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AN ASSESSMENT OF SPATIAL VARIATION OF LAND SURFACE CHARACTERISTICS OF MINNA, NIGER STATE NIGERIA FOR SUSTAINABLE URBANIZATION USING GEOSPATIAL TECHNIQUES

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Abstract

Rapid urbanization rates impact significantly on the nature of Land Cover patterns of the environment, which has been evident in the depletion of vegetal reserves and in general modifying the human climatic systems (Henderson, et al., 2017; Kumar, Masago, Mishra, & Fukushi, 2018; Luo and Lau, 2017). This study explores remote sensing classification technique and other auxiliary data to determine LULCC for a period of 50 years (1967-2016). The LULCC types identified were quantitatively evaluated using the change detection approach from results of maximum likelihood classification algorithm in GIS. Accuracy assessment results were evaluated and found to be between 56 to 98 percent of the LULC classification. The change detection analysis revealed change in the LULC types in Minna from 1976 to 2016. Built-up area increases from 74.82ha in 1976 to 116.58ha in 2016. Farmlands increased from 2.23 ha to 46.45ha and bared surface increases from 120.00ha to 161.31ha between 1976 to 2016 resulting to decline in vegetation, water body, and wetlands. The Decade of rapid urbanization was found to coincide with the period of increased Public Private Partnership Agreement (PPPA). Increase in farmlands was due to the adoption of urban agriculture which has influence on food security and the environmental sustainability. The observed increase in built up areas, farmlands and bare surfaces has substantially led to reduction in vegetation and water bodies. The oscillatory nature of water bodies LULCC which was not particularly consistent with the rates of urbanization also suggests that beyond the urbanization process, other factors may influence the LULCC of water bodies in urban settlements.

Keywords: Minna, Niger State, Remote Sensing, Land Surface Characteristics

1. Introduction

The rapid rate of population growth has triggered the need for settlements that provide for shelter, human socioeconomic activities and food supplies that meet human need. The resultant activities on the earth’s surface grow over time as well as create a parasitic relationship with other land uses. The increase in population growth and human settlements is one of the major constructs that reshape the nature of land use cover system of the earth surface with one growing at the expense of another. This relationship according to Coale and
Hoover (2015) do not only affect planning and societal development but also influence energy consumption (S. Wang, Ma, & Zhao, 2014), pollution (Farhani and Ozturk, 2015; Liddle, 2014; Q. Wang, Zeng, & Wu, 2016) and global warming and climate change scenarios (Elmhaegen et al., 2015; Garschagen and Romero-Lankao, 2015; Henderson, Storeygard, & Deichmann, 2017).

Population growth on the other hand has resulted in a rapid rise in urbanization in both developed and developing parts of the world. The menace of this rapid urbanization rate impact not only on human comfort, but also exert significant influences on the nature of Land Cover Change (LCC) patterns of the environment, in addition to pressures exerted on other components of the human environment including the depletion of available (Feng, Chen, Hayat, Alsaedi, & Ahmad, 2017; Guo and Shen, 2015; Jiang, Wu, Liu, & Deng, 2014; Koop and van Leeuwen, 2015; Prosdocimi, Kjeldsen, & Miller, 2015), depletion of vegetal resources (Liu et al., 2015; Price and Bradstock, 2014; Zhou, Zhao, Zhang, & Liu, 2016) and modification of human climatic systems (Henderson, et al., 2017; Kumar, Masago, Mishra, & Fukushi, 2018; Luo and Lau, 2017; Mathew, Chaudhary, Gupta, Khandelwal, & Kaul, 2015).

The urbanization process results in Land Use Land Cover Change (LULCC) of a given location. The observed LULCC is due to; the influence of human activities on land cover through various activities such as farming, deforestation, construction and sand filling of former colonies of water bodies. The modification of the land cover types arises from the quest to meet man’s requirements for survival in urban centers. While these demands required in urban centers increase proportionally to the rate of urbanization especially construction, the vital cover of the earth surface that is being modified frequently exerts a potency of seeding a feedback action to the human environment. This feedback either negative or otherwise, underscore the needs to critically study the effect of urbanization LULCC.

