Land use land cover change monitoring and prediction in Makurdi local government area, Nigeria, using remote sensing and GIS techniques

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(Received: Sep 27, 2021; in final form: Apr 17, 2022)

Abstract: This paper demonstrates how to predict land use and land cover change and focused on Makurdi Local Government Area precisely. The study investigates the spatio-temporal variations in land cover in Makurdi local government area within periods: 1991, 2001, 2013, and 2020. Additionally, the future scenario of land cover was predicted for the year 2030. The land cover classification was done using the Maximum likelihood classifier in the ENVI 5.3 software environment while the prediction was implemented with the Cellular Automata (CA) Markov chain modelling tool in Idrisi TerrSet 18.31 software. Results shows between 1991 and 2020, that the natural environment such as dense vegetation, water body and wetland resources have been threatened due to the drastic reduction of 55.02km^2 (89.70%) loss, 0.03km^2 (11%) loss and 13.15km^2 (56.54%) loss respectively, The social environment- built up area, barren land and agricultural land have expanded by 37.10km^2 (381.00%) gain, 5.24km^2, (42.54%) gain and 25.96km^2 (3.69%) gain respectively. The explanation for this outcome could be connected to the rise in human population which has increased the demand for agricultural land, infrastructural development, and housing. The study was able to successfully project the land use/cover for 2030 using the CA Markov chain model.

Keywords: Land use and cover changes (LUCCs), Cellular Automata (CA-Markov), GIS, Remote Sensing.

1. Introduction

Land use and cover changes (LUCCs) are among the most important changes on the land surface which have considerable influence on the environment and environmental processes. Thus, LUCCs are recognized as the main driving force of the global ecosystem change (Behera et al., 2012; Zhang et al., 2015). The urban populations in most developing countries have grown by 40% between 1900 and 1975. According to them, the trend will continue adding approximately 2 billion people to the urban population of the presently less-developed nations for the next 30 years. In similar way, Arnfield observed that the world is becoming increasingly urbanized with (45%) of the population already living in the urban areas in the year 2000. He projected half of the world living in urban areas by 2007. It was further estimated that by the year 2025, (60%) of the world's population will live in cities. The demand for land cover data has rapidly increased over the years as an indispensable means of planning and implementation of developmental projects. Land cover (LC) data are important for planners, policy makers, and land resource management stakeholders (Ezeomedo et al., 2013). Therefore, accurate and up-to-date land cover change information is necessary for understanding the trend of changes and futuristic extrapolations (Hamad et al., 2018). Remote sensing (RS) and geographic information system (GIS) are essential tools used to obtain accurate and timely spatial data of land use and land cover, as well as analysing the changes in a study area. Remote sensing images can effectively record land cover situations and provide an excellent source of data, from which updated land cover information and modifications can be extracted, analysed, and simulated efficiently through specific means. Therefore, remote sensing is widely used in the detection and monitoring of land cover at different scales. The Markov chain and Cellular Automata (CA-Markov) model, a mixed model, is the hybrid of the Cellular Automata and Markov models. This model effectively combines the advantages of the long-term predictions of the Markov model and the ability of the Cellular Automata (CA) model to simulate the spatial variation in a complex system and this mixed model can effectively simulate land cover change. Therefore, this study will monitor and predict land cover changes in the Makurdi LG using the CA-Markov Chain technique.

1.1 Aim and objectives of the work

The aim of this study is to determine the LULC changes over time in Makurdi for future effective planning. The objectives are as follows:

1. Acquisition of multitemporal Landsat imageries at four years (1991, 2001, 2013 and 2020).
2. Land use /land cover extraction using the maximum likelihood classifier on ENVI software..
3. Assessments of land use/ land cover changes between 1991 and 2020.
4. Predicting future land use/land cover change scenario for 2030 using the Cellular automata and Markov chain model.

1.2 Study area

Makurdi town, the capital of Benue state lies between latitudes 7^0 37″ and 7^0 47″ North of the equator, and between longitudes 8^0 28″ and 8^0 40″ East of the Greenwich Meridien.

Figure 1 shows the map of Makurdi Local Government Area. The town is situated astride River Benue in North central Nigeria, about 300 kilometres south of Jos and 450 kilometres from Enugu in the South. The city of Makurdi as currently defined politically, covers a radius of 10 kilometres. The city stretches from the Nigerian Airforce base in the East along Gboko road to Adaka village along Ankpa road in the West. In the South it is bounded by Apir village while in the North it is bounded by Agan Toll gate.

The River Benue traverses through the town from the Northeast to the Northwest thereby bifurcating it into two major parts: - the northern and southern parts known commonly as North bank and South bank districts.

Makurdi town lies in the gently rolling lowland fertile alluvial plains of the Benue River in the Guinea Savannah vegetation belt that consists of vast wetlands and Marshes that are intermittently punctuated with tributary stream channels. The city is therefore surrounded by vast fertile agricultural lands that are the hub of production of myriads of agricultural crops. Consequently, agriculture is the mainstay of the local economy and the main supplier of nutritional needs of the local population, the city and the entire country.

1.3 Significance of the study

The study of land use change referred to as change detection and the growth of urban centres have gained prominence in the recent years. This is partly due to the fact that there is an increasing need for proper land use planning to control various urban problems. Remote sensing techniques are of immense practical use for resources evolution and environmental. In fact, it has emerged as the most efficient and effective way to obtain large amounts of timely accurate information about terrain. Urban land use change monitoring compared, using high-resolution remote sensing technology to monitor more efficient time saving, saving a lot of manpower, material resources and time, improve the urban land use database building and database and update efficiency. The growth of city without planning will lead to create many complex urban problems. This study aspires to locate specific pattern of development in the process of urbanization so that conclusions can be used to predict future change scenarios. The result of this research will be informative to urban planners and government for sustainable decisions.

