area of change increased for slum, open space, roads, and other urban areas, while it decreased for vegetated areas. Although the proportion of the land area occupied by slums (Figure 5a,b) was smaller than other land use categories, its total net gain was higher compared to the others (Figure 7).

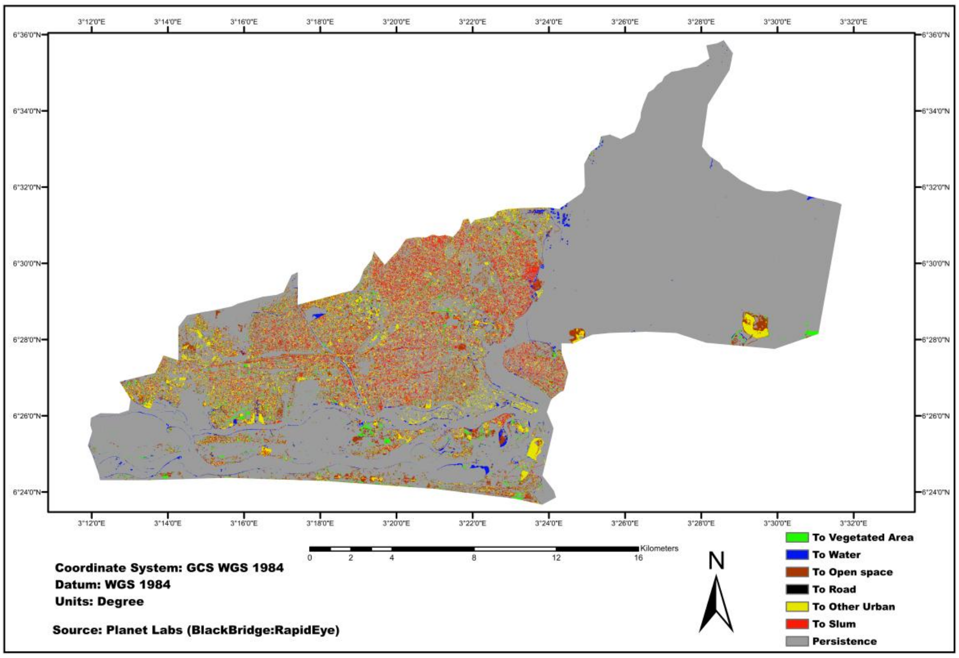


Figure 6. Detected changes in the research area between 2009 and 2015.

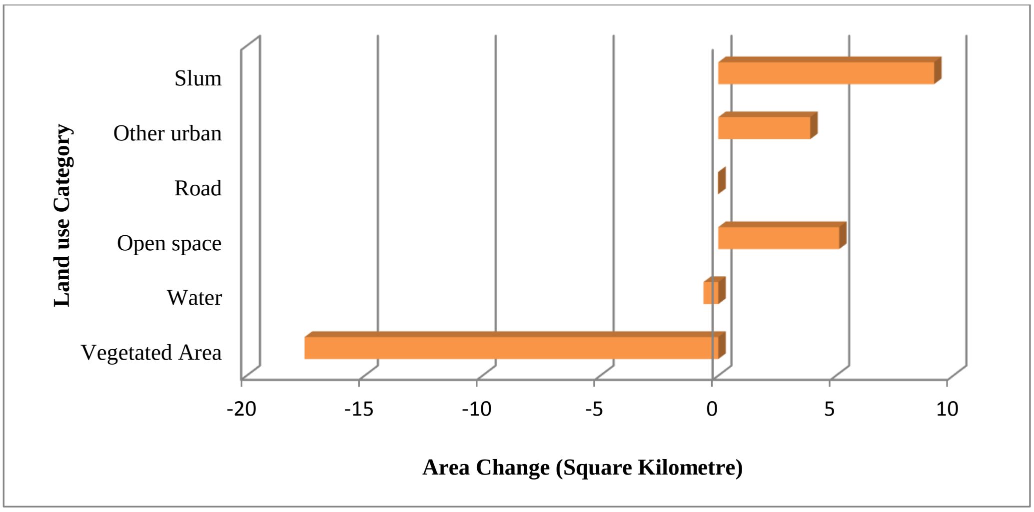


Figure 7. Area change of land use categories in the research area from 2009 to 2015.

