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Geospatial Analysis of Urbanization Trend and its Effects on the Vegetal Cover of Jos South Local Government Area of Plateau State, Nigeria

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Abstract

The high rate of urbanization coupled with population growth has caused changes in land use. Therefore, understanding and quantifying the spatio-temporal dynamics of urbanization and its driving factors is essential for monitoring mechanisms and decision making. The study aimed at determining how urbanization trend affect land cover and vegetation changes in Jos South Area. Landsat TM for 1991, ETM$^+$ and operational land imager (OLI) for 2003 and 2015 was obtained and preprocessed using Erdas Imagine 2014, Idrisi software and ArcGIS 10.2. Supervised Maximum Likelihood Classification was used to generate land use and land cover maps. Confusion matrix was used to derive overall accuracy and results were above the minimum and acceptable threshold level. Land Change Modeler was run to model land use and land cover changes in Jos South Area to predict future urban land use changes. Six land cover transitions were incorporated in the modeling process. Makovian transition estimator was used to model the transition potential matrix. This result was used to make prediction using CA_Markov chain analysis for year 2039. The results revealed that there was an increased in built up areas in the last 24 years from 535.68 ha (1.18%) in 1991 to 4608.99 ha (10.17%) in 2003 and 15600.96ha (34.43%) in 2015 at the expense of vegetated areas. The prediction results showed built up will increase from 15600.96 ha (34.43%) to 20972.88 ha (46.29%), bare ground will decrease from 6691.23 ha (14.77%) to 5719.23 ha (12.62%), farmland will decrease from 3874.32 ha (8.55%) to 3418.74 ha (7.55%), while vegetation will also decrease from 4675.86 ha (10.32%) to 3125.34 ha (6.90%). The study concluded that geospatial techniques are a viable tool for assessing urbanization trend. It was recommended that high resolution imageries such as IKONOS be made readily available, because urban areas have complex and heterogonous features, and this will provide better information in mapping these areas.

Keywords: Geospatial, Urbanization vegetation, Land cover, Remote sensing

Introduction

The rapid changes of land use and cover than ever before, particularly in developing nations, are often characterized by rampant urban sprawling, land degradation, or the transformation of agricultural land to shrimp farming ensuing enormous cost to the environment (Sankhala and Singh, 2014). The increase in carbon dioxide temperature of the atmosphere, regulation of

Nutrient cycle of carbon dioxide and photosynthesis shifting in population provision of income through the sale of fuel wood/firewood has increased rate of evaporation and alteration of fluvial competence and capacity (Mustafa, 2010).

Settlement expansion has now become a central component in current strategies for managing land as a resource and in monitoring environmental changes. Settlements represent the most profound human alteration of the natural environment through a spectrum of urban land use activities (Ifatimehin and Ufuah, 2006) which include, but are not restricted to, transportation, commercial, industrial, residential, institutional, and recreational land uses. The expansion that ensues as a result of increase in the demand for these land uses explains the underlying and fundamental cause of urban expansion which is population increase.

Usually land uses and urban growth in remote sensing involves the analysis of two registered, aerial or satellite multi-spectral bands from the same geographical area obtained at two different times. Such an analysis aims at identifying changes that have occurred in the same geographical area between the two times considered (Radke *et al.*, 2005). Herold *et al.* (2005) also noted that one of the advantages of remote sensing is its ability to provide spatially consistent data sets covering large areas with both high detail and high temporal frequency, including historical time series.

The basic premise in using remote sensing data for change detection is that the process can identify change between two or more dates that is uncharacteristic of normal variation. Numerous researchers have addressed the problem of accurately monitoring land-cover and land-use change in a wide variety of environments (Shalaby and Tateishi, 2007).

Jos metropolis is a mid-sized city under the pressure of urban growth. Timely and accurate assessments of urban growth scenarios and associated environmental impacts are crucial for urban planning, policy decision, and natural resource management (Adzandeh *et al.*, 2015).Many Studies have shown that there remain only few landscapes on the earth surface that is still in their natural state (Fasal, 2000). This is due to natural processes and disasters, as well as intense pressure from anthropogenic activities such as deforestation, urbanization, intensive agriculture and mineral exploitation (CARPE, 2003, Lambin *et al.*, 2003; Ndjomo, 2008; Sarma *et al.*, 2008).

Jos South Local Government Area of Plateau State in Nigeria is witnessing rapid urban land use and land cover changes largely due to high population growth (Vivan *et al.*, 2013). Understanding the rapid growth dynamics, developments of urban sprawl and quantifying the spatial extent of urbanization requires a geospatial tool (Araya and Cabral, 2010). Living conditions deteriorate continually, particularly in cities of the developing countries. This is due to poorly planned human interference and limited access to adequate information and appropriate technology. Hence, in order to effectively monitor settlement growth, it is not only necessary to have the information on existing land use land cover but also the capability to monitor the dynamics of land use resulting out of both changing demands of increasing population and forces of nature acting to shape the landscape.

The aim of the study was to analyze urbanization trend and how it affects vegetal cover in Jos south LGA, Plateau state. With the objectives to create a land use land cover map of the study area, determine the effect of land use land cover change on vegetal cover and project the future pattern of land use land cover in the area for 24years (2039).

The Study Area

Jos Plateau is situated between latitudes 10°11′N and 8°55′N and longitude 8°21′E and 9°30′E (Figure 1). The study area (Jos south LGA) is located at latitude 9° 30′ to 10° N and longitude 8° 30′ E. It is situated at the north western part of the state with its headquarters at Bukuru, which is about 15 km from the state capital, Jos. The local government area has total land area of about 1,037 km^2 with a population of 306,716 (NPC, 2006). It has an average elevation of about 1,150 metres above mean sea level and the highest peak some 20 km eastwards from Jos-shere hill, rising to 1777 metres above mean sea level. It has a cool climatic condition due to its altitude. The coldest period is between November and February with an average mean daily temperature of 18°C, while it gets warm between March and April before the onset of rain. The rainy season, which is between the months of May and October, has its peak in August. The mean annual rainfall varies between 1347.5 and 1460 mm per annum (Michael, 2012).

