Evaluating the Effect of Land use Land Cover Changes on Land Suitability for Crop Production Using Remote Sensing and GIS

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Abstract

The impact of Land Use Land Cover Changes (LULCC) on agricultural land from 1986 to 2016 was examined using Remote Sensing (RS) and Geographic Information System (GIS) in Kwara State, Nigeria. The aim of the study was to show how a GIS tool could be incorporated into a Multi Criteria Analysis (MCA) and an Analytical Hierarchy Process (AHP) model to assess the suitability of land. Under several conditions which define suitable land for arable cropping, the structural design of an integrated GIS-MCA-AHP was anticipated to correspond with the decision maker's preferences. Additionally, the integration was anticipated to quantify the extent of land cover modifications and assess how removal of vegetation would affect the soil. As a major factor in the analysis, the Normalized Differential Vegetation Index (NDVI) was employed with GIS and Remote Sensing (RS) technologies, and as secondary, MCA and AHP models. In Arc-Map (GIS) 10.3.1, the RS data imagery from 2016 was used and recognized by NDVI satellite images. The images were categorized according to RS data, field study data, and geographical factors. The variables were soil texture, depth, pH, organic carbon, rainfall, temperature, slope, elevation, and land use land cover. To examine the extent of land use and land cover changes in relation to soil types and land suitability, the MCA-AHP model employed a weighted sum overlay. The results showed that farming accounted for 46% of all land use, and that LULCC was primarily to blame for the loss of arable land and environmental degradation. The proportion of the total land area used for farming (farmland), the built up area, bare land, and water bodies increased from 34 to 46, 15 to 30.4, 5 to 10, and 3 to 4%, respectively. Forest land, on the other hand, saw a drop from 43 to 9.6%. While 11.40% of the total land area was highly suitable for arable cultivation, 19.30% was moderately suitable, 30.40% was marginally suitable, 23.12% was currently unsuitable, and 15.78% was permanently unsuitable. The study shows that the AHP model was useful for calculating land use weights that were comparable to those calculated using other techniques. The model was helpful in making planning decisions for land use, and thus could be useful in managing sustainable agriculture. It was concluded that in addition to the fast rate of deforestation, increasing anthropogenic activities were degrading arable land at the study site.

Keywords: Remote sensing, GIS, NDVI, Multi-Criteria Analysis, Analytical Hierarchy Process, Land Suitability

Introduction

Land Use and Land Cover (LULC) are distinct but intertwined. Natural occurrences like floods, climatic changes, and ecosystem dynamics may potentially be the cause or factor in land cover changes (Mallupattu and Sreenivasula, 2013). So, it is crucial to understand the current LULC as well as the dynamics of Land Use (LU) arising from both changing demands of growing populations and forces of nature interacting to form landscapes in order to make wise and optimal use of land (Ruiz-Luna, 2002). Traditional LU surveys are expensive, time-consuming, labour-intensive, and conducted infrequently (Ruiz-Luna, 2002). Furthermore, Olorunfemi (1983) hinted that traditional maps were gradually becoming obsolete, particularly in contexts that change quickly, as pertains to Nigeria. Additionally, using conventional surveying methods makes it difficult to identify changes and analyze them in time series (Olurunfemi, 1983; Aboyade, 2001). In recent times, GIS and remote sensing methods have been used for LULC analysis. They are of crucial relevance in creating precise LULC maps and tracking changes at regular periods of time (Aboyade, 2001). These contemporary methods may be the only way to get the required data in the case of inaccessible or difficult to reach places. According to Xiaomei and Rong (1999), gathering sufficient evidence regarding LULC is crucial for updating LC changes and managing natural resources. These data (proofs) can be obtained either manually by visiting the areas in question or through the use of data from remote sensing systems.

Remote sensing is a method utilized all over the world to unearth and comprehend the physical processes impacting the earth's surface (Hudak and Wessman, 1998; Aboyade, 2001). Monitoring LULC and urbanization and maintaining natural resources depend on change detection. According to Briassouls (2000), remote sensing techniques are crucial for field surveys because they provide a detailed description of the land cover. He reported that remote sensing techniques can accurately analyze regional LULC and provide information on the spatial and temporal distribution of vegetation. Using remote sensing and GIS, Arvind et al. (2006) found that physiographic conditions and varied climate have contributed to the establishment of various LULC and satellite data analysis showed that much of the area had been used for agricultural activities. GIS is an integrated system of computer hardware and software that can collect, store, display, analyze, retrieve, and manipulate (spatial) data to support development-oriented management and decision-making (Arvind et al. 2006). Remote sensing and GIS are geographical instruments with a variety of applications (Long et al., 2008) be it in agriculture (Yeh and Li, 1998), ecosystems (Fung and Ledrew, 1987; Aboyade, 2001) or in integrated eco-environment assessment.

Research activities on LULC have become very necessary because of their effects on ecosystems (EL-Raey et al., 2000; Hathout, 2002). The results of such studies are applied to resolve LULC-related issues, explain past and present circumstances, and forecast future ecosystem conditions (Ruiz-Luna, 2002). GIS aids better decision making through modeling and taking inventory of agricultural land. Infrastructure development for geographic data and/or tools is essential for sustainable agriculture (Joerin et al., 2001). Hence, data on LULC, an assessment of the suitability of land, geographical distribution, and changes that take place are crucial components of land use planning. Planners can manage huge and complex data with the aid of GIS and Multi-Criteria Analysis (MCA) (Briassouls, 2000). The three main applications of land planning include selecting a place, assessing the suitability of the land, and use of collaborative decision support systems (Joerin et al., 2001). In particular, since the turn of the twenty-first century, the integration of GIS and MCA has significantly improved land evaluation (Briassouls, 2000; Mallupattu and Sreenivasula, 2013). Rational cropping systems are highly regarded in land suitability studies to achieve the best possible use of the land for certain goals (FAO, 1976; Sys et al., 1991). Suitability depends on the type of available land and the type of crop that would be cultivated. As a result, certain criteria would have to be assessed to categorize or define if a location is suitable for a given purpose. It is in this regard that Saaty (1980) developed the Multi Criteria Evaluation (MCE) decision making through the use of the Analytical Hierarchy Process (AHP). The AHP approach was created to outline spatial decision making when a set of substitutes must be chosen based on a set of unclear or insufficient criteria. The results obtained from using the AHP are subsequently integrated into a GIS for suitability mapping. Malczewski (1999) demonstrated that MCE is a decision-making tool that can be used to assess a variety of alternative choices for various criteria as well as numerous objectives. An objective and methodical approach to problem-solving is to integrate MCE and GIS data. Human value judgments and analyses of the significance of the criteria are crucial elements of a multi-criteria problem (Ruiz-Luna, 2002). Nevertheless, using MCE in conjunction with GIS can help in achieving set goals (Moldovanyi, 2003) and the AHP model can be used in this regard. The integration of GIS and MCE has significantly enhanced conservative map overlay techniques in LU suitability evaluations.