In light of the foregoing, Many researchers explore the potential of aerial photography (Fensham and Fairfax, 2002; López, Bocco, Mendoza, & Duha, 2001; Mas et al., 2004) and remote sensing (Green, Kempka, & Lackey, 1994; Joshi et al., 2016; Lillesand, Kiefer, & Chipman, 2014) data in studying the effect of urbanization on vegetal cover change with surface vulnerability (Mukherjee, Krishna, & Patel, 2018; Tayyebi, Shafizadeh-Moghadam, & Tayyebi, 2018; Wellmann et al., 2018) over a long period, but are often deficient in terms of data consistency. The application of Remote Sensing (RS) data as well as RS techniques of data mining provide a frontier through which events of the past can be compared to what is obtainable today. Changes over a given period of time are capable of revealing great a deal of
information regarding nature, and magnitude of change that may occur over time. The strength of remote sensing as a tool for data collection is based on it’s capabilities to store information that has occurred. Thus, providing a data bank that enables continues tracking of changes that might exist when comparisons are made with present day data.

Geographical Information System (GIS) to provides a tool that allows for the integration of different but spatially referenced data about a phenomenon under study with a high degree of accuracy and appealing results. GIS is a cost effective-tools through which geospatial information related to changes on the earth surface can effectively be managed and integrated towards determining cause and effects. In addition, GIS provides an effective technique for the integration of multi layer information that might have direct or indirect impact regarding scenario occurrences (Ferreira et al., 2015; Hughes et al., 2016; Kaliraj, Chandrasekar, & Magesh, 2015). The versatile nature of GIS favors it employment in different LULCC studies. Thus, many numerous studies have applied GIS in LULCC including; Ayele et al. (2018); Debnath, Debnath, Ahmed, & Pan (2017); Jin, Yang, Zhu, & Homer (2017); Shrivastava and Nag (2017); Shuaibu and Sulaiman (2012). These studies successfully implement RS techniques and other auxiliary data in GIS environment by treating each of the data sets as a separate geospatial data either as a point, polygon, line or linear feature. The processing of these data sets often employ different tools available in the commercial geospatial processing applications.

The evolution computer technology resulting in the availability of effective data storage, retrieval and manipulation along with large storage capacity of data has aided the effective integration of RS technology with GIS. Exploration in the utilization of this advancement has resulted in effective integration of RS data with GIS for effective decision making. The utilization of remote sensing data offers a useful insight about changes that reshape the earth cover over time, this is often better utilized if, and these changes can be tracked at regular intervals to provide knowledge regarding how rapid these changes take place. In an attempt towards the effective capturing of slight changes on land cover, the RS techniques becomes an inadequate tools since multiple layer information will be required. Rather the use of numerical approach through the utilization of RS data to generate series of algorithm and mathematical expression may be explored. Studies that have combined the use of RS data and development of mathematical algorithm includes; Metternicht (2001); Nemmour and Chibani (2006); Oguz and Zengin (2011); Willhauck, Schneider, De Kok, & Ammer (2000) among several others. These researches had proven effective in the aspect of data integration and predictive capabilities, however; spatial reference becomes inadequate
especially in mathematical modeling. In fuzzy logic, arguments and string conditions become too many to reflect reality thus, the need to develop a more geospatial application that can effectively manage multi layer information in determining land cover changes.

As a result of the effective, integration of RS data in the GIS environment, many studies evolve to study the pattern of LULCC patterns (Ayele, et al., 2018; Debnath, et al., 2017; Green, et al., 1994; Metternicht, 2001; Oguz and Zengin, 2011; Tayyebi, et al., 2018). The integration of these techniques according to Corner, Dewan, & Chakma (2014); Dewan and Yamaguchi (2009), along with the pre-and post-classification techniques has extensively been explored with interest on pre-change vector as well as multi date classification. Other studies in an attempt to achieve the same goal of analysis, adopted Normalized Difference Vegetation Index (NDVI) (Rawat and Kumar, 2015; Yengoh, Dent, Olsson, Tengberg, & Tucker III, 2015; Zhu et al., 2016) and principle component analysis (Dronova, Gong, Wang, & Zhong, 2015; Rokni, Ahmad, Solaimani, & Hazini, 2015). The premise of these techniques is that change in the pixels as a result of change in spectral reflectance value for the period under study can be infrared but however, they are deficient in the effective identification of change nature (Dewan and Yamaguchi, 2009). To effectively manage the pre and post classification comparison techniques along with methods, (though may often create difficulties) have emerged as the most effective method for identification of LULCC studies. The pre and post classification technique is most effective in urban environments where similarities in spectral response patterns in different Land Cover (LC) features may appear highly similar. In addition, the technique can be employed using RS data from sensors with different spatio-temporal spectral resolution (Dewan and Yamaguchi, 2009).