The Jos Plateau is dominated by three rock types. The Older Granites date to the late Cambrian and Ordovician. The Younger Granites are emplacements dating to the Jurassic, and forming part of a series that includes the Air Massif in the central Sahara. There are also many volcanoes and sheets of basalt extruded since the Pliocene.The Younger Granites contain tin which was mined since the beginning of the 20th century, during and after the colonial period. The original woodland vegetation of the Jos region has long been cleared for mining and agricultural activities, turning the region into open savannah grassland with widely spread eucalyptus and acacia trees, and cactus hedges which are used for land/boundary delineation (Michael, 2012).

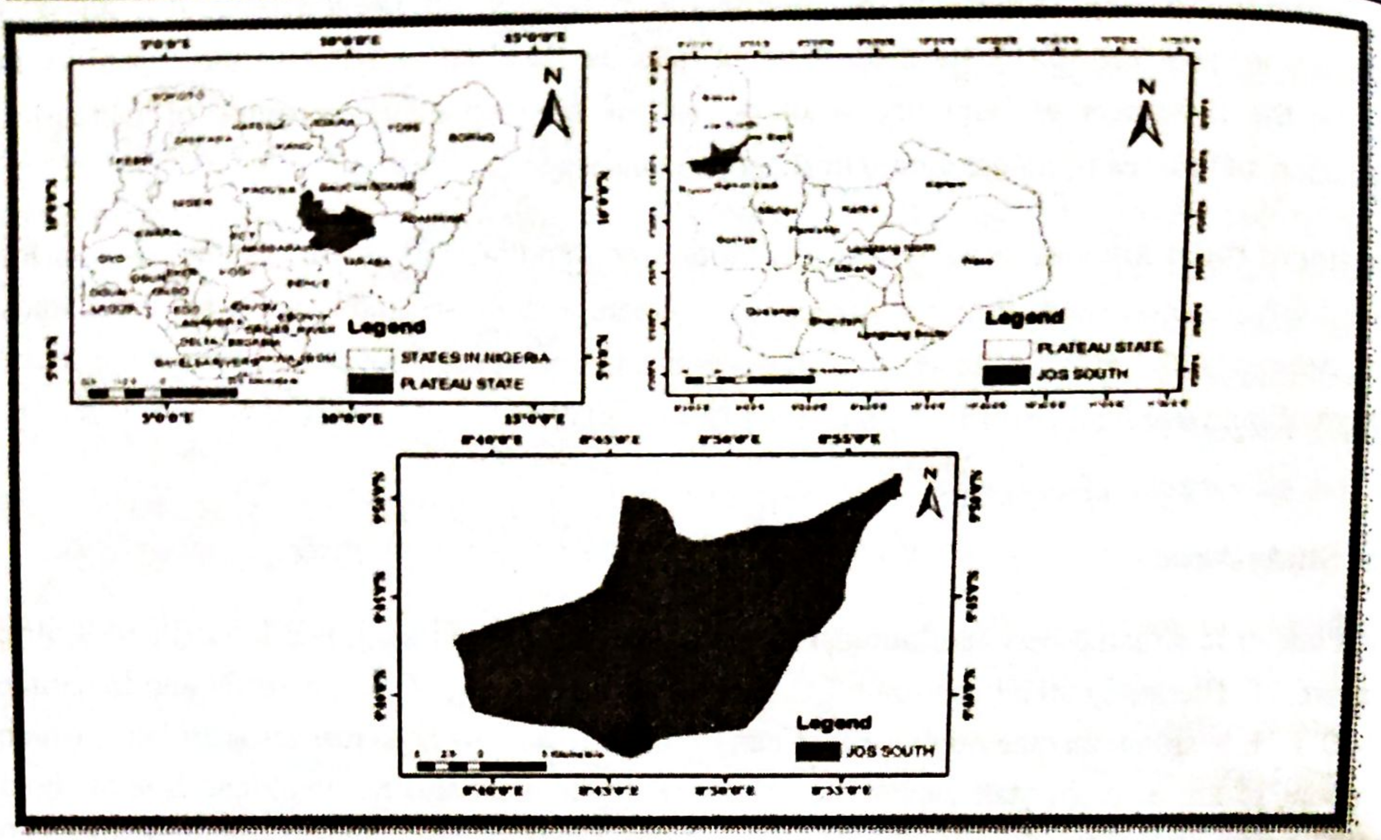

Figure 1: Plateau State showing Jos south Local Government.

Materials and Methods

Three, Landsat imageries of TM, ETM^{+}, and OLI were employed and acquired in the same season and the same level of resolution for the periods 1991, 2003 and 2015. Thus, they were conducive for comparison of changes and patterns that occurred in the time under discussion. The images were downloaded from the United States Geological Survey (USGS). It is also important to state that Jos south L.G.A which was carved out using the local government boundary map and Nigerian Administrative map was obtained from NASRDA. And, spatially referenced in the Universal Transverse Mercator (UTM) projection with datum World Geodetic System (WGS) 1984 UTM zone 32N.

The Landsat Thematic Mapper (TM) of 1991, the enhanced Thematic Mapper (ETM+) of 2003 and Operational land imager of 2015 were made to pass through processes of Image Pre-Processing (Mosaicking, Clipping Study Area, Image Stretching And Layer Stacking). A supervised classification was performed on false colour composites (bands 4, 3 and 2) into the following land use and land cover classes; Built-up area, vegetation, Bare land, Rock out crop, Farmland, and water bodies. Information collected during the field surveys was used to assess the accuracy of the classification.

