International Scholars Journals

Advanced Journal of Environmental Science and Technology ISSN 2756-3251, Vol. 15 (7), pp. 001-010, July, 2024. Available online at www.internationalscholarsjournals.org © International Scholars Journals

Full Length Research Paper

Spatiotemporal Analysis of Land Use/Land Cover Changes in Ilorin Emirate (1986-2006) Using Landsat Data

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Accepted 2 April, 2024

This paper examines changes in land-use and land-cover pattern in Ilorin Emirate in Nigeria between 1986 and 2006. Landsat images of Ilorin Emirates at three epochs (1986, 2000 and 2006) were used. An administrative map of local governments in Kwara State and a land-use map of Ilorin were used as base maps. Global Mapper Software was used for the image enhancement; image classification was done with environment for visualizing images (ENVI) software and was later exported to the ArcGIS for further processing and analysis. The land consumption rate and land absorption coefficient was determined to aid the quantitative assessment of change. Subsequently, an attempt was made at projecting the observed land-use / land-cover for a period of 14 years ending at 2020. The result of the work shows a gradual growth in built-up land between 1986 and 2000 and this tends to grow more rapidly between 2000 and 2006. It was also observed that the change by 2020 may likely follow the trend observed in 2000 and 2006. It is recommended that the information from the results of this work should be use to optimally and effectively plan and manage the study area.

Key words: Land-use, land-cover, land consumption rate, land absorption coefficient, change detection.

INTRODUCTION

Background of study

Land is the foundation of all forms of human activity, from it we obtain the food we eat, the shelter we need, the space to work and the room to relax (Briassoulis, 2000). Land represents about 29% of the Earth's surface. The use of land is known as land-use morphology, it varies considerably from place to place. Metropolitan areas in Nigeria are growing at an unprecedented rate, creating extensive urban landscapes. Many of the farmlands, wetland and savanna in Nigeria of 1960s have been transformed during the past 50 years into human settlements. The changes in Nigeria are pervasive, but without a clear understanding of how the changes can be analyzed and their impacts known. It is not until a spatial and temporal study of these landscape transformations is carried out that we can begin to appreciate the changes and estimate the impacts they may have on the environment.

In the simplest form, land-use is referred to the use in which a piece of land is put to. It centres on the human activities that relate to a particular parcel of land. The magnitude of land-use change varies with the time interval being examined as well as with the geographical area. Moreover, assessment of these changes depends on the source of the data used, the definitions of land-use types, the spatial distribution, and the data sets used. Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times (Singh, 1989). Change detection is an important process in monitoring and managing natural resources and urban development because it provides quantitative analysis of the spatial distribution of the activities of interest. Macleod and Congation (1998) identified four aspects of land-use change detection that are important: (i) detecting the changes that have occurred (change / no-change), (ii) identifying the nature of the change, (iii) measuring the areal extent of the

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change and (iv) assessing the spatial pattern of the change.

Population is a very important factor or agent of change in land-use in an area. For instance, as population increases, construction of dwellings increases, thus engendering conversion of cropland and forest land to settlements. These urban land-uses are of various types which could be for industrial, commercial, government, as well as transportation purposes.

The underlying causes of land-use change could be broadly categorized into two: proximate (direct or local) and underlying (indirect or root) (Lambin et al., 2003). The proximate causes of land-use change refer to how and why local land-cover and ecosystem processes are modified directly by humans. The underlying causes explain the factors responsible for these local actions. In general, proximate causes are a local land-use which is as a result of land-use decisions made by individual land-owner or other entity that controls individual land. Underlying causes originate from regional factors such as government policy, regional/global economics. However, it is the interaction of drivers at multiple scales which eventually leads to change in land-use. For instance, biophysical drivers of land-use change, such as, droughts resulting from climate change or loss of soil fertility due to erosion may be as important as human drivers, which include economics and policy. The interaction of these biophysical drivers of change with cultural or social drivers of change could include deforestation, urbani-zation, desertification and afforestation.

Information on land-use serves as a major input for any program on energy conservation, for monitoring environ-mental hazards and for the enhancement of equitable distribution of resources. Information on land-use change has also been found to be of great importance in the political administration of many countries. Remote sensing and spatial analysis have been recognized and used as powerful and effective tools to monitor land-use change. Satellite remote sensing collects multispectral, multi-date and multi-spectrum data can be used to construct broad-scale land-use data bases and provides valuable information in under-standing and monitoring the process of land-use change.

The aim of this study is to study the pattern of land-use /land-cover change in Ilorin emirate in the last 20 years using multi-epoch data. It is intended to develop a probabilistic model of land-use change and predict likely changes that would take place in the same area over the next period of 14 years.