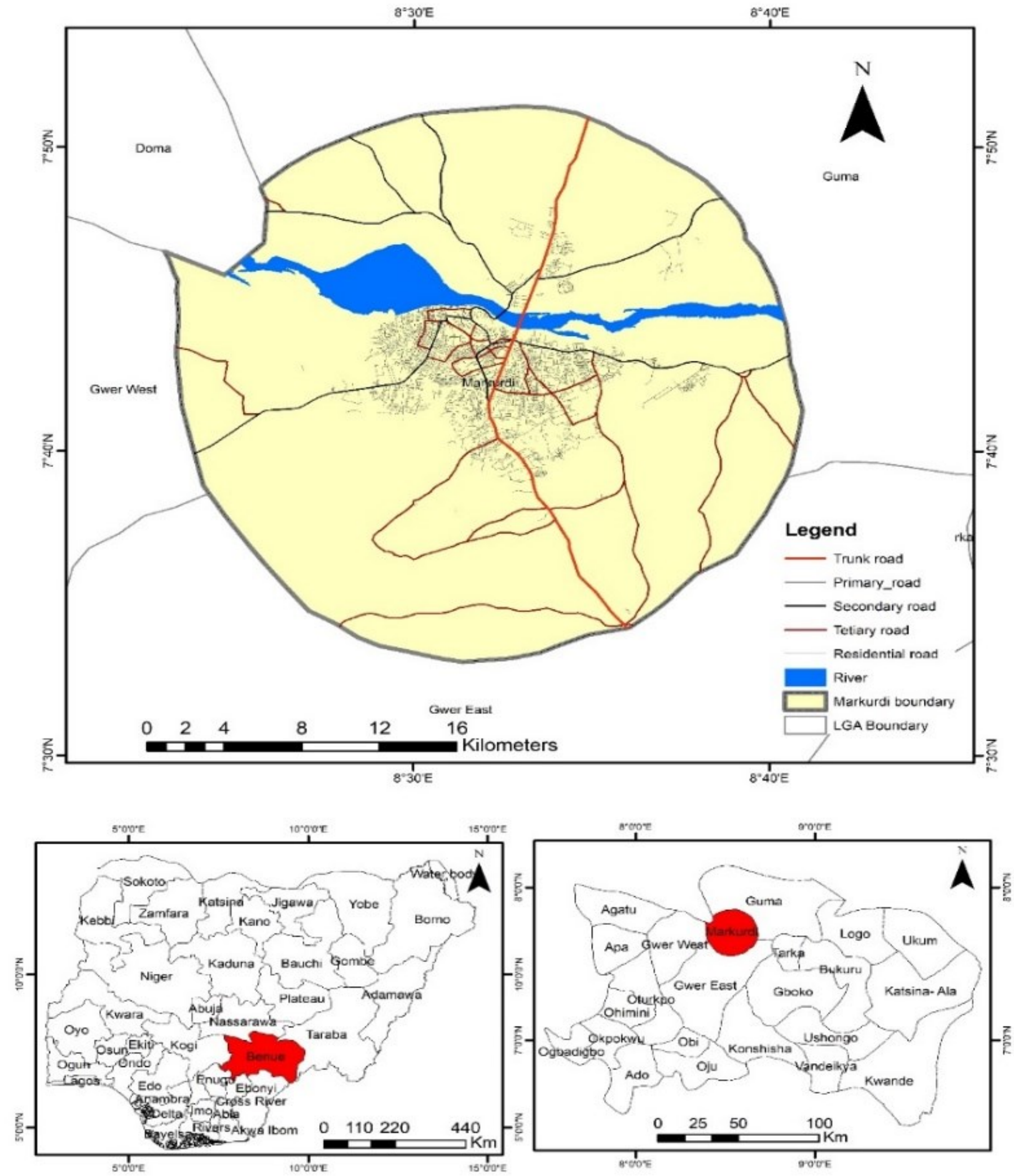

Figure 1. Map showing Makurdi Local Government Area

1.4 Land Use and Land Cover Change

Land use and land cover are essential components in understanding the interaction between human activities and the environment. According to (Abbas et al., 2010), The terms "land use" and "land cover" are often interchanged. United Nations Food and Agricultural Organization (UNFAO) (1997) define land use as "the total of all arrangements, activities, and inputs that people undertake in a certain land cover type." Land cover "is the observed physical and biological cover of the earth's land as vegetation, rocks, water body or man-made features." Liping et al., (2018) define land cover as the biophysical characteristics of the earth's surface, including the distribution of vegetation, water, soil, and other physical features of the land. Land use refers to how humans and their habitat have used land. In general, land cover is the physical covering of the earth, such as vegetation, soil, water, while land use is how humans have modified land to suit their needs.

Land use affects land cover, and changes in land cover affect land use. Changes in land cover by land use do not necessarily imply the degradation of the land (Rawat et al., 2015). However, changes in land use driven by various socioeconomic, demographic, political, and industrial causes would result in degradation in ecosystem services. Li et al., (2016) state that to understand the human and biophysical processes of land use and land cover changes (LUCC), researchers focused on the various forces driving LUCC. These drivers include socioeconomic, demographic, political, technological, biophysical, and industrial provide adequate support for developing urban land planning and management regulations.

Researchers have studied land cover in different areas by using different methods to detect land cover change. Lambin (1997) reviewed the various methods used to detect land cover change. Similarly, Parker et al., (2003) reviewed multi-agent systems for the simulation of land-use and land-cover change. The review aimed to give insight into how multi-agent models can overcome the limitations of the existing models in land cover studies. Rawat et al., (2015), monitored land use and land cover change using remotes sensing and GIS techniques: A case study of Hawalbagh block, district Almora, Uttarakhand, India. The study highlights the importance of digital change detection techniques for nature and location of change of the Hawalbagh block. Similarly, Ashaolu et al., (2019) assessed the spatio-temporal pattern of land use and land cover change in Osun drainage basin. The result underscored the increasing anthropogenic activities in the basin that influenced recharge rate, surface runoff, incidences of soil erosion, etc., in Osun drainage basin. Some authors that have studied land use and land cover at different levels include Brown et al. (2012), Kumar, et al., (2014), Lillesand, et al., (2004), Subedi, et al., (2013).

1.5 Land Cover Classification Schemes

For many years, agencies at the various governmental levels have been collecting data about land, but for the most part they have worked independently and without coordination. Too often this has meant duplication of effort, or it has been found that data collected for a specific purpose were of little or no value for a similar purpose only a short time later. The need of Federal agencies to have a standardised land use and land cover pattern led to the formation of an Interagency Steering Committee on Land Use Information and Classification early in 1971. The objective of the committee was the development of a national classification system that would be receptive to inputs of data· from both conventional sources and remote sensors on high-altitude aircraft and satellite platforms, and that would at the same time form the framework into which the categories of more detailed land use studies by regional, State, and local agencies could be fitted and aggregated upward from Level IV toward Level I for more generalized smaller scale use at the national level.
Anderson 1971 is of the opinion that there is no one ideal classification of land use and land cover, and it is unlikely that one could ever be developed. He states that since land use and land cover is constantly changing there is no logical reason why inventory of land use and land cover should remain the same. Furthermore, each classification is made to suit the needs of the user, and few users will be satisfied with an inventory that does not meet most of their needs (Verburg et al., 2006). In attempting to develop a classification system for use with remote sensing techniques that will provide a framework to satisfy the needs of the majority of users, certain guidelines of criteria for evaluation must first he established.