Saaty (1977, 1980, 2000, and 2001) introduced the model as a multi-criteria decision-making strategy that was intended to assess and categorize complex mathematically based decision-making. The author employed the strategy for the first time in the 1970s, and since then it has been widely applied and redefined. The model employs a multi-level hierarchical framework for its goals, standards, substandard, and options. Through the use of a number of pairwise comparisons, pertinent data are obtained. If the comparisons do not yield outcomes that are entirely consistent, the model offers a way to remedy the situation. Also, the model incorporates a useful technique for evaluating a decision maker's assessments to ensure consistency thus lowering the level of prejudice (bias). In addition to classifying and weighing selection criteria, assessing the data gathered, and speeding up the decision-making process, AHP is a recognized method for dealing with complex decision-making (Hossain et al., 2007). At each level of the hierarchy, pair-wise comparisons could help to increase relative weights (i.e., priorities) and highlight the importance of the criteria (Hossain et al., 2007). One of the helpful decision-making tools is the development of weights in pair-wise comparisons (Saaty, 1997; 2001). The Objectives of this study were to: 1) determine the extent to which MCA and AHP models could be integrated with GIS for land suitability analysis; 2) develop a structure for integrating GIS, MCA, and AHP in order to incorporate decision makers' preferences out of a variety of factors in determining suitable land for crop production; 3) assess the magnitude of LC changes; and 4) determine the effects of vegetation removal on soil.

Materials and Methods

Study area

This study was carried out in Kwara State, one of the 36 States that make up the Federal Republic of Nigeria. The state is located between latitudes 7°45' and 9°30'N and longitudes 2°30' and 6°25'E, (Kwara State Ministry of Information, 2002). Kwara State is bordered by the Republic of Benin and the Niger River on the west and the north respectively (Figs. 1a. and 1b.). The study covered an area of 36,825 km^2 which was about the total area of Kwara State (Federal Office of Statistics, 1995).

The rainy season, which lasts from April to October, and the dry season from November to March are the two seasons that characterize the humid tropical climate of Kwara State. The mean monthly temperature in the state ranges from 25 to 37 °C (Ajadi et al., 2011). The mean annual rainfall is between 1000 and 1500 mm (Ajadi et al., 2011). The study area is between 900 and about 1000 meters above sea level. Crops which do well in the study area include tomato, pepper, millet, cassava, yam, cowpea, maize, and rice. The study area is semi-arid and a major rain-fed agricultural zone. The study area is situated in Nigeria's southern Guinea savannah region. The vegetation of the study area is primarily a derived savannah which is composed of tall grasses with dotted trees and shrubs (Ajadi et al. 1993). The region serves as a transition between the high forests of the southern half of the country and the Sudan Savannah zone in the north.

Data sources and collection

The required climate, topography, and soil data for the study were gathered from a variety of sources. Satellite images were used to remotely collect data on land use and land cover. Using a geographical resolution of 30 m, agricultural LULC information was retrieved from 2016 Landsat imageries in real-

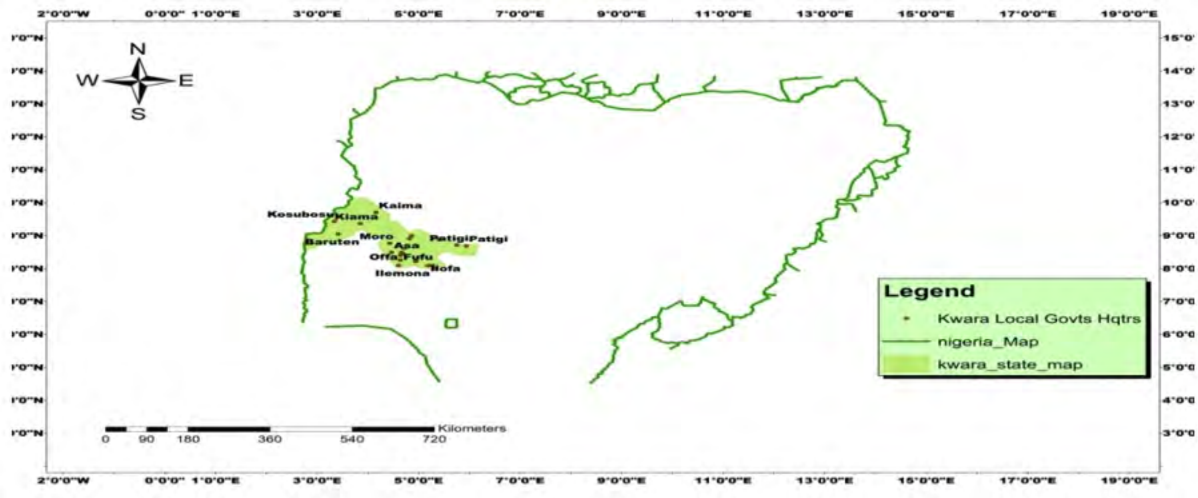

Fig. 1a Map of Nigeria showing the study area in Kwara State

Fig. 1b Kwara State showing the study area

time. Also, the topography, as calculated by the digital elevation model from the Shuttle Radar Topological Mission (SRTM), was used to determine the length and degree of elevation (Gelay and Minale, 2016).

Research methodology and data extraction

The AHP and MCA models were applied in this study's approach to assess the appropriateness of the study area using GIS software. Figure 2 provides an illustration of the methodologies, approaches, and data inputs used to accomplish the stated goals. Four stages were followed to complete the study.

LULC maps for 1986, 2000, 2010, and 2016 were created using the Landsat imageries obtained. For geometric rectification, the satellite data were imported in an image format into the GIS program ERDAS IMAGINE. The sensor system caused the geometric aberrations in the satellite image. These data were geo-referenced to a coordinate system so that they could be used in conjunction with other geographical data. With a Root Mean Square Error (RMSE) of less than one pixel, ground control points were used to geo-reference the images from 1986, 2000, 2010, and 2016. The photos were geo-referenced using the Universal Transverse Mercator (UTM) projection and datum World Geodetic System (WGS) 1984 UTM zone 31.The NDVI was used to process 2016 data set, and also as a tool to quantify vegetation by measuring the difference between near-infrared (which vegetation strongly reflects) and the red light (which vegetation absorbs). The spectral response of NDVI was calculated using equation (1) from the individual measurement.

$$NDVI = \frac{(NIR-Red)}{(NIR+Red)} \qquad (1)$$

NDVI, a tool widely used by researchers in remote sensing, always ranges from -1 to +1. However, there is no distinct boundary for each type of land cover. For example, negative values are likely to represent water. On the other hand, values close +1denote dense green vegetation. Values close to zero NDVI indicate no green leaves/vegetation which could be an urbanized area or bare land. The NDVI value range from -0.1 to +0.1was utilized to classify the images into five categories namely farmland (crop cover), bare land, built-up areas, forests, and water bodies. Each category was determined and a color assigned after data processing. Changes in the size (in hectares) of each class were determined after the land use/land cover maps of 1986, 2000, 2010, and 2016 were collected and analyzed.