Studies have been conducted on the land-use of various cities in Africa. For instance, Wu et al. (2003) investigated the factors influencing urban land-use in Nouakchott, Mauritania. They concluded that population growth is the only factor responsible for urban expansion in Nouakchott. Tewolde and Cabral (2011) studied urban sprawl and its impact on other land in Asmara, Eritrea. The result of the study indicated that the built-up area has tripled in size between 1989 and 2009. In the study of Mundia and Aniya (2006) on land-use in Nairobi, they cover the period between 1976 and 2000. They con-cluded that urban expansion has replaced agricultural farmlands and other natural vegetation, thereby affecting habitat quality and leading to serious environmental degradation. In Nigeria, Barredo and Demicheli (2003) in their study on urban sustainability issues in African countries focussed on urban expansion in Lagos. They described land-use simulation for the city of Lagos using an improved version of CA model prototype. The work included a twenty-year simulation run until 2020. Also, Adeniyi and Omojola (1999) carried out a study of land-use and land-cover change in Sokoto - Rima Basin of North - Western Nigeria between 1962 and 1986. The work revealed that land-use and land-cover of the areas was unchanged before dam construction while settlement alone covered most part of the area. However, during the post - dam era, land-use/land-cover classes changed but with settlement still remaining the largest. Barredo and Demicheli (2003) note that “urban population and expan-sion is increasing in developing countries particularly Africa. These immense urban agglomerations, which often show a dramatic sprawl coupled with an explosive population growth, have social consequences and are disastrous to the environment”.

An attempt has been made to document the growth of Ilorin and its environs in the past using Landsat imageries (Olorunfemi, 1983; Zubair, 2008). However, full coverage of the entire emirate has never been achieved. In the previous studies, maps and aerial photographs were processed using the traditional methods of maps and photo interpretation. In recent times, the multi-dimensional dynamics of landuse / land-cover particularly in settlement expansion, requires more powerful and sophisticated spatial models and tools that geographic information system (GIS) and remote sensing provide. Moreover, recent changes in global climate and its immense consequences requires that changes in land-use / land-cover, which is one of the principal causes of climate change should be monitored on a regular basis in every part of the world.

Study area

Ilorin is the present day capital of Kwara State in the north central Region of the Federal Republic of Nigeria. It is a pre-dominantly Islamic City and presently inhabited by people of diverse culture. The Entire Ilorin community comprises of five Local Government Areas namely- Ilorin West, Ilorin South, Ilorin East, Asa and Moro. These Local Government Areas are all under one entity known as Ilorin Emirate. Ilorin emirate in Kwara state is as shown in Figure 1. The study area only covers 5.57% of the state and it has 38% of the entire population of the state.

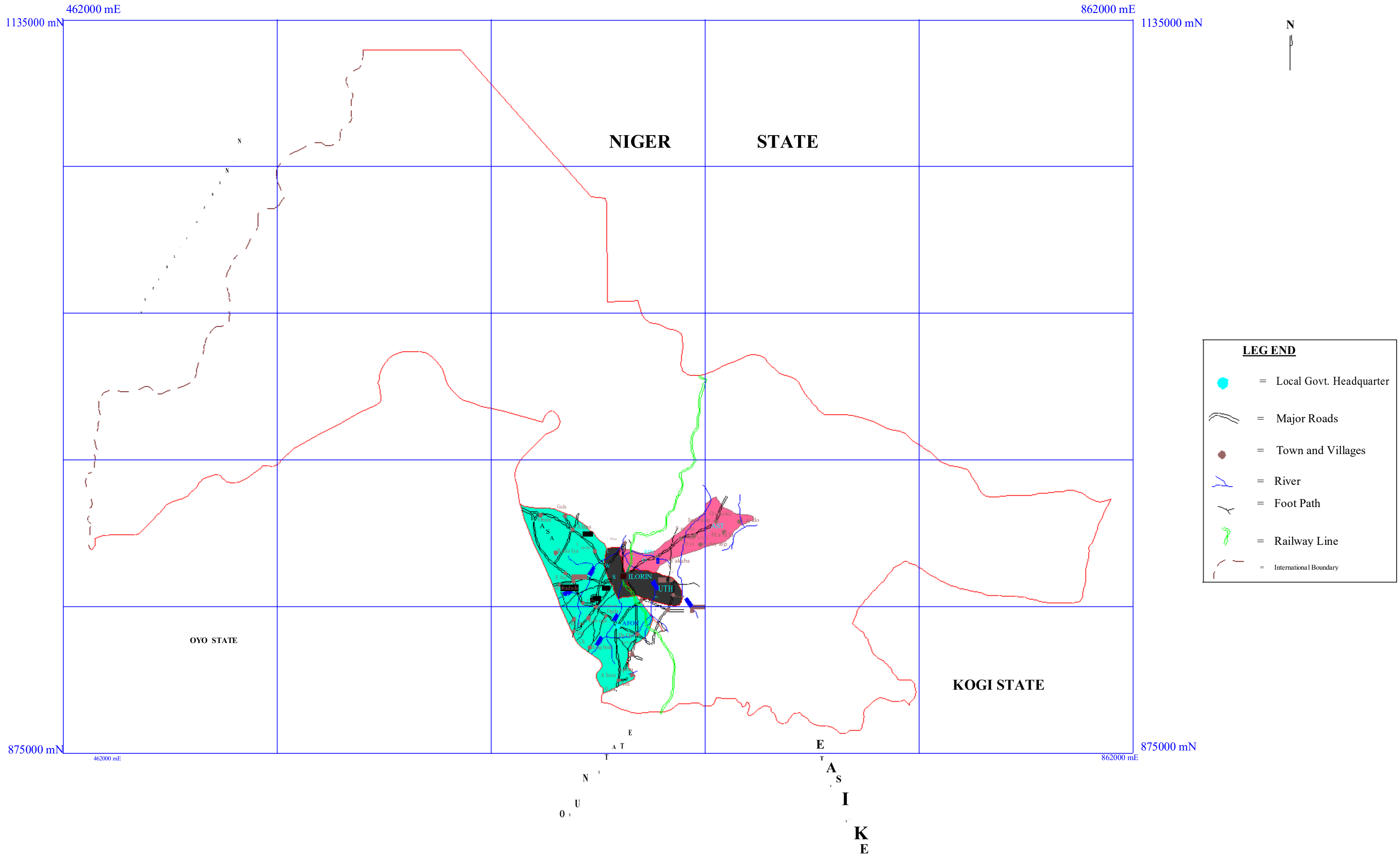

Figure 1. Map of Kwara State in Nigeria showing Ilorin Emirate.