Because classified land cover maps from remotely sensed images contain various types of errors, it is the responsibility of the researcher to find out those errors so as to make the produced land cover maps become reliable and easily interpretable by users. To do so, the accuracy of a classified map has to be assessed and compared with a referenced data using an error matrix. The accuracy assessment in this study was made using the original sub-sected image for 1991 for the study periods of 2003 and 2015. It was computed by dividing the total number of correctly classified pixels (i.e., the sum of the elements along the major diagonal) by the total number of reference pixels. It shows an overall result of the tabular error matrix.

The classified land cover maps of 1991, 2003 and 2015 were used as input parameters and LCM was applied to identify the locations and magnitude of the major land use and land cover changes and persistence. Moreover, the spatial trends of major transitions between land use and land cover categories of special interest in the study area have been quantified.

Results and Discussions

Land Use Land Cover Maps of the Study Area

The land cover maps generated after running a maximum likelihood supervised classification as well as a post classification algorithm is presented in Figure 2. As shown from the figures, there has been an increase of built up areas with respective values 1.18% of the study area in 1991 to 10.17% in 2003 and 34.43% in 2015, the statistics is indicated in Table 1.

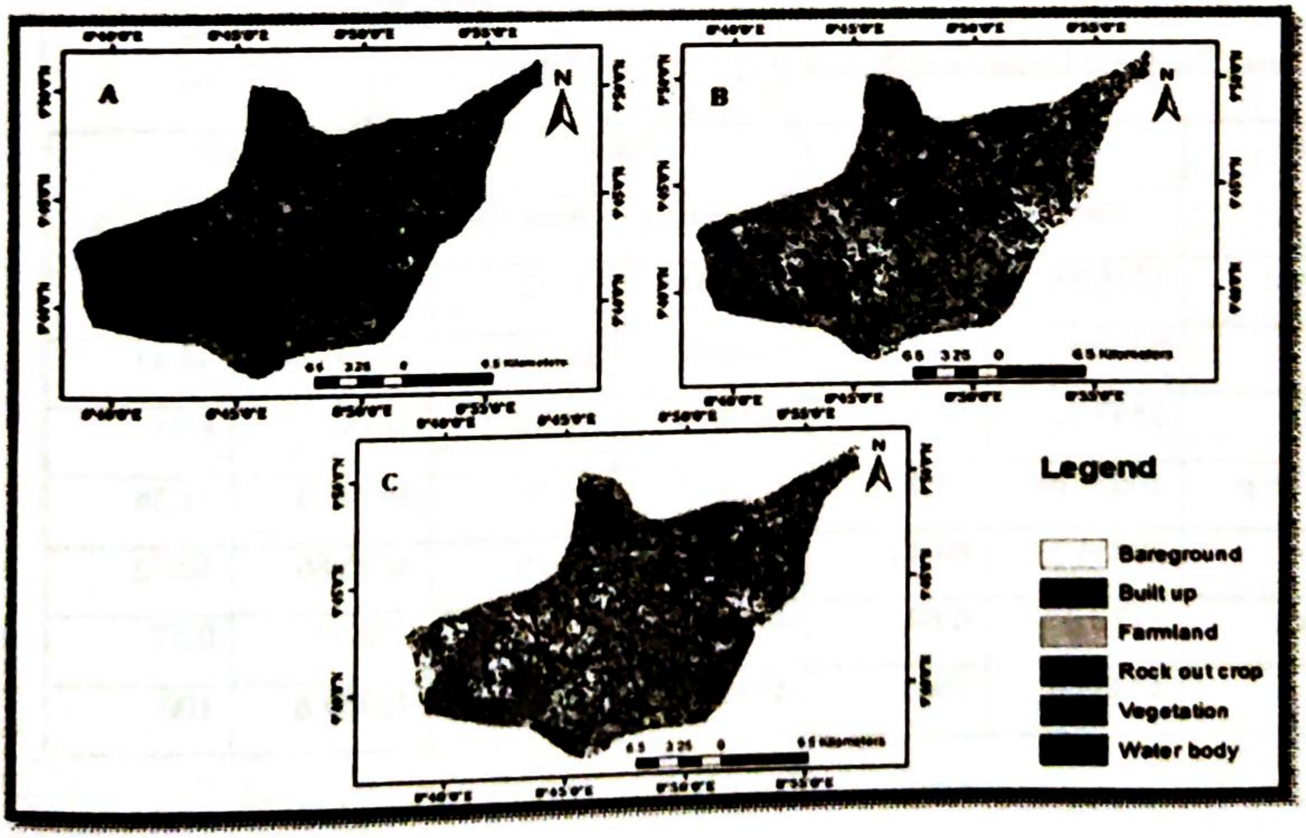

Figure 2: Land Use Land Cover Map of Jos South LGA 1991-2015.

Open areas (bare ground) have also shown a consistent increase between the study periods. However, there have been a decrease of vegetated areas as clearly shown in 1991, 2003 and 2015 images (Figures 2a, b and c) respectively. In 1991 vegetated areas covered 66.40% of the study area (from Figure 2a and Table 4.1) vegetation was the most dominant land cover class in the study area but showed a continuous decrease from 66.40% in 1991 to 10.32% in 2015. Because of the successive decrease of vegetation areas, built up areas have dynamically increased in the study periods. This could be due to an increase of population growth associated with high demand for land and urban supplies.

The values presented in Table 1 represent the distribution area of each land use land cover category for each study year. Built-up in 1991 occupies the least class with just 1.18% of the total classes. Furthermore, vegetation occupies the highest portion with 66.40% in 1991 and decreased to 31.46% and 10.32% in 2003 and 2015 respectively. Also, farming seems to be practiced moderately, occupying 5.73% of the total classes in 1991, was increased to 19.07% in 2003 and drastically reduced to 8.55% in 2015. This may be due to the fact that the city is just moving away from the rather traditional setting where farming seems to form the basis for living. Apart from this, the time of the year in which the area was imaged which happens to fall within the onset of harmatan could also be a major contributing factor to the observed classification, contributing to the high percentage of bare ground and the low percentage of water bodies.

