Spatial Dynamics of Urban Transition using Remote Sensing

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Abstract
Monitoring urban sprawl is a vital component of assessing landscape changes as it directly affects the quality of life of any populace. Remote sensing technology has the potential for acquiring detailed and accurate land-use information for management and planning of urban regions. This study focused on the use of remotely sensed data to investigate the spatial extent of urban landscape transition in Eti-Osa LGA, taking into consideration the nature and dynamics. For the two time periods investigated in this study (1984 - 2000 and 2000 - 2006), urban land-cover increased by 4.7% (929 hectares) and 5.4% (1250 hectares) respectively. Furthermore, results of analysis carried out in the study showed that the highest contribution to urban landscape change was from the sand (bare) class (559 hectares from 1984 – 2000 and 758 hectares from 2000 – 2006 respectively). Results of landscape metrics analysis revealed high levels of fragmentation in the urban landscape for the time periods evaluated. Based on the current landscape trends and patterns, a 10 year forward simulation from 2006 to 2016 was performed using IDRISI Land Change Modeller algorithm. The forward prediction analysis revealed that by 2016 urban class would increase by 2,220 hectares (466 hectares from water, 1,192 from sand (bare) and 562 from vegetation). Based on these results it's recommended that the Lagos State Government take drastic steps towards ensuring that mitigative or preventive measures are put in place via effective policy implementation thereby combating the devastating threat of urban sprawl in the area.

1. Introduction

Although an accurate definition of urban sprawl is widely debated by a number of researchers (Galster et al., 2001 and Johnson, 2001), a general consensus of this phenomenon is that it's characterised by unplanned and uneven pattern of growth driven by multitude of processes that result in inefficient resource utilization (Bhatta, 2010). Sudhira and Ramachandra (2007) noted that the direct implication of sprawl is change in land-use and land-cover of the region as sprawl induces the increase in built-up and paved area. Urban sprawl is often uncoordinated and extends along the fringes of metropolitan areas with incredible speed. Commonly, sprawl invades upon prime agricultural and resource land in the process. Land is often developed in a fragmented and piecemeal fashion, with much of the intervening space left vacant or in uses with little functionality (Torrens and Alberti, 2002). Jat et al., (2008) noted the importance of remote sensing and geographic information system (GIS) as tools for monitoring and planning purposes. Unlike conventional surveying and mapping techniques, remote sensing has proven to be a cost effective and technologically sound method of analysing urban sprawl (Haack and Rafter, 2006, Jat et al., 2008, Ji et al., 2006, Martinuzzi et al., 2007 and Yang and Liu, 2005). Environmental remote sensing has demonstrated to be an effective method of obtaining information regarding the nature and properties of objects on the earth surface and in the atmosphere through use of data from sensors which record electromagnetic radiation reflected or emitted from those objects (Danson et al., 1995). Remote sensing data are especially important in the areas of rapid land-use changes where the updating of information is tedious and time-consuming. The monitoring of urban development is mainly to find out the type, amount, and location of land conversion that has occurred (Yeh and Li, 1999). Lin et al., (2007) noted that monitoring and simulating urban sprawl and its effects on land-use patterns and hydrological processes in urbanised watersheds are essential in land-use and water resource planning and management. The study area, Eti-Osa local government area (LGA) is surrounded by water bodies, which have resulted in the occurrence of make shift houses along the beaches, the lagoon, the natural water drainage channels, sometimes extending as far as 50 – 100 meters beyond the shore into the water bodies. Most of these structures built beyond the shore would only be obvious on

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high resolution imagery or pan sharpened medium resolution imagery. The amount and location of changes can assist in prioritising infrastructure improvements such as schools, health facilities, roads and other infrastructure (Haack and Rafter, 2006). One of the prerequisite for understanding urban sprawl is successful land-use change detection (Jain, 2009), a process that can be achieved using remotely sensed data. With a wide range of techniques used for land-use change detection to study urban sprawl, it's only a matter of choosing the right technique based on the available data. According to Lin et al., (2007), composition, configuration and connectivity are primary descriptions of landscape or land-use pattern, when land-use change resulting in land-use/ cover pattern changes is being assessed. The use of spatial metrics in quantifying the extent and nature of urban landscape changes is vital in having a proper understanding of landscape dynamics. McGarigal and Marks (1995) define spatial metrics as numeric measurements that quantify spatial patterning of land-cover patches, land-cover classes, or entire landscape mosaics of a geographic area. A number of studies have noted the importance of utilising spatial metrics in quantifying urban growth, sprawl and fragmentation (Hargis et al., 1998, Hardin et al., 2007 and Herold et al., 2002). In the study conducted by Herold et al., (2002), the analysis showed the importance of spatial metrics measurement in providing an accurate characterisation of spatial urban growth pattern in the study area. Through the use of computed patch metrics computed for every patch in the landscape, deductions could be made as to the fragmentation and nature of spatial changes existing in the area. The aim of this study was to investigate the spatial extent of urban landscape transition in Eti Osa LGA, taking into consideration the nature and dynamics of land-cover changes using remotely sensed data. The key objectives were as follows:

i. to determine the spatial extent of urban change in Eti-Osa LGA using remotely sensed imagery,
ii. to investigate the effects of urban transition on the spatial structure of urban landscapes in the study area, and
iii. to predict the likely extent of urban sprawl in Eti-Osa LGA

2. Methods

2.1 Study Area

Although Lagos state is the smallest state in Nigeria, with an area of 356,861 hectares of which 75,755 hectares are wetlands, it has the highest population, which is over five percent of the national estimate (Olujimi, 2009). Lagos state is situated on a coastal plain along Nigeria's south-western Atlantic seaboard. The study area, Eti-Osa LGA, is located within the southern area of Lagos state (6°26′ 34″N, 3°28′ 29″E), just below the Lagos lagoon. Figure 1 shows the study area.