RS has offered an effective tool for relating the interaction between population, environmental changes and human environment (Dewan and Yamaguchi, 2009; Miller and Small, 2003; Tuholske, Tane, López-Carr, Roberts, & Cassels, 2017). Space-born satellites provide useful information that enables the evaluation of such scenarios over time. Although, RS data might sometimes be vulnerable to interference by factors such as cloud and other aerosols affecting visual evaluation (Weitkamp, 2006; Winker et al., 2009), information generated from spaced based instruments is cost effective, durable, relatively accurate and reliable compared to the conventional methods of survey (M. Chen, Mao, & Liu, 2014; Congalton and Green, 2008; Hyyppä et al., 2000). Moreover, the challenges of vulnerability to interference by cloud cover and other atmospheric contents can effectively be managed using different image correction technique and additional ground reference data. (Camps-Valls, Tuia, Bruzzone, & Benediktsson, 2014; Hagolle, Huc, Villa Pascual, &
Dedieu, 2015; Pohl and Van Genderen, 1998). In terms of application, wide ranges of RS research exist in urban growth and LC changes. In terms of urban growth (Hadi et al., 2016; Hegazy and Kaloop, 2015; Mahboob, Atif, & Iqbal, 2015; Megahed, Cabral, Silva, & Caetano, 2015; Sakieh, Amiri, Danekar, Feghhi, & Dezhkam, 2015; X.-P. Song, Sexton, Huang, Channan, & Townshend, 2016) and urban heat related studies (Azevedo, Chapman, & Muller, 2016; Coutts et al., 2016; Hu and Brunsell, 2015; Mirzaei, 2015; Santra, 2016). RS-based data sources and techniques provide a method through which data related to structural variation in LULCC pattern can be understood to mitigate irreversible changes that might occur as a result of LC alteration. For effective change pattern estimation, rate, types of LC change and prediction of feature magnitude changes, RS technique becomes a viable tool. In addition for every sustainable development, data related to structural changes in LC is critical for policy formulation, implementation and effective conservations.

Scant literature exists on the spatio-temporal changes in LC, that has greatly influences the expansion of Minna metropolis of Niger state Nigeria. Little or no research exists on the official categories of land in Minna using both ground observation data. Literature such as Akinrinmade, Ibrahim, & Abdurrahman (2012) and Morenikeji, Umaru, Liman, & Ajagbe (2015) attempted a classification of LULC types of Minna using RS but emphasis of these studies were on the quantification of land cover amounts. LC amount is grossly in inadequate to support complex decision making especially in a developing countries context where resource availability is a challenge. In terms of government attempted data only Government (2007) provides a background regarding population, climate and nature of mineral deposit with no information regarding vegetal cover classification. This further indicates the lack of land use pattern categories in the state and might translate to government planning to be based on population data without reference to land use patterns within the metropolis. Numerous factors identified by Dewan and Yamaguchi (2009) to be responsible for the lack of this vital information to include; lack of geospatial expertise in government agencies saddled with responsibility of developing such a vital information, bureaucracy, financial constrain and absence of coordination among the relevant agencies. This research therefore, attempts to study the LULC change pattern of Minna, Niger State using geospatial techniques, remotely sensed data and socioeconomic data to provide empirical studies that will guide policy makers regarding patterns of land used changes in the study area.

