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Projection of Future Changes in Landuse/Landcover using Multi-Layer Perceptron Markov Model Over Akure City, Nigeria

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I. A. Balogun ^α & K. A. Ishola ^σ

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Keywords: urbanization, MLP, landuse/landcover, landsat.

1. INTRODUCTION

The fast increasing population due to the socio-economic and infrastructural growth has led to the demand for space in most of the cities around the globe. This has attracted the attentions of relevant scientific communities in most of the developing countries. Evidence has revealed that the world is becoming progressively urbanised, with 45% of the population

already living in urban areas in the year 2000 (Arnfield, 2003). It has been estimated that by the year 2025, 60% of the world's population will live in cities (UNEP 2002; Ichimura 2003). World population is forecast to reach 9 billion by 2050, with almost all the growth in developing countries (UN Development Programme 2010). The UN predicts that 60% of the world's population will be living in cities by 2030 and that nearly all the population growth will be in the cities of developing countries. Urbanization process refers to the transformation of natural vegetation into anthropogenic surfaces which are lands covered with buildings, roads, parking lots, and other paved surfaces associated with socio-economic growth and development of an area. During this process, the surface biophysical properties including soil moisture, material heat capacity, surface reflectivity and emissivity are altered.

FAO (2010) reported that the rate of deforestation in Nigeria between 1990 and 2010 was averagely 409,650 ha or 2.38% per year. On a local scale, Ishola et al. (2016) noted that the modification of natural vegetation in a neighbouring Abeokuta city in Nigeria is the main driver of LULCC and attributed this to the compelling socio-economic factors like rural-urban migration, the demand for space as a result of increasing population, and lack of urban monitoring and planning. However, the future scenarios owing to these compelling factors were beyond the scope of the study.

LULCC assessment specifically involves identifying the spatial and temporal changes of living and non-living features that are occurring within ecosystems (Roy et al., 2014). It involves the ability to quantify the human-induced changes, alteration and transformation of the surface features using multi-temporal data sets. Detecting, describing and understanding such changes are of considerable interest, not only to ecologists or conservationist, but also to environmental scientists and resource managers (Salami, 1999). In fact, insights on land cover change especially in relation to natural vegetation are a pressing issue for sustainable development because these changes can lead to land use conflicts and other environmental consequences (EEA, 2007). Natural

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vegetation is a multifunctional land cover which could be retained to counter-balance built-up density, as well serve as carbon sinks, and aid ecosystem and biodiversity. Hence, their losses cannot be ignored because; they pose a major threat to the environment and ecosystem health. In this respect, it is imperative that the LULC dynamics be adequately monitored and analyzed. Furthermore, the decisions about the quantities, purposes, and related consequences of land use are still poorly understood (Oyinloye et al., 2004). Therefore, proper geo-management of land and availability of detailed, accurate and up-to-date geo-information require an urgent intervention (Lemmens, 2001). That is, understanding LULC dynamics is critical for the planning and protection of the environment, and ecosystem and biodiversity (Hansen et al., 2008; Gomez et al., 2011)

Land-cover mapping determines the current composition and distribution of land surface attributes, and this is subsequently used as the basis for assessing future change (McDermid et al., 2005; Miller and Rogan, 2007; Schulz et al., 2010; Carmelo et al., 2012). However, modeling the complex dynamic systems of the land surface features has been challenging (Ahmed, 2011). Some popular tools have been developed to

model urban growth and land cover changes including Geomod (Pontius and Spencer, 2005), SLEUTH (Silva and Clarke, 2002), Land Use Scanner (Hilferink and Rietveld, 1999), Environment Explorer (Verburg et al., 2004), SAMBA (Castella et al., 2005), Land Transformation Model (Pijanowski et al., 2000), and CLUE (Kok and Veldkamp, 2001). These tools make use of a number of methods such as Markov Chain (Balzter, 2000), Cellular Automata (Sante et al., 2010), Logistic Regression (McConnell et al., 2004), and Artificial Neural Network (ANN) (Civco, 1993). More details on the characteristics of each tool are discussed in the literature (Pontius et al., 2008). This study used the Multi-layer Perceptron (MLP), a type Neural Network method with more than one hidden layer, in order to model and project future land cover change scenarios (Ahmed and Ahmed, 2012). The MLP decides about the parameters to be used and how they should be changed to better model the data. It undertakes the classification of remotely sensed imagery using the back propagation algorithm. The MLP also performs a non-parametric regression analysis between input variables and one dependent variable with the output containing one output neuron (Atkinson and Tatnall, 1997).