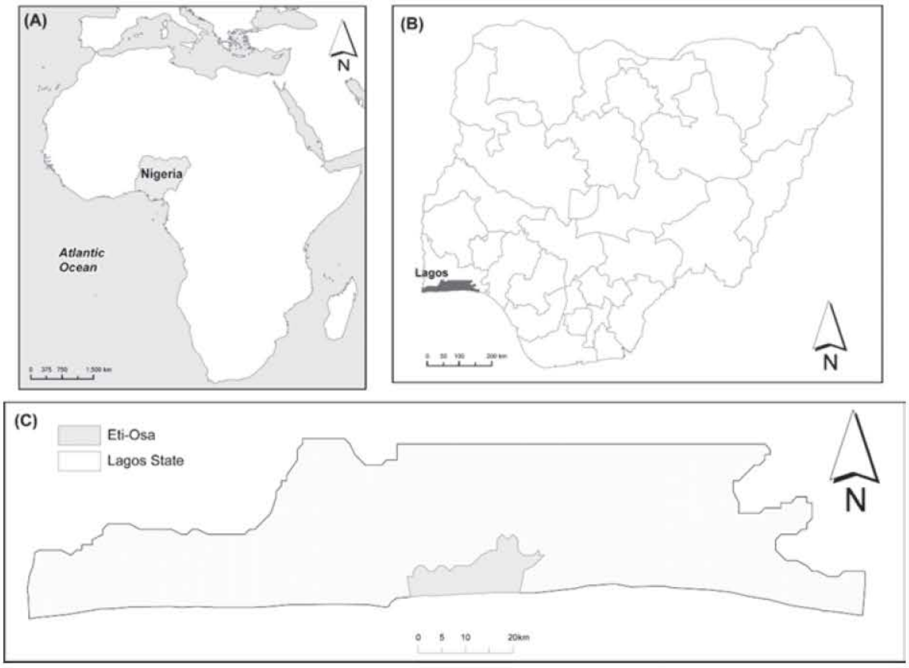

Figure 1 Map of study area showing: (a) location of Nigeria in Africa, (b) Lagos state in Nigeria, and (c) Eti-Osa LGA in Lagos state (Source: www.fews.net)

Table 1: Table showing details of LandSat image datasets used for the study

Date of image acquisition	Sensor	Path(s)	Row(s)
December 1984	LandSat 5	191	55 / 56
February 2000	LandSat 7	191	55 / 56
December 2006	LandSat 7	191	55 / 56

Table 2: Table showing the intended classes and their definitions

Urban	All built up structures including residential and commercial, roads, shanties, make shift buildings, freight containers and all other structures containing Aluminium, zinc or asbestos
Water	All water bodies including the ocean, lagoon, lakes creeks and rivers
Sand (bare)	All Sandy surfaces and deposits, Bare/ undeveloped surfaces which appear to be lightly vegetated
Vegetation	All forms of vegetation including those growing on land, in between urban structures and on water

2.2 Data Acquisition

For this study LandSat images were downloaded from the GLCF (Global Land-cover Facility) and USGS (United States Geological Surveys) websites respectively. Table 1 presents the image datasets used for the study. The image datasets used in this study were acquired during the dry season as to avoid problems of seasonality variation. The image datasets were processed to level 1G for 1984 and level 1T for the 2000 and 2006 respectively, implying the images were radiometrically and geometrically corrected. The topographic sheet covering parts of Eti-Osa LGA was acquired as a scanned map and digitized giving rise to undershoot/ overshoot, misplaced points and dangle. These errors where corrected by careful post editing of the digitised map by comparing this with the satellite image and aerial photographs. All datasets were acquired in or georeferenced to the Universal Transverse Mercator (UTM) Zone 31 coordinate system with World Geodetic System (WGS) 84 datum. Other secondary sourced datasets used for the study were included the following: digital administrative maps of Nigeria, Lagos state and Eti-Osa LGA sourced from the FEWS Net (Famine Early Warning Systems Network) as shapefiles and a digital elevation model (DEM) raster derived from a SRTM (Shuttle Radar Topography Mission) image over the study area downloaded from USGS website using the Earth explorer (Figure 1).

2.3 Image Pre-Processing

To effectively utilize the information contained in all the bands filters were applied to remove the effects of atmospheric particles cause by absorption and scattering of radiation from the earth surface during acquisition (Lu et al., 2002). Conversion of digital numbers to absolute radiance is important in data processing activity involving qualitative applications especially when reflectance of objects are measured over time using different sensors (Lillesand et al., 2008). This was done using the IDRISI RADIANCE function. Bands 1, 2, 3, 4, 5 and 7 were used in the classification process. Since the satellite images covering the study area contained geometric distortions it passed through the process of rectification and restoration. The images were geometrically corrected using the AFFINE and RESAMPLE commands in IDRISI.