Different techniques of remote sensing data analysis exist; ranging from image identification and classification based on spectral characteristics to object based classification schemes. The later classification systems have been applied in several remote sensing image
analysis researches with wide variability of success. The spectral based classification techniques employed the use of image pixel where features of the same spectral pattern are grouped into one class representing a particular land cover type (Aplin and Smith, 2008; Blaschke et al., 2014; Hussain, Chen, Cheng, Wei, & Stanley, 2013). Although this approach has tested most effective but it still suffers limitations when pixels of an image containing two or more spectral properties are to be identified and classified, especially when the pixel’s spatial extend varies from land cover extent of interest (Myint, Gober, Brazel, Grossman-Clarke, & Weng, 2011; Nogueira, Penatti, & dos Santos, 2017; Teodoro, Gutierres, Gomes, & Rocha, 2018; L. Wang, Sousa, & Gong, 2004; Whiteside, Boggs, & Maier, 2011; Yu et al., 2006). The implication of spectral variation within one pixel often results to misclassification and conflict of information. In the light of these shortfalls of the pixel based image classification technique, an object based classification scheme was developed to enhance accuracy and as an improvement over the conventional approach. Various approaches to object based oriented classification techniques exist (J. Chen et al., 2015; Cheng et al., 2015; Cheng, Han, Zhou, & Guo, 2014; Gokturk et al., 2015; Li, Zang, Zhang, Li, & Wu, 2014). These techniques have proven effective in much literature but the effectiveness and application depends on the spatial extent and homogeneity of the surface characteristics. For example, in an urban environment object based classification can be done at ease since urban surfaces contain features of similar characteristics which can be identified and classified into land cover type. However, when the spatial extent increases, land cover characteristics becomes complex thus, affecting accuracy and reliability of classification. In addition, object based image classification will requires input data of high resolution which often requires large storage space; and due to their size, processing becomes extremely slow affecting the application of object based interpretation. Advancement from object based image classification is the use of object based oriented classification techniques that utilizes different machine learning languages to identify and group similar colors into a single land cover type. Successful application of this technique has been shown in the work of Lang (2008); (Mallinis, Koutsias, Tsakiri-Strati, & Karteris, 2008); Tzotsos and Argialas (2008) Duro, Franklin, & Dubé (2012); Niu and Ban (2013)

A remedy to the difficulties associated with pixel-based classification according to Blaschke, et al. (2014); Li, et al. (2014); B. Song et al. (2014); Tuia, Flamary, & Courty (2015) is to operate at the spatial scale of the object of interest rather than at the extent of the image pixels. This makes the technique an efficient, versatile, reliable and cost effective method of
image analysis application. The issue of remote sensing sensors which influence image quality prior to classification according to Bukata, Jerome, Kondratyev, & Pozdnyakov (2018); Gu, Lv, & Hao (2017); Toth and Józków (2016) has direct correlation with the accuracy of classification especially the pixel based approach. The advancement in science and technology has favored the fabrication and development of multisensory spaced platforms that can measure different environmental parameters thus, improving reliability and accuracy (Desheng and Xia, 2010; Myint, et al., 2011).

This research therefore; identifies the different LULC types and explores the characteristics of LULC patterns using remotely sensed data. The specific objectives of this research however, is (i) to identify the land cover types in Minna, (ii) to evaluate the LULC changes of Minna between 1976 to 2016 (iii) to determine the spatio temporal change characteristics of land for the period under review.

2. Methods

Landsat (MSS, TM and ETM+) were acquired at different epoch from the USGS satellite operated by (US) government for 1976, 1986, 1996, 2006 and 2016. The acquired images were used to identify and, evaluate the LULC types and LULC change pattern of Minna to determine the expansion pattern. The acquired images were subjected to geometric corrections to remove cloud, smoke and dust haze effects, which might influence the result of analysis. The downloaded images were classified using supervised classification. The different images bands were layer stacked and band 4, 3 effective throughout the composite. Reference data of variable resolution and scale where used for both training area selection and evaluation of classification accuracy as presented in Table 1. A total of 100 ground base control points were established for both training area selection accuracy assessment of the classified images. For effective and efficient classification, a band composite of 2018 image using band 654 was developed and used for sampling.