Table 1: Land Use Land Cover Distribution (1991, 2003, 2015).

Land cover	1991		2003		2015	
classes	Area(Ha)	Area (%)	Area(Ha)	Area (%)	Area(Ha)	Area (%)
Bare ground	1146.6	2.53	4629.51	10.22	6691.23	14.77
Built up	535.68	1.18	4608.99	10.17	15600.96	34.43
Farmland	2597.31	5.73	8638.29	19.07	3874.32	8.55
Rock out crop	10633.68	23.47	12730.5	28.10	14208.3	31.36
Vegetation	30084.21	66.40	14255.01	31.46	4675.86	10.32
Water body	312.12	0.69	447.3	0.99	258.93	0.57
Total	45309.6	100	45309.6	100	45309.6	100

In addition, rock out-crop occupies 23.47% in 1991, 28.10% in 2003 and increased to 31.36% due loss of vegetation in 2015. Bare ground on the other hand occupies 2.53% in 1991 and increased to 10.22% and 14.77% in 2003 and 2015 respectively. It is also visible from Figure 2a and Table 1 that water body had the lowest proportion occupying 0.69% in 1991, increased to 0.99% in 2003 and showed a little decrease to 0.57% of the study area in 2015.

Accuracy Assessment of the Classification

The overall accuracies performed in this study period 1991 were 75.06% (Table 2), in 2003 was 98.26% (Table 3) and during 2015 it was 93.26% (Table 4). As mentioned by Anderson *et al.* (1976) for a reliable land cover classification, the minimum overall accuracy value computed from an error matrix should be 85%. However, Foody (2002) showed that this baseline makes no sense to be a universal standard for accuracy under practical applications. This is because a universal standard is not exactly related to any specific study area.

Table 2: Confusion matrix for land cover map of 1991.

	Reference map								
Classified Map	Landcover classes	Bare ground	Built up	Farmland	Rock out crop	Vegetation	Water body	Total	Users accuracy
	Bare ground		0	0	0	0	0	211	100
	Built up	0		0	0	0	0	124	100
	Farmland	1	67		0	0	0.49	138.49	50.55
	Rock-out crop	0	2	163		0	0.259	637.26	74.07
	Vegetation	0	2	102	3		0.2758	388.28	72.37
	Water body	0	0	0	0	0		0	0
	Total	212	195	335	475	281	1.0276	1499.03	
	Producers accuracy	99.4	60.72	13.89	98.99	100	100		
	Over all accuracy	75.06							

Table 3: Confusion matrix for land cover map of 2003.

		Reference Map							
	Landcover classes	Bare Ground	Built Up	Farmland	Rock Out Crop	Vegetation	Water Body	Total	Users Accuracy
Classified Map	Bare Ground	[redacted]	0	0	0	0	0	519	100
	Built Up	2	[redacted]	0	0	0	0.0026	759.003	99.74
	Farmland	0	13	[redacted]	0	0	0.1368	95.1368	86.19
	Rock-Out Crop	0	25	0	[redacted]	0	0.0161	1551.02	98.39
	Vegetation	0	0	0	0	[redacted]	0	51	100
	Water Body	0	0	0	0	0	[redacted]	0	
	Total	521	796	82	1526	51	0.1555	2975.16	
	Producers Accuracy	99.54	98.8	100	100	100	100		
	Overall Accuracy	98.26							

Table 4: Confusion matrix for land cover map of 2015.

		Reference Map							
	Landcover classes	Bare Ground	Built Up	Farmland	Rock Out Crop	Vegetation	Water	Total	Users Accuracy
Classified Map	Bare Ground	[redacted]	0	0	0	0	0	320	100
	Built Up	133	[redacted]	0	0	0	0.1196	965.1196	86.20693228
	Farmland	0	2	[redacted]	0	0	0.0161	124.0161	98.37432398
	Rock-Out Crop	0	58	10	[redacted]	0	0.0319	2135.0319	96.81354176
	Vegetation	0	0	0	0	[redacted]	0	205	100
	Water	0	0	0	0	0	[redacted]	0	
	Total	433	892	132	2067	205	0.1676	3749.1676	
	Producers Accuracy	71.64	91.2	92.18	100	100	100		
	Overall Accuracy	93.05							

Overall Accuracy

Foody (2002) also noted that Anderson *et al.* (1976) did not explain in detail about the criteria of map evaluation for universal applications. Moreover, Lu *et al.* (2004) noted that the accuracies of change detection results highly depend on many factors, such as: availability and quality of ground truth data, the complexity of landscape of the study area, the change detection methods or algorithms used as well as classification and change detection schemes. So, the overall accuracies for 2003 and 2015 maps were above 85% based on Anderson's criteria, but the overall accuracy of 1991 was 75.06% which is not up 85% based on Anderson's criteria, however this may be due to the availability and quality of ground truth data, the complexity of landscape of the study area, the change detection methods or algorithms used as well as classification and change detection schemes, (Lu *et al.*, 2004).