4.2.2. Quantification

Table 7 presents the pattern of LULC change in the study area. Water is the dominant land cover type in the study area, accounting for 47–48% of the two time points, followed by vegetated area (20–25%). This two land cover types contributed to the high percent of persistent land use observed during this time interval (81.1%). Vegetated area suffered the highest loss among the land use categories with a net loss of about 6%. This is common in urban areas, where the vegetated area is usually encroached upon during urban expansion, especially when it (vegetated area) is near urban areas [64] Overall, swapping of land area was observed in all the land use categories in this time interval, implying simultaneous loss and gain by all the land use types (except roads). However, the swap change is larger than the net change for slums, other urban areas, water, and open space, implying spatial reallocation rather than net quantity changes for these land use categories.

Table 7. Land use and land cover changes in the period 2009–2015 (%).

Land Use	Total 2009	Total 2015	Persistence	Gain	loss	Total Change	Swap	Absolute Value of Net Change
Vegetated area	25.34	20.14	18.62	1.52	6.73	8.25	3.05	** 5.20
Water	48.08	47.90	46.92	0.98	1.17	2.15	1.96	** 0.19
Open space	6.99	8.51	2.37	6.14	4.62	10.77	9.25	1.52
Road	3.47	3.46	3.46	0.00	0.01	0.01	0.00	0.01
Other urban	11.22	12.38	6.73	5.64	4.49	10.13	8.98	1.16
Slum	4.89	7.61	3.01	4.60	1.88	6.48	3.76	2.72
Total	100	100	81.11	18.89	18.89	37.78	26.99	10.79

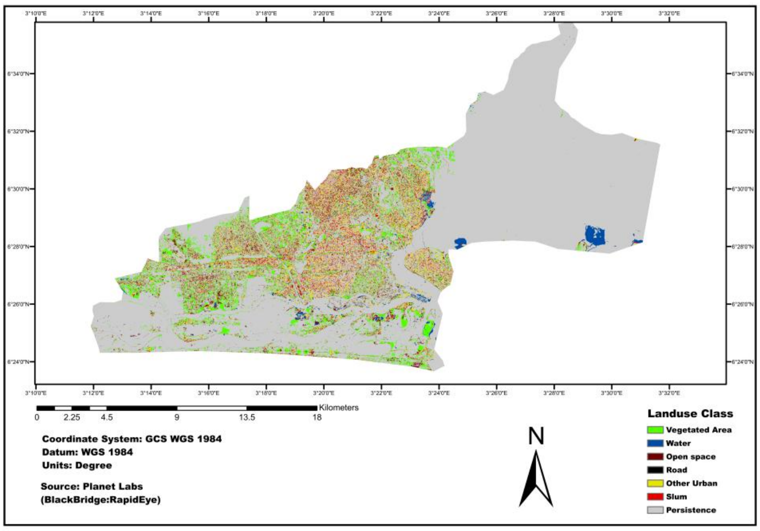
** means net loss.