Table 1: Data types used in the research

| S/No. | Data Type      | Details | Year             |
|-------|----------------|---------|------------------|
| 1     | Landsat MSS    | 60 m    | 1976 and 1986    |
| 2     | Landsat TM Image | 30 m   | 1996 and 2006    |
| 3     | Landsat ETM+ image | 15 m | 2016           |
| 4     | Spot Image     | 1 m     | 2015             |
| 5     | Google Earth Image | 6 m  | 2018            |
| 6     | Street Guide Map | 1.50,000 | 1991         |
1. Image Processing

All satellite imageries were studied to enable the identification of features of similar spectral bands. Image classification in this research was employed to assign unique spectral band to a feature by utilization of a process referred to as signature editor. In this process, each feature on the map were given a unique signature as inferred from the composite image and the ground based control points used in developing training samples. The processed satellite images were subject to qualitative evaluation using their spectral characteristics and properties to ascertain the uniqueness of different LULC types in the study area prior to classification.

The training samples were developed from a Global Position System (GPS) generated points during reconnaissance to enhanced accuracy of locating training samples. Six training samples presented in Table 2 were developed for each class and then refined, renamed and merged after examination of statistical attributes as referred to by Dewan and Yamaguchi (2009). The generated training samples where run on 120-150 selected sample sites on the imageries ranging between 300-800 pixels using maximum likelihood classification. A supervised maximum likelihood classification is a classification algorithm used to obtain highly accurate results from a remotely sensed data with an assumption that each class has a Gaussian distribution. Pixels are classified by computing the distance from one pixel to each class mean value, in units of the standard deviation in a giving magnitude to the class with the smallest value. The maximum likelihood classification technique offered a rebuts and reliable result compare to the object based oriented classification which was developed to enhance image analysis using computer programming such as Python (Hafiz, 2011) among several others. The limitation of the application of object oriented classification technique lies on the fact that rather the use of spectral reflectance pattern, classification are based on features as it appear on an image. Conversely, object of similar pattern becomes complex to identify. In addition the classification system can only be applied in relatively homogeneous urban areas where interests of intricate and conflicting features are less present thus, affecting its application on complex terrain with different land cover types.

Prior to quantitative evaluation of LULCC evaluation, the classified images were subject to accuracy assessment where the 1976 and 1986 images appeared with several classes to incorrectly classify in supervised classification. These images have low accuracy level of between 51-70 percent while the reminder where having accuracy between 75-96 percent of LULC. The low accuracy value obtained in some of these images, where largely
due to misclassification of bared surface and rock outcrop due to their similarity in spectral characteristics and satellite sensors.

Table 2: Land used land cover classification system employed in the research

| Land-cover types    | Description                                                                                                                                 |
|---------------------|---------------------------------------------------------------------------------------------------------------------------------------------|
| Developed Area      | All residential and industrial areas, settlement and transportation infrastructural network.                                                  |
| Water body          | River, permanent open water, lakes, ponds, canals, and reservoir. Their presence indicates the availability of water for human and agricultural use. |
| Vegetation          | Trees, shrubs and semi-natural vegetation, deciduous coniferous and mixed forest, palms, orchards, herbs, climbers’ gardens, inner-city re-creational areas, parks, playgrounds. |
| Farmlands           | All agricultural lands both on small and large scale, it involves grass-land and ridges.                                                     |
| Rock outcrop        | This referred to exposed rock either due to denudation or human activities.                                                                      |
| Bare surface        | This referred to sand land, and areas which has no vegetal covered.                                                                                       |

2. Location of Study Area: Minna Niger State, Nigeria

Minna is located on longitude 9° 32' 30” to 9° 42' 30”N and 6° 20' 00” to 6° 37' 30”E as shown in Figure 1. Minna belongs to the savanna types of vegetation characterized by tall trees with thick barks that enable them resist high rate of evapotranspiration during dry season; Seasonal grasses grow evergreen during the wet season and dry-up during the dry season. The climate of the study area according Adefolalu (1980) is characterized by average rainfall of over 300mm lasting for a period of six months. During this period the vegetation is green, with farmlands at its peak and water bodies developing to their peak volume. The onset of the dry season marks the cessation of the precipitation, with the period characterized by severe high temperatures, high rates of evapo-transpiration and evaporation resulting in loss of soil moisture and receding water bodies. The study area is characterized by distribution of channel networks that are primarily fed by precipitation and the elevation varies from 150meters as minimum to about 350m commonly found around the eastern part of the study area. There exist a few isolated outcrops of rock mostly of igneous formation that have been exposed to agents of denudation over time (Amadi and Olasehinde, 2010; Mohammed, Aboh, & Emenike, 2007).