2.4 Image Classification

For this study, maximum likelihood classification (MLC) was used. It is preferred by most researchers as it's a robust classifier that has been shown to be superior to other algorithms using medium and high resolution multispectral imagery (Baatuuwie and Leeuwen, 2011 and Onojeghuo and Blackburn, 2011). Based on statistics (mean; variance/covariance), a (Bayesian) Probability Function is calculated from the inputs for classes established from training sites. Each pixel is then judged as to the class to which it most probably belongs (Eastman, 2006). The classes used and their definitions are shown in table 2.

2.5 Accuracy Assessment

Accuracy assessment was conducted by selecting a sample of reference locations, and comparing the classifications at these reference locations to the classifications provided by the land-cover map. The reference sample was selected independently of data used for training and /or developing the classification procedure (Stehman, 1997). Aerial photographs, topographic sheets and existing Landsat images acquired in 1984 and 2000 were used to assess the accuracy of the land-cover classification maps for 1984 and 2000 respectively. For the 2006 land-cover classification map, a high resolution IKONOS satellite imagery of the study area acquired in 2005 was used for accuracy assessment. The data used for training and testing image classifications were complemented with DGPS field surveys of selected locations across the study area.

2.6 Change Detection
In order to determine the spatial extent of urban transition the classified images were recoded to define the urban landscape as one class and all other land-covers types were combined into a non-urban class. A post-classification comparison was adopted to determine the changes in urban class using IDRISI. The urban transition maps showing urban expansion, urban loss, other land-cover classes and unchanged urban landscape were based on the difference between the urban land-cover in the baseline (1984) and assessment (2000 and 2006) maps for the study area.

2.7 Urban Landscape Spatial Structure
The changes in urban land-cover and spatial characteristics were determined using FRAGSTATS software, a computer software program designed to compute a wide variety of landscape metrics for categorical map patterns (McGarigal et al., 2002). The metrics used in this study included: total class area (CA), number of patches (NP), largest patch index (LPI), edge density (ED), Euclidian mean nearest neighbour distance (ENN_MN), area weighted mean patch fractal dimension (FRAC_AM) and contagion (CONTAG). These metrics were selected based on their effectiveness and simplicity as demonstrated in a number of similar studies (Herold et al., 2002, Onojeghuo and Blackburn, 2011 and Araya and Cabral, 2010).

2.8 Urban Landscape Forward Prediction Analysis
For this study, urban sprawl was investigated using the IDRISI Land Change Modeller (LCM). This integrated software is used for analyzing land-cover change, projecting its course into the future, and assessing its implications for habitat and biodiversity change. LCM uses either a Multi-Layer Perceptron (MLP) neural network or Logistic regression while change detection is based on a series of empirically evaluated sub-models. A few site and driver variables were tested and those with the highest values used for predicting urban sprawl. Lower values could also be used if they are likely to influence final results. Using GIS operations buffers were created to the urban and sand (bare) reclassified maps for the years being assessed. A buffer was also created for the roads layer. The road basis layer was extracted as input for the prediction model and results from distance operations tested. Some of these were selected as static/ dynamic variables in the prediction model. Two land change models where created: 1984 to 2000 and 2000 to 2006. The distance map is a vital component of the land-use prediction. The distance maps were created for urban and sand (bare) reclassed maps for 2006. The normalised entropy for the urban class was generated using a 5x5 neighbourhood matrix in the LCM Landscape pattern and change analysis tab. It was calculated to evaluate what areas are prone to change after 2006. Two prediction methods were used, each yielding a hard and soft prediction. The first included all the transition sub models while the second included none of the sub models. The predictions performed assumed that urban growth trend between 2000 and 2006 continued and there were no external forces driving change.

3. Results

3.1 Image Classification
Figure 2 shows the Landsat images (1986, 2000, and 2006) classified using MLC technique. The error matrix for the accuracy assessment was generated using the classified maps and a second signature map to produce kappa values. An IKONOS image and Google earth imageries were used as surrogate data to create a second training data set. The Google Earth imageries were dated 11/13/2000 (for the 2000 assessment) and 12/10/2006 (for the 2006 assessment). A second training data set was created to assess the accuracy of 1984 Landsat classified image. Details of the accuracy assessment are presented in the following section.

3.2 Accuracy Assessment
Table 3 presents the error matrix and accuracy assessment results for land-cover classifications for 1984, 2000 and 2006 respectively. The accuracy assessment also displayed the Kappa values. The overall Kappa (k) coefficient was 0.9744 for the 1984 classification, 0.9514 for the 2000 classification and 0.9101 for the 2006 classification. The overall classification accuracies for the maps of 1984, 2000 and 2006 were 98.9%, 97.7%, and 96.3% respectively. Given the accuracy values were sufficiently accurate; the maps were used for change detection and subsequent analysis.

3.3 Landcover Change Detection
The results of analysis show that urban class had no net loss between 1984 and 2006. The urban area expanded by 929 hectares between 1984 and 2000 and 1250 hectares between 2000 and 2006, a shorter time interval.