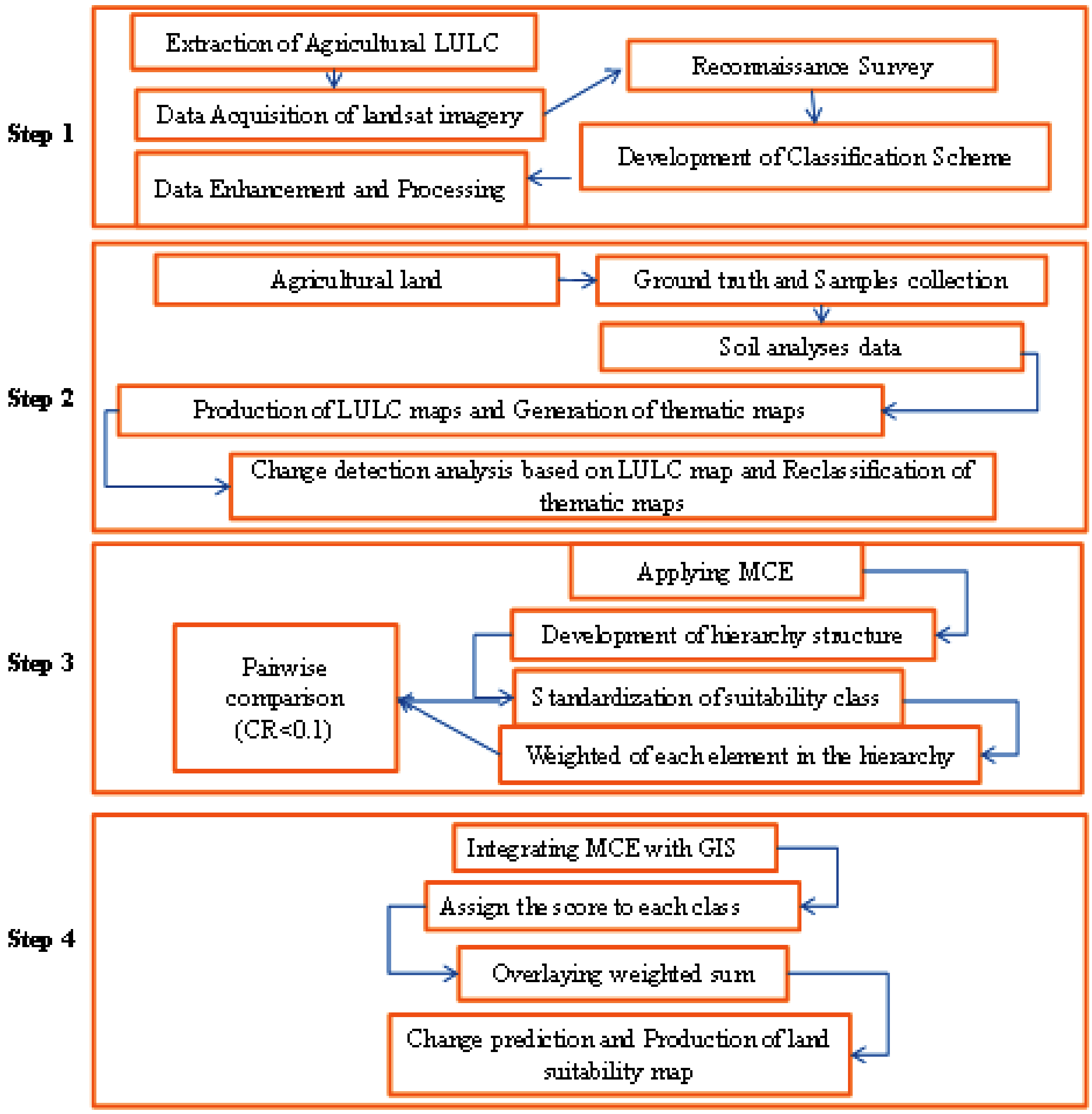

Fig. 2 Schematic method of the study

Change detection and direction in land cover

Data analyses: The following data analysis techniques, as defined by Zubair (2008), were applied to determine the reasons and the direction of changes in land cover:

1. Based on the LULC types obtained for each year, areas in hectares were computed, and the findings compared.
2. The Markov Chain and Cellular Automata Analysis approach was applied to forecast changes.

Satellite data

The study was covered by four epochs of Landsat imagery of 1986, 2000, 2010 and 2016. (Table I). The Global Land Cover Facility (GLCF) provided the images from 1986 and 2000; the National Space Research and Development Agency (NASRDA), Abuja, Nigeria, provided the images from 2010. According to the United States Geological Survey's (USGS) protocol, the 2016 imagery was processed using NDVI (http://earthexplorer.usgs.gov, 2016). The 4 epochs were chosen because they allowed easy comparison of the changes and trends observed during the course of the investigation.

The three steps mentioned above were utilized to spot changes in the LU types.

Area, in hectares, was used to compare the percentage change for each year (1986, 2000, 2010 and 2016) and for each LULC type. The measured change was then divided by the total change multiplied by 100 as given in equation (2) to determine the percentage change:

$$Trend(\%) = \frac{Observedchange}{Sum\ of\ changes} \times 100 \qquad (2)$$

To obtain the annual rate of change, the percentage change was divided by 100 and multiplied by the duration of study i.e.,1986-2000 (14 years), 2000-2010 (10 years) and 2010-2016 (6 years) with an addition of 14 years projection (2016-2030).

The Markov Chain Analysis was created for the second approach (step) since it is a practical tool for modeling LC changes. When the processes and changes in the landscape are difficult to describe, the model is applied. A Markovian process is one in which the system's future state can be entirely predicted based on its current state. The study was then used to describe how land usage changed over time and then as a basis for predicting changes in the future. The projection was created by creating an evolution probability matrix of the LU change from time one to time two, which revealed the type of change and served as the basis for projecting to a later time period. The final technique (step) determines the precise location and degree of change using overlay procedures. This technique used to map out different areas of change in the outcome using the reclassification module of idrisi32.

Topography factor

Slope is a fundamental topographic component of land evaluation and mapping of land suitability. It is useful in enhancing the appropriateness of analysis when combined with other variables (Wilson and Gallant, 2000). The digital elevation model (DEM) was used to generate slope gradient. The shuttle radar topography mission (SRTM) supplied this DEM (Coltelli et al., 1996). The USGS's 30 m spatial resolution DEM data (http://earthexplorer.usgs.gov, 2016) was utilized. The slope layer was created using the slope function of the Spatial Analyst Toolbox in Arc GIS 10.3.1. The slopes were

TABLE 1

Characteristics of satellite images of land

Sensor/Data Type	Production date	Spatial Resolution (m)	Source
Landsat image	1986-05-20	30	GLCF
Landsat image	2000-05-15	30	GLCF
Landsat image	2010-05-10	30	NASRDA
Landsat image	2016-05-05	30	USGS

then converted to percentages. The cells of the output raster include slope values (a lower slope value indicates a flatter terrain while a higher slope value indicates a steeper terrain). For example, a flat field with a smooth surface would better for rice cultivation as it would facilitate uniform and equal distribution of water.

Soil factor

Soil is a crucial part of the ecosystem because it provides nutrients and water to plants. Thus, practically, all plants including crops depend on soil as a growth medium. To assess the suitability of a piece of land, the physical and chemical characteristics of its associated soil must be known. The soil characteristics chosen for this study were texture, pH, EC (dS m^{-1}), organic carbon (OC) (g kg^{-1}), CEC (cmol kg^{-1}), available P (mg kg^{-1}), total N (g kg^{-1}), and exchangeable bases cmol(+) kg^{-1}. Ground truth verification was done to ascertain soil sample location, soil samples were collected from profile pits. During the field trips, a Global Positioning System (GPS) was employed. After determining the land use and land cover changes (LULCC) using the NDVI, soil samples were collected. NDVI, a potential indicator of crop growth and vigour, was used to delineate vegetation areas, bare soils, forest, built up areas and water body (FAO, 1996, 2002).

The most popular vegetation index for identifying LULCC and tracking vegetation health is NDVI (FAO, 2002). Landsat satellite imagery was obtained from USGS and utilized to construct the NDVI in the study area using ERDAS IMAGIN 10 image processing software (http://earthexplorer.usgs.gov, 2016). As previously stated, the NDVI calculation for a specific pixel always yields a value between -1 and +1. In the absence of green leaves or no vegetation, the value is close to zero. Close to +1 (i.e., 0.8–0.9) denotes the highest level of green leaf density, such as dense forests. The classes for water body and bare land were also obtained independently (FAO, 1996; 2002).

