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Spatio-temporal analysis of landscape changes in different land use

PhD Thesis

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To HIS Infinite intelligence, and my family.

Author's Statement

I declare that this PhD thesis of P1301 Geography study program has been completed independently, under the supervision of Doc. RNDr. Vilém Pechanec, PhD. All the materials and resources are cited with regards to the scientific ethics, copyrights and laws protecting intellectual property. All provided and created digital data will not be publicly disposed without the consent of the Department for Geoinformatics, Faculty of Science, Palacký University Olomouc.

In Olomouc, May 30, 2018.

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Table of Content

1 Introduction

Landscape is a highly dynamic system which has natural and social interrelated components that are largely influenced by constant change (Izakovičová et al. 2017). Landscapes are defined by repeated dynamics of change, which may be revealed by transitions in landscape structural characteristics. Changes in landscape is currently one of the primary issues in global sustainable development and environmental challenges (Halmy 2015; Wei 2015; Parsa and Salehi 2016). Socioeconomic development, intensified agriculture and rapid human population growth have led to elevated urban growth and urbanization, which consequently induced human-built environment (Deep and Saklani 2014; Gong 2015; Nwaogu et al. 2017). Several factors (human and physical/environmental) in human-built terrain with urban areas in particular are compounded processes which unavoidably cause changes in land use (Lambin 1997). A form of mutually interrelated significant associations has been reported between increased urbanization, agricultural extension and socioeconomic indices (Parsa and Salehi 2016). For instance, expanded urban growth and intensified agriculture influence the societal economy whereas, many socioeconomic factors are good determinants of urbanization and agricultural processes. Urbanization and intensified agriculture are critical environmental challenges in most regions of the world (Samat 2011), which are often associated with poor management mostly in developing countries (Deep and Saklani, 2014; Weber and Puissant, 2003). This poor planning and management strategies coupled with increasing population lead to profound adverse impacts on the environment through deforestation, conversion of natural lands to settlements, soil degradation, loss of biodiversity and entire landscape changes (Quan et al. 2015). A comprehensively updated data about the land use changes in the past, present, and integration of the future are pertinent to comprehend and appraise various socioeconomic and environmental impacts of the land use changes (Williams and Schirmer 2012; Wilson and Chakraborty 2013). Sequel to these, the stakeholders including government, decision-makers, landscape planners and agriculturists at every level need land use information for sustainability. Therefore, evaluating land use from the past to present as well as predicting the future changes is paramount for the land managers.

Conventional approaches for land use change mapping and detection in Nigeria and in most developing countries are not only expensive but also tedious, time and energy sapping. Therefore, the application of geoinformatics methods has brought great relieve as land use-cover areas of different scales can easily be mapped, analyzed and accessed at affordable cost (Wang and Zhang 2001; Reveshty 2011). Due to dearth of data, complexity of factors, and rarity of observing all socioeconomic and natural phenomena, researchers focusing on landscape changes have adopted modelling to investigate land use change patterns and predict future land use and trends.

Different land use change models such as CLUE (Indrova and Kupkova 2015), Agent-Based Modeling (Zhang et al. 2011; van Oel 2010), artificial neural network (Pijanowski et al. 2002; 2009), cellular automata (Clarke et al. 1995; Benjamin et al. 1996; Feng et al. 2018; Gong et al., 2015), Markov chain (Arsanjani 2018; Pechanec et al. 2017; Iacono et al. 2015; Opeyemi 2006), GEOMOD (Schneider and Pontius 2001; Pontius and Batchu 2003), Land Change Modeler (Arsanjani 2018), SLEUTH (Candau and Clarke 2000; Herold et al. 2003; Goldstein et al. 2004), Scenarios for InVEST (Bassi and Baer 2009; Rukundo et al. 2018) and statistical analysis (Schneider and Pontius 2001; Xie et al. 2014; Fasona et al. 2011) have been developed and employed for the prediction of the changes and associated dynamics in space and time. Space and time have been identified as the two most essential universal parameters, where natural and human forces amalgamate to create-and perpetually alter-the naturally existing landscape into either a cultural or semi-cultural landscape, thus producing an entirely different and uncommon feature (Žigrai 2011).

Spatio-temporal analysis of landscape changes is the best approach to ascertain how nature and man influence the environment in relation to their impacts on land use, and this technique has been successful (Koomen and Beurden 2011; Montesino Pouzols et al. 2014). It is of important to state here that most studies on landscape change and pattern have been performed at the national and international level, but many of these works employed landscape metrics being the most widely approach for landscape pattern analysis. Although, landscape metrics can prompt the comprehension of spatial distribution characteristics of landscape elements and quantifying the structure of landscape, yet landscape change analysis based on landscape metrics can neither elucidate a spatial difference of land use at the field scale, nor the landscape trajectory in time. Therefore, this work analyzed landscape changes by examining on the interrelations between human activities and physical processes especially in socioeconomic and ecologically valuable areas that direct policymakers to formulate reasonable decisions for sustainable development. This work used the potential tools of GIS to assess the interactions and changes from human activities and natural features and their roles in landscape transformations under contrasting land use at different time. The dissertation is beyond just understanding the landscape pattern or structural distribution but focused at appraising the space-time dimension of landscape phenomena as induced by either man or nature. The thesis is structured in two major sections which were divided into various chapters as to cover the goals of the work. The first section treated mainly the theoretical and conceptual framework including brief definition of landscape changes and related terminologies, the driving factors, role of GIS, space-time analysis, methods for analyzing past, present and future changes and related literatures. The second section on the other hand, discussed the researches performed in relation to the primary aim of the PhD programme. These were presented as case studies (Case study 1-4): case study 1- GIS as tool for mapping land use-cover changes in a rapid urban growing area and effects on the landscape (Is Nigeria losing its natural vegetation and landscape? Assessing the landuse-landcover change trajectories and effects in Onitsha using Remote Sensing and GIS); case study 2- GIS as tool for identifying landscape changes due to natural hazard (landslides) and its drivers; case study 3 - GIS and statistics as tools for identifying landscape changes to non-natural hazard (human-induced) processes; case study 4 - GIS as a tool for identifying and predicting of landscape changes and drivers (Prediction modelling of land use development by appraising the drivers of landscape changes in Dřevnice River Basin, Southeast Moravia, Czech Republic).

2 Objectives of the work

It has been found that several drivers (such as political/institutional, cultural, and natural/spatial) combined forces to change the landscape in space and time; thus, these drivers are better studied together rather than as a single key driver. The thesis analyzed landscape changes in distinct land use by applying defined optimal forms of GIS and statistical tools for space-time landscape change analysis in Nigeria and Czech Republic focusing on:

(1) a growing urban hub area (Onitsha, Nigeria), by appraising the changes, drivers and effects.

(2) landslide hazard (Jos, Nigeria), by identifying the changes, vulnerability areas, drivers and effects.

(3) intensive agricultural watershed (Nigeria), by evaluating the changes, drivers and effects in different land use.

(4) Dřevnice River Basin (Czech Republic), by identifying and analyzing the changes, drivers and predicting future of the landscape changes in the area.

It is in these contexts that the four case studies of the dissertation thesis were actualized. Therefore, this thesis aimed at *analyzing landscape changes by identifying the changes, the drivers of the changes, and impacts on the land resources in different land use using GIS in combination of some statistical techniques.* This main goal will be achieved with objectives structured as follows:

1. To evaluate change in land use and its effects on the landscape in Onitsha from 1987 to 2015.

2. To identify Jos landslide vulnerable areas, driving forces and effects on landscape using GIS.

3. To quantitatively analyze the effects of spatio-temporal changes in Imo watershed landscape in relation to biodiversity under different land use using GIS and statistical tools.

4. To investigate the changes at Dřevnice River Basin, identify the drivers and effects as well as predict the future changes for the different land use.

5. To assess the landscape changes, the drivers and effects from various case studies in different land use.

6. To appraise the results qualitatively and quantitatively as well as visualize and present them in form of tables, figures and maps by jointly using GIS and some statistical techniques.

It is important to state here that the research objectives 5 and 6 were designed for all the case studies whereas, the objectives 1, 2, 3, and 4 were designed for case study 1, 2, 3, and 4 respectively.

3 Theoretical Background

3.1 Definitions and delimitation of terms

Land cover

Land cover according to FAO (2000) is defined as the observed bio-physical cover on the Earth's surface. Based on this definition, land cover in this work involves what grows and can be visible on the studied areas. It is usually determined by analyzing satellite and aerial imagery. Land cover is commonly used in natural sciences especially landscape ecology or physical geography (Bičík et al. 2015).

Land use

Land use can be defined as the land characterized by the structural features, activities and inputs undertaken by people in a given land cover type to produce, modify or preserve it (FAO 1998). On the other hand, Lambin et al. (2006) views land use as the eminent purpose for which humans explore and harness land cover

Landscape

The term 'landscape' has several definitions based on diverse interpretations from different fields, people and place (Fig.1). The inconsistences in definitions of landscape makes it difficult to establish consistent management policies. Landscape is defined as the "total character of an area of the Earth" (Alexander von Humboldt) It has been defined as a heterogeneous land area made up of a multiple of interacting ecosystems with repeated uniformity (Forman and Godron 1986). Landscape could also be termed as an area with spatial heterogeneity in at least one aspect of interest. On the other hand, the European Landscape Convention defines landscape as "an area, as perceived by people, whose character is the result of the action and interaction of natural and/or human factors". It is also of important to note that a landscape is not necessarily defined by its size; rather, it is defined by a spatially heterogeneous area relevant to the feature to be considered at any given scale.

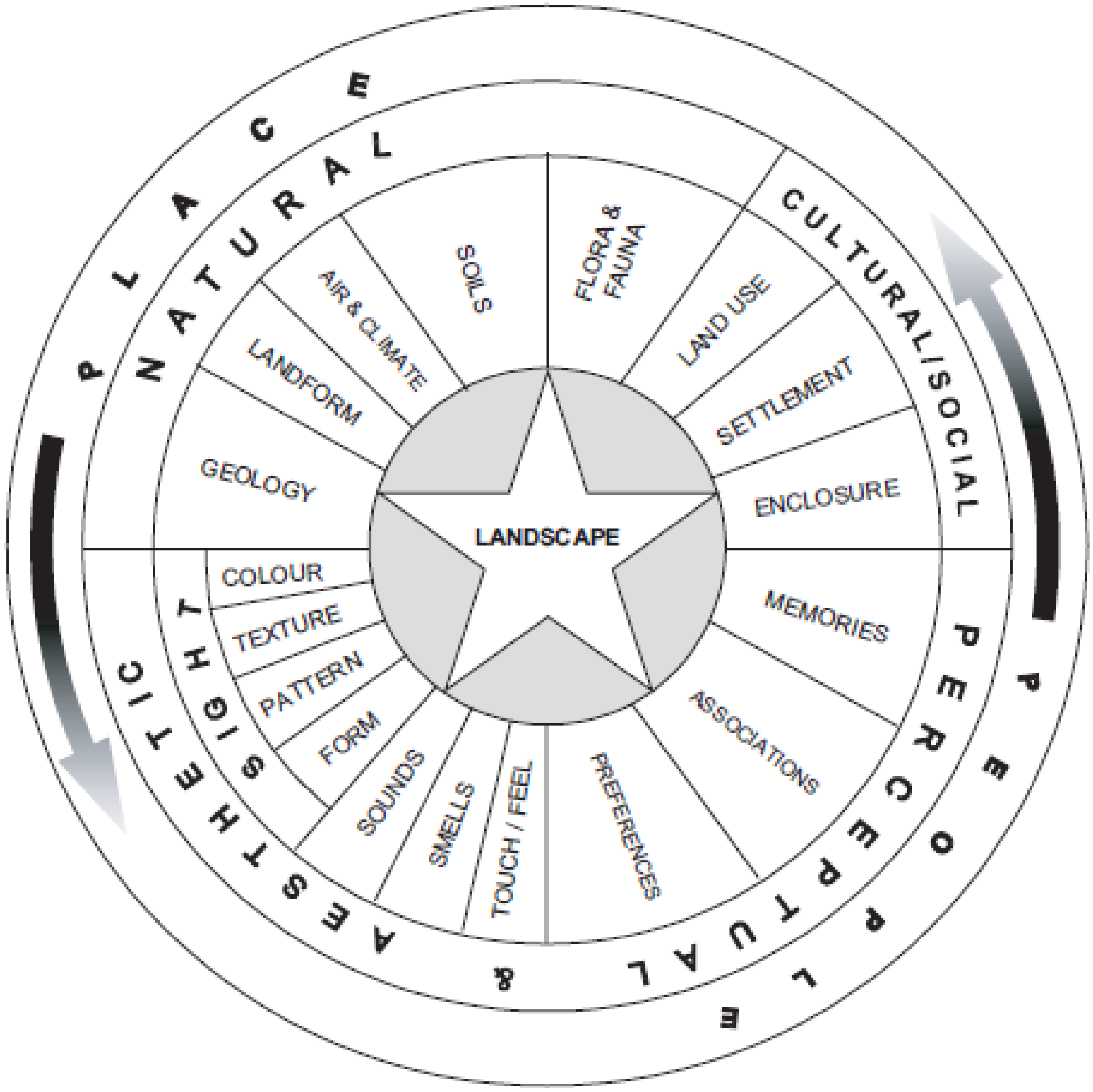

Fig. 1. What Landscape is? (adapted from Panagiotis 2013).

Landscape means not only a complex phenomenon that can be explained and evaluated using objective scientific methods, it also points to subjective observation, hence it has a perceptive, aesthetic, artistic and existential meaning (Lowenthal 1975; Cosgrove and Daniels 1988). Landscape covers the complexity of natural elements (water, soil, climate, habitats, vegetation, and natural cycles) as well as many social elements (settlements, agriculture, exploitation of raw materials, infrastructural developments) (Bičík et al. 2015). In summary, land use is what the land cover is used for and landscape is the product of land use over time.

Landscape structure

Landscape structure is comprised of two components (such as composition and configuration) and is defined based on the certain spatial pattern which is being represented. The composition of a landscape is defined by the spatial components that are imbedded in the map and assumed to be of significant to the landscape function in consideration. The configuration of a landscape on the other hand, is defined based on the spatial character, organization and context of the elements.

Landscape function

Landscape function could be defined by the features in consideration and can be an array of different items that support life and maintain the earth's system as often referred to 'ecosystem services'.

Swaffield (1991) classified landscape into three categories based on function: visible-land landscape, interactive landscape, and perceptual landscape. According to him, landscape as land focuses upon all the physical and systematic descriptions of 'landscape' which center immediately the real land situation. The interactive landscape on the other hand tends to be the most interesting aspect because it explains the vast meanings in which 'landscape' addresses its functional inter-relationships between the man and land. The perceptual landscape describes landscape as a human occurring feature acquired from land but obviously autonomous from it.

Landscape Quality

Landscape quality can be defined as its value in relation to its rarity, location and landscape characteristics/attributes. Landscape quality is directly linked to the landscape's sensitivity to change since the higher the quality of landscape is the more sensitive it will be to change (Panagiotis 2013).

3.2 Types of landscape, landscape change and why analyze landscape changes?

Types of landscape

Landscape is primarily classified into two broad types namely natural and cultural (artificial). However, like the definition, landscape has been categorized into different types by various fields of interest. For instance, it could be rural, urban landscape, designed landscape or might be defined in terms of the existing landcover to include mountain landscape, forest landscape, ocean landscape, and so on.

Landscape change

Landscape change might be defined as the visible transition in a given area of land because of change in land use-land cover driven by either man or nature. From this definition of landscape change, it could be concluded that landscape change is synonymous with land use-cover change. Therefore, in this study we might be switching/interchanging in their usage.

Why analyze landscape changes?

There are several reasons for analyzing landscape changes. Some of the reasons have been highlighted and discussed in this work which include to:

- keep history and values of the past and preserve them legally;
- conserve natural monuments, heritage sites and LPAs (Antrop et al. 2005);
- support biodiversity and nature conservation (Nwaogu et al. 2017; Dramstad et al. 2001; Haines-Young et al. 2000);
- promote economic development and sustainability;
- establish precision agriculture, and restore or maintain human, food or environmental security;
- foster environmental or climate change adaptation and mitigation (Pechanec et al. 2018a);
- enhance planning efficiencies by knowing the past and predicted future (Van Hoorick 2000);
- enrich tourism and recreational activities (Vos and Klijn 2000);
- restore or preserve aesthetic values;
- boost research and educational purposes and to produce historical, current and future maps.

In most cases, researches on landscape changes focused in critical environmental degraded areas with acute deforestation, severe soil/gully erosion, problems of urban sprawl and menace of natural hazards.

Contemporarily, many researchers in various ecological fields are focusing on the causes, processes, and effects of land use-cover change (Wu and Hobbs 2002). This is because present landscapes are the outcomes of several layers of past natural processes and human disturbances, thus, a historical perspective is necessary to fully understand (Russell 1997). In other aspects of ecology (soil, animal or plant ecology), the researches in these disciplines might be incomplete without the knowledge of the landscape changes or land use changes in any areas of interest. For example, a landscape history is a vital source of information for proper planning and managing cultural landscapes (Blaikie and Brookfield 1987) for effective land use monitoring and planning (Marcucci 2000), and for conservation and restoration ecology.

3.3 Challenges of landscape change studies

- Dichotomy and balance between spatial pattern and functional processes (Bürgi et al. 2005)
- Challenges of extrapolating results in space and time (Bürgi et al. 2005)
- Landscape terrains (Nwaogu et al. 2018)
- Diversity in land ownership (Antrop 2005)
- linking data of different qualities (Bürgi et al. 2005)
- Dearth of accurate data and funding
- considering culture as a driver of landscape change (Bürgi et al. 2005)
- Lack of Expertise and technical know-how

Most studies on landscape changes were primarily conducted focusing on only spatial pattern with little attention to landscape processes and function which are in the real sense the principal cause of the spatial trends. The landscape ecologists are major culprits in this bias perception because in some cases they failed to realize that thorough understanding of landscape changes, clearly demands complementary knowledge of the underlying processes. The landscape terrain tends to be another challenging factor militating against effective landscape change studies especially in the developing countries where the standard technologies/facilities are either unavailable or insufficient. For example, in Nigeria it is very rare to find a comprehensively thorough research on the land use changes caused by either landslide, soil erosion or flooding due to poor data collecting and analyzing tools (Nwaogu et al. 2018).

Extrapolating results in time and space: It is obvious that landscape change studies and results are often peculiar in processes, purpose and contexts, scale and resolution, and material and methods used. This is because of the uniqueness of each landscape coupled with time disparities that make it difficulty in transferring findings achieved in one landscape to the other (Veldkam and Lambin 2001). For instance, severe soil erosion might be a primary cause of landscape changes in 'landscape A' but this might have several drivers (such as deforestation and increase in population) as remote causes. On the other hand, soil erosion might also be a principal agent for landscape changes in 'landscape B' but with different remote drivers (such as intensive agriculture, poor soil fertility, or climate change). Therefore, results from 'landscape A' might not be compatible with 'landscape B' context, and this will not yield meaningful solution, thus, becoming problematic in landscape studies. Another factor that militates against successful landscape studies is land ownership. This problem is specific in developing countries where vast land areas belong to either communities or individuals who detect what could be done on their landed properties. In this case, conducting any studies on land use changes becomes uneasy because the researcher (s) must convince the land owners with several proves why embarking on such landscape assessment is significant. And in some cases, the land owners are uneducated people, hence multitudes of negotiations including financial sacrifices are paid before performing any studies (Antrop 2005).

Connecting data of different qualities has been reported as one of the major problems confronting global landscape change studies (Bürgi et al. 2005). For example, as the drivers of landscape changes cut across natural and social sciences, integrating data from both fields becomes cumbersome. This is because (1) the researches are performed at different scales or resolution (Vogt et al. 2002), (2) natural sciences usually have georeferenced data which might be problematic with social science data, (3) researchers in the natural sciences prefer quantitative data and analyses whereas, their social sciences counterparts are more dependent on qualitative (Bürgi and Russell 2001; Vogt et al. 2002). Dearth of compatible data and funding have negative effects on landscape studies (Arsanjani et al. 2016). Landscape change assessment may be hindered when there are no data or when existing data are not compatible with data from other sources due to inappropriate resolution. The landscape change scientists are in dilemma of either considering socio-culture as a driver of landscape change or ignoring it as significant driver (Bürgi et al. 2005). This is because, socio-culture is one of the most complex factors of land use change and neglecting it leads to invalid results (Nassauer 1997; Naveh 2001). Several authors have affirmed the interwoven relationship and strong connection between the people and environmental change, and such as tight linkage cannot be separated in the study of land use change (Christensen1989; Magnuson 1990). Another factor that has been reported as limiting the success of landscape change studies is poor knowledge of advance and contemporary techniques and land use change models especially among most researchers in developing countries (Aring 2012).

3.4 Drivers of landscape changes

Driving forces of landscape changes, according to Burgi et al (2005) are described as the forces that induce discovered landscape changes and are prominent mechanisms in the progress and development of the landscape. Other authors referred these forces as keystone processes (Marcucci 2000) and pilot drivers (Wood and Handley 2001) of landscape changes. It is necessary to mention here that the pace, speed and magnitude of landscape changes are determined by the pace of technological advancement, cultural and socio-economic changes (Antrop 2005). Since the 18th century, rapidly significant changes especially due to elevated population and intensified urbanization restructured unique landscape features and this trajectory could be identified and understood in three periods/era (the Pre-18th century landscapes, the Landscapes of expanding industrialization and cities from the 19th century to the Second World War, and the Post-World war landscapes (Fig. 2)).

3.5 Types of driving forces

Though, many authors have reported the impacts of several factors as drivers of landscape changes, but these could be part of the five main types which were identified by Brandt et al (1999) including natural, socio-economic, political, technological, and cultural driving forces. Burgi et al (2005) and Plieninger et al (2016) further differentiated these five major drivers:

- The natural driving forces involve the physical parameters such as soil, climate, relief, water, vegetation characteristics, and natural interventions (swift or slow-acting) prevalence at respective study locations. The natural driving forces have also been known as ‘biophysical factors’ (Turner II et al. 1993; 1995) which are usually identified as ‘indirect drivers’ because they can induce land cover changes through climate change and they control the decisiveness of land use resource distributions (e.g soil fertility rate) (Turner II et al. 1995).

- The socio-economic driving forces are firmly attached to the prevailing economy. This is because human socio-economic demands are demonstrated in political policies and regulations, thus, strong bond is formed between the socio-economic and political driving forces.
- The culture undoubtedly has the most significant influence on landscapes. Or it could rather be said that landscapes play vital roles in the peoples' culture. In other words, culture constitutes and constructs landscapes, while in turn landscapes breeds, nurtures and preserves culture (Nassauer 1997).
- Technology as a driving force is often overlooked in many land use change studies, but it has substantial imprint on the landscapes. For example, the impacts of the ultra-modern market and smart city on the vegetation composition or transportation system can never be over-emphasized. Imagine the influence of either a multi-metro lines or tunnels on the settlement patterns. In fact, with time, technology might probably supersede other driving forces as agent of landscape changes (Kienast et al. 2004).

3.6 Characteristics of driving forces

The driving force of landscape change could be distinguished as having attributes of either spatial, temporal, and/or institutional scale of the system in consideration. For example, people in a given society in time will definitely react to economic situations, as mediated by institutional factors, which drive land cover changes (Lambin et al. 2001). Other authors on the other hand, have characterized driving forces of landscape changes under primary, secondary, and tertiary with the notion that driving forces have to be interpreted in fixed scales of explanations (Blaikie and Brookfield 1987). Primary driving forces as the key or immediate drivers of change in land use (e.g. deforestation); secondary driving forces as the intermediate drivers of change (e.g. soil erosion or climate change), and tertiary driving forces as the remote causes of change (e.g. population growth or policies). In addition, driving forces of landscape changes can be featured as intrinsic and extrinsic or intentional and accidental driving forces (Bürgi et al. 2005).

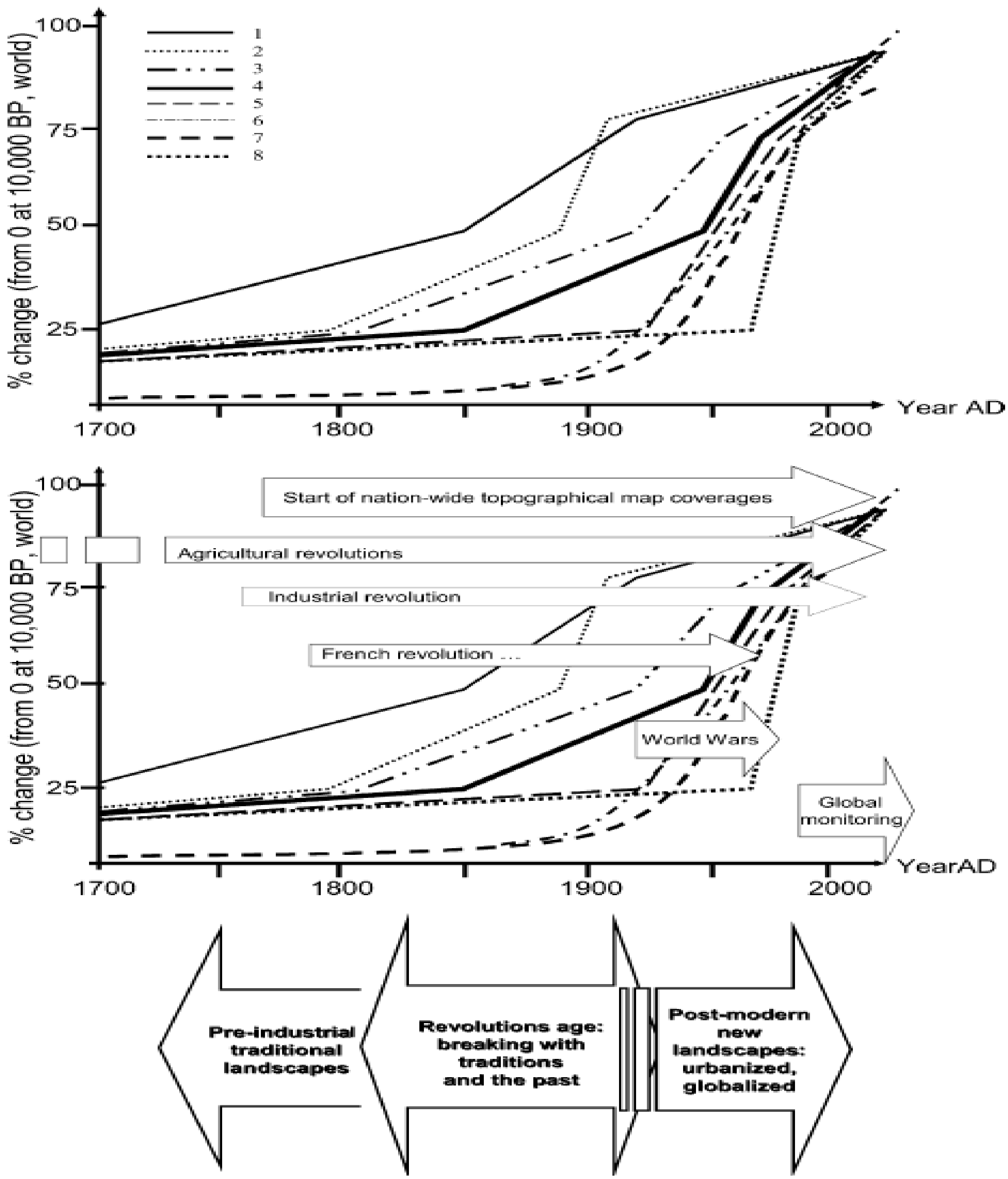

Fig. 2. Three major classified periods of landscape changes (adapted from Antrop 2005).

3.7 Landscape change driving forces: the theory and rationale

To satisfy their growing economic and social needs, the society device several means geared towards either adapting or manipulating both environmental and sociocultural phenomena for their welfare. This quest for humans' satisfaction has created complexity in the processes and forms of landscape changes which requires consolidated hypothesis and models linking the socio-cultural and ecological systems for sustainability. It is good to reiterate here that the land use system is significantly affected by various drivers at varying scales or resolution. For instance, the change in policy by a small village head to reduce fallow periods from 7 years to 4 years can remarkedly influence the land use pattern. On the other hand, at the regional level, the distance to the river, urban area or major highway could be the prime causation of the land use change and trend.

3.8 Landscape changes and driving forces: quantification of the relationships

A-three distinct approaches has been identified in quantifying the interactions between landscape change and prevailing driving forces by Bürgi et al. (2005) as:

- Theories and physical laws: this first approach attempts using theories and physical laws appraising the different relationships as directly on the prevailing processes.
- Empirical methods: the second approach employs empirical techniques including statistical analysis (linear regression, logistic regression, multinomial regression, or multivariate) in quantifying the defined models based on the past land use change information (Pijanowski et al., 2000; Serneels and Lambin, 2001). The challenges and critiques of this approach centers on the fact that the results are usually characterized by limited explanation because of the relatively small sample size and shot-term frame of the analysis (Hoshino, 1996; Veldkamp and Fresco 1997). Studies with long-term history of land use changes, produce more robust and stable explanations of the land use trajectory (de Koning et al. 1998; Hoshino 2001).
- Use of expert knowledge: this was identified as the third method to quantify the relations between driving forces and land use change irrespective of the geographical location. The employment of expert knowledge is mostly required in models such as Cellular Automata Markov Chain (MC), CA - MC Hybrid, Neural Networks, DINAMICA, SCENARIOS for

InVEST and GISCAME (Silva and Clarke 2002; Iacono et al. 2015; Harmáčková and Vačkář 2015; Fürst et al. 2010; Sponagel et al. 2005).

3.9 Land use change models' validation: justification and critiques

Validation (synonymous with verification) is the process of ascertaining that a software system meets certain specifications and that it fulfills its intended purpose. Validation of land use models is an indispensable concept in the applications of land use change models especially in the consideration of space-time dimension. Validation of land use change models is usually rooted on the juxtaposition of model results for a past time scenario with the presently existing changes in land use (Bürgi et al. 2005). This validation prompts the use of land use data for a different year than the data used in model calibration. The duration gap between the two years for which data are available should be sufficient to validly compare the observed and simulated changes. A set of scientists who gave credibility to model's validation are of the opinion that "validation of a land-use model is therefore not a process to test if a model is perfect, but an operation that assesses how well the model achieves the intended motive" (van Vliet 2013; Balci 1997; Jakeman et al. 2006).

On the contrary, there are many other scientists who are of the school of thought that land use models can never be validated (Konikow and Bredehoeft 1992; Oreskes et al. 1994). They consolidate their arguments by pointing out the following among others:

- Land use is and open system that is dynamics with constant changing elements and processes. Therefore, it is erroneous to demonstrate the truth of any valid theory, except for a closed system. For example, it is hypothesized that increase in human population will lead to increase in agricultural land area as to provide enough food. But this preposition is no longer valid in the present world because the real-world data reveals an increase in population, with required food without an increase in agricultural area due to technological advancement. This preposition was closed in initial situation, but was never closed for technological advancements. This supports that land use system like many other earth systems are not close but open.
- Most often, models are employed for simulations exceeding the calibration period and over a time-span that is far longer than the validation period. Hidden errors (which were not visible) within the short time span of the validation period could probably increase

rapidly leading to tangible contradiction in the experimental results. Besides, there is high probability that future circumstances will differ from those in the validation period.

In these contexts, it could be concluded that the validation (calibration or verification) of a land use model remains debatable. This therefore presents some constraints on the application of such models to either assess future land use changes, or changes in another area. It is ideal to emphasize that a successful validation signifies that under the given conditions, the model's changes simulation changes were adequately accurate. This constitutes impediments on the period for which extrapolations can be performed, as unpredictability and uncertainty soars with time. This further affirms that predicting "black swan events" or "unknowns" with a model might produce some questionable results (Makridakis and Taleb 2009; Pawson et al. 2011). In summary, the models should at best be applied in terms of what-if scenarios instead of as sink and hook approach.

4 Applications of some/selected GIS software in the study of landscape change: an overview

4.1 ArcGIS

ArcGIS like other GIS programs such as IDRISI has been severally applied in landscape change studies. These among others encompass; land use, agriculture, flora-fauna analyses, mining, transportation, urbanization, population, disaster management, health and security, utilities distribution, hydrology, soil and geomorphology, glaciers, and climate change effects.

For instance, ArcGIS was used by Brus et al. (2012) to examine the challenges associated with visualization of landscape heterogeneity of habitats. This showed that information entropy can be used to visualize uncertainties in the landscape structures. Additionally, it gives an explanation where uncertainties (transition zones as ecotones) may occur within a given landscape. In the analyses of the landscape fragmentation in selected locations of the Pannonian region of Czech Republic, ArcGIS was employed in in assessing landscape by mapping and computing the values of the entire studied area. The study concluded that the impacts of the landscape fragmentation could further enhance the susceptibility of the landscape for invasions of alien species and decline in hunting activities of indigenous species (Pechanec et al 2013). ArcGIS tools were applied to analyze the relations between agricultural landscape and ecosystems services in the Horňácko region, which extended to the White Carpathians Mountains Protected Landscape Area (Czech Republic). ArcGIS was a key geospatial tool used in this study. The landscape changes in the Carmel triangle-shaped mountain, Israel was also studied using ArcGIS devices. The result produced a quantitative method for measuring changes over a long period of time and which consequently promoted landscape planning in the region (Sonis et al. 2007). In Spain, Peña (2005 2007) used ArcGIS to examine the change in land use-cover and processes involved for 44 years. The authors found a significant decline in traditional agriculture and conversion to forestry or intensive croplands due to rural-urban drift. ArcGIS and multi-criteria system analyses have been combined as effective decision support technologies for the evaluation of landscape changes in Trkmanka stream catchment area, South Moravia of the Czech Republic (Pechanec et al., 2015). The result consolidated subsequent landscape studies as it concurred to the obtained outcomes of past landscape change studies (Hermann et al. 2014; Gorsevski et al. 2013; Segura et al. 2014).

Other studies where ArcGIS was used in landscape change analyses were in the fields of ecosystem dynamics (Ranson et al. 2001; Pechanec et al. 2014), forest and vegetation (Bucini and Lambin 2002), habitat mapping (Oindo et al. 2003; Vogiatzakis 2003), natural hazards assessment (Pechanec et al. 2011) and sand dune encroachment (Ghadiry et al. 2012).