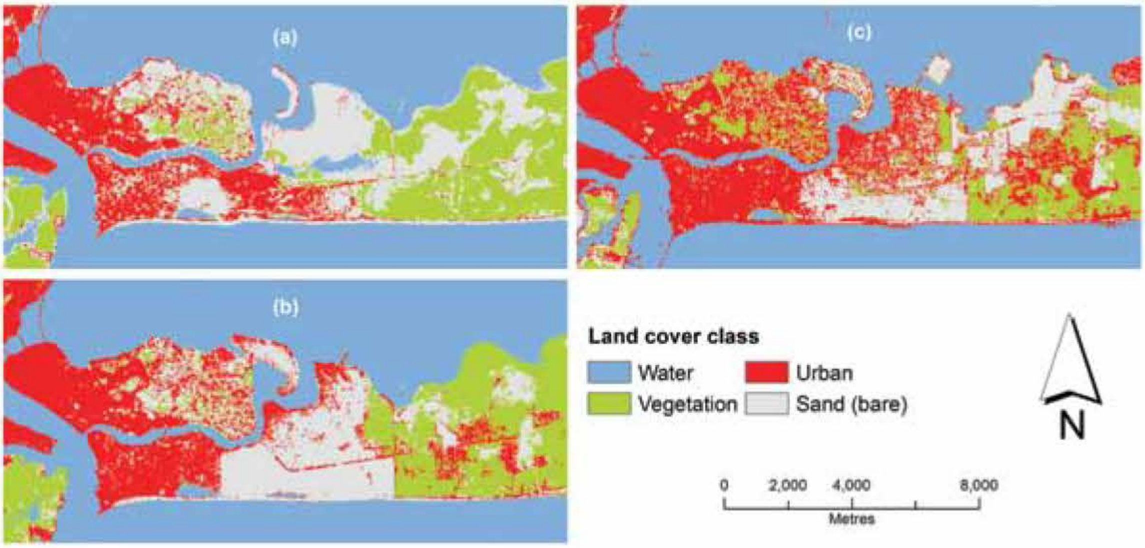

Figure 2: Results of Land-cover Classification of Eti-Osa LGA for (a) 1986, (b) 2000, and (c) 2006

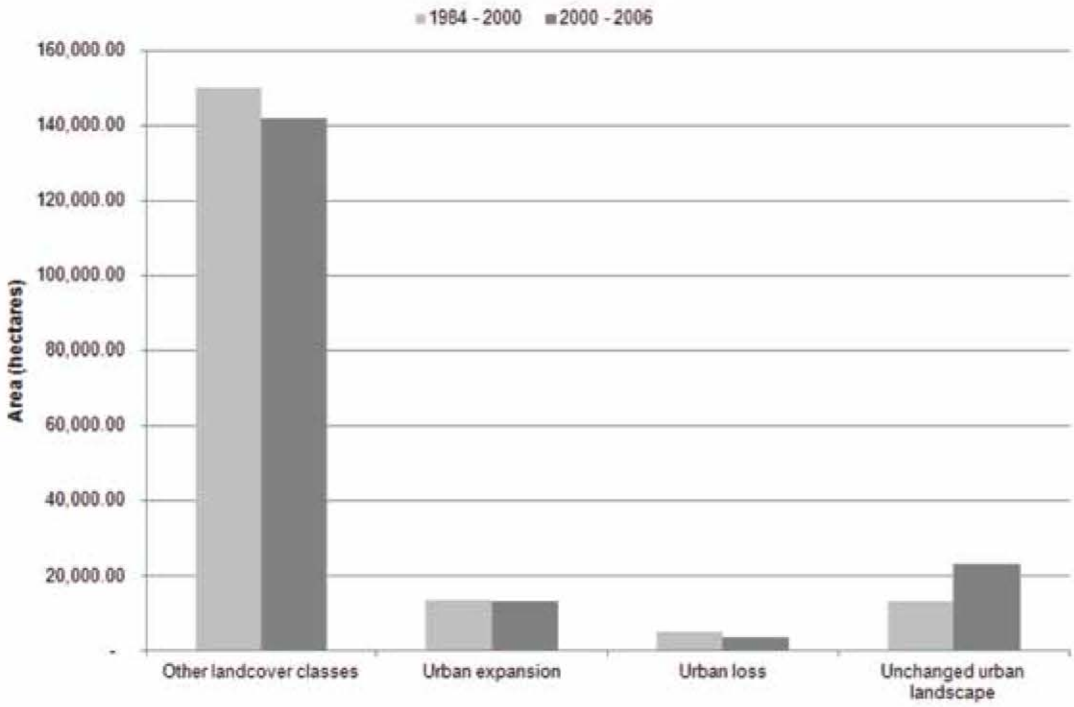

Figure 3 Graph showing transition patterns of urban landscape for 1984 – 2000 and 2000 – 2006 respectively

The highest net loss between 1984 and 2000 was in the Sand (bare) class (653 hectares), while it was the Vegetation class between 2000 and 2006 (706 hectares) (see figure 3). The urban class was used as an indication of the extent of urban sprawl. From the analysis, the highest contribution to the changes in the Urban class was from the Sand (bare) class with 559 hectares from 1984 – 2000 and 758 hectares from 2000 - 2006. Figure 3 shows the change detection map of urban image recoded from the land-use cover maps for the three separate years (1984, 2000 and 2006). As shown in figure 4, distinct physical patterns of urban sprawl were identified.