Climate data

Climate is an important factor that influences crop development, growth, and yield. Rainfall and temperature were used as the climatic variables in this study. The Inverse Distance Weighted (IDW) spatial interpolation function in the Arc GIS 10.3.1 platform was used to create the raster datasets; after ten years of data were collected as a point layer from the Kwara State Meteorological Agency. All of the prepared raster data layers (criteria) were assigned to the Kwara State Universal Transfer Mercator local coordinate system (UTM). The capability levels for each of the criterion tiers were determined based on literature, specialized knowledge, and the authors' practical experiences. Then, Arc GIS 10.3.1 was used to reclassify the layers into several tiers. The final suitability map for the land was ranked as highly suitable-SI, moderately suitable-S2, marginally suitable-S3 and not suitable-N.

Ground truth data, samples collection and analysis

Field studies

For the purpose of locating the geo-morphological units and observing the real interpretations, field investigations and ground truth were conducted. To reflect the various mapping units (pedons) shown on the Landsat imagery, nine soil profile pits as representative pedons (1.5 m width and 2 m length) were dug to a depth of 1.5 to 2.0 m). The morphological properties of the soil profiles were described according to the methods prescribed by FAO (1990). Then, soil samples were taken from each genetic horizon of the profiles. The samples were air-dried, softly crushed, and put through a 2 mm sieve and then analyzed in a lab according to standard laboratory methods.

Generation of AHP structure

AHP is a popular technique for making decisions. Saaty (1977; 2000) proposed the fundamental premise of this methodology by contrasting two elements based on the relative relevance of each in the present. The criteria and sub-criteria needed for the land suitability evaluation are arranged in the first step of the AHP technique and then established in a hierarchical structure. The main objective, which is the appraisal of land appropriateness, is at the top of the hierarchy. Applying this phase to the assessment of land suitability, the choice criteria pertinent to the objective were utilized to locate and arrange the hierarchical structure shown in Figure 3. Including and accommodating both qualitative and quantitative factors for determining the suitability of a piece of land is possible with such a structure. The objectives can be identified at the highest level, and the traits can be assembled at the lowest level. Following the creation of the AHP, the comparison matrix between the alternatives, criteria, and sub-criteria was used to follow the hierarchical structure.

Weights of the criteria

The most important multi-criteria decision-making procedure is the AHP. The procedure is carried out using a set of standards and/or sub standards that are utilized to create a hierarchical structure by allocating the weight of each standard in a comprehensive decision-making process (Miller et al., 1998). By providing a structural foundation for pair-wise assessment of design requirements and elements, the analytical hierarchical approach reduces the complexity of the decision-making process (Saaty 1977; Miller et al., 1998). By using a pair-wise comparison method and the relative significance of the criteria, the analytical hierarchical process calculates weight values by considering two (criteria) at a time (Miller et al., 1998). The AHP determines the weights for each criterion using the pair-wise comparison matrix by taking the eigen-value associated with the highest eigenvector of the finished matrix and setting the factor total to unity (Malczewski 1990; Feizizadeh et al., 2014).

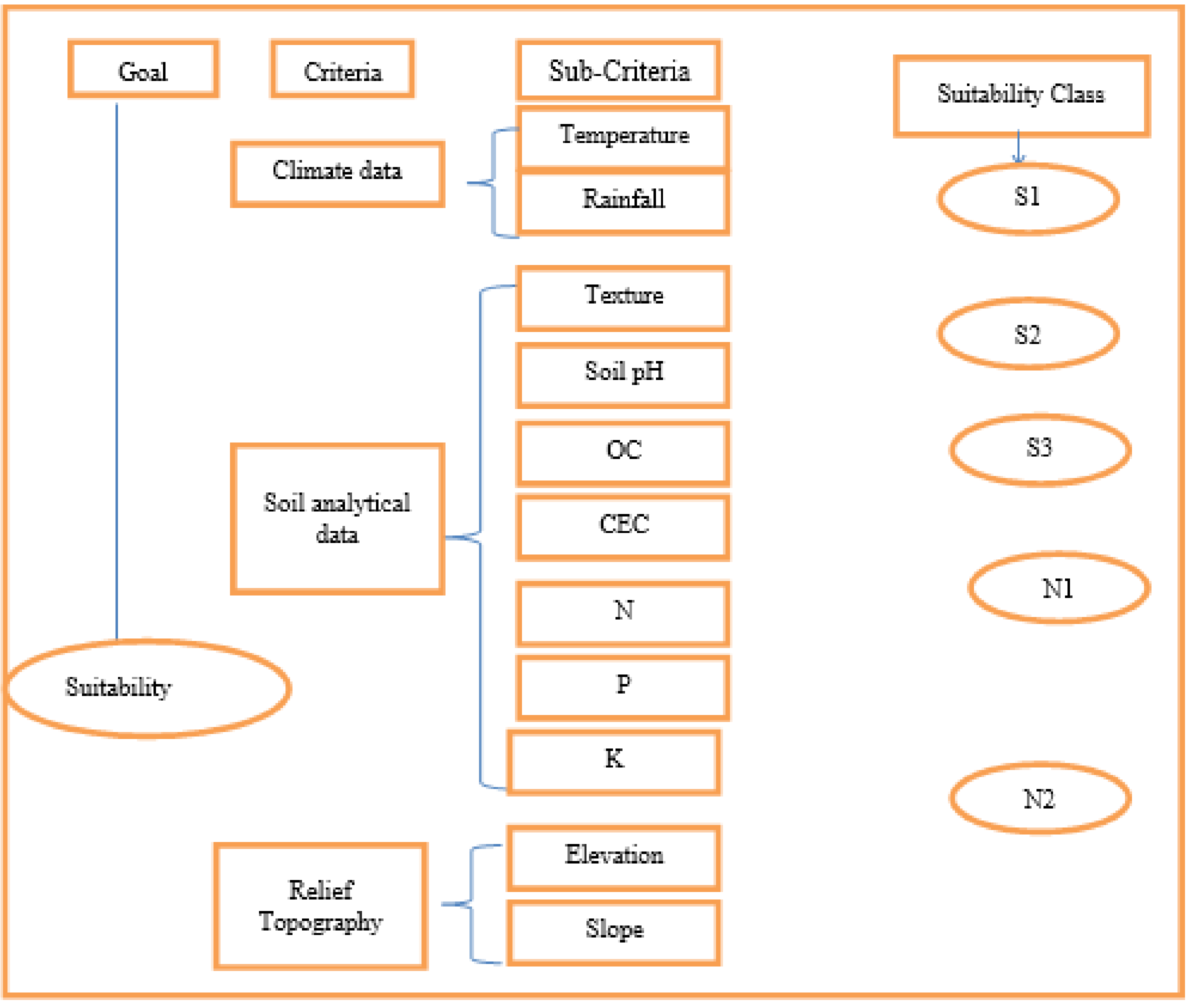

Fig. 3 Analytical hierarchical structure for land suitability evaluation

Development of a comparison matrix at each level of hierarchy

The pair-wise comparison matrix was created using the scale of 1to 9, where 9 represents extreme importance and 1 represents equal relevance of the in-between criterion of the matrix, in accordance with the analytical hierarchical procedure stated above. The Pair-Wise Comparison Matrix (PWCM) rates the relative weight of two variables in relation to the suitability of the soil being studied. The PWCM was used to compare two elements and to determine the relative weight of the criterion, sub-criteria, and suitability classes. However, the accessible values for the pair-wise comparisons are members of the set [9, 8, 7, 6, 5, 4, 3, 2; 1/2, 1/3, 1/4; 1/5, 1/6, 1/7, 1/8, 1/9] based on the following scale. A score of 9 means that the row factor is more significant than the column factor. A value of 1/9, on the other hand, denotes that the row factor is less significant than the column element. The rating value for the column and row components is 1 when both are equally significant. In other words, a value of unity was assigned to the diagonal element (i.e., when a factor is compared with itself). The pair-wise comparison matrix has a reciprocity condition, which is formally represented as n (n-1)/2 for n number of components. Following the creation of a pair-wise matrix, the Saaty (1977; 1980; 2000), approach was used to determine the relative weights/eigenvectors.