Change Analysis Results of Land Change Modeler (LCM)

The results of the cross-tabulation comparison of both land use and land cover maps in figures 3a, b, and c, revealed that there have been marked changes in all land use and land cover classes between 1991, 2003 and 2015. During the period 1991 - 2003 the total built up areas increased by 4227 ha (representing an increase of 9.33% of the total study area) and lost 154 ha (0.34%) of the study area) as indicated in Figure 4.3a. While vegetation areas decreased by 19409 ha (42.84%) of the total study area and gained 3580 ha (7.90%) with a net loss of 15829 ha. Similarly, water bodies lost 80 ha (0.18%) and gained 216 ha (0.48%). Furthermore,rock out-crop lost 4606ha (10.17%) and gained 6703 ha (14.79%).The proportion of areas covered with farmland areas gained 7361 ha (16.25%) and lost 1320 ha (2.91%), while the proportion of bare ground gained 4153 ha (9.17%) and lost 670 ha (1.48%). The increase in farmland areas in 2003 study period has been associated to an increasing trend of plantation of common food crops grown in the area which include Irish potatoes, sweet-potatoes, maize, millet, Acha, tomato and many other varieties of vegetables.

The built up areas have also continued to increase with a gain of 12671 ha (27.97%) in the period 2003-2015 shown in Figure 3b. Similarly the consistent decrease of vegetation areas have been also seen in this time with a loss of 11476 ha (25.33%). From figure 4.3c, the overall changes occurred for the last 24years in built up areas have shown an increase of 15177 ha gain (representing an increase of 33.50% of the total study area) with a loss of 112 ha (0.25 % of the study area). Whereas vegetation areas have lost 26458 ha (58.38% of the study area) and gained only about 1050 ha (2.32%) of the study area.

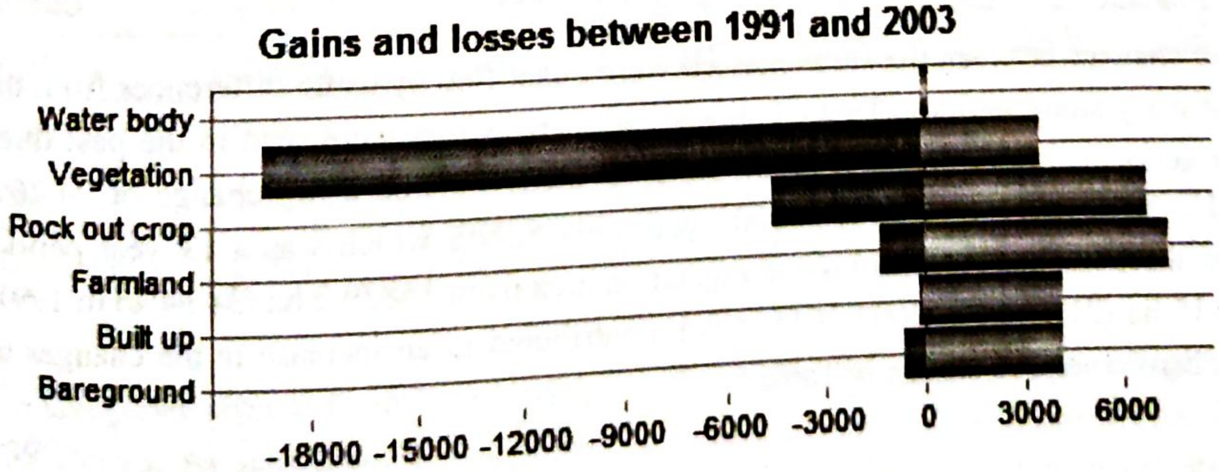

Figure 3a: Gains and losses of land cover classes in (ha), 1991-2003.

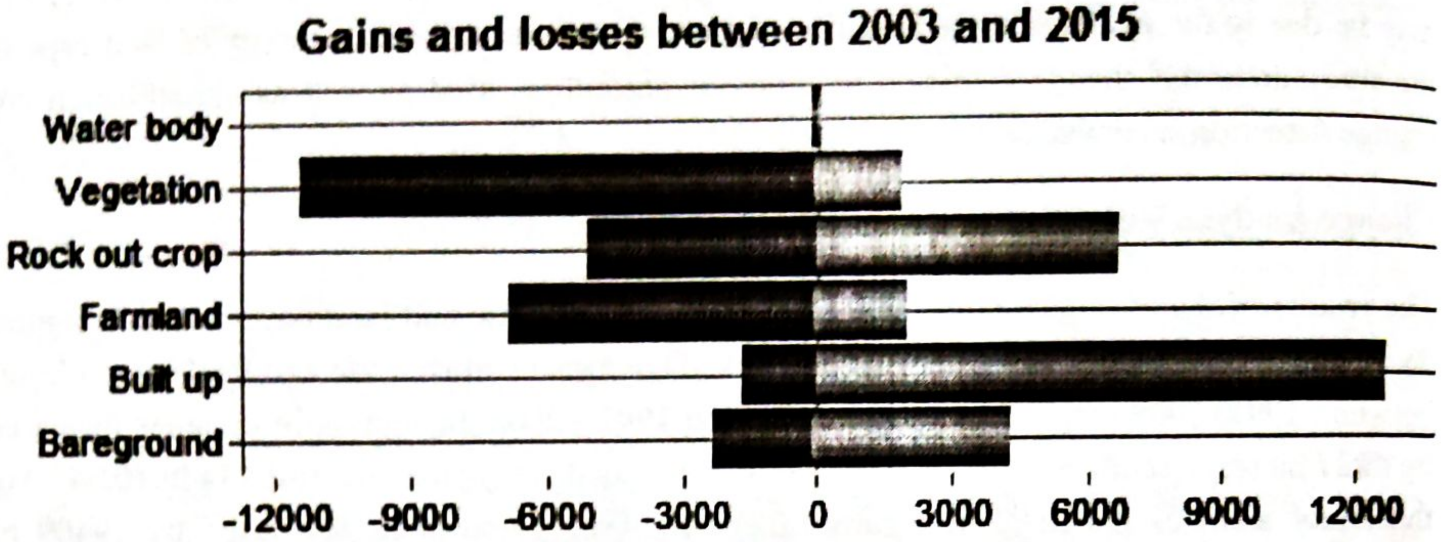

Figure 3b: Gains and losses of land cover classes in (ha), 2003-2015.