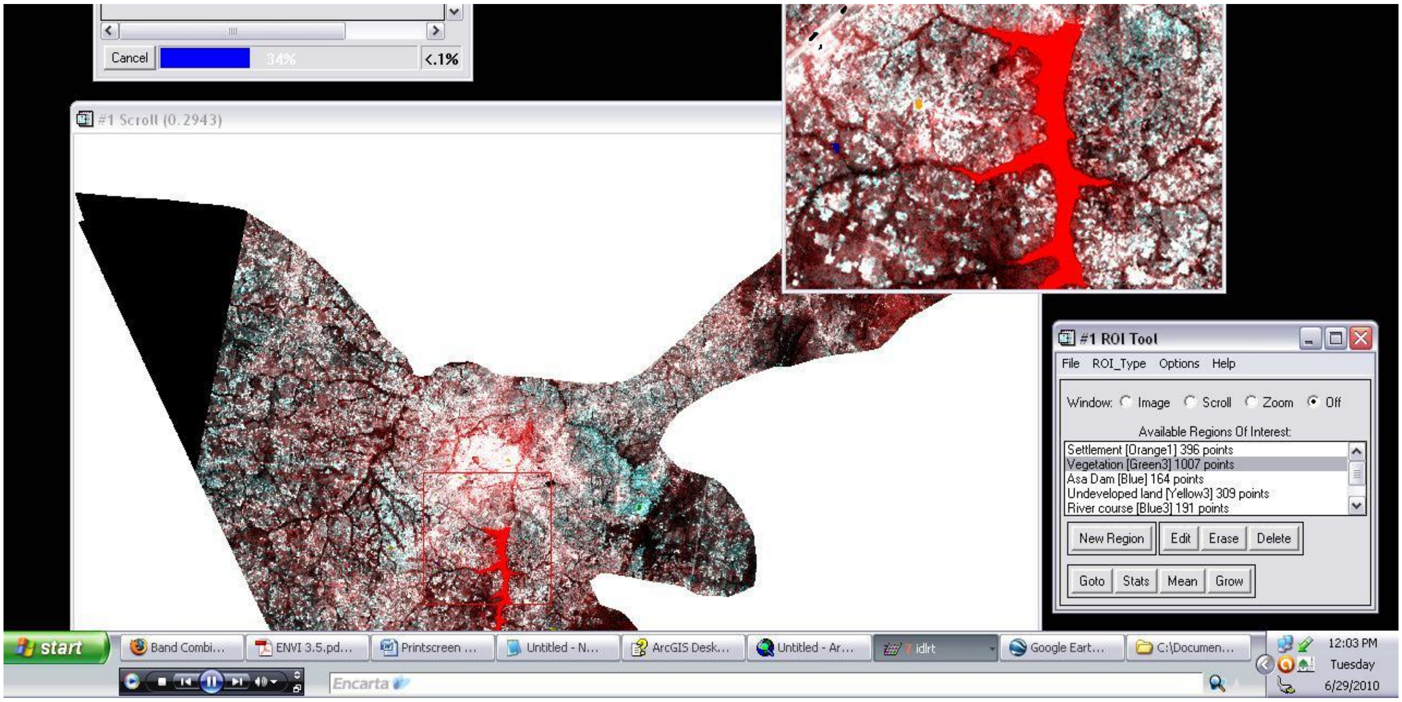

Figure 2. Classification process using region of interest as training set.

MATERIALS AND METHODS

Data acquired and source

In this study, three multi-date Landsat satellite images of Kwara State were procured, for the years 1986, 2000 and 2006. All images were obtained from the National Space Research and Development Agency in Abuja (NASRDA). It is also important to state that Ilorin emirate council were demarcated using the local government boundary map and Nigerian Administrative map also obtained from NASRDA. A land-use map of the study area, which provided baseline information for the study, was obtained from the office of the Kwara State Surveyor General. These were brought to Universal Transverse Mercator (UTM) projection in zone 31 in ArcGIS.

Data preprocessing

The main data preprocessing operation used in this work is image enhancement. Image enhancement is the totality of operations performed on the image data to modify it; it is a useful way of improving its pictorial quality (Eastman, 2009). Often, such enhancement modifications increase the visual distinction between features in a scene and thereby improve interpretability of the image. In the process, new image data set is created from the original data. Image enhancement ensures that to a great extent, much information is revealed for subsequent analysis. Contrast stretching and digital filtering operations were perfomed in this work to enhance visual analysis of the images.