4.2 Idrisi GIS

Idrisi GIS especially with its Land Change Modeler (LCM) extension has been widely applied in landscape change analyses (Eastman 2009; Václavík and Rogan 2009). The software has been used to assess landscape changes as influenced by tropical rainforest deforestation (Koi and Murayama, 2010), urban growth (Aguejdad and Houet 2008), soil erosion (Gaucherel and Houet 2009) and habitat fragmentation (Gontier et al. 2009). Idrisi GIS has also been applied in the predictive land use change modelling of Litovelské Pomoraví PLA, Czech Republic (Pechanec 2005) and Tehran metropolitan area (Arsanjani 2011). Several other authors have studied landscape changes by examining the impacts of climate change, population growth and urbanization on land use changes in different geographical regions and times frame using Idrisi GIS (Faleiro et al. 2013; Brook et al. 2008; Maclean and Wilson 2011; Mantyka-Pringle et al. 2011; Sala et al. 2000; Thomas et al. 2004; Pereira et al. 2010; Brook et al. 2008; Asner et al. 2010).

4.3 ERDAS-Imagine

Many other studies have employed ERDAS-Imagine in landscape studies (e.g. Khromykh and Khromykh, 2014; Butt et al. 2015; Jiang et al. 2013; Hazarika et al. 2015; Mishra et al. 2015; Gebreslassie 2014; Petersen et al. 2005; Zhang et al. 2011; Gandhi et al. 2015). In studying the effects of flooding on landscape, report attested that Sterling Geo used the ERDAS Imagine Spatial Modeler to rapidly extract the areas of flooding captured by Landsat 8 in UK. The researchers analyzed water and vegetation indices data by integrating the ERDAS GIS tools which produced the results that enabled adaptation and mitigation of such natural menace on the landscape (Winter 2015). On the other hand, Khromykh and Khromykh (2014) analyzed the spatial structure of Tom valley landscapes and their changes due to natural and anthropogenic drivers from the end of XIX century by combining ERDAS-Imagine with ArcGIS. The scientists did not only generate a robust geodatabase of the "Tom river valley" but also revealed the hidden trends of landscape dynamics in different parts of the valley.

In Pakistan, ERDAS-Imagine and its algorithms were reportedly applied in the land cover/land use change detection in Simly watershed. The result revealed a significant shift from Vegetation and Water cover to Agriculture, Bare soil/rock and Settlements cover, which shrank by 38.2% and 74.3% respectively (Butt et al. 2015).

In the Indian Upper Brahmaputra floodplain, the land-use changes driven by river dynamics along two tributaries was evaluated using ERDAS-Imagine. The study reported significant land-use change with respect to increase in settlement and agriculture and a decrease in the grassland. The discovery concluded that the area affected by erosion–deposition and river migration comprised primarily of the agricultural land (Hazarika et al. 2015). Still in Upper Brahmaputra floodplain, another study developed a methodology to identify the suitable landscape zones for the development of the organic farming using ERDAS, QGIS and Analytical Hierarchy Process (Mishra et al, 2015). Similarly, in Africa, Gebreslassie (2014), applied for the land use-land cover dynamics evaluation in Huluka watershed of the Central Rift Valley, Ethiopia between 1973 – 2009. The findings helped the concerned agency to ameliorate the rapid degradation of vegetation on the Huluka watershed. Another report where ERDAS was used in the assessment of a willow-dominated riparian area located in southeastern Oregon-USA has been in scientific record (Petersen et al., 2005). ERDAS Imagine was intensively used in the quantitative analysis of the temporal changes of land use characteristics between 1988-2004 in Beijing Hanshiqiao Wetland Nature Reserve (Zhang et al. 2011). In the North-central Nigeria, ERDAS GIS was employed to study the rocky landscape of Wanba and environs and the study successfully produced a modified geological map of the area (Ogunmola et al. 2015). Using ERDAS, the quantification of the spatio-temporal patterns of settlement growth in a metropolitan region of Ghana successfully revealed that built-up areas drastically increased in the last 13 years (Acheampong et al. 2017). Other popular areas where ERDAS Imagine was actively applied included wildfire risk monitoring (Pueblo Bonito 2013).

4.4 Manifold GIS

There have been large scientific reports on the applications of Manifold System in Landscape analyses in different parts of the world (Bertaglia et al. 2007; Haklay 2010; Raes and Steege 2007; Tang and Wong 2006; Mottet, et al. 2006; Taillefumier & Piegay 2003). For instance, an analysis which focused on eight countries of the European Union (Austria, Germany, Spain, France, Greece, Italy, Portugal and the United Kingdom) defined geographic distribution and relative marginality of livestock in terms of the general landscapes using Manifold System and Idrisi (Bertaglia et al. 2007). On the other hand, Mottet (2006) evaluated the agricultural land use change and its drivers in mountain landscapes focusing on the Pyrenees. Manifold System was one of the key GIS software tools which enabled the image processing and classification used in this study. In a similar study in one of the highland regions of Europe, a multivariate GIS-based approach including Manifold System was applied to two municipalities in the Southern French Prealps to ascertain the current land use changes in pre-alpine Mediterranean mountains, and also in volunteered geographical information Haklay (2010).

4.5 MapDotNet

ISC's MapDotNet has been applied in many areas of land use-land cover such as agriculture, transportation, forestry, telecommunications, urban planning, social amenities and facilities management. In the USA, the City Transportation Agency established a project known as 'ITS-Powering Intelligent Traffic Systems' where MapDotNet GIS software was used in the visualization and analysis of complex street networks and signal infrastructure datasets (http://www.mapdotnet.com). The Mexican Mining and post-mining landscape programmes are typical research were Edge Wall Multi-touch Teknol tool that uses the MapDotNet UX WPF map control and the MapDotNet UX Web Services were employed to achieve landuse-cover restoration for the sustainability in Mexico. It is of important to state that forestry and forest management in the developed countries especially, North America has revolutionized through the introduction of cutting edge timber management using ISC's MapDotNet software (http://www.mapdotnet.com). Mechanized Agriculture has been driven by precision rearing-cultivation of plants and animals to boost food supply. In the USA, ISC's MapDotNet is improving husbandry, agro-chemical application and disease tracking (Imager Software, Inc. –ISC, 2014). In addition, the City of Richmond uses MapDotNet UX and Bing Maps for Enterprise to visual property, zoning and land use data. This new technology has not only increased their daily profit but has also promoted the efficiency of their tasks.

4.6 MapInfo

The application of MapInfo in landscape (including land use-landcover) and other environmental and human related studies is no longer a mirage across the continents. There are evidences of empirical researches that have recently given great popularity to MapInfo GIS (Gemitzi and Tolikas 2007; Alaeddinoglu and Can 2011; Namdeo et al. 2002; Palo and Kikas 2003; Nkambwe and Arnberg 1996). For example, in the fields of urbanization and intensive agriculture Lundström-Gilliéron and Schlaepfer (2003) examined the dynamics of a typical landscape for selected Western European regions at five chronosequential decades(1950s-1990s). This study further attempted to investigate the decrease of the brown hare population with respect to the observed changes in the landscapes using MapInfo GIS technology. MapInfo was also used in another study which identified, assessed and classified the natural-based resources with vital potential for tourism development in the western part of Lake Van basin, Turkey (Alaeddinoglu and Can 2011). In Africa, the integration of MapInfo and IDRISI have been employed to analyze land use competition in the Tlokweng area of Gaborone, Botswana. The modalities developed by this research have progressed towards allowing the rent of urban land to operate on the rural-urban fringe hence becoming useful in reducing resistance to the expansion of the village and discouraging in-filling that increases congestion (Nkambwe and Arnberg 1996). Other areas where MapInfo GIS had significant roles included landuse-environmental modelling of the Yermasogia's aquifer of Cyprus in the coastal region of Europe (Gemitzi and Tolikas 2007), in conservation of potential NATURA 2000 areas in Estonia and in prediction of future urban sprawl (Palo and Kikas 2003).

4.7 ILWIS GIS

ILWIS GIS is one of the top open source GIS software that has been widely applied in landscape studies (Akwei et al. 2013; Hengl et al.2009; Hendrikse 2000). As the knowledge of nature conservation values of agricultural land provides a useful input to land use planning, several research works have been conducted in this area. For example, in Romania ILWIS software was used to landslide vulnerability and effects on the landscape (Armaş et al. 2045). In Sudan Africa, the relationships between environmental changes and desertification effects on landscape changes were analyzed using the ILWIS (Ali and Adam 2003). Other recorded successful applications of GIS in landscape change assessment were observed in the use of QGIS, GRASS, SAGA, GeoDa and MOLUSCE (Neteler 2012; McGarigal and Marks 1995; Rocchini et al. 2013; Wehburg et al. 2013; Piha et al. 2007; Cassettari 1993; Anselin, 2004, 2005; Wise et al. 2001).

5 Time-space analyses in GIS

5.1 Analysis

Analysis means to breakdown something into different parts, pieces, reasons, or steps and examine how those disintegrated parts are related to each other. It is the process of disintegrating a complex concept, topic or substance into smaller parts to gain a better understanding of it (https://en.wikipedia.org/wiki/Analysis). Others define analysis as the process of breaking up a concept, proposition, linguistic complex, or fact into its simple or ultimate constituents and concise. In geography, geographical analysis or Spatial analysis or Spatial data analysis is being used. Therefore, spatial or geographical analysis is defined as a distinct analysis that focuses on detecting patterns, exploring and modelling relationships between such patterns in order to comprehend the direct and remote processes accountable for the observed patterns. Thus, spatial data analysis highlights the role of space as a potentially principal explicator of socio-economic systems, and tries to strengthen understanding of the working and representation of processes, patterns, space, and spatial phenomena (Fiscer 2001 2006). Geographical or spatial analysis is a new research paradigm that gives a special set of approaches and procedures for analyzing occurrences that are located in geographical space. Spatial analysis involves spatial modeling, which includes models of location-allocation, spatial relations, spatial selection and search, spatial optimization, and space-time.

5.2 Modelling

Modelling in lay man's definition, is a means of comprehending the challenges associated in creating something. It is about structural representations of features in the 'real world' and giving room for innovations to be investigated. Modelling is central to every activity in the process for building or constructing an artefact of some form or other. In effect, a model is a way of expressing a unique view of a distinguishable system of some kind. Model can also be seen as an abstraction, which permits individuals or groups to focus on the most relevant of a (complex) problem by keeping out irrelevant details. Since there is a limit to how much a person can understand at any one time, models are built to promote in activities such as the development of sophisticated software systems. In geography, scholars often refer to classic definition by Haggett (1965) which defines modelling as "a simplified version of reality, built in order to demonstrate certain of the properties of reality". Therefore, it could be summarized that modelling is a practice established for thorough understanding of the broad interacting system encompassing all human, socio-economic and physical environment within the earth's surface.

5.3 Prediction

Prediction is a statement or proposition about the future: what might occur based on past and/or present observations. Therefore, **predictive modelling** could be defined as the process of applying known results to create, process, calibrate and validate a model that can be used in forecasting future conditions outcomes.

5.4 Classification of models

Surprisingly, model or modelling has no universally acceptable classification as all are suggested typologies. This might be attributed to it definition roots where several meanings and functions have been ascribed to model by various scholars. The concept 'model' has been applied or described in a form of diverse contexts which has made it cumbersome to define even the vast classes of usage without ambivalence. However, some general classifications or types include (Chorley 1964):

i. Apriori and Aposteriori Models;

ii. Descriptive and Normative Models; and

iii. Hardware and Software Models.

Aposteriori is used when the model is developed to represent the theory while, apriori' is based on the type of procedure used in applying models in scientific explanations. For instance, in some scenarios, the model is developed in advance as to represent a proposition, this can be referred as apriori. Descriptive and Normative Models: The 'Descriptive' models are behavioral and socially-oriented and suggesting the existence of phenomena in reality, while the 'Normative' models elaborates how they ought to be based on certain specified conditions. Hardware and Software Models: The 'Hardware' models are based on the use of some visible devices or concrete material; e.g. physical objects, planning or defense project models whereas, the non-physical objects, conceptual, symbolic or features are software models (Chorley and Haggett 1967). The software models could be statistical or geographical or land use models.

On the other hand, Longley et al. (2011) categorized models as static models, Individual and aggregate models, cellular models and cartographic models. The authors defined static models as set of models that represent a system at a single point in time. For example, the Universal Soil Loss Equation (USLE): $A = R*K*LS*C*P$ [where A represents the predicted erosion rate, R stands for the Rainfall and Runoff factor, K denotes the Soil Erodibility factor, LS is the Slope Length Gradient factor, C is the Crop/Vegetation and Management factor, and P is the support Practice factor]. The Individual and aggregate models are models used when it is impossible to model the behavior of every individual element in a system. Example is Agent-based models. The cellular models represent the surface of the Earth as a raster, each cell having a number of states that changes at each iteration by the performance of specific rules (e.g. Markov chain, Cellular automata). The cartographic models included map algebra which are used in the transformation of many cells to single whole.

In addition, another scientist has attempted classifying models in a broader context which is reported to be relatively the most extensive and complete classification. This classification work of Harvey (1969) consists of three major categories with sub-classes as follows:

1. Natural Analogue System Model

a) Historical Analogue

b) Spatial Analogue

2. Physical System Model

a) Hardware Model

(i) Scale (Iconic)

(ii) Analogue

b) Mathematical Model

(i) Deterministic

(ii) Stochastic

c) Experimental Design model

3. General System Model

a) Synthetic

b) Partial

c) Black Box

5.5 Space-time analysis in GIS: theory and rationale

Space-time analysis has not only paved way in modern geography, map making and GIS, but has come to revolutionize the discipline. The introduction of space-time in GIS has given it a new definition. GIS is used to be defined as a computerized device of maps, performing operations such as overlay and buffers that could be comprehended in physical terms, rather than as a device of large collections of geographic facts that might or might not have been organized into maps. But the full incorporation of space-time has lifted GIS over the horizon in terms of definition, concept, context and applications. space-time analysis in GIS has resolved most of the long-standing critiques of GIS that GIS is more concerned with geographic fact relative geographic knowledge (Goodchild 2013). Geography as a discipline that cuts across diverse fields (such as human, social, economic, political, cultural and physical) has been finding it difficult to integrate all the fields and all their parameters in any geographical studies. For example, a combination of the knowledge of with knowledge of landscape ecology is meaningless without the context provided by space and time, and the interactions that exist between socio-economics and ecological variables at a place in time, in a coupled natural–human system. As at about 6-7 decades ago, it has been impossible for such valid integration to be achieved in geography. Today, space-time in GIS has provide a formal substantiation of the argument that geography is the integrating discipline (whether of sciences, social sciences or arts) (Goodchild 2013). Today, with the advent of space and time analysis, GIS architectures have progressed far beyond the monolithic systems of the 1980s into the networks of distributed services represented by cyberGIS. According to Richardson (2013), the space-time innovation has functioned as a core change agent in geography, cartography, GIS and many related fields, greatly reorganizing conventional relationships and structures, expanding research horizons, and transforming the ways geographic data are presently collected, mapped, modeled, and used, both in geography and in science and society. Historical GIS will never disregard and must grapple to work within and accept the benefits of its acquired concept of time and space (Richardson 2011). With this new development, future time GIS work is minimally confined, in the sense that its temporal and spatial constructs are not necessarily compelled by past concepts or practices and can more unreservedly be designed based on researcher's or modeler's needs.

The framework of time geography (Hägerstrand 1970) prompts the understanding of the association between the spatial identities of individuals and intra-area accessibility, as well as clarifying the latter. In this respect, four primary concepts can be identified (Fig. 3): the space-time path, the space-time prism, the potential path area (PPA), and the potential path tree (PPT). The space-time path represents an individual's true spatial identity; it can be perceived in form of progressive movements and stationary activities (Neutens 2011). On the contrary, the space-time prism never relates to real behavior, but reveals individual travelling likelihoods by creating a prism incorporating all feasible space-time paths (Neutens 2008). The shape of the prism relies upon three types of restraints: capability restraints, connected to an individual's physical impediments and potential; coupling restraints, which acknowledges that individuals require to ration portion of the space-time path with other features, such as fellow humans or materials by which they relate; and authority restraints, which refer to policies, laws and other rules that deter reachability to such areas as NP core zones (Hägerstrand 1970).

5.6 Overview of selected studies on space-time analysis in GIS

Since the inception of space-time in GIS, many scholars in the field of geography, cartography, GIS, ecology and other science and social science disciplines have fully embraced the new paradigm. It has brought successful results to many scientists in the used to be difficult research areas; hence, new grounds are daily broken in the contemporary scientific fields. In this section of the thesis, some of the studies shall be discussed, though more consideration will be given to the fields related to this work.

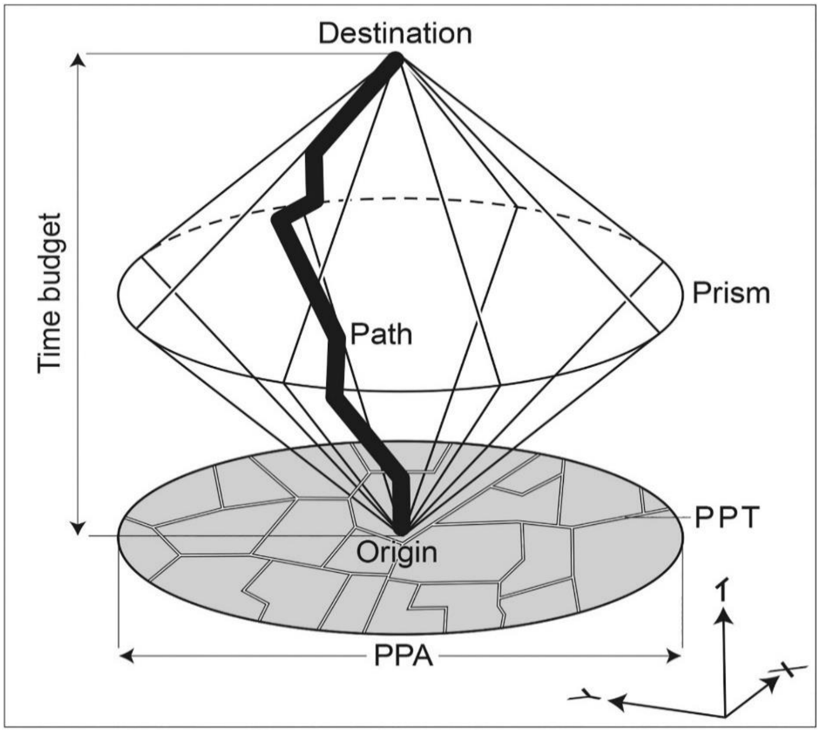

Fig. 3. Geographical time concepts.
Source: adapted from Neutens et al. (2008).

Social scientists like their science counterparts have also identified the relevance of temporal processes to spatial phenomena and patterns. For instance, in human geography, Massey (1999) highlighted a consolidated understanding of space and time, and conception of cities as open space-time potentials of social interactions. The author further proposed a re-thinking of the meaning of space and history as a process of "the continuous creation of novelty," in contrast with oversimplifications of space as static (Massey 1999). There has also been reports on spatio-temporal representation in GIS and measurement theories of time geography (Couclelis 1999). In environmental sociology, Elliot and Frickel (2015) successfully located patterns of urban industrial polluting sites in area using long-term iterative interactions between social and biophysical features.

As one of the Natura 2000 areas, Goričko Landscape Park in Slovenia witnessed tremendous improvement in its agri-environmental climate schemes as space-time analysis was used to integrate and analyze land use and socio-economic related data of the area. The result is significantly contributing to farmers active participation in the schemes which enhances sustainability (Natalija et al. 2018). In Lefka Ori, Crete, Greece, space-time analysis was integrated with ArcGIS tools such as fuzzy mapping and geo-statistics in the landcsape improvement which in turn stimulated the understanding of species and plant community spatio-temporal interactions (Vogiatzakis 2003). In a recent study which cut across five major cities in Europe (e.g. Warsaw, Budapest, Prague, Bucharest and Sofia), space-time GIS was used to analyze and understand the transformations which have occurred in the urban configuration as well as the future perspectives of the inertias of change in such cities (Garcia-Ayllon 2018).

The developing countries were not left out in exploring the advantages of space-time analysis in GIS. For example, the land cover changes between 2000-2010 in the Middle East (including Iran and neighboring countries) were evaluated and predicted the future land cover patterns for 2030 considering the historical changes (Arsanjani 2018). The study found significant changes from most of land use to bare lands with grasslands and shrublands indicating the most loss. In East Africa (Rwanda), space and time dynamics of ecosystem services of forests and other land use were assessed (Rukundo et al. 2018). The authors revealed a drastic loss in ecosystem services due to more than 40% loss of forest area to agriculture and they emphasized that population pressures should not be ignored if sustainability is it be met. On the other hand, in the Lacandon tropical rainforest, southeast Mexico, Navarrete-Segueda et al (2018) employed space-time coupled with GIS to quantify forest-soil quality including C stock in the different landscape units; even when such stocks are difficult to assess in such heterogeneous landscapes where the soil properties and the forest structure and functionality vary in space and time. The study observed that Carbon pools of vegetation and soil in tropical rainforest depend on soil properties at the landscape-scale. Similarly, in another developing country, Amazon (Brazil), the space-time dynamics of deforestation and fragmentation, complexity of the landscape structure as well as the current and historical land use and biophysical variability of the region were analysed (Delgado et al. 2018).

Other studies with the applications of space-time analysis of landscape using GIS include: land use change effects on soil loss rates in Calabria region of Italy (Conforti and Buttafuoco 2017), mountain landscape of Berchtesgaden National Park, Germany (Schamel and Job 2017) and Corcovado National Park (Carlos et al., 2018), coastal landscape, North Carolina (Tateosian et al. 2014), Forested landscapes, Canada (Krougly et al. 2009), mining and post-mine (Coyan et al. 2017; Chen and Tan 2008), and Yellow River landscape (Tami and Gary 2018). Furthermore, similar related studies have been reported in the areas of urbanization and transportation (Vandenbulcke et al. 2009; Roman et al. 2018; Buyantuyev et al. 2010).

5.7 Methods for analyzing past landscape changes

Several methods have been adopted in analyzing historical landscape changes in GIS, but this work will briefly discuss only few of the methods such as overlay operation, transition matrix.

Overlay

Overlay in GIS operation has been described a process that superimposes multiple data sets (which represent different themes) together for the purpose of distinguishing possible interrelations between them (Clarke 1997).

Transition matrix

Transition matrix (also known as stochastic matrix or probability matrix or substitution matrix, or Markov matrix) is a square matrix used to describe the transitions of a Markov chain with each of its entries being a nonnegative real number representing a probability (Gagniuc 2017).

Confusion matrix

Confusion matrix (also known as error matrix) is a matrix table that summarizes the relationship existing between two different data/image and is often applied in land use change studies. From a confusion, the overall accuracy, producer's accuracy, omission errors, user's accuracy and commission errors of images could be achieved (Jensen 2005).

Cross tabulation matrix

Cross tabulation matrix (also referred to as contingency table) is a means that quantitatively permits one to compare the relationship between two or more parameters or images. It is one of the validation methods.

Kappa statistics

Kappa statistics is one of the important methods used in accuracy assessment during image classification processes. It serves as a validation technique because it could be used in comparing an observed accuracy with an expected accuracy (random chance) (Jensen 2005).

Conversion resistance

Conversion resistance is one of the land-use type specific settings that is used to measure or determine the temporal dynamics of the simulation processes (Verburg 2015).

Simulation

Simulation in land use can be defined as the manipulation of a specific land use model so that it operates on time and space to constrict it, thus aiding the modeler to analyze, understand and interpret the interactions that might not be ideally visible due to their separation in time and space (Bellinger 2004).

Validation

Validation can be defined as the process of verifying that a software system satisfies certain specifications and that it fulfills its intended purpose. It is the third stage in modelling process after calibration (when model is tested using several specific parameters and context such as training periods or dates) and simulation. Based on model outputs and aims, validation of simulation maps can be either hard or soft-classified (Pontius and Cheuk 2006). Some validation techniques apply to both types of map (e.g. cross tabulation matrices and indices, congruence of model outputs), whereas others are specific to only one. To validate hard-classified simulation maps methods such as land use-cover change indicators, feature and pattern recognition and error analysis are employed while, for soft-classified maps or other data, methods such as receiver operating characteristics (ROC), area under curve (AUC) (Mas et al. 2013) or ANOVA and post-Hoc are used. On the other hand, DEM accuracy in land use studies can be assessed using statistical methods (range, mean, standard deviation, RMS error, average kriging), spatial visual methods (profile analysis and compare with reference data from GPS, hill shade observation), and non-spatial visual methods (histogram, spatial autocorrelation which is related to visualization). Analytical hierarchy process (AHP) is also important because it can also be termed as a validation tool which is applied for determining or calculating factor (criteria) weights in multi-criteria evaluation models.

6 Methods of Landscape Change Prediction

In this section of the paper, the review of the spatially explicit landscape change prediction methods which are primarily focusing on the land use change models. The use of geospatial and statistical methods has recently become popular in landscape studies including Linear regression, Logistic regression, Multinomial regression, Markov chain, Cellular automata, The Hybrid (MC-CA), Artificial Neural Network, Agent-based, and others. The brief overview of them have been summarized covering the geostatistical models (Table 1), their implementation and output (Table 2), their application software, development, capabilities and input (Table 3), and their strength and weakness in landscape/land use change predictions (Table 4).

6.1 Regressions models

Regression analysis is a vital statistical method used to investigate the association of a dependent variable with one or more independent variables. More complex methods of regression exist, which are intended for different types of dependent variables and data structures. Regression Analysis and its major types have been widely used in Land use- land cover change modeling (Table 1). *Linear regression* is a model that estimates the coefficients of a linear equation, involving one or more independent variables, that best predict the value of the dependent variable.

Table 1. Comparison of the regression/statistical models used for landscape change prediction

Regression Models	Dependent variable type or data structure	Application land use class/type & examples
Linear regression	Continuous	Vegetation: Weiss et al. (2001); Settlement: Chen (2002); Urban growth: López et al. (2001); Agriculture: de Wolff et al. (2000).
Logistic regression	Discrete bivariate	General Land use: Verburg, et al. (2004);
		Agriculture: Xie et al. (2014);
		Coastline assessment: Fasona et al. (2011). Ecosystem services: Serneels and Lambin (2001). Vegetation and deforestation: Schneider and Pontius (2001).
Multinomial Regression	Discrete multivariate	Deforestation and agriculture: Mertens et al. (2002)
		Agriculture: Speybroeck et al. (2004)
Ordered Logit/probit	Discrete ordered	Transport and deforestation: Chomitz and Gray (1996).
Tobit Analysis	Censored continuous	Forestry and Agriculture: Chomitz and Thomas (2003)
Simultaneous regression	Interdependent relations	Soil: Ben-Dor and Banin (1995)
Multilevel models	Hierarchically organized data sets	Agriculture & Urbanization: Qian et al. (2010).

Linear regression is a frequently used technique; however, in LUCC modelling, this regression is less popular because linear regression can only be applied for continuous dependent variables.

Instead, logistic or multinomial regression is used, because land use is normally expressed as a discrete variable. An exception is NDVI data, which range between -1 and 1 and belong therefore to continuous data. Linear regression can also be used to derive input data, e.g. trends of population growth out of census data, or for validation. In linear regression analysis, it is possible to test whether two variables (or transformed variables) are linearly related and to calculate the strength of the linear relationship if the relationship between the variables can be described by an equation of the form $Y = \alpha + \beta X$. *Logistic regression* deals with the estimated probability of the event Y (the dependent variable) based on independent variables (X), the occurrence of the phenomenon can affect Y. The variable Y takes only the values 0 and 1, where 0 indicates that the variable did not occur, while 1 indicates that the variable occurred (e.g. occurrence or non-existence of buildings). This denote a vector of independent variables as x = (x1, x2, ..., xn) and a dependent variable as y = g (x) = β0 + β1x1 β2x2 + + ... + βnxn where βi are coefficients. Logistic regression model uses CLUE including CLUE-S or Dyna-CLUE respectively (Pechanec 2014). *Multinomial logit models* are used for the case of a dependent variable with more than two categories. This type of regression is similar to logistic regression, but it is more general because the dependent variable is not restricted to two categories. Each category is compared to a reference category, e.g. all types of forest conversion are compared to the stable forest category.

Artificial Neural Networks (ANN) and *GISCAME* are also subcategories of empirical geospatial statistics. ANN models require formal statistical training to develop and can implicitly detect complex nonlinear relationships between different LULC types. ANN can be developed using multiple different training algorithms. A major limitation to ANN application in landscape change prediction is that it is prone to overfitting. GISCAME on the other hand was coined from GIS as geographic information system, CA for cellular automaton, ME representing multi-criteria evaluation and was formerly called “Pimp Your Landscape”. It considers the landscape as an integrative layer for interactions between different land use types, land users, and ecosystem processes, which contribute to the provision of ecosystem services (Fürst et al. 2010). GISCAME is based on three methodological approaches namely; cellular automaton (modified), geographic information system, and multi-criteria evaluation.

6.2 Markov chain (MC)

Markov chain is a probabilistic state-transitional model with LULC at time (t +1) and strictly a function of LULC at time (t). In this model, the transition rules for any given LULC class/type are dependent on the historical transition probabilities which are independent from status or dynamics of adjacent cells.

6.3 Cellular automata (CA)

Though CA is a spatio-temporal extension of the Markov transitions models yet, can function as a state-transition model with neighborhood component. The transition rules of CA are defined by the current state of a cell, as well as by status of neighboring cells. Several general parallel CA-based land use simulation systems have been developed for users to implement parallel CA applications and in the operating background of CA. Examples include the cellular automata environment for systems modeling (CAMEL) and cellular programming environment (CARPET); SLUTH (slope, landuse, exclusion, urban extent, transportation and hillshade) model, formerly called the Clarke Cellular Automaton Urban Growth Model; LEAM "Land use Evaluation and Impact Assessment Model"; duo - Urban Evolution Dynamic Modelling (Batty et al., 1999); DINAMICA model or model METRONAMICA, and Dynamic Urban Evolution Model (DUEM) (Heppenstall et al. 2012). The primary limitation of CA falls on the difficulty in the implementation of the transition rules especially where there are no existing standard techniques to define those rules. However, the development of Multi-Criteria Evaluation, and fuzzy logic has been used to resolve the challenge.

DINAMICA EGO (hereafter DINAMICA) uses transition probability maps that are based on the weight of evidence and genetic algorithm methods. These maps simulate landscape dynamics using both Markov chain matrices to determine the quantity of change and a cellular automata approach to reproduce spatial patterns. DINAMICA has been applied to a variety of studies, such as modeling urban growth, tropical deforestation from local to basin-wide scales, and fire regimes (Soares-Filho et al., 2002).

6.4 The CA-MC models

The integration of CA-Markov promotes the transition probabilities of one pixel to be a function of neighboring pixels. The combinations of CA-Markov tools have been used to resolve most of the challenges of integrating the natural and human variables in land use change forecasts. CA model is affected by neighborhood type, neighborhood size and cell size parameters, the hybrid has helped in resolving these problems.

6.5 Land Change Modeler (LCM)

Land Change Modeler (LCM) is an innovative land planning and decision support system that is fully integrated into the TerrSet software. LCM as typical tool for simulating and improving Ecological Sustainability promotes the modeling of land use changes. The LCM was first introduced to IDRISI 15.0 (Andes product) in 2006. Now LCM operates in IDRISI Selva 17.0 as one of many models for landscape and environmental modeling. Model LCM also works as an extension to ArcGIS software from ESRI. Extension is available for ArcGIS version 9.3 to the latest version of ArcGIS 10.3 (Pechanec 2014). Land Change Modeler simplifies the complexities of change analysis with an automated, user-friendly workflow. Land Change Modeler allows you to rapidly analyze land cover change, empirically model relationships to explanatory variables, and simulate future land change scenarios. LCM like other models has unique features which make it important in landscape and land use change projection (Table 2 and Table 4).

6.6 Agent-based modeling (ABM)

Agent-based modeling (ABM) also known as 'agent-based systems' (ABS) or 'agent-based modeling and simulation (ABMS)' is a natural method for describing and simulating a system composed of real-world entities especially when using object-orientated principles. Modeling with agents is more related to 'reality' than other modelling approaches. Agent-based simulations provide an opportunity to represent and test social theory which cannot easily be described using mathematical formulae. Modeling using agents has its roots in artificial intelligence and a new approach for modeling systems, working with so-called 'Agents' (Pechanec 2014). Agent is real (living or inanimate) or abstract object capable of managing him/itself and his/its surroundings and able to communicate or interact with other agents (Verburg et al. 2004). Based on interactions with the environment and with others, agents are able to make decisions which in most cases consequently change their behavior. ABM recognizes and attempts to model the role of human policy-making in landscape change. ABM assumes that agent influences landscape and land use change in space and time. In ABM, landscape and land use trends emerge from interactions between human and natural processes. It is pertinent to note that in implementation, most studies used *genetic algorithms* which based on the 'survival of the fittest principles' to modeled Land use change while integrating ABM and GIS (Heppenstall et al. 2012). ABM has more advantages than weakness (Table 4) and has been widely applied in the predictions of landscape and land use change (Table 2).

6.7 The CLUE model

The model CLUE (Conversion of Land Use and Its Effects) is a dynamic simulation model using empirically derived relations between landscape/land use change and driving forces from cross-sectional analysis at multiple scales (Verburg et al. 2004). CLUE was developed in 1996 in the Netherlands followed by transformation to CLUE-S and dyna-CLUE. The model was designed for continental and national use. Because of the vastness of the studied area CLUE model worked on the principle of relative distribution of land cover in the pixel. The model produces better results at larger scales (e.g continental) compared to smaller scales (e.g. local). CLUE was developed to simulate land use change using empirically quantified relations between land use and its driving factors in combination with dynamic modeling. The model differs from most other empirical models because it gives the possibility to simulate multiple land-use types simultaneously through the dynamic simulation of competition between land-use types (Verburg et al. 2004).

6.8 Scenarios for InVEST (Integrated Valuation of Environmental Services and Tradeoffs)

Scenarios for InVEST is a product of The Natural Capital Project's vision geared towards bringing together the people and institutions to incorporate the values of WWF, NCO organizations and ecosystem services into decision making for lasting sustainable development. It is out of these precepts that this Primer model "Scenarios for InVEST" was formed. The scenarios were developed using a combination of a spatially explicit land-use and cover change (LUCC) model and information on land-use plans and permits. The model aimed to combine information on historical trends in land-cover change with available spatial planning data. It is one of the newest Landscape change methods which creates maps from LULC using developed scenarios (Table 3).