Table 3: Error matrix and accuracy results for land-cover classifications

(a) 1984 image classification							
		Reference map					
		Water	**Bare (sand)**	**Vegetation**	**Urban**	**Total**	***User's Accuracy (%)***
Classified map	Water	10899	0	0	0	10899	*100*
	Bare (sand)	105	894	0	29	1028	*87.0*
	Vegetation	0	14	1115	0	1129	*98.8*
	Urban	0	0	0	1331	1331	*100*
	Total	11004	908	1115	1360	14387	
	Producer's accuracy (%)	*99*	*98.5*	*100*	*97.9*		
	Overall accuracy (%)	*98.97*					
(b) 2000 image classification							
		Reference map					
		Water	**Bare (sand)**	**Vegetation**	**Urban**	**Total**	***User's Accuracy (%)***
Classified map	Water	3179	0	0	0	3179	*100*
	Bare (sand)	0	451	0	17	468	*96.4*
	Vegetation	0	86	388	0	474	*81.9*
	Urban	0	3	0	417	420	*99.3*
	Total	3179	540	388	434	4541	
	Producer's accuracy (%)	*100*	*83.5*	*100*	*96.1*		
	Overall accuracy (%)	*97.67*					
(c) 2006 image classification							
		Reference map					
		Water	**Bare (sand)**	**Vegetation**	**Urban**	**Total**	***User's Accuracy (%)***
Classified map	Water	4197	0	0	0	4197	*100*
	Bare (sand)	0	452	44	34	530	*85.3*
	Vegetation	5	29	115	0	149	*77.2*
	Urban	66	31	1	681	779	*87.4*
	Total	4268	512	160	715	5655	
	Producer's accuracy (%)	*98.3*	*88.3*	*71.9*	*95.2*		
	Overall accuracy (%)	*96.29*					

Table 4: Results of Landscape metrics analysis performed for urban landscape

Metrics	**Year**		
	1984	**2000**	**2006**
CA (Hectares)	2,147.04	3,075.75	4,325.58
NP	893	1281	1938
LPI	4.4147	9.28	14.13
ED	30.40	41.55	68.74
FRAC_AM	1.24	1.22	1.27
ENN_MN	63.3292	66.22	57.38
CONTAG (%)	43.58	42.19	39.61

The pattern of urban development for 1984 – 2000 and 2000 – 2006 were *leapfrogging* and *polynucleated* respectively. Galster (2001) describes the patterns of sprawl as either compact, scattered, linear, polynucleated or leapfrogging development. The polynucleated pattern of urban sprawl between 2000 and 2006 indicates some degree of planning, such as building of new estates, had occurred over time.

3.4 Changes in Urban Landscape and Spatial Structure

Table 4 presents the results of landscape metrics analysis conducted in the study. Araya and Cabral (2010) noted that NP indicates the aggregation or disaggregation in the landscape, while LPI measures the proportion of total landscape area comprised by the largest urban patch. The results showed that NP (i.e. *urban blocks*) increased by 43.5% and 51.3% for time periods 1984-2000 and 2000-2006 respectively.

