ABOVEGROUND TREE BIOMASS AND LAND USE LAND COVER CHANGE IN BURU COMMUNITY FOREST, TARABA STATE, NIGERIA

BY

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CERTIFICATION

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DEDICATION

This thesis is dedicated to God Almighty through Jesus Christ who is the reason for my existence, to whom all Glory, Honour, and Adoration will forever be returned to you. Also, your Grace and Mercy that brought me this far can never be undermined.

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ABSTRACT

Remote Sensing (RS) techniques are widely used to estimate Aboveground Tree Biomass (ATB) and for Land Use Land Cover (LULC) classification. Information on ATB and land use changes is essential for development of management strategies for forest ecosystems. Outputs from biomass assessment and LULC classification are constrained by the quality and time of remotely sensed data acquisition. In Nigeria, there is limited information on suitable months for RS data acquisition for estimating ATB and LULC. Therefore, this study was designed to determine the suitable month for RS data acquisition for ATB estimation and LULC classification in Buru Community Forest (BCF), Taraba State, Nigeria.

Landsat imageries of BCF for April, July and December in 1988, 2000, 2008 and 2018 were obtained, based on availability. Twenty (50 m x 50 m) plots were demarcated in BCF and their coordinates were obtained. In each plot, trees with Diameter at Breast Height (DBH, cm) ≥ 5.0 were enumerated and wood core samples obtained. Landsat imageries were classified into LULC. The LULC Changes (LULCC, %) were estimated and projected from 2018 to 2048 using standard methods. Probability (%) of the classified LULCC to remain unchanged from 2018 till 2048 was determined. The DBH and Total Height (TH, m) of trees were measured, while Wood Density (WD, g/cm^3), stem volume (m^3) and ATB (t/ha) were calculated following standard procedures. Spectral bands of imageries from each month were extracted and used to estimate RS-ATB (t/ha). Suitable month for RS-ATB estimation was selected using highest adjusted coefficient of determination (R^2_{adj}), Root Mean Square Error (RMSE), Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The ATB was compared with RS-ATB for 2018 following standard procedures. Data were analysed using descriptive statistics, T-test and linear regression at $\alpha_{0.05}$.

Six LULC were identified: Less Disturbed Forest (LDF), Disturbed Forest (DF), Farmland, Water Body (WB), Bare Land (BL) and Built-up Area (BA). The LULCC was highest and least in DF (68.70%) and BA (5.13%), respectively. Projected LULCC were: 51.99 (LDF), 31.08 (DF), 12.28 (farmland), 1.65 (WB), 2.58 (BL), and 0.43 (BA). Probability matrix varied from 9.50% (BA) to 69.90% (DF). This suggested that there was a high probability for DF to remain unchanged by 2048. Tree DBH, TH and WD were: 22.56±0.35, 12.86±0.19 and 0.47±0.01, respectively. Stem volume and ATB were 414.66±12.75 and 281.30±0.33, respectively. The highest RS-ATB were 271.66 (1988), 196.60 (2000), 174.50 (2008) and 152.80 (2018) for July (RMSE=444.12, R^2_{adj}=94.94%, AIC=246.59, and BIC=21.02), while the least were 148.70 (1988), 146.89 (2000), 122.84 (2008) and 152.60 (2018) for April (RMSE=522.31, R^2_{adj}=93.00, AIC=253.08, and BIC=21.34). Estimated ATB (1923.60±101.78) did not differ significantly (t=0.89) from RS-ATB (1910.00±65.67). This implied that RS technique was suitable for aboveground tree biomass estimation in BCF.

Imageries from the month of July were the most suitable remotely sensed data for estimation of aboveground tree biomass in Buru Community Forest, Taraba State, Nigeria. Remote sensing techniques sufficiently predicted aboveground tree biomass and provided accurate land use land cover classification for the forest.

Keywords: Aboveground tree biomass, Landsat imagery, Land cover classification, Buru Community Forest

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CHAPTER ONE

INTRODUCTION

1.1 Background

The application of Remote Sensing (RS) data in the study of aboveground biomass estimation has gained the attention of many researchers, due to its timeliness as well as the availability of historical data and high spatial resolution (Zhu and Liu, 2015). In the same vein, Land Use Land Cover Change (LULCC) has been identified to be one of the key drivers of deforestation and forest degradation across the globe (Gasparri *et al*., 2010). Deforestation and forest degradation processes have received much attention in recent decades, as a result of the roles played by forests in Aboveground Biomass (AGB) conservation and carbon sequestration. These roles can never be overemphasised, as forests remain one of the key players in climate change mitigation and adaptation. Among these roles are species conservation and diversity, flood control, water conservation, and increase in agricultural yields among others. On the other hand, Man's needs for food, shelter, and other activities such as urbanisation, industrialisation, and mining activities among others have exerted much pressure on the environment (forests). Many forest areas have been converted to other uses ranging from residential areas to farming land, logging sites, industrial activities, *etc*. thereby reducing most of the forest canopies to below the 10% threshold to meet up with man's needs (FAO, 2004). These anthropogenic activities resulted in increased global warming.

Global climate change is one of the most difficult problems that humanity is now facing (Vashum and Jayakumar, 2012). Consequently, studies related to forest ecosystems and their roles in carbon sequestration alongside the pattern of use in which land is being subjected to have received a lot of attention globally. However, there is inadequate information on the carbon sequestration potential of tropical forest globally. In Nigeria, very little information exists on the carbon sequestration potential of the remaining forest cover such as Buru Forest. Buru forest is a community forest located at the foot of the Mambila plateau in Taraba State, Nigeria. The forest has experienced little disturbance and therefore could serve as an important carbon sink. However, there is no documented evidence of its carbon sequestration potential as well as the trend of degradation/deforestation. This could hinder the sustainable management of this important renewable natural resource which plays a significant role on the livelihoods of people living around the forest as well as helping to mitigate the effects of climate change.

The application of Remote Sensing (RS) data in the study of aboveground biomass estimation has gained the attention of many researchers, due to its timeliness as well as the availability of historical data and high spatial resolution (Zhu and Liu, 2015). Remote sensing is a system of acquiring information or data from its target through various levels of wavelengths without coming in contact with the object by means of measuring the reflected or emitted energy from its target; this is done with the aid of cameras and related object mounted on moving or stationed devices which are further processed for final use by the end-users (Jensen, 2007). The application of RS and Geographic Information System (GIS) in the forestry sector has helped to advance development, in natural resources monitoring and evaluation, and decision-making, among others (Kai *et al.,* 2012). Hence, the applications are used for land use/land cover change classification, estimation of deforestation, forest fire monitoring, biomass, volume, and growth detection of large forest areas over a short period.

Brown (1997) defined biomass as oven-dry matter in tons per unit area and can be expressed as above or below-ground biomass. Aboveground biomass (AGB) includes living and dead standing trees, shrubs, dead wood, and litter while belowground biomass includes root biomass. In forest ecosystems, AGB constitutes a greater portion of the carbon stock hence, attention is given more to its estimation in the tropical forest ecosystem than the belowground biomass (Gibbs *et al.,* 2007). As a result, precision must be key during its estimation since the belowground biomass, carbon sequestration potential, timber volume can as well be estimated from its (Basuki *et al*., 2009).

1.2 Statement of Problems

Forest has become a center of attraction in the 21st Century due to its roles in carbon sequestration and climate change mitigation. As a result, this has necessitated numerous studies on aboveground biomass and forest carbon estimation and Land Used/Land Cover Change (LULCC). However, there is little or inadequate information on most tropical community forests such as the Buru community forest. This is partly because biomass estimation in tropical forests remains challenging (Basuki *et al*., 2009). The destructive approach to aboveground tree biomass (AGTB) estimation is difficult, expensive, time-consuming, and can cause degradation of the forest. Furthermore, the forests have become a hideout for hoodlums coupled with difficult terrain making consistent data collection for AGTB almost impracticable. Consequently, most forests in Nigeria lack information in terms of carbon sequestration, thus, uncontrolled greenhouse gas emission.

In recent times, many researchers have tailored their research interests toward remote sensing. Particularly in forestry, where several biophysical variables of trees were regressed to spectral information obtained from remote sensors to estimate aboveground biomass, carbon sequestration, and tree volume, among others. However, most of the remote sensing data used are obtained during the dry season (from November to April). During this period, cloud cover was considered a major determinant factor for its acquisition with little or no attention given to variation in plants' components. However, plants respond differently to incoming and reflected electromagnetic radiation which might vary across seasons or months.

In recent times, LULC changes have become an issue of global interest, mainly as the result of various uses to which land is being subjected into, in order to meetup with endless needs of man. Consequently, most natural resources are stretched beyond limit thereby unable to provide the services expected from man. Buru community forest which is undergoing similar pressure has no records as to what extent these changes have occurred nor plans made available for sustainable purposes.

1.3 Objectives

1.3.1 Main Objective

The main objective of this study is to assess the effects of seasonal variation on RS data used for estimating AGTB and LULC change in Buru Community Forest (BCF), Taraba State Nigeria to determine the optimum season for biomass data acquisition and provide baseline information of LULC change.

1.3.2 Specific Objectives of the Study

The specific objectives of this study are to;

i estimate aboveground tree biomass in Buru Community Forest,

ii determine most suitable season for remote sensing data acquisition for AGTB estimation,

iii determine Land Use Land Cover Change of Buru Community Forest between 1988 and 2018, and

iv predict the Land Use Land Cover Change of Buru Community Forest for 2028 and 2048.

1.4 Justification

Buru community forest still contains reasonable amount of less disturbed forest thereby making it one of the carbon banks within Buru community. However, there is no information on the amount of aboveground tree biomass from the forest community, consequently carbon sequestered over time remain unknow. Therefore, there is need to documents the amount of aboveground tree biomass as well as carbon sequestered within Buru community forest. Accurate estimation of AGTB is vital to assessment of carbon in forest reserves (Niiyama *et al*., 2010). This information also helps the forest managers to determine the precise status of the forest, thereby applying the appropriate managerial strategies with the view of ensuring sustainability. The application of RS and GIS techniques is very efficient in the estimation of AGTB from the forest (Gasparri *et al*., 2010). During this process, some tree components such as height, diameter at breast height, and density were usually regressed with RS data to estimate AGB (Basuki *et al*., 2009). This and many others had led to an increasing interest in the application of RS to estimate AGTB. This was as a result of its capability in terms of timely acquisition of temporal and spatial data over the planet (Lu *et al*., 2012). Recently, there has been a renewed global interest in biomass research, due to the need for predicting forest biomass and carbon stocks (Moore, 2010). The Kyoto Protocol of the UNFCCC has been one of the leading drivers which made clear mechanisms whereby post-1990 carbon storage in forests can be used as an allowable carbon sink to offset some greenhouse gas emissions (IPCC, 2003; Moore, 2010) thereby mitigating climate change.

Biomass information is uncertain for most forests in Nigeria, including the Buru community forest. Therefore, it is important to have documented information on AGTB of forests across the Nation owing to the roles they play in global climate change amelioration (Wang, 2006; Tan *et al.,* 2007). Recently, studies were carried out on the estimation of AGTB and carbon stock across the various vegetation (mountain and non-mountain forest) through field inventory and remote sensing in Nigeria. However, no study of such was conducted in the Buru community forest, despite her contributions in carbon sequestration among other functions, in the community in particular and Kurmi local government area at large. This study in Buru community forest becomes necessary, as carbon lost is based on the amount of forest removed as the various pattern of land use/cover changes ongoing within the forest community remain unknown (Huoghton, 2005).

Furthermore, few research works carried out in Nigeria on aboveground tree biomass have mainly focused on the Southern part of the country. Meanwhile, the study area used for the research lack records of carbon stock. Thus, the carbon model when developed for the study area will help in monitoring and reporting the state of carbon sink within the forest at a commitment period on a regular interval. In the same vein, REDD which has been identified as an economic way of combating global climate change, thus mitigating the impact of global warming; required accurate, reliable, and cost-effective means of biomass estimation at a consistent interval for effective policy implementation.

Remote sensing has widely been applied in natural sciences in terms of resource monitoring and management which have played vital roles in policymaking. These policies have gone a long way in salvaging the environment as these resources are kept under consistent watch periodically through the application of RS techniques (Silleos *et al*., 2006). In obtaining RS data for aboveground biomass estimation, there should be an appropriate period for such data acquisition whereby the forest component will adequately reflect spectral bands that will explain the variation in AGTB of the study area. Among these plant components, chlorophyll is their major driver. Chlorophyll is a green colour pigment that resulted in increment, growth, wellbeing, and biological and chemical components of the plants thereby manifesting on the outer looks of the tree as it changes with season (Sheikh *et al*., 2017). Furthermore, the chloroplast, stomata, and moisture content of the plant which vary across seasons need to be considered as they could influence the data component across the season (Sheikh *et al*., 2017). A remote sensing data collection method factoring these conditions was applied to acquire appropriate remote sensing data from Buru community forest while maximizing this variation effect, and consequently providing a better period for estimating AGTB for the study area. Also, Dymond *et al.* (2002) observed that, in the estimation of forest growth attributes, re-measurement data across seasons can contribute to the precision of aboveground biomass and carbon monitoring. These plant attributes fluctuate with season. Therefore, it might respond differently across the data obtained from the imagery in dry and rainy seasons.

Over time, activities such as industrialisation, urbanization, farming, and mining activities among others have been the major causes of LULCC. These anthropogenic activities, alongside natural phenomena, have been the major drivers of global LULCC in our environment in the 21st century (Kumar *et al*., 2013). There is need to know the extent to which these changes have occurred over time within man's environment. On this note, information from aerial photographs had been of great help to the resource manager to facilitate managerial policy that can lead to optimal maximization of the natural resources alongside the various pattern at which LULC changes within the study site at a consistent interval. With the rate at which the environment changes and consistent pressure on the natural resources, aerial information has become a major mechanism for monitoring environmental degradation thereby resulting in natural resources conservation (Opeyemi, 2006). Therefore, this study becomes a necessity within the study area mentioned along with the methodology adopted.

1.5 Scope of the Study

This research work is limited to application of RS/GIS in the estimation of AGTB, carbon, and LULC change alongside ground-truthing which for this research is referred to as "AGTB and LULC Mapping and change detection in Buru community forest, Nigeria". The research work is limited to Buru community forest, Taraba State, Nigeria. Data on tree diameter at: the base, breast height, middle, and total height, merchantable height, wood core samples, coordinate points, and Landsat imagery were collected and used in the analysis.

CHAPTER TWO

LITERATURE REVIEW

2.1 Aboveground Biomass Overview

The AGB is the dry weight of an aboveground woody plant, its branches, leaves, stumps, and twigs. Its estimation becomes necessary if the calculation of biomass energy, carbon storage, and sequestration potential of a forest and its productivity are required (Zhao *et al.*, 2015). The roles of AGB estimation in sustainable forest management alongside monitoring general change in forest stands and carbon accounting can never be overemphasized (Tian *et al.,* 2014). In addition, Burt *et al*., (2021) observed that AGB houses a greater amount of carbon stock in an ecosystem, but the amount remains uncertain in most forests. This shows that AGB measurement is of great importance, as it reveals forest potential in terms of quantifying the amount of carbon sequestered, timber potential value, and fuel energy among others. Also, changes in AGB affect both gross and net primary production alongside climatic factors. Over time, AGB estimation has mostly been carried out by destructive field inventory for precision purposes. However, it is not visible in most cases, as some terrains are difficult to access, labour intensive, and it is destructive in nature. Consequently, such a method is discouraged majorly due to the destructive nature involved. In the recent past, the non-destructive method has been given significant attention, as AGB estimation is mostly carried out through allometric equations developed from field inventory (Liang *et al*., 2012).

In recent times, AGB can also be estimated from forest field inventory, though this is limited in the area of spatial data. Furthermore, it is challenging in the area of difficult terrain, and is capital intensive, especially when data from large areas are required. The forest manager must always have inferences drawn from such data (inventory) to enable him to manage the resources sustainably. As a result, the forest's biomass must be adequately estimated and be made known for further and future references, as well as devising a suitable means of managing it for optimum productivity (IPCC, 2007).

2.2 Forest Biomass

In our ever-changing environment, the role of forest as a carbon sink is gaining World attention as most research are geared towards sustainable environmental policy and renewable energy. Warsaw framework, which has become a tool in assessing and evaluating the role of forest performance in carbon sinking as well as rewarding for this role based on the outcome of the Conference of Parties in 2013 where REDD+ was perceived and adopted as one of the best options in combating global climate change. Nath *et al*., (2019) noted that despite the breakthrough recorded in different methods of biomass estimation, it is still challenging to compute carbon in tropical and sub-tropical forests with high degrees of uncertainty. This sometimes occurs as a result of inconsistencies in the adoption of the method to employ. Variations in biomass estimation methods affect both local, regional and global biomass outcomes. This, in turn, limits the precision of RS application in AGB estimation.

Biomass estimation is of great importance, due to its role in the global carbon cycle and timber exploitation, as such, it should be accurately estimated in other to have a true picture of what is contained in the forest as well as its potential. As this will serves as a baseline to checkmate the increase or decrease of the forest content for onward reporting.
Carbon stock is obtained from biomass through the assumption of 50% amount of biomass to be the quantity of carbon stock on the biomass (Chenge and Osho, 2018). Though the felling of trees and oven drying them to obtain biomass is the most precise method for obtaining biomass, this method seems not to be environmentally friendly. The outcome of this method is often used to corroborate the non or less destructive method, such as field inventory, Aerial data among others (Clark *et al*., 2001; Wang *et al*., 2003).

2.3 Methods of Aboveground Biomass Estimation

The AGB is known to be the major pool of carbon sequester among vegetative pools. As a result, its estimation methods and procedures have gained attention in recent decades.

Several methods have been applied in the estimation of AGB, such as destructive and non-destructive methods (King *et al*., 2005; Chave *et al*., 2005; Næsset and Gobakken, 2008). Both methods have widely been used by the researcher in estimating AGTB as well as resource monitoring. This has gone a long way to help a forest manager in putting sustainable plans in place.

Ideally, in order to obtain the exact amount of carbon stored in a tree, the dry tree mass which is term as biomass will then be converted to carbon through the conversion factor and subsequently carbon dioxides. Though the biomass can be estimated through volume conversion and expansion factor or developed models of allometric equations (Mugasha *et al*., 2013). Oftentimes, the most easily measurable variables (diameter and height) of the trees are used in the estimation as they are believed to be more correlated with the aboveground biomass. Generally, once variables needed to estimate the amount of AGB are available, the use of developed biomass is more convenient.