A land use and land cover classification system which can effectively employ orbital and high-altitude remote sensor data should meet the following criteria (Anderson 1971):

- The minimum level of interpretation of accuracy in the identification of land use and land cover categories from remote sensor data should be at least 85 percent.
- The accuracy of interpretation for the several categories should be about equal.
- Repeatable or repetitive results should be obtainable from one interpreter to another and from one time of sensing to another.
- The classification system should be applicable over extensive areas.
- The categorization should permit vegetation and other types of land cover to be used as surrogates for activity.
- The classification system should be suitable for use with remote sensor data obtained at different times of the year.
- Effective use of subcategories that can be obtained from ground surveys or from the use of larger scale or enhanced remote sensor data should be possible.
- Aggregation of categories must be possible.
- Comparison with future land use data should be possible.
- Multiple uses of land should be recognized when possible.

The multilevel land use and land cover classification system described in Anderson (1971) has been developed because different sensors will provide data at a range of resolutions dependent upon altitude and scale. In general, the following relations pertain, assuming a 6-inch focal length camera is used in obtaining aircraft imagery.

An attempt has been made to include sufficient detail in the definitions presented here to provide a general understanding of what is included in each category at Levels I and II. Many of the uses described in detail will not be detectable on small-scale aerial photographs. However, the detail will aid in the interpretation process, and the additional information will be useful to those who have large-scale aerial photographs and other supplemental information available. The land cover classes as used in this study (Anderson, 1971; Omogunloye et al., 2012), are defined as follows:

- **Urban or Built-up Land**: This comprises areas of intensive use with much of the land covered by structures
- **Agricultural Land**: This may be defined broadly as land used primarily for production of food and fibre.
- **Rangeland**: Rangeland historically has been defined as land where the potential natural vegetation is predominantly grasses, grass-like plants, forbs, or shrubs and where natural herbivory was an important influence in its precivilization state.
- **Forest Land**: Forest Lands have a tree-crown areal density (crown closure percentage) of 10 percent or more, are stocked with trees capable of producing timber or other wood products and exert an influence on the climate or water regime
- **Water**: The delineation- of water areas depends on the scale of data presentation and the scale and resolution characteristics of the remote sensor data used for interpretation of land use and land cover.
- **Wetland**: wetlands are those areas where the water table is at, near, or above the land surface for a significant part of most years
- **Barren Land**: Barren Land is land of limited ability to support life and in which less than one-third of the area has vegetation or other cover. In general, it is an area of thin soil, sand, or rocks.

Cellular Automata Markov Chain for Land Cover Prediction: Modelling of land use and land cover is a scientific field that is growing rapidly because of its importance in identifying the effects of the humans on the environment. In view of this importance, scientists have constituted an international organization named Land use and Cover Change (LUCC) organization that is connected with the International Geosphere Biosphere Program and the International Human Dimensions of Global Change Program (Pontius & Chen, 2006). Furthermore, many algorithms and methods have been developed for modelling land use and cover**.**

One of the approaches that have been developed for forecasting Land use/ Land cover (LULC) is Cellular Automata (CA) which is defined as a dynamical discrete system in space and time that works by specific rules on a uniform grid-based space (Obiefuna et al., 2013; Odunuga et al., 2007) . CA involves cells and transition rules that are used to identify the state of a certain cell. It is especially interesting for land use and land cover modelling because of its ability to represent a complex system by a small set of rules and states with spatio-temporal behaviour (Hadi, et al., 2014). CA was successfully compiled in one of the models in the IDRISI software that, hence, gives this model power and easiness for performing modelling LULC. CA Markov is a model in the IDRISI software. This model is a powerful tool for modelling and predicting land use and land cover change. It is a methodology that has been used widely in LULC modelling as it takes into consideration spatial interaction and stimulates multi LULC types. In this research, an approach of detecting the change and predicting the change of a specific year is applied. This approach is an integrated method of remote sensing, GIS, and modelling (CA method), as the RS and GIS is used for detecting the change and providing basis data for CA model, the latter is used to predict the future LULC map.

The Markov model is often used in monitoring, ecological modelling, simulation changes, trends of the LULC and to predict the amount of the land use change and the stability of future land development in the area of interest (Parsa, et al., 2016; Weng, 2002; Subedi, et al., 2013). Equation (1.0) explains the calculation of the prediction of land use changes (Kumar, et al., 2014)

$$\boldsymbol{S}\,(\boldsymbol{t},\boldsymbol{t}\,+\,\mathbf{1})\;=\;\boldsymbol{P}_{\boldsymbol{ij}}\;\times\boldsymbol{S}\,(\boldsymbol{t}) \text{--} \qquad (1)$$

Where ***S (t)*** is the system status at time of ***t***, ***S (t + 1)*** is the system status at time of **t + 1**; $\boldsymbol{P_{ij}}$ is the transition probability matrix in a state which is calculated in Equations (2.0 and 2.1) respectively:

$$\|\boldsymbol{P}_{\boldsymbol{ij}}\| = \left\| \begin{matrix} \boldsymbol{P}_{1,1} & \boldsymbol{P}_{1,2} & \cdots\cdots\cdots & \boldsymbol{P}_{1,N} \\ \boldsymbol{P}_{2,1} & \boldsymbol{P}_{2,2} & \cdots\cdots\cdots & \boldsymbol{P}_{2,N} \\ \cdots & \cdots & \cdots\cdots\cdots & \cdots \\ \boldsymbol{P}_{N,1} & \boldsymbol{P}_{N,2} & \cdots\cdots\cdots & \boldsymbol{P}_{N,N} \end{matrix} \right\| \text{--} \qquad (2)$$

Where $\left(\mathbf{0} \le \boldsymbol{P}_{\boldsymbol{ij}} \le \mathbf{1}\right)$

P is the transition probability; ***Pij*** stands for the probability of converting from current state ***i*** to another state ***j*** in next time; $\boldsymbol{P_N}$ is the state probability of any time. Low transition will have a probability near (0) and high transition have probabilities near (1) (Kumar, et al., 2014).

Markov Chain determines exactly how much land would be estimated to change from the latest date to the predicted date. The transition probabilities file is the output in this process, which is a matrix that records the probability that each land cover class will change to every other class. Through the Markov chain modelling, the analysis of two different dates of the LULC images induces the transition matrices, a transition area matrix and a set of conditional probability image (Hamad, et al., 2018).

2. Methodology

2.1 Software/Hardware Used

The following software and hardware were used for this study:

- Environment for Visualizing Images (ENVI) classic version 5.3 was used for the classification of the Landsat imagery.

- ArcGIS version 10.3 was used for analysis, manipulation and presentation of data.
- TerrSet version18.31 (IDRISI): was used to predict land cover change between the years under study.
- Google earth served as ground truthing imaging for image interpretation.

2.2 Data Acquisition

The study used four years 1991, 2001, 2013 and 2020 satellite imageries were downloaded from the United States Geological Survey USGS Earth Explorer portal shown in Table 1.