Table 2. Comparison of land use change models: Implementation and output

Model and Algorithm	Historical development continuation	Data Driven	Land suitability	Expert knowledge combination	Neighborhood relationship Result	Actor relationship result	Application Examples
Statistical-based (e.g. regressions)	Feasible	Yes	Feasible	No	Feasible	Feasible	Vegetation (Schneider and Pontius, 2001); Agriculture (Xie et al. 2014); Coastline studies (Fasona et al. 2011).
Cellular Automata (CA)	Consistent	Yes	Feasible	Yes/No[1]	Consistent	Unlikely	Landuse-cover (Silva and Clarke 2002); wildfire propagation (Clarke et al. 1995); Transport (Benjamin et al. 1996).
Markov Chain (MC)	Consistent	Yes[1]	Unlikely	Yes/No[1]	Unlikely	Unlikely	Urban planning (Weng 2002); Landscape (Turner 1987); Transport (Iacono et al. 2015); Agriculture & forest (Opeyemi 2006).
CA - MC Hybrid	Consistent	Yes[1]	Feasible	Yes/No[1]	Consistent	Feasible	Land use change (Silva and Clarke 2002); Urban growth (Wang 2001).
Agent-based	Feasible	Yes	Feasible	No	Feasible	Consistent	

							Energy & climate change (Zhang et al. 2011; water management (van Oel et al. 2010).
Neural Networks	Feasible	Yes[1]	Feasible	Yes/No[1]	Feasible	Feasible	Land transformation & model (Pijanowski et al. 2012).
CLUE	Consistent	Yes	Feasible	No	Feasible	Feasible	Agriculture & forestry (Veldkamp and Fresco 1996).
LCM	Consistent	Yes	Feasible	No	Consistent	Feasible	Nature Reserve (Malach 2009); Settlement (Indrova and Kupkova, 2015).
GEOMOD	Feasible	Yes	Feasible	No	Feasible	Unlikely	Watershed (Benešová 2008);
DINAMICA	Feasible	Yes[1]	Feasible	Yes/No[1]	Feasible	Unlikely	Forestry & Agriculture (Soares-Filho et al. 2002);
SCENARIOS for InVEST	Feasible	Yes[1]	Consistent	Yes/No[1]	Consistent	Consistent	Wetlands (Harmáčková and Vačkář 2015).
GISCAME	Feasible	Yes[1]	Feasible	Yes/No[1]	Consistent	Consistent	Land use-landscape (Fürst et al. 2010; Rukundo et al. 2018). Soil & relief (Sponagel et al. 2005).

[1] Supports or requires expert knowledge or data driven based on the change potential creation procedure

Table 3. Comparison of land use change models: application software, development, capabilities and input

Evaluation Parameter	CLUE	Land Change Modeler (LCM)	GEOMOD	SCENARIOS for InVEST	Markov Chain (MC)	Cellula Automata (CA)
Cost/price	Free	Commercial	Commercial	Free	Free	Free
Application type	Stand-alone	Component of IDRISI & Add-In ArcGIS	IDRISI Component	InVEST Component	Stand-alone / Component of IDRISI	
Stability	High	Low	Medium	Very low	High	High
Support data format	ASCII	Raster-RST (Idrisi format)	Raster-RST (Idrisi format)	Raster-Esri GRID	ASCII	
Development	Long, custom development team.	Long, custom development team.	Long, custom development team.	New: just beginning	Long, custom development team.	Long, custom development team.
LULC Input	1 map	at least 2 maps	at least 2 maps	1 map	1-2maps	1-2maps
Defining potential transition	Numerical values	Automatic	Automatic	Nil	Automatic	Automatic
Works with area history	very limited	Yes	Yes	Nil	Yes	No
Defining factors	Yes	Yes	Yes	Yes	Yes	Yes
Main purpose	Distribution of each LULC cells in relation to user-specified values based on the area's suitability.	Identification of LULC changes and derived trends.	Modeling category 1 changes in the future.	Creating maps from LULC development scenarios.	LULC change simulation.	LULC change simulation.

ASCII is the most common format for text files in computers and on the internet. In ASCII file, each alphabet, numeral or special character is represented with a 7-bit binary number (a string seven 0s or 1s). 128 possible characters are defined. (Adapted and modified from Pechanec 2014).

Table 4. Comparison of Land use change model: Strength and weakness

Model Name/Type	Variables Needed	Strength	Weakness
Spatial-statistical	Land use Data/map; Geospatial attributes.	Ease of computation; Future trends can be predicted based on historical data; Provides a statistical platform for more advanced modeling; Can deal with multivariate components; Allows for an evaluation of the “fit” of the model prediction and the data.	Need data over long period of years to predict trends; Measurement errors in explanatory variables; Needs more methods to be performed before producing simulated maps; Not confined to single equation; Not all variables are linear/non-linear at same time as assumed during modeling; Difficult at times to define and integrate human parameters.
Markov Chain (MC)	Land use map	Ability to develop a prediction model with just two years of data; Ability to calculate performance even if data for some years is missing; Number of land classes is insignificant; Transition probability maps are developed.	Lack of dependence on functional mechanisms; Devoid of simple assumptions of stationary makes analyses difficult; Depends on predictions of system behavior over time; Produces non-geospatial output.
Cellular Automaton (CA)	Built-up pixels/cells	Permits coding of several rules; modeling from the known to the unknown/developed cells; Good spatio-temporal and neighborhood interaction analysis.	Negligence of human behavior influence on the spread of built-up areas; Exclusion of biophysical data; Allows for modeling of one land class.

The Hybrid: CA-MC	Land use map; No ancillary data.	Best model for Spatial–Temporal Pattern stimulation; Gained from the advantage of both CA and MC models; Can produce a multi-class map.	presence of non-real edges on the modeled maps contrast reality; No variables has utmost importance; Constraints from several factors such as slope, aspect, elevation and existing land-use proximity.
Agent-Based	Land use; socioeconomic; utilities data.	Geospatial features; Gives attention to very data; Gives every variable individual attention; Includes socioeconomic data; Combines the CA operation to detect changes in land use.	Large data requirement; Agents' behavior requires coding.
GEOMOD	Land use map	Operates at any spatial scale; Can predict land use change in space, time and value; Capable of using many kinds of spatial data.	Large size of input databases required; High cost of implementation; Applicability only for unplanned land-use change.

7 Case Studies

7.1 Landscape changes in a rapid growing urban hub (in Onitsha, south-east Nigeria)

7.1.1 Introduction

Nigeria is one of the largest country in Africa in relation to population and land area. The diversity of the vegetation landscape (Sahel savanna, Sudan savanna, Guinea savanna, Rainforest, montane forest, derived/woody forest, mangrove forest, and fresh-water swamp forest) makes it a biodiversity rich country. With annual urban growth rate of 4%, and more than 50% of the population living below 5 USD per day (FAOSTAT, 2006), there is high dependent on the natural resources. The continuous growth in population has caused increase in the exploitation of vegetation, soil, and water. Technological advancement and elevated human needs have deprived the environment the potential of sustaining its carrying capacity. Incessant need for more food, shelter, firewood, charcoal, timber, soil, quality water, industries, and services, has brought severe degradation to the natural vegetation ecosystem (UNEP 2005) which in turn created substantial effects on the land use-cover.

Land cover can be referred to every biophysical feature on the earth's surface including plants, water, topography, soils, and rocks (Lambin 1997; Obade et al. 2013) while, land use on the other hand, refers to how people use the landscape – whether for development, conservation, or multiple uses (Anderson et al. 2001; Jansen et al. 2002). Landscape change might be defined as the visible transition in a given area of land because of change in land use-land cover (LULC) driven by either man or nature. From this definition of landscape change, it could be deduced that landscape change is synonymous with land use-cover change. Therefore, in this study we might be attempting to interchange in their usage.

LULC change is a continuous process, and the change rate could either be gradual or spontaneous (Lambin et al. 2001). Five types of causes for landscape changes were outlined by Lambin and Strahler (1994). These were: (i) human-induced modification of vegetation cover and landscapes, (ii) human-induced global warming and/or greenhouse effect, (iii) ecological and geomorphological processes, (iv) inter-annual climate variability, and (v) long-term natural changes in climate conditions. To facilitate sustainable management of the natural resources, vital tools and techniques are needed to detect, describe, and predict the land use changes. And these tools have prompted accurate information on the change and have effectively supported many recent studies on landscape change detection (Wu et al. 2017; Arnici et al. 2017; Varamesh et al. 2017; Fenta et al. 2017).

Assessment of the LULC trajectories enables an understanding of the relationships between man and the environment for sustainability. The impacts of LULC change on the environment could be long-term, and cut across living organisms (animals, man, plants, microbial), and non-living components (climate, soil, and elements) (Foley et al. 2005). An appraisal of the dynamics of LULC change with knowledge of its underlying causes (drivers) is rapidly being considered an essential area of research on either local, regional, or global scale. In the past, inadequate data was the key challenge confronting both researchers and planners in the field of landscape change but, advent of Remote sensing and GIS has brought efficiency and reliability. As a major source of information on land cover, aerial photograph remains an essential source of LULC data (Cots-Folch et al. 2007) especially in the developing countries. Today, the availability of Landsat and many commercial remote-sensing satellites has made LULC data accessible at all scales including multiple spatial, thematic, and temporal resolutions. And GIS has further enhanced mapping, modelling, and prediction of landscape changes. The integration of Remote sensing and GIS tools brought a new paradigm in environmental studies. As good LULC change evaluation tools, Remote sensing and GIS have been widely adopted in environmental resources management, and have severally been applied in LULC classifications (Lambin 1997; Feranec et al. 2000; Feranec et al. 2007; Heymann et al. 1994), and change detection (Overmars et al. 2007; Pontius et al. 2001; Mas et al. 2014).

The 'trajectories of change' concept has gained wider usage in theory and application. Trajectories of change can be defined as spatio-temporal pattern of interactions between variables that modify the effects on man and nature on the environment (Kasperson et al. 1995). According to Mertens et al. (2000), trajectories of change concept is complex and depends on several circumstances including biophysical factors, geographical contexts, and human policies. However, the generic paths of change can be identified, for example, the typical sequences of LULC change prevalent across tropical regions (Lambin 1997). Trajectories of change in general is highly associated with demographic phenomena and long-term induced processes on either agriculture and soil (Boserup 1965), landscape (Trop 2017; Hernández et al. 2016), vegetation (Prasetyo et al. 2016), ecosystem and energy (Mörtberg et al. 2017), watersheds (Wang et al. 2013), or governance-economic policies (Clarke et al. 2016). Besides human beings, natural forces such as climate (Fernandes et al. 2016), and environmental hazards (Salvadori and De-Michele 2015) are also at the central force of the trajectories of change concept. The trajectories of LULC change in this work referred to replacement of LULC classes by another for a given sampling unit over several years.

Onitsha is one of the largest commercial city in Africa (Efe 2005). It is faced with the challenges of providing a growing population with food, water, shelter, sanity, and basic amenities (Efe 2005; Okafor 1986). Urbanization has created rapid growth of housing/industrial estates, proliferation of ghettos, slums, and shanty areas to accommodate the increased population, and has necessitated anthropogenic activities which consequently altered the LULC (Okeke 2016). Natural forests and grasslands are being converted to arable lands, commercial centers and residential areas. Thus, many plant species and their associated ecosystem services have been lost. During the last two decades in the study area, 0.2-0.4 hectares of land was lost annually to soil erosion due to high rate of deforestation while, more than 3 % of the total vegetation cover was replaced by either settlement, sand deposits or floodplain (Okeke and Umeji 2016). The government, the agriculturists and the urban planners have increased the number of housing units and facilities development, established more commercial towns, and expanded arable lands to satisfy the growing population. Many studies have been focused on modelling and detecting the LULC change without identifying the primary effects on plant species (Wu et al. 2017; Arnici et al. 2017; Varamesh et al. 2017; Fenta et al. 2017). This study therefore aimed at evaluating changes in land use and its effects on the landscape in Onitsha from 1987 to 2015.

7.1.2 Materials and methods

Study area

The study area (Onitsha) and its environs lie between latitude 6^0 32'N - 6^0 58'N and longitude 6^0 02' E - 6^0 57' E (Fig. 4). Onitsha has a rapid population growth of 623,274 with a metropolitan size of 1,003,000 persons (Abuloye et al. 2015). It is currently one of the fastest growing cities in the world. Onitsha as a commercial hub of Nigeria and Africa became the focus of this study. It is located within the humid tropical rainforest belt of Nigeria with an annual rainfall of about 200 cm to 300 cm, and annual mean temperature ranging from 26 ^{0}C – 29 ^{0}C (Oguntoyinbo 1978). The geological setting is predominantly sandstone formation underlain by a shale formation (Ezechi and Okagbue 1989).

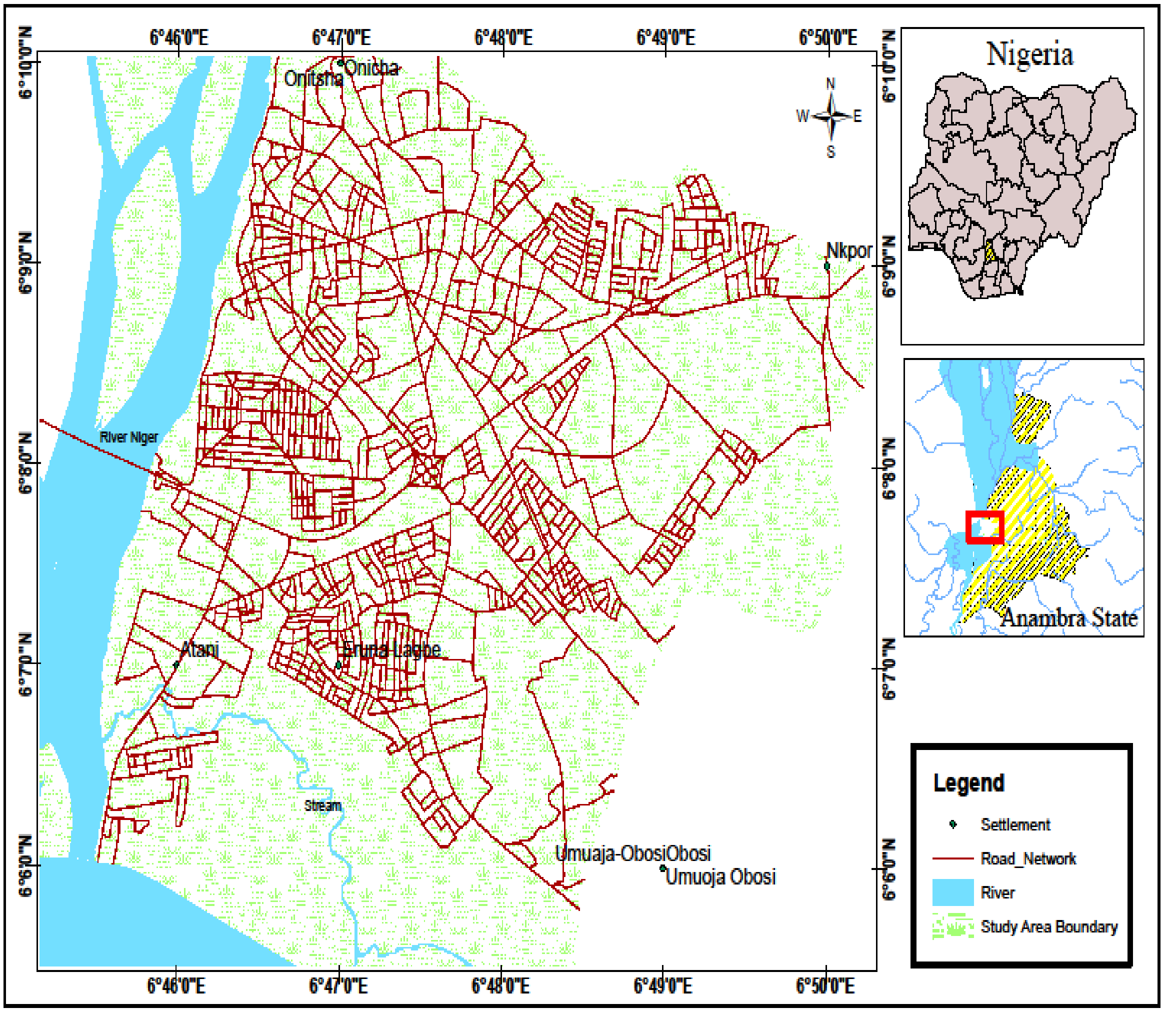

Fig. 4. The study area- Onitsha in Anambra state, Nigeria

The soil is mainly of porous-red and brown sandy derived from the underlying Ameki Formation and Imo Shale (Obiadi et al. 2011). The vegetation ranges from thick rainforest to savanna. The area supports extensive man-made vegetation community which mainly includes cashew orchard and palm trees. Human activities such as housing, agriculture and construction works have greatly modified the natural vegetation, and subsequently, contributed to the severe gully erosion and floodplain problems that are prominent in the area.

Data: collection, pre-processing, classification, accuracy assessment, and land use-land cover (LULC) change analysis

Data collection:

Ancillary and satellite data were used for this study (Fig. 5). The ancillary data included:

- the topographic (base) maps, and geographical layers of the study area, which were roads, rivers, ecological and geographical boundaries, and land-cover maps obtained from the National Space Research and Development Agency, Abuja (NASRDA), and the United States Geological Survey (USGS).
- GPS collected ground truth data for the LULC classes and coordinates,
- data from oral interview with the local people,
- data from previous researches.
- dominant plant species, photographs and field notes recorded in 2015 during a field survey;
- Google Earth images used as reference data during the classification and validation phases of the analysis;
- population data from the national population commission (NPC).

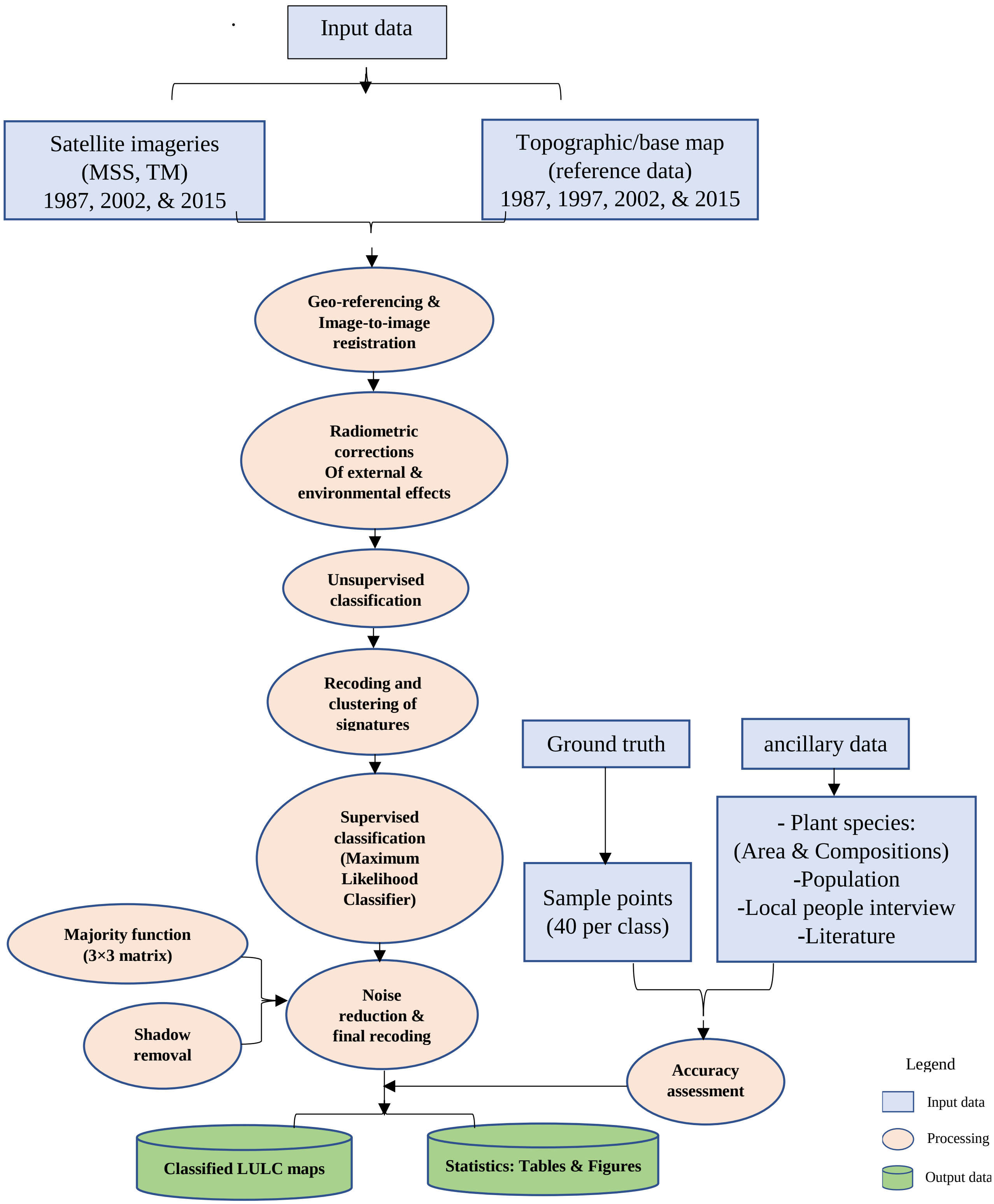

Fig. 5. Flowchart of research methodology

Table 5: Data Characteristics and Source

Data type	Year	Path & Row	Resolution	Source(s)
Landsat Image (MSS)	1987	p189, r056	30 m	NASA[a]
Landsat Image (TM)	2002	p189, r056	30 m	USGS[b], NASRDA[c].
Landsat Image (TM)	2015	p189, r056	30 m	USGS.
Topographic/ Base map(s)	1987, 1997, and 2007		1:50,000	FSN[d]

[a] = National Aeronautics and Space Administration;

[b] = United States Geological Survey;

[c] = National Space Research and Development Agency (Nigeria);

[d] = Federal Surveys of Nigeria.

The data from the ground truth served as the reference points, and were acquired from January to September 2015 for the 2015 image analysis. The ground truth data were used for image pre- and post-classification and overall accuracy assessment of the classification results. Satellite and topographic data were also collected (Table 5).

The population data was derived from the National Population Census (NPC 2006), while the settlement data were derived from the LULC classification.

Data processing and classification

Supervised and unsupervised classifications was employed. This was carried out on the satellite images covering the study periods. The classifications supported LULC classes visual appropriateness. Firstly, the unsupervised classification was performed on the images and the features generated were clustered into defined classes of interest. This was followed by a supervised classification which included field visit and identification of LULC classes.

Table. 6: Land Use-Land cover (LULC) classification

LULC class	Categories	Description
Built-up area	Residential, Commercial, Industrial, Recreational, and educational.	Public, private, government, and commercial estates, Shopping malls, markets, stores, warehouses, trade-fair centers. Production sites, manufacturing factories for textiles, plastics, and leather products, Government facilities, and settlement.
Sand deposit	Open land and non-vegetated land.	Bare surfaces, sand deposits, rock outcrops, accumulation of sediments from river erosional and denudational processes. Man, also influenced this LULC class.
Vegetation	Thick forest, Light/crop fields.	Evergreen forest and mixed forests with higher density of trees, fallow lands, crop fields/arable lands or agricultural lands.
Riparian Vegetation	Trees, shrubs, grasses.	Type of vegetation found in water logged/riverside areas. Alluvial scrublands. Others include hydrophytes such as algae, water lilies, duck weeds.
Water bodies	Wetlands, ponds, rivers, streams, dams.	Areas cover by open water such as river, ponds, Lagoons, dam, reservoirs, and water-logged area.
Floodplain	River floodplain.	Floodplain formed due to lowland terrain. The river and streams eroded silts and deposits.

The classification scheme was developed to include; built-up area (settlement), sand deposit (bare soil surfaces), water (waterbodies), floodplain, and vegetation including thick vegetation, light vegetation (arable land), riparian vegetation (Table 6). The classification scheme gave a broad classification where the LULC classes were identified by a single digit. The band 4, 3 and 2 images were imported into the ENVI (version 4.7) software to form color composite of the study, using the vector frame in ArcGIS 10.1 software environment. The region of interest (ROI) was created from the map of the study area and saved as shape file. The clustered features were used to reclassify the images by introducing a maximum likelihood classifier which classifies the pixels in relation to the maximum probability of similarity with a specific class. To rectify noise effect and smoothen the classes, the final classified images were then filtered using a neighborhood majority function which replaces the center pixel in the 3 x 3 matrix with the most common data file value. Furthermore, there was cases of major misclassification of features such as shadow, in this case, recoding was applied. The degree of accuracy of each classified image was evaluated by a set of 280 random (reference) points based on the number of classes (40 points per class). These reference points were overlaid on the images and each point was designated to one of the land-use classes.

The topographic maps were scanned and imported into ArcGIS environment. They were rectified (UTM WGS84) to the salient land-use layer with a nearest-neighbor resampling (RMSE <0.5 pixels, or <15 m). The projections from the Landsat images were imported to consolidate the georeferencing/rectification of the topographical maps. To correct atmospheric, environmental and sensor related effects, radiometric corrections and histogram equalization were carried out in the ENVI 4.7 and ArcGIS 10.1 for all the images (Boori et al. 2015).

In addition, a confusion matrix was developed for every map. Each row showed land-use classes in the classified map while, each column represented the reference land-use classes. By using the matrix, the overall accuracy (%) and kappa co-efficient (K) were generated for each classified map (Congalton 1991; Rosenfield and Fitzpatirck-Lins 1986). The Kappa co-efficient is calculated by the formula [Eq. (1)]:

$$K=P(A)-P(E)/1-P(E) \qquad \text{Eq.(1)}$$

Where, P(A) = the number of times the k raters agree, and P(E) = the number of times the k raters are expected to agree only by chance (Gwet 2002; Viera and Garrett 2005).

We also assessed the user’s and producer’s accuracies. The user’s accuracy measured the fraction of each class which is correctly classified in the map as a given class while, producer’s accuracy evaluates the percentage of land-use class which is correctly classified as the actual landscape present on the ground.

The population growth rate, the land consumption coefficient, and their projections were also calculated. These helped to understand the ratio of built-up areas to population vis-a-vis the relationships and effects on the LULC. The population growth rate and projection were calculated using the formula [Eq. (2)]:

Population growth rate (G) = $[P(t_2) – P(t_1)] / [P(t_1) (t_2-t_1)]$ Eq. (2)

Where, $P(t_1)$ = the size of the growing population at the initial time (t_1); $P(t_2)$ = The size of the growing population at present time (t_2); (t_1) = Initial year; (t_2) = Present year.

And for this study the arithmetic numerical projection equation was used to project the population. The general equation is given as [(Eq. (3)]:

P(projected) = $P (t_1) + P (t_2-t_1)$ Eq. (3)

Where, P(projected) = The size of the projected population at present time; (t_1) = Initial year; (t_2) = Present year; $P(t_1)$ = The size of the growing population at initial time (t_1).

The land consumption coefficient (LCC) was also calculated [(Eq. (4)]:

LCC(t_n) = LU(projected) (t_n) / P(projected) (t_n) Eq. (4)

Where; LCC(t_n) = Land Consumption Coefficient at the given year; LU (projected)(t_n) = Land use (km^2) of Onitsha at the given year; P(projected) (t_n) = Population of Onitsha at the given year.

In 2015, the number of dominant plant species in each LULC class was counted and recorded in the field while, update for the previous years was gathered from the ministry of forestry, local communities, and past literature. A principal component analysis (PCA) followed by a Monte Carlo Permutation test with 499 permutations in the Canoco software (ter Braak and Šmilauer 2012) was used to evaluate the relationships between the dominant plant species and the LULC classes. Plant species data were log-transformed (y'= log10 (y+1)). Ordination diagram was produced by employing the CanoDraw program software which prompted the presentation and visualization of the PCA result.

Table 7: LULC area, change differences, classification accuracy, and Kappa statistics

LULC Classes	Area (Km^2)			%			Area difference (in km^2)		
	1987	**2002**	**2015**	**1987**	**2002**	**2015**	**1987-2002**	**2002-2015**	**1987-2015**
Built-up Area	20.7	35.2	42.8	19.0	32.3	39.2	14.0	7.5	22.0
Water Body	10.1	8.4	8.0	9.3	7.7	7.4	-1.3	-0.3	-2.1
Thick Vegetation	21.6	16.2	12.1	19.8	14.9	11.1	-5.3	-4.1	-9.4
Light Vegetation	35.9	29.5	16.5	32.9	27.0	15.1	-6.2	-13.0	-19.4
Sand Deposit	3.4	4.6	7.7	3.1	4.2	7.0	1.1	3.0	4.2
Flood Plain	8.9	9.7	15.4	8.2	8.9	14.1	0.6	5.6	6.5
Riparian Vegetation	8.4	5.3	6.6	7.7	4.9	6.0	-3.1	1.2	-1.8
TOTAL	**109**	**109**	**109**	**100**	**100**	**100**			
Overall Classification Accuracy (%)	90.7	92.4	95.5						
Kappa Statistics (K)	0.89	0.93	0.96						

7.1.3 Results

Overall LULC changes

The LULC area and changes for Onitsha municipal was created for 1987, 2002, and 2015, (Table 7; Fig. 6). In 1987, light vegetation (35.9 km^2) recorded the highest area which represented 32.9 % of the total LULC. Built-up area, 35.2 km^2 (32.3 %) had the highest LULC area in 2002. Our result revealed a remarkable increase in built-up area by more than 100% in 2015 when compared with that of 1987. Sand deposit recorded an increase difference of 1.1 km^2, 3.0km^2, and 4.2 km^2 between 1987 and 2002, 2002 and 2015, 1987 and 2015 respectively.

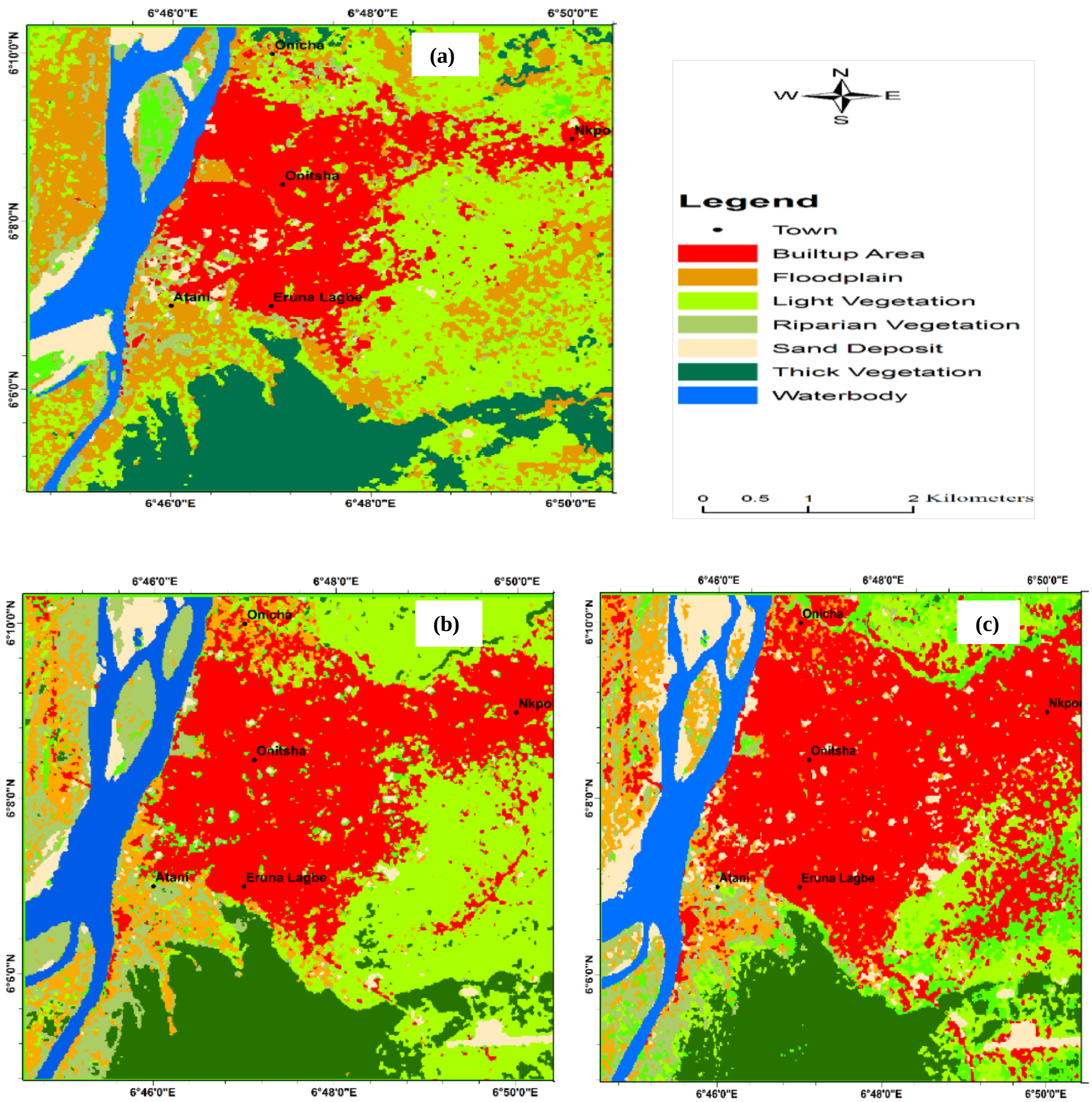

Fig. 6. Land use-land cover (LULC) change maps (a) 1987 (b) 2002 (c) 2015

The areas covered by floodplain also showed a high increase of 6.5 km^2 in 2015. Generally, thick and light vegetations, and waterbodies revealed continuous decrease throughout the study period due to inflated anthropogenic activities as postulated in the first hypothesis.

The cross-tabulation matrix (Table 8) revealed that substantial LULC changes occurred between 1987 and 2015. The result indicated that light vegetation had about 75% decrease during the 28 years of study. On the other hand, the thick vegetation recorded more than 80% decrease from

1987 to 2015. Floodplain increased from 8.9km^2 in 1987 to 15.4 km^2 in 2015 with most of the increase gained from the vegetation areas (thick, light, and riparian). The 3 classes of vegetation (thick, light, and riparian) monitored had constant decline trend in size due to increase in human population and housing (Fig. 7a) as stated in the second hypothesis. An upsurge in population was projected (Fig. 7b) which will consequently lead to elevated land consumption (Fig. 7c).