Development of a classification scheme

Based on a priori knowledge of the study area for over 20 years and a brief reconnaissance survey with additional information from previous research in the study area, a classification scheme was developed using a supervised method. The land-use types classified are: built-up, tarred surfaces, vegetation, water body and bare soil. Image classification assigns the decision making process to the computer. The intent is to replace sometimes the vague or ambiguous interpretations of the analyst by more quantitative and repeatable processes. Image classification of satellite data by computer has the potential for efficient and consistent mapping of large areas of the earth's surface.

Because image classification is essentially a decision making process with data that can exhibit considerable statistical variability, we must rely on the mathematical tools of statistical decision theory. At best, the decision to classify a pixel into any particular classes is referred to as statistically intelligent "guess", which has some associated probability error. Consequently, it is logical for the decision made at each pixel to minimize some error criterion throughout the classified areas, that is, over a large number of individual pixel classifications. An intuitively satisfying and mathematically tractable classification theory having the aforementioned property shows maximum likelihood classification (Brito et al., 2006). This is what was used to carry out the classification under this study. Ten training sites were used on each image with two sites for training one land-use class. Figure 2 displays the classification process. The classification scheme developed and their descriptions are shown in Table 1.

Accuracy assessment

For the purpose of accuracy assessment, each classified image (250 reference pixels) was generated using stratified random distribution process. The collected base maps were used to find the land-cover types of the reference points. The overall accuracies obtained for 1986, 2000 and 2006 were found to be 86.19, 86.46 and 91.12% respectively. According Eastman (2009), land-cover classification accuracy of 85% and above are considered accurate.

Table 1. Land-use and land-cover classification scheme.

S/N	Classification	Description
1	Built-up	All residential, commercial and industrial areas, villages settlements and transportation infrastructure
2	Tarred surfaces	Tarred road surfaces and open concrete surfaces
3	Vegetation	Trees, shrub land and semi natural vegetation, deciduous, coniferous and mixed forests, palms, orchids, herbs, climbers, gardens and grasslands
4	Water Body	River, permanent open water, lakes, ponds, canals and reservoirs
5	Bare soil	Fallow land, earth and sand land infillings, construction sites, excavation sites, solid waste landfills, open space and exposed soil

Methods of data analysis

Three main methods of data analysis were adopted in this study.

1. Calculation of the area in hectares of the resulting land-use / land-cover types for each study year was done, and subsequent validation of the results was done by comparing it with ground truthing.
2. Calculation of land consumption rate and absorption coefficient.
3. Markov chain and cellular automata analysis for predicting change (Parker et al., 2003; Alejandro and Servet, 2003; Gamerman, 1997; Gilks et al., 1996; Bucher and Culik, 1984; Burks, 1970a).

The first method was used for identifying change in the five land-use types. The comparison of the land-use / land-cover statistics assisted in identifying the percentage change, trend and rate of change between 1986 and 2006. In achieving this, the first task was to develop a table showing the area in hectares and the percentage for each year (1986, 2000 and 2006) measured against each land-use land-cover type.

The land consumption rate (LCR) and land absorption coefficient (LAC) formula are given as follows:

$$LCR = \frac{A}{P} \qquad (1)$$

$$LAC = \frac{A^{i}_{2} - A^{i}_{1}}{P^{i}_{2} - P^{i}_{1}} \qquad (2)$$

Where A is area extent of the study area in hectares, P is the population, A^{i}_{1} and A^{i}_{2} are the area extents (in hectares) for the early and later years, and P^{i}_{1} and P^{i}_{2} are population figure for the early and later years respectively (Yeates and Garner, 1976). LCR is equal to measure of progressive spatial urbanization of a study area and LAC is equal to measure of change of urban land by each unit increase in urban population. 2020 population figures were estimated from the 2006 population census obtained from National Population Commission of Nigeria (NPC) and then using its recommended 2.1% growth rate based on the 1963 / 1991 censuses.

In estimating the 2020 population figures, the following equations were used:

$$n = (r / 100)\, p_0 \qquad (3)$$

$$p_n = p_0\,(n * t) \qquad (4)$$

Therefore: $$p_n = p_0\,((r / 100) * p_0) * t) \qquad (5)$$

Where: r is the growth rate (2.1%), n is annual population growth, t is number of years projecting for, p_n is estimated population for projected year (2020) and p_0 is base year population (2006). It should be noted here that the closest year population available to each study year as shown previously were used in generating both the land consumption rates and the land absorption coefficients as given in Table 3.

The Markov model treats the land-use as a stochastic process where the later state (of a land-use type) is only related to its immediate preceding state but not to any other previous states. For instance, the transition from a state i to a state j with intermediate preceding state k of a cell is defined by a probability function generally denoted as:

$$P_{ij} = \sum_{K=1}^{r} p_{ik}\, p_{kj} \qquad (6)$$

In the cellular automata approach, each cell in the system has one finite number of states. The state of each cell is updated according to local rules, that is, the state of a cell at a given time depends on its own state and the states of its nearby neighbours' at the previous time step (Eastman, 2009). In this research, a 3 × 3 mean contiguity filter was used for the modeling of 2020 map (Figure 3).

DISCUSSION

The results of this research were presented in form of maps, charts and statistical tables. These include the

0	1	0
1	1	1
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Figure 3. The 3 × 3 mean contiguity filter for cellular automata.

Table 2. Land consumption and absorption rate.