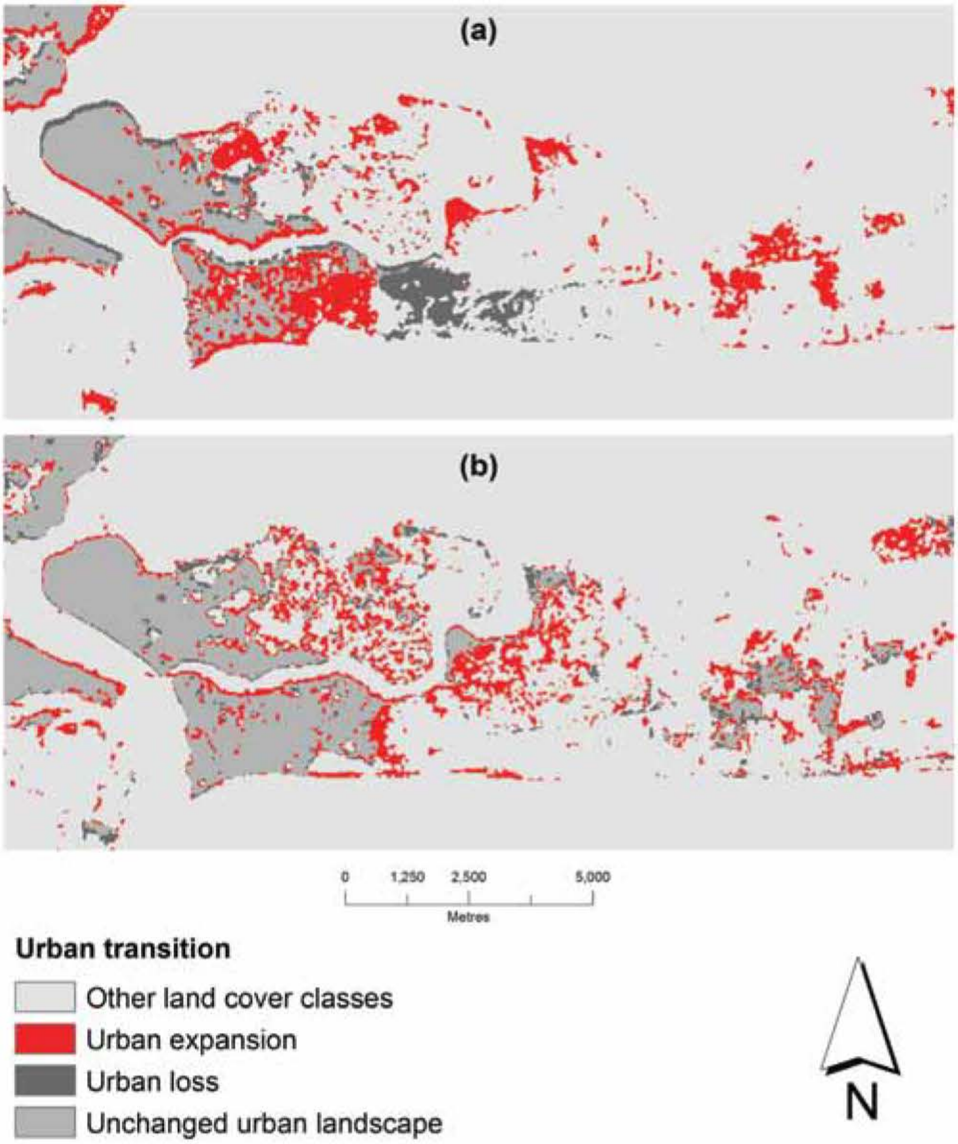

Figure 4: Change detection maps showing transition patterns of urban landscape for 1984 – 2000 and 2000 – 2006 respectively

This suggests that urbanisation within the two time periods were characterised by dispersion and the development of isolated, fragmented or discontinuous built-up areas. The rise in NP and CA indicates urban expansion over the 22 year interval. For the two time periods investigated in this study (i.e. 1984 to 2000 and 2000 to 2006), the urban landcover class increased by 4.7% (929 hectares) and 5.4% (1250 hectares) respectively. LPI increased by 110.2% and 52.3% for the two time periods 1984-2000 and 2000-2006 respectively, indicating considerable growth within the urban core area particularly for the first time period. The ED index increased by 36.7% and 65.4% for the time periods 1984-2000 and 2000-2006, this indicating an increase in the total length of the edge of urban patches resulting from land-use fragmentation. The fractal dimension (FRAC_AM), which ranges between 1 and 2, describes the complexity and fragmentation of patches using a perimeter-area proportion. Results of landscape metrics analysis shows that for the three years the patches are complex and fragmented. Overall, the FRAC_AM spatial index was slightly higher than 1 indicating a moderate shape complexity (Araya and Cabral, 2010). This demonstrates the complex nature of urban transitional changes experienced in the study area as against the occurrence of compact rectangular patches with relatively smaller areas. The decreasing CONTAG and increasing ED values indicate a higher fragmentation of the area in 2000 and 2006 respectively. This validates the results of urban and non urban classified images for 1984, 2000 and 2006 (figure 3). Non-urban landscape of 1984 and 2000 were converted to urban classes which were spatially more heterogeneous and fragmented. Between 1984 and 2000 ENN_MN increased by 4.6%, indicating an increase in the distance between urban patches. For the time period, 2000 – 2006, ENN_MN decreased by 13.3% indicating a reduction in the distance between built-up patches thence suggesting coalescence. The contagion spatial index measures to what extent landscapes are aggregated or clumped (Martinuzzi et al., 2007). Results of landscape metrics analysis showed that in 1984 the urban landscape of the study area was dominated by relatively greater number of highly fragmented patches. However, there was a decline in the contagion index between 1984 and 2006 (decline of 1.4% and 2.6% for 1984 - 2000 and 2000 - 2006 respectively) indicative of a less fragmented urban land-cover. The use of landscape metrics have proven to be useful indicators for understanding general trends of landscape dynamics (Araya and Cabral, 2010). Remmel and Csillag (2003) noted that it is extremely difficult to statistically compare results of spatial indices.

3.5 Forward Prediction Simulation of Urban Landscape

A forward prediction for urban sprawl in 2016 (10 years after the latest satellite scene acquired) was performed to visualize how the land-cover classes would be given its current trends. Hence, these predictions were performed assuming the urban growth trend between 2000 and 2006 continued and there are no external forces driving change. This however is never the case as there could be natural disaster or changes in land-use policies that could alter the trend of sprawl. The Eti-Osa area is flood prone due its proximity to the Atlantic Ocean and low elevation. Results of the forward prediction analysis shows that by 2016 urban class would increase by 2,220 hectares, most of it as a result of intense loss mainly from sand (bare) class (1,192 hectares). Figure 5 shows the net change between the land-cover classes between 2006 and 2016 and contributions to the net change in the urban class during the predicted 10 year period. Results of the Markov chain analysis showing the transition probability and transition area matrix values for the study area are presented in table 5. Results of the forward prediction showed that by 2016 urban class would increase by 2,220 hectares (466 hectares from water, 1,192 from sand (bare) and 562 from vegetation).