2.3 Image Pre-processing

Creation of Colour Composite: A false colour composite was created which is a combination of three raster images. In Landsat 4 TM, band 4 was assigned to red, band 3 to green and band 2 to blue (RBG432). The combination of this band produces a false colour composite where the vegetation is represented as dark red, crop as pink or red, built up as cyan, bare land/soil as white and water as blue or black; Landsat 7 ETM+ contains band 5 as red, band 4 as green and band 3 as blue (RBG543) while in Landsat OLI/TIRS, band 6 was assigned to red plane, band 5 to green, and band 4 to blue plane (RGB654). In this false colour composite, vegetation is depicted as green, water in blue, bare soil in shades of brown and built-up areas in shades of purple. Each band was combined using Envi classic 5.3.

2.4 Image Classification

2.4.1 Selection of Classification Scheme

The LULC classes were classified into the following six classes according to Anderson et al. (1976) classification scheme level 1: Water body, Built-up, Agricultural land, dense vegetation, wetland and barren land. See table 2.

2.4.2 Supervised classification

A Maximum Likelihood classification was executed for each image. This method assumes a normal distribution of DN (Digital Number) values, allowing the function to determine the probability of a pixel belonging to a specific feature class and assign each pixel to the highest probability class (Lillesand et al., 2004). Classifications were often repeated numerous times after additional training sites were added to achieve satisfactory results. Agricultural areas were occasionally classified as Wetlands, requiring additional polygons to be digitised to properly classify the image.

2.4.3 Post classification

The image classification was executed, and the output was set on to a post-classification also known as refinement stage. This operation is referred to as the clean-up operations. Before then, an accuracy assessment was conducted for all images. The classified image was exported as .TIF file and imported into the ArcGIS environment. The raster was converted to vector using the "*Raster to Polygon tool*" located in the "*Conversion tool*" in the ArcToolBox.

2.4.4 Accuracy assessment

In order to determine the level of accuracy of the classification workflow, a confusion matrix operation was performed and generated. The summary of the reliability and accuracy assessment of the classified satellite imageries are depicted in the next chapter.

$$\text{Overall accuracy} = \frac{\text{Total number of correct classified points}}{\text{Total number of points}} \times 100 \quad (3)$$

Where, the Total number of correctly classified points is the number of points that have same class values from the classification output and the ground-truth. The Total number of points is the number of the random points created.

Table 1. Data Collection Table

S/N	Dataset	Path/Row	Date	No. of Bands	Spatial resolution	Format	Source
1	Landsat 4 TM	188/55	07/01/1991	7	30m	GeoTIFF	United States Geological Survey (USGS)
2	Landsat 7 ETM+	188/55	02/11/2001	8	30m	GeoTIFF	
3	Landsat 8 OLI/TIRS	188/55	29/12/2013	11	30m	GeoTIFF	
4	Landsat 8 OLI/TIRS	188/55	30/11/2020	11	30m	GeoTIFF	

Table 2. Land cover classification scheme used

S/N	Class	Description
1	Water body	Sea, rivers, ponds and a small lake
2	Built-up	Residential, commercial, and industrial areas, settlements, and transportation infrastructure
3	Agricultural land	Cropland and pasture fields, grassland, and fallow land
4	Dense vegetation	Areas dominated by natural trees, such including riparian forest
5	Wetland	Marsh or swamp
6	Barren land	Tilled farmland, sand-filled land, and rocky area

3. Results and analysis

3.1 Temporal pattern of land use/cover between 1991 and 2020

As a result of the post-classification of land cover carried out on the study area, all the land cover classes experienced changes within the years considered, a period of 29 years (1991-2020).

The negative values (Table 4) depict 10 years interval negative changes in the land use/cover classes that is, decrease in LULC classes. The positive values depict increase in LULC class.

In Table 3, 1991 and 2001 of the agricultural land cover/use class occupied 703.47km^2 and 703.95km^2 which is (84%) and (84.45%) of land covering the study area. It further increased in 2013 and 2020 (Figure 2) to 723.44km^2 and 729.43km^2 representing (86.79%) and (87.50%). As population increase, the demand for food equally increases resulting to food scarcity if not properly checked. The Federal Government of Nigeria has put in place various agricultural agencies to train farmers to improve and expand agriculture that can feed the growing population.

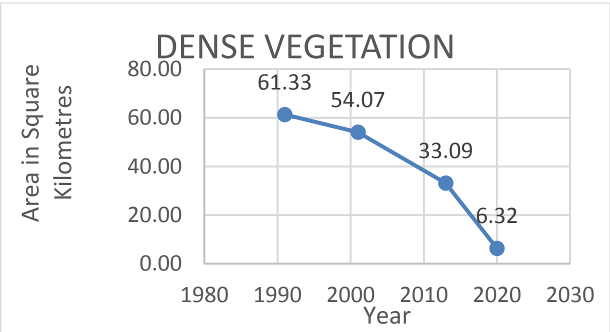

Figure 2. Agricultural land distribution across the epochs 1991, 2001, 2013 and 2020

Between 1991 and 2020 (Figure 3), the dense vegetation land cover/use class has reduced drastically from 61.33km^2 to 6.32km^2. Research has shown that the study area is investing heavily into agriculture. This results in the conversion of large area of dense vegetation into agriculture by government and private sectors. Also, as settlements increase, human activities move towards forested areas to create space for agriculture or more infrastructural development.

In 1991 (Figure 4), barren land occupied 12.32 km^2, which represented (1.48%) of the entire land of the study area. In 2001 and 2013, there was a decrease in the area of barren land of 8.37 km^2 and 9.20km^2 which represents (8.37%) and (9.20%) respectively as against what it was in 1991. This can be attributed to agricultural activities in the area as the study area is known for its high agricultural activities. Over the period of 7years between 2013 and 2020, the barren land had increased to 17.55km^2, which represents (2.11%). This increase could have been due to the increased population in the urban settlements resulting in the construction of buildings and increased clearing for farming.