In addition to the use of models in aboveground biomass estimation, remote sensing models are useful tools in the hands of forest managers in quantifying the structure, pattern, and health conditions and identifying the general growth of the forest. They may as well make the available state of timber to be extracted, the energy available, and protectability or cover for wildlife. Furthermore, remote sensing models of aboveground biomass with ground inventory data have proven to be a great tool in conventional forest management planning.

2.3.1 Direct/Destructive Method of Aboveground Biomass Estimation

The direct method of aboveground biomass estimation is a situation whereby trees are harvested from the field and all parts (leaves, branches, and main stems) except the roots are oven dry to a constant temperature to obtain a portion of the trees, which contained no moisture. Though, the method is the most accurate but destructive due to tree harvesting. The method is destructive (He *et al*., 2018), expensive, and not practicable in difficult terrain on largescale bases. However, He *et al.* (2008) successfully applied the method in coniferous and broadleaved mixed forests, in Northeastern China. During the process, they destructively sampled 122 trees in other to estimate the above and belowground biomass for the stand. This led to model development where the diameter was used as an explanatory variable in predicting the biomass of the stand. This was on the basis that stem occupied the largest pool of biomass among other bio-physical properties of the trees. Though Allometric equations for biomass estimation and monitoring are of great importance but challenging, time-consuming, expensive, and not environmentally friendly (Colmanetti *et al.*, 2020). In recent decades, the study of this kind is been discouraged because of their destructive nature. Moreover, few of the destructive studies carried out (Zhao *et al.,* 2015; Vargas-Larreta *et al*., 2017; Djomo and Chimi, 2017) are not from Nigeria. Since this method relies on destructive sampling across the reserve, several species are under-represented on the biomass obtained, which indicates an erroneous estimation of the application of models developed on such species within the site on another species from another site. Recurrently, most selected trees harvested might not adequately represent the various diameter class within the stand.

Several allometric equations have been developed and applied in various tropical forests. Tree dendrometric variable varies from species to species and from one side to the other. As a result, an equation developed outside from a different location and or outside a specific location may result in an erroneous estimation of AGB and carbon (Basuki, *et al.,* 2009). Since models are species and site-specific, it signifies that trees must be destructively sampled across species and sites for adequate representation, to develop an allometric equation that can fit in for the entire stands with a good predictive ability (Lau *et al*., 2019; Burt *et al*., 2021). Similarly, in other to successfully mitigate climate change, the amount of AGB and carbon stock in the tropical forest must be known and consistently monitored (Fayolle *et al*., 2018). Accurate estimation of the AGB and carbon depends mainly on the availability of reliable allometric equations developed by destructive sampling methods which can then be used in converting other biophysical properties of trees into AGB and carbon. This implies mass destruction on the forest stand, which is contrary to IPCC compliant with the use of non-destructive methods such as remote sensing (Lin *et al.*, 2016).

2.3.2 Indirect Methods of Aboveground Biomass Estimation

Indirect methods of Aboveground biomass estimation have to do with other means of AGB estimation apart from the destructive method of trees from forest stands. Several methods among this are volume conversion factor, use of the developed allometric equation, and application of RS and GIS among others (Shao *et al*., 2017). Advances made as a result of this in the area of RS and GIS have contributed significantly to the accurate estimation of AGB and carbon stock of the forest ecosystem (Rahman *et al*., 2017); which gradually brings to an end the destructive method of AGB estimation which are site and species-specific. Remote sensing/GIS application on AGB estimation is now a trending pattern in recent decades. This is due to but not limited to it a timely and wide area of coverage during data acquisition, particularly in complex forest ecosystems. The forest is known to play an important role in global climate change amelioration which made a periodic estimation of AGB inevitable. Furthermore, the estimation of the amount of AGB and carbon stock is an important process, which needs due and timely attention to enable it to gain access to the carbon credit market (Mugasha *et al*., 2013). The biomass serves as an indicator of the carbon storage capacity and the potential carbon pool size and productivity of a forest ecosystem (Li *et al.*, 2015).

Inventory aboveground biomass and aerial data were successfully integrated with estimating AGB with wide area coverage. RS techniques for estimating AGB have to do with the use of a sensor to sense reflected energy from the forest and analyse it through the developed remote sensing equation (Lu, 2005). Accurate estimation of forest AGB has become increasingly important for a wide range of end-users. Furthermore, field inventory and use of Terrestrial Laser Scanning (TLS) application in the semi-deciduous forest of eastern Cameroon have proven the successful applicability of a non-destructive TLS approach against the destructive sampling method in modeling (Momo *et al*., 2018).

To know the amount of AGB in a forest stand, there is a need for the application of regression mode (Lu *et al.,* 2012) to regress inventory AGB and the AGB obtained from aerial data which can future be used for future prediction. Furthermore, Lu *et al*. (2014), reviewed the following steps as a condition for AGB modeling:

1. spelled out the tree growth variables known to be a contributor in AGB estimation.
2. note the variables that could better explain variation on AGB while avoiding multicollinearity among variables.
3. using statistical software to mark out various variables and their contributions to the models.

4. conducting data reduction analysis on the extracted image data and
5. using the extracted variables on the algorithm.

The application of RS in AGB estimation and carbon stock in complex tropical forests of Africa, including Nigeria, has not been adequately documented. Few kinds of research carried out have concentrated on a single time (dry season) data for aboveground biomass estimation. Thus, accurate estimation of AGB becomes a focal point in quantifying the carbon stock of a particular ecosystem.

2.4 Deforestation in the Face of Climate Challenge

The demand for food and other agricultural-related products, as well as threats from climate change, has resulted to the deforestation and degradation of several protected forests (Boletta *et al.,* 2006). The current orientation on agribusiness coupled with the Nigerian government's principle of "produce what you eat and eat what u produce" has greatly degraded the Nation's forests reserve. This is a result of a lack of proper orientation on the sustainable environment management plans to the farmers, as such, they destroyed forests indiscriminately.

Carbon which is a component of aboveground biomass is present in the atmosphere as carbon dioxide which is made up of about 0.04% of the atmosphere (Vashum and Jayakumar, 2012). Carbon becomes the center of attraction as a result of its being a greenhouse gas which has greatly influenced global climate change (Vashum and Jayakumar, 2012). Global climate change had greatly been influenced by human activities such as agricultural activities, logging, grazing, industrial activities, burning of fossil fuel, forests depletion, and environmental degradation among others. However, our vegetation has its means of regulating such effects on the environment as it ameliorates the condition which is majorly done by the forests while sequestering the carbon. The forest absorbed the carbon from the atmosphere and stores it in form of tree biomass.

Among the five-carbon pools (aboveground, belowground, soil organic matter, litterfall, woody debris) itemised by the Intergovernmental Panel on Climate Change (IPCC), AGB constitutes the major component of the carbon pool. As such, estimating the amount of AGB, will go a long way in helping the forest manager to know and monitor the amount of carbon lost to any kind of deforestation activities and further made known the forest's potential in ameliorating climate change (Vashum, 2012).

It was observed that an approximate rate of 200,000 ha/year had undergone deforestation between 1998 and 2002 globally (UMSEF, 2007). Gasparri *et al*., (2008) estimated the emission of CO_2 from deforestation activities in the Chaco forest to be about 57,000 Gg/year which outwear the amount of emission due to transport from fossil fuel in Argentine. Where it was noted that in the recent past, innovation in the agricultural sector which resulted in commercialization has led it to become a source of greenhouse gases as well as being next to fossil fuels. Furthermore, it was resolved that forests played a dual role; (1) Carbon bank or pool through trapping of atmospheric carbon and storing it as Biomass and (2) carbon emission sources through other anthropogenic activities.

Forest being a carbon pool, and carbon being a major driver of climate change has necessitated several research on trying to relate the role of forest biomass to climate change. Comparingly, every 0.5% loss of homogeneous forest will result in a 30% loss of carbon stock within the same period (Vieilledent *et al*., 2016). The carbon stocks in tropical forests are likely to decrease as a result of climatic factors. This could be a result of a decrease in tree diameter and height which are the major component of biomass and carbon stock alongside a loss in species abundance which in turn affect species distribution of the forest ecosystem. Similarly, Madagascar's experience of carbon emission through anthropogenic activities on forest land was observed to be of similar magnitude as that of climate-induced carbon emission (Vieilledent *et al*., 2016).

Studies on the roles of climate change on food production and natural resources management by researchers are of global interest. This has been triggered by the Millennium Development Goals (MDGs) which focuses on eradicating extreme poverty and hunger. Africa is now longing to identify the appropriate major to mitigate and adapt to climate change (FAO, 2010). Amid extreme hunger and poverty in Africa, we must balance Agricultural development while conserving natural resources, otherwise, we may be solving one problem at the expense of others.

One of the fundamental principles of mitigating climate change is the REDD+ mechanism, which is calculating the emissions factors, which is the amount of CO_2 emissions or removals from the atmosphere per hectare from LULC change. Here, the aboveground biomass is an estimate of the emissions factors from the various component of the forest environment. This implies urgent calls to the improvement of the cost-efficiency of these methods within the context of REDD+. Furthermore, REDD+ identifies the need to incorporate communities' participatory-based forest management to be able to manage the forest and in turn mitigate climate change sustainably (Mateo-Vega *et al*., 2017).

2.5 Remote Sensing and Geographic Information System

2.5.1 Brief Description of Remote Sensing and Geographic Information System

Remote sensing is known to be the art and science of communicating with an object of interest without direct contact. This is achieved through sensing and recording reflected or emitted energy which is being pre-processed at various collection centers before making them available to the users. While GIS on the other hand is an environment where data from remote sensing are being handled in a meaningful and efficient manner following the demand of the end users.

Colwell (1983), defined RS as the "collection of data on human's environment and its resources through the use of a camera mounted on stationed or moving platform without touching the object and analysing of the data to obtain the needed information for application by end-users". These data are obtained by measurement of spectral reflectances which are emitted differently across the wavelengths and are captured by the sensors which are processed into meaningful information for final use. In the same vein, GIS is observed as a system that processes information obtained via RS data from forest growth attributes and other related natural resources for decision-making by the resources manager (Alo, 2017).

Remote sensing has widely been applied in the management of both the environment and its resources. The environmental components have to be remotely subjected to analysis over time to ascertain their status amid the changing environment (Silleos, *et al.,* 2006). Recently, there had been a global interest in researching in the pattern in which man uses forest and non-forest resources alongside trying to find out the various natural components that tend to occupy an area of interest. Remote sensing techniques had been able to provide such information, also making a future prediction of LULC changes possible (Singh *et al*., 2017). Therefore, RS is widely applied in the resource monitoring of LULCC (Hua *et al*., 2017).

While the GIS complement or provide the finishing platform for RS through the analysis of the data as requested and deliver the same to the end-users (Zeleke and Hurni, 2001). Landsat multitemporal data was successfully used in monitoring land in Hawalbagh block, district Almora, Uttarakhand, India (Rawat and Kumar, 2015) wherein four classes were identified and classified. In their research, it was revealed that the major land cover in the study area is vegetation. Surprisingly, the vegetation gains more area of about 3.51% as a result of the afforestation programme carried out from 1990 to 2010. On the other hand, barren land lost 5.46% to vegetation, agriculture, and built-up. These Land Use Land Cover Changes (LULCCs) were multi-temporally and spatially analysed over a large area within a short time and at a lower cost compared to the traditional method.

2.5.2 Elements of Remote Sensing and Geographic Information System

Remote sensing systems have the following elements which made them complete in carrying out their functions (Campbell, 1987). This includes the following:

i. there must be energy to illuminate the object of interest for it to be captured by the satellite.
ii. the illuminated energy passes through the atmosphere as it travels from the source to the targeted objects of interest.
iii. once the illuminated energy made its way through the atmosphere, it strikes the objects of interest where parts of the energy are absorbed, transmitted, and reflected based on its components.
iv. once the energy has interacted with the object of interest, the reflected energy has to be recorded by the RS sensor.
v. the recorded illuminated energy is acquired from the sensor, where it is further pre-processed and made ready for researchers who will again process it based on their needs.
vi. The acquired data have to be analysed by various tools based on the demands or needs of the end-users.
vii. Finally, the processed result obtained can now be put into use by the end-users based on the interpretation of the outcome.

2.6 Remote Sensing Potentials in Estimation of Forest AGB /Carbon Stocks

The complexity of the forest's structure, difficult topography, and uncertainty of forest security, have posed enormous challenges in obtaining relevant data from the forest. On the contrary, RS techniques have proven its potentials in addressing such challenges. Also, it has become a major player in environmental-related studies where historical data becomes the bases for comparison and future forecasts. Furthermore, spectral information on vegetation obtained from remote sensing has successfully been regressed with tree growth variables in the estimation of AGB (Maselli *et al*., 2005).

D'Oliveira *et al*. (2012) estimated aboveground biomass using remote sensing data (airborne lidar) in a Brazilian tropical forest, during the processes, areas where selective loggings were carried out, were identified across the stand and mapped out. Similarly, vegetation information obtained from airborne Light detection and ranging (Lidar) was regressed with field biomass. Here, the findings revealed the Lidar to be a good predictor of field biomass with a correlation (R^2) of 0.76 and RMSE of 125 g/m^2 for shrub biomass and a pseudo R^2 of 0.74 and RMSE of 141 g/m^2 for total biomass (Li *et al*., 2017). In the same vein, models developed with the Lidar data were found worthy of predicting the total and shrubs biomass across the Great Basin, of the U.S.A. The need for remote sensing data application becomes necessary to complement inventories which tend to be expensive and time-consuming.

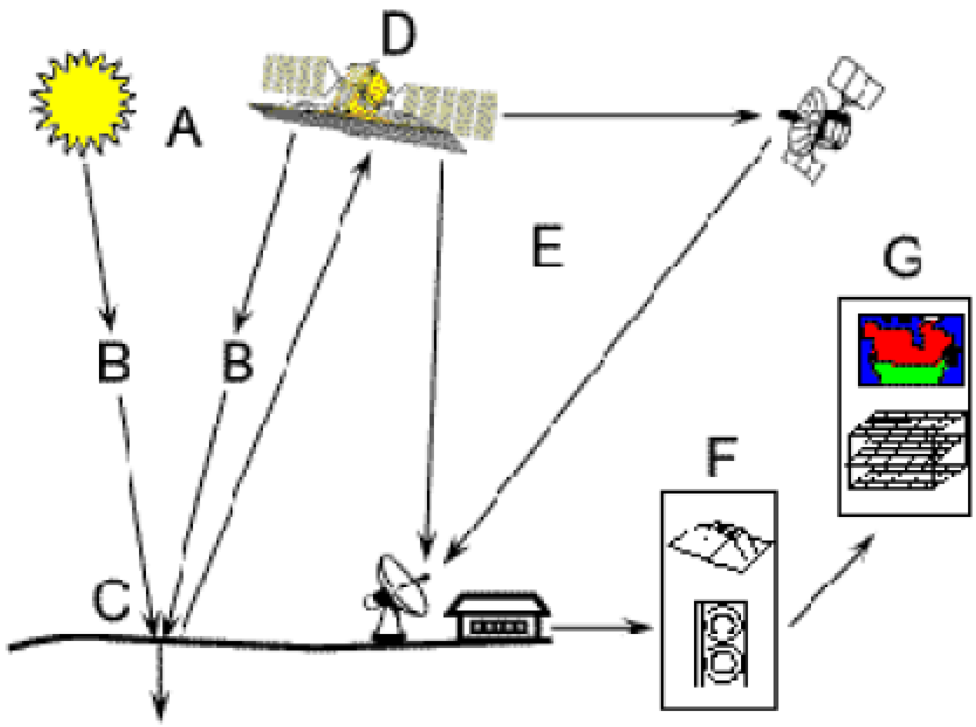


Figure 2.1: Elements of Remote Sensing and Geographic Information System (Campbell, 1987)

2.7 Spectral Response

Plants exhibit different reactions at different times, across different locations, and at different ranges of wavelengths. When the wavelengths are of higher spectral resolutions, different plant species captured can be grouped or classified under different species groups or classes. Also, different states of physiological and morphological makeup from different species of some plants were examined and observed to have exhibited unique spectral signatures at a different range of multi-spectral wavelengths (Ariana *et al.,* 2006).

2.7.1 Vegetation indices

Vegetation indices are known for their roles in estimating tree variables from remotely sensed data. The data obtained across short and long wavelengths depends on the contents of the chlorophyll and some biophysical components of the plants (biomass, leaf tissue, and water content) (Jensen, 2007). Some vegetation indices such as NDVI, RATIO, and TVI, were compared in estimating tree growth variables which lead to the establishment of the relationship between the growth variables and the indices (Payero *et al*., 2004). Likewise, Ferreira and Huete (2004) use vegetation indices in differentiating the Brazilian cerrado and monitoring their seasonal variations.

Raw bands and some other derived vegetation indices obtained from Landsat were successfully applied in identifying and separating various grassland management practices adopted in Eastern Kesas (Price *et al.,* 2002). Huete *et al*. (2002) also use various vegetation indices to compare the performances of different sensors across different sites, where a strong correlation was observed between the plant growth variables and the vegetation indices across the sensors. In like manner, Peddle *et al.* (2001) were able to assess the potentials of some vegetation indices in relation to some tree growth variables information through Airborne data. Similarly, crop damage was successfully assessed by Silleos *et al.* (2006) via a space remote sensing application. Silleos *et al.* (2006) observed that image processing has a far-reaching consequence in remote sensing

applications since the end product is been obstructed by several factors ranging from the instability of the sensors to atmospheric conditions. As such, data corrections are inevitable especially when vegetation indices (Vis) are to be compared over a certain period (Lu *et al.,* 2004).

Rahimzadeh-bajgiran, *et al*. (2018) was able to detect and classify the severity of Spruce Budworm (SBW) in a forest in Quebec, Canada where Landsat 5 data with several VIs were used. The NDMI was the best single index in detecting defoliation, while, the combination of NDVI, EVI, and NDMI could give a better outcome since error rates for both SBW defoliation detection and classification were reduced. Among the three indices, it was observed that NDVI and NDMI correlate stronger with the chlorophyll of the trees and leaf area index respectively. Though, the synergy between the two happens to be a good detector of vegetation change. Chlorophyll index green (Chlgreen) and GNDVI were proven to better detect changes in the canopy than NDVI. However, NDVI was more outstanding in identifying defoliation than the others.