Year	Land consumption rate	Year	Land absorption coefficient	Population
1986	0.014	1986 / 2000	0.0078	524,379*
2000	0.012	2000 / 2006	0.0784	790,185**
2006	0.02			904,102*

*Data obtained from the Nigeria National Population Commission; **Researchers' estimate.

static, change and projected land-use / land-cover of each class.

Land-use / land-cover distribution

The land-use and land-cover distribution for each study year as derived from the maps are presented in the Table 3. The table and chart built-up in 1986 occupies 3.46% of the total classes while it increased to 8.82% in the year 2006. However, the increase recorded between 2000 and 2006 is alarming. While built-up area increased by 2067 ha between 1986 and 2000 (a period of 14 years), there was an increase of 8928 ha between 2000 and 2006 (in a period of only 6 years). Also, tarred surfaces increase steadily from the year 1986 and 2006 although with higher increase between 2000 and 2006.

Bare soil decreased slightly between 1986 and 2000 but decreased again by 2006. The fact that bare soil reduced in 2006, even lower than what it was in 1986, suggests that many open spaces within the urban areas have been built-up or tarred. Water bodies recorded an increase of 6 ha between 1986 and 2000, and 4 ha between 2000 and 2006.

Vegetation continued to decrease from 1986 to 2006. Judging by the percentage change, one may conclude that encroachment into the vegetation areas was not serious. However, a close look at the increase in built-up area sends warning message. Between 1986 and 2000, vegetation decreased by 1524 ha. This could be seen as moderate, but between 2000 and 2006, there is a decrease of 1062 ha. The change between this six-year period accounted for over 40% of the total reduction recorded from 1986 to 2006 and an equivalent of almost 70% of the change recorded between the fourteen-year period (1986 to 2000). We can therefore infer that, almost 1000 ha of land available for farming have been converted to other uses between 1986 and 2006. This may be a threat to farming and food supply as farmland is being reduced at such a high rate. This increase thus contributed to the physical expansion of the Emirate as evident in the increase in land consumption rate from 0.012 to 0.02 and land absorption coefficient by 0.0784 between 2000 and 2006 (Table 2). The trend, rate and magnitude of the observed changes are presented in Table 4. The land-use and land-cover distribution of Ilorin Emirate in 1986, 2000 and 2006 are graphically displayed in Figure 7.

An important aspect of change detection is to determine what is actually changing and which land-use class is changing to the other. This information will reveal changes and classes that are "relatively" stable overtime. This information will also serve as a vital tool in decisions management. This process involves a pixel to pixel comparison of the study year images. Table 4 shows the observed changes between 1986 and 2006. Maps generated are shown in Figures 4, 5 and 6. Looking at the nature of change, no class is actually stable during this period. However, vegetation has decreased while other land-use classes have increased.

Table 3. Land-use and land-cover distribution (1986, 2000 and 2006) and 2020 projection.

Land-use categories	1986		2000		2006		2020 Projection	
	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)
Built-up	7091	3.46	9158	4.47	18086	8.82	26231	12.79
Tarred surfaces	85	0.05	187	0.09	403	0.20	1641	0.80
Vegetation	120661	58.83	119137	58.08	118075	57.57	110707	53.98
Water body	4089	1.99	4095	2.00	4099	2.00	4655	2.27
Bare soil	73162	35.67	72511	35.36	64425	31.41	61855	30.16
Total	205088	100	205088	100	205088	100		

Table 4. Trend and rate of land-use change of Ilorin Emirate between 1986 and 2006.

Land-use categories	1986 to 2000		2000 to 2006		Annual rate of change	
	Area (ha)	% Change	Area (ha)	% Change	1986 to 2000	2000 to 2006
Built-up	2067	22.57	8928	49.36	1.61	8.23
Tarred surfaces	102	54.54	216	53.98	3.90	9.00
Vegetation	-1524	-1.28	-1062	-0.90	-0.09	-0.02
Water body	6	0.15	4	0.10	0.01	0.02
Bare soil	-651	-0.90	-8086	-12.55	-0.06	-2.09