Table 8: Cross-tabulation matrix of LULC classes between 1987-2015(area in km^2)

		1987							
	Class	Built-up Area	Water Body	Thick vegetation	Light vegetation	Riparian vegetation	Sand Deposit	Flood Plain	TOTAL
2015	Built-up Area	11.2	1.6	4.4	21	2.5	0.8	1.2	42.7
	Water Body	0.2	4.0	2.0	0.5	0.9	0.3	0.1	8.0
	Thick Vegetation	2.5	1.3	4.7	1.4	1.0	0.2	1.0	12.1
	Light Vegetation	3.1	0.4	2.0	9.0	0.5	0.6	0.9	16.5
	Riparian Vegetation	1.9	0.4	1.6	0.5	1.0	0.2	1.0	6.6
	Sand Deposit	1.0	0.7	1.3	1.5	0.3	0.2	2.7	7.7
	Flood Plain	0.8	1.7	5.6	2.0	2.2	1.1	2.0	15.4
	TOTAL	20.7	10.1	21.6	35.9	8.4	3.4	8.9	109

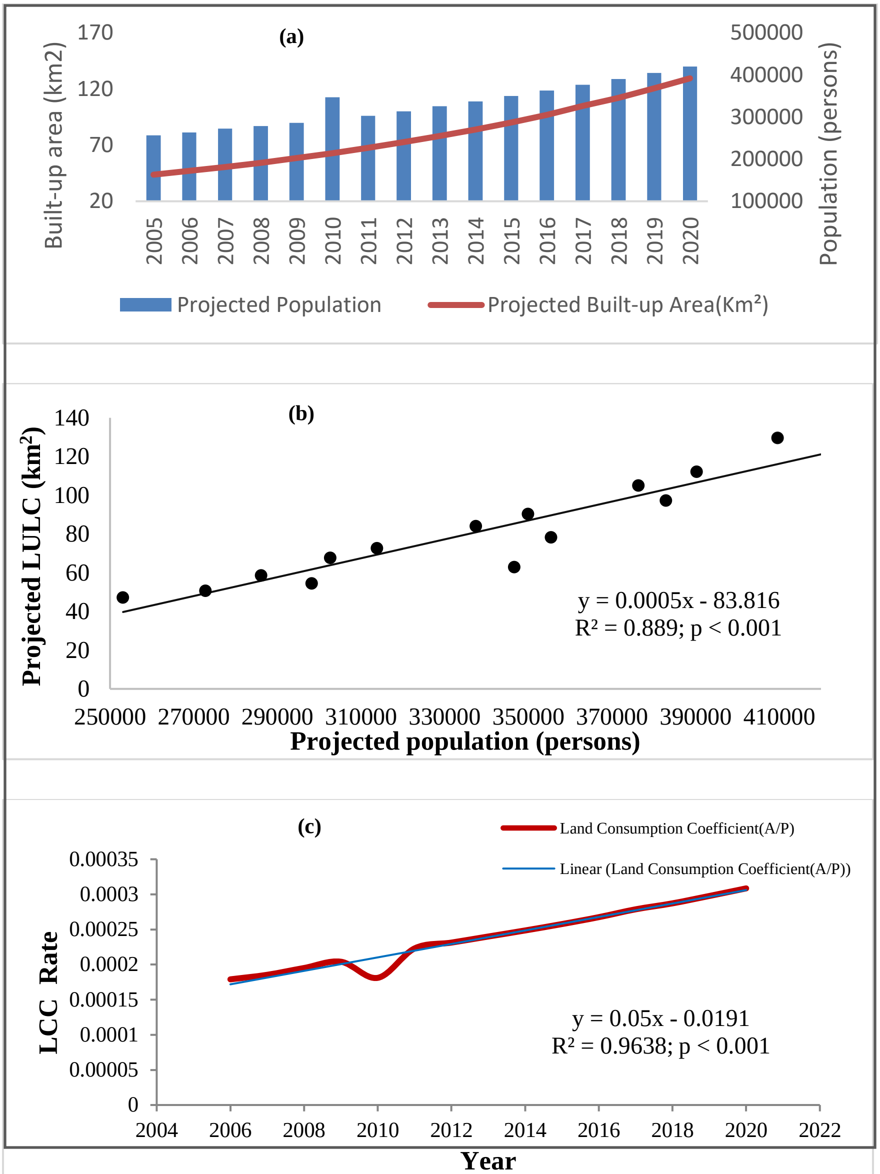

Fig. 7: Summary of statistical analysis of the study area (a) population and built-up area (b) Projected LULC and population from 2005-2020 (c) Relationship between Land Consumption Coefficient rate and years

Classification accuracy

The overall classification accuracies for 1987, 2002, and 2015 was 90.7%, 92.4%, and 95.5% respectively. In addition, the image classification for 1987, 2002, and 2015 produced an overall kappa coefficient of 0.89, 0.93, and 0.96 respectively (Table 7). 2015 showed the best classification accuracy when compared with either 1987 or 2002. Producer's and user's image classification accuracies and their Kappa coefficients were also generated (Table 9).

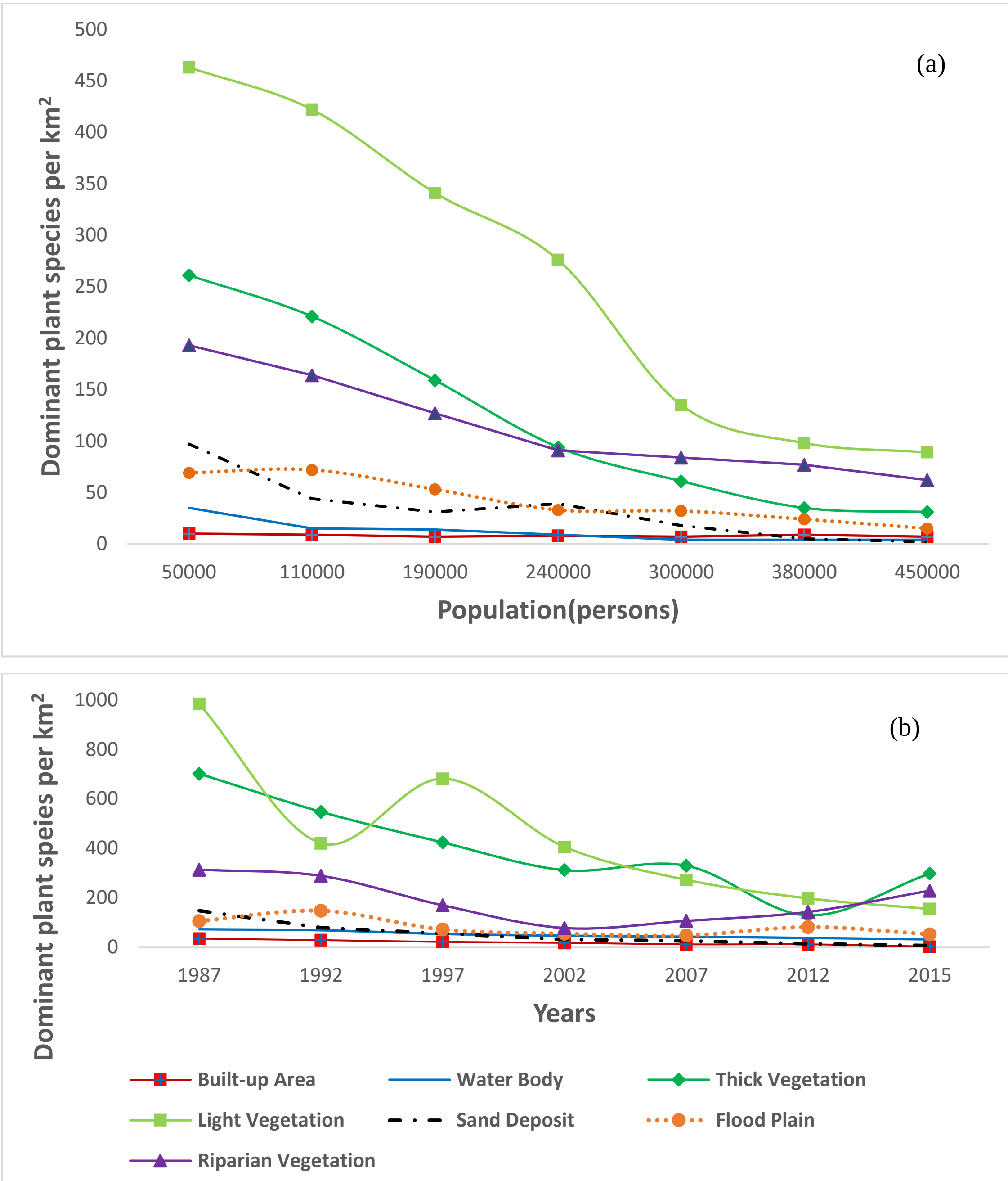

Fig. 8. Relation between the number of dominant plant species per km^2 and (a) population (b) year in each LULC in the study area from 1987-2015.

Vegetation and plant species

The number of dominant plant species decreased with increase in population for most of the LULC classes (Fig. 8a). Time also influenced the plant species decrease. For example, the number of the dominant species (per km^2) recorded under light vegetation in 1987 and 1997 was 983 and 701 while, thick vegetation had 681 and 423 respectively (Fig. 8b). Between 1987 and 2015, 84.3 % of dominant plant species were lost under the light vegetation while, 71.9 % was lost under the thick vegetation.

The results of the PCA revealed that the first ordination axis and all ordination axes significantly differ ($p < 0.001$) in the plant species distribution under the different LULC classes (Fig.9). The percentage of explained variability by the first axis and all ordination axes was 50.6 and 39.7 respectively. The result further showed that the key plant species were related with four LULC groups. The first group was residential housing; second group was grazing area; third group was farmland, and the last group included fluvial-water erosion, floodplain-soil erosion and infrastructural development. The first, second and the third groups had the highest number of the plant species lost to the LULC change.

7.1.4 Discussion

Overall landuse-landcover (LULC) changes

Three types of vegetation (thick, light, and riparian) classified showed constant decline trend in areas. Several reasons might be responsible for this decline. First reason was probably because of rapid increase in human population. High number of people in the area would have led to increase deforestation due to the need for settlements, food, and basic infrastructural development (Boori et al. 2015; Antwi et al. 2014; Semwal et al. 2004). Second reason could be because of increase logging for timber and firewood by the local people (Butt et al. 2015a).

Table 9. Producer's and User's images classification accuracies and Kappa coefficient

LULC Classes	**Classification accuracies (%) and kappa coefficient**					
	Producer's			**User's**		
	1987	**2002**	**2015**	**1987**	**2002**	**2015**
Built-up Area	94.3	96.7	98.8	91.8	95.5	99.1
Water Body	92.1	91.9	97.4	90.6	93.0	98.0
Thick Vegetation	99.2	99.7	100.0	100.0	99.5	100.0
Light Vegetation	89.6	94.2	94.6	87.1	90.8	90.8
Sand Deposit	85.7	83.6	90.5	89.4	88.2	90.0
Flood Plain	83.9	89.9	90.8	74.7	86.5	91.2
Riparian Vegetation	90.3	94.1	96.7	92.0	91.9	96.4
Overall Classification Accuracy (%)	90.7	92.4	95.5	89.4	92.2	95.1
Kappa Statistics (K)	0.89	0.93	0.96	0.87	0.91	0.95

The relationship between rapid population growth and LULC change indicated that substantial LULC change occurred, and will continue if increasing population continues. Other possible causes of decrease in thick, light, and riparian vegetation could be increased urbanization and establishment of estates and housing units (Aina 1992). In agreement with our result, land area for vegetation in Ramnagar was reported to have decreased from 10.29km^2 in 1990 to 7.29km^2 in 2010 due to increase in settlement Rawat et al. 2013).

Built-up areas (settlement) recorded remarkable increase across the years observed with more than 100% increase in 2015. One of the primary reasons for increase in settlement could be that Onitsha (the study area) has become a commercial hub center in Nigeria and Africa (Agunwamba et al. 1998; Saadu et al. 1996). There have been high emigrants into the city from within and outside Nigeria due to the recent industrial and commercial development in the area. The population growth caused higher demand for settlements, and basic amenities.

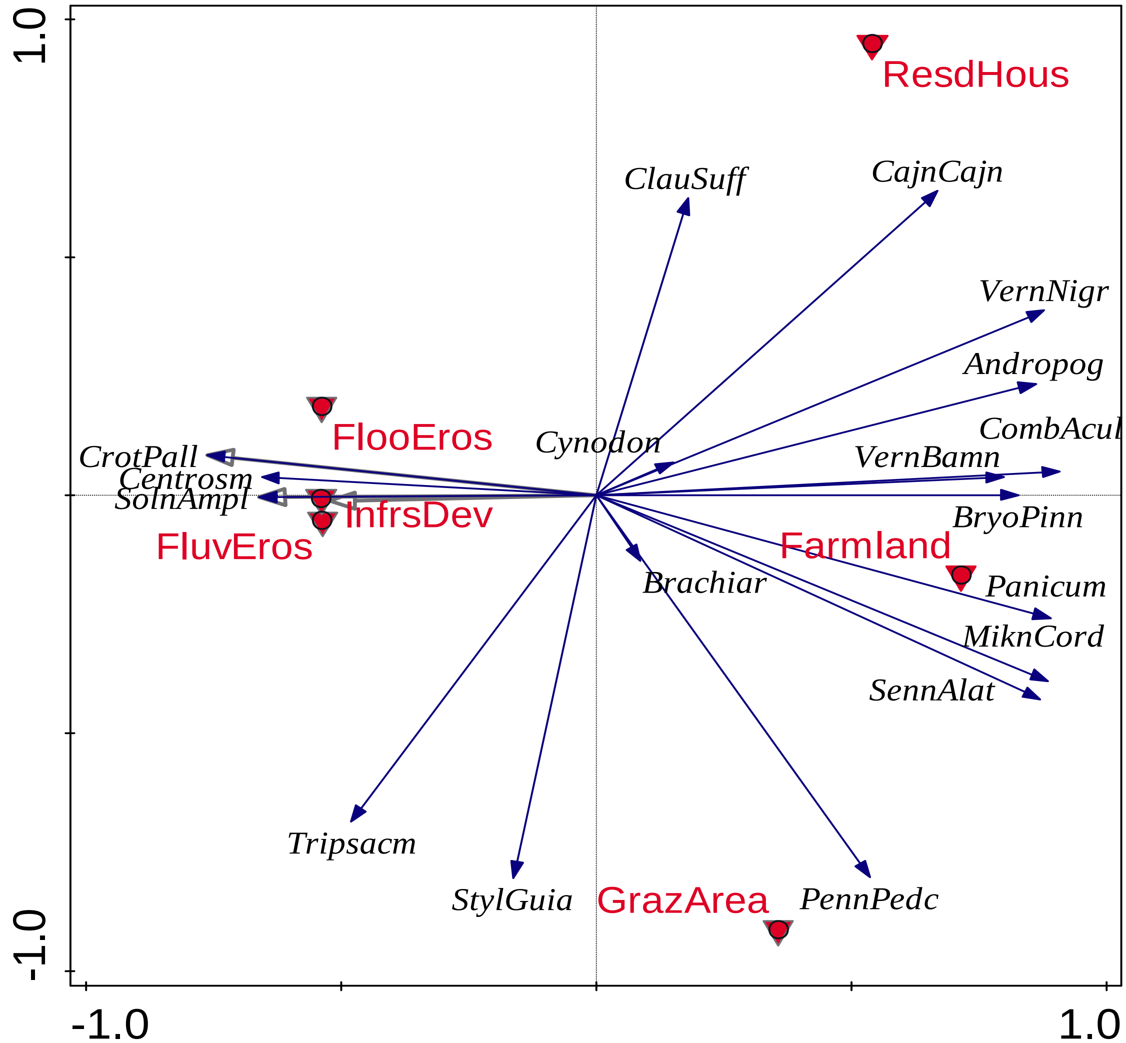

Fig. 9. PCA showing major plant species lost under each land use-cover in the study area

Abbreviations for the land use-cover were ResdHous: Residential Housing, FlooEros: Flood plain-Soil erosion, GrazArea: Grazing area, Farmland: Farmland, FluvEros: Fluvial-Water Erosion, InfrsDev: Infrastructural Development; Abbreviations for the plant species were *BryoPinn: Bryophyllum pinnatum*, *ClauSuff: Clausena suffruticosa*, *SennAlat: Senna alata*, *SoleAmpl: Solena amplexicaulis*, *CrotPall: Crotalaria pallida*, *MikaCord: Mikania cordata*, *AndrGaya: Andropogon gayanus*, *BracDecu: Brachiaria decumbens*, *CynoDact: Cynodon dactylon*, *PaniMaxi: Panicum maximum*, *TripLaxu: Tripsacum laxum*, *CajaCaja: Cajanus cajan*, *CentPube: Centrosema pubescens*, *StylGuiS: Stylosanthes guianensis*, *VernBame: Vernonia bamendae*, *VernNigr: Vernonia nigritiana*, *PennPedi: Pennisetum pedicellatum*, *CombAcul: Combretum aculeatum*

Higher demand for goods and services required more industrial settings which subsequently increased the built-up areas at the expense of the light vegetation (arable land), and other vegetative landcover types. Between 2000 and 2010, the government increased budget allocation fund for industrial development, and this favored urbanization against natural vegetation. Our finding was consistent with previous studies on the role of population growth in LULC change (Antwi et al. 2014; Rawat et al. 2013; Taylor 1993; Alfred et al. 2016; Braimoh and Onishi 2007). It has been documented in Nigeria that in 1976, 100,000 residential structures accommodated 2-3 million people in each of the major states with an average of 29 persons per structure (Taylor 1993). However, with the latest population increase, major urban centers like Onitsha with more than a million persons would need larger settlement areas. In Indian state of Uttarakhand, similar report was documented by Rawat et al. (2015), revealing increase in built-up areas to due population growth.

A slight decline in water bodies revealed in our study might be attributed to anthropogenic activities of land reclamation for housing, and road constructions. More exploitation of the water resources by the growing population could have also caused the drying up of some streams and river tributaries (Butt et al. 2015a). In addition, increase evaporation rate due to increase temperature, high seepage, and percolation (Keller et al. 2000) could be contributing factors to the decline in water areas. Accelerated rate of surface run-off because of the absence of the plants roots to with-hold water might also be a further explanation for the decrease in water areas (Butt et al. 2015b).

Uncontrolled deforestation caused severe soil erosion and enhanced surface run-off which consequently led to accumulation of sediments and silts. The outcome of this process increased the areas for floodplain, sand deposit, and bare soil surfaces (Butt et al. 2015a; Keller et al. 2000; Ali et al. 2008; Mendoza et al. 2011). Indiscriminate dumping of municipal solid wastes into the water bodies was observed in our study. This could probably be another reason for decreased water area, increase floodplain and sand deposit since the wastes obstruct water flow (Hazarika et al. 2015). Furthermore, the reclamation of the rivers and streams promoted an overflow especially during the wet seasons. This factor also created more land for flood plain and sand deposits while, the riparian vegetation became reduced. Though not within the scope of this study: there has also been reports on the poor soil fertility in the area (Jemo et al. 2014) because of significant increase in the land consumption rate over the years (Fig. 6c).

Remarkable decline in the plant species was found in the study area during the study time. Several authors have recently reported high rates of plants species decline due to settlements, and agricultural activities (Davis et al. 2017; Sylvester et al. 2017; Smith et al. 2017; Jiang et al. 2017), which was intensified by population growth and rapid urbanization (Fahey and Casali 2017; Kleemann et al. 2017).

Classification accuracy

Thick vegetation recorded almost 100% classification accuracy while, floodplain and sand deposit showed the lowest percentages accuracies among all the classified LULC classes. This might be explained by the distinct features of the thick vegetation which obviously separated it from other LULC classes. The thick vegetation in dominated by evergreen forest and high-density trees. The sand deposits and the floodplain were often confused with each other and with wetlands in some cases. This therefore reduced the reliability of their accuracies when compared with other LULC types classified. The classification was reliable and acceptable for further analysis based on the overall classification accuracies of more than 90% recorded.

7.1.5 Conclusions

In applying Remote sensing and GIS, the objective of this study was achieved with the conclusion that land use-cover was substantially altered in the area, and this consequently affected the landscape during the 28 years of research. The vegetation classes were the most negatively affected LULC type whereas, the built-up areas increased in all the years investigated. Population growth and increasing socio-economic needs and activities were the key factors responsible for the change in land use-cover which consequently modified the landscape. The number of dominant plant species decreased with increase in population and settlements. Residential housing, grazing area, and farmland had the highest number of the plant species lost to the landscape changes. Although, climate had minimal effect on the landscape features but, human activities were the most agent of the changes detected. As human population, continuous to increase, the vegetation and water will continue to lose their areas to settlement, floodplain and sand deposit. Remote sensing and GIS have shown great advantage in the evaluation of the trajectories and effects of LULC change in Onitsha municipal. The study recommended the emancipation of the local people by the government and stakeholders as the most sustainable solution. These indigenous people should be encouraged to intensively plant trees as well as protect the old and new plants. Also, building of houses should be regulated by including proper environmental impact assessment (EIA) before approval and constructions.

7.2 Landscape changes caused by landslide-a consequent of altered land use (Jos in northern Nigeria)

7.2.1 Introduction

Landslide is a geological phenomenon, which occurs due to changes in slope movements especially, when the down slope weight (driving force) exceeds the soil strength (resisting force). Landslides are very prominent where slope stability has been compromised and can be stimulated by severe rainfall, erosion, volcanic activity, earthquakes, saturation of slope with water, LULC changes, groundwater modification, environmental disturbance, and slope terrain alteration by human activities, or any combination of these factors. In arithmetic term, landslide can be represented as the probability of spatial occurrence of slope failures, given a set of geoenvironmental conditions (Guzzetti et al. 1999). Landslide susceptibility (LS) maps are important delineators of areas with different potentials for future landslide movement. According to Carrara et al. (1995), the LS maps could be simple estimation of landslide-prone geological units developed from geological maps, or they could be complex computer generated mathematical models linking several factors that influence slope stability. The magnitude of landslide could be assessed at micro, medium, and large-scale levels. Contemporarily, Remote sensing and GIS technologies are being used to monitor and map landscape structures, identify spatio-temporal changes, and the causal factors (Luzi et al. 1999). There have been numerous methods to analyze the vulnerability of slope movements using geoinformatics (Akpan et al. 2015; Carrara 2003; Igwe, 2015a; Rasyid et al. 2016; Van Western et al. 1997) with majority focusing on the comparison between the determining factors and the territorial distribution of the movement observed. Remote sensing and GIS make it feasible for modelling and statistical analyzes of the physical and socioeconomic processes which occur on the Earth's surface including slope instability (Irigaray 1995). The application of geospatial techniques in developing the spatial database of landslide and its causative agents has been successfully used in the vulnerability analysis and in the effective modeling of slope instability (Rasyid et al. 2016; Shirzadi et al. 2012; Dai and Lee 2002). Although, these new technologies have been fully adopted in the developed countries but, their applications are still lacking in the developed countries (Akpan et al. 2015; Igwe 2015b). In Nigeria for example, recent researches on landslide susceptibility revealed that limited studies with application of GIS are performed in the region (Ojigi et al. 2012; Igwe 2013, 2015a, 2015b; Akpan et al. 2015).

Over the years, environmental challenges such as extreme flooding, improper building patterns, poor drainage facilities, rock falls and landslide have detrimental effect on the built-up environment of Jos South. Environmental indicators showed that Jos South is rapidly becoming high vulnerable to slope failures, rock falls and landslide due to anthropogenic activities including Tin mining, rock blasting, and farming (Habu 2014) causing rapid landscape changes. However, if these acute land resources exploitation and environmental hazards are not properly monitored, they might in near future result into serious catastrophe and uncontrollable social risks for the inhabitants. The problem is compounded by the fact that it is rare finding any research which applied land use modelling technology such as GIS in landslide vulnerability assessment in the study area. Therefore, appraising the geospatial status of landslide susceptibility in the area is important at this period that the increasing population and species diversity are under threats. The study aimed at identifying Jos landslide vulnerable areas, driving forces and effects on landscape using GIS. In this context, the study attempted to address the following questions: (i) what are the main drivers of the landslide? (ii) where are the most vulnerability areas and how significant are the effects on the landscape? (iii) does seasonality play any role in the landslide occurrences?

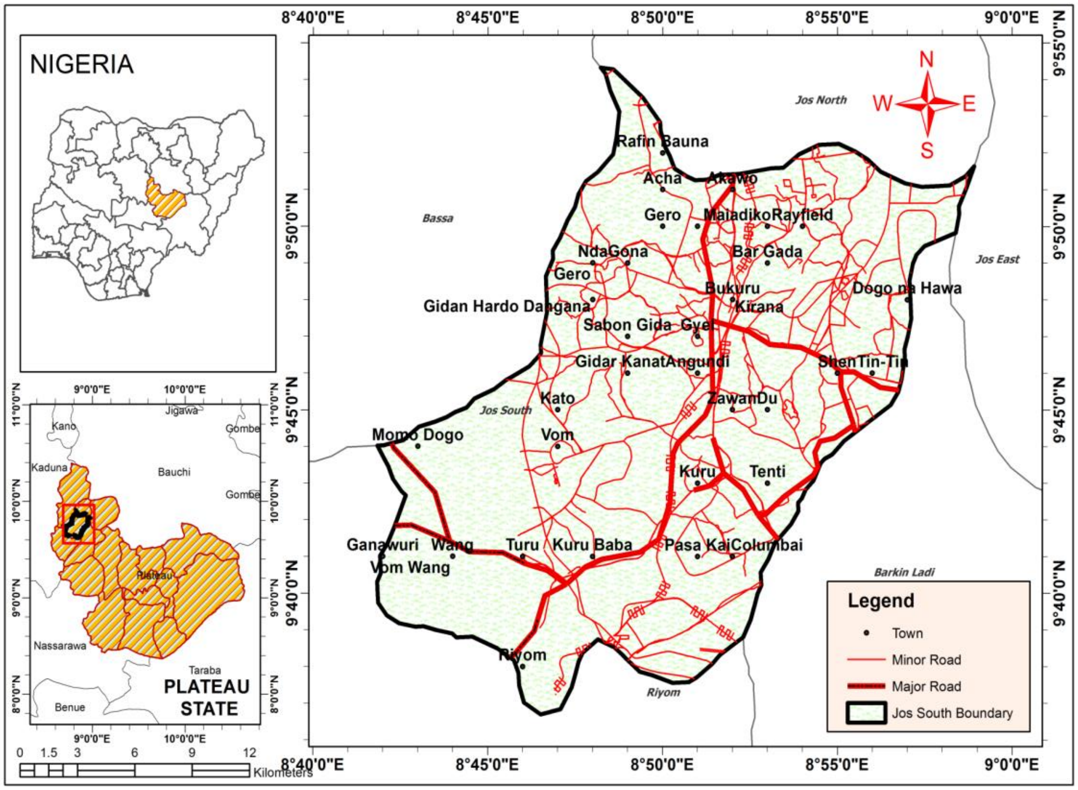

Fig. 10. Jos south in Plateau State, Northern Nigeria - the study area

7.2.2 Material and method

Study area

The Jos in Plateau state is located in the north-central part of Nigeria. Jos South lies between latitudes 8° 30' N and 10° 30' N and longitude 8° 20' E and 9° 30' E (Fig. 10), with a population of 306,716 (NPC 2006). Geologically, Jos South is dominated by younger granites which were intruded into older granite rocks. Due to its high altitude (1100 m -1500 m), the area has cool climatic condition with annual temperature ranging from 18 ^{0}C – 22 ^{0}C, and annual rainfall ranging from 1000 mm to 2500 mm (Usman 2013; Abimbola et al. 2011; Olowolafe 2003). Lateritic soils of granitic and basaltic formation occupy extensive areas of land (Olowolafe 2003). The original woodland vegetation has been significantly reduced for mining, settlement and agricultural purposes.

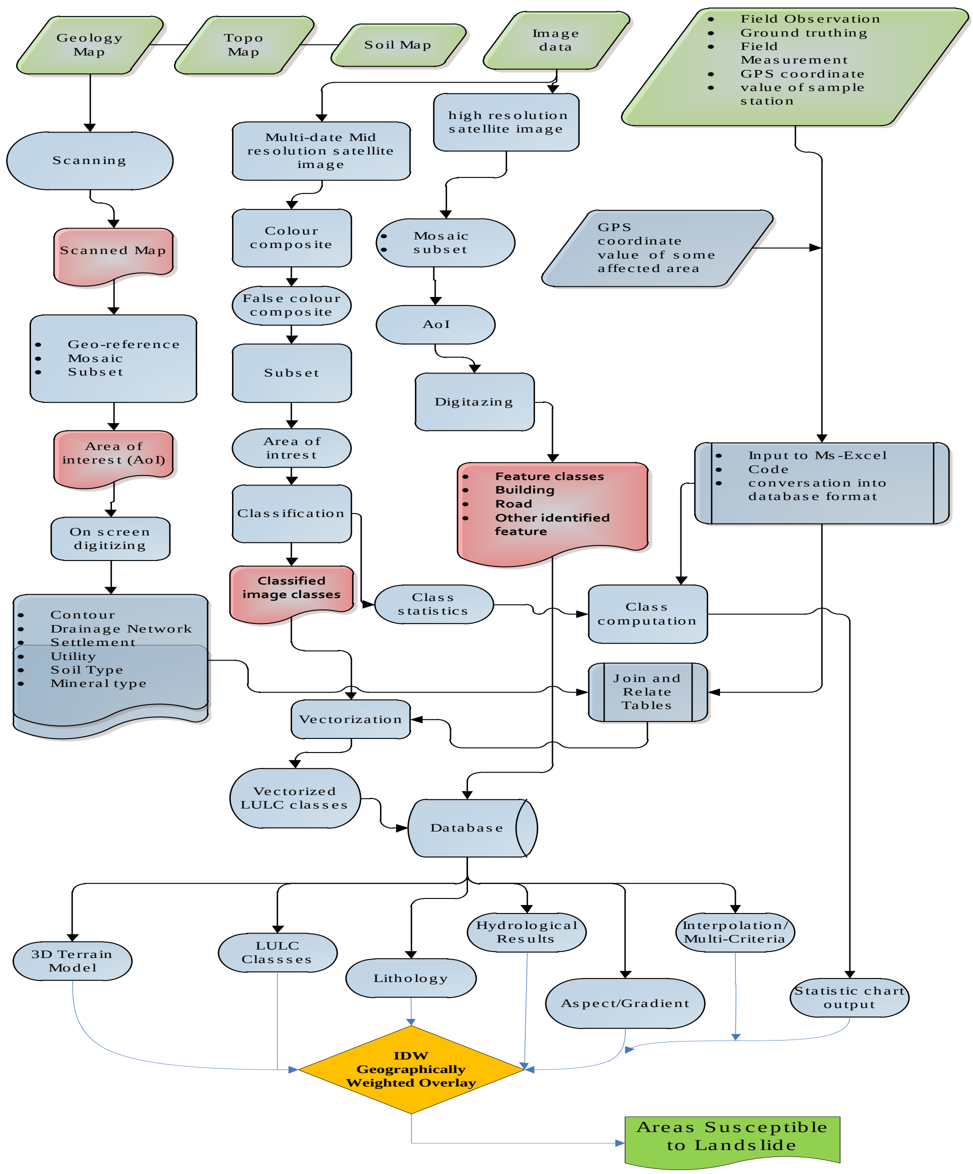

Fig. 11. Schematic flow diagram of the study methodology.

Data collection and analyses

The adopted methodology for the study is shown in Fig. 11. Both spatial and non-spatial data were collected including satellite data (Landsat, SPOT images, Ikonos and Quickbird), GPS points, aerial photos and topographic maps on drainage, climate, soil, geology, settlements, demography, administrative and relief maps covering 60 years from 1955- 2015 were partly available and used for the study. Others were LULC data, and data on the socioeconomic attributes. The Landsat ETM+ contained information on the LULC, and was acquired at the resolution of 28 m from GLCF. DEM and TIN were acquired from the Shuttle Radar Topography Mission (SRTM), and the Landsat data from GLCF and were modified using Z attribute value. The slope was later generated from the DEM. The topographic maps were collected from the Federal Surveys at the scale of 1: 12, 500. The soil and mineral data were extracted from the topographic map of scales 1: 100,000 and 1: 250, 000 respectively from the Geological Survey of Nigeria. The average rainfall data was gathered from Nigerian Meteorological (NMNET) station covering 60 years' period.

The topographic maps and remote sensing images served as the secondary data, and were used to produce a preliminary landslide susceptibility map to be verified through field observations. The field surveys were performed by walking round the landslide areas throughout the months in 2015 with at least twice visit each month. A total of 34 days was used for the fieldwork. Spatial and attribute data were collected on drainage, land use and land cover, soil, geology, Lineament, geomorphology, slope, population and human activities. The field samplings were scheduled in 2nd week and last week of every month from November to May while, June to October had 4 times observations each (that is a visit per week) because these months are the seasons with extreme rainfall. The collected data helped in verification exercises by validating comparisons between the susceptibility condition as predicted on the preliminary susceptibility map and the real field condition. In addition to consolidating the identification of the dominant factors for the landslide incident in the study area, the field data facilitated the revision of the ranks and weights assigned to different thematic maps and its classes.

All preprocessing, classifications, and other analyses were performed using ArcGIS version 10.1, ENVI version 4.7, and Surfer 10 tools. However, before prepossessing, georeferencing, and classification, the topographic maps were scanned and digitized. To delineate the study area, the topographic and administrative maps covering the study area were geo-referenced with root mean square error (RMSE) of 0.00002. Using the ENVI version 4.7 software, the image was imported using the Geo-tiff format in band 4,3,2 of the Landsat image. Subsequently, the bands of interest were selected and layer stacked. From the stacked bands, a colour composite of bands 4, 3 and 2 was generated and re-sampled in a new display. After the colour composite, the image subset was created using the region of interest (ROI) vector frame created in ArcGIS 10.1 from the study area map and imported into ENVI 4.7 environment as shape file. With this, the ROI of the study area was delineated from the satellite image scene. For the image classification, the FAO land cover classification system together with the field information was used, and the LULC types were generated (Table 10). To determine the area extent of LULC, the classification tool in ENVI 4.7 was used to subset the colour composite (combination) image which was classified using maximum likelihood classification to define the LULC classes. After the classification, confusion matrix was computed using ground truth data. The classified LULC classes were exported to ArcGIS as shape file (vector files) where overlay operation was carried out with other thematic layers after the post classification processes. Other analyses included spatial modelling and surface interpolation.

Table 10. Classified Land use-cover types and overall classification accuracy

S/N	Classes	Description	Area (Km^2)	%
1	Bare surface	Open land and non-vegetated land.	5.6	1.1
2	Built-up area	Residential, Commercial, Industrial, Government facilities and settlement.	56.3	11
3	Mining site	Areas for the exploitation of the natural/mineral resources such as tin, coal, gravels, and others.	30.7	6.1
4	Rock outcrop	Type of vegetation found on rocky areas or the part of a rock formation that is exposed on the surface of the ground.	393.6	77.2
5	Vegetation	Evergreen forest and mixed forests with higher density of trees.	17.7	3.5
6	Waterbody	Areas cover by open water such as river, ponds, Lagoons, dam and water logged area	5.8	1.1
	Image classification accuracy			
	Overall Accuracy (%)			90.5
	Kappa Coefficient (K)			0.79

The spatial analysis extension of GIS allows interpolation of the landslide causative agents at unknown location from known values. This prompted the creation of a continuous surface which helped to understand the scenarios of landslide causal factors in relation to the study area. The spatial distribution maps of landslide causative factors and areas susceptible to landslide were produced by employing the inverse distance weighted (IDW) in the ArcGIS spatial analysis extension. Other spatial analysis performed included; spatial analysis based on location, spatial analysis based on attribute of feature class, polygon overlay, analysis based on distance, buffering, and spatial interpolation and spatial analysis of surface.