Standardization of criteria and the rating of suitability classes

According to crop requirements, all criteria maps for land suitability analysis are typically provided in ordinal classes or values (like S1, S2, S3, N1 and N2) that indicate the degree of appropriateness with respect to sub-criteria (Sehgal, 1999). It involves determining the relative weight of each set of classes inside a criterion. Standardization is the method used to produce the normalized score for each appropriateness class. Additionally, because all the chosen criteria could be expressed in various units, they must all be converted to the same unit and standardized to be used with the weighted overlay approach. All criteria maps' vector layers were changed to raster layers. The suitability map in Arc GIS 10.3.1 was finally produced after the raster layers underwent a new classification and were used as input data for the weighted overlay. The value of each chosen criterion for the examination of comparative importance was standardized by the reclassification method in the spatial analysis toolbox of Arc-GIS software. Equation 3 demonstrates the usage of the Consistency Ratio (*CR*) to prevent bias in criteria weighting which represents the *CR*, where RI stands for random index and *CI* for consistency index.

$$\text{CR} = \frac{CI}{RI} \qquad (3)$$

The CR, which primarily relies on the consistency index and random index, makes it easier to determine potential events and assesses the decision maker's inconsistencies (Cengiz and Akbulak, 2009; Chen et al., 2010).

$$\text{CI} = \frac{\lambda\text{max} - \text{n}}{n-1} \qquad (4)$$

Equation 4 shows the consistence index where max is the principal or highest eigenvector of the computed matrix and n specifies the order of the matrix. According to computed matrix order, the Random Index (RI) indicates the consistency index's mean value (Saaty, 1977, 1980). The weight value of the matrix reveals inconsistencies, and the method (AHP) may not produce results that are meaningful if the value of CR is more than 0.10. (Saaty 1977, 1980, 2000).

Integrating data into GIS

The processed images must be integrated into the GIS to create agricultural land use and land cover in order to meet the goals of the study. A land suitability map was also created using the AHP data (Fig. 4). Arc GIS 10.3.1 was used to create the map of land use, land

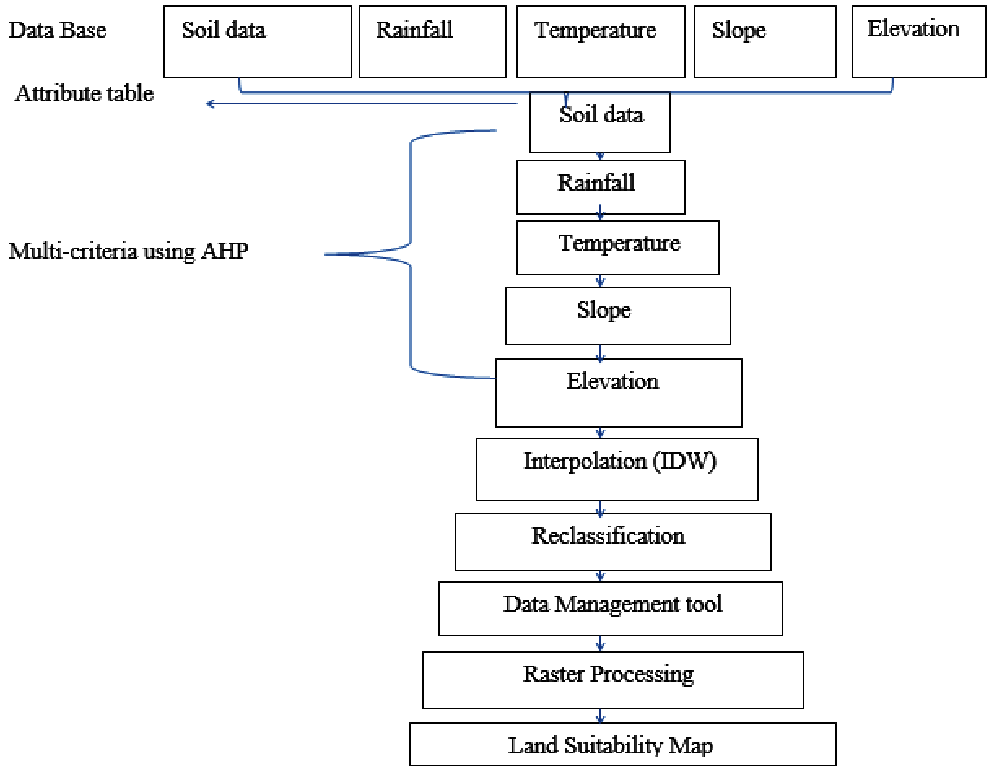

Fig. 4 Data integration into GIS

TABLE 2

Pair-wise comparison matrix of chemical properties for multi-criteria decision making

Criteria	OC	Ph	CEC	N	P	K	Ca	Mg	Na	EC
OC	1	3	3	4	4	5	5	6	7	8
pH	1/3	1	2	3	3	4	4	5	6	7
CEC	1/3	½	1	2	2	3	3	3	4	4
N	¼	1/3	½	1	2	2	3	3	4	4
P	¼	1/3	½	½	1	2	2	3	3	4
K	1/5	¼	1/3	½	½	1	2	3	3	4
Ca	1/5	¼	1/3	1/3	½	½	1	2	2	3
Mg	1/6	1/5	1/3	1/3	1/3	1/3	½	1	2	3
Na	1/7	1/6	¼	¼	1/3	1/3	½	½	1	2
EC	1/8	1/7	¼	¼	¼	¼	1/3	1/3	½	1

TABLE 3

Synthesized matrix of chemical properties for multi-criteria decision making

Criteria	OC	pH	CEC	N	P	K	Ca	Mg	Na	EC
OC	1	3	3	4	4	5	5	6	7	8
pH	0.3	1	2	3	3	4	4	5	6	7
CEC	0.3	0.5	1	2	2	3	3	3	4	4
N	0.3	0.3	0.5	1	2	2	3	3	4	4
P	0.3	0.3	0.5	0.5	1	2	2	3	3	4
K	0.2	0.3	0.3	0.5	0.5	1	2	3	3	4
Ca	0.2	0.3	0.3	0.3	0.5	0.5	1	2	2	3
Mg	0.2	0.2	0.3	0.3	0.3	0.3	0.5	1	2	3
Na	0.1	0.2	0.3	0.3	0.3	0.3	0.5	0.5	1	2
EC	0.1	0.1	0.3	0.3	0.3	0.3	0.3	0.3	0.5	1
Sum	3	6.2	8.5	12.2	13.9	18.4	21.3	26.8	32.5	40

TABLE 4
Normalized pair-wise comparison matrix of chemical properties and computation of criterion weights

Criteria	OC	pH	CEC	N	P	K	Ca	Mg	Na	EC	Weight
OC	0.3	0.5	0.4	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.3
pH	0.1	0.2	0.2	0.2	0.2	0.2	0.02	0.2	0.2	0.2	0.2
CEC	0.1	0.08	0.1	0.2	0.1	0.2	0.1	0.1	0.1	0.1	0.1
N	0.1	0.05	0.05	0.08	0.1	0.1	0.1	0.1	0.1	0.1	0.1
P	0.1	0.05	0.05	0.04	0.07	0.1	0.09	0.1	0.09	0.1	0.1
K	0.06	0.05	0.03	0.04	0.03	0.05	0.09	0.1	0.09	0.1	0.06
Ca	0.06	0.05	0.03	0.02	0.03	0.02	0.04	0.07	0.06	0.08	0.04
Mg	0.06	0.03	0.03	0.02	0.02	0.01	0.02	0.04	0.06	0.08	0.03
Na	0.03	0.03	0.03	0.02	0.02	0.01	0.02	0.02	0.03	0.05	0.02
EC	0.03	0.02	0.03	0.02	0.02	0.01	0.01	0.01	0.02	0.03	0.02
											$\Sigma = 0.97$