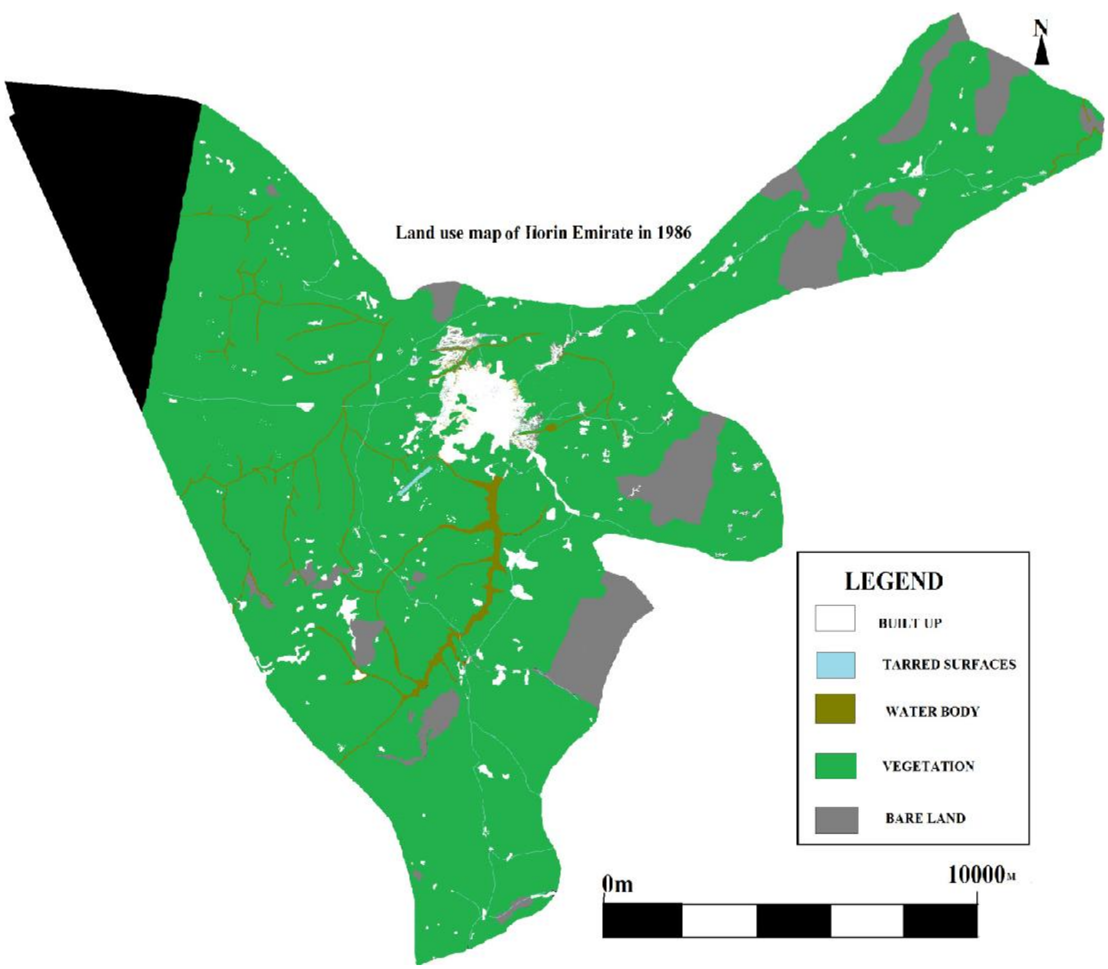

Figure 4. Land-use map of the study area in 1986.

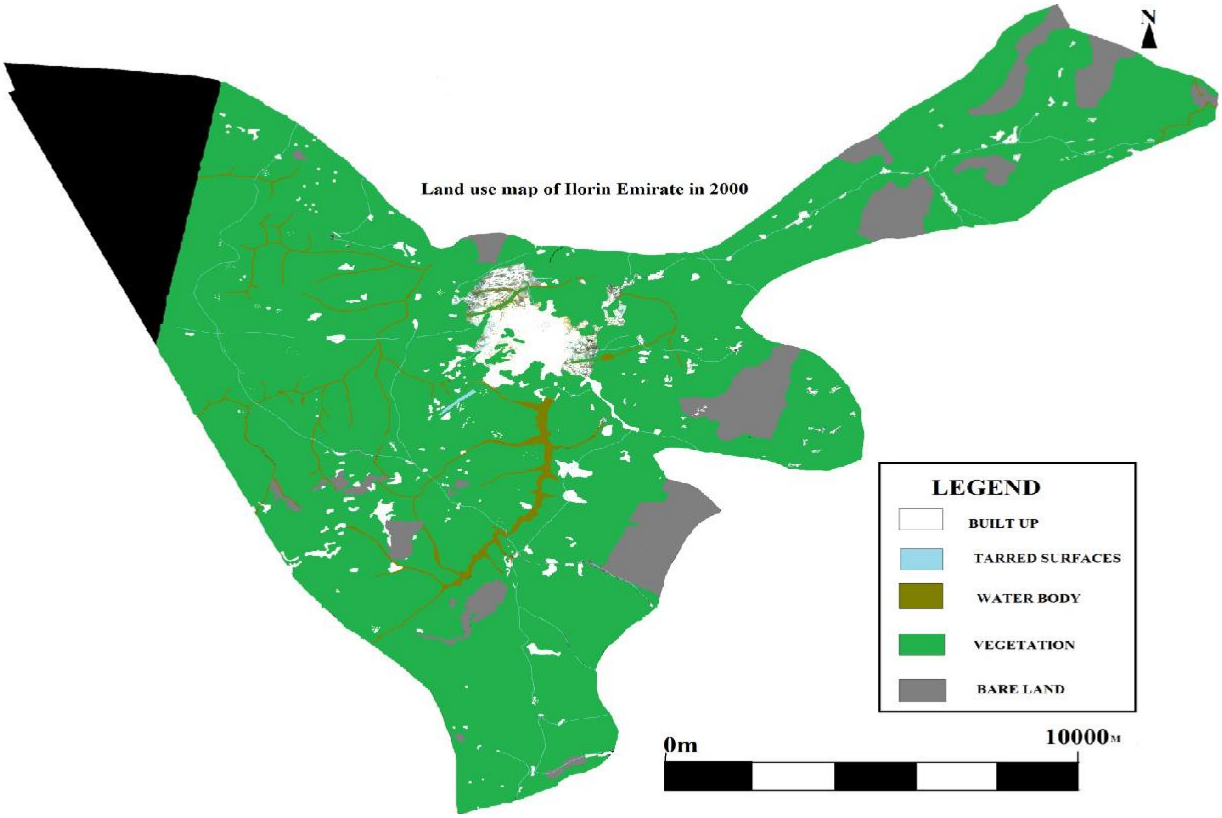

Figure 5. Land-use map of the study area in 2000.