2.7.2 Interaction between Vegetation indices and its target

High-resolution images which are of many bands are more detailed and can give a better estimate of AGTB compared to low-resolution images. However, when a study is tailored towards historical and large area coverage, it becomes deficient. As a result, lower resolutions which usually have much of the historical data such as Landsat with wide area coverage become more important (Powell *et al*., 2010). Despite the medium resolution of Landsat imageries, it's still one of the most widely used in terms of AGB estimation. This is due to the historical data it has as well as the spatial resolution (Powell *et al*., 2010; Lu *et al*., 2012).

Dymond *et al.* (2002) observed that, in the estimation of forest growth attributes, remeasurement data across seasons can attribute to the precision of carbon monitoring. A lot of research had been carried out with coarse-resolution images at different seasons of the year to estimate AGB with a wide area of coverage, though this is limited in differentiating information from a heterogeneous stand (Blackard *et al*., 2008). Zhu and Liu (2014) collected remote sensing data from three different time series for estimating AGB through the NDVI index from Landsat images in Southeast Ohio Columbus, USA. It was observed that the index used for AGB estimation, correlated more with the season of slow growth (off-season) than that of the peak of growth (Peak season).

2.8 Landsat Overview

Landsat had gained the attention of many researchers as a result of its historical data, high spatial resolution, and multitemporal data which is widely applied in the area of aboveground biomass estimation (Zhu and Liu, 2015). Landsat has made tremendous progress in the area of its application which was aided by synergizing the two partners: the National Aeronautics and Space Administration (NASA) and the United State Geological Survey (USGS) towards achieving her goals (Wulder *et al*., 2019). The USGS has become a repository of pre-processed Landsat data outputs (from Multispectral scanners to OLI sensors) for several purposes to meet up with end users' needs across the globe (Micijevic *et al.,* 2021).

Landsat had consistently supplied data for its users since 1972 to date with a wide area of coverage (Wulder *et al.,* 2019). Since the launching of Landsat 1 in 1972, it had been providing information for certain locations and was majorly for change detection which was peculiar to her (Belward and Skoien, 2015). Later in 2008, the policy was reviewed, leading to free access to Landsat data across the Globe (Woodcock *et al*., 2008). The review in policy brought us to the era of mass application of the data in research related to land use land cover change over a large area, (Wulder *et al*., 2012) due to her historical data availability. As a result of its importance, Landsat Global Archive Consolidation (LGAC) put effort towards easing the accessibility of these data by ensuring that data collected from other receiving stations across the globe are made available in a usable format through its repository (USGS). These efforts have made much data available at little or no cost (Wulder *et al.,* 2012). In as much as the data are made available, Landsat suffers some setbacks which emanated from several factors ranging from: platform instability, the state of the atmosphere at the time of the collection, and the angle at which it was collected among others, leading to data correction such as a geometric and radiometric correction to put the data on a similar platform that can be more suitable for further analysis and comparison. These posed great challenges to users, as the correction tools are not readily available with some users having no idea about the need for its corrections (Hemati *et al.*, 2021). However, these limitations have now been broken, through the availability of the corrected products from collections 1 and 2 (Dwyer, *et al.,* 2018). Consequently, the scope of applicability of the Landsat data usage in aboveground biomass and carbon estimation, land use land cover change analysis, and time-series studies has greatly increased.

2.8.1 Landsat Legacy and Generations

The invention and launching of Landsat-1 in 1972 marked a new era for the remote sensing industry where data and its acquisition became of global interest (Pecora, 2020). This has attracted several sectors such as educational, environmental, and health among others through her data availability on land use land cover information (Wulder *et al*., 2019). Also, Landsat 1 was the first earth observation satellite to be near the polar orbiting (Townshend and Justice, 1988) with the following characteristics; Four (4) bands, six (6) bits, sixty meters (60 m) spatial resolution, Multispectral Scanner System (MSS) alongside Return Beam Vidicon (RBV). Furthermore, the Launching of Landsat 2 in 1975 was aimed at complementing Landsat 1 in the area of complete global area coverage of periodic data. The emergence of Landsat 3 was to improve on Landsat 2 regarding RBV, which was on both sides of the cameras, with 40m resolution of the panchromatic and thermal band, with little performance at the time of launch (Hemati *et al*., 2021).

On the other hand, the upgrading of Landsat 3 leads to deviation from MSS to the thematic Mapper (TM) in the late 1970s as the successor (Markham *et al.*, 2004). The architectural makeup brings about more stability and improvement in the area of geometric, radiometric, and spatial resolution compared to the MSS. Furthermore, the TM innovation came with the fear of the unknown to its performance (Markham *et al.*, 2004). This led to the engagement of Landsat image Data Quality Analysis (LIDQA) following the launch of Landsat 4 in 1982 which was onboard a Global Positioning System (GPS), 7 bands, 8 bits, 30m spatial resolution also became the first to collect thermal infrared data. The launching of Landsat 5 was to complement some lapses observed in Landsat 4. Similarly, the launch of Landsat 5 in 1984 which was intended to operate for a period of three years ended up being the longest-operating satellite in the history of Landsat this was the result of the failure of Landsat 6, which was launched in 1993 to achieve orbit (Fgure 2.2).

Also, Landsat-7 was again launched in 1999 with Enhance Thematic Mapper Plus (ETM+) and function through to June 2003 when it encountered Scan Line Corrector (SLC) error leading to gaps in data acquired, all efforts made to correct the gaps in September 2003 proves abortive (Markham *et al*., 2004). This led to the correction or gap-filling of all data obtained from that period with the sensor. Lastly, the launch of Landsat 8 in 2013 onboarded Operation Land Imager (OLI) alongside Thermal Infrared Sensor (TIRS). Despite its high spatial resolution, 30m spatial resolution was still present as this was incorporated to ensure continuity of data incorporation with its predecessors. Some of the additional features that came with this Landsat are 12 bits, coastal, and cirrus bands.

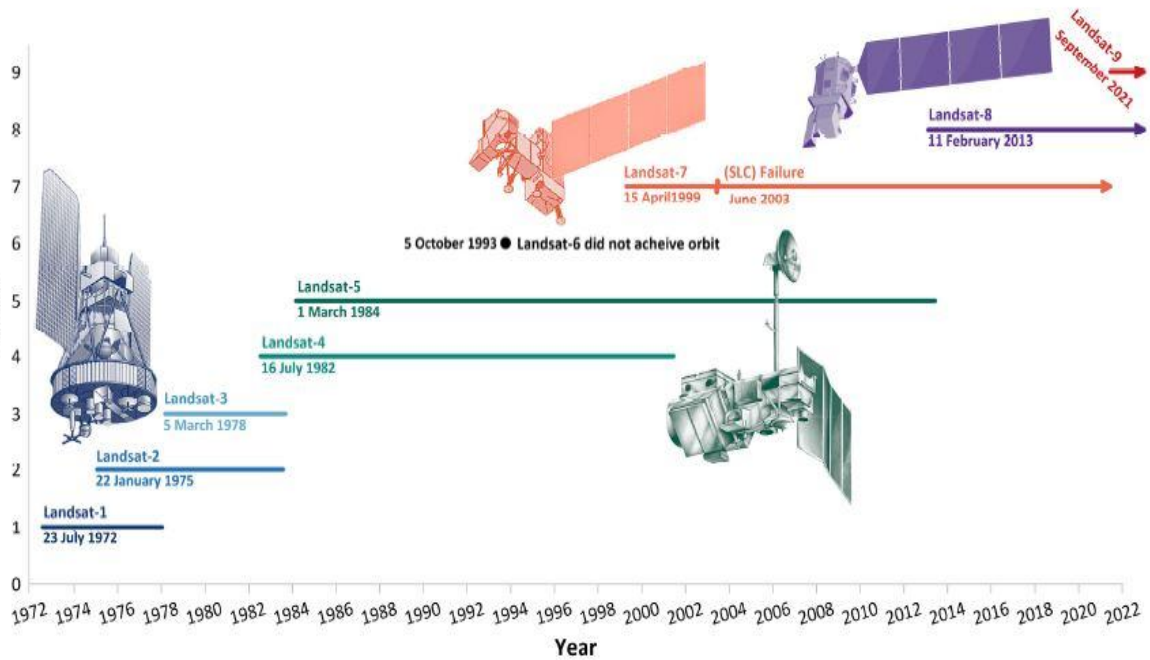


Figure 2.2: Images of Landsat satellite and their time of operation (Hemati *et al*., 2021).

In recent decades, several earth observations satellites (CubeSats, National programs, and satellite constellations) emerges and most of them with high resolution and are commercialized, yet the relevancy of Landsat remains on the increase making it a point of reference for several research especially when a study has to do with either historical data for land use land cover change or large area of interest (Wulder *et al*., 2019). Moreover, there is no other long-term uninterrupted earth observer program that is freely accessible as the Landsat. Also, its global coverage, provision of free data policy, and uninterrupted data collection have made it outstanding among others (Goward, *et al*., 2017). This is in line with achieving her set goal of continuity of data supply from across the globe (Wulder, *et al.,* 2008). Furthermore, this mission propelled the launching of Landsat 8 in 2013 to ensure historical data availability and continuity. In other to ensure continuity, in 2014 the United States implemented the Sustainable Land Imaging (SLI) programme. This was targeted at three main things: a. sustainability, b. reliability, and c. continuity of Landsat data supply to ensure that it maintains its footprint beyond the 2030s through its partnership with NASA and USGS (Hemati *et al*., 2021). This led us to the next Era of technology where we await the launching of Landsat 9 with OLI 2 alongside thermal infrared 2 (Masek *et al*., 2020) as it has become a tradition for Landsat to always have at least two of her Satellite to always be in orbit over the earth.

2.8.2. Landsat Archive and Data Characteristics

Landsat which is known for its global imaging and consistency has continued to supply historical data which has given room for several uses related to commercial, education, and several other sectors. But then, there was a barrier in the area of high cost where an image was costing up to $4,400 also restriction of the right to sharing had limited the extensive spread of the use of the products (Wulder *et al.,* 2012). As a result, a lot of users could not afford it as only a few could afford to purchase less of what they ought to have used. This led to the underutilisation of Landsat data and the inability to explore the data beyond doubt (Figure 2.3).

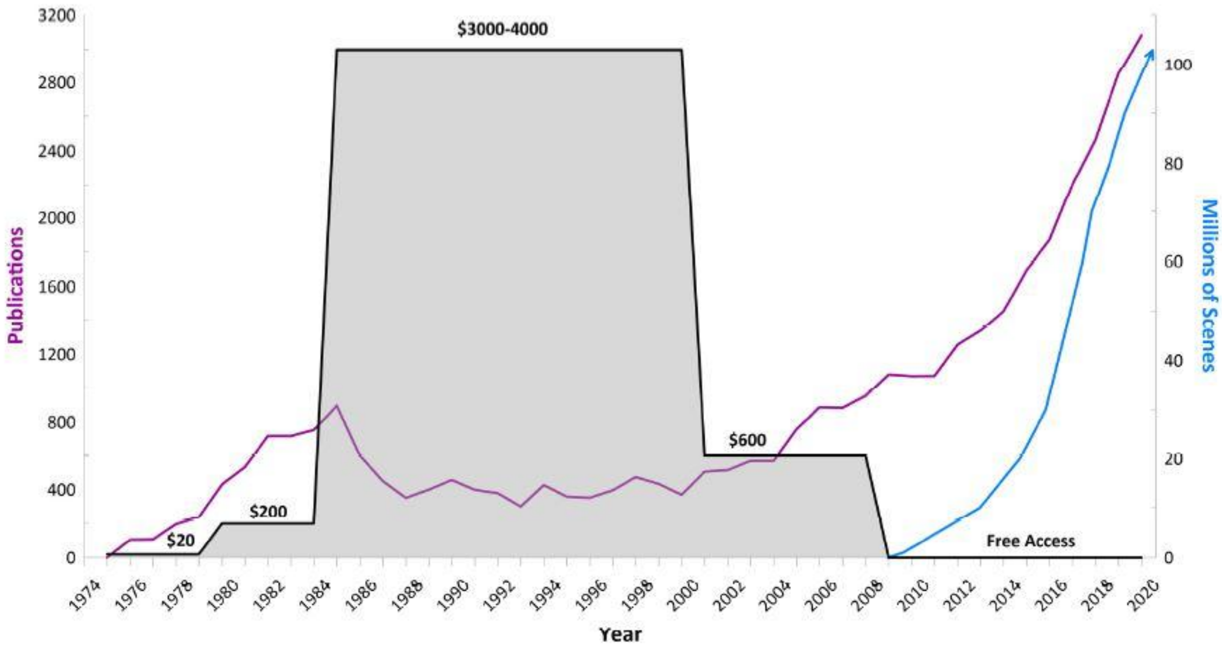


Figure 2.3: Impact of Landsat policy on Research Publication from 1974 to 2020. c

The Purple line showed the trend of published articles that encompassed "Landsat" on their captions or other parts of the articles within the Scopus repository, while the blue line is showing the downloaded images from the repository of USGS, and the black line indicates the prices of Landsat images (Wulder, 2012). It was obvious that data availability greatly encourages research and publication, as this was obvious from the change in policy by Landsat in 2008 (Wulder *et al*., 2012) which made Landsat data open-source.

The data repository of Landsat was containing less data as of early 2000 where estimated images of 4 million and 1.9 million were found at International Co-operators and USGS respectively (Goward *et al*., 2006). This came up as the result of the deficiency of the early Landsat (MSS and TM) in the area of inbuilt storage capacity, data transmission, and the inability of data collection from various stations to the repository for further uses (Markham *et al*., 2004; Goward *et al*., 2006). However, the open-source policy of 2008 and the need to bridge the gap for data availability prompted the LGAC, alongside the complimenting of earlier deficiency of the early Landsat (MSS and TM) contributed to data availability (Wulder, 2016). To enhance the new policy (2008), the repository is being updated with around 1,200 data on daily basis from Landsat 7 and Landsat 8 with an annual data download in millions (Wulder, 2019).

Most studies carried out on earth observation data depend majorly on radiometric and geometric pixel-based registration between sensors and also band-to-band bases (Hemati *et al*., 2021). Consequently, the emanation of Landsat Collection 1 in 2017 (Dwyer *et al*., 2018), had undergone some level of pre-processing thereby enhancing productivity. Meanwhile, Landsat Collection 2, which was made available in 2020 had further enhanced geometric and radiometric calibration accuracy thereby improving products' quality.

The Collection 2 reflectance-based calibration approach is of good precision, owing to the radiometric and geometric corrections. Though not in all circumstances that Landsat data required top of atmospheric correction; in a situation where it has to do with only a single date image classification, atmospheric correction might not be necessary. Unlike study that has to do with multitemporal data for LULC classification of large area coverage, which will necessitate atmospheric correction due to the comparison of several images across different locations and dates (Song *et al*., 2001). Furthermore, since the data are inconsistent, the application of this correction will make it much more reliable. Therefore, applications or studies that have to do with time series and large-area data (Zhu and Woodcok 2014; Hermosilla *et al*., 2015) will require atmospherically corrected data.

Radiance directly captured the amount of light leaving the object and the atmosphere. This energy, interact with the atmosphere leading to its decrease before its acquisition. While TOA Reflectance measures the differences between the amount of energy that reaches the object of interest and the amount that leaves it.

Below are the factors that necessitate the conversion of DNs to TOA reflectance while working with multi-temporal data.

1. To remove the cosine effect of solar Zenith Angles due to the time difference among data acquisition.
2. To compensate for different values of the exo-atmospheric solar irradiance arising from spectral bands difference.
3. To correct for the differences occurring from data obtained at various times due to variations in sun distance at various points of data collection.

Computation of Radiance from DNs (for TM and ETM+).

$$L_\lambda = M_L Q_{cal} + A_L \qquad 2.1$$

where

L_λ = TOA Spectral Radiance

M_L=Band specific multiplicative rescaling factor from (Radiance_Multy_Band_X, where X=Band number).

A_L= Band specific additive rescaling factor from the metadata (Radiance _ADD_BAND_X, where X in the Band number)

Q_{cal}= Quantized and calibrated standard product pixel values (DN).

The computation of TOA Reflectance (For OLI)

$$\rho_\lambda \frac{\pi L_\lambda d^2}{ESUN_\lambda . COS\theta} \quad 2.2$$

Where ρ_λ = Planetary Top of Atmosphere reflectance

π = mathematical constant (3.142)

L_λ = spectral Radiance at the sensor's aperture (w/m^2)

d = earth Sun distance (astronomical unit).

$ESUN_\lambda$ = mean exo-atmospheric solar irradiation (w/m2 μm).

θ = solar zenith angle (degrees) (Zhu and Woodcok 2014; Hermosilla *et al*., 2015).

2.9 Effect of Seasonal Time Series on Forest Stand

2.9.1 Effect of Seasonal Variation on Landsat Time Series Data for Aboveground Biomass

Photosynthetic activities in the green plant are driven by chlorophyll, a green colour pigment that resulted in the increment, growth, well-being, and biological and chemical components of the plants (Sheikh *et al*., 2017). Again, chlorophyll is greatly influenced by several factors ranging from moisture contents, temperature, and precipitations among others. These factors contribute to the maximum amount of chlorophyll recorded in the summer season, followed by the spring season, and finally by the autumn season. Consequently, the number of light absorptions and reflections by the images will vary across the wavelength. In research conducted by Sheik *et al*. (2017) to determine the effect of chlorophyll on some species in the Yousmarg grassland ecosystem, there it was discovered that chlorophyll is highest during summer. Again, the results reveal the summer season to be the highest period of chlorophyll content and growth activities though, the chlorophyll content varied from species to species. Chlorophyll is the main driver during the photosynthesis process and absorbs the incoming solar radiation in form of electromagnetic energy mainly from the visible wavelength of the electromagnetic spectrum to manufacture carbohydrates and oxygen from the water and CO_2 it takes in (Mishra and Mahananda, 2013).