TABLE 5
Multi-criteria decision making on LULCC and land suitability data using Pair-wise comparison matrix

Criteria	Soil depth	Rainfall	Temp	Slope	Elevation
Soil depth	1	3	5	7	9
Rainfall	1/3	1	3	5	7
Temp.	1/5	1/3	1	3	5
Slope	1/7	1/5	1/3	1	5
Elevation	1/9	1/7	1/5	1/5	1

TABLE 6
Synthesized matrix for multi-criteria decision making on LULCC and land suitability data

Criteria	Soil depth	Rainfall	Temp	Slope	Elevation
Soil depth	1	3	5	7	9
Rainfall	0.3	1	3	5	7
Temp.	0.2	0.3	1	3	5
Slope	0.1	0.2	0.3	1	5
Elevation	0.1	0.1	0.2	0.2	1
Sum Total	1.7	4.6	9.5	16.2	27

TABLE 7
Computation of criterion weights on LULCC and land suitability data showing normalized pair-wise comparison matrix

Criteria	Soil depth	Rainfall	Temperature	Slope	Elevation	Weight
Soil depth	0.6	0.7	0.5	0.4	0.3	0.5
Rainfall	0.2	0.2	0.3	0.3	0.3	0.3
Temp.	0.1	0.1	0.1	0.2	0.2	0.1
Slope	0.1	0.04	0.03	0.1	0.2	0.1
Elevation	0.1	0.02	0.02	0.01	0.03	0.02
						$\Sigma = 1$

CR = CI/RI = 0.1/1.12
CR = 0.08

TABLE 8
Present inconsistency indices randomly (RI) for n = 10

N	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.46	1.49

cover changes, and appropriateness from the composite layer images of their weights.

Results and Discussion

Description of LULC types

Figures 5 to 8 show the coefficient maps of LULC rate in Kwara State in the years 1986, 2000, 2010, and 2016. The figures display the location of the LULC distribution according to each year's Landsat imagery. In this study, 6 types of land use land cover classifications were found as described in Table 9 based on spatially explicit data generated. Figures 5 to 8 show the pattern of land use land cover in Kwara State from 1986 to 2016, and Fig. 9 shows the anticipated change for the year 2030. According to the data, there have been periodic increases or changes in the percentage of agricultural and built-up areas, including land used for building, the expansion of cities and villages, the establishment of institutions, and farming operations. On the other hand, because of deforestation and removal of soil for the construction of roads and buildings, the amount of vegetation cover (forest) lands has reduced over time. Moreover, improper land use and management had exposed land surfaces, leading to erosion. Throughout most of Kwara State, erosion has produced sandy surface soils, hills, and undulating terrains. Between 1986 and 2016, both the built-up area and the bare land had markedly increased (Table 10). The built-up area increased from 15% in 1986 to 30.4% in 2016 while the bare land increased from 5% to 10% during the same period. The farmlands and the area covered by water bodies had also increased from 34% and 3% in 1986 to 46% and 4% in 2016, respectively. The forest land, on the other hand, decreased from 43% in 1986 to 9.6% in 2016. Suleiman et al. (2014) in their study on land use land cover in Ilorin and its environs, reported that in 1986, forest and other vegetation cover accounted for 52% of total land cover while the built-up areas and water bodies accounted for 12% and 0.5% respectively. They further reported that by 2000, the built-up areas had increased to 25% while the forest land had decreased to 27%. Mamman et al. (2014) also reported that while the built-up area in Ilorin increased by 23.8%, the vegetation cover decreased by 24.7%.

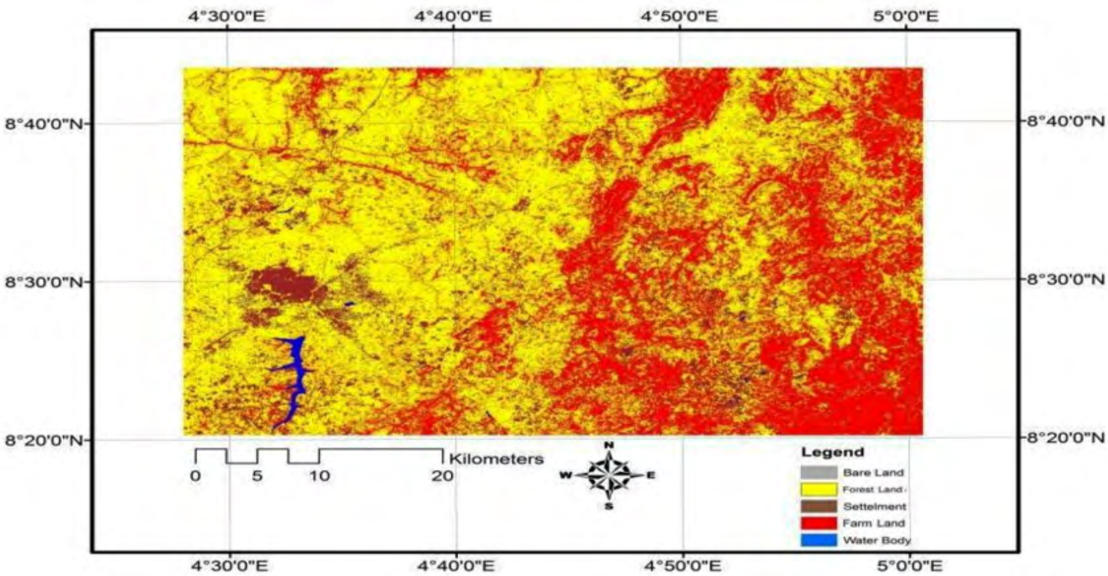

Fig. 5 Land use and land cover image (NASRDA, 1986)

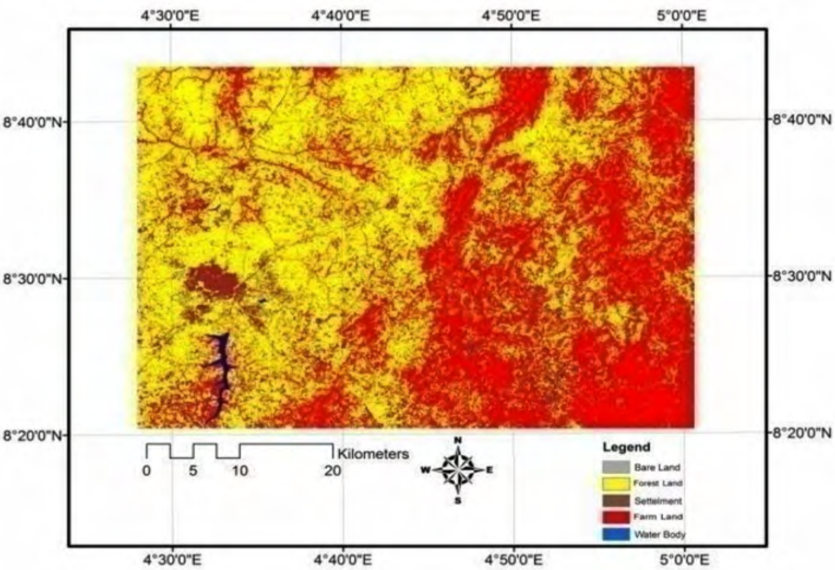

Fig. 6 Land use and land cover image (GLCF, 2000)