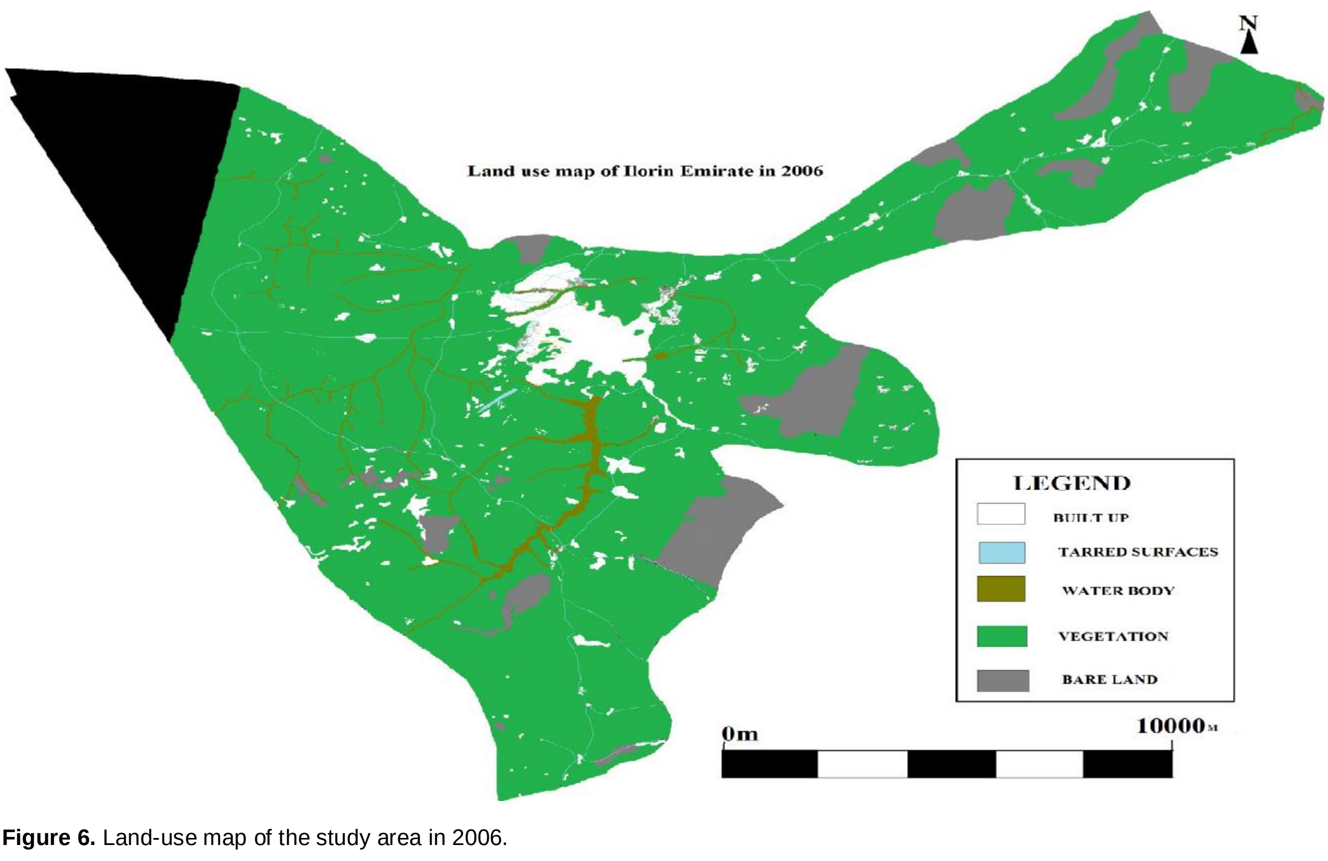

Figure 6. Land-use map of the study area in 2006.