4.3. Intensity Analysis

4.3.1. Category Level

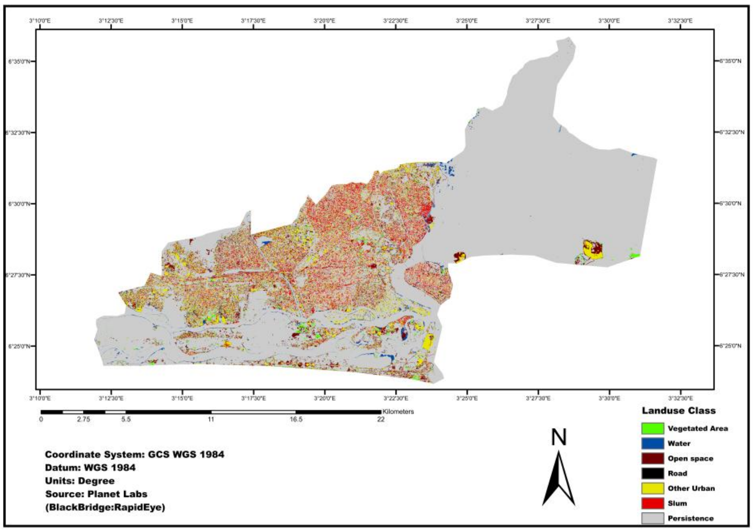
The interval level of intensity analysis required at least two time intervals, in order to compare the size and speed of change across different time intervals. However, this study utilized one time interval (2009–2015) due to the unavailability of data; hence, the interval level was excluded. The category level of the intensity analysis gives information about which land use category is relatively dormant or active during a particular time interval. The map showing category loss and gain in the research area is given in Figure 8a,b, respectively.

It could be observed from Figure 9a that *vegetated area, slum, other urban area*, and *open space* were actively losing their land areas to other land use categories during this interval. Although the right side of the bar shows water was dormant, the left side shows that water also lost some of its land area during this time interval. The dormant state of water bodies during this time interval could be attributed to its large size, and if the size included in the domain is reduced, it could become an active class, as well. As Pontius, R.G., et al. [39] noted in their study of Central Kalimantan (Indonesia), the large size of a persistent land use category could influence the result of intensity analysis; hence, it is important to also consider the area change of the bar to obtain a better insight on intensity changes of different land use categories. Furthermore, while slums, other urban areas, and open spaces were actively losing, they were also actively gaining (Figure 9b), making them the most active land use categories in the study area between 2009 and 2015.



(**a**)

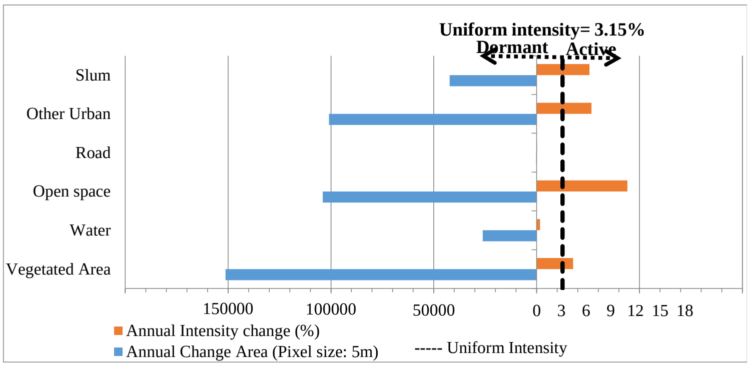
Figure 8. *Cont.*



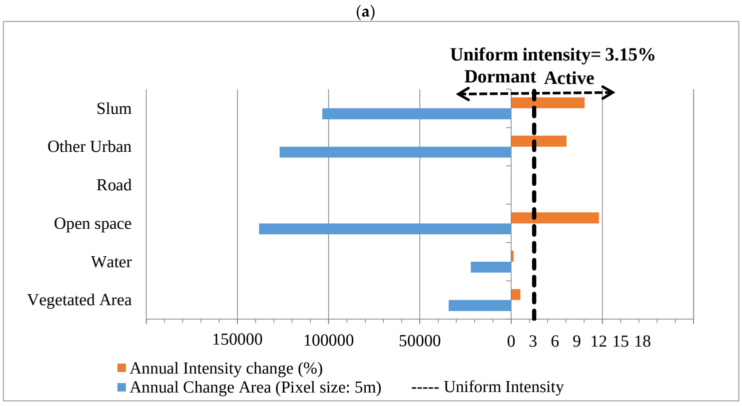
(**b**)

Figure 8. (**a**) The category loss intensity analysis map of the research area; and (**b**) the category gain intensity analysis map of the research area.