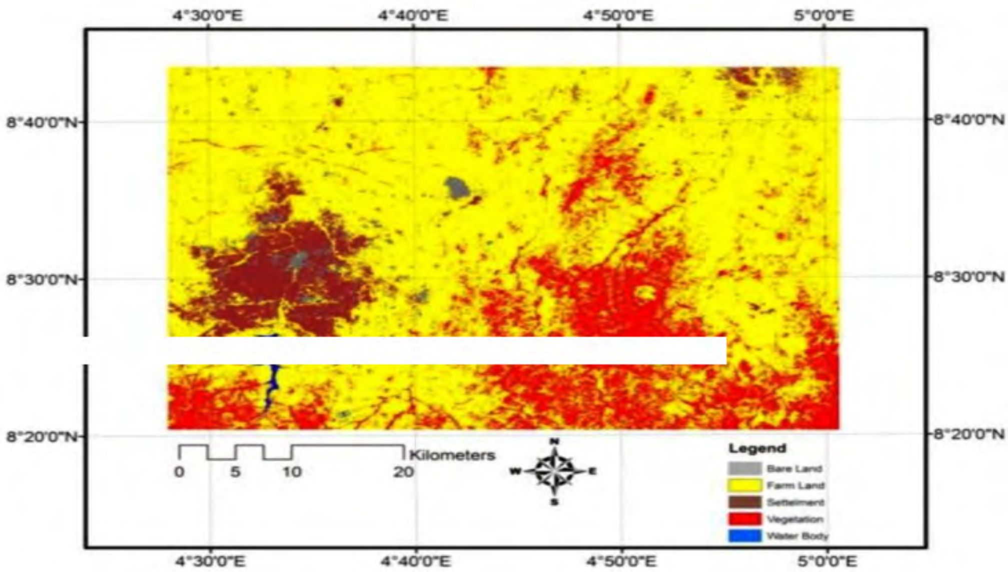

Fig. 7 Land use and land cover image (NASRDA, 2010)

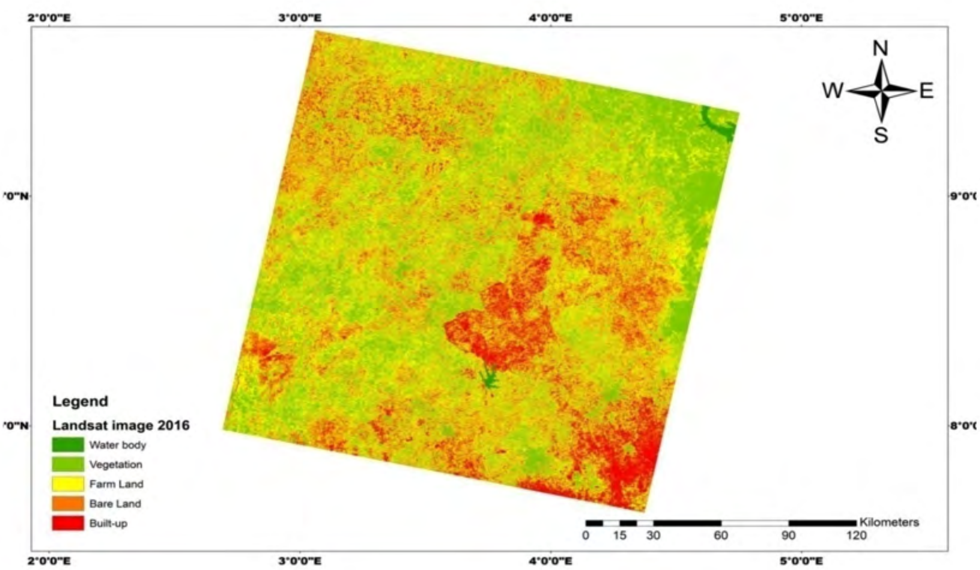

Fig. 8 Land use and land cover image 2016

TABLE 9
Land use land cover in 1986, 2000, 2010 and 2020 and their projection to 2030

Landuse	1986	Area	2000	Area	2010	Area	2016	Area	2030	Area
Land cover	(ha)	%	(ha)	%	(ha)	%	(ha)	%	(ha)	%
Farm land	497,284.2	34	602,567.4	39	685,354.3	41.5	723,541.4	46	789,254	49
Bare Land	952,57	5	135,204.3	6	153,214.2	8	158,897.5	10	159,972	11
Built-Up	123,364.1	15	302,432.6	25	506,734.5	28	623,452.7	30.4	713,987	33
Forest Land	646,165.3	43	324,567.5	27	132,456.1	18.5	112,254.2	9.6	103,145	5
Water Body	874,76	3	874,76	3	874,89	4	874,89	4	712,34	2
Total		100		100		100		100		100

The land use land cover imagery between 1986 and 2016 shows that enormous changes had occurred in the study areas during the period. The changes could be attributed to high rate of development such as increased urbanization and population density, illegal and unregulated quarrying, unregulated timber extraction, exploitation and deforestation of forest/ vegetation, uncontrolled livestock grazing, exposure, and excavation of agricultural land for construction purposes. These activities resulted in nutrient mining from the soils in the study areas. Consequently, these activities caused nutrient depletion from agricultural lands leading to low agricultural produce and food insecurity (Suleiman et al., 2014).

The projection for 2030 LULC

Figure 9 shows LULC projection and direction of changes for 2030. Comparison of the areas covered by the different suitability classes (Table 9) and their projections in Fig. 9, indicate a dynamic and heterogenous land usage in Kwara State contributed by human activity and natural factors. The major land use land cover categories identified in the study areas include farm land, forest land, bare land, built-up areas and water bodies.

The projection reveals that farmland would cover the largest area of 789,254 ha followed by built-up area of 713,987 ha and bare land of 159,972 ha (Table 9). The major environmental implications would be loss of vegetation (land degradation), regular conversion of forest into shrub land and then to grassland as well as decreased water bodies. These projections give a worrisome outlook. Ajadi et al. (2011) had reported that reduction in forest and vegetation covering the study areas had caused eco-degradation, leading to loss in plant and animal species, landslides, slips, gullies and loss of arable land. The results of