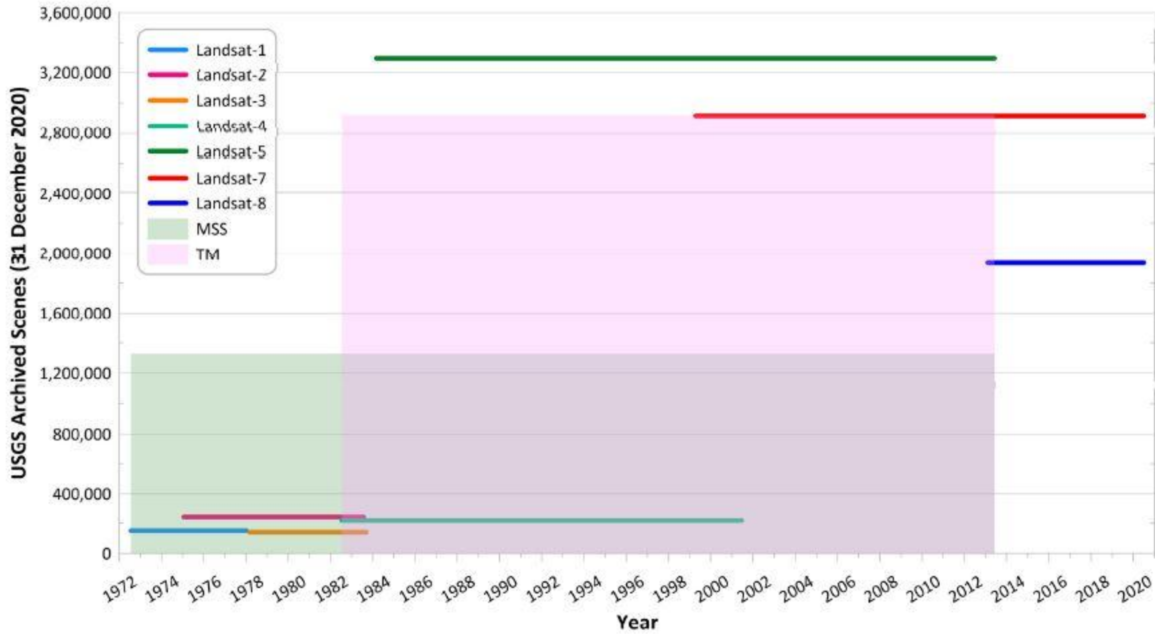


Figure 2.4: Landsat Sensors and Images (9,177,028) Acquired from 1972 to December 2020. (Hemati *et al.,* 2021).

More knowledge about the spatial aboveground biomass (AGB) of our forests is needed to enhance the precision of carbon estimation. To this effect, several researchers have successfully used Landsat data which are known for their historical data and large area coverage to spatially monitor forest structure (Zhu and Liu, 2015). Several researchers have explored empirical approaches in aboveground biomass estimation with the use of only single (peak) season Landsat data which may result in inaccuracy due to saturation problems (underestimation of high AGB values) (Gasparri *et al*., 2010).

The use of spectral information obtained from different seasons has a different effect on the outcome of tree aboveground biomass estimation. Zhu and Liu (2015), applied seasonal Landsat NDVI time-series data in eleven countries of Southeast Ohio, where it was revealed that NDVI in the fall season correlates more with AGB than that of peak season, and this can improve the estimation of aboveground biomass as it reduces the error effects due to saturation. Seasonal time series images have the potential for improving the accuracy of estimating aboveground biomass, and this has not been duly explored. Several studies seem to have used seasonal times series data, meanwhile, they only succeeded in using multitemporal Landsat data of a particular season in different periods (Powell *et al*., 2010). While some used a single image that correlated most to AGB across the season to develop their prediction model (Gasparri *et al.,* 2010). On the contrary, they did not fully explore the seasonal variation effects of multi-temporal Landsat data (Zhu and Liu, 2015). Furthermore, Dymond *et al*. (2002) suggested that there is a need to enhance our forest growth variables monitoring by exploring seasonal Landsat time-series data.

Remote sensing data collected from the forest stand could vary with the time (season) of collection, as forest structure is strongly correlated with the quantity of AGB it contains (Zhu and Liu, 2015). In the same vein, information captured during the fall season when the forest is just springing up could vary from the peak season when the forest growth activities are at their peak.

Mishra and Mahananda (2013), try to investigate the changes in chlorophyll contents of Teak leaves from the inception of the leaf buds to leaf fall. During early April, the leaf buds appeared, growth and development commence up to September. After that period, senescence sets in, after which the leaf fall commences in January. This is an indication that chlorophyll contents increase from April to September having the inception of leaf buds to the complete maturity of the leaves in this species.

2.9.2 Spectral Response Reaction to Seasonal Variation

Most data obtained at the moment of the early active stage of growth, have a strong correlation with the wavelength at the region of infrared due to its high reflectance ability which is captured across the wavelength. The outcome from the data sets across growing seasons and time seems to reflect the true situation of inventory data at the extremes of glowing stages of tree growth (Maselli *et. Al.,* 2011). This is an indication of the fact that data taken from different dates will respond differently to plant growth variables.

2.10 Climate Change

Over time, climate change has been greatly influenced by human activities, ranging from agriculture, industrialisation, urbanisation, and logging activities among others. These activities have resulted in to global warming, poor agricultural yield, loss of faunal and flora, and general degradation of the environment (Li, *et al.,* 2012). Agriculture has become the order of the day in several parts of Africa, as the increasing demand for food continues. As climate change increases, agricultural activities continue to place more demand on forest ecosystems which tend to be their next option to maximize productivity. Climate change has recently, threaten the means of human survival in agriculture which in turn, has led to the loss of forest stands as Man strives for survival (FAO, 2010). On the other hand, the Agro-Forestry principle has been adapted in other to maximize higher output without much interference on the forest ecosystem while contributing to carbon sequestration.

2.10.1 Climate Change Impact

There is an urgent need for scientists across the globe (developing and developed countries) to intensify studies on climatic change mitigation and adaptation which is ravaging the planet (FAO, 2010). This call for a collaborative approach, as the adverse effects of climate change, are increasing at an alarming rate and thereby leading to the exertion of much pressure on the forest’s environment. These have resulted in the degradation of the environment, food insecurity, farmers’-herders’ crisis, and inconsistent income generation among others which are capable of impoverishing human existence.

The forest products (timber and non-timber), which are capable of improving the human standard of living when managed sustainably, is however been misused by uncontrolled human activities

(FAO, 2010). All hands must be on deck, in adapting to the sustainable measure of mitigating climate change in other to avert further effects on the environment.

For some decades, Africa has experienced a consistent decline in food production which has affected her economy and most especially, the rural dwellers where the foods are majorly produced. This decrease in food production will eventually not meet up with her growing population in the nearest decades (FAO, 2006).

Africa must harness its natural resources by developing its irrigation system to meet up the challenges of food insecurity resulting from climate change as well as exploring modern technology in resource management and utilization (Christopher *et. al.*, 2010). Like other developing countries, Nigeria is prone to the impact of climate change, looking at its environmental features, social structures, population size, and rate of increase which in turn increase its demand for energy, food, and shelter (FAO, 2010).

The impacts of climate change on African households who majorly rely on timber and non-timber forest products for their sources of living are becoming threatened, as such, urgent attention is needed towards adaptive measures or coping strategies in the face of climate change (Christopher *et al.,* 2010). These impacts could vary spatially or seasonally based on the various activities carried out by the inhabitants.

2.10.2 Climate Change Mitigation

Africans have not taken into cognisance of the potential that abounds in the global carbon market. As a result, there is an urgent need to educate them on the means of maximizing the hidden potential in the carbon credit market. This will bring all hands on deck to ensure sustainable use of the forest in order not to lose out on the market. Furthermore, other means of sustainable land uses such as Agro-forestry can be adopted to curb hunger while enhancing the potential of the tree crops in ameliorating the environment (Christopher *et al.,* 2010).

It has become glaring, that the information gap between the negotiators and those most impacted (locals who directly or indirectly depend on the forest) by the effects had not been bridged, consequently, the recommendations or conclusion reached hardly get to the grassroots (FAO, 2010). Furthermore, the most challenging issues faced by the Locals that needed urgent attention ended up unattended to, leaving them to their plight as some of these effects are location specific. Therefore, there is a need for the enlightenment of Africans towards adapting to the changes brought about by global climate change as the world prepared to curb the global climate challenges. During the Post-Kyoto protocol in 2012, much was discussed about Africa regarding climate change adaptation and mitigation. Africa has become a thing of concern in terms of climate change adaptation and mitigation during the meeting.

In Africa, it is believed that REDD is the most sustainable means of forest management. REDD was identified as the focal point of the United Nations (UN) mitigating climate change as is been given due diligence in forming part of the Post-Kyoto-Protocol. REDD has gained the attention of apex bodies such as the UN and other most industrialised Nation such as; France, Germany, Italy, the United Kingdom, Japan, the United States, Canada, and Russia. This was noted and taken into action at the Bali action plan conference, in 2007. During this action plan, there was negotiation whereby well-managed forests, which have proven their capability in reduction of emissions can asses some financial benefits.

REDD mechanism, has finally bridged the gap between forests and climate change, as the forest is known for its enormous roles played in climate change mitigation. REDD implementation has impacted several African countries in reducing emissions while integrating climate change mitigation.

2.10.3 The United Nations and Reduction of Emission from Deforestation and Forest Degradation (UN-REDD) Programme

The UN-REDD programme came to be as a result of the collaborative need towards enhancing REDD+ with the view of achieving its purpose of emission reduction. This led to the synergy among UN-REDD and FAO, UNDP, and UNEP, thereby resulting in emission reduction in many countries which was her Goal. This has improved the standard of living among participating communities at the same time, improving forest productivity. In addition, it helps capacity building which aims at carbon payment mechanisms alongside developing other forest products. UN-REDD aims at incorporating developing countries into subsequent REDD+ programmes while strengthening REDD+ by incorporating Paris and Accra principles as well as integrating them among the decisions maker (Kilawe, 2011).

2.10.3.1 REDD+ Readiness

The forestry sector and other appendages of government synergise to realise the goal of REDD+ readiness towards sustainable environmental management. Where attention was given to the
stakeholder and the relevant body to ensure an appropriate inventory of carbon is taken and forwarded to the relevant body for necessary action (Kilawe, 2011). The implementation is in three phases;

i. preparatory and planning by country according to REDD+ readiness guidelines. Here, the country's efforts, and multilateral or bilateral activities are synergised toward participating in a REDD+ mechanism.
ii. putting plans and strategies of REDD+ mechanism into action.
iii. haven ascertain the contributions of a Country towards emission reduction, and incentives will be given as a means of recognition and encouragement to sustain her efforts.

2.10.4 Climate Change Adaptation

A sustainable ecosystem management plan could be a good adaptation measure for climate change in Nigeria. As such, ecosystems such as forests, wetlands, and grassland, could serve as protection through barricading against natural disasters as this means is one of the cheapest and most sustainable for protecting such natural phenomena (Christopher *et.al.,* 2010). Similarly, climate change can be mitigated through the multipurpose roles played by wetlands in providing means of livelihood, a sustainable source of water for other flowing water, and at the same time serving as a habitat for several other amphibians (Christopher *et. al.*, 2010)

Different communities have their peculiar risk factor, as such, adaptation responses have to be location-specific (Ma, 2005). Climate change adaptation is inevitable as our environment keeps changing along with an increase in global warming. Therefore, man must look for the appropriate measure of managing any renewable sources of livelihood such as wetlands, forests land, and other ecosystems towards measuring up with climate change. Also, the population increase must be regulated as this will, in turn, increase man's search for food, shelter, and clothing to the detriment of the environment (Borokini, 2010).

2.10.5 Effects of Climate Change

Climate change has affected a series of ecosystems negatively. The effects on forest and wetland ecosystems among others have in turn affected humanity. Tiega (2010) reported how climate change affected Komadugu, Yobe River which borders Nigeria and Niger through an irregular change of its course over the 20th century. This change could lead to a country gaining or losing its territory to its neighbouring country. Moreover, this has resulted to siltation, thereby reducing the water volume as well as the living organism and their habitats. Over the years, farmland and irrigation along the riverbank were threatened by erosion and shortage in rainfall as the result of climate change leaving the inhabitants with inadequate drinking water (Tiega, 2010). The findings further showed that both short and long-term effects of climate change mostly affect developing countries where the poor farmers are mostly at the receiving end.

Climate change which has lasted for decades continues to affect agricultural production as this necessitates irrigation farming as complementary means of survival in the Sahel region. In the same vein, climate change since 1970s has continued to affect the Sahelian countries as farming in this region is reliant on three months with exception of river banks. Climate change has affected the Sahel region for decades, as crop farming is being supported by an irrigation system as a result of a few months of the rainy season. Lake chards which have low salinity and serve as sources of irrigation, fishing, and domestic purposes among others have suffered losses due to population increase, poor environmental awareness and management, and climate change effects. This loss has negatively impacted the surrounding communities whose sources of livelihood were majorly linked to the lake. Consequently, poverty becomes the order of the day as social vices continue to rise amidst hunger, bad health, degraded environment, underdevelopment, etc. Tiega, (2010).

2.11 Land Used and Land Cover Change

Generally, change is known as the increase or decrease in the size of an object over time. Detecting the state of change of an object has to do with the general process of observing the differences that occur over time on an object or features (Singh, 1989).

The term Land Use Land Cover (LULC) change connotes two entities that are mostly interchanged (Rawat and Kumar, 2015). The term Land Use can simply refer to the pattern or means by which Man tend to utilize or subject land to meet his contemporary need at the moment while Land Cover Change is the differences, which occur as a result of human or natural phenomena on land thereby making it to lose out or gain into it formal status (McConnell, 2015). Similarly, LULCC is the various pattern in which land is been used, alongside natural occurrences which resulted in diverse forms of changes on land (Pielke *et al.,* 2011).

To adequately manage the natural resources, there is a need for consistent studies on changes that occurs in the land features and how lands are been put to use by Human. To carry out change detection, the use of multitemporal datasets becomes inevitable as it presents information on the former and latter status of the land cover and how a man put it into use in other to meet up with his economic and social needs (Lu *et al.,* 2004). The relevancy of multitemporal data sets of Landsat has made waves in studies related to change detection across boards. As a result of the application of the knowledge of change on land features, studies related to that are currently of interest to a lot of resources manager which has brought about consistent innovativeness on various techniques related to LULC change. Recently, anthropogenic activities had occurred worldwide to meet man's day-to-day needs for survival and this has directly or indirectly led to the LUCC (Li *et al.,* 2016). Studies had shown that global environmental changes such as emissions of greenhouse gases, and global climate change had led to the loss of biodiversity, as these have been closely linked to LULC changes (Li *et al.,* 2016).

The LULCC being a major driver of global change has significantly impacted our ecosystem, which in turn affects the biological cycle and biodiversity within the ecosystem (Verburg *et al*., 2004). Besides, LULCC also plays a role in the sustainable development of the social economy (Yin *et al*., 2011; Caldas *et al*., 2007). The greater proportion of the Earth's surface, at one point or the other, had undergone LULCC. As the world advances, human pressure on land becomes intensified, leading to constant demand on land thereby resulting in several changes in land cover types.

According to Liping *et al.* (2018), a mathematical relationship can be established or drawn from the previous pattern of changes on land towards knowing what the future is likely going to be. Once this is known and the effects are assessed, an action plan can commence in the right direction for sustainable bases. Furthermore, the pattern in which LULC will change depends majorly on the source of livelihood or economic activities of the human being as time unfold. This is an indication that land use is a major driver of Land cover which has resulted in environmental degradation, loss of biodiversity, reduction in water volume and quality, and atmospheric pollution. LULC change is driven by population growth, which will result in to increase in demand for agricultural land, industrial land, and construction of social amenities, among other needs. Furthermore, as periodic documentation of information on the status of environmental resources becomes very necessary, RS and GIS application becomes inevitable in meeting up with such demands.

2.11.1 Change Detection Techniques

Several studies have deployed a series of techniques in detecting LULC change in recent times (Liping *et al*., 2018; Hemati *et al*., 2021). The goals were all geared towards a comparison of spatial change occurrences at a certain time interval through observation of certain variables or indices that underwent changes and measuring the extent of the changes (Green *et al*., 1994). One of the basic roles played by RS data on change detection is the fact that any resulting change in the features of interest, the same thing will be obtained in the reflectance value which is different from the one caused by other atmospheric conditions, environmental conditions or change due to technicality (Deer, 1995). To detect change digitally, the following factors are key players which must always be put into consideration: spatial resolution, spectral resolution, and temporal resolution. As such, care must be taken in the selection of the techniques or the algorithm to go by (Lu *et al*., 2004). In land cover change prediction models, the known is used to estimate the unknown for a certain period (Paegelow and Olmedo, 2005). In a complex system such as the forest ecosystem, Cellular Automata (CA) has been proven to be much more reliable in modelling the ecosystem. This is due to its ability to describe a random probability, nonlinear and spatial distribution of the forest component. Nevertheless, the limitation of CA in terms of transition probability of change from class A to class B can be complemented through synergizing CA and Markov i.e. CA_Markov which can better be used in forecasting the future state of the various LULCC (He *et al*., 2006; Wu *et al.,* 2010; Zhao *et al.,* 2012).

There is no doubt, the recent developmental changes springing up in most developed countries have attracted rural-urban migration thereby increasing pressure on LULC. Therefore, urgent attention must be given to the siting of some developmental projects in rural communities to decongest the urban area from the rising population (Li *et al.,* 2016). Kayet and Pathak (2015) revealed that the Very Dense Forest (VDF) area of Saranda Forest, Jharkhand reduced to 8.61% and Open Forest (OF) increased to 7.03% between the years 1992 and 2014 as a result of human activity such as mining.

2.11.2 LANDSAT Application in Land use Land Cover Change

Kaswanto *et al*. (2010) successfully apply Landsat imagery in detecting the transitional changes in forest and grassland in the agricultural and built-up areas. Mengistu and Salami (2007) studied the LULC change detection using Landsat imagery in a region of South-Western Nigeria and they revealed that forest area has decreased, while a corresponding increase was noticed in shrubland/farmland complex and settlement/bare surface. An assessment of variation in forest cover has become a vital element in the present-day system of managing natural resources and identifying environmental deviations. Much of recent research has publicized that, the overpowering population pressure, practicing unscientific cultivated methods, and the lack of consciousness about the significance of forests among the people are the key reasons for deforestation/degradation of the forest.

2.12 MARKOV MODEL

Markov chain model is centered on the systematic movement of the forest from one state to the other (Muller and Middleton, 1994). It is commonly applied in change simulation, extents, and patterns in which LULC has changed. Markov chain model applied the use of probabilities to analyze and present change in LULC from one state of the environment to the other within a stipulated time (Coppedge *et al*., 2007). Moreover, the outcome can be used for future prediction of LULC change and the growth pattern of the environment (Dadhich and Hanaoka, 2011).