II. MATERIALS AND METHODS

a) Study area

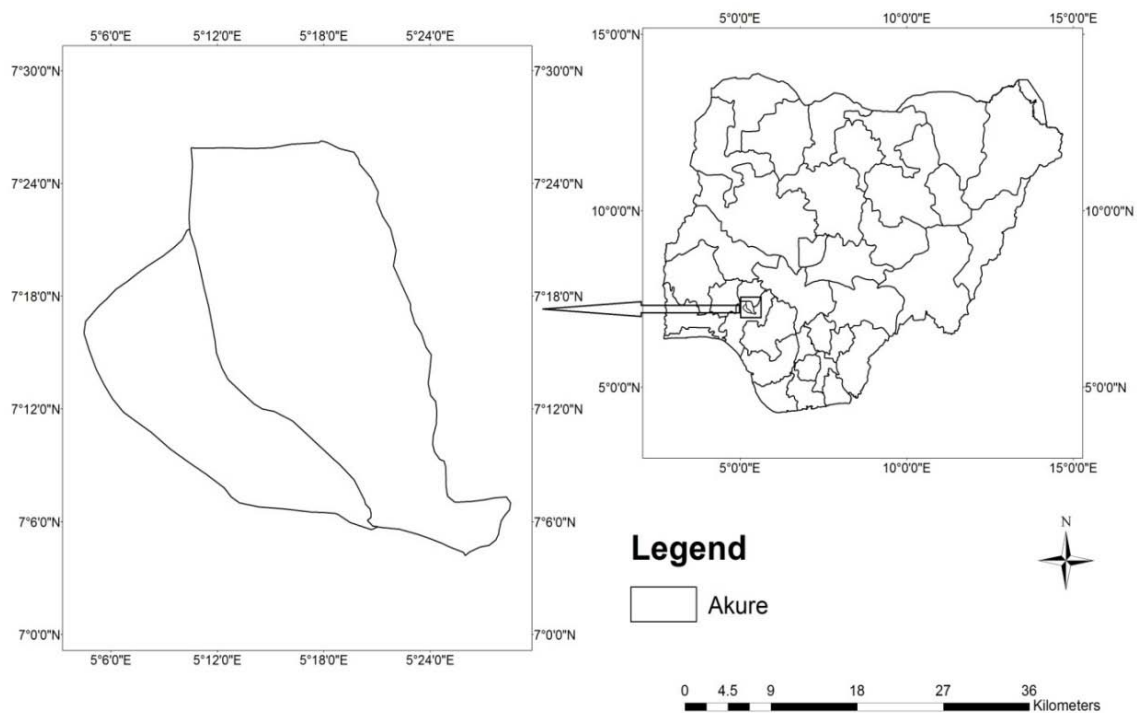


Figure 1: Map of Nigeria showing the location of the study area

The city of Akure in Ondo State, Nigeria has received wide attention in recent times. The rapid growth of the city, particularly within the last few decades, has made it one of the fastest growing metropolitan areas in the South-western Nigeria. Its increasing population and observed rapid rate of expansion in land use has been attributed to the socio-economic growth of the area (Balogun et al., 2012; Oyinloye and Fasakin, 2014). Akure area has witnessed tremendous growth in the size of built-up areas, number of immigrants, transportation and commercial activities. It is geographically situated between longitude 5°06'E to 5°38'E and latitude 7°07'N to 7°37'N (see figure 1) and lies on a relatively flat plain with roughly 370m above sea level. It is situated in the humid tropical region of Nigeria with average rainfall of about 1500 mm per annum. The annual average temperatures range between 21.4 and 31.1°C, and mean annual relative humidity is about 77.1% (NiMET, 2007). Its population has increased from 71,006 people in 1963 to 340,021 in 2006 (NPC, 2006), and has been estimated to increase annually by more than 5%. The increase in annual growth of the population has been tied to the administrative role of the town and its long standing role as a centre of economic activities attracting a large spectrum of immigrants into it.

b) Materials

The study adopted Landsat multisensory and multitemporal datasets acquired from the archives of

United States Geological Survey (USGS) including, Landsat thematic mapper (TM), enhanced thematic mapper plus (ETM+), and operational land imager/thermal infrared sensor (OLI/TIRS) covering 1986, 2000, and 2014 respectively (see Table 1). The study area is located in the Landsat path 190 and row 055 of the World Reference System (WRS-2).

The images were captured at different periods, thus, the different atmospheric conditions of the imageries. However, the atmospheric corrections with other corrections like geometric, radiometric, and topographic of the imageries were carried out in GIS environment. The radiometric correction employed the algorithm of Chander and Markham (2003) with the addition of an atmospheric correction. The 2000 image was used as the base image for geometrical correction due to its better visual quality. Geometric correction of the 2000 scene was based on Ground Control Points (GCPs) identified on the topographical maps of the area, and nearest neighbour resampling to a 30-meter pixel size with RMS error of 0.25. The 1986 and 2014 imageries were co-registered to the base image using additional GCPs into UTM projection with geometric errors of less than one pixel, so that all the images have the same coordinate system (Adedeji et al., 2015).

Table 1: Description of the Landsat imageries used (USGS, 2014)

City	Path/row	Sensor	%Clou	Date acquired	Resolution
Akure	190/055	Landsat5 TM	0.00	17/12/1986	30m/120m
		Landsat7 ETM+	0.00	15/02/2000	30m/60m
		Landsat8 OLI/TIRS	0.59	14/12/2014	30m/100m

c) Methods

i. Image classification

The acquired satellite imageries for the three examined dates were classified into four broad land cover classes based on the sample set created according to a total of 100 identified training samples (see Table 2). Training samples are representative of the desired land use classes (Magidi, 2010) and were determined based on ground truthing, researcher's personal experience and physiographical knowledge of the study area (Jensen, 2007). On average, 20 to 25 training samples for each land cover class were selected. All the images were analyzed with respect to their spectral and spatial distribution in order to develop the training sites (Ahmed, 2011). A chosen band combination (RGB = 432) was used to develop polygons around each training site of similar land cover. Then a unique identifier was assigned to each known land cover type (Ahmed and Ahmed, 2012). Afterwards, the statistical characterizations (i.e., signatures) of each

land cover class were developed and a supervised maximum likelihood classification method with a uniform prior was used for all classes. This procedure has proven to be a robust and consistent classifier for multi-date classifications (Wu et al., 2006). Each composed image was ordered into 4 area classes: water, vegetation, built-up and bare soil as described in Table 2. Furthermore, a distance threshold was adopted for each class to remove the pixels that probably do not belong to that class and was determined by examining interactively the histogram of each class in the generated distance image. Pixels with a distance value greater than the threshold were assigned a class value of zero in the thematic image. The accuracies of the classified imageries were checked with a stratified random sampling method of 200 reference pixels for each examined dates. This sampling number is thought to be a compromise between statistical rigor and practical limitations (Wu and Murray, 2003). The confusion/error matrices (not shown) were basically

used to assess the overall, producer's, and user's accuracy of classification results, as well as the kappa

coefficient. This is an important method for evaluating per-pixel classification (Weng, 2002).

Table 2: Details of the land cover types

Land Cover Type	Description
Built-up Surface	All infrastructure—residential, commercial, mixed use and industrial surface areas, asphalt road network, pavements, rocks, parking lots, and other man-made structures.
Water Body	River, permanent open water, lakes, ponds, canals, permanent/seasonal wetlands, low-lying areas, marshy land, and swamps.
Vegetation	Trees, natural vegetation, mixed forest, gardens, parks and playgrounds, grassland, vegetated lands, agricultural lands, and crop fields.
Bare Soil	Fallow land, earth and sand land in-fillings, construction sites, developed land, excavation sites, open space, bare soils, and the remaining land cover

ii. *Land cover change detection analysis*

Change detection analysis was carried out on Landsat images of different years (i.e. 1986, 2000 and 2014) to analyze the pattern and trend of change in the study area using Land Change Modeller (LCM) for ecological sustainability and Markov Chain model (Eastman, 2006). Using LCM requires mainly two time categorical maps and so the classified maps (say 1984 (time-1) and 2003 (time-2)) were used as inputs for the change analysis. This enabled us to understand the gains and losses, the net transition of areas and contributions among the land use/land cover classes; and to quantify the changes that occurred from time-1 to time-2 (Eastman, 2006).

iii. *Projection of future land cover changes*

There exists several land use/cover change modeling techniques, but the right simulation technique / model depends on the scope of study, availability of datasets, objective of the research, and the accuracy of the prediction (Pontius et al., 2008; Ahmed, 2011). Considering accuracy and wide acceptability, both the Markov Chain (Basharin et al., 2004) and MLP modeling techniques (Atkinson and Tatnall, 1997) were applied in this study to project the future changes of land cover. A detailed description on the MLP Markov modeling technique has been comprehensively described by Ahmed and Ahmed (2012). The observed changes in land cover that is, the transitions from other land cover types to built-up areas, were used as the dependent variables; while the spatial variables such as the distance from all land cover types to built-up areas, water body, vegetation, and bare soil; the empirical likelihood transformation, were used as the independent variables. These two types of variables were used to train the MLP Markov model and to produce the transition potential maps between the historical years.