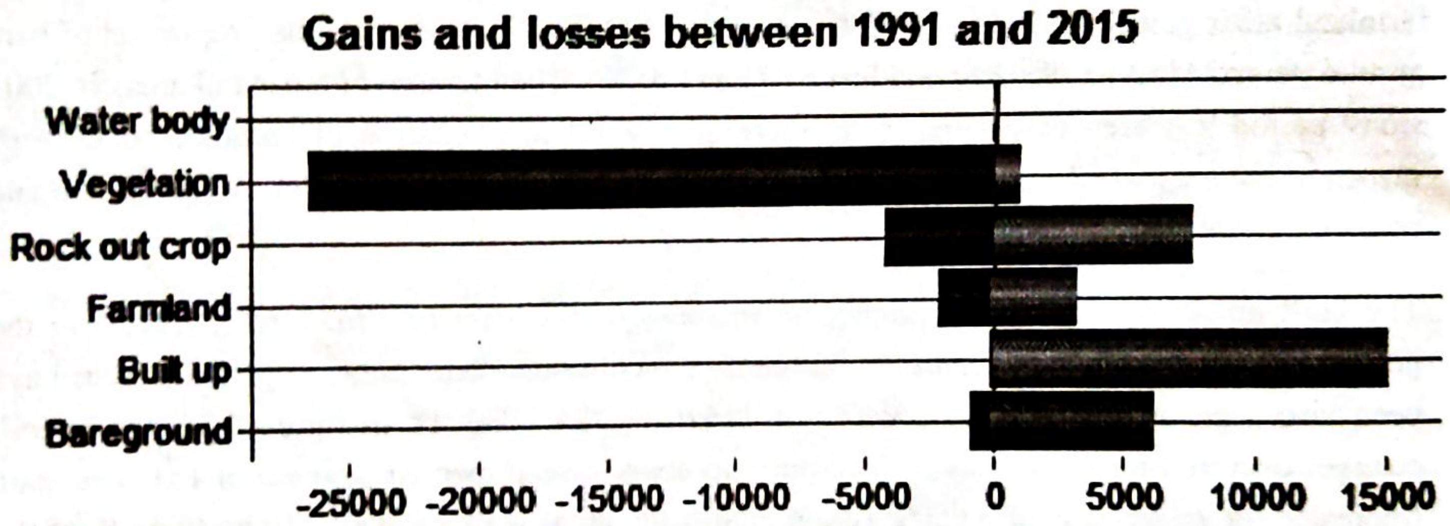

Figure 3c: Gains and losses of land cover classes in (ha), 1991-2015.

The land cover changes between the study periods were quantified by using differences from the late periods to early study periods. Table 5 shows the changes that were seen in the past three distinct study years quantified through LCM. Built-up areas showed a big change of 24.26% between 2003 – 2015 rather than 1991 – 2003 with only 8.99% which was a 13–year period. Following this, there has been a great loss of vegetation area from 15829.2 ha (34.94%) in 1991-2003 to 9579.15 ha (21.14%) in 2003-2015 which contributed to an increase in the changes of built up areas, bare ground as shown in Table 5.

Table 5:Comparison of changes in land cover classes between 1991-2015 using LCM

Land cover classes	2003 – 1991		2015 – 2003		2015 – 1991	
	Area (Ha)	Area (%)	Area(Ha)	Area (%)	Area(Ha)	Area (%)
Bare ground	3482.91	7.69	2061.72	4.55	5544.63	12.24
Built up	4073.31	8.99	10991.97	24.26	15065.28	33.25
Farmland	6040.98	13.33	-4763.97	-10.51	1277.01	2.82
Rock out crop	2096.82	4.63	1477.8	3.26	3574.62	7.89
Vegetation	-15829.2	-34.94	-9579.15	-21.14	-25408.35	-56.08
Water body	135.18	0.30	-188.37	-0.42	-53.19	-0.12

Transition Probability Matrix

The transition probability matrix records the probability that each land cover category will change to the other category. This matrix is produced by the multiplication of each column in the transition probability matrix, the number of cells of corresponding land use in the later image.

r the 5 by 5 matrix table presented below, the rows represent the older land cover categories and the column represents the newer categories. Although this matrix can be used as a direct input for specification of the prior probabilities in maximum likelihood classification of the remotely sensed imagery, it was however used in predicting land use land cover of 2039.

Table 6: Transitional Probability table derived from the land use land cover map of 1991 and 2015.

Land cover classes	Bare ground	Built up	Farmland	Rock out crop	Vegetation	Water body
Bare ground	0.2431	0.4354	0.1256	0.1319	0.0402	0.0239
Built up	0.1087	0.6722	0.0582	0.0998	0.0506	0.0105
Farmland	0.0742	0.5405	0.1786	0.1739	0.0315	0.0012
Rock out crop	0.0878	0.257	0.037	0.5178	0.0996	0.0008
Vegetation	0.1824	0.3756	0.0968	0.2411	0.1024	0.0017
Water body	0.0313	0.2577	0.0061	0.0452	0.1972	0.4625

Row categories represent land use land cover classes in 1991 whilst column categories represent 2039 classes. As seen from the table, bare ground land has a 0.2431 probability of remaining bare ground and a 0.4354 of changing to built-up in 2039. This therefore shows an undesirable change (reduction), with a probability of change which is much higher than stability. Bare ground has a 0.2431 the probability of changing to bare ground, Built up during this period will likely be class with a 0.6722 probability of increasing built up in 2039. Farmland also has a 0.5405 probability as high as to decrease to built-up in 2039 which signifies stability. Rock out crop has a 0.5178 probability of remaining Rock out crop.