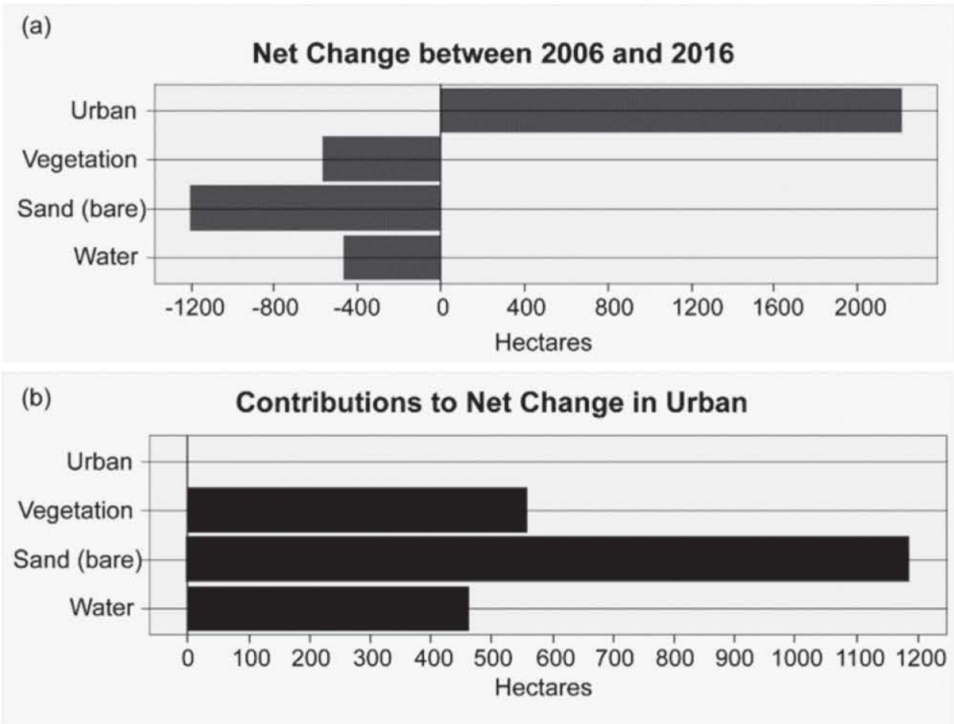

Figure 5 Results of forward simulation for all land-cover classes showing (a) net change between 2006 and (b) contributions of other land-cover classes to the net change in urban class

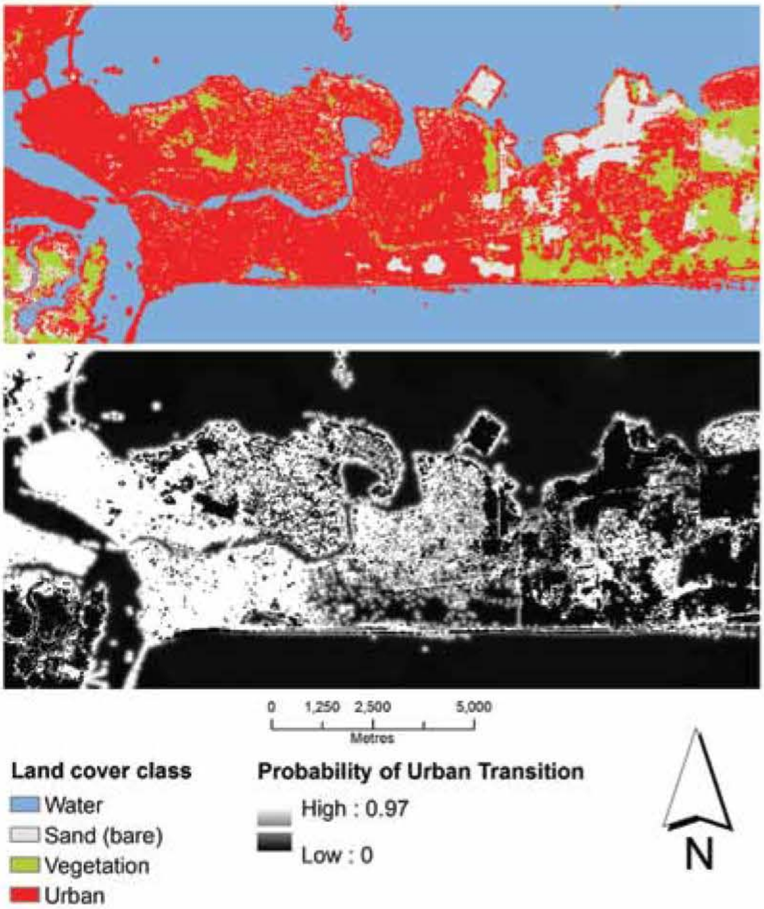

Figure 6: Forward simulation results showing: (a) Map of possible land-cover classes and (b) transition probability maps of Eti-Osa LGA in 2016

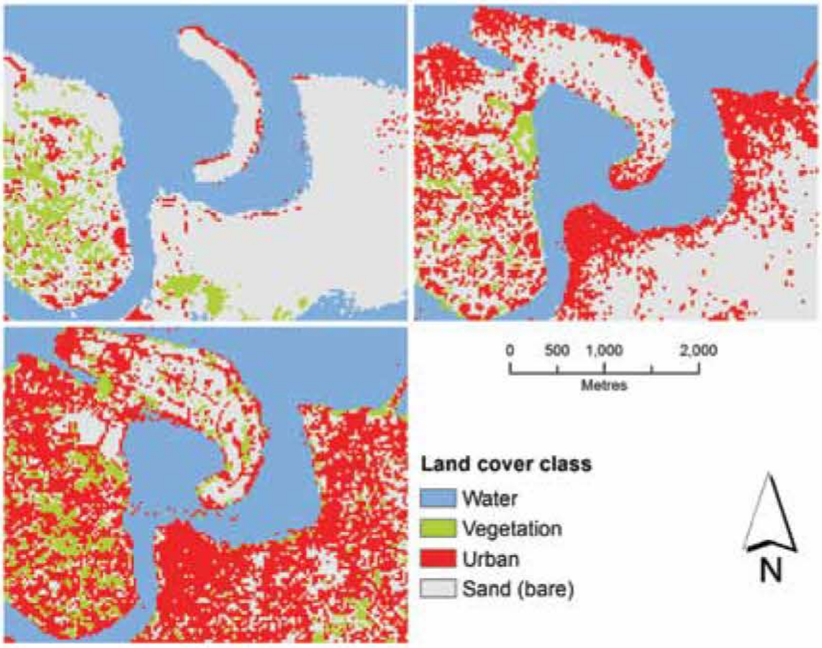

Figure 7: A section of Eti-Osa LGA showing transitions from water to sand (bare) and then urban through 1984, 2000 and 2006