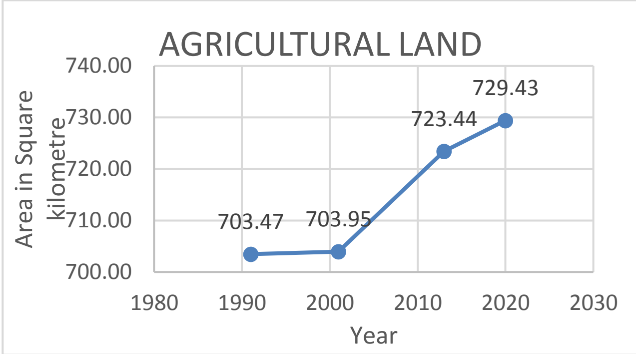

Figure 3. Dense vegetation distribution across the epochs

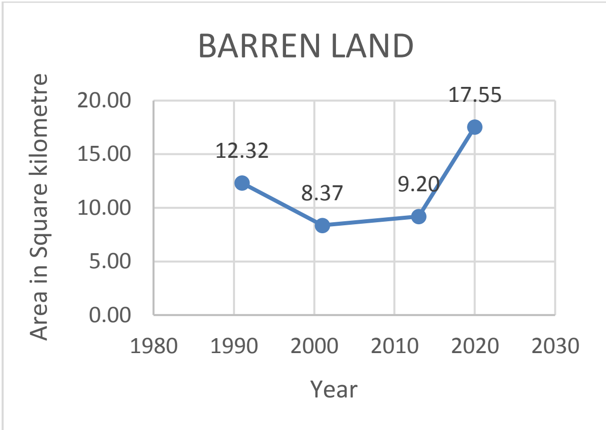

Figure 4. Barren land distribution across the epochs

The built-up land cover/use class (Figure 5) occupied 9.74km^2 around 1991 which formed (1.17%) of the land covering the study area. In 2001, the land cover/use class had increased in area by 21.46km^2 representing (2.57%) of the study area. In 2013, the land cover class increased by 36.03km^2 which is (4.32%) of the study area as it drastically increased to 49.84km^2 in 2020. This can be explained by the increasing population growth between 1991 and 2020. The obvious consequence of this population expansion on natural resources cannot be over emphasised.

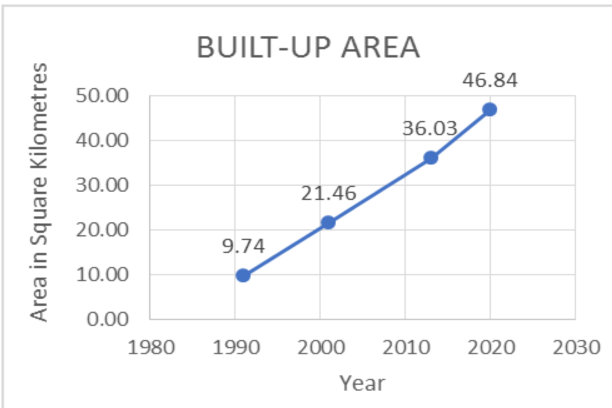

Figure 5. Built-up area distribution across the epochs

The water-body (Figure 6) cover/use class, in 1991, 2013 and 2020 occupied 23.38km^2 23.79km^2, and 23.36km^2 which formed (2.81%), (2.85%) and (2.80%) respectively of the land cover of the study area. In 2001, the land cover class had increased in area to about 35.68km^2. The area of the water-body in 1991, 2013 and 2020 appears very close to each other which could have been as a result of seasonal phenomenon while the area of water body in 2001 could be as a result of sand mining as it is an activity in the area.

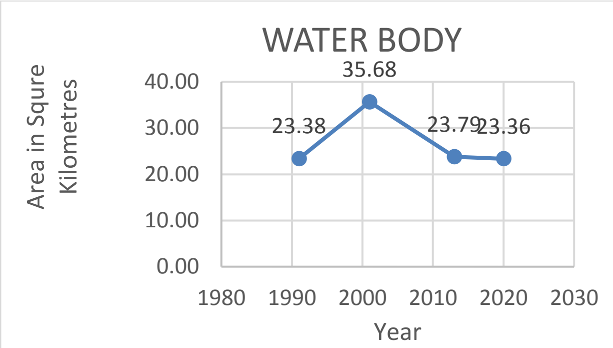

Figure 6. Water body distribution across the epochs

In 1991, the wetland land cover/use class occupied 23.26 km^2 forming (2.79%) of land covering the study area (Figure 7). It drastically decreased between 2001 and 2013 from 10.04km^2 to 8.03km^2 representing (1.20%) and (0.96%) respectively. In 2020, land cover/use increased by 10.11km^2. Cooper and Moore, 2003 states that wetlands play a key role in agriculture as certain crops thrive best in rich wetlands soils.

The respective graphical views of the combine Land cover distribution across the epochs classes from 1991 to 2020 in Table 3 and the Change detection among the classes in 10yrs interval from 1991 to 2020 are shown in Figure 8 and Figure 9.

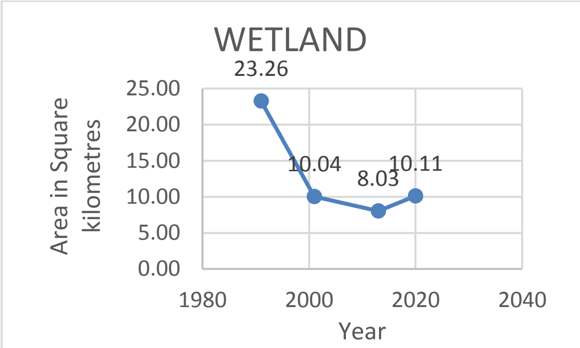

Figure 7. Wetland distribution across the epochs

Table 3. Land use land cover distribution across epochs 1991, 2001, 2013 and 2020

CLASS	1991		2001		2013		2020	
	(Sq km)	(%)	(Sq km)	(%)	(Sq km)	(%)	(Sq km)	(%)
Agricultural land	703.47	84.40	703.95	84.45	723.44	86.79	729.43	87.50
Barren land	12.32	1.48	8.37	1.00	9.20	1.10	17.55	2.11
Built up	9.74	1.17	21.46	2.57	36.03	4.32	46.84	5.62
Dense vegetation	61.33	7.36	54.07	6.49	33.09	3.97	6.32	0.76
Water body	23.38	2.81	35.68	4.28	23.79	2.85	23.36	2.80
Wetland	23.26	2.79	10.04	1.20	8.03	0.96	10.11	1.21
Total	**833.50**	**100.00**	**833.57**	**100.00**	**833.59**	**100.00**	**833.61**	100.00

Table 4. Change detection statistics

CLASS	1991-2001		2001-2013		2013-2020		1991-2020	
	(Sq km)	(%)	(Sq km)	(%)	(Sq km)	(%)	(Sq km)	(%)
Agricultural land	0.48	0.07	19.49	2.77	5.99	0.83	25.96	3.69
Barren land	-3.95	-32.06	0.83	9.92	8.35	90.76	5.23	42.45
Built up	11.72	120.33	14.57	67.89	10.81	30.00	37.10	380.90
Dense vegetation	-7.26	-11.84	-20.98	-38.80	-26.77	-80.90	-55.01	-89.70
Water body	12.30	52.61	-11.89	-33.32	-0.43	-1.81	-0.02	-0.09
Wetland	-13.22	-56.84	-2.01	-20.02	2.08	25.90	-13.15	-56.53