Water shade, stream order, and other drainage morphometric analyses were generated from the drainage map while LULC and its class statistics were generated from the classified image. The initial preparation of the landslide susceptibility maps involved using the built-in multi-criteria evaluation (MCE) module in ArcGIS 10.1 environment. In relation to all weighted overlay for multi-criteria analysis, the model was broken into sub-models, and input layers were identified as shown in Appendix Fig. 1. The input factors were converted to grid raster. Each cell for each criterion was reclassified into a common preference scale between either 1 to 6, or 1 to 5 depending on the number of the sub-factors. In either cases, 6 or 5 was assigned the most landslide determinant factor. In other words, the landslide factors were weighted according to their level of influence to causing landslide. The most landslide causative factors were assigned highest weight and the lowest weight given to the least factor, and expert knowledge of the study area which was acquired by field survey was employed for this justification. To finally build the landslide vulnerability map, the weights of each thematic layer was multiplied by the ranks of the raster classes. And finally, the values were summed up and divided by the total weights of the themes by applying the Index Overlay Method (Pathak, 2016) with formula:

$$S = \sum Wi\ Sij / \sum Wi \qquad \text{Eq. (5)}$$

Where,

S = output score;

Wi = weight for each themes;

Sij = rank for each class (in raster).

Thus, prepared map was validated with the landslides dataset and a satisfactory model (Appendix Fig.1) was created to suitably represent the landslide susceptibility status of the study area. For the landslide model, eight input criteria were considered: drainage, land use and land cover, soil, geology, Lineament, geomorphology, and slope; and drainage had the highest influence and weighed higher than others (Appendix Table 1).

7.2.3 Results

LULC types were classified, and their areas and percentages in relation to the entire study landmass were; bare surface (5.6 km^2; 1.1%), built-up area (56.3km^2; 11%), mining site (30.7 km^2; 6%), rock outcrop (393.6 km^2; 77.2%), vegetation (17.7 km^2; 3.5%), and water (5.8 km^2; 1.2%) (Table 10). The overall image classification revealed 90.5% accuracy with 0.79 kappa coefficient. Several landslides drivers were identified including drainage, land use-land cover change, soil, geology, lineament density, geomorphology, and slope. The impact of each factor was evaluated by introducing them one after the other in the weighted overlay model. The contributing percentages for the factors were Drainage length (21%), LULC (19%), Soil (16%), Geology (13%), Lineament density (12%), Geomorphology (10%), and Slope (9%) (Appendix Table 1).

Mining sites covered an of 1.02km^2 representing 4.73% of the landslide susceptible area with a weight of 6 represented severely high instability area (Table 11). Rock outcrop is highly instable to landslides, and had about 43% of the areas covered by landslides. The average rainfall revealed that places with average rainfall of 2000 mm and above were highly instable to landslides (Table 11). Drainage also had a high percentage weight as landslides causative factor (Appendix Table 1). The areas with high vulnerability to landslides had stream and rivers of average length 3.05 km and above and with high density (Fig. 12a). In addition, heavy rainfall is also an important factor which increases and aggravates the weight of drainage. The study discovered that landslides increase with rainstorms. For example, at the most landslides prone sites (Sabon Garki, Gyel Gura, Chunbeng, Guru Topp, Vom Latya Rayfield 1 and 2) (Appendix Fig. 2) the frequency of landslides occurrences coincided with the months (June-October) which have the highest rainfall (Appendix Fig. 3). Thus, revealing that seasonality has a key role in landslides incidents in the study area.

Table 11: Summary of overall results of the analyses on landslides and driving factors

S/N (Code)	Class/Type/% Raise	Landslides area (km^2)	% of total	Weight	Instability
Overlay/integration results of the landslide layer and LULC layer					
	Class				
1	Bare surface	0.07	0.32	2	Low
2	Built-up area	1.92	8.91	5	Very high
3	Mining site	1.03	4.75	6	Severely high
4	Rock outcrop	9.34	43.36	4	High
5	Vegetation	8.99	41.73	1	Very low
6	Waterbody	0.21	0.93	3	Moderate
	TOTAL	21.56	100		
Integration of landslide layer and geology layer					
	Type				
BB	Basalts, Trachyte & Rhyolite	0.65	3.02	3	Moderate
OGH	Hornblende gneiss	7.7	35.7	2	Low
JYG	Granite	13.21	61.28	1	Very low
	TOTAL	21.56	100		
Integration of landslide layer and soil layer					
	Type				
ACf	Acrisol mining	20.71	96.1	5	Very high
CMo	Cambisols	0.85	3.9	4	High
	TOTAL	21.56	100		
Integration of landslide layer and mean rainfall layer					
	Average annual rainfall (mm)				
1	500	6.94	32.19	1	Very low
2	1000	5.2	24.12	2	Low
3	1500	5.15	23.89	3	Moderate
4	2000	3.14	14.56	4	High
5	2500	1.13	5.24	5	Very high
	TOTAL	21.56	100		
Integration of landslide layer and Slope layer					
	Percentage Raise				
1	4	1.33	6.11	1	Very High
2	6	5.2	23.89	2	High
3	13	3.14	14.43	3	Moderate
4	25	5.15	23.68	4	Low
5	52	6.74	31.89	5	Very Low
TOTAL	100	21.56	100		

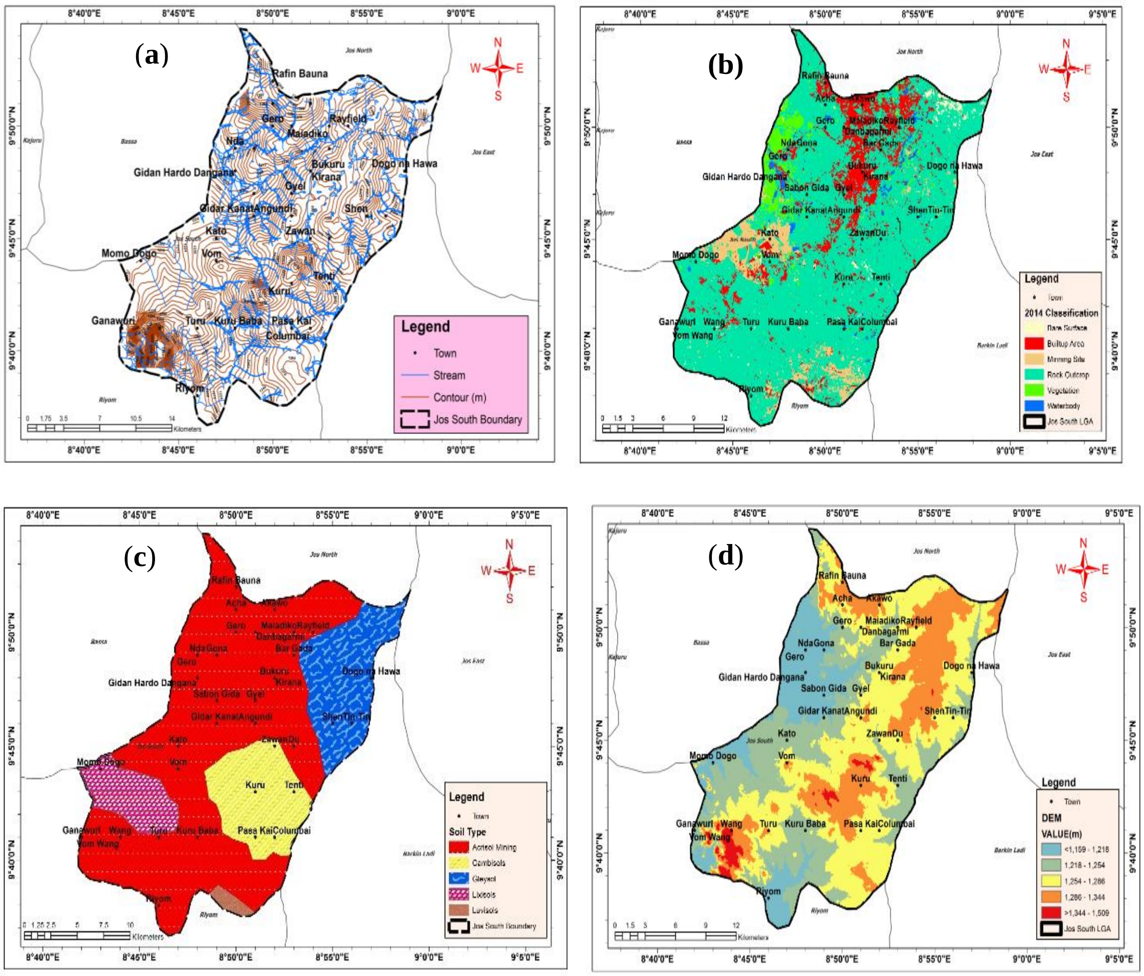

Fig. 12. Jos South showing (a) Drainage and contour (b) Land use-land cover classification (c) the dominant soil types (d) Digital Elevation Model (DEM)

Table 12. Overall statistics of the susceptibility areas (in km^2) including ranking, area mean/SD, and area range (in km^2)

S/N	Ranking	Landslides area	% of total area	Mean/SD	Range
1	Severely high	0.31	0.06	0.10±0.01	0.01 - 0.1
2	High	19.79	3.88	0.13±0.75	0.01 - 7.31
3	Moderate	234.85	46.01	1.13±15.71	0.01 - 226.66
4	Low	175.51	34.39	0.63±4.69	0.01 - 50.68
5	Very low	79.94	15.66	0.97±5.01	0.01 - 36.53
	TOTAL	510.4	100		

The availability of mineral resources such as Tin, and Columbite which have been extensively mined since 1902 till date has devastated the arable land. The study area is therefore littered with several mine spoils and ponds in addition to severe erosion, and flooding of the landmass which acerbated the landslide. Mining and mined sites, rock outcrop, and built-up areas were the LULC classes that have the highest influence on the landslide (Table 11, and Fig.12b).

Soil types found in the study area included, Gleysol, Lixisol, Luvisol, Cambisols and Acrisol mining see (Table 11, and Fig. 12c). Acrisol mining covered about 80% of the area, and was formed from strongly weathered acidic soil with low base saturation and high susceptibility to landslide. Due to Acrisol mining, soil factor weighed (16%) representing 3rd position among the landslides causative factors in our study (Appendix Table 1).

However, other factors such as geology, lineament, geomorphology, slope, and population also contributed to the shallow landslide but, these have low percentage weight when compared to drainage, LULC, and soil (Appendix Table 1, and Fig. 13). The overall result revealed that less than 0.1% of the area had severe landslide, while moderate landslide type covered about 235 km^2 of the landslide area (Table 12). However, none of the towns was found in the severely high landslide area though some areas have high tendency for landslide susceptibility (Table 13).

Table 13. Landslides vulnerability in relation to settlements (Appendix Fig. 2).

S/N	Ranking	Susceptible towns in Jos South
1	Severely high	None
2	High	Gidar Kanat, Sabon Gida, Gidan Hardo Dangana, Gona, Nda, and Gero.
3	Moderate	Acha, Akawo, Angundi, Bar Gada, Bukuru, Danbagarmi, Du, Gero, Gona, Gyel, Kato, Kirana, Kuru Baba, Maiadiko, Momo Dogo, Rafin Bauna, Rayfield, Riyom, Sabon Gida Riyom, and Sabon Gida.
4	Low	Dogo na Hawa, Ganawuri, Shen, Tenti, Tin-Tin, Turu, and Zawan.
5	Very low	Columbai, Kuru, Pasa Kai, Vom Wang, and Wang.

High and moderate landslide areas recorded the highest number of settlements (Fig.14). In relation to vulnerable factors, Population (representing 40%) weighed the highest among the factors substantially affected by landslides while others were land use and land cover (Appendix Table 2). The results further revealed that high and severely high landslide susceptible areas tend to be found in places between 500-1200 meters above sea level (Fig. 12d, and Fig.15), instead of the very highest steep areas. For example, areas raised with less than 15% showed more instability than areas raised by 20% and above (Table 11). This indicated that gentle slopes have significant effect on the landslide susceptibility than the steep slopes hence, slope factor had the lowest weight % among the factors contributing to landslide in the area (Appendix Table 1).

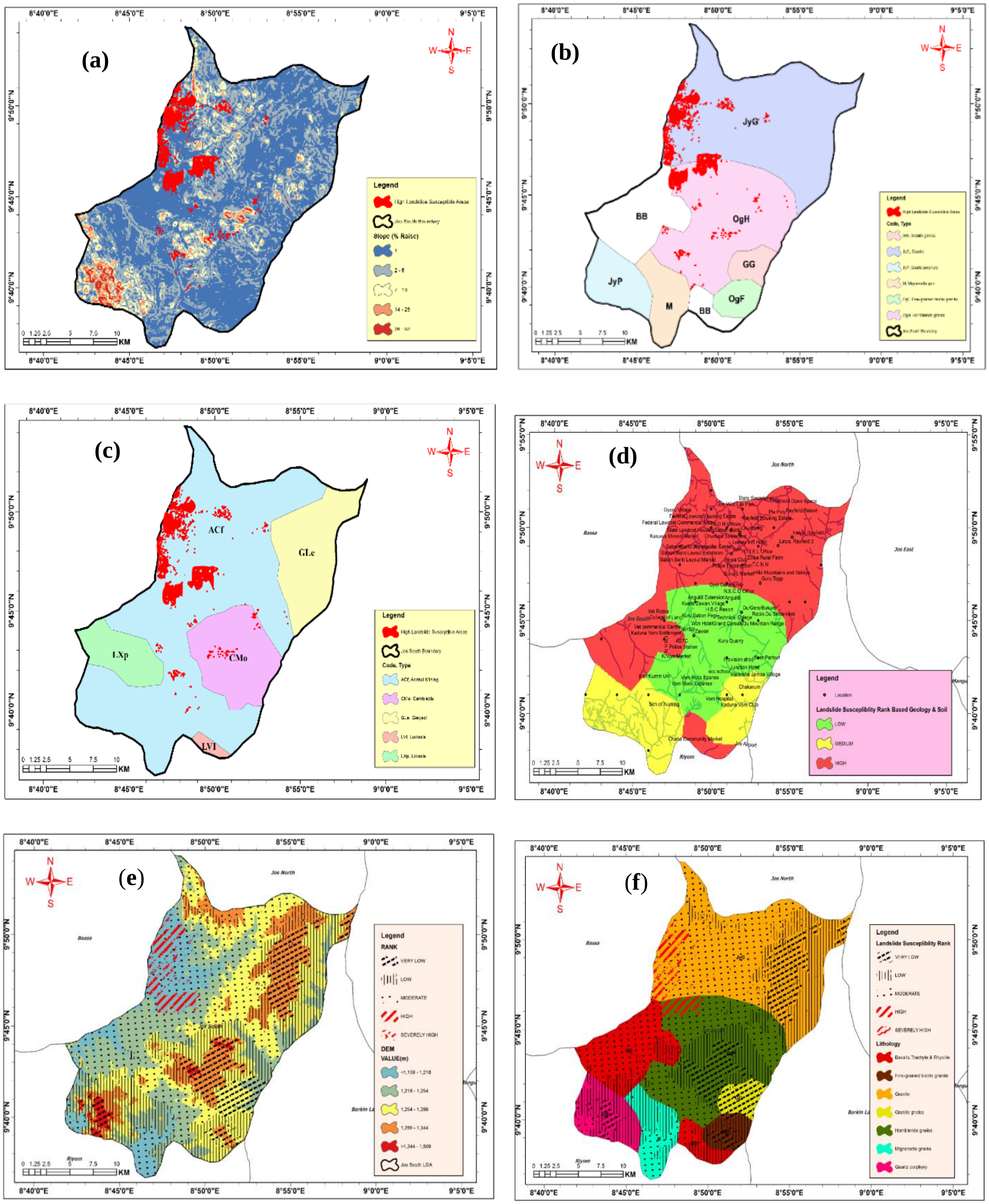

Fig. 13. Jos south map showing (a) The results of integration of landslide layer and Slope layer (b) The results of integration of landslide layer and Geology layer (c) The results of integration of landslide layer and Soil layer (d) landslides susceptibility based on Geology and Soil. Landslides susceptibility areas overlay with (e) elevation (f) geology.

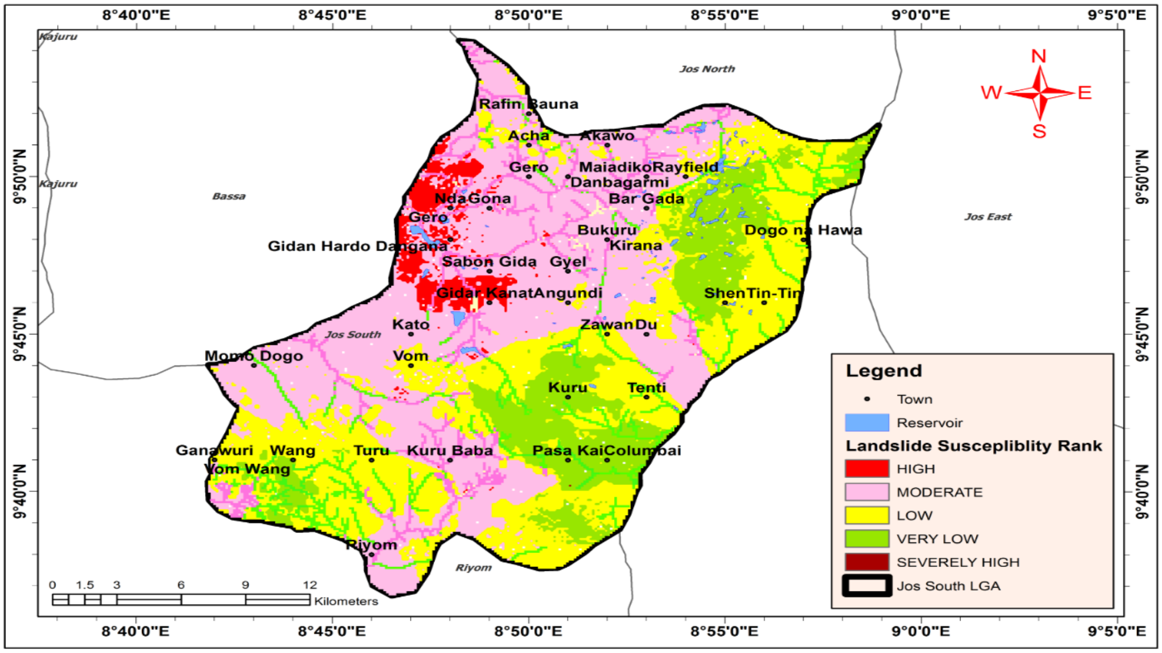

Fig. 14. Overall/Final Result of Jos South landslide susceptibility**.**

7.2.4 Discussion

On average, the relief height of Nigeria is below 700 meters but our study area (Jos South) is exceptionally high when compared to other provinces in the country. The digital elevation model (DEM) shows that the level of elevation is high in most parts of Jos South, with elevation ranging between 1,277 m to 1,411 m yet, shallow zones with less than 1,200 m high tend to show higher level of susceptibility to landslide. The indication that the gentle slopes which were more vulnerable to landslide occurrences in our study could be attributed to other factors such as the presence of the valley, and water saturated soil within the gentle slope zone (Pathak 2016). Shallow landslide at the lower base of the steep highlands have been reported by several authors (Hsu 2016; Pathak 2016; Claessens et al. 2007; Akpan et al. 2015).

In our study for example, we discovered that streams and rivers were mostly concentrated along the gentle slope areas as compared with the steep slope, and this might have weakened the bedrocks which triggered the shallow landslide.

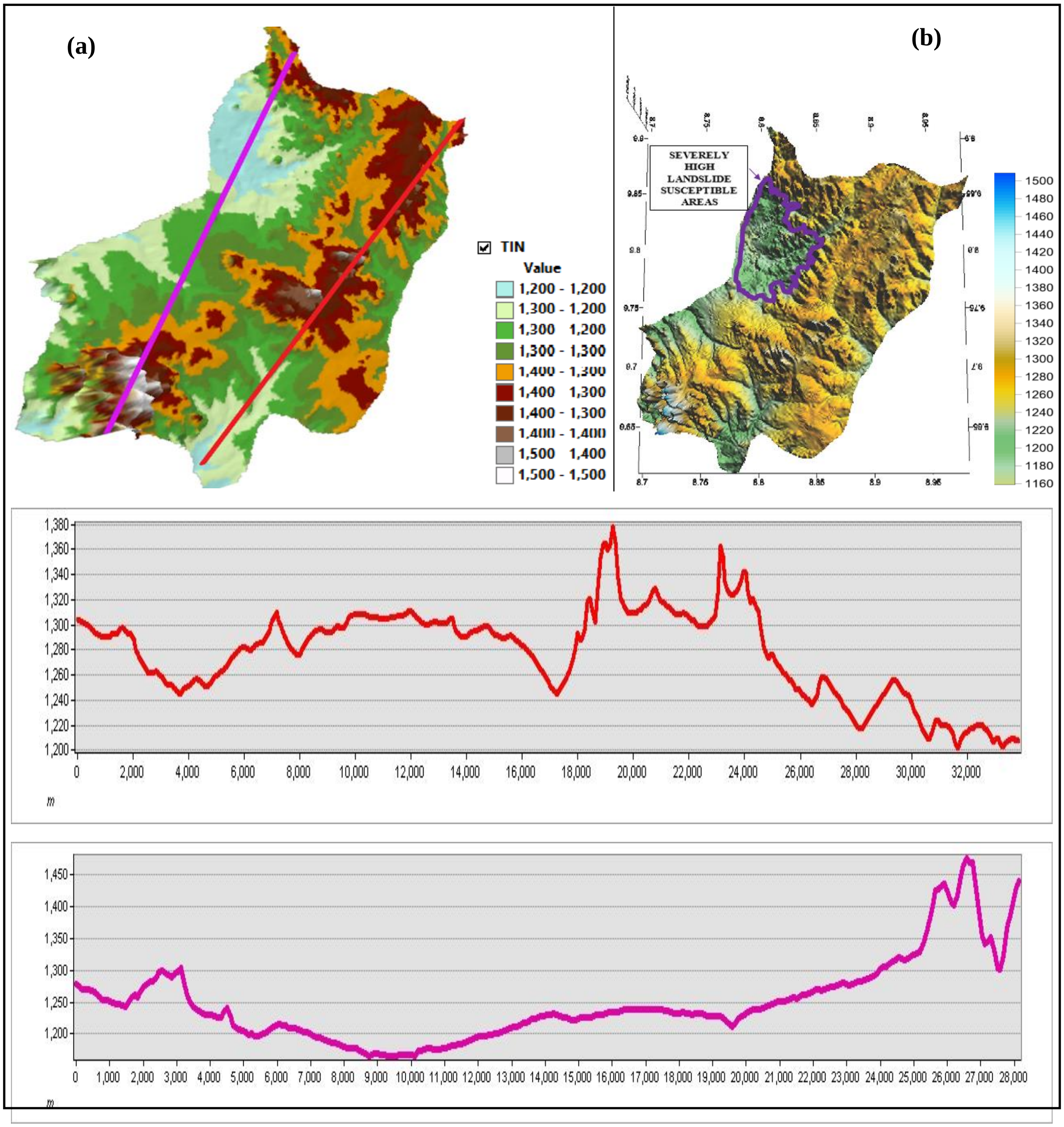

Fig. **15.** (a) Cross section & profile graph of Jos South (Lineament), (b) 3D exaggerated surface of Jos South Geomorphology showing the severely high landslide susceptible areas.

This result was consistent with the report by Claessens et al. (2007) in a study conducted on the Ugandan foot-slopes of Mount Elgon where shallow landslides were discovered to have occurred at a relatively large distance from the water divide, on the region of more gentle convex slope, indicating that the drainage concentration in form of (sub)surface flow was the major remote cause of the landslide. In southern Nigeria, at the Obot Ekpo Landslide site, Akpan et al. (2015), also reported shallow landslides, and he related the water saturation of the underlying rocks due to extremely frequent heavy rainfall as the main cause. However, our finding was inconsistent with some other studies where steeper slopes tend to be more responsible to landslide incidents (Guzzetti et al.1999; Carrara et al.1995; Carrara 2003; Van Western et al.1997; Irigaray 1995).

The long-term spatio-temporal variations in landslide was observed to be substantially related to the monthly rainfall in our study (Appendix figure 3). Higher incidents of landslide were recorded between June to October as compared with other months. This could be explained by the tropical torrential rainfall between June and October (Harp et al. 2004). Furthermore, the interception of the rain water, and runoff close to the trees could have increased the mass instability thus, consequently enabled the weakening of the soil components which resulted to the landslide (Greenway 1987). Greenway (1987) reported the effects of vegetation cover on slope stability. And this can be more devastating when the benefits from the plants are lost due to deforestation through severe human activities as in the case of our study area, Southern Nigeria, and Eastern Uganda (Igwe 2015a; Akpan 2015; Mugagga 2012).

Many studies have reported significant increase in landslide incidents with land use changes (Glade 2003; Gorsevski et al. 2006; Meusburger and Alewell 2009; Wasowski et al. 2010). Transportation, settlement, and other infrastructural development also promoted landslides. In Nigeria and in many other developing countries for instance, major motor-highways, built-up area, urban development, and agricultural activities have been identified as contributing factors to landslides (Swanson and Dyrness 1975; Akpan 2015; Igwe 2015b; Mugagga 2012; Knapen et al. 2006). More so, increase in population between 1955-2015 increased human activities and pressure on the land resources which consequently reduced the stability of the slopes (Knapen et al., 2006). In Uttarakland, one of the dense populated area in India, Panikkar and Subramaniyan (1997) carried out landslide hazard assessment using GIS based weighted overlay method. The authors revealed that population growth accelerated deforestation and urbanization which in turn prompted and exacerbated landslides.

The influence of soil in mass movements cannot be underestimated. Soil plays a dual role because it is a by-product of the landslide process and at the same time it is an important causal factor. The most essential properties in soil stability are those that influence the rate of water movement in the soils and the capacity of the soil to hold water (Sidle et. al. 1985). Shallow landslides were common in our study area because the Acrisol mining soil which dominated this region has high instability to landslide due to several anthropogenic activities which serve as contributing factors.

However, the geology of the study area is mostly covered by granite, and landslide as a geomorphological factor often occur on areas that are covered with sedimentary rocks. Unpropitiously in our site, environmental and human-induced weathering has modified the mechanical, mineralogical and hydrologic attributes of the regolith, and weakened the bedrocks leading to slope instability (Shanmugam 2015; Igwe 2013; Maharaj 1995; Yokota and Iwamatsu 1999; Wakatsuki et al. 2005).

7.2.5 Conclusion

The result from this study is uniquely important because contrary to many findings that landslides are most common in steep slopes, our finding showed the gentle slopes to be most vulnerable to mass-wasting defined as shallow landslides. The causal factors identified in order of their percentage weight were drainage, land use and land cover, soil, geology, lineament density, geomorphology, and slope. Acrisol mining soil, seasonal rainstorm, and increased human population with their rapid activities especially, intensive open-cast Tin mining and farming contributed substantially to the landslide. The tools of geoinformatics have proved very efficient with satisfactory result in the assessment of the landslide and its vulnerability areas. Similar studies should be further applied in the South-Eastern Nigeria where severe gully erosions and landslides have recently become major environmental threats. However, afforestation might reduce excess soil moisture yet, proper family and land use planning could be more sustainable by decongesting the area and reducing the high human pressure on the land resources.

7.3 Landscape changes vs biodiversity (Imo watershed from south-east to south-south Nigeria)

7.3.1 Introduction

In exception of aquatic and some biospheric components, lands (including landscape, plants, soil, climate and underlying ecological processes) supply numerous functions and services to every live on earth (De Beenhouweret al. 2013; Diwediga et al. 2017; Munoz et al. 2013). Globally, billions of human populations including more than 70% inhabitants of Sub-Sahara Africa (SSA) primarily depend on land resources for livelihoods (Akanni 2013; Ayanlade et al. 2017; Ayanlade and Drake 2016; Beresford et al. 2017; Ghosal 2011). Lands directly and indirectly provide other essential ecosystem services such as global water regulation and balance (Tao et al. 2018), carbon sequestration (Foley et al. 2005; Wang et al. 2018;) and climate mitigation (Shrestha et al. 2017). Unfortunately, the land has been recently threatened with severe changes due to acute pressure of human disturbances on natural landscapes at different spatio-temporal scales (Conacher and Sala 1998; Geist and Lambin 2002; Lambin et al. 2001; Szymura et al. 2018). These unsustainably increasing anthropogenic activities are hitherto limiting the ecosystem service potentials of the land resources. Based on the type and the magnitude of land use-land cover change (LULCC), ecosystems became reflects of different processes, structures, functions, and dynamics, forming unique and complex interactions among various landscape components (vegetation, soil, and nutrients) (Adeel et al. 2005). In SSA for example, inappropriate land use and management systems promote land resources degradation and poor soil quality leading to loss of biodiversity (Erb et al. 2009; Portman 2013; Primdahl et al. 2013; Zornoza et al. 2007). According to Russell (1997), the contemporary landscapes are the products of past and present human-nature induced processes, hence a spatio-temporal approach is needed to understand the dynamics involved.

The emanating landscape integrates physical and biological components (DeFries et al. 2004; Foley et al. 2005; Szymura et al. 2018), following transitions in soil features and consequently in flora diversity and productivity (Matson et al. 1997; Padonou et al. 2017; Zerbo et al. 2018). However, many authors have reported the strong correlation between LULCC, soil properties and plant productivity in different ecosystems (Dörner et al. 2010; García-Orenes et al. 2013; Nwaogu et al. 2017a), yet full comprehension on the impacts and drivers of landscape change is still a major challenge especially in Nigeria and other tropical regions because of its physical, socioeconomic and ecological implications (Geist and Lambin, 2001; Lambin et al. 2003; Nwaogu et al. 2017b). Thus, in the region, rapid biodiversity losses are severe threats to nature conservation especially in the intensive agricultural watershed of Southern Nigeria where contrasting land use changes prevails. For example, the tropical rain forests are continuously being converted to either grasslands, arable lands or urban lands whereas, the wetlands are becoming crude-oil mining sites due to increase in population and demand for natural resources (Arokoyu 2010; Ayanlade 2015; Mmom and Gerhart 2001). These anthropogenic interventions in the study area do not only have direct effect on the plants biodiversity but are indirectly related to intensified adverse effects of climate change, soil erosion, and soil infertility (Anejionu et al. 2013; Fagbohun et al. 2016; Nwaogu et al. 2017b; Nwaogu et al. 2018). However, there have been previous studies on Imo watershed (Amangabara 2015; Okoro et al. 2014; Emeghara 2010), yet these studies focused on either drainage morphology, water resources management or agricultural development on short-term basis, and did not covered changes in landscape due to long-term transition in land use.

There are also empirical approaches to evaluate an impact of landscape changes on biodiversity conservation which are based on the relationships between various sets of landscape characteristics (Machar et al. 2017a; Samec et al. 2018). To create empirical models, a relatively large amount of information about the studied site is necessary, and this has implications for the high demands on the amount of input data in the model (Vondrakova et al. 2013). Empirical models are widely applied to large regions with complex and varied arrangements and structures, and where there is diverse relief and different land use categories (Tucek et al. 2014). The aim of this case study is to examine landscape changes the change drivers and their effects on soil and plant biodiversity in multiple land use for a long-term period. The particular research serves as a milestone towards restoring and increasing biodiversity through regulated human activities and introduction of sustainable agriculture and logging in Imo watershed, Nigeria.

7.3.2 Materials and methods

Study area

The research was performed in the Imo watershed (4° 50' 00''N to 6° 02' 00''N and 6° 04'10''E to 7°34' 15''E) which is the largest agricultural watershed in Nigeria with an approximate landmass of 4321.4 km2 (Fig.16). It is at altitudes between 52 and 340 m above sea level. The average annual temperature is 28.5 °C. The warmest month is February, with a maximum average temperature of

30.2 °C, and the coldest month being September, with a minimum average temperature of 16.7 °C. The average annual precipitation reaches 1845.8 mm which is distributed principally between April and October (FORMECU 1998). According to the USDA soil taxonomy and World Reference Base of international union of soil science working group, the dominant soil is Ultisols (WRB 2006). A soil pH in the watershed ranges from 5.32 to 6.44 (Larbi et al. 2000), with sandy and, loamy-sand textural characterizations (Udom and Ogunwole 2015).

The primary land use in the study area are arable land, forest land, grassland, shrubland (on the hills), urban land, and wetland (Fig.17). About five decades ago, larger portion of the area was covered by forest, which has been drastically cleared due to increasing population and alarming demand for land in agriculture and other human uses. The anthropogenic activities compounded land degradation and loss of biodiversity and arable land increased at the expense of forest during the study periods (Table 14).

Land use changes determination

A space-time analysis covering 1991-2016 was conducted to appraise the prevailing landscape changes in the study area. To determine and establish the historical trends and extent of change in the different land use over the 25 years, three Landsat images were used: one MSS image from 1991 and two TM+ images from 1998 and 2016. Though, in the final analyses, only 1991 and 2016 were used because significant change was not found between 1991 and 1998. For example, none of the land use recorded more than 5% change between 1991 and 1998. Arable land was 705.6 km^2 in 1991 and 712.9 km^2, forest land recorded 2259.3km^2 in 1991 and 2263.1 km^2. The used images were chosen from the highest vegetation growing season and in utmost clear sky state to enhance effective comparability. To ameliorate errors in the classification process, all the images were pre-processed using standard methods, and passed through topographic, geometric and atmospheric corrections. To compare ground cover changes quantitatively, all images were transformed to have same spatial resolution (30 m) by applying a pixel standardization method (Hernández et al. 2016a).

Supervised classification which involved the selection of representative areas of each land use-cover to derive their spectral values was applied. This was defined by using the statistical decision criterion of maximum likelihood and assigning pixels to the class which has higher probability (Chuvieco, 2002).