Afterwards, future scenarios of LULCC were predicted for 2028 and 2042 using the Multi-Objective Land Allocation (MOLA) algorithm (Khoi and Murayama,

2010). The quantities of modifications were determined by the Markovian conversion probabilities (Eastman et al., 1995). After this, a multi-objective allocation was run to allocate land for all receivers of a set class (Khoi and Murayama, 2010; Eastman, 2012). The results of the reallocation of each set class were then overlaid to produce the final predicted maps.

III. RESULTS AND DISCUSSION

a) *Land cover changes*

This section presents the various classes of land use/ land cover adopted in this study, and the analysis of the changes that have taken place over time (Figure 2).The overall accuracies of the classified images revealed 91.67% in 1986, 85.83% in 2000, and 88.33% in 2014. The Kappa coefficients were observed to be 0.81, 0.74, and 0.76 for 1986, 2000, and 2014 respectively (Table 3). The Kappa coefficient is a measure of the proportional/percentage improvement by the classifier over a purely random assignment to classes (Ahmed et al., 2013).

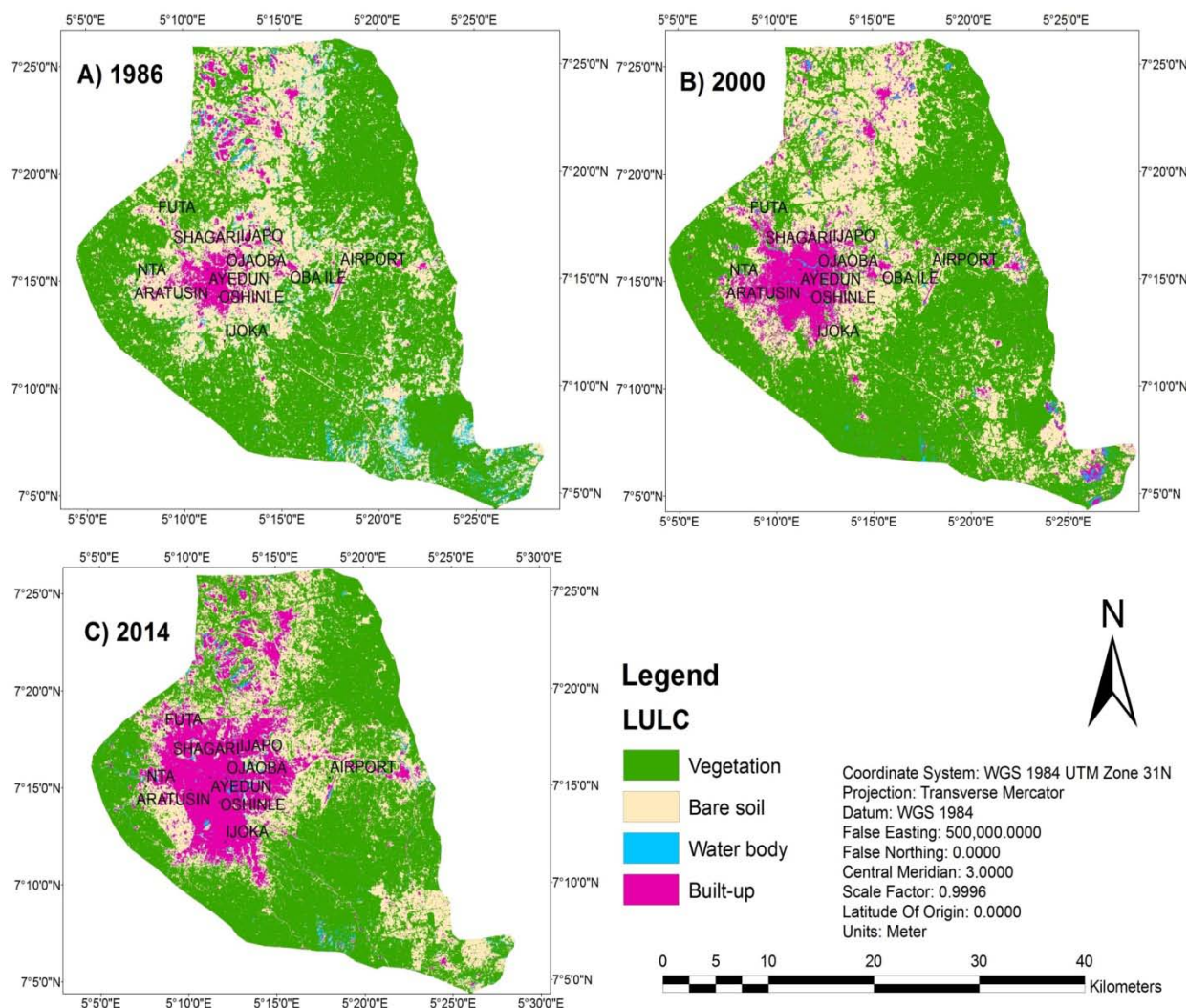


Figure 2: Spatial distribution of Landuse/Landcover maps of Akure for A) 1986 B) 2000 and C) 2014

Table 3: Accuracy assessments of the Land cover classes

Year	User's Accuracy (%)				Producer's Accuracy (%)				Overall	
	Water Body	Vegetation	Built-up Area	Bare Soil	Water Body	Vegetation	Built-up Area	Bare Soil	Accuracy (%)	Kappa Coefficient
1986	75.00	98.78	66.67	77.42	100.00	92.05	100.00	88.89	91.67	0.81
2000	0.00	83.33	88.89	93.75	0.00	98.48	72.73	69.77	85.83	0.74
2014	0.00	91.46	81.82	88.00	0.00	96.15	90.00	68.75	88.33	0.76