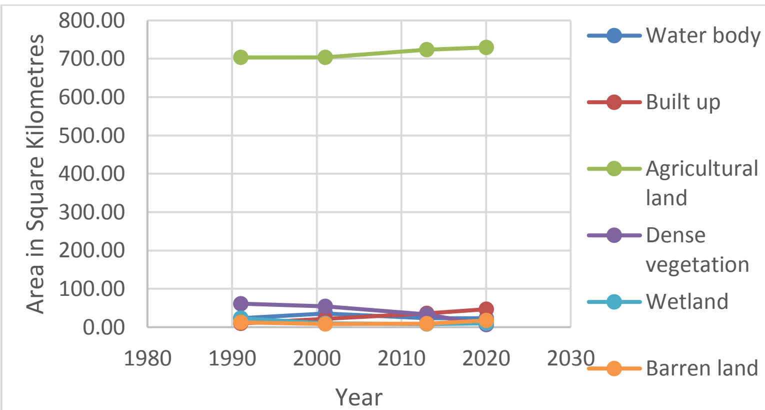

Figure 8. Showing combine Land cover distribution across the epochs classes from 1991 to 2020

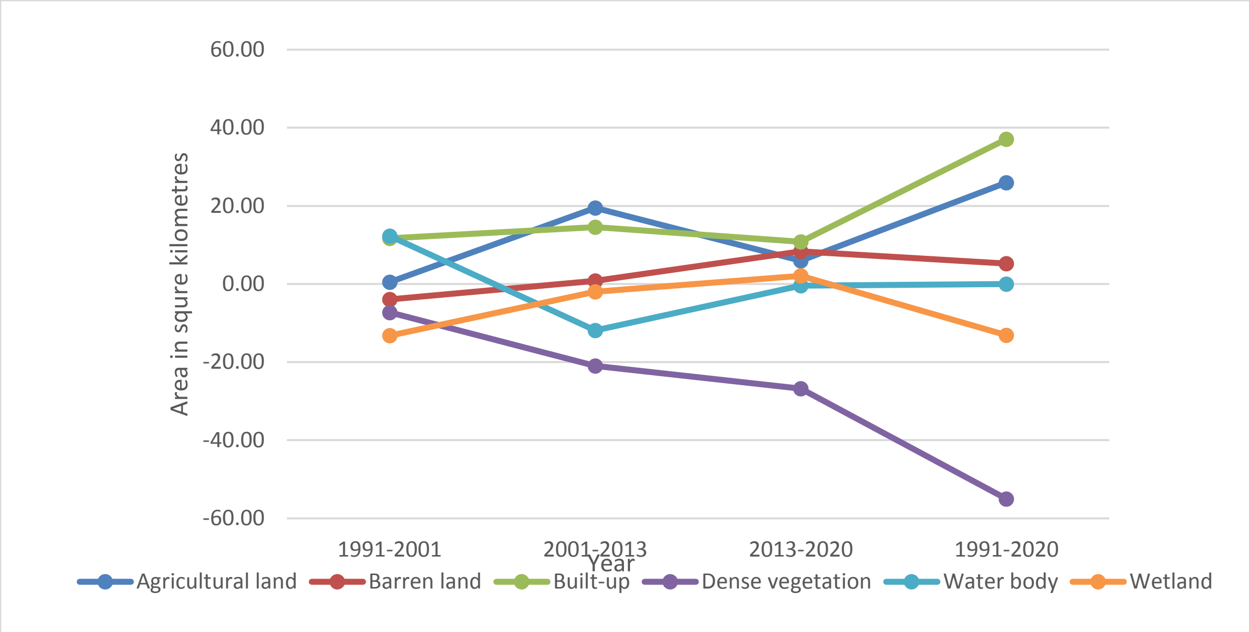

Figure 9. Change detection among the classes in 10yrs interval from 1991 to 2020

3.2 Spatial distribution of land use/cover between 1991 and 2020

From 1991 to 2020 (Figure 10a to 10d) there is a progressive increase in built-up areas. Dense vegetation diminishes as we progress through the years. Barren land is seen mostly within the river and in developing areas of settlements. Wetland is seen to be reducing as agricultural land increase across the years which could be as a result of conversion of wetland areas to agricultural usage whereas in 2030 projected year (Figure 11), there is tendency of having a massive development and built-up activities that would negatively have an impact on natural environment.