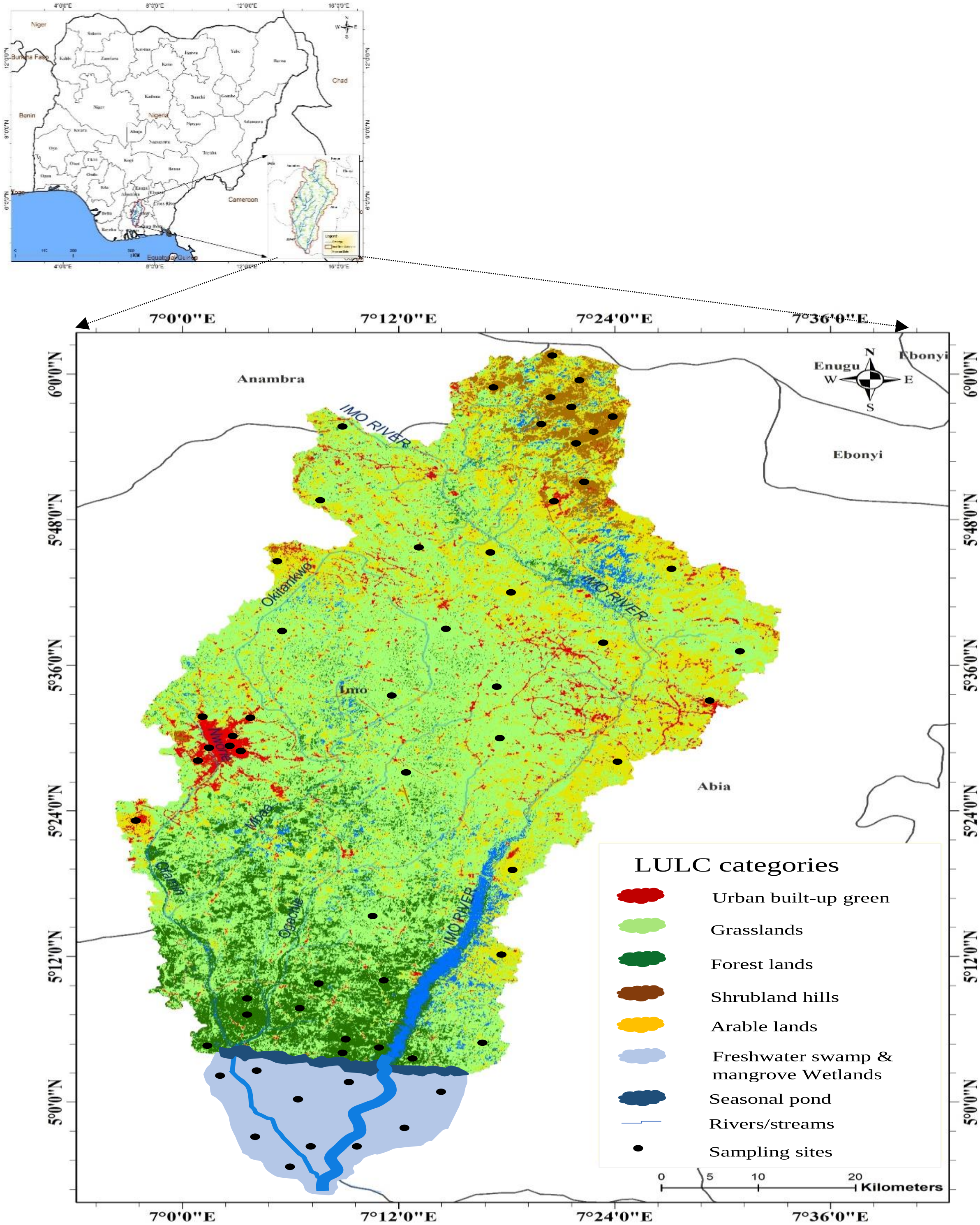

Fig. 16. Study area showing land use-cover (LULC) and sampling sites in 2016.

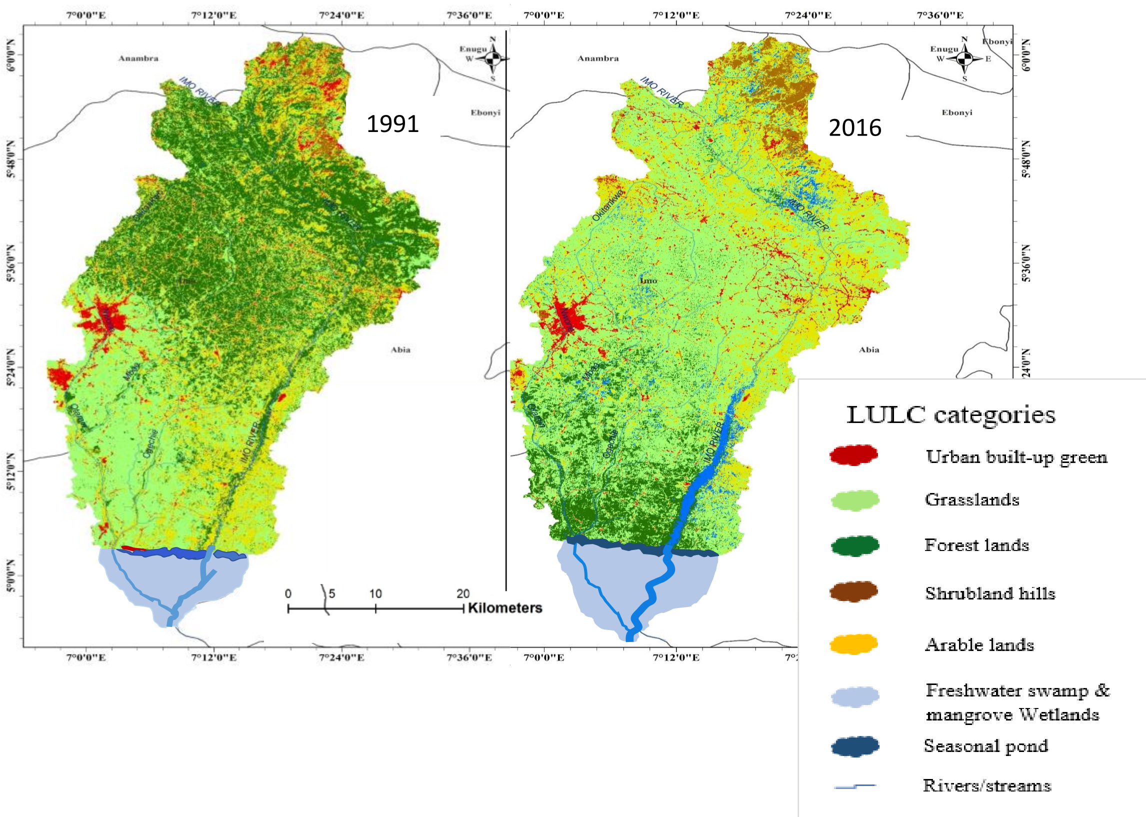

Fig.17. Land use - cover changes for 1991 and 2016.

To classify the Landsat images, five information sources were used as references: (i) Aerial photographs of 1991, 1998 and 2016, (ii) High resolution images which are available in Google Earth (http://earth.google.com), (iii) Field observations in 2015 and 2016, which was conducted to acquire control points for the land use-cover which showed more confusion, (iv) Relevant information/data on plants and soil in relation to land use were collected from government established Agricultural and Research institutions covering 1991, 1998 and 2015, and (v) In 2016, informal interviews were conducted with the village heads and other senior inhabitants of the watershed, to get past and present information about the landscape changes.

Table 14. Land use-cover statistics for the Imo watershed, Nigeria.

Land Use	Area (km^2)‡ 1991	2016	Slope range§ (°)	Diff‡	Description§	Dominant plants species§
AL	705.6	998.8	1.5-12	(+)	Cultivation areas with mainly food crops and few cash crops.	*Arachis hypogaea, Manihot esculenta, Dioscorea alata, colocasia, Zea mays, Cajanus cajan.*
FL	2259.3	483.1	3-13	(-)	Thick and broad-leave forest areas with tall trees and large canopies.	*Leucaena leucocephala, Gliricidia sepium Pentaclethra macrophyllaBenth, Elaeis guineensis. Musa spp, Vernonia nigritiana*
GL	672.5	2351	2-14	(+)	Areas with herbaceous plants species and less than 10% short trees and shrubs cover.	*Andropogon gayanus, Brachiaria decumbens, Lablab purpreus, Pennisetum pedicellatum, Panicum maximum, Panicum purpureum.*
SL	113.7	132.3	4-27	(-)	Highlands ranging between 578-936m a.s.l.	*Lovoa trichilioides Harms, Combretum aculeatum, Dichrostachy cinereal, Vernonia amygdalina. Chromolaena odorata.*
UL	368.1	182.6	2-12	(-)	Residential plots with recreational parks, and green gardens.	*Dacryodes edulis, Anacardium occidentale, Citrus sinensis, Citrus aurantifolia, Mangifera indica, Psidium guajava.*
WL	190.8	163.5	0-11	(-)	Floodplain, freshwater swamps and mangrove-marshes.	*Rhizophora racemosa, Avicennia germinans, Rhizophora Mangle, Nypa fruticans, Sparganium eurycarpum, Najas spp.*
WB	11.4	9.7	< 2	(-)	Rivers and seasonal ponds.	Not sampled

‡derived from authors' analysis; §Authors' survey/sampling in 2016; + denotes increase in area; - denotes decrease in area. LULC categories: arable land (AL), forest land (FL), grassland (GL), shrubland hills (SL), urban built-up green (UL), freshwater swamp and mangrove wetland (WL) and waterbodies (WB).

Seven land use categories based on FAO taxonomy were considered in the classification: Arable land (AL), forest land (FL), grassland (GL), shrubland hills (SL), urban built-up green (UL), freshwater swamp-mangrove wetland (WL) and water body (i.e. ponds, rivers and streams) (Table 14; Fig. 16). It is important to state here that water body was not considered in the study because no sampling was conducted there. All the sites were georeferenced using data from GPS and their locations were added in the maps. The current land use was registered on 2016 map for each site (Fig. 16), following the information from field observations. Classification accuracy was appraised using a confusion matrix between the reference data (ca.125 verification points on the ground for each image) and the classified data (Chuvieco 2002; Hernández et al. 2015). In the end, a global accuracy of 90% and 95%, and Kappa's coefficient of 0.88 and 0.91 were recorded for the 1991 and 2016 images, respectively. This accuracy is reasonably acceptable, considering the size of the study area analyzed (4321.4 km^2) (Ellis et al. 2010). The values of lower accuracy occurred between Arable land and Grassland, and between Water body and Wetland due to their spectral resemblance radiating confusion in the classification algorithm (Altamirano and Lara, 2010). ENVI 4.7 (Exelis Visual Information Solutions, Boulder, Co.) software was employed for the pre-processing and image classification. The landscape transitional dynamics were analyzed by observing the changes in the different land use during the study periods. Land use-cover maps for the study years were generated using the data derived from the classification and ArcGIS/ArcMap 10.1 (ESRI, Redlands, California, USA) software. The transition matrices on the land use maps analysis covering the different periods was performed using the IDRISI Land Change Modeller (Eastman 2012; Pechanec et al. 2017). The transition matrices were representatives of the landscape areas that had a transition from class *i* or class *j* between two consecutive images (Pontius et al. 2004).

Plant biodiversity indicators

At the sampling sites, plant diversity analysis was evaluated for the herbaceous (vegetation) community. Vegetation cover for the herbaceous layer was visually estimated through in-situ observations experts. Plant functional groups composition, percent cover, and above ground biomass (AGB) of the plant community were determined based on quadrat ($2\times2m^2$). Species indices [richness (*R*), diversity (*H* ') and evenness (*E*)] were computed as biodiversity indicators at the quadrat level. Species richness (*R*) was determined as the number of species identified in each quadrat, whereas Shannon index (H', Eq. (6)) and evenness index (E, Eq. (7)) were calculated using the following Equations (Chen et al. 2016; Deng et al. 2014; Revermann et al. 2016):

$$H' = -\sum_{i=1}^{s} \mathrm{P}i * \ln(\mathrm{P}i) \qquad \text{Eq. (6)}$$

$$E = H' / \ln s \qquad \text{Eq. (7)}$$

where S is the total species numbers of the herbaceous (vegetation) community, and Pi is the proportional density of species i (number of individuals of species i divided by the total number of individuals of all species).

Soil properties and RUSLE factors

From each land use, soil sampling sites (Fig. 16) were chosen based on the plants sampling points, existing knowledge of the area and considering landscape variability based on altitude and soil features. For effective evaluation and comparison, soil samples under different land uses were selected. Water was excluded from the sampled land use because it was not suitable for establishing agricultural soil quality. Ten replicates sites for each land use were chosen to achieve better landscape representation, making a total of 60 soil-sampling sites. Soil sampling was performed in September 2016, reaching a depth of 30 cm at 4 random points at each site. Before taken to the laboratory for analysis, the 4 samples were composited for each site, and plant roots, residues and pebbles were removed. They were air dried and sieved to pass through a 2-mm mesh. The samples were analyzed for chosen soil chemical, physical and biological properties based on study objectives. Soil bulk density (D^b) was calculated as the ratio of dry soil weight and the volume of the soil (Black and Hartge 1986). The concentration of soil organic carbon (OC) was determined according to the Walkley and Black method (Schnitzer 1982), while the soil total nitrogen (TN) concentration was determined using the Kjeldahi method (Bremner and Mulvaney 1982). Soil pH was measured using acidometer. Soil respiration (R^S) was determined between 10:00 hrs and 14:00 hrs in the field with three replications, by applying a closed chamber system with an infrared gas analyzer (SRC-1, PP systems, Hitchin, UK). The measurements were successfully executed by positioning chambers on the surface of the top mineral soil layer after clearing the organic layer. Soil organic matter (OM) was obtained through oxidation with a mixture of dichromate and sulfuric acid, and this was measured colorimetrically (Schulte 1995).

The impacts of soil erosion were assessed by combining the RUSLE-based factors (Pechanec et al. 2015; Renard et al. 1997). including rainfall erosivity of soil particles (R-factor), soil erodibility index (K-factor), and the vegetation cover index (C-factor, Pechanec et al. 2018a). The R-factor is derived based on Eq. (8) using the average annual precipitation data of the area (Diwediga et al. 2017). In addition, the Eq. (8) was effectively applied in West African landscape to compute R-factor (Le et al. 2012; Tamene and Le 2015).

$$R = 0.577 * Pa - 5.766 \qquad \text{Eq. (8)}$$

where R is annual rainfall erosivity (MJ mm $ha^{-1}h^{-1}y^{-1}$), and Pa is average annual precipitation (mm) of nearby stations. The K-factor values were derived from Le et al. (2012) based on World Reference Base with Ultisols as the dominant soil (WRB 2006). To determine C-factor as a factor of soil erosion potential, the satellite image of land use-cover was adopted, and the values were estimated using the normalised difference vegetation index (NDVI) data of the Landsat image obtained from (http://www.earthexplorer.usgs.gov) by applying Eq. (9) (Diwediga et al. 2017; Le et al. 2012; Tamene et al. 2014).

$$C = \exp [- 2.5 * NDVI / (1 - NDVI)] \qquad \text{Eq. (9)}$$

Statistical analysis

Prior to the statistical analysis, all vegetation variables were natural-logarithm transformed and standardized to meet the assumptions of normality and linearity according to Grace et al. (2016) and Zuur et al. (2009). All data were expressed as mean ± standard error. One-way ANOVA and mean comparison using the Tukey's HSD test were conducted to evaluate the differences in vegetation cover, above ground biomass, biodiversity indicators and soil properties among the different land use with the STATISTICA 13.0 software (Statsoft, Tulsa, OK, USA). Additionally, correlation/regression analysis was performed to test the degree of relationship between the selected parameters.

Redundancy analysis (RDA) followed by a Monte Carlo Permutation test with 999 permutations in the CANOCO 5.0 software (Ter Braak and Smilauer 2012) was implemented to evaluate the interactions between the plant species and the land use. Ordination diagram was produced by applying the CanoDraw program which prompted the presentation and visualization of the RDA result.

7.3.3 Results

Biodiversity and vegetation indicators

A decline in the species diversity was found across all the land use between 1991 and 2016 with FL recording more than 41% decrease (Table 15). AL showed an increase in species evenness by about 36% and on the contrary, a decreased species diversity by 35%. GL increased in species richness from 43 to 51 during the study years. AGB indicated a decrease trend across the land use with FL having the highest drop by at least 30%.

Significant difference ($P < 0.05$) in the cover of all species was found across the land use (Fig.18a). More than 50% loss of all species was found during the study in all the land use. AL and FL recorded the highest loss of all species with at least 60% rate for each while, GL revealed the lowest loss of less than 10% between 1991 and 2016. There was significant difference in the average loss of shrubs during the study period (Fig.18b). Although, higher cover of shrubs was observed in 1991 than 2016 across the land use, except SL which had also high shrubs in 2016.

The shrubs decreased by 72%, 70%, 33%, and 16% in FL, UL, GL and SL respectively. In general, grasses were the most abundant species among all the community functional groups identified in the study (Fig.18c). High cover of grasses was exceptionally found in 2016 than 1991. Although, the grass species increased by more than 100% under AL and FL and by 70% under GL, but no significant changes were found in SL, UL and WL.

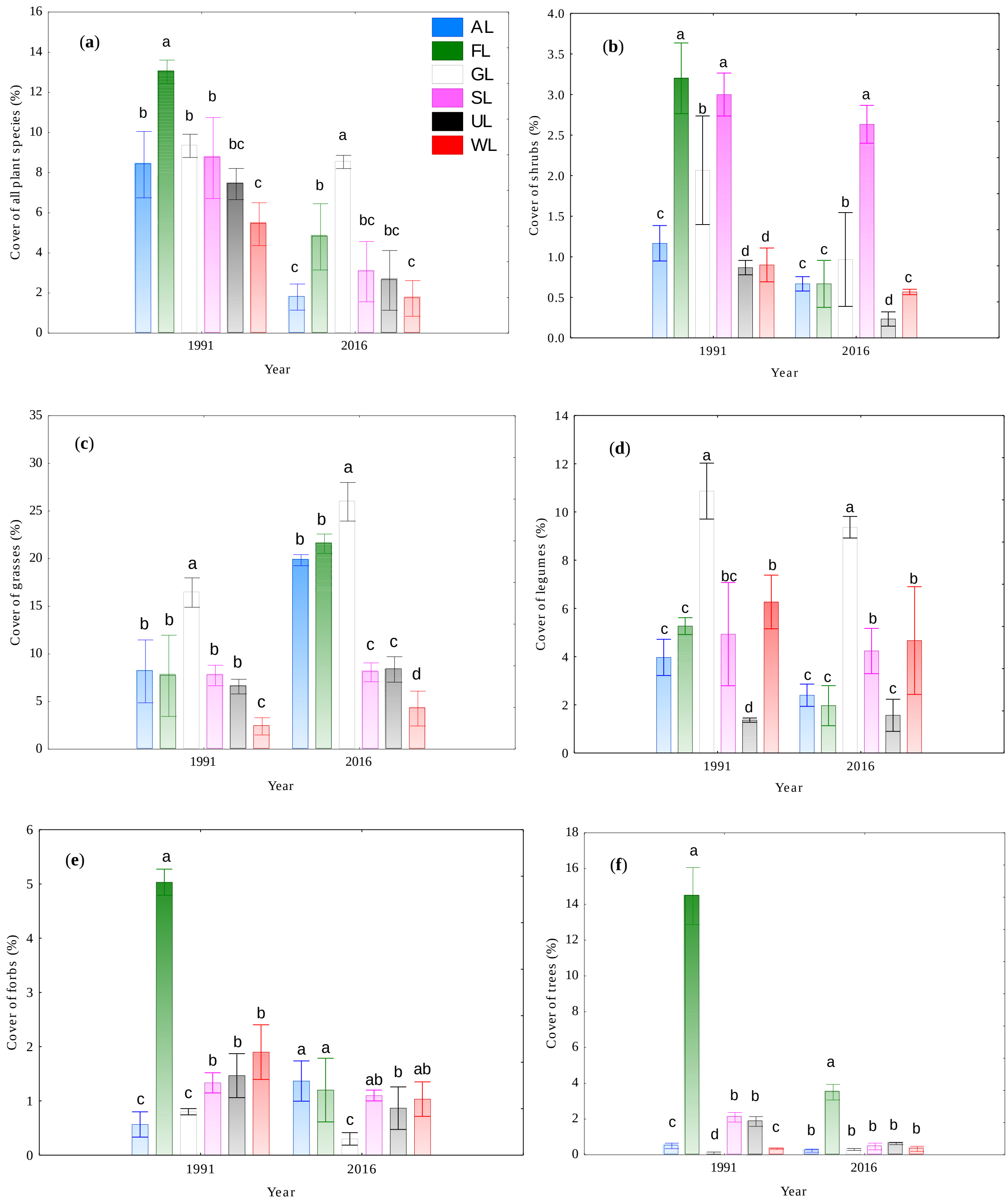

Fig. 18. Cover (in %) of community functional group between 1991 and 2016 for (a) All plant species, (b) Shrubs, (c) Grasses, (d) Legumes, (e) Forbs and (f) Trees. The bars represent the standard error of the mean. Different letters on the bars indicate significant differences among the various land use at $P < 0.05$. Description of the abbreviations for land use are: Arable land (AL), forest land (FL), grassland (GL), shrubland hills (SL), urban built-up green (UL), freshwater swamp and mangrove wetland (WL).

The legumes like the grasses had a favorable growth in the GL during the study years (Fig. 18d). UL recorded relatively low cover of legumes with approximately less than 4%. Forbs revealed remarkably high average cover under FL in 1991 which was about 82% higher than as obtained in 2016 (Fig.18e). Generally, forbs recorded low cover in the study area, yet the loss across the land use was not significant except under FL. The trees were the highest individual plant species lost during the study period and FL accounted for the largest decrease of more than 75% (Fig.18f).

Table 15. Summary of soil properties and plant biodiversity indicators for the study area (Mean ± SE)

Land use	R-factor	K-factor	C-factor	D^b	pH	OC	TN	OM	R^S	*H'*	*E*	*R*	AGB
1991													
AL	386±45	0.10±0.0	0.19±0.04	1.22±0.01	6.2±0.3	5.9±0.8	0.51±0.04	3.81±0.07	NA	2.0±0.03	0.42±0.0	NA	NA
FL	307±12	0.18±0.03	0.43±0.06	1.15±0.02	6.6±0.9	12.6±1.1	1.47±0.09	8.24±0.03	NA	4.1±0.01	0.13±0.0	68±4.1	161±29
GL	389±27	0.09±0.0	0.22±0.01	1.30±0.08	6.2±0.1	8.1±0.9	1.11±0.07	4.01±0.03	NA	2.7±0.03	0.28±0.01	43±5.2	103±37
SL	375±9	0.12±0.01	0.30±0.02	1.19±0.01	6.3±0.1	6.8±0.4	0.93±0.05	4.91±0.09	NA	1.8±0.01	0.49±0.07	NA	101±14
UL	394±23	0.13±0.01	0.27±0.05	1.33±0.04	6.4±0.4	5.3±0.4	0.67±0.08	2.75±0.01	NA	1.6±0.01	0.51±0.09	NA	75±16
WL	353±18	0.15±0.02	0.40±0.03	1.09±0.02	5.7±0.2	9.4±0.7	1.03±0.01	6.60±0.09	NA	2.1±0.01	0.37±0.01	NA	126±48
2016													
AL	441±32	0.31±0.0	0.09±0.0	1.35±0.09	6.1±0.5	3.6±0.4	0.28±0.01	1.55±0.04	0.32±0.0	1.3±0.0	0.57±0.08	28±2.1	47±5
FL	365±19	0.29±0.02	0.26±0.01	1.21±0.07	6.4±0.1	6.1±0.3	0.73±0.09	4.02±0.01	0.55±0.02	2.4±0.01	0.53±0.06	22±3.8	112±23
GL	417±11	0.22±0.0	0.10±0.0	1.43±0.01	6.5±0.3	6.5±0.6	0.89±0.06	2.51±0.02	0.37±0.0	2.5±0.02	0.19±0.0	51±6.6	77±6
SL	401±36	0.19±0.0	0.16±0.01	1.29±0.03	6.3±0.2	5.7±0.2	0.42±0.04	3.33±0.01	0.40±0.01	1.6±0.07	0.38±0.0	30±4.5	84±9
UL	425±17	0.20±0.0	0.07±0.0	1.47±0.05	6.5±0.7	3.2±0.1	0.44±0.05	1.90±0.01	0.29±0.0	1.1±0.03	0.44±0.01	19±3.3	39±3
WL	382±13	0.18±0.01	0.35±0.02	1.12±0.02	6.1±0.4	4.6±0.5	0.91±0.03	4.17±0.02	0.46±0.02	1.2±0.04	0.61±0.02	36±4.1	91±4

Factors: R-factor (MJ cm ha^{-1} h^{-1}), D^b = Bulk density (g cm^{-3}), OC = Soil organic carbon (g kg^{-1}), TN = Soil total nitrogen (g kg^{-1}), OM = Soil organic matter (%), R^S = Soil respiration (g h^{-1} m^{-2}), *H'* = Shannon diversity index, *E* = Species Evenness, *R* = Species Richness, AGB = Aboveground biomass (g m^{-2}). LULC categories: arable land (AL), forest land (FL), grassland (GL), shrubland hills (SL), urban built-up green (UL), freshwater swamp and mangrove wetland (WL).

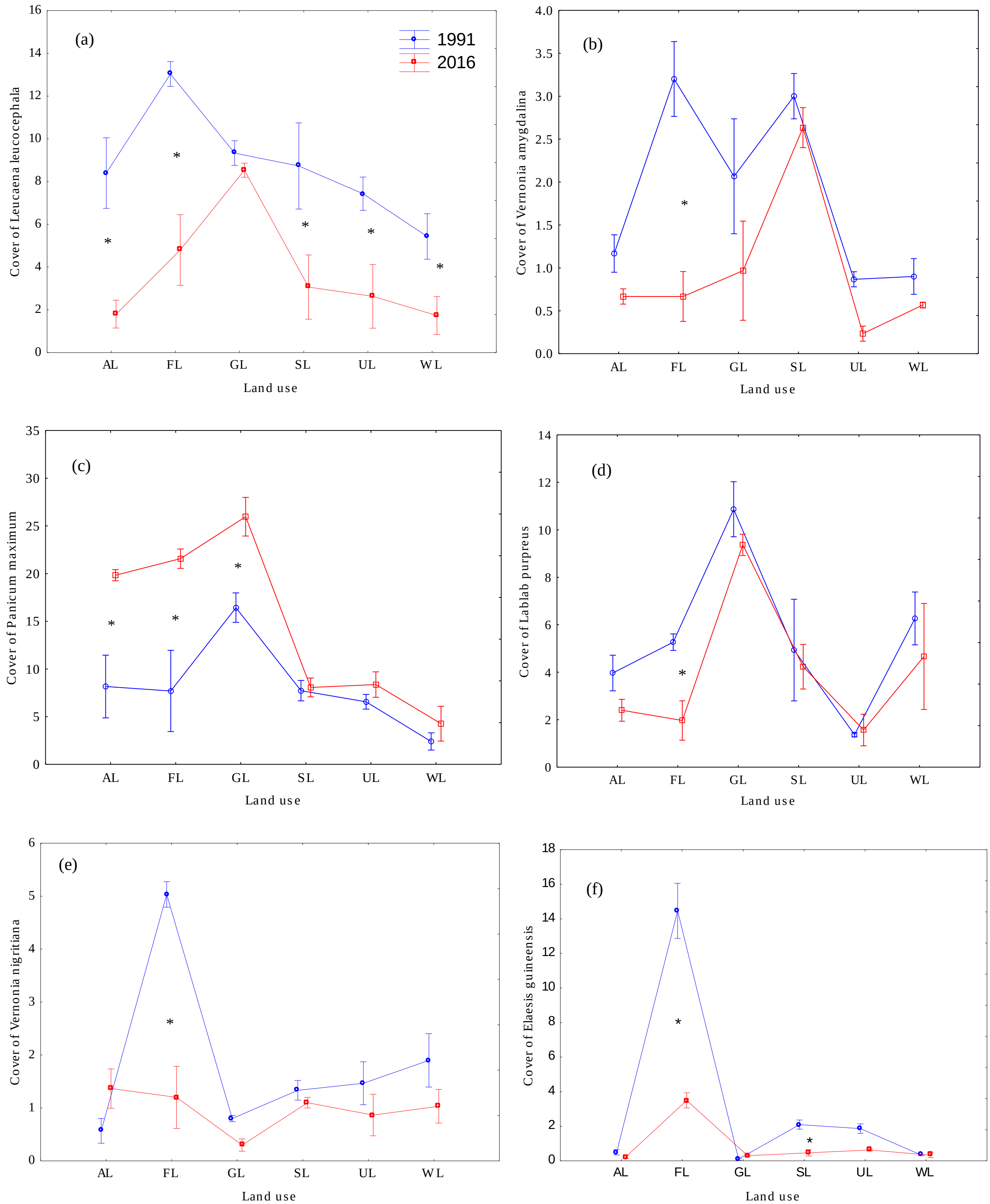

Fig. 19. Cover (in %) of dominant plant species of major community functional group between 1991 and 2016 for (a) *Leucaena leucocephala*, (b) *Vernonia amygdalina*, (c) *Panicum maximum*, (d) *Lablab purpreus*, (e) *Vernonia nigritiana* and (f) *Elaeis guineensis.* Asterisks (*) represent significant differences between the years (P < 0.05). The bars represent the standard error of the mean. Description of the abbreviations for land use are: Arable land (AL), forest land (FL), grassland (GL), shrubland hills (SL), urban built-up green (UL), freshwater swamp and mangrove wetland (WL).

In relation to the individual species, *Leucaena leucocephala*, *Vernonia amygdalina*, *Panicum maximum*, *Lablab purpreus*, *Vernonia nigritiana* and *Elaeis guineensis* were the most identified species with high coverage (Fig.19). Statistically significant differences between the years of study were found in the cover of L. *leucocephala* in all the land use except GL (Fig.19a). FL recorded the highest cover, while WL followed by AL had the lowest. *V. amygdalina* is a shrub and its cover difference between 1991 and 2016 was significantly high under FL but drastically increased under UL (Fig.19b). The grass species, *P. maximum* was highly significant in AL, FL and GL during the study period (Fig.19c). *P. maximum* had at least 60% increase under AL, FL and GL in 2016 when compared with 1991. *L. purpreus* is a leguminous which showed a significant difference in years under FL but had high cover in GL (Fig.19d). *L. purpreus* was at least 50% higher in coverage under GL when compared with the cover in other land use. *V. nigritiana* is the only forb species found to be dominant in the study especially under FL (Fig.19e). Across the land use except AL, *V. nigritiana* had higher cover in 1991 in comparison with 2016. A remarkably high cover of *V. nigritiana* was found in 1991. *E. guineensis* as a common tree species found in the study area indicated more than ten times higher in FL than as found in other land use in 1991 (Fig.19f). AL and GL accounted for the lowest coverage in both 1991 and 2016. In summary, AL, FL, and GL recorded higher number of species decline relative to SL, UL and WL during the study years (Fig.20). Trees, shrubs and legumes formed the larger number of the disappearing species.

Soil parameters

The concentrations of soil nutrients (such as OC, TN and OM) were relatively higher in 1991 relative to 2016 (Table 15). FL recorded higher soil OC, TN and OM contents than any other land use during the study period. The soil nutrients concentrations were more than 50% higher in 1991 when compared with the contents found in 2016. All the soil chemical properties decreased across the land use except pH which was higher in 2016 under GL and WL. However, there were no available data for soil respiration (R^S) in 1991, but the records under FL and WL were relatively higher than the values observed under UL and AL. The values for the bulk densities (BD) also varied with some increase across the years and in the different land use. For example, AL, GL and UL increased by 59%, 43% and 42% respectively between 1991 and 2016.

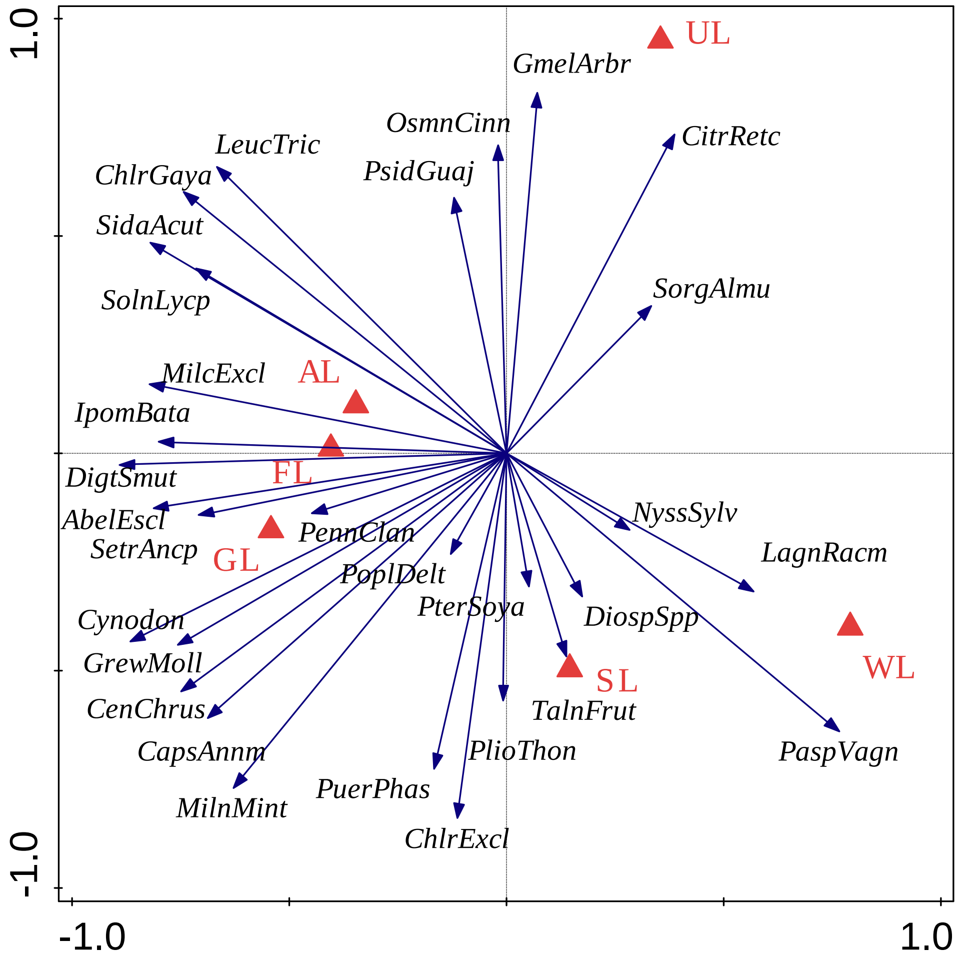

Fig. 20. A biplot ordination redundancy analysis showing the most extinct/disappearing plant species in the different land uses between 1991 and 2016 in the study area. LULC categories: arable land (AL), forest land (FL), grassland (GL), shrubland hills (SL), urban built-up green (UL), freshwater swamp and mangrove wetland (WL). Details of species abbreviations are *Talinum fruticosum (TalnFruit), Abelmoschus esculentus (AbelEscl), Leucaena trichandra (LeucTric), Sida acuta (SidaAcut), Ipomoea batatas (IpomBata), Solanum lycopersicum (SolnLycp), Capsicum annum (CapsAnnu), Pueraria phaseoloides (PuerPhas), Sorghum almum (SorgAlmu), Milicia excelsa (MilcExcl), Populas deltoids (PoplDelt), Diospyros spp (DiospSpp), Nyssa sylvatica (NyssSylv), Pterocarpus soyauxii (PterSoya), Chlorophora excelsa (ChlrExcl), Chloris gayana (ChlrGaya), Cenchrus ciliaris (Cenchrus), Cynodon dactylon (Cynodon), Milinis minutiflora (MilnMint), Digitaria smutsii (DigtSmut), Setaria anceps (SetrAncp), Pennisetum clandestinum (PennClan), Grewia mollia, (GrewMoll), Pliostigma thonaigii (PlioThon), Psidium guajava (PsidGuaj), Citrus reticulata (CitrRetc), Gmelina arborea (GmelArbr), Osmunda cinnamomea (OsmnCinn), laguncularia racemosas (LagnRacn), Paspalum vaginatum (PaspVagn).*

Environment, vegetation and management (RUSLE factors) parameters

The soil erodibility index (K-factor) and rainfall erosivity of soil particles (R-factor) increased rapidly across the land use except WL (Table 15). The K-factor of AL, GL, FL, UL, and SL increased by 68%, 59%, 40%, 35% and 33% respectively. In 1991, FL and WL had relatively high cover management (C-factor) of 0.43 and 0.40 respectively, but the C-factor of FL decreased drastically by about 40% while that of WL decreased by just 12% after 25 years. UL had the highest C-factor decrease of more than 70%, whereas AL and GL had a decrease of at least 50% each, during the study period.