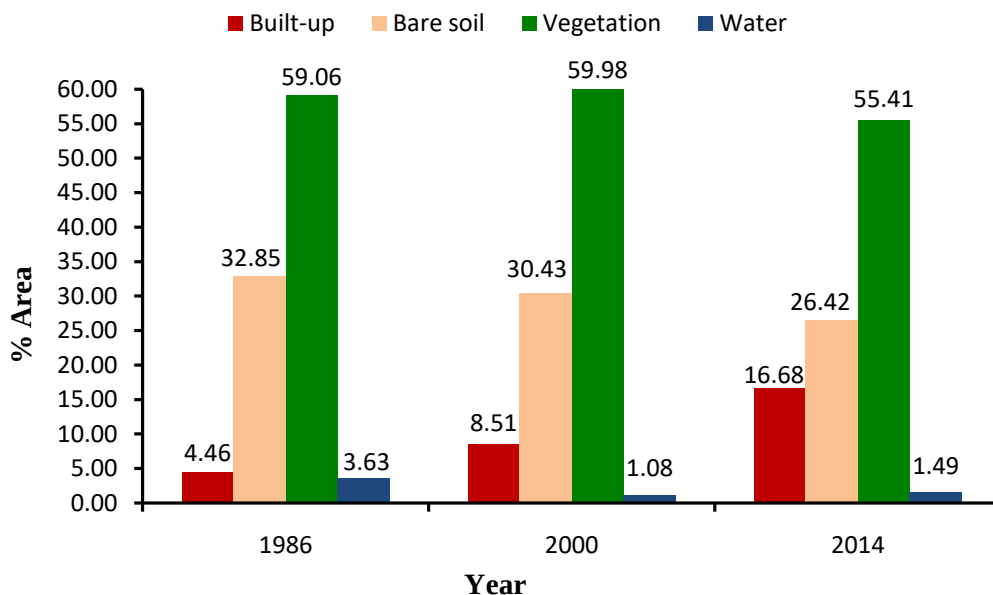
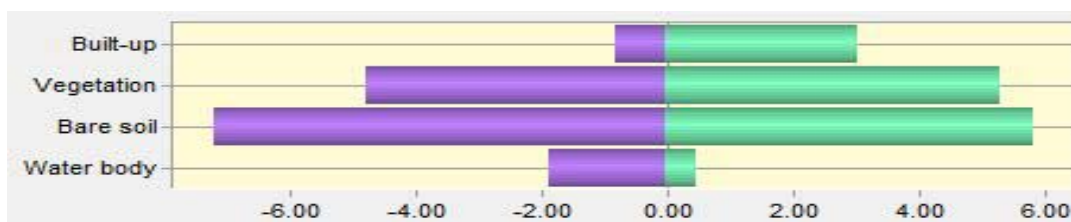


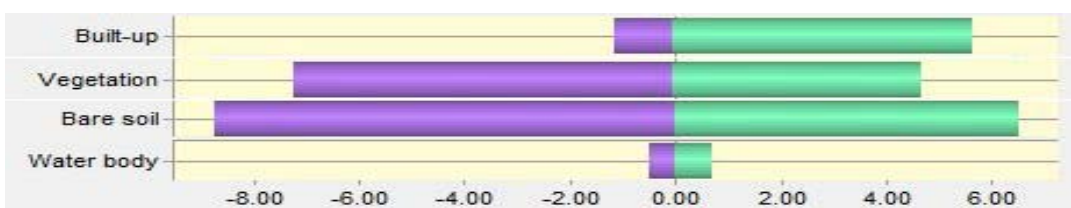
Figure 3: Percentages of area covered by landcover types in Akure

The analysis of the spatial-temporal pattern of the land cover changes presented in Figures 2 and 3 revealed that, the proportion of Built-up area exhibits an increasing trend, while other land cover classes decreased in the proportion of area covered over the years. Figure 3 shows that vegetation covers the largest proportion/percentage of this area followed by bare surfaces throughout the period under study. Although the percentage area covered by Built-up has increased over the years from 4.46% in 1986 to 16.68% in 2014. This is obvious in the loss of percentage area covered by vegetation (59.06%) and bare soil (32.85%) in 1986 to 55.41% and 26.42% respectively in 2014, as a result of the increasing socio-economic factors (population, economic, technological and institutional growth). These have triggered competition for space for various urban development purposes such as residential, commercial, recreation, institutional, industrial, transportation etc, thereby increasing the built-up area and consequently decreasing vegetation and bare soil areas. If the above

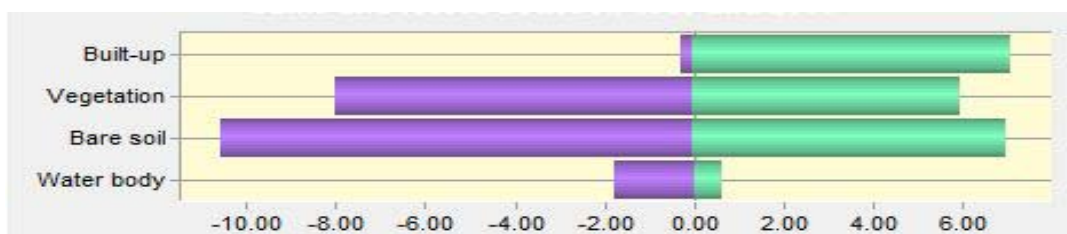
enumerated factors are left unchecked with appropriate urban planning and development policies, the city might be facing serious environmental, bioclimatological and health challenges in no distant time. Balogun et al. 2011 reported the existence of urban heat island (UHI) intensity of 4°C in the city. The consistent increase in the built up area will continue to affect the environment through enhanced releasing of pollutants to the atmospheric environment and subsequent degradation of the local climate. Balogun et al. (2014) observed that the carbon monoxide (CO) concentrations at the urban area were 2-3 times higher than that of the rural site. The increase in built up area can often leads to continual loss of biodiversity on a long term and also increases potentials for flooding. Among all the land cover classification, there is little/no significant percentage area covered by the water body throughout the period under investigation Further analyses were conducted to understand these patterns of conversion throughout the period of study.