Nevertheless, the Markov chain is limited in terms of model simulation which has to do with aerial images across the environment. However, it remains an effective and powerful tool in the hand of an environmental modeler when carrying out research related to LULC change (Yang *et al*., 2012).

The formula for the future prediction of LULC change is given by conditional probability as follows:

$$\sum_{I=1}^{m} Pij = 1, i = 1,2, \ldots\ldots\ldots\ldots m \qquad 2.3$$

$$P=P_{(IJ)} \begin{vmatrix} P11 & P12 & P13 & P14 \\ P21 & P22 & P23 & P24 \\ P31 & P32 & P33 & P34 \\ P41 & P42 & P43 & P44 \end{vmatrix}$$

where: Pij = the probability of transition from one land use to another, m = the type of LU of the area studied, and Pij values are within the range 0–1.

2.12.1 CA–MARKOV CHAIN MODEL

In other to improve the modelling of LULC, there is a need to synergise various techniques such as cellular automata and Markov chain (Liu *et al*., 2007; Qiu and Chen 2008; Yang *et al*., 2012). The recent application of the CA_Markov chain model in spatial image prediction had been successful (Wang *et al*., 2012). Furthermore, the outcome from CA–Markov uses LULC change prediction of area extent, alongside a pattern of aerial modelling of CA. As such, the synergy between cellular Automata and the Markov chain model can greatly improve the modelling of spatial data for LULC change (Yang *et al*., 2012). Application of GIS in LULC mapping obtained from aerial images alongside the

CA_Markov model can contribute significantly towards simulating future LULC change (Wang *et al*., 2012).

In the operation of the synergized CA–Markov modelling, the Markov act in the area of transition matrices of the multitemporal resolution of LU change (López *et al*., 2001); while the Cellular Automata model act in the area of local transition of the spatial resolution images (Guan *et al*., 2011). CA which is a model built-up in Idrisi Terrset software that works with discrete variables to predict LULCC for a future time, through synergizing of its with Markov has greatly contributed to the trending topic of LULCC (Beneson and Torrens, 2004).

In conclusion, the destructive method of aboveground biomass estimation can no longer stand as the method is not environmentally friendly, though the most precise in AGB estimation. The destructive method has also led to instability in land use land cover of the forest ecosystem. In addition, the models developed from the destructive method are usually limited in the area of general application since few species are usually collected from limited locations for the model's calibration. Models are site and species-specific, as such, applying such models on the general stand could be associated with some errors, coupled with the different forms of LULC within the forest ecosystem. He *et al.* (2008) applied a similar method in coniferous and broadleaved mixed forests, in North-eastern China, where few species were destructively sampled to model AGB. On the other hand, the inventory method is also limited in areas with difficult terrain, complex forest ecosystem, insecurity from accessing forest land, and the high cost of data collection (Mugasha *et al*., 2013). Olorinfemi *et al.* (2019) estimated aboveground biomass and carbon stocks in the forest vegetative zone of Nigeria through the inventory method, where many resources must have been committed to data collection. However, it becomes inefficient to estimate aboveground biomass at a consistent interval through the destructive and non-destructive inventory methods, as these make consistent reporting of AGTB in line with UN-REDD policy impracticable. Therefore, this necessitates the application of remote sensing techniques where aboveground biomass can be estimated through satellite images and reported at a consistent interval in Buru Community Forest. Furthermore, the data for such analysis should be collected at a time that best correlates with the aboveground biomass on the field to increase the precision of its estimation. In the same vein, the pattern at which the forest is reduced needs to be accessed, to ascertain the amount of carbon gained or lost at commitment periods.

CHAPTER THREE

METHODOLOGY

3.1 The Study Area

This study was carried out at the Buru community forest, which is about 2,054.7 ha located at the foot of the Mambila Plateau in Kurmi Local Government Area of Taraba State, Nigeria. It is located between latitudes 6.972º and 7.047 º and latitudes longitudes 10.882 º and 10.927 º (Figure 3.1).

3.2 Climate and Vegetation

The climatic conditions of Buru include rainy season that spans from the end of April and early May to October ending and early November while the dry season commences from the end of November to early April with a mean annual rainfall of 1780 mm (Chapman and Chapman, 2001).

The following species are found in the study area; *Anthonotha noldeae , Beilschimiedea mannii, Carapa grandiflora, Celtis occidentalis, Chrysophyllum albidum, Croton macrostachyus, Deinbolia pinnata, Diospyros montbutensis, Dombeya ledermanni, Entandrophragma angolense, Ficus exasperata, Garcinia smeathmeanii, Khaya grandifoliola, Leptaulus zenkeri, Macaranga occidentalis, Oxyanthus speciosus, Pleiocarpa pycnantha, Polyscias fulva, Poulteria altissima, Pterygota mildbraedii, Santiria trimera, Strombosia schefflerii, Symphonia globulifera,* S*yzygium guineense, Tabernaemontana contorta, Treculia obovoidea, Trichilia prieuriana, and Zanthxylum zanthxyloides.* (Akinsoji, 2013).

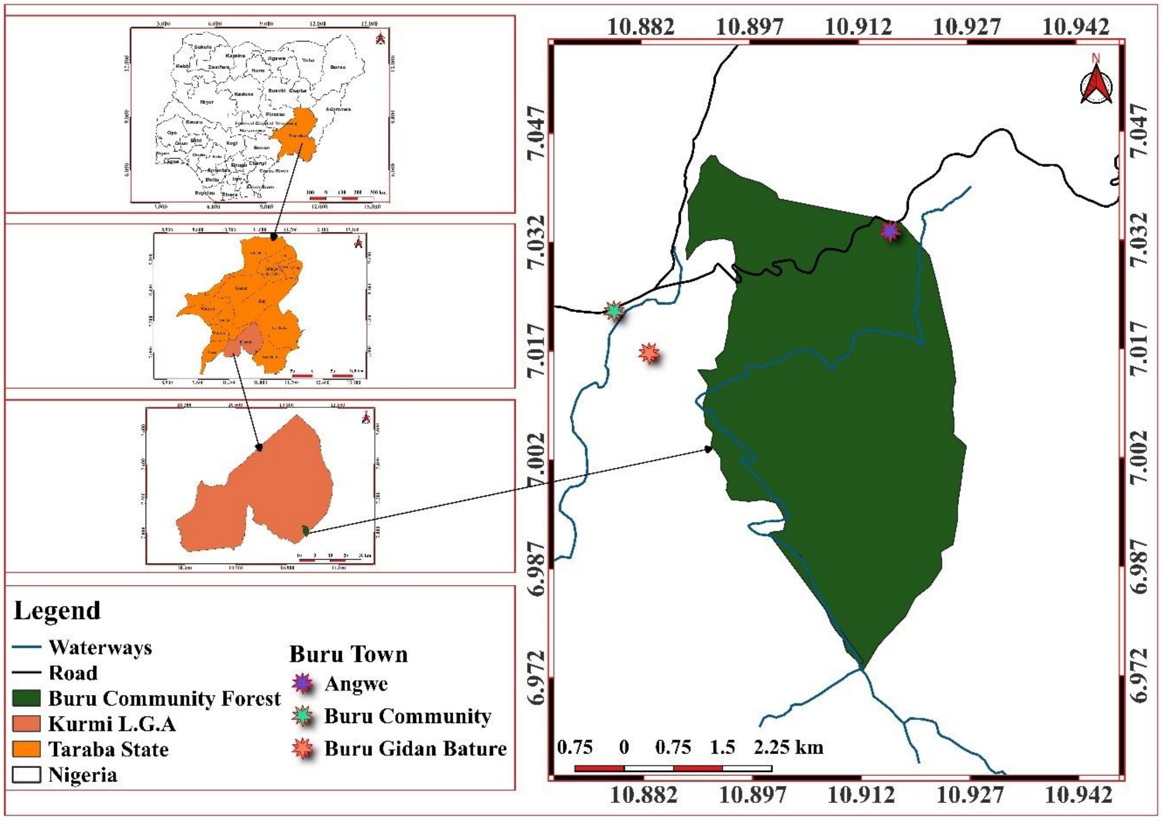


Figure 3.1: Buru Community Forest, Taraba State, Nigeria

3.2.1 Topography and Drainage

Buru community forest has a rugged mountainous topography that cut across the forest, with an average elevation of 472.80 m. The alluvial plains section of the forest comprises freshwater flood plains. The forest also has undulating plains land, which attracts settlement to that particular area (Akinsoji, 2013).

3.3 Method of Data Collection

3.3.1 Reconnaissance Survey of the Study Area

A reconnaissance survey was carried out in the Buru Community Forest to familiarise me with the forest ecosystem and obtain the necessary information that helped in the planning of field data gathering. These include; vegetation cover, LULC, topography, and terrain. It was observed that there was the presence of anthropogenic activities in some parts of the forest, which present the forest at varying levels of disturbance.

3.3.2 Field Inventory data

3.3.2.1 Selection of Sample Plots

Sequel to the information obtained during the reconnaissance survey, Buru Community Forest was divided into less disturbed and disturbed forests. Therefore, stratified random sampling technique was adopted for the selection of sample plots. Plots allocation to each stratum was proportional to size using 0.6 % sampling intensity. The less disturbed and disturbed forests have 12 and 8 sample plots, respective making a total of 20 plots of 50 m x 50 m. The randomly selected plots were traced on the field through Global Positioning System (GPS) and plots were laid while the required variables were collected (Das and Singh, 2012).

3.3.3 Measurement of the growth variables from Tree Sampled Trees in Buru Community Forest

Trees with diameters ≥ 5 cm were identified and enumerated from each sampled plot area. Identification of trees was carried out by the use of local taxonomist, who provided the local names of the trees. Species that could not be identified were tagged on the envelope in line with the recording sheet. The growth variables obtained from the sample plots include:

i. Wood core samples,
ii. Diameter at the Base (DB),
iii. Diameter at the Breast Height (DBH),
iv. Diameter at the Middle (DM),
v. Merchantable Height (MH),
vi. Total Height (TH).

During the inventory process, coordinates were taken for tracking specific land features within the forest which served as guide for identification and classification on the satellite imageries.

3.3.4 Extraction of core sample from Tree Sample in Buru Community Forest

Five core samples were collected from each species through the use of increment borer, which was inserted into live-standing trees. The core samples were kept in an airtight envelope to preserve the water content from evaporation.

3.3.5 Spatial Data Acquisition

The imageries were obtained from https://earthexplorer.usgs.gov, through the path and row (186/55) search of the study area. The images were acquired from Landsat (TM, ETM+, and OLI) at Level 1 and set at a cloud cover of less than 10% for viewing and downloading purposes. The data collected were Landsat 5 TM, of 1988 and Landsat 7 ETM+ of 2000, 2008, and Landsat 8 OLI of 2018 (Table 3.1). The choice of the Landsat satellite was based on wide-area coverage, the record of historical data for man's geographical area, and free data policy. The data from the satellites were collected for the months of July and December.

3.4 Method of Data Analysis

3.4.1 Estimation of Wood Density from Core Samples

The length and diameter of the cores samples were measured with a measuring tape and calliper respectively, and the volumes were calculated using equation 3.1(Chenge and Osho, 2018).

$$V = \frac{\pi}{4} D^2 L \qquad 3.1$$

Where V = *volume of the tree core sample (cm*^{3}*)*

D = *diameter of the tree core sample (cm)*

L = *length of the tree core sample (cm)*

$$\pi = 3.14$$

The core samples obtained were further oven-dried until constant weights were obtained at a constant temperature of 105°C. The dry weight was divided by its fresh volume, which gave the wood density (FAO, 1997) as shown in equation 3.2:

$$\mathrm{WD} = \frac{\mathrm{SDW}}{\mathrm{SV}} \qquad 3.2$$

Where WD = *wood density in (g/cm*^{3}*)*

SDW = *sample dry weight (g)*

SV = *volume of core sample. (cm*^{3}*)*

Table 3.1: Spatial Data Images and the Pattern of their Collection

Year	Sensor Type	Data Type	Months	Resolution	Path and Row (scene/tile)
1988	TM	Spatial	July	30m	186/55
		Spatial	December	30m	186/55
2000	ETM+	Spatial	July	30m	186/55
		Spatial	December	30m	186/55
2008	ETM+	Spatial	July	30m	186/55
		Spatial	December	30m	186/55
2018	OLI	Spatial	July	30m	186/55
		Spatial	December	30m	186/55

3.4.2 Estimation of Tree Volume of Buru Community Forest

The volume was estimated using the equation 3.3:

$$V = \frac{\pi}{4} D^2 L \qquad 3.3$$

Where V = *volume of the tree sample (m*^{3}*)*

D = *diameter at breast height of the sample tree (cm)*

h = *height of the sample tree (m).*

3.4.3 Estimation of Aboveground Stem Biomass of Buru Community Forest

The Aboveground Stem Biomass (AGSB) was obtained by multiplying the volume of each tree by its specific Wood Density (WD).

The aboveground stem biomass of the forest calculated with equation 3.4.

$$ABG = AGSB_{est} = V * \rho \qquad 3.4$$

Where $AGTB_{est}$ = *aboveground tree biomass (t/ha)*

V = *Volume (m*^{3}*)*

ρ = *Specific gravity (wood density) (g/cm*^{3}*).*

The AGSB per plot was obtained by summing the AGSB of individual trees for each plot sampled as presented in equation 3.5:

$$AGSB_j = \sum_{i=1}^{n} (ASGB_i) \qquad 3.5$$

Where $AGSB_j$ *is the total tree aboveground stem biomass in plot j, (j = 1, 2,...n),* $AGSB_i$*is above tree ground stem biomass of tree i in plot j.*

3.4.4 Estimation of Aboveground Tree Biomass of Buru Community Forest.

The estimated aboveground stem biomass was expanded to account for crown components of the tree such as branches and leaves, *etc*. This was done by multiplying the estimated stem biomass by Biomass Expansion Factor (BEF). A default value of 3.4 provided by IPCC (2006) for tropical forests was used. This is expressed in equation 3.6.

$$AGTB = AGSB_{est} * \text{BEF} \qquad 3.6$$

Where : $AGTB$ = *Aboveground Tree Biomass*

$AGSB_{est}$ = *Aboveground Stem Biomass estimates*

BEF = Biomass Expansion Factor and is 3.4 = default value of biomass expansion factor for tropical forests

3.4.5 Estimation of Carbon Stock of Buru Community Forest.

The tree aboveground carbon stock in each plot was estimated by multiplying the tree aboveground biomass by 0.45 (Whittaker and Linkens, 1973). This is expressed in equation 3.7.

$$AGTC_j = \sum_{i=1}^{n}(AGTBi)x\ 0.45 \qquad 3.7$$

Where	$AGTC_j$	=	*Aboveground tree carbon in plot j, (j = 1, 2,...n), (t/ha)*
	$AGTB_i$	=	*aboveground tree biomass tree i in plot j, (t/ha)*
	0.45	=	*conversion factor.*

3.5 Models for Aboveground Tree Biomass and Carbon Stock of Buru Community Forest Using Remote Sensing data (wet and dry seasons) and Inventory Data

3.5.1 Preliminary Analysis of Landsat Variables

The remotely sensed images were acquired as stated in Table 3.1.

The images were obtained as L1T product which is radiometrically and geometrically corrected to an extent.

3.5.1.1 Radiometric Corrections

Before this correction, the acquired imagery was extracted and imported into ERDAS Imagine 2014 environment where it was saved in a compatible format, one band after the other according to the number of bands required. The radiometric corrections were carried out to correct some radiometric distortions on the imageries arising from the interaction between the incoming and reflected radiation with the atmospheric conditions and remote sensors. These corrections were subject to several factors ranging from; sensor types, sensor platforms, and atmospheric conditions, among others. Also, the data were calibrated to known (absolute) radiation or reflectance units to facilitate the comparison of data and accurately represent the reflected or emitted radiation measured by the sensor.

3.5.1.2 Geometric Correction

This was carried out to correct some geometric distortion on the images arising from the sensor's platform instabilities, as well as to integrate the geospatial data into a compatible format. The various imagery of TM, ETM+, and Landsat8 of 1988, 2000, 2008, and 2018 were registered to the WGS 84 and UTM Zone 32 coordinate system and geo-referenced.

3.5.1.3 Conversion of Digital number to Radiance and Top of Atmospheric (TOA) Reflectance

The data from Landsat were obtained in Digital Numbers (DNs) format which necessitates its conversion to TOA reflectance. A similar conversion was applied to data obtained from TM and ETM+ from DNs to radiance and letter to reflectance. While OLI data were converted from DNs to Reflectance.

3.5.1.4 LAYER STACKING AND SUB-SETTING OF THE STUDY AREA

This process brings all the required bands together, to work with them as one entity by simply alternating the bands to get the desired composites. The shape file of the study area was overlaid on the composite bands for 1988, 2000, 2008, and 2018 to obtain the subsets for the period under investigation.

3.6 Computation of Spectral Variables for Biomass Estimation

The values of the various spectral variables were extracted from the respective plots as laid on the composites obtained from the downloaded Landsat images of 1988, 2000, 2008, and 2018. The

spectral variables that best explain the amount of variation of AGTB were used to estimate AGTB for the period under investigation. The spectral variables are listed in equations 3.8 to 3.27.