Species diversity showed significantly negative correlations with species evenness and R-factor ($P < 0.05$), but positive correlations with TN and OM and OC ($P < 0.001$) (Table 16). Species richness revealed significant relationships with OC, AGB, C-factor and K-factor. On the other hand, AGB was positively affected by OM and C-factor, but negatively affected by BD, pH and R-factor. Species richness and OM increased with increasing OC, C-factor, decreased with increasing BD and R-factor. In addition, C-factor strongly affected OC.

7.3.4 Discussion

Biodiversity and vegetation indicators

Species diversity decreased in time in study area and FL had the highest decline. This might be attributed to the increase in human activities such as agriculture, deforestation and urbanization due to rapid population growth which in turn drastically reduced the forest ecosystem and consequently challenges to biodiversity conservation (Mustin et al. 2017; Pechanec et al. 2018b). Several authors have previously reported a loss of biodiversity caused by human growth and urbanization (Chisté et al. 2018; Dai et al. 2018; Dimobe et al. 2015; Lim et al. 2018; Neuenschwander and Adomou 2017; Rastandeh et al. 2017; Revermann et al.2016). FL declined extremely, and excessive exploitations of forest resources have been known as a primary cause of biodiversity losses (Janssen et al. 2017; Machar et al. 2017b). Besides anthropogenic disturbances, abiotic factors such as climate was discovered as a key factor to loss of diversity in the study area especially under FL. For example, FL recorded accelerated R-factor during the study years which was an indication that severe rainstorm caused by climate change (Chapungu and Nhamo 2016; Trimble and van Aarde, 2014; Udoh 2015).

Table 16. Correlation analysis among the biodiversity indicators, soil properties and other ecological factors.

	H'	*E*	*R*	AGB	D^b	pH	OC	TN	OM	R^S	R-factor	K-factor	C-factor
H'	1												
E	-0.71*	1.00											
R	0.64	-0.60	1.00										
AGB	0.44	0.00	0.69*	1.00									
D^b	0.18	-0.64	0.00	-0.74*	1.00								
pH	0.55	-0.22	0.03	-0.03*	0.02	1.00							
OC	0.84**	-0.54	0.41*	0.79	-0.23	0.33	1.00						
TN	0.55*	0.00	0.60	0.64	-0.41	0.02	0.59	1.00					
OM	0.63*	0.25	0.06	0.92**	-0.85*	-0.15	0.53*	0.64	1.00				
R^S	0.31	0.28	-0.02	0.96*	-0.80**	-0.10	0.62*	0.57	0.91	1.00			
R-factor	-0.19*	-0.26	0.09	-0.92*	0.78	-0.01	-0.55	-0.61	-0.96*	-0.95*	1.00		
K-factor	-0.08	0.53	-0.32*	0.80	-0.83	-0.16	0.29	0.44	0.90*	0.90	-0.95*	1.00	
C-factor	0.33	0.10	0.26*	0.83*	-0.53	0.11	0.61*	0.20	0.68*	0.87*	-0.80*	0.75	1

* Indicates significant at $P < 0.05$, and ** significant at $P < 0.001$.

Factors: *H'* = Shannon diversity index, *E* = Species Evenness, *R* = Species Richness, AGB = Aboveground biomass, D^b = Bulk density, OC = Soil organic carbon, TN = Soil total nitrogen, OM = Soil organic matter, R^S = Soil respiration.

Although, GL had an increase in species richness yet, it recorded low diversity biomass. This revealed that though herbivory promoted community abundance but did not reflect any positive effects on species diversity and AGB. This result was in contrast with the report of Rolo et al. (2018) that forest disturbances decreased functional diversity and increased AGB. More than 50% of all species were lost in AL, FL, and GL than UL, SL, and WL. This could be explained by the facts that AL, FL, and GL suffered more threats from intensive human activities from agricultural practices (slash-burn, shifting cultivation, over-grazing), logging for timber and domestic uses (An et al. 2018; Lim et al. 2018; Marieke et al. 2015; Rastandeh et al. 2017; Udoh 2015). On the contrary, the WL experienced minimal disturbances in the study which was triggered by isolated pockets of mining points (Edwards et al.2014), and the SL was minimally disturbed by man but by soil erosion because of its location at the high altitudes in the area. For example, many authors in the past have attested that altitude and soil characteristics were most essential determinants of plants diversity loss in West Africa than traditional human activities (Nacoulma et al. 2011). On the contrary, several authors in Nigeria have reported severe loss in wetland biodiversity in the region due to rapid human activities and conversion of the wetland ecosystem to other economic uses (Adekola and Mitchell 2011; Ayanlade and Proske 2015; Olalekan et al. 2014). Other work which was inconsistent with this present study revealed that wetlands suffered from significant changes in species composition and species richness caused by human disturbance (Zhao et al. 2014).

The grasses and legumes revealed higher coverage in the GL, and grasses were the only community functional group that increased over the years. The activities of the ruminants might have enhanced the growth of the vegetation by dominant species to increase the colonization of the rare species as well as increasing the seed bank (Klaus et al. 2018; Niu et al 2016). This was also a good reason for observed species richness under the GL than in other land use in the study. For example, native perennial grasses such as *P. maximum* had more than 60% increased with increased grazing (i.e. in 2016 than in 1991). Similar observation was found in the Hoa Binh Province of North Vietnam where *P. maximum* became dense over time (Phan et al. 2012). However, our study was inconsistent with the recent work from other authors who reported that grazing led to the strong decline of native plant richness declined increasing productivity (Eldridge et al. 2018). The dissimilarities in the results could be attributed to differences in climate, soil, herbivores and grazing intensities and duration.

Generally, forbs recorded low cover in the study area but showed high coverage in FL in 1991 than as obtained in 2016. This was probably because most forbs in the area were annual species and tend not to have much seedings and reproductivity and high vulnerable to disturbances when compared with other species such as grasses or shrubs. The excruciating heat of the tropical sun might also have contributed in the low cover of the forbs in the study area. Thus, FL was the most favorable land use for the species which consequently decline with increasingly compounded human pressure. *V. amygdalina* was a dominant shrub species because besides it having a bitter and unpalatable teste for animals, it stores water in stems and can reproduce easily through vegetative or seed. More so, *V. amygdalina* was commonly observed in the higher elevations of the landscape with less human disturbance and better plant succession (Hernández et al. 2016a). *E. guineensis* was dominating tree species in the FL than in AL, GL or other land use because unlike the shade in FL climate and fire from the traditional slash-burn farm practice as well as browsing by the grazers in the AL and GL hindered the trees survival (Okoro et al. 2017). However, the expansion of *E. guineensis* has been reported as a treat to biodiversity because it requires the deforestation of other plant species for its plantation (Paterson and Lima 2017)

Soil parameters

Soil nutrients (OC, TN, OM) were found to decrease drastically with time across the land use types. The acute impacts of anthropogenic activities were not only exerted on the vegetation but also on the soil components. The soil and plants compositions have strong interwoven/mutual relationship thus, a shift on one will hitherto change the status of the other (Hernández et al. 2016b; Wang et al., 2016). The decrease in OC, TN and OM might be explained by the critical depletion and absence of plant litter due to low floristic coverage caused by rapid population growth and over exploitation of the land resources. This finding was in line with many authors attestation that intensive agriculture whether on the forest, arable or grassland has critically adverse effects on the soil quality (Chen et al. 2016). Increase in soil OC has been studied to be linked with increase in TN content (Chen et al. 2016). The dynamics of OC and TN stored in soils have been reported to depend on the balance between inputs, mainly from plant leaf and root detritus, and outputs through decomposition (Davidson and Janssens 2006). The current study found higher soil nutrients in the FL, WL and SL This might be related to higher vegetation cover (in FL), and minimal disturbance in WL and SL when compared with AL, GL or UL. This finding was in agreement with the recent work in Mo river basin, West Africa where higher OM, OC and TN were higher in forest soils than the agricultural soil (Diwediga et al. 2017). In the same study region several research works have reported similar observations (Diwediga et al. 2015; Fontodji et al. 2009; Sebastia et al. 2008;). In the context that soils of natural vegetation formed the basis for the potential fertility, similar differences in terms of OM, OC and TN concentrations between the arable and forest soils have been affirmed in southern Nigeria, as a result of agricultural land use prompting the loss of soil fertility (Udom and Ogunwole 2015). The agricultural interventions and other practices promoting the loss of vegetation cover caused a substantial reduction of OM, OC and TN inputs consecutive to the loss of biodiversity.

The conversion of the FL to GL was found to be a reason for increased pH under the GL in 2016. This could be attributed to increased herbivore activities, urine and faeces on the top soil. In contrast to our finding, there has been some previous results where a decrease in soil pH was reported following the conversion of grasslands to forest lands (Chen et al, 2016; Tully et al. 2015; Berthrong et al. 2009). The differences in results could be because of the reverse in the land use conversion between the studies. In terms of the soil bulk density, values generally increased across the land use during the study years. AL, GL and UL recorded the highest increase which could be explained by acute soil disturbances (Wang et al. 2016). Thus, the over utilized land use had more bulk density than the natural, more OM content or less disturbed soils in our study. For example, Ritter (2007) found lower bulk density the surface soil layer due to elevated OM content from increased afforestation. Lower soil respiration (R^S) was observed under UL, AL and GL relative to FL and WL. It might be associated with poor soil microbes, OC and vegetation cover which were adversely influenced through over-exploitation by man, animal, erosion and leaching processes. For example, forests have been known as better promoters of distinctly different microbial communities when compared with arable lands since the agricultural lands have low-quality litter (Bossio et al. 2005).

Environment, vegetation and management (RUSLE factors) parameters

Substantial increase in R-factor and K-factor were observed in all the land use except WL. The K-factor of AL, GL, FL, UL, and SL increased by 68%, 59%, 40%, 35% and 33% respectively. The alarming rates of human interventions in the sites were the primary causes of these rapid increase in the rainfall erosivity and soil erodibility factors. This finding was consistent with other reports on the same issue and from the same study region which revealed high rainfall erosivity and soil erodibility in the area due to decreasing vegetal cover caused by anthropogenic activities (Anejionu et al. 2013; Aukema et al. 2017; Ezemonye et al. 2012; Fagbohun et al. 2016; Nwaogu et al. 2018).

Although, all the land use especially FL and WL had relatively high C-factor at the initial study year, but overly the C-factor values decreased in time. The unduly removal of the vegetation and soil cover was a major cause as the soil became exposed to extreme environmental forces (such as erosion, leaching, surface run-off) (Chapungu and Nhamo 2016; Ehigiator and Anyata 2011; Udoh 2015).

Species diversity revealed an inverse trend with species evenness and R-factor but was directly associated with TN, OM and OC. The negative relationship amongst diversity, evenness and R-factor was a reflection of typical scenario in most tropical region because of the heterogeneity in the floristic composition and human-inducement. This result agreed with the work of Revermann et al (2016) in dry tropical woodlands of South Africa where species evenness was found indicating inverse pattern to species richness. Deforestation coupled with climate change made the soils became very hydrophobic due to high levels of poorly humified organic matter, which led to severe erosion and depleted OC (Benito et al. 2003; Lal 1996). On the other hand, in this study it was found that increased in C-factor due to cover management enhanced soil quality which consequently increased TN, OM and AGB (Ross 1993; Silva-da et al. 2017; Zeng et al. 2017).

7.3.5 Conclusion

In exception of GL, all land use had substantial loss in individual plant species and community functional group between 1991 and 2016. The highest loss of biodiversity with low species diversity and richness was observed in FL because greater destruction and degraded area occurred in forest which has more dependable resources for rural livelihood. The coverage of grass species (especially, *P. maximum, B. decumbens, P. purpureum, A. gayanus, P. pedicellatum*) increased due to free-range grazing and removal of light-shedding plants during the study period. Though, grazing increased species richness, yet there was no improvement in species diversity, above ground biomass and soil nutrients. Therefore, further attempts to convert the forests to either grassland or arable land pose severe threats to biodiversity in the area. This study is a milestone for comprehending the signal extent of landscape change which is essentially necessary to compliment efforts by various stake-holders in nature conservation towards ameliorating deforestation. In conclusion, to restore and increase biodiversity, it is imperative to regulate human activities by introducing sustainable agriculture and logging in the watershed.

7.4 Landscape changes in Dřevnice River Basin, Southeast Moravia (Czech Republic)

7.4.1 Introduction

Ecosystems including river basins have been experiencing many threats by environmental factors which either make or mar their ecological status. The capability to either resist disruptions or revert to its native development lies on the intensity of the external disturbance and features of the environment; thus, the greater this capability is, the more stabilized the ecosystem would be. Ecological stability is an area's resilience to human or natural disturbances and its potential to repeatedly regenerate.

Ecological stability of a given landscape is a concept with numerous definitions based on individual researchers view which were perceived as a function of time and space**.** Several authors focusing mainly on natural ecosystems, have defined ecological stability with respect to resistance, resilience, constancy, persistence. inertia, elasticity, cyclicity, and integrity (Larsen 1995; Holling 1973; Orians 1975; Zonneveld 1977; Ulrich 1987; Kay 1991; Jargensen 1992). Therefore, the tenacity of a system such as river basin as a stability feature is closely linked with the spatio-temporal dimension of ecosystem (Grimm et al. 1992). However, opinions about ecological stability differ, because ecological status is influenced by several factors (Belcakova 2005; Halaj et al. 2013) such as physical and socioeconomics (including population growth) which affect the landscape.

Landscape is a highly dynamic system which has natural and social interrelated components that are largely influenced by constant change (Izakovičová et al. 2017). Time and space have been identified as the two most essential universal parameters, where natural and human forces amalgamate to create-and perpetually alter-the naturally existing landscape into either a cultural or semi-cultural landscape, thus producing an entirely different and uncommon feature (Žigrai 2011). Change in landscape is one of the basic focus in global environmental change and sustainable development. And several multinational and international research organizations have reported rapid landscape changes due to change in land use caused by anthropogenic and physical processes. For example, contemporary information revealed that more than half of the world's population settles in urban areas, and the United Nations has predicted that by 2050, two-third of the world's population will live in urban areas (United Nation 2000). This paradigm increase in population has pushed nations to meet the elevated demands for necessities such as land, water, shelter, food, and energy. A major concern related to this urban sprawl is land use change, which can seriously modify the landscape in areas with heightened urban spread (Tian et al. 2016).

The decision-makers are saddled with the responsibility of ascertaining the safety and welfare of the inhabitants. Thus, there is the need to understand the past-present status in landscape change and to extrapolate future scenarios. Land use changes and associated challenges will probably linger as primary issues in the future, and for the stakeholders to critically project future landscape development, they need to evaluate the spatio-temporal variations, the magnitude, and the driving forces of these changes. To guarantee the adequacy of the future land resources for sustainable development, land use changes must be accurately detected and mapped. However, it is cumbersome to appraise land use transitions in mega-scales with simple field surveys or sampling methods especially when the ecological stability indices (resistance and resilience) are involved.

The stability of a given landscape an ecosystem is a concept that has been described as a crucial feature in land use state and transition models (Holling 1973; Williams et al., 1993; Bestelmeyer et al. 2003; Stringham 2003, Hobbs and Suding 2009). The scientific field has nowadays recorded tremendous growth of many landscape change simulation and models which are making it easier to monitor the changes (Nwaogu et al. 2018). Researchers in various academic areas, ranging from those who report in favour of modelling to those concerned with the causes and consequences of land use dynamics, have applied different models integrated with GIS (Stürck et al. 2015). These landscape models are vital tools for promoting the awareness of macro-scale change dynamics and impacts in support of policy design process based on established needs (Stürck et al. 2015). Top on the lists of the most widely used models were Cellular Automata (CA), Markov chain, Agent-based and CLUE (Nwaogu et al. 2018). Further development has proved that a robustly hybrid multidisciplinary model such as CA-Markov model is the most effective method for modelling the probability of spatiotemporal change in LULC along with GIS. The prediction potential of the model has been demonstrated in many studies as the best landscape change model, and is available in IDRISI software packages developed by Clark Labs at Clark University, with the combination of GIS and remote sensing functionalities.

As in other regions, the landscape change driving forces (biophysical, socio-economic, and proximity characteristics) are paramount pinnacles in comprehending the change-drivers-prediction syndromes in the Dřevnice River Basin, Southeast Moravia (Czech Republic).

As in other regions, the LULC change driving forces (biophysical, socio-economic, and proximity characteristics) are paramount pinnacles in comprehending the change-causes-prediction syndromes in the Czech Republic. Although several categories of drivers were initially measured in this study, but only the outstandingly significant factors were used.

The main goal of the study was *to evaluate the rate at which Dřevnice River Basin changes from 1990 to 2050*. To achieve this goal, two objectives were designed such as:

(i) to identify the major land use and the change driving forces.

(ii) to predict the future changes for the different land use.

7.4.2 Materials and methods

Study area

The study area is Dřevnice river basin which is one of the rivers in the Czech Republic located in the left tributary of the Morava River. It is an important river with average discharge rate of 3.15 $m^{3\text{-}S}$ into Morava river which flows into Danube and Danube into the Black Sea. Dřevnice river originates from the Vizovice Highlands (Vizovická vrchovina) at the highest elevation of 560 m and flows to the lowest elevation (182 m above sea level) in Otrokovice which is in Central Moravian Nivy where it enters the Morava River (Jakubová 2014). Dřevnice river is 41.6 km long with basin area of 435.2 km^2.

It flows passing through many settlements including Kašava, Březová, Slušovice, Lípa, Želechovice nad Dřevnicí, Zlín and Otrokovice. The Slušovice Dam is constructed on the river. The slope of the river is predominantly between 5°-15° which covered have of the territory which just a minimal area with slope above 25° (www.dibavod.cz).

Geologically, Dřevnice river basin is basically underlain by quaternary terraced sediments, which are formed by weathered slope sediments of clays and admixtures of sandstone with a subsoil made of clay shale (Kadlecová 2010). These weathered and flood deposited materials formed soil types which were classified as Eutric Gleysol and Fluvi-eutric Gleysol (Šerá et al. 2008). The valley slopes are covered with deluvial sand-stone sediments - thicker deluvial sediments it is located mainly on the left valley slope of Dřevnice, which is often found in the Rack village. Deluvial sandy and sandy sediments are particularly widespread in the south of the valley slope which ranges from Zlín to Otrokovice (Jakubová 2014, 2016).

Floristically, the catchment area of the Dřevnice river, is characterized by *Aegopodion padagrariae, Bidention tripartite* and *Phaladidetum arundinaceae* though natural (flood) and human disturbances have to a large extend affected the plants composition. The lower part of the river catchment area especially, is defined by the dominant growth of invasive plant species such as *Reynoutria japonica, Helianthus tuberosus* and *Aster x salignus* (Sher et al. 2000).

Table 17. Landuse, codes and description from CLC

Number in cov_all	**Description**	**Corine LC TAG**
0	urban area	11x-13x
1	urban green area	14x
2	farm(arable) land	211
3	pasture and meadow	231
4	orchard	222
5	other agriculture areas	243
6	forest	3xx
7	water	51x

Data collection and analysis

Data for this study which were calculated post-extraction from the Corine land cover database covering four-time periods: CLC 1990, 2000, 2006, 2012. The calculations were performed in script work of CLC predict executed by experts (Pechanec, V., Doležalová, J., Macků K.) who have the skill by using the principle of Markov chains and these were written in R script interface. The output is used as an input file (in CLUE (Verburg 2015; Verburg 2010; Pechanec 2014) for the proceeding task on 'demand'.

From the four periods CLC data, eight land use types (Table 17) were categorized namely: urban area, urban green area, arable land, pasture, orchards, other agriculture land, forest, and water.

In respect to the drivers, after the initial simulation/analysis 16 drivers were identified as the most significant forces for land scape changes in the study (Table 18). The drivers were: aspect, % built-up, distance to urban, distance to forest, distance to pipelines, distance to water, urban distribution/density, elevation(dmr), population growth, individual owned farmlands (lpis), population density, precipitation, relative height, soil protect, slope, and temperature. With image resolutions of 100 meter / px, the land use change detection and prediction was started in the year 2012 with the forecast extending to year: 2050.

Table 18. Overview of major identified land use change drivers with names and sources

Drivers	**Datasets**	**Notice**
DMR	DMR 5G (CUZK)	
Slope	DMR 5G	Calculated in ArcGIS
Aspect	DMR 5G	Calculated in ArcGIS
Relative elevation	DMR 5G	Calculated in ArcGIS
Average year precipitation	Precipitation (CZECHGLOBE)	Modified Czech Adapt
Average year temperature	Temperature (CZECHGLOBE)	Modified Czech Adapt
Distance to road/railway	ArcCR / OSM	Calculated in ArcGIS
Distance to water bodies	ArcCR/OSM	Calculated in ArcGIS
Distance to urban areas	Corine LC	Calculated in ArcGIS
Distance to forest	Corine LC	Calculated in ArcGIS
Distance to pipeline, power lines	UAP/OSM	Calculated in ArcGIS
Prot of agric. land (soil protect)	BPEJ	
Population density	ArcCR	Calculated in ArcGIS
Growth rates	ArcCR	Calculated in ArcGIS
Percentage of farm(arable)land (LPIS) areas	LPIS	Calculated in ArcGIS
Percentage of the built-up area	OSM	Calculated in ArcGIS

Description of the used model: CLUE/CLUMondo

The Conversion of Land Use and its Effects modeling framework (CLUE) is a land use change model which was developed to simulate land use changes over large areas by applying empirically quantified associations between land use and its drivers in integrated with dynamic modelling of conflicts among different land uses (Veldkamp and Fresco, 1996). In addition, CLUMondo is an extended version of CLUE developed to simulate land use changes, and land intensity changes, due to the increasing demand for multiple and contrasting ecosystem goods and services (van Asselen and Verburg, 2013). CLUMondo model is subdivided into two different modules namely; a non-spatial demand module (the driving factors of change) and a spatially explicit allocation module (the driving factors of locations). The function of the non-spatial demand module is to calculate the change in demand for ecosystem goods and services at the aggregate level. It is of important to state here that the demands are subsequently translated into land use changes in specified locations in the allocation module of the model. The model has many interfaces that enabled the inclusion of necessary land use variables for this analysis. For examples, list of all the diving factors as in this study were input into the suitability layers of the model while, the land system services sub-tool was employed in the table presentations of the values that indicate the types and amount of services that each land systems produces, as specified in the land use matrix. Under the regression analysis and model parameters series of statistical analyses including a multicollinearity/logistic regression analysis were performed and the parameter selection permits the selection of only those parameters that are needed to be included in the model. These analyses enabled the verification of whether or not driving factors are correlated. But before the actual regression analysis, the covariates were checked for correlation, and when the correlation between a pair of covariates became too high (> 0.7), one of the covariates was eliminated from the analysis.

Table 19. Transition matrix for the land use in the study area

	urban area	urban green area	farmland	pasture_ meadow	orchard	other agric. area	forest	water
Urban area	1	0	0	0	0	0	0	0
Urban green area	1	1	1	1	1	1	1	1
Farm/arable land	1	1	1	1	1	1	1	1
Pasture/meadow	1	1	1	1	1	1	1	1
Orchard	1	1	1	1	1	1	1	1
Other agric. area	1	1	1	1	1	1	1	1
Forest	1	1	1	1	1	1	1	1
Water	0	0	0	0	0	0	0	1

To evaluate the results from the performed logistic regression, the goodness of fit was evaluated using the ROC method according to Pontius and Schneider (2001). In this study, acceptable and very good logit model was achieved based on the obtained ROC values which were 8.0 and above Other analyses performed using the CLUMondo model were conversion resistance parameters which include conversion order, elasticity parameters and conversion matrix. The conversion order was used to show changes in land uses in response to land use demands, while elasticity parameters helped in determining the resistance for conversion of specific land use types. On the other hand, conversion matrix revealed what conversions are allowed in this model application. For example, a value ‘1’ denoted that the conversion is allowed, whereas a value ‘0’ signified that such conversion is not allowed (see Table 19). The conversion resistance parameters were subsequently employed to further determine the reversibility of the categorized land use and their changes. In this study for instance, urban area and water were relatively static land use types because either they revealed high capital investment or had irreversible impacts on the environment. On the contrary, in our study, urban green area, arable land, pasture, orchards, other agriculture land, and forest are easily convertible; thus, they had low ecological stability values when compared with water and urban area (Table 19).

Table 20: Calculated resistance index/values to disturbances based on the ecological stability

Land use	urban area	urban green area	farmland	pasture_ meadow	orchards	other agric.area	forest	water
Resistance index	1	0.7	0.2	0.3	0.3	0.2	0.7	0.9

7.4.3 Results

Every land use enabled conversions from one land use to another land use except urban area and water which showed no transition to any other land use (Table 19).

Resistance based on ecological stability measures Urban area followed by water =highest while farm(arable) and other agricultural areas =lowest. Urban green area and forest also revealed reasonable resistance when compared with pastures and orchards. The arable/agricultural areas showed about 80% less resistance disturbances and forces of change when compared with urban areas. The water body indicated only about 10% lower resistance than urban areas where as, pastures and orchards were 30% lower (Table 20). On the other hand, pasture and forest areas have 50% more resistance to perturbation relative to arable or other agricultural lands.

Table 21. Summary of suitability regression coefficient for the land use and drivers of the changes

	urban	urban green	arable	pasture	orchards	other_agri	forest	water
constant	0.93345	-197.63654	7.93550	13.92140	-108.76211	1.19399	0.29870	-6.71929
aspect	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-0.00179	0.00684
% built up	0.00026	0.00000	-0.00015	0.00000	0.00000	-0.00005	-0.00005	0.00000
Urban dist/density	-0.00728	0.00000	0.00000	0.00000	0.00319	0.00000	0.00000	0.00000
Distance to forest	0.00000	0.00185	0.00109	-0.00087	0.00131	-0.00111	-0.01451	-0.00123
Dist to pipelines	-0.00236	-0.00202	0.00000	-0.00070	0.00000	-0.00073	0.00086	0.00000
Distance to water	0.00000	0.00000	0.00000	0.00000	0.00000	-0.00198	0.00000	-0.00356
Distance to urban	0.00000	0.00000	0.00000	0.00000	-0.00297	0.00000	0.00000	0.00000
Dmr (relief)	0.00000	0.00000	0.00000	0.00000	0.00000	-0.00716	0.00000	0.00000
Growthrate(pop)	0.00038	-0.00023	-0.00042	0.00101	-0.00034	0.00000	0.00000	0.00000
Lpis(farmland)	0.00000	**-0.02987**	**0.02592**	**0.01523**	0.00000	-0.00907	**-0.02153**	0.00000
Pop density	0.00370	0.00000	-0.00166	0.00242	0.00000	0.00000	0.00000	0.00000
precipitation	0.00000	**0.09305**	-0.01566	0.00000	**0.06043**	0.00000	0.00000	0.00000
relative height	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
soil protect	0.00000	0.00000	0.00025	0.00027	**0.72373**	0.00030	-0.00027	0.00000
slope	0.00000	**0.08852**	0.00000	0.00000	0.00000	0.00000	0.00184	-0.00659
temperature	0.00000	**15.12132**	0.00000	**-2.05037**	**6.76945**	0.00000	0.00000	0.00000

Urban green area and orchards indicated strong suitability regression coefficient with temperature, whereas that of pasture areas and temperature was strong but negative (Table 21). Urban green area was also suitably correlated with precipitation, farmland (Lpis) and slope. Furthermore, soil and precipitation revealed suitability regression coefficients with orchards.

All the eight-categorized land use increased in their areas between 2012 and 2050 (estimate) except farm/arable land and forest which on the contrary decreased (Fig.20, Fig.21 and Fig.23). Though, decline in forest areas was minimal when compared with the significant drop in farmland areas. Farmland/arable land decreased by about 34%, whereas forest though revealed the largest area, yet a marginal decrease of less than 1% was observed (Fig.24). Urban area increased by about 6% while, orchard and urban green had low areas with relatively insignificant change (Table 22). On the other hand, there was change observed for water.

Table 22. Land use area (ha and km^2 approx.) at the beginning of study and predicted year

Land use	Area in ha (km^2)	
	Year 2012	Year 2050
Urban area	4580 (46)	4846 (49)
Urban green area	181 (2)	220 (2)
Farmland	10250(103)	6756 (68)
Pasture & meadow	2960 (30)	332 (3)
Orchard	208 (2)	4897 (49)
Other agric area	6659 (66)	7815 (78)
Forest	18560 (185)	18532 (185)
Water	111 (1)	111 (1)
TOTAL	43509 (435)	43509 (435)

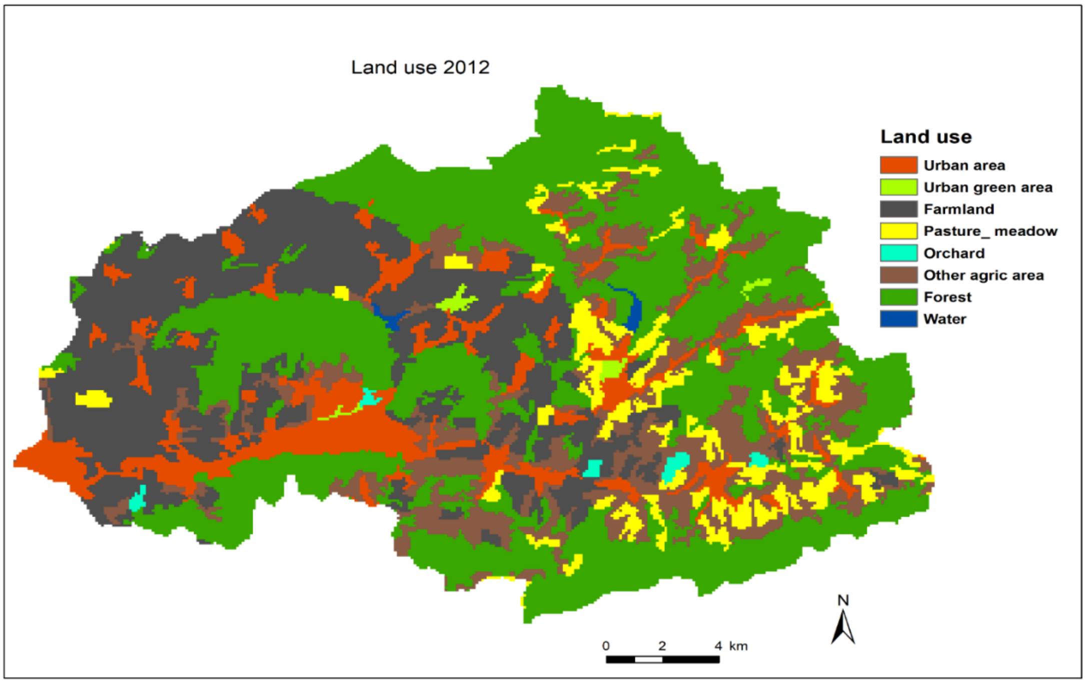

Fig. 21. Land use 2012

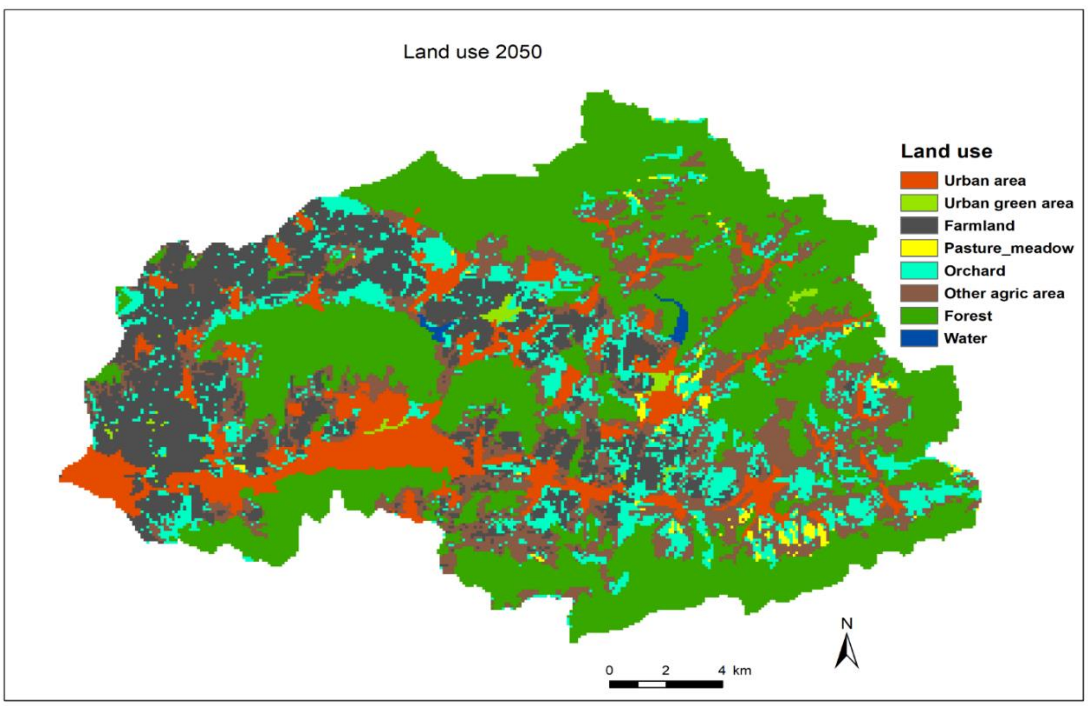

Fig. 22. Predicted Land use for 2050

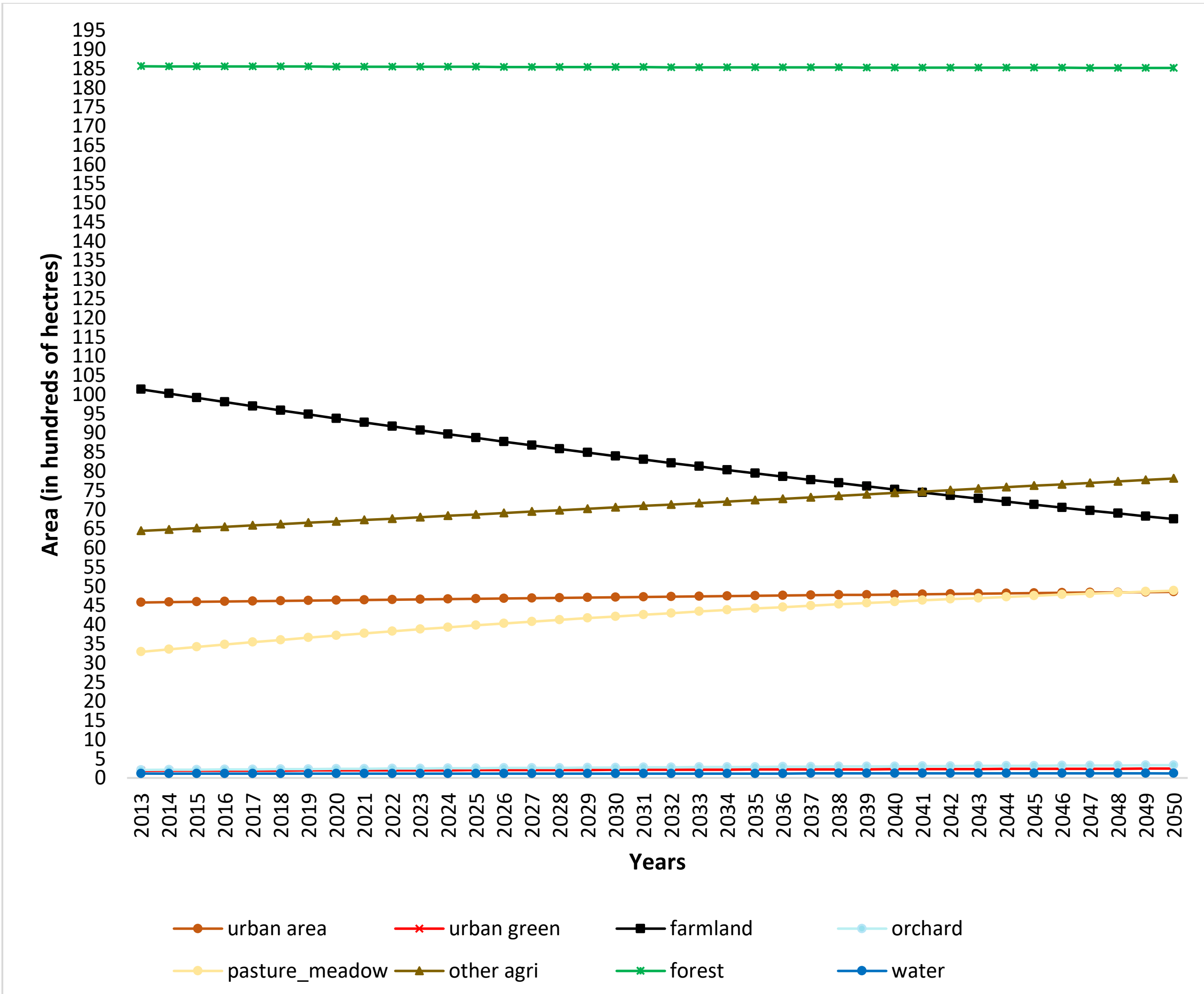

Fig. 23. Land use change trends and predictive values.