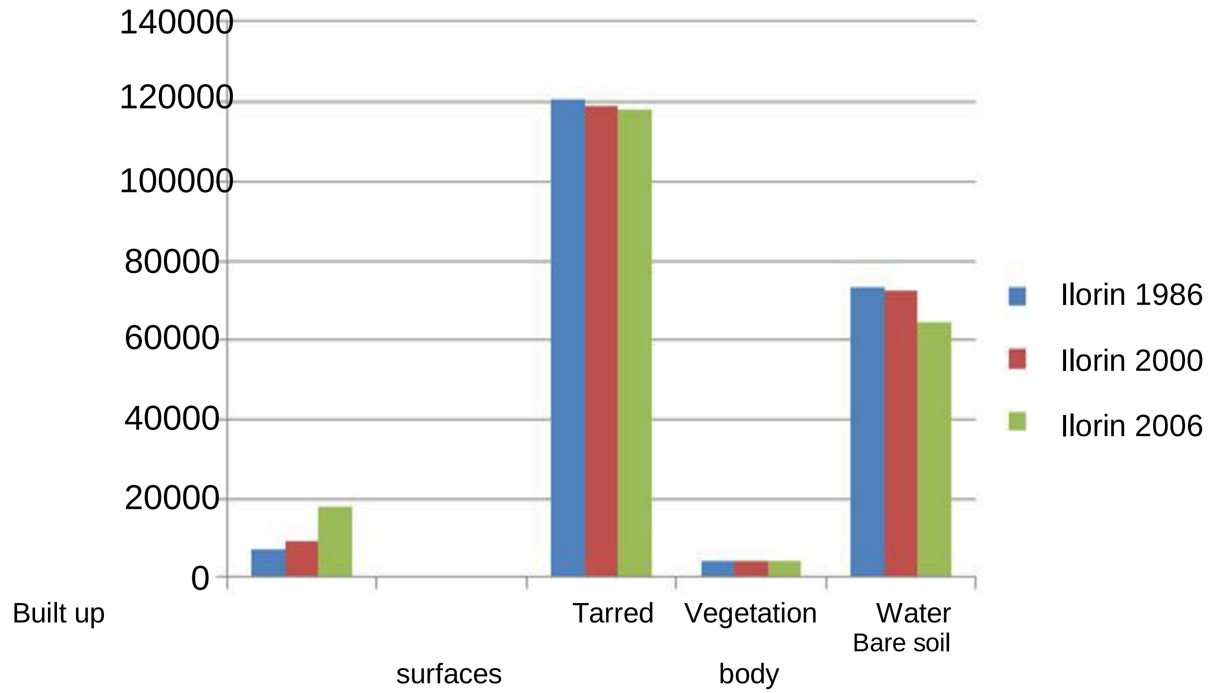

Figure 7. Land-use and land-cover distribution (1986, 2000 and 2006).

Table 5. Transitional probability table derived from the land-use and land-cover map of 2000 and 2006.

Classes	Built-up	Tarred surfaces	Vegetation	Water body	Bare soil
Built-up	0.2871	0.0202	0.3549	0.0385	0.2994
Tarred surfaces	0.1944	0.0842	0.3731	0.0295	0.3188
Vegetation	0.1805	0.0306	0.4430	0.0361	0.3097
Water body	0.2001	0.0392	0.4001	0.0406	0.3200
Bare soil	0.2652	0.0023	0.3546	0.0292	0.3487

Transition probability matrix

The transition probability matrix records the probability that each land-cover category will change to the other category. For the 5 by 5 matrix table (Table 5), the rows represent the older land-cover categories and the column represents the newer categories. This matrix was used in predicting land-use land-cover of 2020.

Land-use Land-cover projection for 2020

Table 3 shows the land-cover distribution at each epoch and land-use and land-cover projection for 2020. Though, vegetation still maintains the highest position in the class, it has reduced greatly from what it was in 2006 while other land-use types have increased. This result suggests a further expansion of urban settlements in the area by 2020. Figure 8 is a graphical display of projected land-use and land-cover of Ilorin emirate in 2020.

CONCLUSION AND RECOMMENDATIONS

The result of this work shows a rapid growth in built-up land and rapid reduction in vegetation between 1986 and 2006. The result of the 2020 projection shows that built-up land will increases tremendously bringing about high reduction in other land-use types particularly vegetation. This situation will lead to further expansion of the built-up land which can further trigger the urban associated problems such as unemployment, poverty, inadequate health, poor sanitation, urban slums and environmental degradation in the area as it is being experienced in big cities of the world. The expansion in the built-up land of the study area possesses the same characteristics with those of other cities in Africa reported by other authors. Since it is impossible to permanently stop expansion of

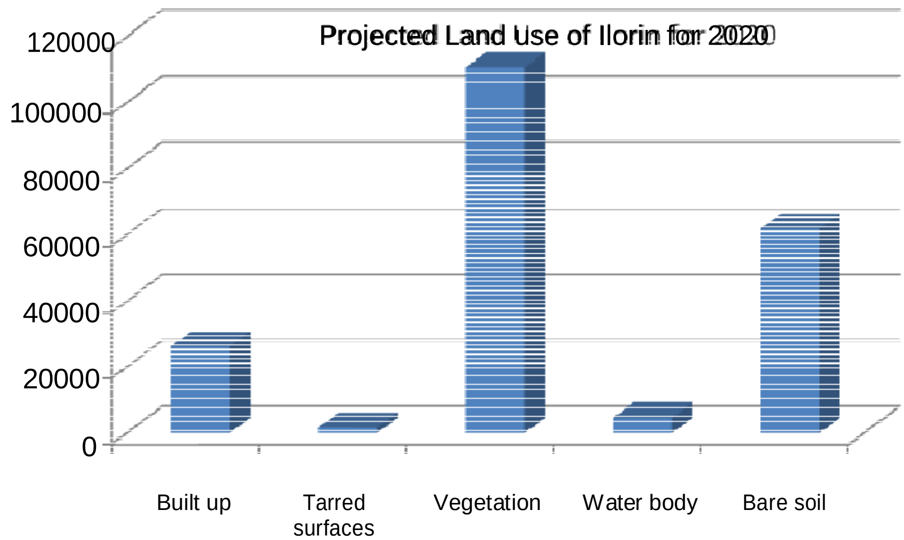

Figure 8. Projected land-use and land-cover of Ilorin Emirate in 2020.

built-up land, stakeholders would need to initiate urban planning that will lead to a sustainable growth of the Ilorin Emirate.

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