The administrative function of Minna resulted in rapid population growth both from inflow of diverse populations from locations both within and, outside the nation. This teeming population brings about needs for: shelter, commercial activities, educational and health services among several others. In response to this, built-up areas and other forms of development have emerged that do not conform principle of sustainable urbanization. Continues growth in this pattern will result to obstruction of water ways, modification of
hydrogeological structures and increase the potential of the occurrence of environmental hazards including flooding and urban heat island.

![Figure 1: Map of (a) Nigeria inset Niger State and (c) study area](image)

3. Determination of Change Detection in Minna

This research uses post–classification change detection approach where change in each of the classified features over times is evaluated quantitatively. The quantitative evaluation is an effective method of detecting the change over time, nature, and geographical point of change occurrence. In this approach, analyze images were overlaid in GIS
environment in order to obtain changes in LULCC for the five epoch (1976, 1986, 1996, 2006, and 2016).

3. Results and Discussion

The LULC types of Minna are presented in Figure 2. Based on the remote sensing and ground control points, six (6) to Seven (7) different land cover types can be identified as developed area, areas covered by, farm land, bared surface, vegetation, exposed rock outcrops and wetlands. The developed regions include; buildings, Educational centers, constructed road networks and other adjoining structures like market, industrial layouts and mechanical workshops. Next to developed areas are the farmlands which become invariably visible adjoining the developed regions. It is on this region that agricultural activity such as crop cultivation and irrigation agriculture takes place. Vegetation is a transitional zone from the farm lands to a relatively dense vegetation containing trees, shrubs and other grasses among several other vegetation compositions. The vegetation is often characterized by scattered trees that shed their leaves during the dry seasons; there is a presence of little or no climbing and under growth, as inferred during the reconnaissance survey as often associated with guinea savanna type of vegetation. Bare surfaces in Minna arise as a result of population growth, urbanization and increase in subsistence agricultural practices. Agricultural practices such as; farming result in loss of large hectares of vegetation through clearing and bush burning. In addition to farming, construction on the other hand greatly result to the development of bared land as the top and laterite soils are often excavated for sand filling and building of structures. The wetland in this research due to similarity in spectral sensitivity, were merged with water body in most of the images classified. Those, water body cover substantial hectares of land as revealed from the remote sensing technique employed. It comprises of small pound water, streams, channel and rivers that runs with direction in response to precipitation, elevation and prevalent geology. Rock outcrop on the other hand becomes visible from their spectral response pattern; however, visibility amount of rock features resulting from the maximum likelihood classification scheme employed varies according to season. During the dry seasons, most of the vegetation part especially grasses are removed due to absent of precipitation; therefore, more rock outcrop became visible in dry season. In wet season on the other hand, vegetation especially grasses might have started or attained it peak of growth thus, visibility of rock outcrop becomes lighter.
The result of LULCC in Minna from 1976, 1986, 1996, 2006 and 2016 are presented in Figure 3. Water body, developed area, farm land, bared surface and rock outcrop were the major LULC types for the period under review. The area experience expansion in all direction but was dominant towards the eastern part of the study area. During the first era (1976) the most dominant land Cover Types (LCT) were vegetation, bared surface and . By 1986 most of the vegetation and bared surface were replaced by developed area and farm lands. The farm lands were more dominant at the northern part of the study area. The rapid declined in the available vegetation is coherent with the creation of Niger State from Sokoto State and the making of Minna as the State Capital. It was during this period that Minna experience rapid expansion and construction of structures to meet the demand of change in function to administrative function. Between the periods of 1986 to 1996, the expansion rate relatively stabilized however, construction of road networks and channelization of Minna drainage system received a significant facelift there by increasing the expansion rate slightly. During the third decade (1996-2006), developed area expanded in all direction placing a greater constrain on vegetation and water body while exposing most of the rock outcrops. Due to this development, farm land begins to decline primarily at the expense of developed area. Available data sited during the course of this research shows that, selling of land at the outscate of Minna became pronounced during this period. Many of the farm land at the fringes of the town were sold and converted to; residential, commercial and educational.
institutions. Figure 3e clearly illustrates the transformation of vegetation and farmlands to developed area by 2016. Between 2006-2016, mark the era of rapid expansion of Minna metropolis. Historical document indicated the development of two major housing estates (M.I. Wushishi and Talba Housing estate) along the western and eastern bypass respectively. In addition, other private properties developers and individual buildings received tremendous increase. This period also coincide with the relocation of federal university of technology Minna to it permanent site and the completion and relocation of National Examination Council (NECO) national head quarter along Minna Bida Road, thereby resulting to increase in higher demand for shelter and proximity to place of work. The successful completion and relocation of central Market to the Old Airport field developed by Urban Shelter Clay and building of the timber shade at the extreme of eastern directly covert the grassland and some minute farmlands to a permanent developed area thus, conversion of vegetation and farmlands to commercial area.