On the other hand, the 0.3756 probability of change from vegetation land to built-up shows that there might likely be a high level of instability in vegetation land during this period. Water body which is the last class has a 0.4625 probability of remaining as water body.

Land Use Land Cover Projection for 2039

The Table 7 shows the statistic of land use land cover projection for 2039. Comparing the percentage representations of this Table 7 and that of Table 1, there exist similarities in the observed distribution particularly in 2015.

Table 7: Projected Land use land cover table for 2039.

Land cover classes	2039	
	Area(Ha)	Area (%)
Bare ground	5719.23	12.62
Built up	20972.88	46.29
Farmland	3418.74	7.55
Rock out crop	11608.11	25.62
Vegetation	3125.34	6.90
Water body	465.75	1.03
Total	45310.05	100.00

This may tend to suggest no change in the classes between 2015 and 2039, but a careful look at the area in hectares between these two tables shows a change though meager. Thus in Table 7, built up (46.29%) still maintains the highest position in the class whilst water body (1.03%) retains its least position.

Rock out crop (25.62%) takes up the next position, followed by bare ground (12.62%), farmland (7.55%) and finally, vegetation (6.90%). As seen in Figure 4, there is likely to be compactness in Jos south local government area by 2039 which signifies crowdedness.

Implications of Findings

Jos south local government is experiencing a fast developmental growth where government allocated land for building at the detriment of vegetation and farmland which needs to be looked in to With the changes shown on the map, if precautionary measures were not taken land for agricultural purposes will start to have a set back and may affect the agricultural activities of the area.

Both Adzandeh *et al.* (2015) and Vivan *et al.* (2013) used remote sensing and GIS techniques in capturing spatial-temporal data to study the land use land cover of Jos metropolis and Jos south respectively. Vivan *et al.* (2003) didn't carry out accuracy assessment in their work but Adzandeh *et al.* (2015) carried out accuracy assessment, they both came to a conclusion that Jos metropolis and Jos south has continued to experience unprecedented growth both in population size and spatial coverage due to migration, educational development, economic growth residential development and pattern of transportation routes at the detriment of farm land and vegetation which also corroborate with findings of this study.

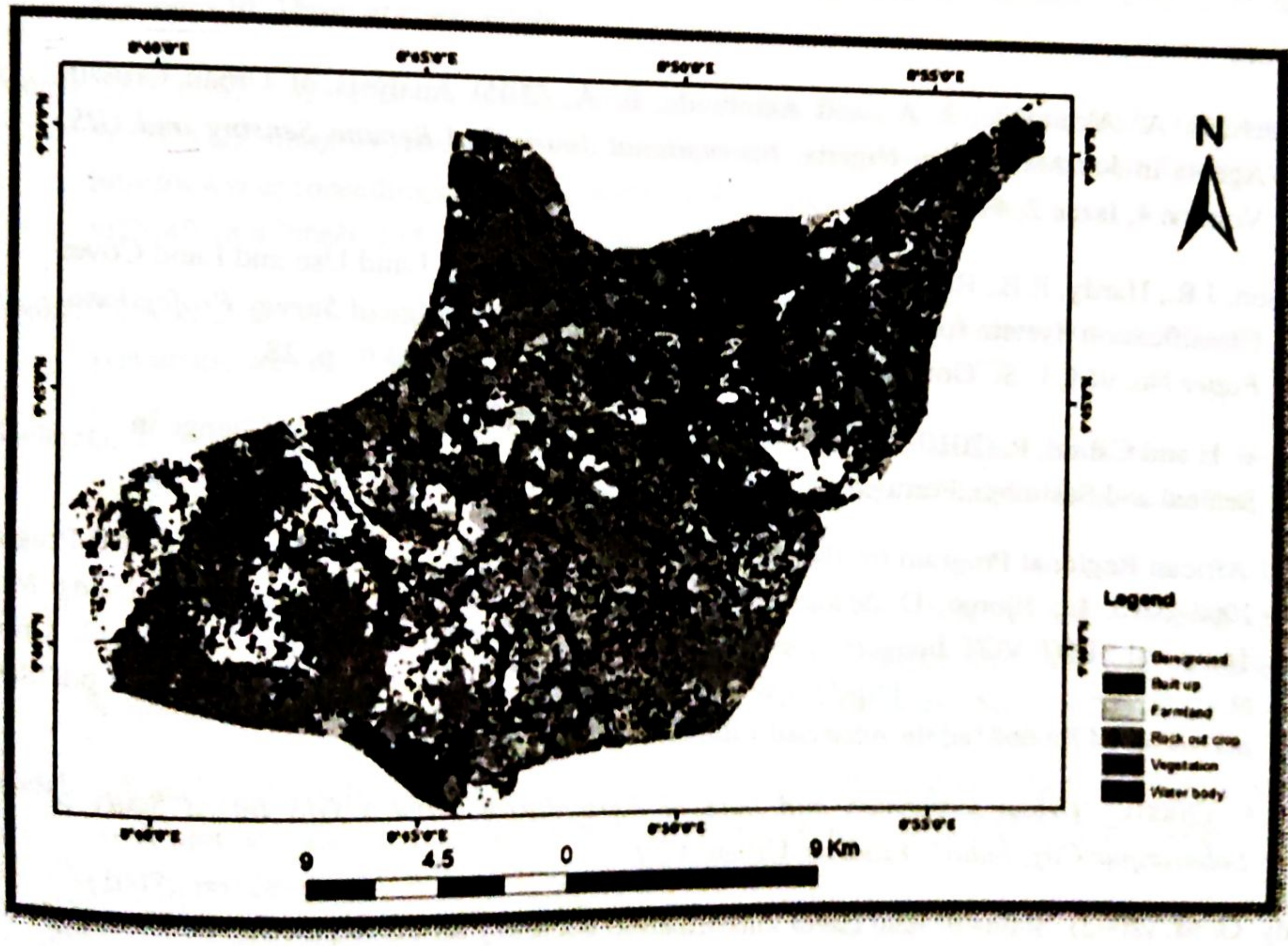

Figure 4: Projected Land Use Land Cover Map of Jos South LGA for 2039, Map Derived from the 1991 and 2015 Land Use Land Cover Map.