(a)

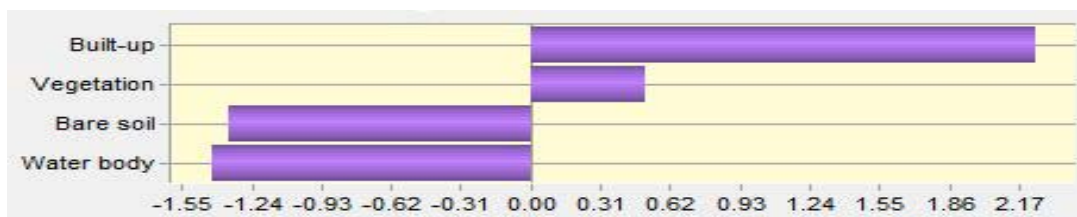


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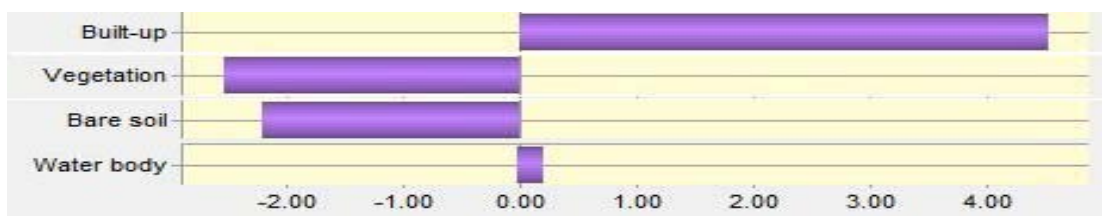


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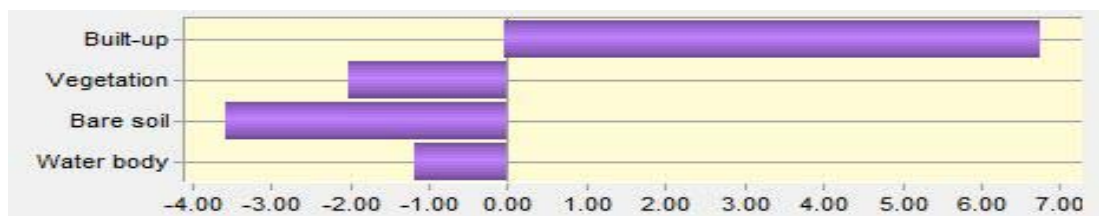
Figure 4: Gains and Losses in Land cover areas between (a) 1986 and 2000 (b) 2000 and 2014(c) 1986 and 2014



(a)

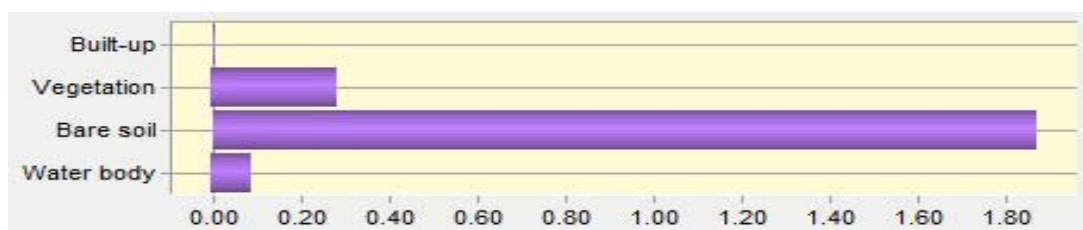


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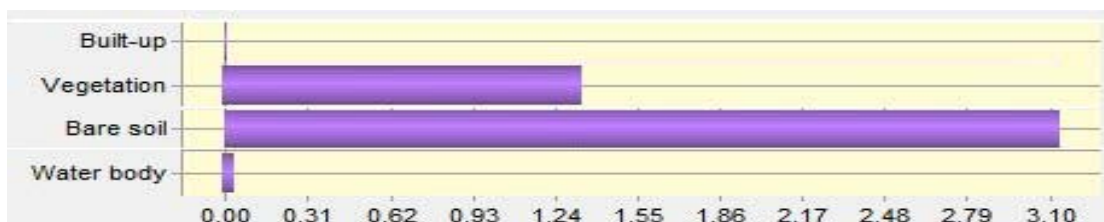


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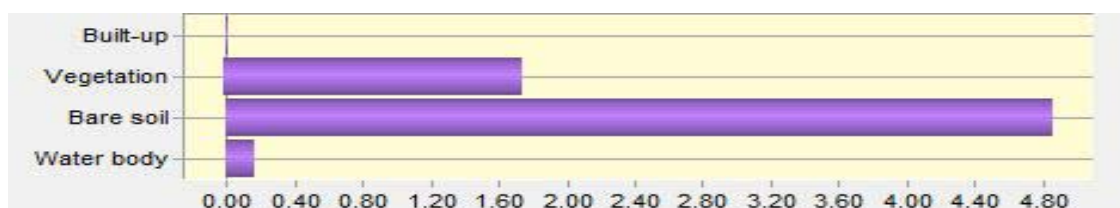
Figure 5: Net Change in Land cover areas between (a) 1986 and 2000 (b) 2000 and 2014 (c) 1986 and 2014



(a)

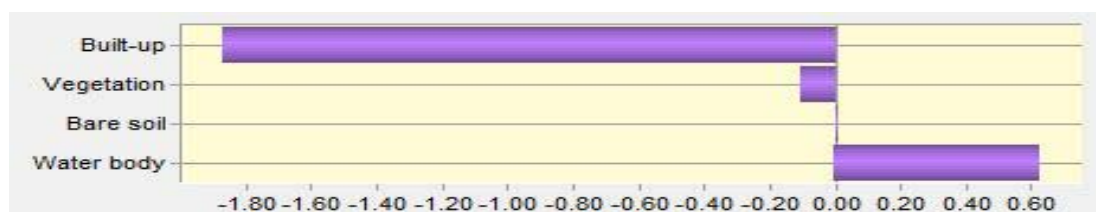


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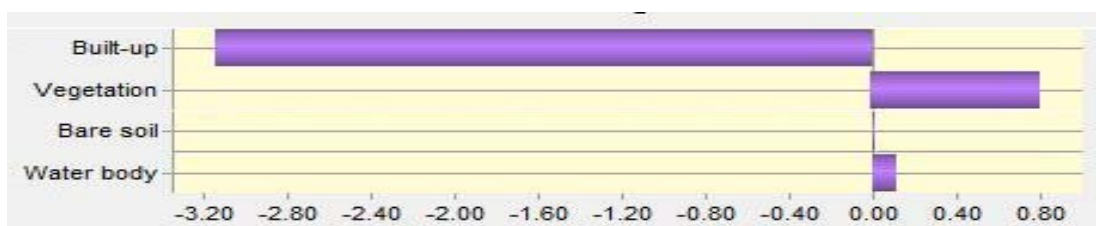