NDVI (Lu *et al*., 2004) $$\frac{NIR-RED}{NIR+RED} \quad (3.8)$$

GNDV (Gitelson *et al.,* 1996) $$\frac{NIR-G}{NIR+G} \quad (3.9)$$

SAVI (Huet, 1988) $$\frac{NIR-R}{NIR+R}(1+L) \quad (3.10)$$

MSAVI (Qi *et al*., 1994)	$\frac{NIR-R}{NIR+R+L}(1+L)$	3.11
NDWI (Gao, 1996)	$\frac{G-SWIR1}{G+SWIR1}$	3.12
MSI (Hunt and Rock, 1989)	$\frac{SWIR}{NIR}$	3.13
NDMI (Suming and Steven, 2004)	$\frac{NIR-SWIR}{NIR+SWIR}$	3.14
EVI (Chaoyang, *et al*., 2011)	$2.5 * \frac{R_{NIR}-R_{Red}}{1+R_{NIR}+6*R_{Red}-7.5*R_{Blue}}$	3.15
Simple Ratio		
OLI5/4 (Lu *et al*., 2004)	$(OLI5)/(OLI4)$	3.16
OLI6/4 (Lu *et al*., 2004)	$(OLI6)/(OLI4)$	3.17
OLI6/5 (Lu *et al*., 2004)	$(OLI6)/(OLI5)$	3.18
OLI6/7 (Lu *et al*., 2004)	$(OLI6)/(OLI7)$	3.19
Image Transformation		
DVI (Clevers, 1988)	$(OLI5)-(OLI4)$	3.20
NR (Lu *et al*., 2004)	$((NIR)+(RED)$	3.21
Normalize Vegetation Indices		
ND64 (Lu *et al*., 2004)	$((OLI6)-(OLI4))/((OLI6)+(OLI4))$	3.22
ND65 (Lu *et al*., 2004)	$((OLI6)-(OLI5))/((OLI6)+(OLI5))$	3.23
ND67 (Lu *et al*., 2004)	$((OLI6)-(OLI7))/((OLI6)+(OLI7))$	3.24
ND43 (Lu *et al*., 2004)	$((OLI4)-(OLI3))/((OLI4)+(OLI3))$	3.25
ND74 (Lu *et al*., 2004)	$((OLI7)-(OLI4))/((OLI7)+(OLI4))$	3.26
B2 to B8 (Landsat 8 Data, 2018)		3.27

The spectral variables are defined as follows:

NDVI	=	*Normalized Difference Vegetation Index,*
GNDVI	=	*Green Normalized Difference Vegetation Index,*
SAVI	=	*Soil Adjusted Vegetation Index,*
MSAVI	=	*Modified Soil Adjusted vegetation Index,*
NDWI	=	*Normalized Difference Water Index,*
MSI	=	*Moisture stress index,*
NDMI	=	*Normalize difference Moisture index,*
EVI	=	*Enhance vegetation Index,*

TNDVI	=	*Transform normalize vegetation index,*
TCIg	=	*Tassel Cap index of greenness,*
TCIw	=	*Tassel Cap index of wetness,*
DVI	=	*Difference Vegetation Index,*
NR	=	*Normaliseed Ratio,*
OLI4	=	*Operational Land Imager Band 4 of Landsat 8,*
OLI5	=	*Operational Land Imager Band 5 of Landsat 8,*
OLI6	=	*Operational Land Imager Band 6 of Landsat 8,*
OLI7	=	*Operational Land.*

3.6.1 Principal Components Analysis of the Spectral Variables

Principal components analysis was carried out to reduce data redundancy thereby compressing much of the information from the original to fewer data without compromising the original data. This new data obtained from the statistical procedure were term as components.

3.7 Determining the Effect of Seasonal Variation on Remote Sensing Data Acquisition in Buru community forest

To identify the optimum season (month) for AGTB estimation through remote sensing application, the inventory data of AGTB were regressed with spectral variables obtained from PCA across the months (July and December) which served as the explanatory variable (Zhu and Liu, 2015).

An empirical (experimental) model for the prediction of aboveground tree biomass was developed to determine the most suitable model for AGTB estimation.

3.7.1 Evaluation and Validation of Aboveground Bole Biomass Models

The models were checked for homogeneity of variance using the scatterplots of residuals against predicted AGTB to ensure that the standard assumptions of regression were not violated. The models were evaluated and compared based on the goodness of fit statistics such as;

(a) Coefficient of Determination (R^2):

The R^2 explained the percentage of the response variable of the linear model that is explained by the independent variables. The higher the value of R^2 the better the fit (equation 3.28).

$$R^2 = 1 - [\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 / \sum_{i=1}^{n}(y_i - \bar{y}_i)^2] \qquad 3.28$$

(b) Adjusted R^2 (R^2_{Adj})

The R^2_{Adj} is a modified version of R^2 that has been adjusted for the number of predictors in the model that was also used. The higher the value the better the fit (equation 3.29).

$$R^2_{adj} = 1 - \left[\frac{(1-R^2)(n-1)}{n-K-1}\right] \qquad 3.29$$

Where n is the number of points in your data sample, and K is the number of independent repressors', i.e. the number of variables in the model, excluding the constant.

(c) Root Mean Squared Error (RMSE)

The RMSE measured how accurately model predicts the response variable and is one of the most important criteria for fit since the main purpose of the model is prediction. Lower values of RMSE indicate a better fit (equation 3.30).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad 3.30$$

y_i= *observed TAGB*, $\hat{y}_i$= *predicted TAGB, n = number of data points.*

(d) Akaike Information Criterion (AIC)

The AIC is a measured technique based on in-sample fit to estimate the likelihood of a model to predict/estimate the future values (Akaike, 1974).

The lower the AIC the better the model

$$AIC = -2\ell + 2K \qquad 3.31$$

Where ℓ *=Maximized log-likelihood and K number of estimable parameters*

(e) Bayesian Information Criterion (BIC)

The BIC is another criterion for model selection that measures the trade-off between model fit and complexity of the model (Stone, 1979). Also, BIC has proven its consistency in model selection in a finite predictors dimension. Its recent modification has been proven to have taken care of diverging variables (Lee *et al*., 2014).

A lower BIC value indicates a better fit (equation 3.32).

$$\text{BIC} = -2\ell + K\log n \qquad 3.32$$

Where ℓ *and* K *are the same as above and* n *is the sample size*

Model selection was based on the highest R^2 and R^2_{Adj}, lowest RMSE, Akaike and Bayesian's information criteria.

(f). T-test

The observed AGTB were compared with the predicted RS-AGTB at α=0.05 (equation 3.33).

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}}} \qquad 3.33$$

where: $\bar{x}_1$ *and* $\bar{x}_2$*= sample means;* n_1 *and* n_2*= sample sizes for the two groups.*

3.8 Land Use/Cover Classification

The various LULC within the study area were identified and classified using available data sources such as; remote sensing imagery; Google Earth, Landsat imagery, and ground truthing. Thereafter, the LULC was classified into six (6): Less disturbed forest; Disturbed Forest; Grasses, shrubs, and farmland; Water body; Bare land; and Built-up Area for the purpose of this study. These classes were in line with Anderson (1971) who made it known that the number of classes to work with should be moderate while considering the basic classes with the most appropriate vital information that will meet the research objectives.

3.8.1 Supervised Classification of Buru Community Forest

Each of the pixels from the enhanced Satellite imagery has a spectral signature which is usually determined by the spectral bands. As such, the imagery obtained was separated into different classes of interest through the supervised classification method. In this supervised classification, information classes are first identified and then used to determine the spectral classes representing them. The goal here is to ensure that the entire study area presented in the images was all assigned to the various LULCs which will lead to the production of an image with the required class.

3.8.2 Post Classification of the Land Use Land Cover of Buru Community Forest

The forest cover of similar spectral reflectance was merged into their respective classes. The statistics of the six (6) classes were generated using the ERDAS Imagine programme. The map of identified LULC in BCF was developed using the ArcGIS programme, and the map was validated in the field to assess its accuracy. The maps produced, were taken to the field to verify the closeness of the classification to the actual field situation as was done by Smith *et al.*(1999). During this process, not less than 300 familiar coordinates (i.e. not less than 50 coordinates points for each of the respective classes) were picked and checked back in the field for validation purposes.

3.8.3 Classification Accuracy Assessment of Land Use Land Cover Change of Buru Community Forest

Kappa statistics were used to determine quantitative, qualitative, and map reliability of the image classification and accuracy assessment (Treitz, 2004). The validation of the classified LULCC was done by randomly picking over 50 points of each class for ground-truthing through Kappa Coefficient (Smith. *et al.*, 1999). The accuracy was determined by the Kappa coefficients obtained (equation 3.34).

$$K_{APPA} = \frac{N\sum^{k} X_{ii} \sum^{k}(X_{i+} \; x \; X_{+i})}{N^{2} - \sum^{k}(X_{i+} \; x \; X_{+i})} \qquad 3.34$$

Where: KAPPA = Kappa index, k = number of matrix files, Xii = observation number on row i and column I (along the diagonal), Xi+ and X+i = total marginal for row i and column i, respectively, N = total number of observations.

3.8.4 Change Detection of Land Used and Land Cover for the Year 1988-2018

The change detection in BCF was achieved through comparison of land use/cover change statistics of the classified imageries obtained for the four study years. This was performed to identify the temporal effects since the quantitative change was examined and as well itemized the areas of the various LULC change categories in accordance with the transition. During this process, the differences between the various LULCC classified were analysed to know the rate and pattern at which the changes occurred across the study periods.

In actualizing the change detection, the area per hectare of each LULC class under each year was estimated and the percentage changes were calculated to obtain the pattern of the changes as in equation 3.35.

$$LULCC = t_1 - t_2 \qquad 3.35$$

Where:

LULCC= land use land cover change (ha)

$t_1 - t_2$= *area difference between the final and initial period (year)*

$$\%\ change\ of\ LULCC = \frac{PL}{TA} \times 100 \qquad 3.36$$

Where:

$\%\ change\ of\ LULCC$= *percent of area change (%)*

PL = particular land use or land cover area (ha)

TA = Total area of the land use land cover (ha).

3.9 Prediction of LULC Change

3.9.1 Application of Markov Chain and Cellular Automata in the Prediction of LULC Change of Buru Community Forest

Markov chain algorithm and Cellular automata were used to predict LULCC in Buru community forest. This adoption was based on the dynamics of the complexity of an ecosystem that is ever-changing from one class to another (Cabral and Zamyatin, 2009). These algorithms used the previous trends of changes from one class to another over the period to simulate future occurrences. This led to the application of Markov and Cellular Automata in the projection of LULCC for 2028 and 2048 based on the time interval from

1988 to 2018. Also, the transition probability matrix of change from one LULC class to another (ie from initial to the later time) was determined for the six (6) LULCC within Buru community forest.

Markov Chain

The formula for the future prediction of LULC change is given by conditional probability in equation 3.37.

$$\sum_{I=1}^{m} Pij = 1, i = 1,2, \ldots \ldots \ldots \ldots . m \qquad 3.37$$

$$P=P_{(IJ)} \quad \begin{vmatrix} P11 & P12 & P13 & P14 \\ P21 & P22 & P23 & P24 \\ P31 & P32 & P33 & P34 \\ P41 & P42 & P43 & P44 \end{vmatrix}$$

where: Pij = the probability of transition from one land use to another, m = the type of LU of the area studied, and Pij values are within the range 0–1.

CHAPTER FOUR

RESULTS

4.1 Results

4.1.2 Data Summary of field inventory used and Aboveground Stem Biomass in Buru Community Forest

The Dbh ranged from 5.0 to 87.40 cm with a mean of 22.56 ±0.35 cm. The THt had a mean of 12.86 ± 0.19 m (Table 4.1). Wood density ranged from 0.19 to 1.10 g/cm^3 with a mean of 0.47±0.0038 g/cm^3. Aboveground stem biomass and carbon are presented in Table 4.1 with a mean of 281.33±0.33 and 126.60 t/ha respectively. The diameter distribution frequency shows the spread of the tree diameter with good numbers of tree at the smaller to medium diameter class for potential succession of the larger diameter class (Figure 4.1).

4.1.3 Effect of Seasonal Variation on Remotely Sensed Data in Buru Community Forest

Table 4.2 shows the result of regression model for Predicting aboveground tree biomass with vegetation indices and spectral bands for wet and raining season. Model one (equation 4.1) with spectral variables obtained from the rainy season had low P-value (0.0010), high R^2_{Adj} (94.94%) and low RMSE (444.12). The 5-Fold Cross-Validation for July, and December is presented in Table 4.3. from the table CV = 3094.57, AIC = 246.59, and BIC = 21.02 which was ranked first, and model two (equation 4.2) (from dry season) was second with P-value = 0.0012, R^2_{Adj} = 94.49%, RMSE = 463.33, CV = 4977.67, AIC = 248.29, and BIC 21.10. For the spectral bands' combination used, it was observed that short wavelengths (red, Near infrared, shortwave infrared, and shortwave infrared 2 band) were the predictors of AGTB from Buru Community Forest from both seasons. However, the goodness of fit statistics revealed model one outperforms model two (Table 4.3). The estimated aboveground tree biomass for 1988, 2000, 2008, and 2018 are presented in Table 4.5 where less disturbed forest area was highest in the year 1988 (491.91 t/ha) and lowest in year 2018 (306.90 t/ha) in in the month of July (Wet season) and was 260.29 t/h and 373.49 t/ha in the same period but from the month of December (dry season).

Table 4.1: **Summary Statistics for the Field Inventory Variables Used and Aboveground Stem Biomass**

Variables	Minimum	Maximum	Mean	Standard Deviation	Standard Error
Dbh (cm)	5	87.4	22.56	15.83	0.35
THt (m)	3.1	46.4	12.86	8.38	0.19
Density (g/cm^3)	0.19	1.1	0.47	0.18	0.0038
Volume (m^3)	16	3814.08	414.66	572.41	12.75
AGTB (t/ha)	170.92	388.38	281.33	14.84	0.33
C (t/ha)	76.91	174.77	126.6	6.68	0.15

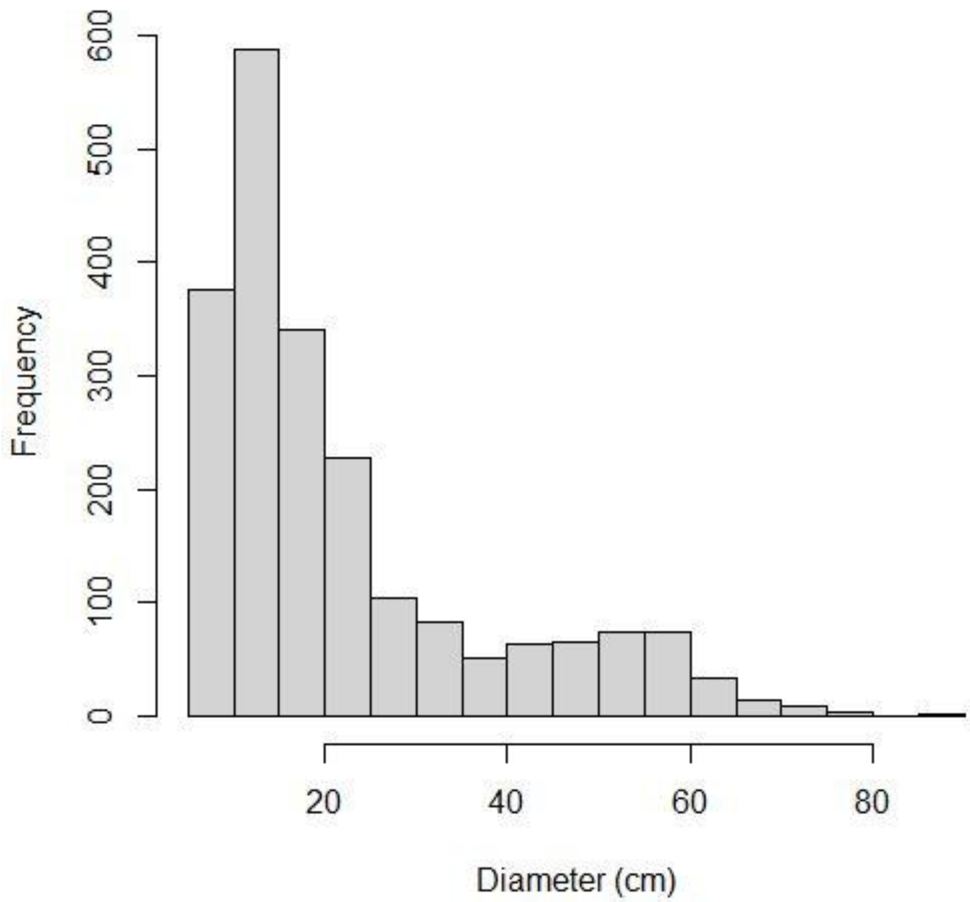


Figure 4.1: Diameter distribution frequency in Buru Community Forest

Table 4.2: Regression Model Result for Predicting Aboveground Tree Biomass with Vegetation Indices and Spectral Bands for the Month of July and December

Period		Parameters							
		Constant	b(SE)	c(SE)	d(SE)	P-Value	R^2	R^2_{Adj}	RMSE
July	AGB=a+b(B5)+c(OLI6/4)-d(ND74)	0.0016	3072 (866)	413 (168)	-6162 (1658)	$0.214e^{-5}$	95.7	94.94	444.12
December	AGB=a+b(B5)+C(OLI6/4)-d(ND74)	0.0001	2195 (7039)	720 (672)	-1666 (1263)	$0.512e^{-3}$	95.32	94.49	463.33

$$\mathrm{AGTB} = 0.00 + 3072(\mathrm{B5}) + 413(\mathrm{OLI6/4}) - 6162(\mathrm{ND74}) \quad 4.1$$

$$\mathrm{AGTB} = 0.00 + 2195(\mathrm{B5}) + 720(\mathrm{OLI6/4}) - 1666(\mathrm{ND74}) \quad 4.2$$

Note:

B5 = Corrected band5 of OLI,

OLI6/4 = Band6/Band4, and

ND74 = (Band7-Band4)/(Band7+Band4),

ND = Normalized difference,

OLI = Operational Land Imager (Landsat8),

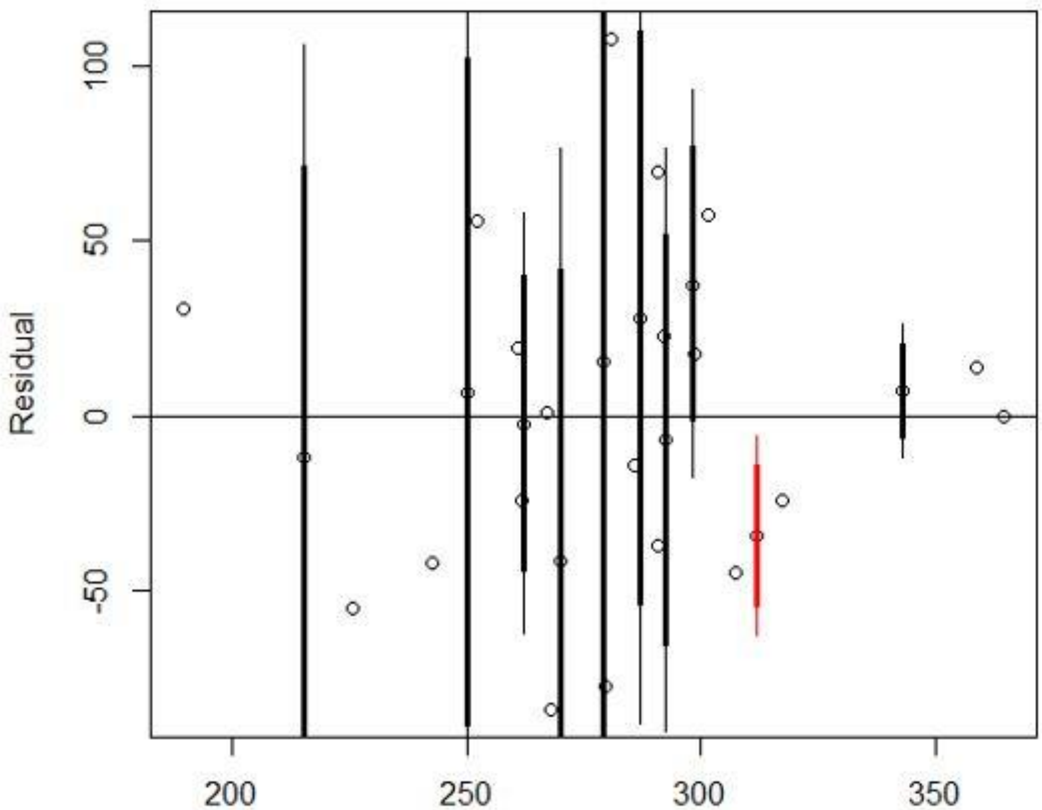
SE = Standard Error,

a,b,c and d = regression parameters.