The graphical representation of the intensity loss and gain for the land categories during this interval is given in Figure 9a,b. The bar to the left gives area of changes (pixel) while the right gives the intensity of the changes (percent). The dotted vertical line gives the uniform intensity. If an intensity bar extends beyond the uniform intensity line, the category is considered to be active and if it is within the line, the category is considered dormant during that time interval.



(**a**)



(**b**)

Figure 9. (**a**) The category loss intensity for 2009–2015 in the research area; and (**b**) the category gain intensity for 2009–2015 in research area.

4.3.2. Transition Level

As observed in the previous section, slums were active (losing and gaining) during the time interval studied in the research area. This brings about the next question of which land category were slums losing to and gaining from? Figure 10 presents the map of the transition and examples of the transition observed in the research area.

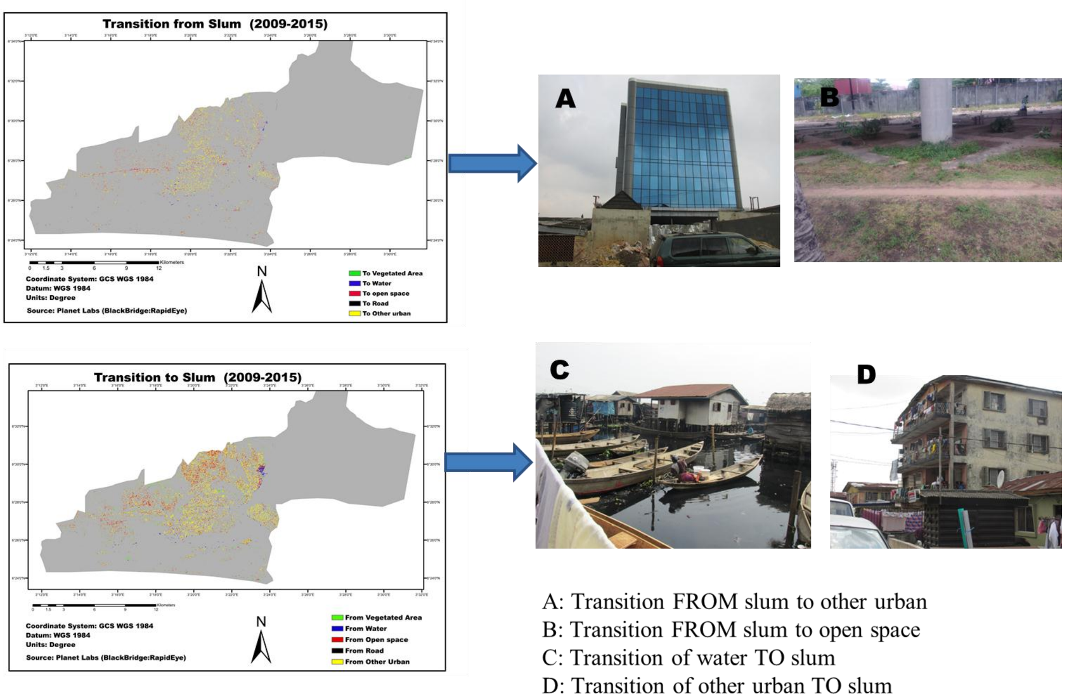
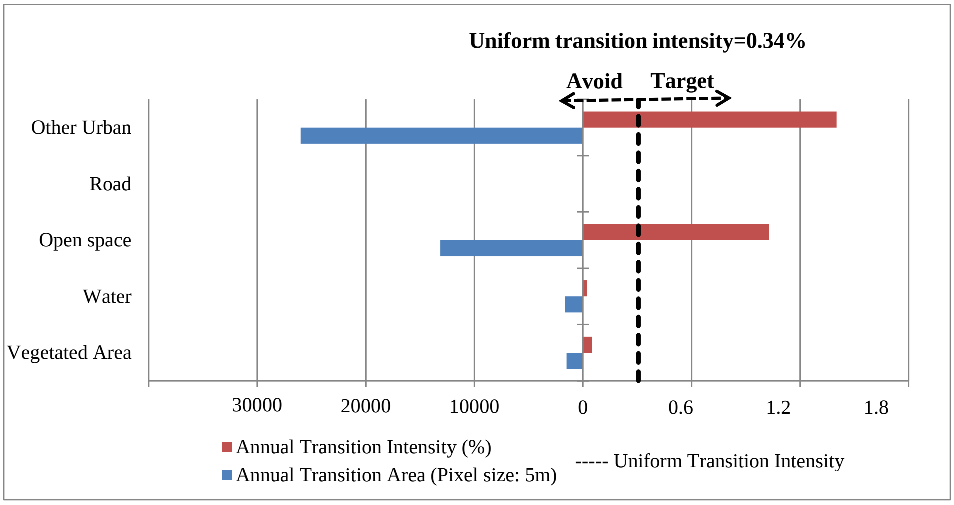