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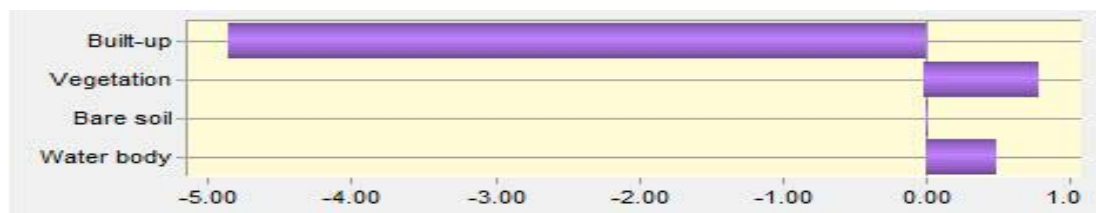
Figure 6: Contributions to Net Change in Built-up areas between (a) 1986 and 2000 (b) 2000 and 2014 (c) 1986 and 2014



(a)

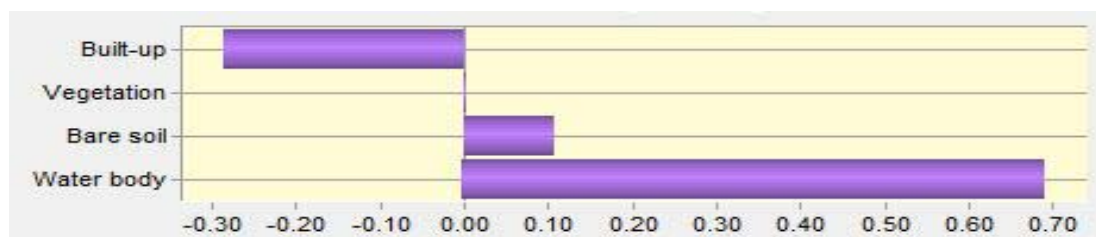


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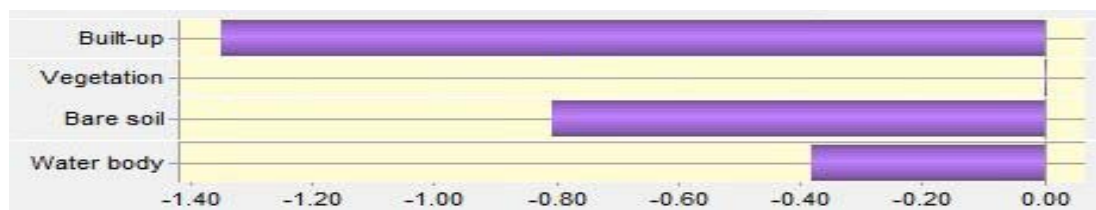


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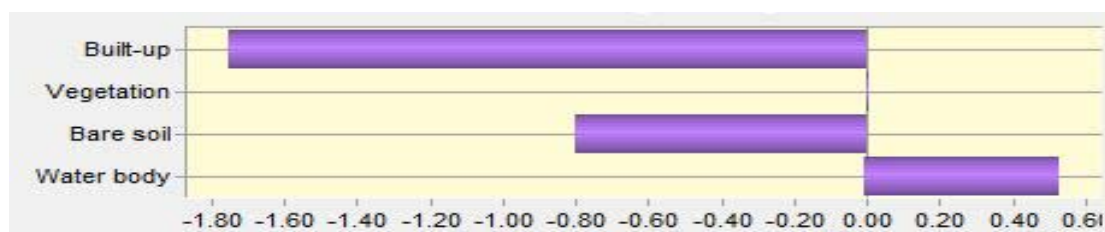
Figure 7: Contributions to Net Change in Bare soil areas between (a) 1986 and 2000 (b) 2000 and 2014 (c) 1986 and 2014



(a)



(b)



(c)

Figure 8: Contributions to Net Change in vegetated areas between (a) 1986 and 2000 (b) 2000 and 2014 (c) 1986 and 2014

The changes in land cover types presented in Figure 4 revealed that, only a small percentage (<2%) of area covered by built-up was lost to other land cover types in both periods (1986-2000, and 2000-2014). Most of the built-up were lost due to demolitions carried out for road expansions, construction of new road networks and buildings without appropriate government approval. However, a significant change occurred in the vegetation and bare soil categories in both periods. These land cover categories lost more land areas than they gained in each of the period (Figure 4). Analysis of the net change in the areas covered by the land cover classes show that, there was significant and progressive change (increased with magnitude >1.5%) in built-up areas in all the periods (Figure 5). The net change of bare soil and vegetation shows a general decrease except for the period (between 1986 and 2000) that vegetation showed a little increase in net change. The conversion patterns between the land cover categories are illustrated in Figures 6-8. It was observed that the bare soil was the major contributor to net change (increasing) in built-up areas followed by vegetation and no significant contribution from water body (Figure 6). Conversely, only water body was converted to bare soil between 1986 and 2000 (Figure 7a). More significant contributions to net change (increasing) in bare soil areas were seen from vegetation in other periods (Figure 7b-c).

Although a few proportion of water body still contributed to the extension of the bare soil areas but not as effective as vegetation in these later periods. However, there were no places where built-up was converted to bare soil type at all. In addition, Figure 8 revealed that the water body is the major contributor to extending vegetated areas. Although a few percentage of bare soil areas were modified to vegetation between 1986 and 2000 (Figure 8a), there was no contributions to net change in vegetation between 2000 and 2014 (Figure 8b). That one land cover category contributes to the net change of another was also established Ahmed et al. (2013).

b) Projection of future land cover change

The analysis of past changes in LULC distributions with regard to spatial explanatory variables enables assessment of the degree to which locations

might likely change in the future. Markov Chain analysis was performed for the multi-temporal land cover images of 1986-2000, and 2000-2014 including predicting for 2028 and 2042 as shown in Figures 9 and 10 respectively. Results of the MLP Markov Chain models focused mainly on providing the knowledge of how much, where, what type of land use/land cover changes will occur from 2014 to 2028 and from 2028 to 2042. It has been observed that the built-up areas showed an increased trend, as other classified land cover types decreased in the previous years. The projected land cover scenarios indicates similar spatial distribution and trend with an expectation of continual expansion in the built-up areas and decreasing vegetation and bare soil surfaces from 2014 to 2028 (Figure 9), and more expansion between 2028 and 2042 (Figure 10). The observed rural (like Airport, NTA, etc) and sub-urban (like FUTA, Oba-Ile, Ijoka, etc) areas with abundant vegetation in the earlier periods will experience significant depletion and surface modifications between 2014 and 2028 (Figure 9). The built-up and the bare surface areas would have expanded towards and encroach these areas by 2028, provided the driving mechanisms such as continual growth in the socio-economic factors are sustained. Figure 10 also indicate that the urban centres are expected to widely extend to the rural areas (like Ipinsa, Ibule, some rural parts of Aule, Oba-Ile and Ijoka, Igoba, and Sasha) by 2042.