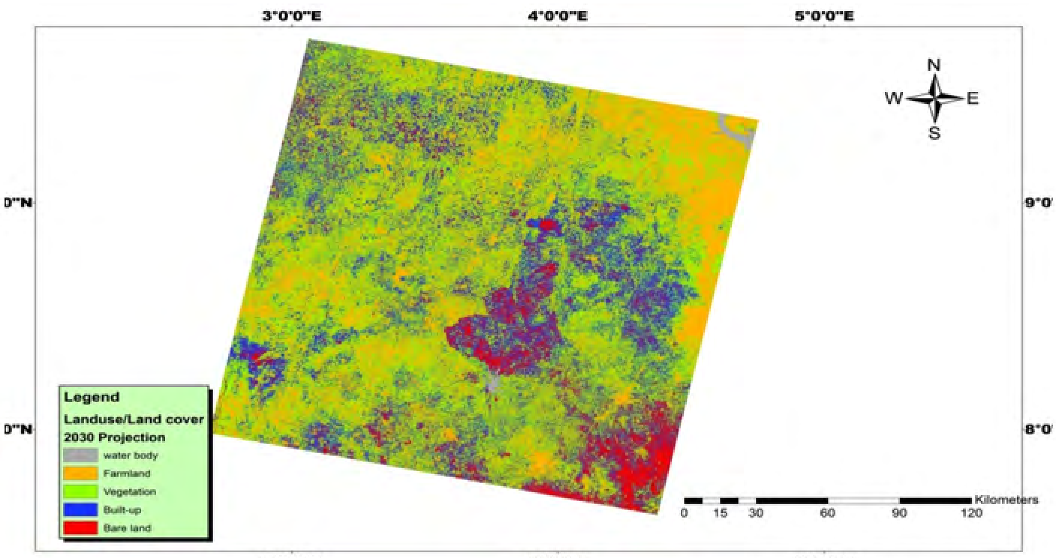

Fig. 9 Projected land use and land cover imagery of 2030 for Kwara State

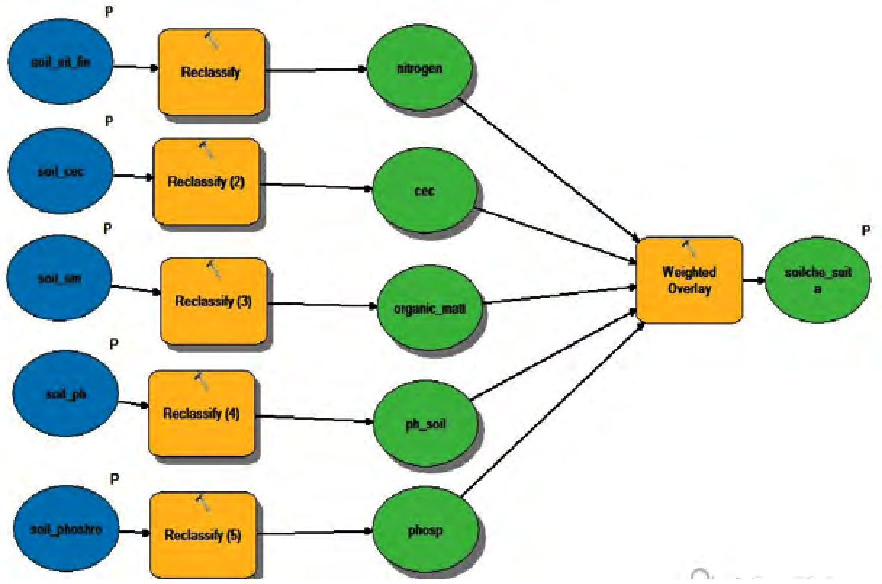

Fig. 10 Land suitability model for arable farming

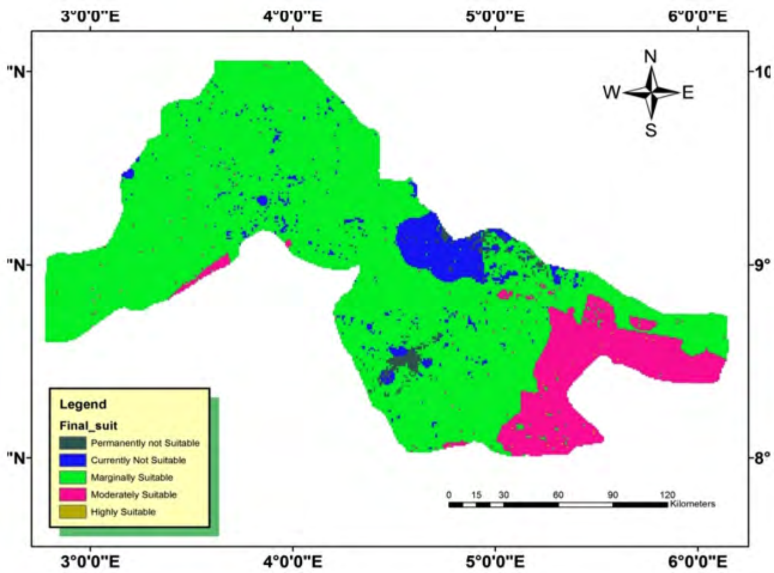

Fig. 11 Land Suitability map of Kwara State, 2016

TABLE 10

Areas covered by suitability classes

Land suitability class	Area (hectares)	Coverage (%)
Highly suitable	450,432	11.4
Moderately suitable	592,302	19.3
Marginally suitable	1,136,354	30.4
Currently not suitable	945,237	23.12
Permanently not suitable	476,345	15.78
Total	3,600,670	100

this study have shown that the current land use is unplanned and unregulated. The study area is at the mercy of rapid population growth. Figure 9 shows that the land cover and forest land have shrunk while the built-up area has expanded. Also, the bare land and farmland have expanded in an uncontrolled and unplanned manner. Thus, the land use being practiced has a negative impact on agricultural land. Lack of a comprehensive land use policy could negatively affect sustainability of both agricultural land and forest land in Kwara State. Moreover, soil fertility losses and forest biomass decline are associated with poor land use, and are threats to agricultural productivity and food security.

Conclusions and Recommendation

The results of this research have revealed that land in the Kwara State of Nigeria has been used for different developmental activities. Consequently, agricultural and forest lands have reduced and become degraded. The study has revealed that the major land uses are forest vegetation, water body and farmland. The forest area has decreased from 43% (646,165.3 ha) in 1986 to 9.6% (112,254.2 ha) in 2016 and a further reduction of 5% (103,145 ha) has been projected to occur by 2030.The area under farmland has increased from 34% (497, 284.2ha) in 1986 to 46% (723,541.4 ha) in 2016 and projected to 49% (789,254 ha) in 2030. Vegetation cover and the area covered by water bodies have also changed. Furthermore, due to land cover changes through deforestation, bare land has increased from 5% (95,257 ha) in 1986 to 10% (158,897.5 ha) in 2016 with a projected increase to159,972 ha i.e., 11% in 2030. The area covered by water bodies increased by 1% between 2000 and 2010 and is projected to decrease by 2% in 2030 due to various anthropogenic activities such as sand filling. Although the effects of climatic and topographic factors on land use and land cover are not predictable, they cannot be discounted. Integrating GIS technology with AHP and MCA models to evaluate land use and land cover has revealed varying degrees (up to 68%, 2.1 million ha) of suitable land for arable cropping. From the data obtained, highly suitable, moderately suitable and marginally suitable areas for arable cropping added up to 61.1% of the study area. These results show that Kwara State has enormous potential for agricultural productivity. Even all or part of the currently not suitable land area could be utilized for arable cropping if properly managed. Thus, agriculture would be a major contributor to the economic growth of Kwara State. Economic growth would be achieved if the right crops are grown on the appropriate soils and given the required management while minimizing uncontrolled land excavation and other land degradation activities. There have been many studies on degradation of natural resources and inappropriate land use the cause of which have been attributed to failure to plan and positively harmonize all land use activities. This study, therefore, recommends an optimal land use planning system to cater for improvement in social conditions of the growing population and conserve land resources for future generations in Kwara State. Furthermore, land use planning would help the state to promote acceptable land use, manage renewable resources and protect land resources thus encouraging community development. In this regard, it would be necessary to make use of GIS technology which has the capacity of updating the database of land, soils and their nutrient status, crop requirements, distribution and pattern of rainfall, temperature levels and topography for the purpose of modeling sustainable development and food security. In conclusion, a comprehensive assessment of land uses and adoption of sustainable land cover management such as forest reserves and protection of water bodies would have to be carried out so as to make more arable lands available through restoration of degraded lands. This endeavour should be a major priority for the Kwara State government.

Acknowledgments

The authors are grateful to the European Union Commission on the ARISE Scholarship to African Students for their financial support to this research and the Department of Soil Science, School of Agriculture, University of Ghana and Faculty of Agriculture, University of Ilorin for the use of their laboratory facilities.

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