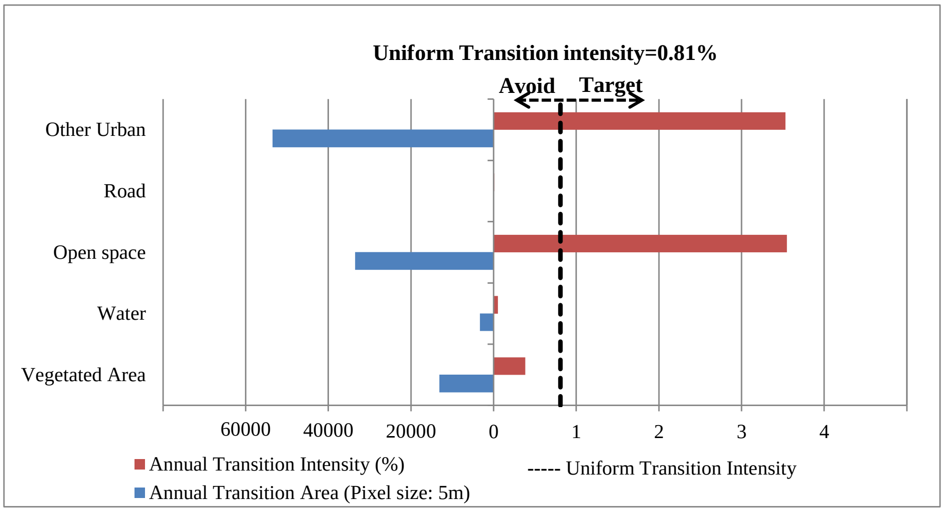
Figure 10. Transition of land use categories in the research area.

Figure 11a,b presents the graphical representation of transition from slum and transition to slum, respectively. The bar extending to the left on the vertical axis shows the observed size of each transition (pixel), while the right side of the vertical axis gives the intensity of transition. The dotted vertical line is the uniform transition intensity and any bar that extends beyond the uniform line denote targets while within the uniform line means it is being avoided.

Figure 11a presents the transition from slum to other land use categories. During this time interval, *other urban areas* and *road* were targeting *slums*, so *slums* experienced high rates of conversion into *other urban areas* and *open space* in the study area. However, *slums* avoid conversion to *water* and *vegetated area* during this time interval. Similarly, slums also targeted other urban and open spaces (Figure 11b). On one hand, slums were targeted by both open space and other urban areas while, on the other hand, slums also target both other urban areas and open space. Hence, the transition observed between slums and other urban areas (slum and open space) is a systematic process of transition [38]. Further, the rate at which other land use categories transition to slums is higher than the rate of transition of slums to other land use categories (Figure 12). This implies that that slum growth is faster than its decline. Although the result shows that water is been avoided by slums, this is not the case as it was observed during the field survey that slums encroached on water bodies in the study area (Figure 10). This omission was due to the large size of water in the study area.



(**a**)



(**b**)

Figure 11. (**a**) Transition intensity analysis "from" slum (2009–2015); and (**b**) transition intensity analysis "to" slum (2009–2015).