A quantitative assessment of the simulated land cover scenarios presented in Figure 11 suggests that approximately 5.04% of areas covered by both vegetation and bare soil in 2014 will be modified to built-up areas by 2028. Similarly, about 4.75% of the same areas will be converted to built-up by the year 2042. In all, there will be a substantial increase in the built-up areas to 21.72% and 26.47% by 2028 and 2042 respectively. This will be evident in the corresponding decrease in the areas covered by vegetation and bare soil. The prediction of the future scenarios of land use change in the study area reveals probable continuous degradation of the forests, light and thick vegetation which will result in more degraded lands. Unabated vegetation loss and degradation could trigger serious environmental problems that are linked to increased surface thermal response, reduced infiltration and increased surface runoff.

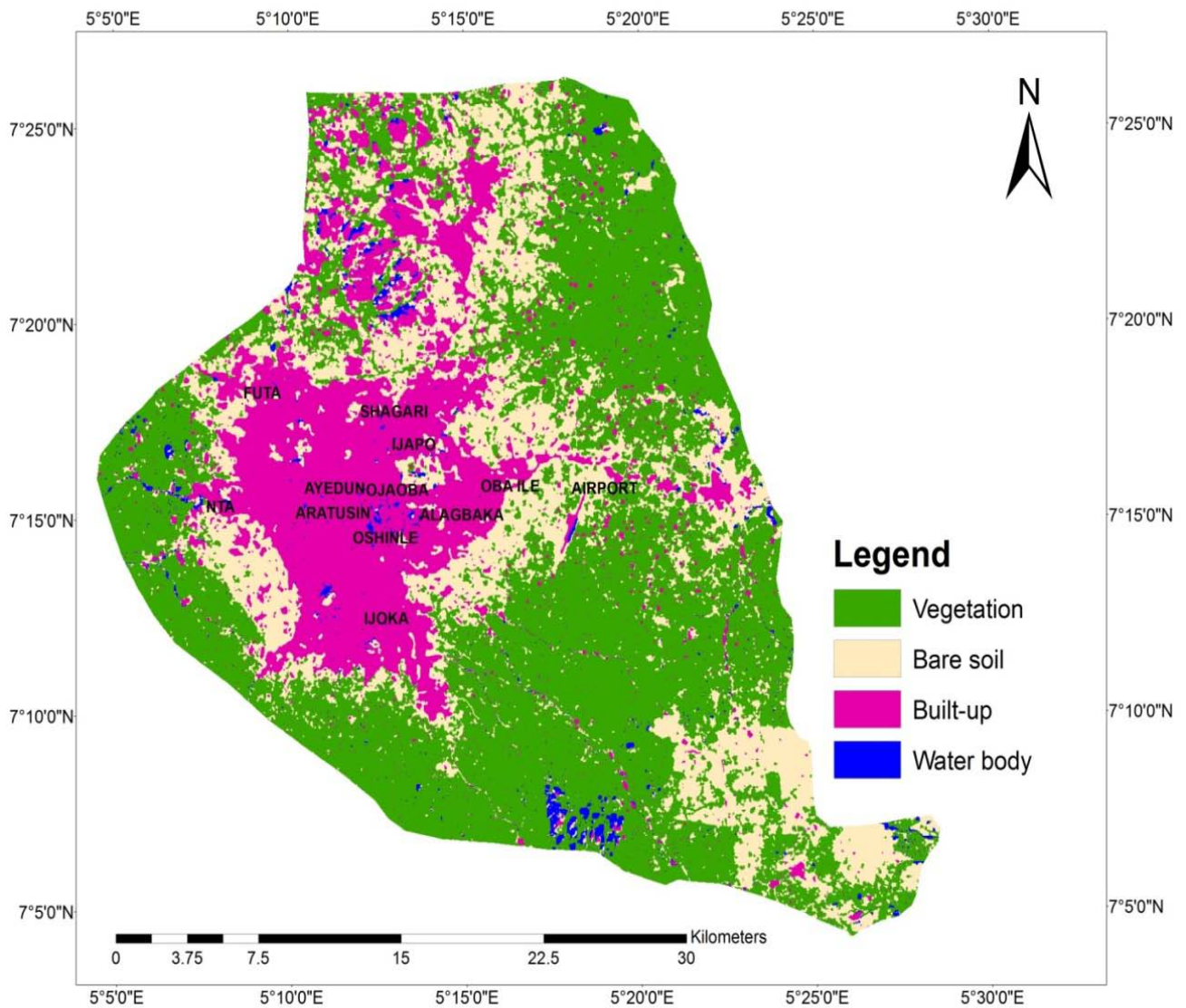


Figure 9: MLP Markov model projected land cover scenario of Akure area for 2028

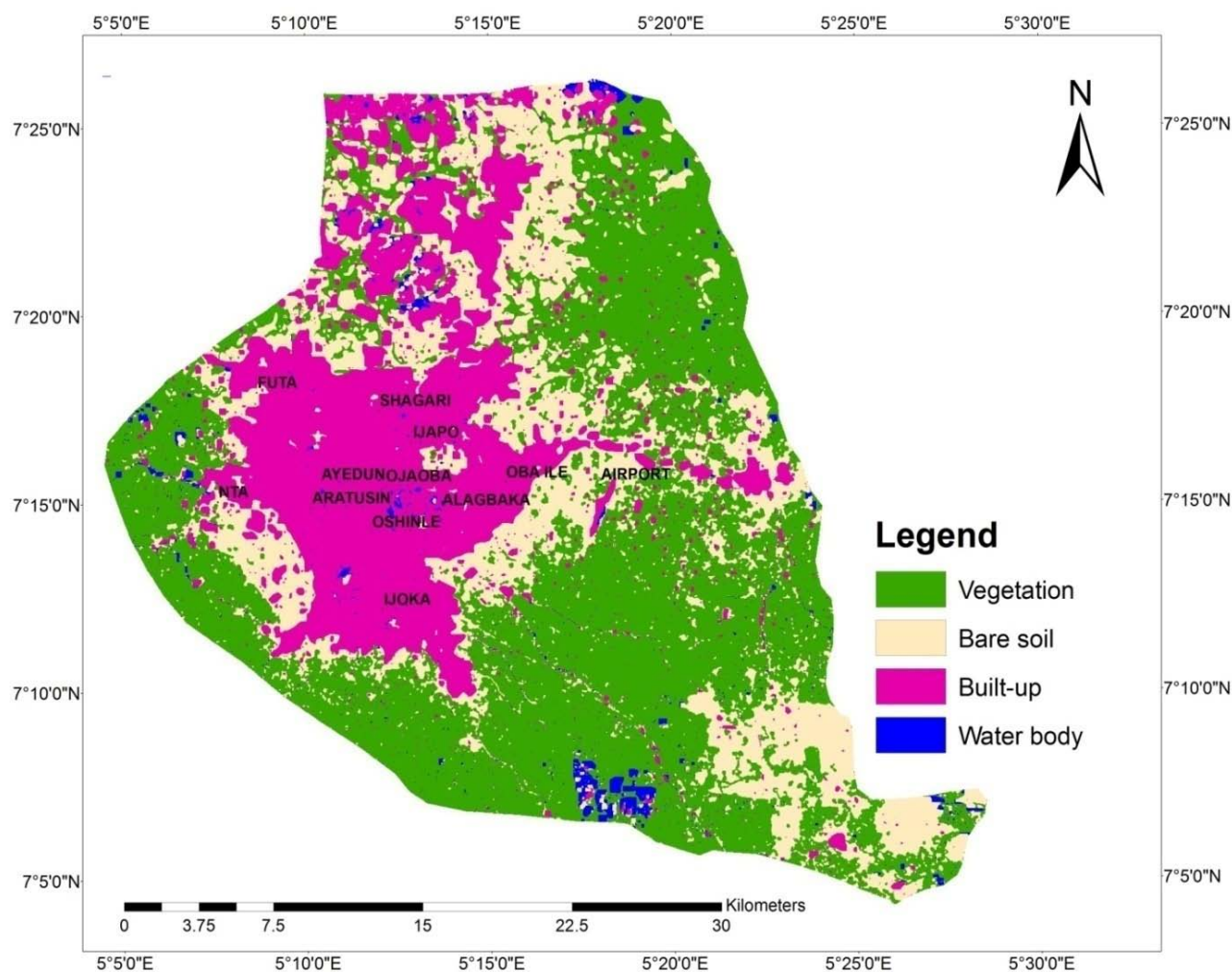


Figure 10: MLP Markov model projected land cover scenario of Akure area for 2042

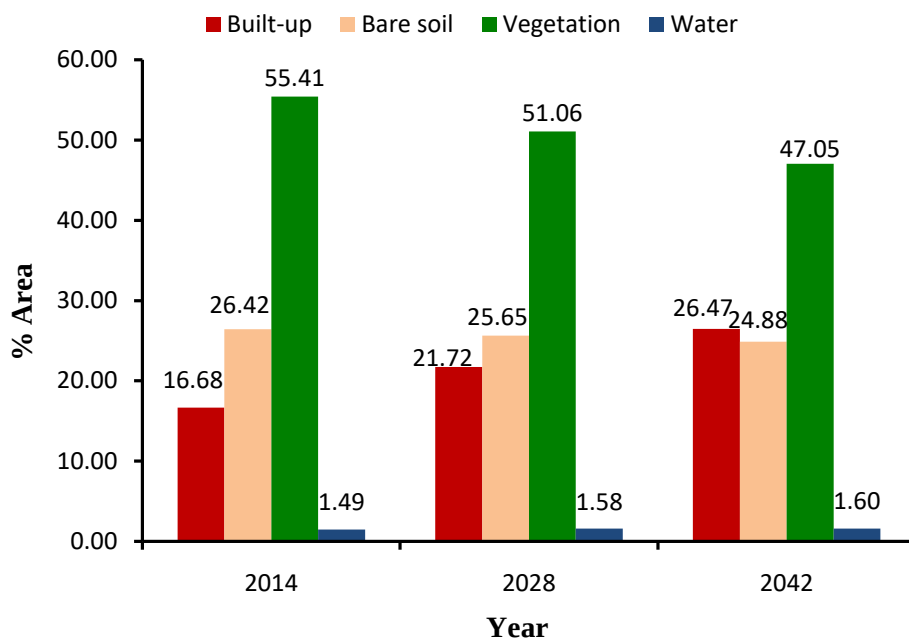


Figure 11: Simulated Percentages of Area covered by landcover types in Akure

III. CONCLUSIONS

This study has examined the past and future LULCC due to urbanization processes over Akure City in Nigeria. The observed rapid increase in built up areas and the continuous depletion of the vegetated areas calls for concern. Most especially, the projected future changes by the year 2028 and 2042 follows the trend of observed between 1984 and 2014, revealing that built-up areas will continue to increase rapidly and the vegetated areas will be reducing drastically. This will have serious implication on the local climate of the city coupled with the enhanced greenhouse gases through the depletion of the carbon sinks. This call for improved urban planning that accommodates urban greening in the future urban developments, considering the mitigating roles of vegetations on heat islands and global warming. Although, the potential modifications and extension of built-up density to the rural and sub-urban areas as projected by MLP model in the subsequent years pose major environmental threats, these areas can yet be explored for business opportunities which will inturn contribute to the socio-economic growth of the city.

Findings from the observed changes in LULC are consistent with that of previous studies, thus the projected changes are reliable because they are based on well-established MLP Markov technique in the literature. The model results can serve as guide to urban planners and policy makers. Furthermore, urbanization has been identified as the major driver of land cover changes. Thus, effective policies that are capable of ameliorating urban sprawl and the environmental impacts should be put in place. Further study will seek to quantitatively assess the impact of this LULCC on the urban thermal field in the future context.

IV. ACKNOWLEDGEMENTS

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