Table 4.3: The 5-Fold Cross-Validation for July, and December

Period	Model	CV	AIC	BIC	R^2_{Adj} (%)
July	1	3094.57	246.59	21.02	94.94
December	2	4977.67	248.29	21.10	94.49

CV=Cross Validation, AIC=Akaike Information Criterion, BIC= Bayesian Information Criterion and R^2_{Adj} =Adjusted coefficient of determination



Predicted versus residual AGTB (t/ha)

Figure 4.2: Residual versus Predicted of the Aboveground Tree Biomass

Table 4.4: Estimates of Aboveground Stem Biomass of Buru Community Forest for the Study Period

Period	**AGTB (t/ha)**			
	1988	2000	2008	2018
July	271.66	196.60	174.50	152.80
December	156.62	176.08	151.07	153.79

The disturbed forest had an AGTB estimate of 241.48 t/h and 212.63 t/ha from the wet season in year 1988 and 2018 respectively, and 177.69 t/ha and 205.43 t/ha AGTB estimates were observed during the dry season from the same time (Table 4.5). The residual plot shows a fairly random pattern, indicating a good fit for a linear model (Figure 4.2).

4.1.4 Image Classification of Buru Community Forest

The 1988 LULCC showed Less disturbed forest; Disturbed forest; Grasses, Shrubs, and Farm land; Water body; Bare land; and Built-up area represented 61.10%, 24.42%, 10.57%, 1.69%, 1.88%, and 0.34%, of Buru community forest respectively (Figure 4.3 and Table 4.6). Land use land cover in Table 4.6 shows a consistent decrease in disturbed forest area from 1988 (1255.41 ha), through 2000 (913.14 ha), 2008 (869.48 ha), to 2018 (864.72 ha). Less disturbed forests, on the other hand, experienced a consistent increase as follows: 1988 (501.75 ha), 2000 (515.07 ha), 2008 (781.56 ha), and 2018 (846.45 ha).

The overall classification accuracy of the LULC of Buru community forest for the period under investigation were 93.83 %, 95.41 %, 93.04%, and 94.14% in year 1988, 2000, 2008, and 2018, respectively (Table 4.7).

4.1.5 Change Trend in Land Use Land Cover in Buru Community Forest

The Less disturbed forest land had consistent negative values indicating net loss across the period while others had net gain and loss at different times. On the contrary, disturbed forests consistently experienced net gain across the study period (Table 4.8). The highest net loss (-390.69 ha) was observed in less disturbed forest areas while the lowest net loss (-3.78 ha) was observed in the water body. In contrast, the highest net gain (344.70 ha) was observed in the disturbed forest while the lowest net gain (0.36 ha) was observed in the built-up area between 1988 and 2018 (Table 4.8).

Table 4.5: Estimates of Aboveground Tree Biomass of Buru Community Forest for the Study Period

Land Cover Type	Season	AGTB (t/ha)			
		1988	2000	2008	2018
Less Disturbed Forest	Wet	491.91	420.69	389.40	306.90
	Dry	260.29	351.08	311.75	373.49
Disturbed Forest	Wet	241.48	247.74	203.91	212.63
	Dry	177.69	247.58	201.89	205.43

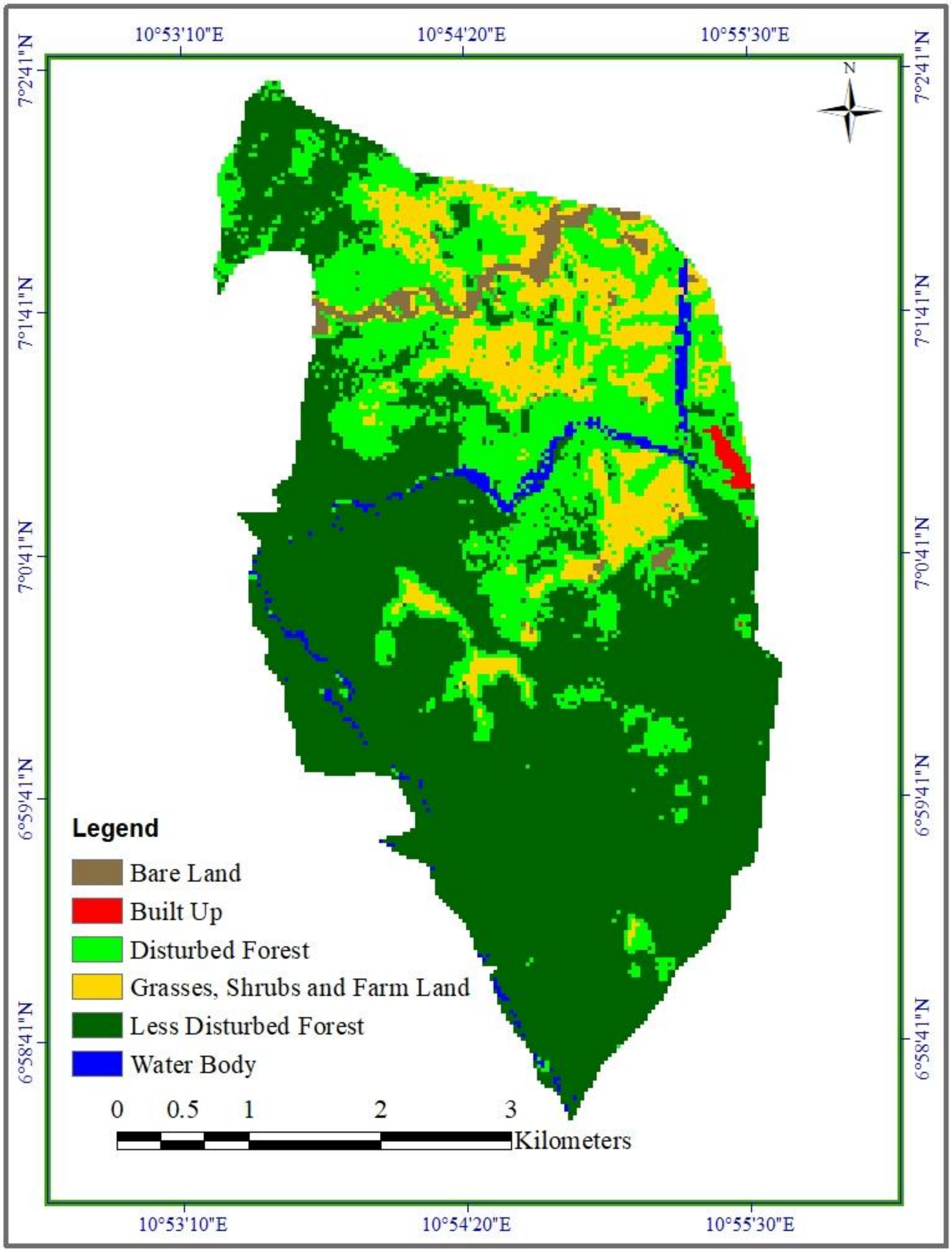


Figure 4.3: Land Use Land Cover Map of Buru Community Forest in 1988

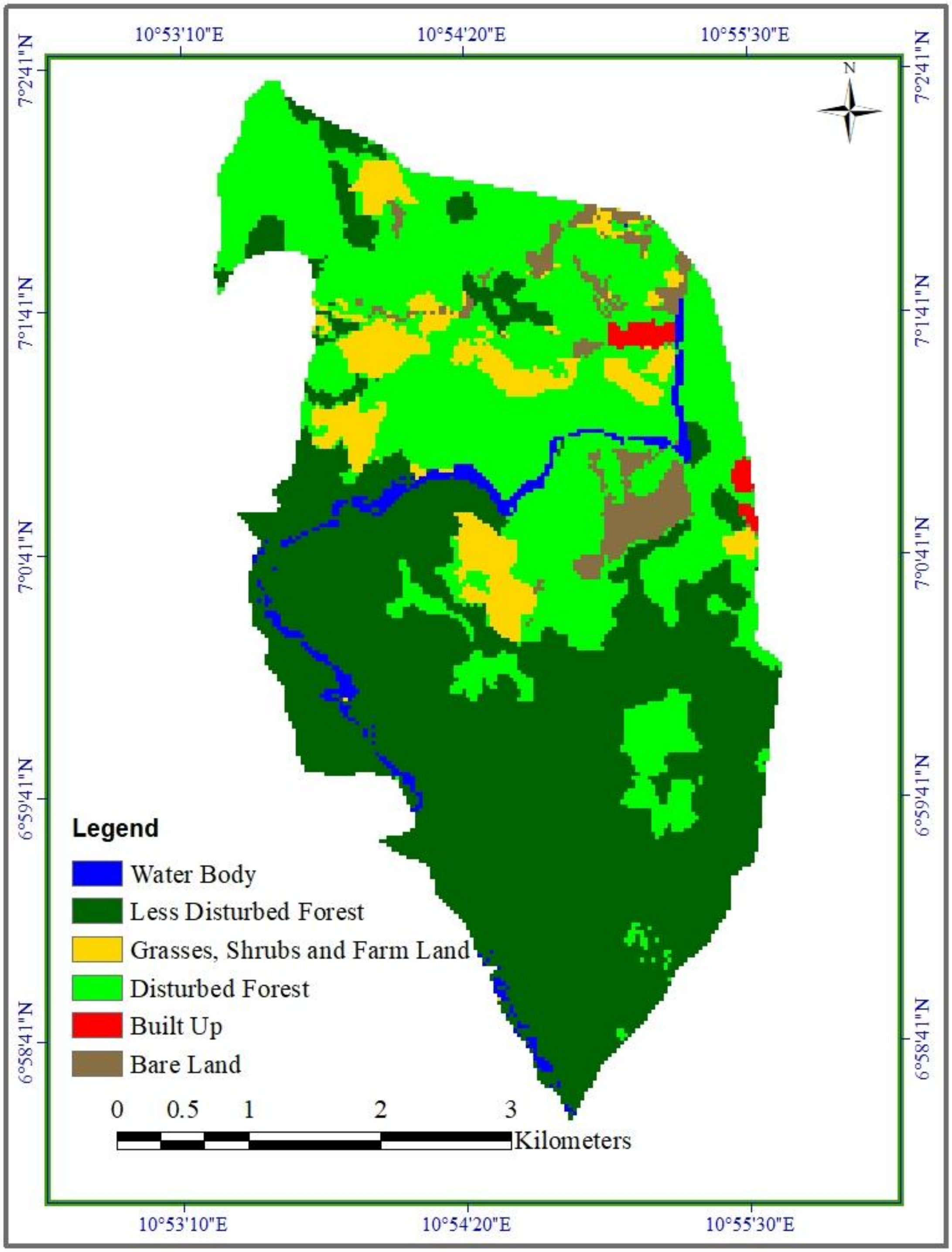


Figure 4.4: Land Use Land Cover Map of Buru Community Forest in 2000

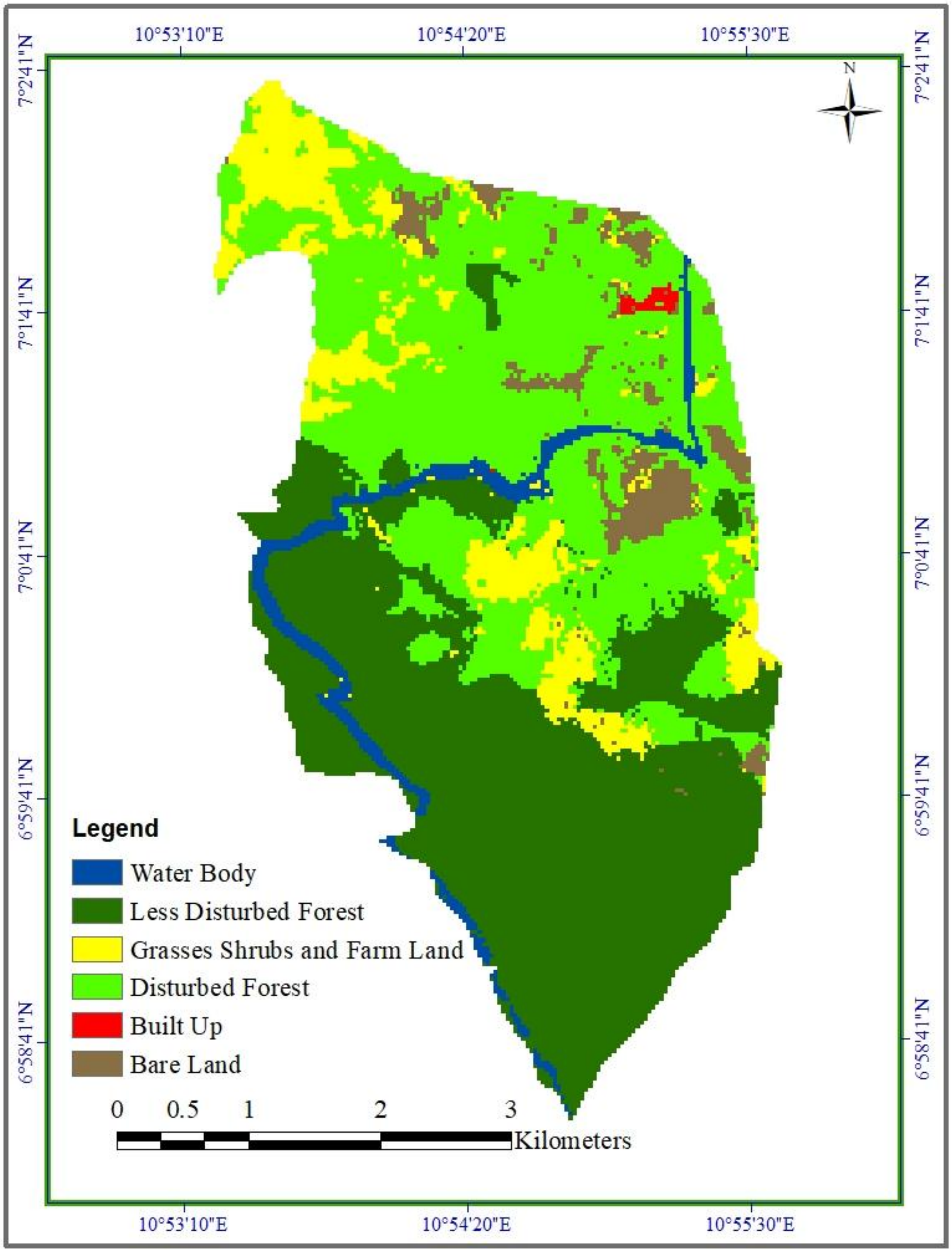


Figure 4.5: Land Use Land Cover Map of Buru Community Forest in 2008

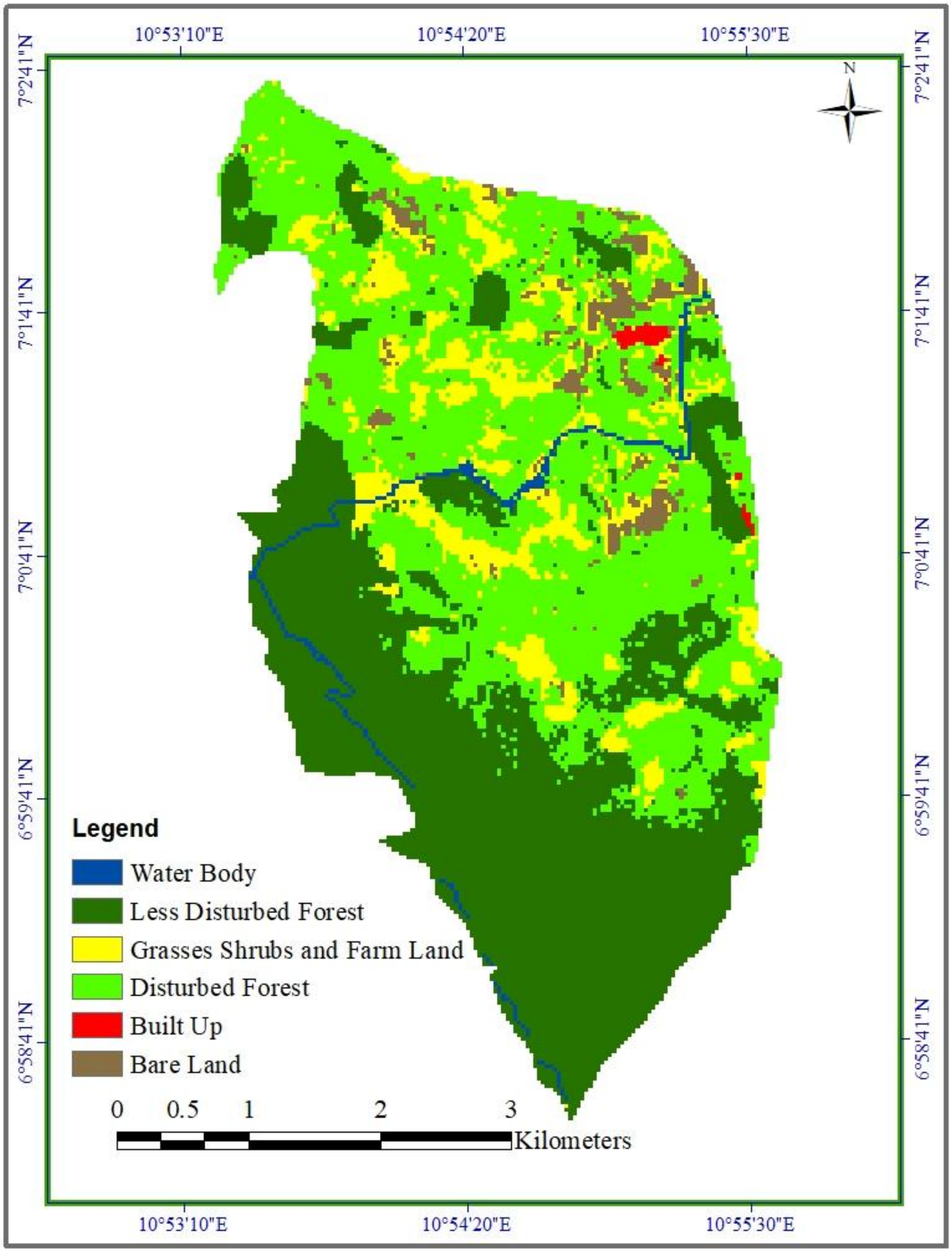


Figure 4.6: Land Use Land Cover Map of Buru Community Forest in 2018.