7.4.4 Discussion

Urban area and water were found to be statically resistance to conversion and had high ecological stability in the study area. This might be attributed to the fact that these land use types especially the urban area is potential for high demand or large land requirements. Many authors have previously studied the relationships between ecological stability, urbanization and water land use (Webster et al. 1983; López et al. 2013; Long et al. 2014; Malekmohammadi and Jahanishakib 2017). And in most of these works which are similar to our findings, built-up areas revealed a high resistance to environmental/external disturbances (Li et al. 2017; Li et al. 2016). In contrast with the result of this present study, water was discovered to be easily converted or have low ecological stability in some other studies (Zhou et al. 2017; Long et al. 2014). Báčová et al. (2013) in the

Lačnovský and the Leskava (Czech Republic) have conclusions which were inconsistent with the results of this study. The authors revealed that because of managerial negligence among the municipal authorities, rivers and streams in urban areas are rapidly losing their natural environmental qualities leading to low ecological stability. Furthermore, some authors have reported an urban ecological sustainability with high ecosystem services degradation (Peng et al. 2017). The report indicated that due to intensified agricultural practices, there was high higher need for water in irrigation. Besides, the agricultural lands were increased at the expense of the water bodies which declined.

On the other hand, arable/agricultural areas were found to show relatively low ecological stability. This could be explained by the reason that arable lands can easily be used for urban developments or could have a season or period (whether short or long) without cultivation. This finding was consistent with the documentations from several studies which emphasized on the roles of anthropogenic activities in ecological resistance or resilience (Bitterman and Bennett 2016; Muchová et al. 2016; Keken et al. 2015). Other authors in Czech Republic have attested the strong relationships between low ecological stability and agricultural activity in the region (Hanusová et al. 2018). Agricultural lands (crop cultivation ore livestock rearing) relatively have high rates of soil erosion, leaching and soil depletion due to the incessant removal of vegetation cover which consequently elevated the ecological instability (Tabenia et al. 2016).

The study observed strong connections between climatic parameters (temperature and precipitation), urban green and orchards. Many authors have in the past reported substantial tie between climate change and urban greening and sustainable development (Mabon and Shih 2018). Sequel to the growing urban heat island (UHI) effect, urban green planning has been considered essential in most developed countries as one of the critical measures for urban climate change adaptation (Gill et al. 2007; Roszenweig et al. 2011).

The arable land and forest areas decreased in favour of other land use during the study. Rapid demand and use of these land use types (arable and forest) for urbanization, pasture and other agricultural practices was probably the reason for the decrease (Szturc et al. 2017). In consistent with the findings of this present study, in Central Europe especially Czech Republic for example, many authors have previously discovered increase in urban areas at the expense of either the arable or forests (Izakovicova et al. 2017; Moravcová et al. 2017; Sklenička and Lhota 2002; Kusková et al. 2008). In other works, titled 'grassland winners and arable land losers' Reif and Hanzelka (2016) reiterated that the pasture areas increased while the arable lands decreased. The authors further described the importance of landscape changes on the biodiversity focusing on the Czech Republic.

In support of this research findings, there has been many studies which have confirmed the decrease in forest areas in Czech Republic and other European countries (Fyfe et al. 2015), in Africa (Boka and Kevin 2018; Wu et al. 2016; Ayanlade and Drake 2016), in Asia (Meyer et al. 2017), in South America (Boers et al. 2017; Staal et al. 2015) and other continents (Thompson et al. 2006; Hufnagel and Garamvoelgyi 2014) due to elevated urbanization caused by population growth, increase in demand for resources and technological development. However, there has been many campaigns on afforestation and protection of the forests by various organisations and the government of the developed countries but the outcomes from these attempts are yet to be fully achieved. Though, from the result, the forest areas in this research might still be in decline till 2050, but the decrease rate becomes lesser with increasing years. This justifies the support for forest conservations in most European countries when compared with the developing countries scenario (Ayanlade and Drake 2016; Zhou et al. 2014).

As investigated in this study, many anthropogenic and environmental factors have been identified as the key drivers for these changes in land use. The driving forces identified in our study were also in reported by previous works in this issue including; population growth, built-up and urbanization (Rydval and Wilson 2012; Nwaogu et al. 2017a), agriculture and soil (Gay-des Combes et al. 2017), climate change (Wu et al. 2016; Hufnagel, and Garamvoelgyi, 2014; Akkermans et al. 2013), soil (Nwaogu et al. 2018), and topography (Helman et al. 2017).

7.4.5 Conclusion

Eight land use were categorized with sixteen drivers identified as paramount to the landscape changes over the study period and area. The study reiterated interactions between land use and ecological stability in the river basin. Urban area and water were found to be statically resistance to conversion and had high ecological stability relative to other land use types. In terms of size, all the land use increased over time except farm (arable) lands and forests due to their intensive utilization and conversion to urban built-up, pasture and/or other agricultural practices. Substantial change in area was found in farmlands relative to forests which insignificant.

The role of climate (precipitation and temperature), population, soil and topography was also found to be significant as the landscape change drivers. CLUMondo proved to be an appropriate land use change model for the realization of the study aim and objectives. The findings from this study will enable future planning policies that seek to conserve the unique natural and ecological features of Czech Republic landscape with particular reference to Dřevnice River Basin.

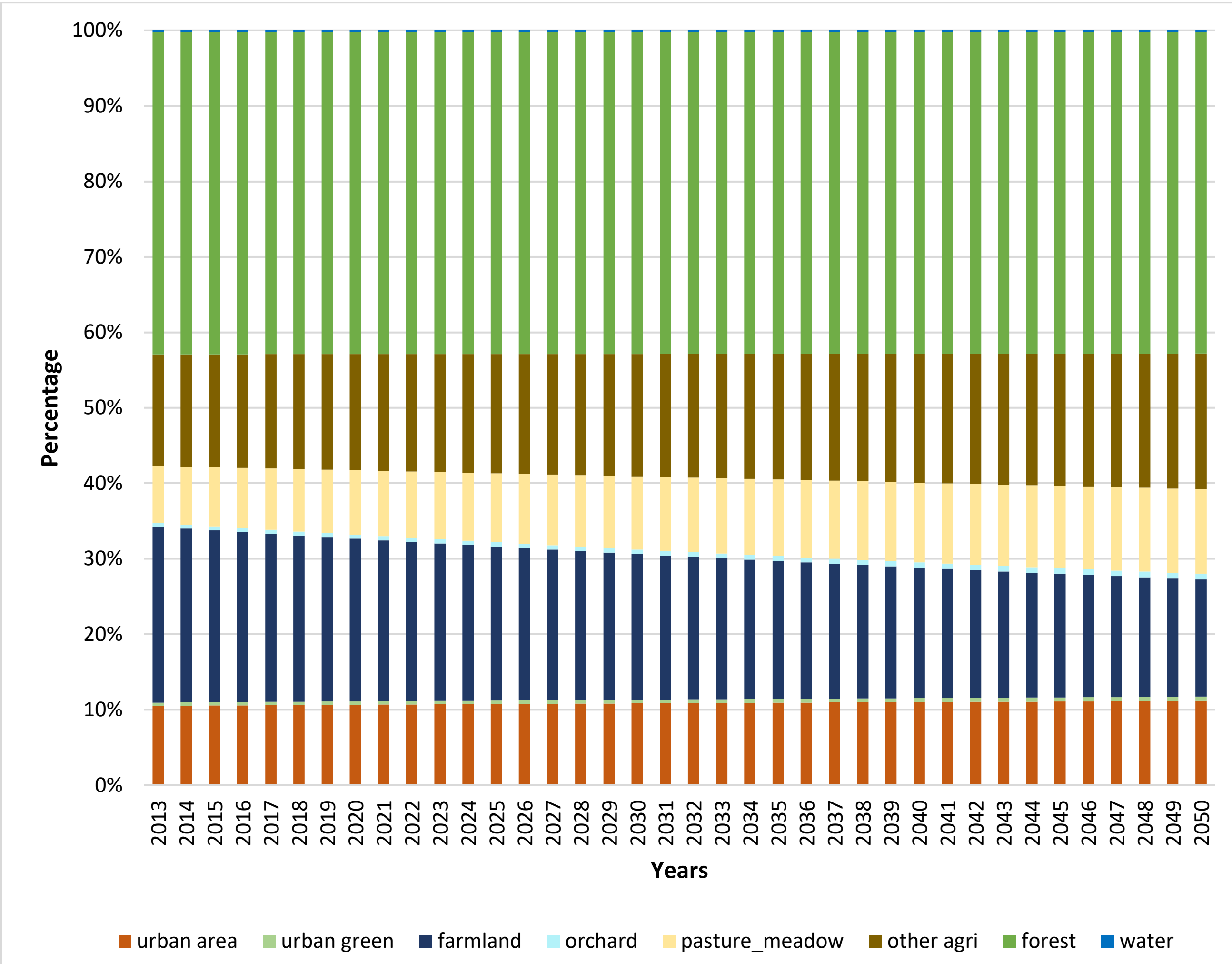

Fig. 24. Percentage of land use changes in areas between 2013-2050

8 Discussion

Prior to the final conclusion, it is necessary to reiterate salient information and issues from the previous discussions with respect to the case studies especially. This will also serve as a medium to summarize overview of impressions based on the author's experiences in relation to the presented work.

Increase in built-up areas because of rapid population growth which consequently led to acute deforestation and intensified agricultural activities was observed as the main driving forces of landscape changes in case study 1 (Onitsha - a growing urban hub). On the other hand, the forest vegetation was drastically decreased when compared with other land use. The author refers to publications which addressed problems related to this study as well as for more information (Nwaogu et al. 2017). Regarding case study 2 (Jos – landslide), built-up area was also a primary driver which induced other remote factors that prompted the landslide and producing landscape changes as final consequence. Another significant driver found was mining which increased deforestation as well. The final results have been presented to be published in Springer and a special issue on ISPRS-International Journal of Geo-Information (GIS for Safety & Security Management, 2018). Case study 3 (Imo – watershed), also revealed that the forest which recorded more than 40% decrease suffered more degradation from the drivers - anthropogenic activities (such as agriculture, urbanization and deforestation). In this study, the impacts of land use change on other factors like soil erosion and soil features were also examined in relation to complementary effects on landscape. The final result of this case study has been submitted for publication in the Journal of Nature Conservation (Bulgaria) in 2018. The final case study (Dřevnice River Basin, Czech Republic), also indicated that the forest area had substantial effect from the driving forces of change relative to other land use. The final results of this study are still under preparation to be submitted to a journal indexed in either WOS or scopus.

Though, forest areas were observed to have shown decrease rates in all the case studies yet, this decline was lower in the case study 4 (Czech Republic) when compared with case studies 1, 2, and 3 (Nigeria). The reason for this could be because of differences in management and socio-economic circumstances. For instance, Czech Republic as a developed country is establishing more and better policies and practices geared towards enhancing nature conservation and sustainable environment relative to the developing country (Nigeria) where such polices are weak.

The primary driving forces were almost relatively similar in all the case studies however, case study 4 showed marginal difference with higher number of identified driving forces. This might be attributed to the differences in geographical settings, socio-economics, and methods. For example, individually owned farmlands and distance from pipelines were not feasible in Nigeria scenarios.

9 Conclusion

The main goal of this thesis is focused on analyzing landscape changes by identifying the changes, the drivers of the changes, and impacts on the land resources in different land use using GIS in combination with some statistical techniques.

This main goal will be achieved with objectives structured as follows:

1. To evaluate change in land use and its effects on the vegetation and landscape in a rapid growing urban hub (Onitsha) from 1987 to 2015.
2. To identify Jos landslide vulnerable areas, driving forces and effects on landscape using GIS.
3. To quantitatively analyze the effects of spatio-temporal changes in Imo watershed landscape in relation to biodiversity under different land use using GIS and statistical tools.
4. To investigate the changes at Dřevnice River Basin, identify the drivers and effects as well as predict the future changes for the different land use.
5. To assess the landscape changes, the drivers and effects from various case studies in different land use.
6. To appraise the results qualitatively and quantitatively as well as visualize and present them in form of tables, figures and maps by jointly using GIS and some statistical techniques.

The previous chapters might have been rather voluminous with many detailed information. Therefore, it is necessarily pertinent to clarify some vital achievements in relation to the study goal and objectives by using the following paragraphs. It is important to state here that the research objectives 5 and 6 were designed for all the case studies whereas, the objectives 1, 2, 3, and 4 were designed for case study 1, 2, 3, and 4 respectively. The objectives (reiterated as structured in Chapter 2) have been accomplished as discussed in the following achievements:

1. ***Evaluating change in land use and its effects on the vegetation and landscape in a rapid growing urban hub (Onitsha) from 1987 to 2015.***

Onitsha in south-east Nigeria is recently becoming one of the top commercial nerve centers in Africa which has increased urbanization at the expense of the natural landscape especially vegetation. This development led to acute changes in the land use during the 28 years study. Data covering the time frame were collected, processed and analyzed to find the degree of changes using GIS and statistical approaches such as maximum likelihood classifier tools, equations for determining population growth rates, and land consumption coefficient at given year. In addition, principal component analysis (PCA) followed by a Monte Carlo Permutation test with 499 permutations in the CANOCO statistical software was used to evaluate the relationships between the vegetation and change in land use as well as the effects on the landscape. Both the cartographic tools of GIS and Ordination diagram from CANO-Draw program software were employed producing the result (Fig.7). The study found that space and time significantly influenced the landscape at it was observed that between 1987-2015 vegetation decreased in area by at least 75% while, built-up increased by more than 100% in this case study. In addition to other observed substantial changes, it was agreed that objective 1 consistent with the main goal has been achieved.

2. Identifying Jos landslide vulnerable areas, driving forces and effects on landscape using GIS.

Though, Jos (northern Nigeria) has been recording series of natural hazards especially landslides yet, little or no studies has been conducted to ascertain its vulnerability, drivers and primary effects on the landscape using GIS. As a matter of this, objective 2 was formulated to address the issue. With the application of GIS data covering various land use variables (such as relief, soil, geology, drainage, land use-cover, settlement, etc.) were collected. The data were further processed and analyzed by scanning, georeferenced, digitizing, vectorizing depending on the data format. Using other GIS tools such as class computation, geographical weighted overlay, 3D terrain models the landslide vulnerable areas, drivers and impacts were identified (Fig. 9). Most landslides prone areas (Sabon Garki, Gyel Gura, Chunbeng, Guru Topp, Vom Latya Rayfield 1-2) (as presented in Table 13 and Appendix Fig. 2) were precisely identified. Drivers such as mining and built-up ranked high on the list of causative factors, whereas the vegetation as one of the landscape indices was found to be the most threatened. GIS was successfully used to study the landslide, but it has been rarely applied in the area and this might be attributed to dearth of monetary, technical, and human resources. Therefore, it is believed that in accordance with the research main goal, objective 2 was attained.

3. Quantitatively analysing the effects of spatio-temporal changes in Imo watershed landscape in relation to biodiversity under different land use using GIS and statistical tools.

Apart from quantitatively analyzing the visibly physical landscape changes, this objective prompted the analyses of the soil properties (organic matter, organic Carbon, total Nitrogen) in relation to their responses to changes in land use which consequently affected the landscape. Furthermore, the effects of space (in terms of different land use; see Fig.14) and time (25 years-

1991-2016; see Fig. 15-17) on this watershed landscape were quantitatively analyzed by focusing on biodiversity indicators. This is because plants and soil are the principal determinants of a landscape structure/characteristics (Chisté et al. 2018; Dai et al. 2018; Diwediga et al. 2017; Udom and Ogunwole 2015), and any change in their composition will definitely have significant effect on the landscape (Nwaogu et al. 2017). Though, this case study was the most laboriously tasking because it involved collection and analyzing of several data using GIS and STATISTICA software yet, its results were promising. Quantitative statistics such correlation analysis, one-way analysis of variance and its post-hoc test, and the multivariate redundancy ordination analysis of CANOCO software packages were integrated with GIS to justify this objective. This study did not only assess the change in landscape but also the interaction between such change and the biodiversity indicators (species diversity, richness and evenness) as a long-term change in these indicators means severe threat to the landscape vice-versa. The study went further in detail to examine the impacts of soil erosion as one of the key drivers of the landscape changes. RUSLE-based factors especially rainfall erosivity of soil particles (R-factor), soil erodibility index (K-factor), and the vegetation cover/management index (C-factor) were introduced for thorough evaluation of the driving forces of landscape change in space and time under the different land use. In this context, and in agreement with the main goal of the study, objective 3 has reasonably been met.

4. Investigating the changes at Dřevnice River Basin, identify the drivers and effects as well as predict the future changes for the different land use.

To investigate the changes, identify the drivers and predict the future scenario in this river basin, CLUE/CLUMondo model was employed to process and analyze the collected data which were partly extracted from CLC 1990, CLC 2006 and CLC 2012. In CLUMondo interface, the logistic regression analysis, suitability layers and land use services tools were used to sort/identify 16 most significant driving factors and define 8 land use. Other model parameters such as conversion order, resistance, and matrix were also potentially used to determine the correlation coefficient and AUC values of the parameter. The capabilities of Idrisi and ArcGIS in completing the analysis and presenting the results can never be overemphasized as overlay operations, transition matrices and information showing the different classified land use and their past, present and future changes were derived. Precipitation revealed suitability regression coefficients with orchards. All the eight-categorized land use increased in their areas during the study period except arable land and forest which on the contrary decreased. On this note, it is sound to say that objective 4 was completed.

5. ***Assessing the landscape changes, the drivers and effects from various case studies in different land use.***

The studies for this work did not only covered different geographical regions (from south-east to northern Nigeria, and from southern Nigeria to Czech Republic, Central Europe) landscape but also focused on diverse land use types. For example, in each case study the prevailing land use categories were not exactly the same: ranging from urban area to vegetation, or from arable land to grassland or forest area and so on. To achieve the goal of this research, geoinformatics tools and operation (such as GPS, aerial photos, satellites images, georectifications, image classifications, overlay operations, confusion and transition matrices and others) were applied for the data collections, data processing and pre-processing, data analyses and in the presentation of the final results in all the case studies. Furthermore, statistical techniques (such as regression analyses) were integrated with GIS in analyzing and publishing the results especially for case studies 1 and 3. In all the case studies (Chapter 7), landscape changes were reasonably assessed by examining the rates of the changes, identifying the key driving forces and highlighting the major effects under the different land use studied using GIS and statistical techniques. Some land use types were observed usurping the areas for another land use. For example, in all the case studies, the forests were either converted to agricultural or urban areas during the time and space for the research. In this regard, it could be concluded that objective 1 was practically fulfilled in line with the main goal of the research.

6. ***Appraising the results qualitatively and quantitatively as well as visualizing and presenting them in form of tables, figures and maps by jointly using GIS and some statistical techniques.***

After collecting and processing the data using GIS and sampling methods, the outcomes were thoroughly evaluated by applying qualitative methods (such as percentages, sum, mean values, simple graphs, standard deviations and errors) and quantitative approaches (Kappa statistics, coefficient of accuracy, regression and multivariate analyses). With the aid of GIS, cartographic and statistical tools, the results were presented in various tables, figures and maps as can be seen in Chapter 7). In the light of this, it could be concluded that objective 6, the final of this thesis has been satisfactorily completed.

By applying GIS in combination with some statistical techniques, the objectives of this study were achieved with the conclusion that land use was substantially altered in the studied areas, and this consequently led to changes in landscape during the different study periods. The forest vegetations were the most negatively affected by the changes whereas, the built-up areas increased in space and time. Urbanization, intensified socio-economic activities and population growth were the key driving factors for the observed changes.

The study recommended the emancipation of the local people (through enlightenment about the need for population control, afforestation, and regulated/sustainable socio-economic activities) by the government and stakeholders as the most sustainable solution. The findings from these studies will enable future planning policies that seek to conserve the unique natural and ecological features of the landscapes with references to Nigeria and Czech Republic.

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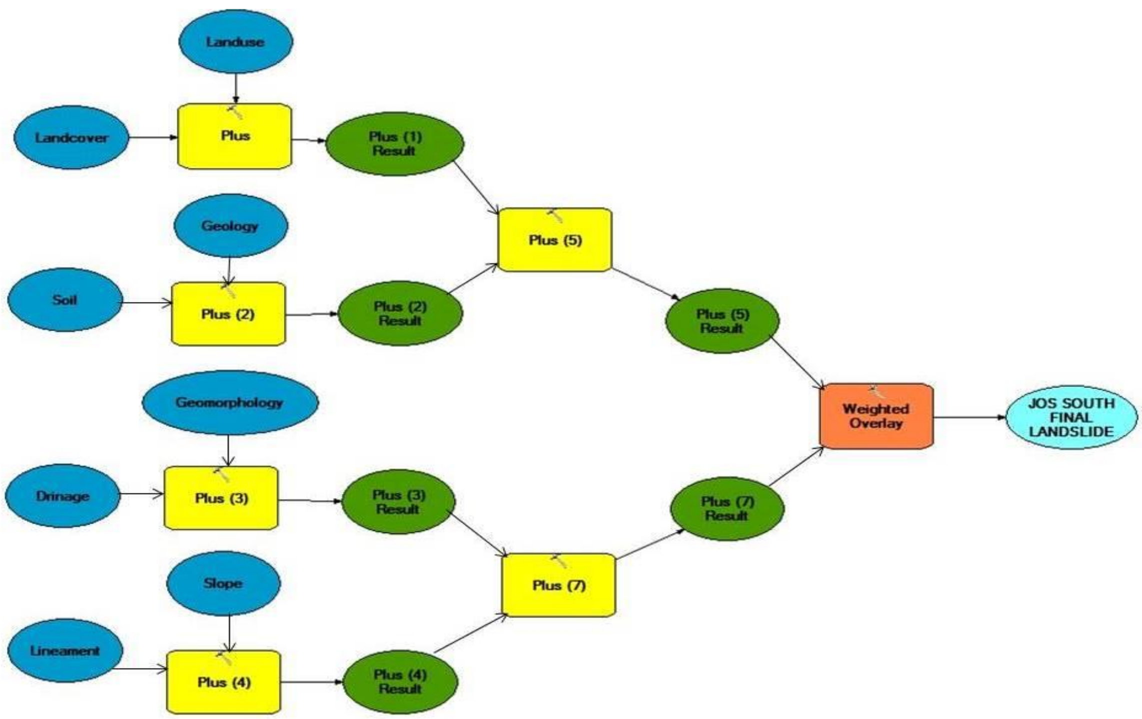
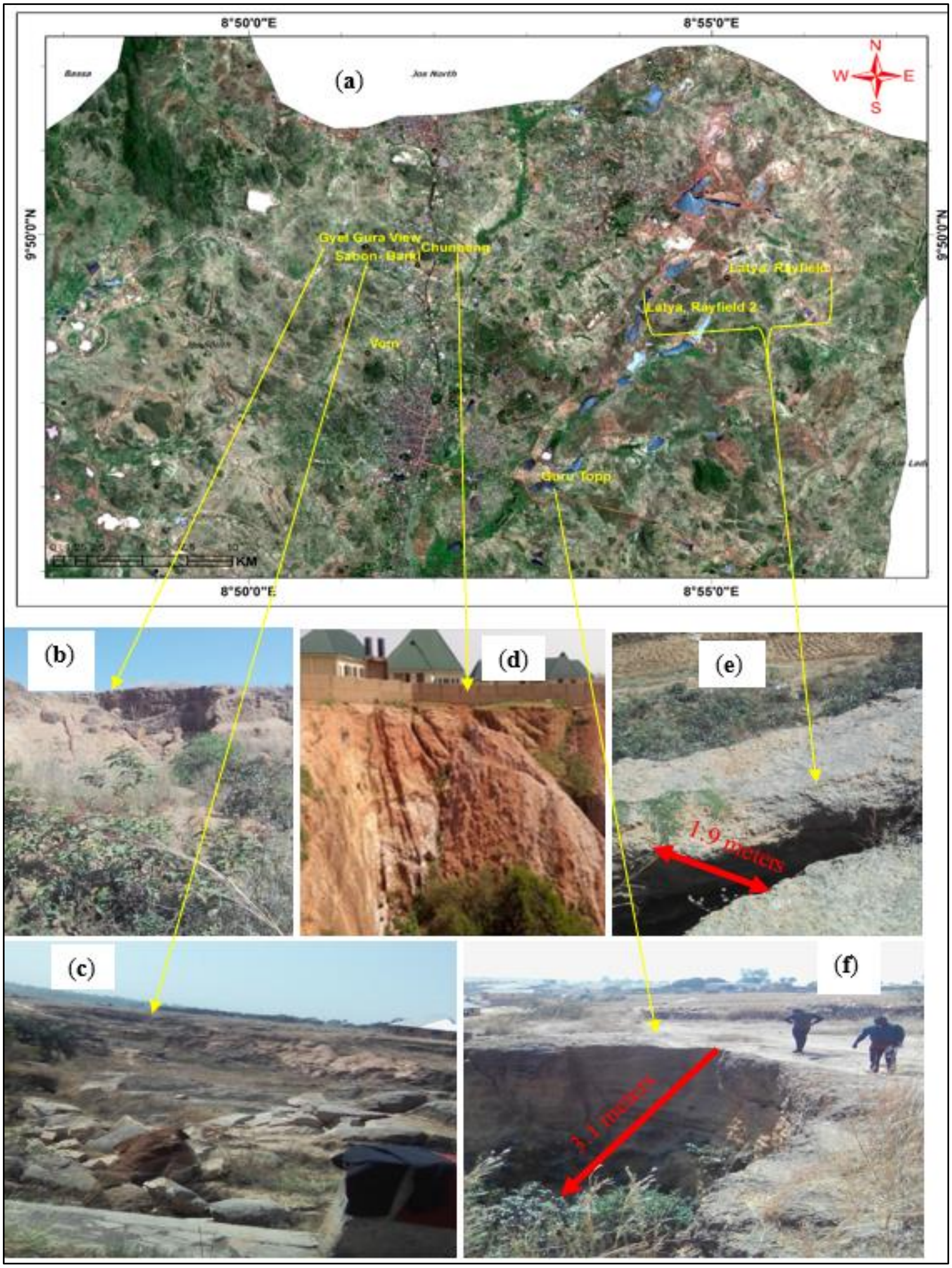
List of Figures

List of Tables

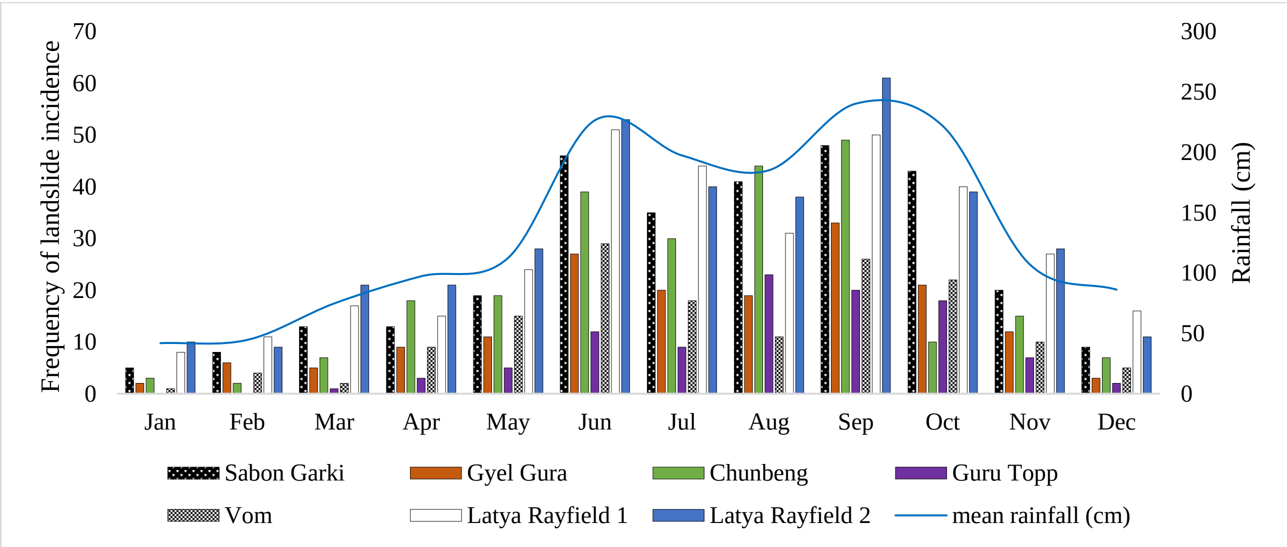
Appendices



Appendix Fig. 1. Analysis Model



Appendix Fig. 2. Study Area-Jos South landslide sites (a) SPOT 5 Image (b) Gyel Gura view (c) Sabon-Garki (d) Chunbeng (e) Latya Rayfields (f) Guru Topp



Appendix Fig. 3: Relationships between seasonal rainfall and prevalence of landslides during the study periods in the most vulnerable sites

Appendix Table 1. Hierarchical Weighted Ranking of Landslide Causative Factors

Key Factor	Sub-factor/Type	Rank	Weight (%)
Drainage	Length (km)		**21**
	<0.005 - 0.33	1	
	0.33 - 0.62	2	
	0.62 - 1.02	3	
	1.02 - 1.75	4	
	1.75 - 3.05	5	
	>3.05 - 6.35	6	
LULC	Type		**19**
	Vegetation	1	
	Rock Outcrop	2	
	Waterbody	3	
	Bare Surface	4	
	Mining Site	5	
Soil	Type		**16**
	Gleysol	1	
	Lixisols	2	
	Luvisols	3	
	Cambisols	4	
	Acrisol Mining	5	
Geology	Rock types		**13**
	Quartz porphyry	6	
	Granite gneiss	5	
	Hornblende gneiss	4	
	Basalts, Trachyte & Rhyolite	3	
	Mignonette gen	2	
	Fine-grained biotite granite	1	
Lineament	Density (m3)		**12**
	0 – 0.152	1	
	0.153 – 0.401	2	
	0.41 – 0.675	3	
	0.676 – 0.979	4	
	0.98 – 1.45	5	
	1.46 – 2.42	6	
Geomorphology	Type		**10**
	Linear Ridges	1	
	Exposed Rocks	2	
	Weathered rock out crops	3	
	Flood Plain	4	
	Alluvial Plain	5	
	Ridge top	6	
Slope	Unit: (m)		**9**
	<1,159 - 1,218	5	
	1,218 - 1,254	4	
	1,254 - 1,286	3	
	1,286 - 1,344	2	
	>1,344 - 1,509	1	
			100

Appendix Table 2: Weighted Ranking of Landslide Vulnerable (susceptible) Factors

Key Factor	Sub-factor/Type	Rank	Weight (%)
Population	Units: per 1000		40
	<87 - 207	1	
	207 - 288	2	
	288 - 370	3	
	370 - 451	4	
	>451 - 457	5	
Landuse	Type		35
	Recreational	1	
	Industrial	2	
	Institutional	3	
	Religious	4	
	Commercial	5	
	Residential	6	
Landcover	Type		25
	Vegetation	1	
	Rock Outcrop	2	
	Waterbody	3	
	Bare Surface	4	
	Mining Site	5	
			100