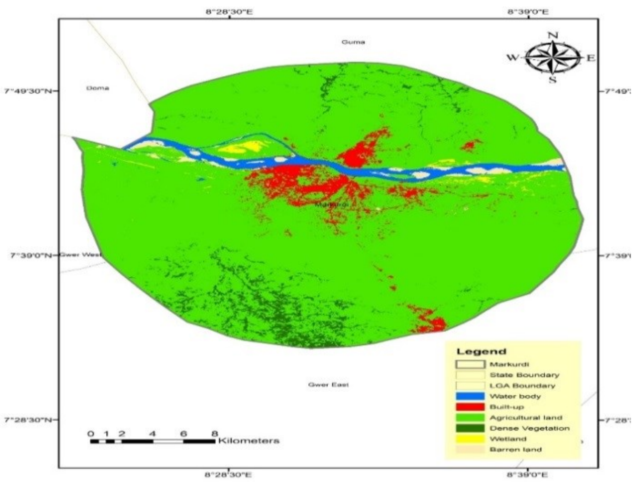

Figure 10a. Makurdi LULC distribution in 1991

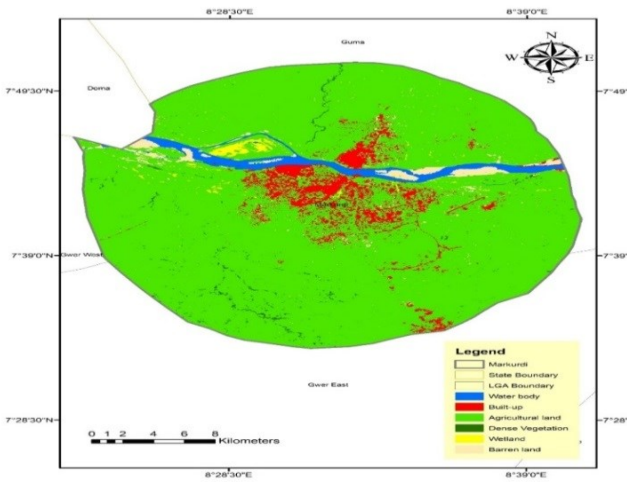

Figure 10b. Makurdi LULC distribution in 2001

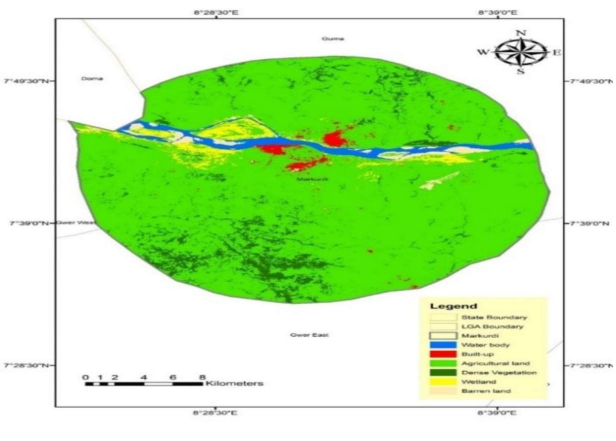

Figure 10c. Makurdi LULC distribution in 2013

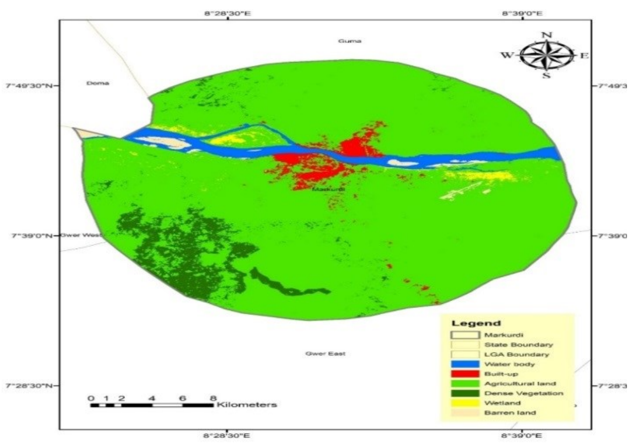

Figure 10d. Makurdi LULC distribution in 2020

3.3 Land cover modeling and prediction using the Markov chain algorithm

The predicted land cover statistics are shown in Tables 5a, 5b and 5c respectively. The land cover for 2030 was predicted based on 2013 and 2020 Land use/ cover classification layers. The Land cover prediction model was validated by predicting 2020 Land use/ cover based on 2001 and 2013 land use/ cover classification layers.

Table 5a shows that between 1991 and 2001, water body has the highest probability of 92.37% to remain as water body in 2001, whereas agricultural land, built-up, dense vegetation, wetland, and barren land had (89.48%), (78.29%), (12.68%), (0.6%) and (10.06%) respectively to remain unchanged. Barren land will not change to dense vegetation from 2013-2020. Whereas, dense vegetation has a high probability of converting to agricultural land with 93.13% probability of change. See table 5b. Table 5c. Shows that the probability of change from wetland to wetland is (10.78%) from 2013-2020, while the probability of future change of wetland to agricultural land is (68.28%). From built -up to retain its state is (55.48%) while built-up to change to agricultural land is (42.53%).

In order to ensure the reliability and/or representativeness of the projected LULC of 2030, the predicted LULC of 2020, and the actual LULC of 2020 were compared using the validation tool in TerrSet. The kappa statistics result reveals that Kappa for no information (Kno: 0.8593), Kappa for location (Klocation: 0.8698) and Kappa for standard (Kstandard: 0.7710) were estimated. This indicated that both the actual and predicted LULC are moderately highly in agreement with the predicted LULC (Table 6). This level of agreement is acceptable. This reveals that the CA_Markov model is capable of predicting the future LULC patterns successfully and correctly

Agricultural land and Barren land in the projection decreased between 2020 and 2030 (Table 7a). From the projected differences from the years (2020 – 2030), in Table 7a, the decrease of 41.04km^2 in Agricultural Land and 11.47km^2 in Barren Land; produced an increase in Built up, Dense vegetation, Waterbody and Wetland increased by 17.77km^2, 24.65km^2, 6.37km^2 and 3.74km^2 respectively. The spatial view is shown in Figure 11.

Table 5a. Transition probability matrix for land cover maps from 1991–2001

Changing from:	**Probability of changing by 2001 to:**					
1991	Agricultural land	Barren land	Built up	Dense vegetation	Water body	Wetland
Agricultural land	**0.8948**	0.0045	0.0218	0.0640	0.0053	0.0097
Barren land	0.0552	**0.1006**	0.0311	0.0014	0.8106	0.0011
Built up	0.1831	0.0039	**0.7829**	0.0018	0.0271	0.0012
Dense vegetation	0.7220	0.0247	0.0029	**0.1268**	0.0024	0.0082
Water body	0.0109	0.0461	0.0138	0	**0.9237**	0.014
Wetland	0.7220	0.0600	0.0291	0.0269	0.1330	**0.0600**

Table 5b. Transition probability matrix for land cover maps from 2001–2013

Changing from:	**Probability of changing by 2013 to:**					
2001	Agricultural land	Barren land	Built up	Dense vegetation	Water body	Wetland
Agricultural land	**0.9437**	0.0001	0.0187	0.0313	0.0006	0.0055
Barren land	0.6506	**0.1663**	0.0068	0	0.1121	0.1663
Built up	0.1876	0.0043	**0.8004**	0	0.0271	0
Dense vegetation	0.7688	0.0247	0	**0.2312**	0	0
Water body	0	0.2270	0.0049	0	**0.7386**	0.0296
Wetland	0.7209	0	0.0024	0	0.0053	**0.2714**

Table 5c. Transition probability matrix for land cover maps from 2013–2020

Changing from:	**Probability of changing by 2020 to:**					
2013	Agricultural land	Barren land	Built up	Dense vegetation	Water body	Wetland
Agricultural land	**0.9313**	0.0123	0.0385	0.0038	0.0034	0.0106
Barren land	0.0834	**0.4295**	0.0739	0.0004	0.4080	0.0047
Built up	0.4253	0.0081	**0.5548**	0.0006	0.0081	0.0031
Dense vegetation	0.9564	0.0048	0.0126	**0.0171**	0	0.0088
Water body	0.0444	0.2280	0.0251	0.0001	**0.6990**	0.0033
Wetland	0.6828	0.0572	0.0182	0.0199	0.1142	**0.1078**

Table 6. Validation of the predicted LULC

CLASS	2020 Actual	2020 Projected
Agricultural land	729.43	687.71
Barren land	17.55	8.18
Built up	46.84	34.55
Dense vegetation	6.32	54.16
Water body	23.36	35.12
Wetland	10.11	13.91
Total	**833.61**	**833.63**

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Table 7a. Difference in land cover distribution for 2020 and 2030 projected.

	2020 actual (Sq km)	2030 projected (Sq km)	Difference
Agricultural land	729.43	688.39	-41.04
Barren land	17.55	6.09	-11.47
Built up	46.84	64.62	17.77
Dense vegetation	6.32	30.97	24.65
Water body	23.36	29.73	6.37
Wetland	10.11	13.85	3.74
	833.61	**833.63**	

Table 7b. Correlation Significant at the 0.05 & 0.01 levels (2-tailed).