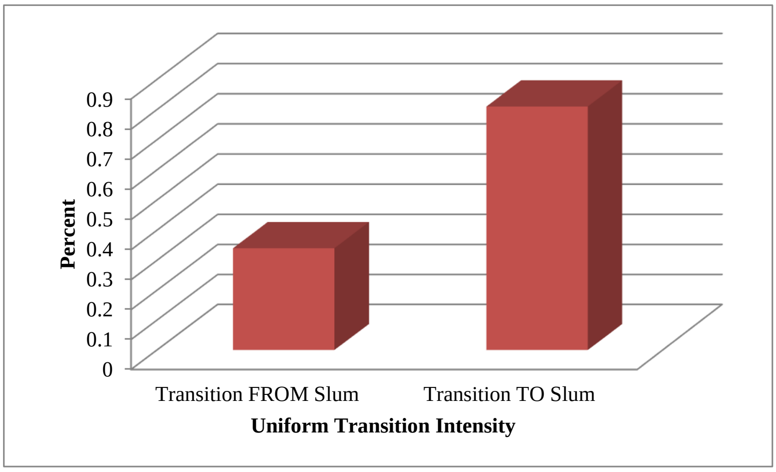


Figure 12. Comparison of uniform transition intensity of slum in the time interval.

5. Discussion

From Pattern to Process

Overall Change: This study utilized RapidEye imagery and intensity analysis to classify and quantitatively analyze the pattern and process of slum growth in Lagos from 2009 to 2015. The overall result showed an area increase in the intensity of land utilized by open space, other urban areas, and slums, and a decrease in the area of land utilized by vegetated area between 2009 and 2015 in the study area (Figure 7). According to [65], the reduction in vegetated area (through conversion to other land use categories) was due to the rapid population growth in the city of Lagos. This was attributed to in-migration rather than natural increase [66,67]. The city has been the economic power and former capital of Nigeria, and continues to be a pulling factor for many migrants with little or no experience to survive in the large cities. Migrants consider only the benefits of moving and not the challenges that might be experienced due to the process of moving [68]]. The implication is that many migrants were absorbed into the already established slum communities leading to their growth.

Process involved in the transition of slum to other land categories: Though the overall result showed a net increase in area coverage of slum, it was observed that some of the initial land area belonging to slum in 2009 had been converted to other land use categories in 2015 (*open space* and *other urban area*). Demolition of existing slums (e.g., Badia, Makoko, Iwaya, Ilubirin) by the Lagos state government contributed to the observed transition of slums to other land use categories in this interval. Some of these demolitions were documented by [69]] in their report "The human cost of a megacity, forced evictions of the urban poor in Lagos, Nigeria". Most often, the Lagos state government response to reduce slum proliferation is slum clearance, after eviction of slum residents, as a means to maintain city standards. However, Nwanna, C.R., et al. [70] argued that most of the observed slum clearance in Lagos is for profit maximization, as most of these slums are located on prime development land. For instance, Ilubirin, formerly a squatter settlement, is currently being converted to a high-income residential apartment. This action is common in squatter settlements in Lagos, primarily due to their illegality. However, in the case of slums where residents have a legal right to the land that their buildings were constructed upon, lease out (or sell) their land to private developers, who then convert them to high-priced rental houses. An example of such is found in Onike and Itire environs. Hence, slum clearance and its redevelopment to high-income residential areas is a form of gentrification in Lagos. Furthermore, squatters along major roads (e.g., Obalende axis) were demolished by the Lagos state government as part of their agenda to beautify the city. Thus, the transition of slums to other land use categories in the study area was due to demolition and gentrification processes.

Process involved in the transition of other land use categories to slum: According to [25], slum tends to evolve into hazardous sites such as water bodies. This trend was also observed in the study area, where slum communities (Figure 10) were found to have encroached on water bodies in the study area. Slum communities near water bodies have a high tendency of encroaching on water bodies. Although the result of the transition level of intensity analysis showed that water bodies were ignored by slums during this time interval, this omission was associated with the large size of water bodies in the study area.