The rapid development of developed area as revealed by this research can be attributed to rapid increase in population, rise in public, private sector and individual household sectors. This result is coherent with the work of Dewan and Yamaguchi (2009) and Corner, et al. (2014). Most of the development projects were undertaking through individual and the public sector to meet societal demand for housing, education, commercial and industrial activities. This pattern of development at the later period (between 1999 till date) was further excoriated by the Public Private Partnership Initiatives (PPPI) where development needs considered critical can be initiated by the society, while it’s development can be financed by the private sector while government provide the enabling environment. In light of this development, many farmlands, vegetation, water body (especially the wetlands) was converted to built-up without recourse to concomitant cost implication on the environmental.

Land speculation was observed among the suburban areas in response to increase in land prices due to increase in demand for housing, educational and infrastructural development. The agricultural land at the city fringes are becoming rapidly develop by public and individual property developers. Most of the recently developed properties appeared to have taking into cognizance the accessibility needs thus, most of the layout were provided with access network as opposed to their previous developed properties especially among individual properties owners. Inference into the distortion and non adherence to the master plan were attributed to poor coordination among the government agencies that are responsible
for approving property development. A typical case of such scenario is the case of agricultural development land at the fridges of Zarumai quarters in Bosso which were significantly encroach by individual residential development. These lands where originally design to meet the development of agricultural research thus, containing both grazing and field lands which were converted to residential areas.
The spatio-temporal change analysis presented in Table 3 revealed that changes has taking place in the different land cover types over times. Vegetation in 1976 covered 299.85 ha considerably declined by 43.99ha as at 1986. Between 1986-1996, 28.63 were lost and, by 2006, vegetation lost was now 84.52ha. Overall evaluation of change between 1976-2016 shows that 219.93ha of vegetation was lost and change into other land used types. Water body on the other hand exhibits an oscillating pattern of change between 1976 to 2016 with some years showing increment while other years shows declining in amount of area covered by water body. For example in 1976, water body covered 74.82ha and declined by 40.23ha by 1986 and by 1996 increase by 8.90ha. Between 1996 to 2006 it also rose to 25ha while between 2006 to 2016 the value declined by 66.30ha. The nature of decline cleared represents a pattern of growth in the developed area. Development pattern at this period exert impact on two major land cover; vegetation and water body. As more vegetal cover is removed by urbanization and agriculture more water body is lost depending on the area where this development is taking place. If, however, the removal of vegetal cover is due to expansion of
agricultural activities (farmlands), the water body is not completely lost since swampy or wetland is not completely changed as the case with built-up.

Developed area in this study had been on the increase since 1976 to 2016 with the grow rate higher in some decades compared to some other decades. In addition, the growth patterns were never the same throughout the study period. For instance in 1976 developed area was just 34.71 ha. This value however, increased to 51.36ha by 1986, 68.02ha by 1996, 72.75ha by 2006 and 116.58ha by 2016. Changes in the developed area pattern between 1967 to 2006 were on the average rate of 12.68ha per decade amounting to increase of this land used type by 38.04ha. Statistical evaluation of the years 2006 to 2016 correspond to the decade with highest urbanization value of 116.58ha more than three times greater than 1976-2006 values. This rapid urbanization period coincide with period of many PPPA by the government resulting to increase in infrastructural development, housing, education, commercial, industrial, small and medium scale business, demographic changes, immigration from the surrounding rural areas in addition to availability of social and basic amenities in the suburb also influences this development rate. The spatial characteristics of developed areas also result to the construction and development of more transportation network especially the road transportation. Many road networks within Minna metropolis were either expanded or upgraded to a dual carriage ways while some residential streets of untilled types were tilled to ease movement within the Metropolis.