		POP (population)	WB (Water Body)	BU (Built Up)	AG (Agric land)	DV (Dense Vegn)	WL (wet land)	BL (Barren land)
POP	Pearson Correlation	1	-.599*	.976**	.980**	-.991**	-.485	.705**
	Sig. (2-tailed)		.014	.000	.000	.000	.057	.002
	N	16	16	16	16	16	16	16
WB	Pearson Correlation	-.599*	1	-.444	-.582*	.560*	-.226	-.654**
	Sig. (2-tailed)	.014		.085	.018	.024	.400	.006
	N	16	16	16	16	16	16	16
BU	Pearson Correlation	.976**	-.444	1	.983**	-.963**	-.665**	.552*
	Sig. (2-tailed)	.000	.085		.000	.000	.005	.027
	N	16	16	16	16	16	16	16
AG	Pearson Correlation	.980**	-.582*	.983**	1	-.956**	-.596*	.562*
	Sig. (2-tailed)	.000	.018	.000		.000	.015	.024
	N	16	16	16	16	16	16	16
DV	Pearson Correlation	-.991**	.560*	-.963**	-.956**	1	.460	-.736**
	Sig. (2-tailed)	.000	.024	.000	.000		.073	.001
	N	16	16	16	16	16	16	16
WL	Pearson Correlation	-.485	-.226	-.665**	-.596*	.460	1	.225
	Sig. (2-tailed)	.057	.400	.005	.015	.073		.402
	N	16	16	16	16	16	16	16
BL	Pearson Correlation	.705**	-.654**	.552*	.562*	-.736**	.225	1
	Sig. (2-tailed)	.002	.006	.027	.024	.001	.402	
	N	16	16	16	16	16	16	16

*. Correlation is significant at the 0.05 level (2-tailed).
**. Correlation is significant at the 0.01 level (2-tailed).

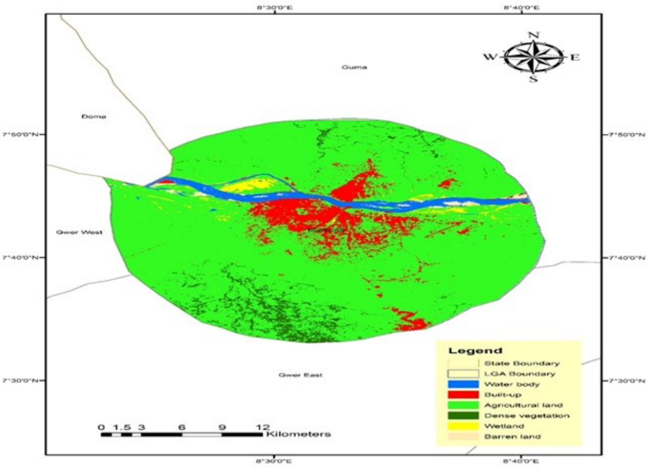

Figure 11. Makurdi LULC distribution for 2030 projection

3.4 Correlation between population and land use/land cover Hypothesis test

H1 = There is a significant relationship between population and landuse/land cover change

H0 = There is no significant relationship between population and landuse/land cover change

In Table 7 Pearson's product correlation of population and water body revealed a strong negative correlation with ***r***(14)= -.599, **p** = .014. This explains that population increase does not affect water body.

Population and built up area shows a strong positive correlation with ***r***(14)= .976, **p** = .000.This explains that as population increase, the built up area will also increase.

Population and agricultural land shows a strong positive correlation with ***r***(14)= .980, **p** = .000. This explains that as population increase, other classes like Dense vegetation and wetland would contribute to agricultural land increase.

Population and dense vegetation shows a strong negative correlation with ***r***(14)= -.991, **p** = .000.

Population and wetland shows a moderate negative correlation with ***r***(14)= -.485, **p** = .057.

Population and barren land shows a strong positive correlation with ***r***(14)= .705, **p** = .002.

4. Conclusions and Recommendations

The use of GIS techniques and remote sensing dataset with statistical calculations has proved significant in understanding the trend of land use/land change in Makurdi local government area of Nigeria. This research has established the usefulness of spatial and temporal analysis approach in detecting land use/land change and evaluating the extent of urban (natural and social environment between 1991 and 2020 using remotely sensed images and GIS technology) growth without depending on the rigorous survey techniques.

It is evident in the study that the social environment- built up area, barren land and agricultural land have expanded by 37.10km^2, 381.00% gain, 5.24km^2, 42.54% gain and 25.96km^2, 3.69% gain respectively. The increase in human population attracted infrastructural development and expansion of housing estate, which consequently impacted negative influence on the natural environment. The LULC projection for 2030 reveals further urban expansion and decrease in agricultural land. The natural environment shows and increases in dense vegetation, water body and wetland.

Correlation analysis conducted between population and land use land cover classes revealed that agricultural land, built-up area, and barren land has a strong positive correlation with *r*= .980, .976 and .705 respectively. This explains that as population increase, the land use land cover also increases.

5. Summary

Table 4 data and the Figure 9 showed the rise and fall trend in the change detection between 1991 – 2020 in % change of sequence: 0.07, 2.77, 0.83 amounting to a cumulative change of 3.69% from 1991 – 2020. From the trend shown by the LULC for Agricultural land projection for 2030, one could notice or expect a decline change by 2030 (Figure 9).

Transition probability matrix sequence for land cover maps for Agricultural land from 1991–2020 similarly followed the trend above with probability sequence of: 0.8948, 0.9437, 0.9313.

The Transition probability matrix co-correlation values in column I of Tables 5(a-c) shows the positive possible contributions of Dense vegetation and wetland to Agricultural land in the future. (Probabilities of Dense vegetation and wetland are all higher than 0.60 in each Transition probability matrix.).

The predicted LULC of 2020, and the actual LULC of 2020 were compared using the validation tool (model) in TerrSet, in order to ensure the reliability and/or representativeness of the projected LULC of 2030. The kappa statistics result reveals the estimated Kappa values for the following: Kappa for no information (Kno: 0.8593), Kappa for location (Klocation: 0.8698) and Kappa for standard (Kstandard: 0.7710). These indicated that both the actual and predicted LULC for 2020 are moderately highly in agreement with the predicted LULC (Table 6). From Table 7a which gives the difference in land cover distribution for 2020 and 2030 projection, Agricultural land and Barren land in the projection were seen to decreased between 2020 and 2030 (Table 7a).

From Table 7b, water body, wetland and dense vegetation all have high negative co-correlation probability values, giving up their space to accommodate enough agricultural land for the increasing population. This can be seen in the co-correlation values, with population as the main variable (Row 1, Table 7b).

This study did not consider various socio-economic factors in the simulation of LULC change. It is therefore recommended that further study should employ biophysical, socio-economic and policy-related factors in a simulation of future land cover changes in the study area which could guide more informed decision making.

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