Conclusions

The study has shown that Jos south will continue to experience unprecedented growth both in population size and spatial coverage due to rural-urban migration, educational development, residential development, economic growth and pattern of transportation routes. Similarly infrastructural facilities, which are regarded as agents of development, should be evenly distributed at various segment of the town so as to achieve a more balanced city growth. The major factors responsible for city growth apart from natural increase (population increase) are through rural-urban migration, economic growth, urbanization, transportation, tourist attraction, good weather and educational development.The study also proved geospatial techniques as a viable tool for assessing urbanization trend.

It was recommended that high resolution imageries such as IKONOS be made readily available, because urban areas have complex and heterogonous features, and this will provide better information in mapping these areas.

Reference

Adzandeh, E. A. Akintunde, J. A., and Akintunde, E. A. (2015). Analysis of Urban Growth Agents in Jos Metropolis, Nigeria. *International Journal of Remote Sensing and GIS*, Volume 4, Issue 2, 41-50.

Anderson, J.R., Hardy, E.E., Roach, J.T., and Witmer, R.E. (1976). A Land Use and Land Cover Classification System for Use with Remote Sensor Data. *Geological Survey Professional Paper* No. 964, U.S. Government Printing Office, Washington, D.C. p. 28.

Araya, Y. H and Cabral, P. (2010). Analysis and Modeling of Urban Land Cover Change in Setúbal and Sesimbra, Portugal. *Remote Sensing*, 2(6), 1549–1563.

Central African Regional Program for the Environment CARPE (2003). The USAID CARPE Program 2003-2010. In: Njomo, D. Mapping Deforestation in the Congo Basin Forest Using Multi-Temporal SPOT-VGT Imagery from 2000-2004. EARSeL Proceedings 7, 1. Available On-line at http://www.eproceedings.org/static/vol07_1/07_1_njomo1.pdf?SessionID=49c6647bb6b81ad3fe Accessed July 31, 2015.

Fasal, S. (2000). "*Urban Expansion and Loss of Agricultural Land-A GIS Based Study of Saharanpur City, India*". Environ. Urban. 12:2.

Foody, G. M. (2002). Status of land cover classification accuracy assessment. *Remote Sensingof Environment*, 80(1), 185–201.

Herold, M., Couclelis, H. and Clarke, K. C. (2005). The role of spatial metrics in the analysis and modeling of urban land use change. *Computers, Environment and Urban Systems*, 29(4), 369–399. doi:10.1016/j.compenvurbsys.2003.12.001.

Ifatimehin, O. O. and Ufuah, M. E. (2006). "An Analysis of Urban Expansion and Loss of Vegetation Cover in Lokoja, Using GIS Techniques". *Zaria Geogr.*, 17(1): 28-36.

Lambin, E. F., Geist, H. J and Lepers, E. (2003). Dynamics of land-use and land-cover change in tropical regions. *Annual Review of Environment and Resources*, 28(1), 205–241.

Lu, D., Mausel, P., Brondizio, E. and Moran, E. (2004). Change detection techniques. *International Journal of Remote Sensing*, 25(12), 2365–2401.

Michael, A. A. (2012). Effect of mining on farming in Jos South Local Government Area of Plateau State. Federal College of Land Resources Technology, Kuru, Plateau State. *Nigeria. Journal of Soil Science and Environmental Management, 3*(4):77-83.

Mustafa, M. (2010). *Seasonal Change in the Greenness of Soybean Leaves: Groundtruthing of NDVI*; research presented to Illinois Junior Science and Humanities Symposium at Southern Ill. Univ. at Carbondale.

Njomo, D. (2008). *"Mapping Deforestation in the Congo Basin Forest Using Multi-Temporal SPOT-VGT Imagery from 2000-2004". EARSeL Proceedings* 7, 1. Available On-line at http://www.eproceedings.org/static/vol07_1/07_1_njomo1.pdf?SessionID=49c6647bb6b81ad3fe Accessed July 31, 2016.

Radke, J., Andra, S., Al-Kofani, O., Roysan, B. (2005). Image change detection algorithms: a systematic survey, IEEE Trans. *Image Process,* 14 (3), pp. 291–307.

Sankhala, S. and Singh, B. (2014). Evaluation of urban sprawl and land use land cover change using remote sensing and GIS techniques: a case study of Jaipur City, India.*Int. J. Emerging Technol. Adv. Eng.*, 4 (1), pp. 66–72.

Sarma, P.K., Lahkar, B.P., Ghosh, S., Rabha A., Das, J.P., Nath, N.K., Dey, S., Brahma, N. (2008). Land Use and Land Cover Change and Future Implication Analysis in Manas National Park, India Using Multi- Temporal Satellite Data. *Curr. Sci.*, 95(2)2: 23-227.

Shalaby, A and Tateishi, R. (2007).Remote sensing and GIS for mapping and monitoring land-cover and land-use changes in the Northwestern coastal zone of Egypt. *Appl. Geogr.*, 27 (2007), pp. 28–41.

Vivan, E. K., Julius, A. B., Okafor, C. I. and Ali, A. Y. (2013).An Appraisal Of Urban Land Use and Land Cover Changes In Jos South Local Government Area Of Plateau State, Nigeria Using *Remote Sensing and GIS*. Department of Environmental Management, Faculty of Environmental Sciences, Kaduna State University, Nigeria. Un-Habitat Juba, South-Sudan, *Ph.D. Candidate*, Department of Geography and Planning, University of Jos, Nigeria.