The geospatial analysis from the Landsat images revealed that expansion from 1976 to 2006 did not occur proportionally to each other. Vegetation for the period under review shows a declined from 54.03% to 18.71% in 2016. Water body on the other hand declined from 13.48% to less than 1percent in 2016. While vegetation and water body shows a tremendous declined in area coverage, farm land and developed areas indicate a significant growth from 0.41% to 10.87% and 2.25% to 27.20% between 1976 to 2016 respectively. A slight increase was also observed in rock outcrop from 4.22% in 1976 to 4.75% in 2016 while bared surface increases from 21.62% to 37.76% for the same period. The high value of change in bared surface was largely due to change in farm land to development of road network and open space development.

The study revealed that the rapid rate of urbanization of Minna has been relatively more rapid during the last decades compared to the 1976-2006 era. The rapid urbanization rate has resulted to the significant changes in LULC pattern with adverse effects on the environment.

| LULC Type    | 1976   | 1986   | 1976-1986 | 1996   | 1986-1996 | 2006   | 1996-2006 | 2016   | 2006-2016 |
|--------------|--------|--------|-----------|--------|-----------|--------|-----------|--------|-----------|
| Area (ha)    | %      | Area (ha) | %         | Area (ha) | %         | Area (ha) | %         | Area (ha) | %         |
| Vegetation   | 299.85 | 54.02  | 255.86    | 49.93   | -43.99    | 3      | 56.20     | -28.63  | 142.71    | 30.6      | -84.52   | 79.92    | 18.7      | -62.79   |
| Water Body   | 74.82  | 13.4   | 34.59     | 6.7     | -40.23    | 43.49  | 10.75     | 8.90    | 68.92     | 14.7      | 25.43    | 2.62     | 0.6       | -66.3    |
| Developed Area | 34.71 | 6.25  | 51.36     | 10.02   | 16.65     | 68.02  | 16.82     | 16.66   | 72.75     | 15.6      | 4.73     | 116.58   | 27.3      | 43.83    |
| Farm Land    | 2.23   | 0.40   | 95.43     | 18.62   | 93.20     | 15.86  | 3.92      | -79.57  | 123.38    | 26.4      | 107.52   | 46.45    | 10.9      | -76.93   |
| Rock Outcrop | 23.41  | 4.22   | 13.17     | 2.57    | -10.24    | 28.59  | 7.07      | 15.42   | 10.70     | 2.29      | -17.89   | 20.31    | 4.75      | 9.61     |
| Bared Surface | 120   | 21.6   | 61.97     | 12.09   | -58.03    | 21.1   | 5.2       | -40.87  | 47.63     | 10.2      | 26.53    | 161.31   | 37.8      | 113.68   |
| Total        | 555.02 | 100    | 512.38    | 100     | 404.2     | 100    | 466.09    | 100     | 427.19    | 100       |
The expansion rate for the period under study shows that in the last 10 years Minna has developed by more than 110 ha.

4. Conclusion

This research has identified, classify the LULC type and examining the Spatio-temporal changes in LULCC of Minna during the last fifty years using RS, geospatial technology and other auxiliary variables. Analysis revealed that built-up area increase from 74.82ha in 1976 to 116.58ha in 2016. Farmlands increased from 2.23 ha to 46.45ha and bared surface increases from 120.00ha to 161.31ha from 1976 to 2016. The study revealed that this growth rate resulted to substantial reduction in vegetation and water body including wetlands. The transformation of vegetation and water body to built up areas and farmlands has resulted to a severe environmental degradation with adverse vulnerability to flood occurrences, growth of slums and ghettos. The study demonstrate the capability of effectively integrating remote sensing data and other auxiliary information in identification of LULC types and helps in understanding the dynamics of LULCC of Minna for sustainable. Areas for further study may include determinants of LULCC of water bodies in urban settlements; and an analysis of the effect of PPPA on the urbanization process.

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