The transition from other urban to a slum is a type of building which has been poorly maintained (Figure 10). This study focused on the older section of Lagos where the colonial style of houses were still common. Most of the colonial style of housing in Lagos is difficult to maintain because of inadequate technical knowhow and unavailability of foreign materials, leading to their poor maintenance [71]. In addition, poor maintenance of existing buildings in the study area is attributed to the poverty level in the city. Approximately 66.9% of Lagos residents' live below the poverty line [72] and, according to [73], poverty is a cause of environmental stress in Lagos. Many house owners lack the required financial resources to maintain/improve their homes.

Furthermore, the Lagos state government concentrated development in other section of the city (Lagos Island axis) during this time interval. Hence, expansion of squatter settlements was observed especially close to the existing ones. Similarly, slum upgrading exercises undergone by the Lagos state government (e.g., Lagos Metropolitan Development and Governance Project, 2006) were primarily through the provision of infrastructural facilities and not the improvement of housing structures in the slum communities. Hence, many buildings from space still had similar textural properties.

6. Conclusions

This study contributes to slum mapping in West Africa, as not many study focus on Nigeria or Lagos, though Lagos had been infamously referred to as a megacity of slums. The study uses object-based image analysis, building on the generic slum ontology and its main contribution is the use of intensity analysis to link pattern and process of slum growth in Lagos. This study showed that through integration of object based image analysis with expert knowledge and geographical information system data, slums could be delineated from other land use categories in Lagos using a RapidEye image. An overall accuracy of 94% and 89%, and kappa coefficients of 0.9 and 0.86, were achieved for the 2009 and 2015 land use and land cover maps, respectively. The study established that from 2009 to 2015, the spatial extent of slums have increased in the study area, with a net gain of about 9.14 square kilometers. This was attributed to population growth due to in-migration to the city.

This study proceeded by utilizing category and transition level of intensity analysis to quantitatively analyze the pattern of slum growth in Lagos. The annual gain and loss intensity of slums in the studied interval were 10.08 and 6.41, respectively, compared to the annual uniform intensity of 3.15, thus making it an active land use category in Lagos between 2009 and 2015. At the transition level of intensity analysis, a systematic process of transition was observed between slums and other urban areas, as well as slums and open space, influenced by the Lagos state government. When the Lagos state government exerts their power in the study area, slums are converted to other land use categories, and vice versa. Further, the calculated uniform transition intensity "to" slum (0.81) was higher than the uniform transition intensity "from" slum (0.34). This implies that slum growth was faster than its decline in the interval studied.

Demolition and gentrification were the major processes contributing to slums losing some of their land area to other land use categories in the study area. Transition of other urban areas to slum was attributed to poor maintenance of existing building structures due to poverty and unavailable resources. Further, slums encroached on water bodies in the study area; however, the transition level of intensity analysis could not capture this process as an active process, because of the size of water bodies in the study area. Conclusively, slums in prime locations were often demolished, while new ones springs up at the least desirable areas (e.g., close to water bodies), partly due to the scarcity of land in the study area.

Slums will continue to be a major challenge to the urban landscape if the status quo persists. It is hoped that the result presented in this paper will assist in policy-driven initiatives on slum management (such as monitoring of land use categories targeted by slums to prevent further encroachment), and contributes to the body of knowledge on slum dynamics in emerging economies, especially in data-scarce countries. Although this study captures the applicability of object-based image analysis and intensity analysis to map and quantitatively link the pattern and process of slum growth in Lagos, there is scope for further improvement. The remotely-sensed data utilized in this study was for two periods (due to limited data availability) which covers the older section of Lagos, leading to the exemption of the interval level of intensity analysis. A broader coverage, including the whole city with more years of remotely-sensed data can give further insight on slum dynamics in Lagos, Nigeria.

Author Contributions: O.S.B. wrote the paper and, jointly with A.R., conceived and designed the proposal and methodology utilized in this study. D.C.-C. provided guidance and valuable contributions at every stage of the development of this work. C.J. and K.G. supervised the research process and gave valuable suggestions to improve the quality of the paper. All authors reviewed the manuscript.

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