Table 5: Results of the Markov chain analysis: transition probability and transition area matrix for Eti-Osa LGA

Land-cover	Transition probabilities				Transition area (hectares)			
	Water	Sand (bare)	Vegetation	Urban	Water	Sand (bare)	Vegetation	Urban
Water	0.90	0.03	0.01	0.06	7,208	-	-	466
Sand (bare)	0.05	0.30	0.16	0.49	-	1,224	-	1,192
Vegetation	0.06	0.32	0.33	0.29	-	-	1,353	562
Urban	0.03	0.13	0.09	0.76	-	-	-	4,325

The sand (bare) class which comprises of sandy surfaces and deposits and lightly vegetated bare/ undeveloped surfaces would be the greatest contributor to urban sprawl in 2016 given the current trend of landscape transition in the study area. Figure 6 shows the results of the forward simulation performed in the study.

4. Discussion

4.1 Causes and Impacts of Urban Sprawl

The change analysis reveals that a lot of reclamation of swamps, vegetation and water bodies had taken place over time. Some of the areas reclaimed to sand (bare) in 2000 had urban infrastructure by 2006. Figure 7 shows part of the study area as it transitioned from water to urban. Adeaga (2009) lists increasing encroachment of urban facilities on urban planes, unprecedented land reclamation, and inadequate drainage paths and blocking of existing ones (some of the make shift drainage channels created in these reclaimed areas tend to be blocked due to poor refuse disposal attitudes) and poor management as causes of heavy flooding in Lagos in general. Poor urban planning or lack of planning as urban development increases is evident in not preventing new development on areas at risk of flooding, leaving unprotected areas that should be left undeveloped, for instance wetlands, because of their role as buffers against flooding risks and also not providing safer sites for the urban poor (Adelekan, 2009). Kolawole (2011) noted that when torrential rainfall occurs in Eti-Osa, there is an influx of alligators and crocodiles into the urban area; putting residents at risk. These reptiles lived in those swamps before they were forced away due to urban encroachment. The study has demonstrates the effects of urban sprawl on changes to the flora/ fauna and wildlife.

5. Conclusions

Communities worldwide need data to compensate for and adapt to current growth while planning for expected future change and its impacts on infrastructure, as well as the surrounding environment (Goetz et al., 2003). This study has demonstrated the potential of using remotely sensing data to obtain accurate and detailed information on urban landscape transition, the dynamics of such changes through the use of spatial metrics and forward simulation of how the entire landscape would be in the future. The overall aim of the study was to investigate the spatial extent of urban landscape transition in Eti-Osa LGA, taking into consideration the nature and dynamics. For the two time periods investigated in this study (i.e. 1984 to 2000 and 2000 to 2006), urban land-cover increased by 4.7% (929 hectares) and 5.4% (1250 hectares) respectively. Results of the analysis showed that the highest contribution to the changes in the urban landscape was from the sand (bare) class (559 hectares from 1984 – 2000 and 758 hectares from 2000 – 2006 respectively). The pattern of urban development for 1984 – 2000 and 2000 – 2006 were *leapfrogging* and *polynucleated* respectively. The polynucleated pattern of urban sprawl between 2000 and 2006 indicates some degree of planning, such as building of new estates, had occurred over time. Furthermore, landscape metrics analysis revealed the presence of high fragmentation in the urban landscape for the time periods evaluated. The study has demonstrated that landscape metrics are useful indicators for understanding general trends of landscape dynamics and transitions. Based on the current landscape trends and patterns, a 10 year forward simulation from 2006 to 2016 was done and the results revealed that by 2016 urban class would increase by 2,220 hectares (466 hectares from water, 1,192 from sand (bare) and 562 from vegetation). The sand (bare) class which comprises of sandy surfaces and deposits and lightly vegetated bare/ undeveloped surfaces would be the greatest contributor to urban sprawl in 2016 given the current trend of landscape transition in the study area. In a similar study Mohan (2010) used remote sensing and GIS techniques to investigate the spatio-temporal land use / land cover changes and the process of urban sprawl in the adjoining areas of NOIDA city in India. Results of the study were used by decision makers and the local council to plan the city more effectively. Consequently, urban expansions were planned over the non-fertile agricultural land so as to foster sustainable urban and environment development in the new urban sprawling areas adjoining to the NOIDA City at the threshold of the 21st Century. Overall, this study has shown that the threat of urban sprawl is on the rise within Eti-Osa LGA of Lagos state putting the lives of the inhabitants at great risk and devastation of the ecosystem. It is recommended that the Lagos State Government take drastic steps in ensuring mitigative or preventive measures are put in place via effective policy implementation to combat the urban sprawl in the study area.

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