Table 4.6: Area Statistics of Buru Community Forest from 1988, 2000, 2008, and 2018

LULC Classes	1988 Area		2000 Area		2008 Area		2018 Area	
	ha	(%)	Ha	(%)	ha	(%)	ha	(%)
Less Disturbed Forest	1255.41	61.10	913.14	44.44	869.58	42.32	864.72	42.09
Disturbed Forest	501.75	24.42	515.07	25.07	781.56	38.04	846.45	41.20
Grasses Shrubs and Farm Land	217.17	10.57	421.65	20.52	219.87	10.7	238.14	11.59
Water Body	34.74	1.69	122.4	5.96	82.98	4.04	30.96	1.51
Bare Land	38.61	1.88	60.03	2.92	87.48	4.26	67.05	3.26
Built-up	7.02	0.34	22.41	1.09	13.23	0.64	7.38	0.36
Total	2054.7	100	2054.7	100	2054.7	100	2054.7	100

Table 4.7: Classification accuracy verification values of Buru Community Forest

LULC Classes	1988		2000		2008		2018	
	Producer's Accuracy (%)	User's Accuracy (%)	Producer's Accuracy (%)	User's Accuracy (%)	Producer's Accuracy (%)	User's Accuracy (%)	Producer's Accuracy (%)	User's Accuracy (%)
Less Disturbed Forest	100	78.1	100	86.11	97.47	83.7	100	77.95
Disturbed Forest	98.85	93.48	97.59	93.1	93.9	81.91	100	81.32
Grasses, Shrubs and Farm Land	100	100	98.73	98.73	97.59	98.78	97.67	88.42
Water Body	66.25	98.15	85.39	100	81.4	98.59	87.93	100
Bare Land	99.07	100	94.17	99.12	92.86	100	96.12	100
Built-up	95.83	100	98.31	100	98.33	98.33	85.71	100
Overall classification Accuracy (%)	93.83		95.41		93.04		94.14	
Kappa Coefficient	0.93		0.94		0.92		0.93	

Table 4.8: Change in Area of Buru Community Forest from 1988 to 2000, 2000 to 2008, 2008 to 2018 and 1988 to2018

LULC Classes	1988-2000		1988-2008		2000-2008		2000-2018		2008-2018		1988-2018	
	Ha	Area (%)	ha	Area (%)	Ha	Area (%)	Ha	Area (%)	ha	Area (%)	ha	Area (%)
Less Disturbed Forest	-342.27	-27.26	-385.83	-30.73	-43.56	-4.77	-48.42	-5.30	-4.86	-0.56	-390.69	-31.12
Disturbed Forest	13.32	2.65	279.81	55.77	266.49	51.74	331.38	64.34	64.89	8.30	344.70	68.70
Grasses Shrubs and Farm Land	204.48	94.16	2.70	1.24	-201.78	266.27	-183.51	-43.52	18.27	8.31	20.97	9.66
Water Body	87.66	252.33	48.24	138.86	-39.42	-32.21	-91.44	-74.71	-52.02	-62.69	-3.78	-10.88
Bare Land	21.42	55.48	48.87	126.57	27.45	-77.52	7.02	11.69	-20.43	-23.35	28.44	73.66
Built-up	15.39	219.23	6.21	88.46	-9.18	-73.49	-15.03	-67.07	-5.85	-44.22	0.36	5.13

The trends of change observed among the various LULCs of the study area was that, while some areas of Buru community forest underwent gains and losses, some parts of the forest remained unchanged. Between 1988 and 2018, the unchanged area of less disturbed forest was highest (772.92 ha), followed by the disturbed forest area (328.50 ha) and the area with the least unchanged was built-up area (0.45 ha), (Table 4.9). The Land-use transfer matrix shown in Tables 4.10 and Table 4.11 revealed the probabilities showing the movement pattern of the various classes for the projected period of 2028 and 2048 respectively. The Rows and Columns of the table present the current state and the future prediction of the LULCC.

4.1.6 Future Prediction of Buru Community Forest

Markov chain and Cellular Altimeter (CA_Makov) were employed for future predictions of LULC in Buru community forest for 2028 and 2048. Wherein the predicted 2028 with less disturbed forest; disturbed forest; grasses, shrubs, and farm land; water body; bare land; and built-up area had an area statistic of 775.62 ha, 905.85 ha, 247.14 ha, 31.86 ha, 83.25 ha, and 10.98 ha, respectively (Figure 4.7 and Table 4.12). The LULC of the third decade (2048) were predicted as follows: less disturbed forest; disturbed forest; grasses, shrubs, and farm land; water body; bare land; and built-up area had an area statistic of 1068.21ha, 638.55 ha, 252.27 ha, 33.84 ha, 53.01 ha, and 8.82 ha, respectively (Figure 4.8 and Table 4.12). It was observed that disturbed and less disturbed forest areas were more than every other LULC on the predicted outcome of 2028 and 2048. Where disturbed and less disturbed forest areas had 905.85 ha and 775.62 ha in 2028. While 1068.21 ha and 638.55 ha were observed in less disturbed and disturbed forests area respectively in 2048 as shown in Table 4.12.

Table 4.9: Gains Losses, and Unchanged Area in Land Used Land Cover of Buru Community Forest from 1988 to 2018.

1988 to 2018	Less Disturbed Forest (ha)	Disturbed Area (ha)	Grasse, Shrubs and Farm Land (ha)	Water Body (ha)	Bare Land (ha)	Built-Up (ha)
Losses	482.49	173.25	156.42	21.15	33.57	6.57
Unchanged	772.92	328.5	60.75	13.59	5.04	0.45
Gains	91.8	517.95	177.39	17.37	62.01	6.93

Table 4.10: Transition Probability Matrix of Land Use Land Cover Transfer from 2018 to 2028 of Buru Community Forest

		2028					
		Less Disturbed Forest	**Disturbed Forest**	**Grasses, Shrubs and Farm Land**	**Water Body**	**Bare Land**	**Built-up**
2018	Less Disturbed Forest	0.79	0.18	0.03	0.01	0.00	0.00
	Disturbed Forest	0.10	0.75	0.15	0.01	0.00	0.00
	Grasses, Shrubs and Farm Land	0.00	0.27	0.40	0.00	0.29	0.04
	Water Body	0.19	0.04	0.15	0.63	0.00	0.00
	Bare Land	0.06	0.70	0.01	0.00	0.23	0.00
	Built-up	0.00	0.83	0.01	0.00	0.04	0.13

Table 4.10: Transition Probability Matrix of Land Use Land Cover Transfer from 2018 to 2048 of Buru Community Forest

	LULC	2048					
		Less Disturbed Forest	**Disturbed Forest**	**Grasses, Shrubs and Farm Land**	**Water Body**	**Bare Land**	**Built-up**
2018	Less Disturbed Forest	0.62	0.30	0.07	0.01	0.00	0.00
	Disturbed Forest	0.15	0.65	0.16	0.01	0.02	0.00
	Grasses Shrubs and Farm Land	0.02	0.47	0.28	0.00	0.20	0.03
	Water Body	0.24	0.15	0.15	0.39	0.02	0.00
	Bare Land	0.13	0.66	0.09	0.00	0.13	0.00
	Built-up	0.05	0.76	0.09	0.00	0.04	0.06

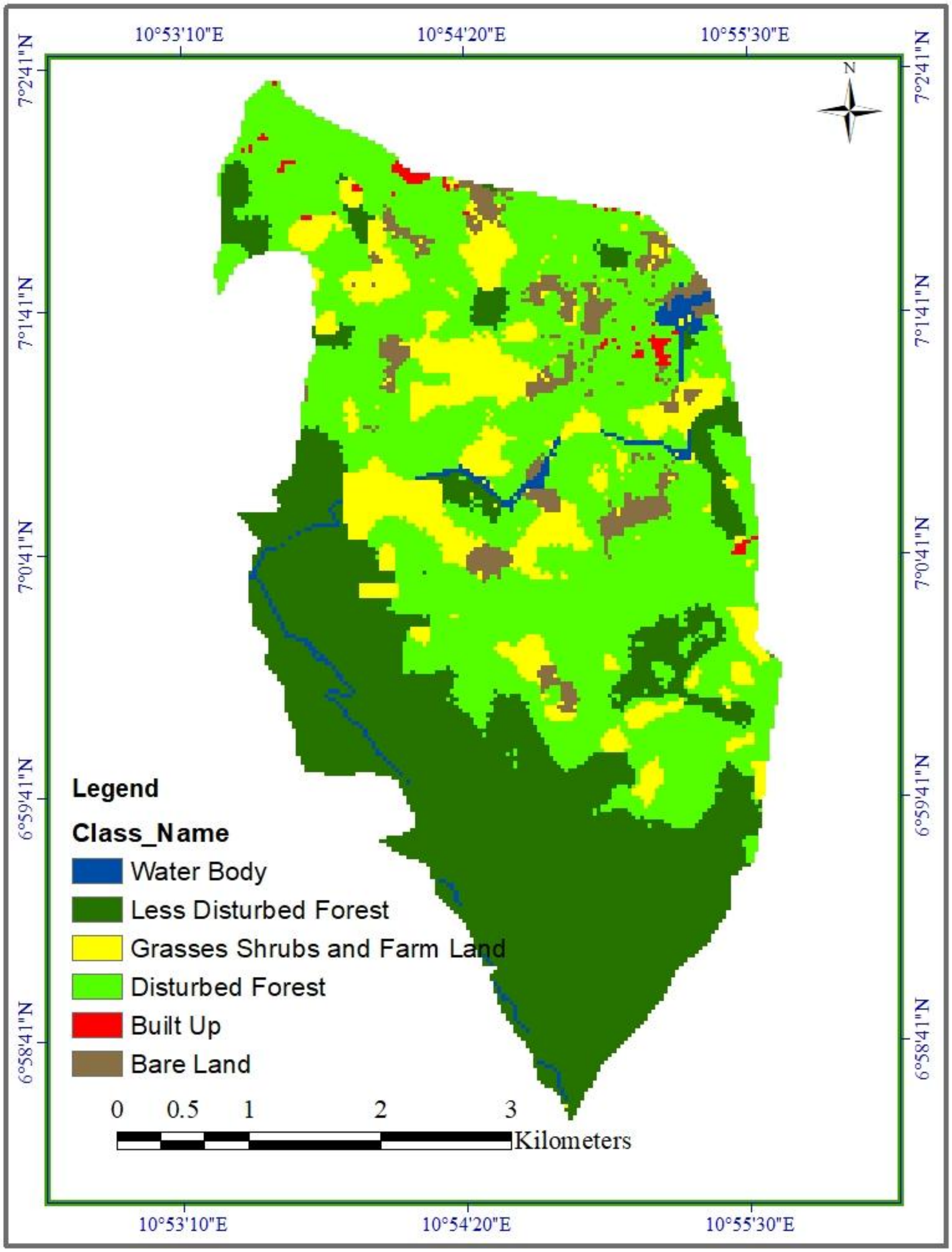


Figure 4.7: Predicted LULCC of Buru Community Forest for Year 2028

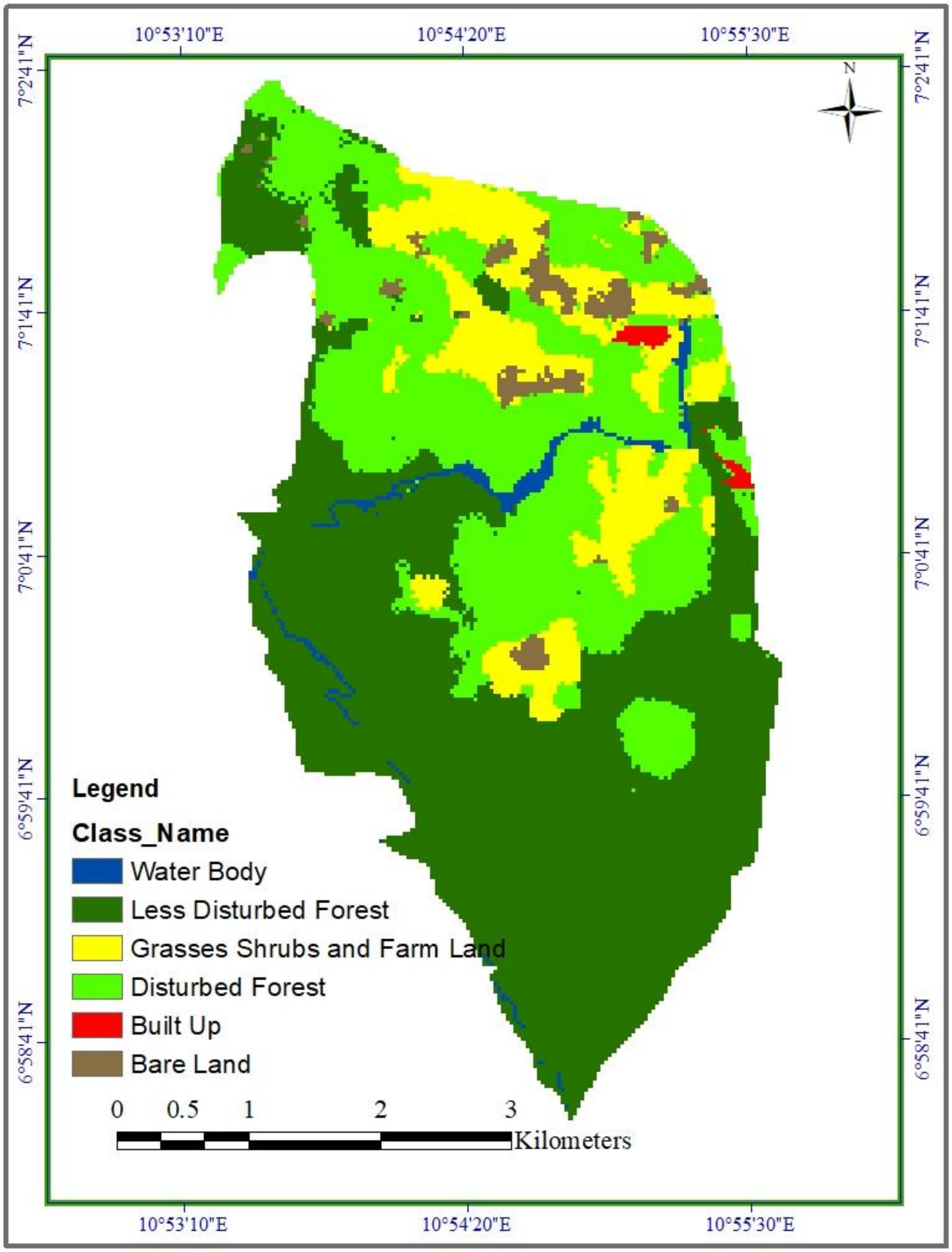


Figure 4.8: Predicted LULCC of Buru Community Forest for year 2048

Table 4.12: Area Statistics for year 2028, 2038 and 2048

LULC	2018		2028		2048	
	ha.	**Area (%)**	**ha.**	**Area (%)**	**ha.**	**Area (%)**
Less Disturbed Forest	864.72	42.09	775.62	37.75	1068.21	51.99
Disturbed Forest	846.45	41.2	905.85	44.09	638.55	31.08
Grasses Shrubs and Farm Land	238.14	11.59	247.14	12.03	252.27	12.28
Water Body	30.96	1.51	31.86	1.55	33.84	1.65
Bare Land	67.05	3.26	83.25	4.05	53.01	2.58
Built-up	7.38	0.36	10.98	0.53	8.82	0.43
Total	2054.7	100	2054.7	100	2054.7	100

CHAPTER FIVE
DISCUSSION

5.1 Estimation of Aboveground Tree Biomass of Buru Community Forest

The findings in this study revealed AGTB from the less disturbed and disturbed forests to be 317.62 t/h (142.93 t/ha), and 205.61 t/ha (92.52 t/ha) respectively. The much greater aboveground tree biomass in the less disturbed forest compared to the disturbed forest could be due to greater anthropogenic activities that took place in the disturbed forest area of Buru community forest. The apparent differences in the amount of AGTB in Buru community forest had shown that the community forest needs urgent attention in other to rescue the less disturbed forest part of the forest while regenerating the disturbed part of the forest. However, the finding from the two strata, shows that Buru community forest is also contributing to housing carbon as one of the tropical forests. The perceived role of the Buru community forest is not far from Ngo *et al.* (2013) who stated that tropical forests contain large reserves of carbon that are vulnerable to perturbation linked to human activities, including deforestation and climate change.

Furthermore, this finding is not far from that of Vicharnakorn *et al.* (2014) who reported a mean AGTB estimate of 388.52 t/ha in a tropical forest site in Thailand using Landsat TM data. Hansen *et al.* (2015) reported a mean TAGB estimate of 462 t/ ha in a tropical forest in Tanzania using Airborne laser scanner data. Lu *et al.* (2012) reported TAGB estimates of 110–500 t/ha in a tropical forest in Brazil using Landsat TM data. This infers that Buru community forest like every other forest must have been contributing to ameliorating climate change within the locality. However, anthropogenic activities have become a major threat to this service (carbon sequestration). This must be tackle if the forest community must continue to render this service. This assertion corroborates with Akinsoji (2013) who identifies human activities in search of livelihood in Buru community forest to be the major source of forest degradation, as part of the forest areas are converted to farmland among others. Also, a similar scenario was observed in Madagascar where carbon emission was majorly through anthropogenic activities (Vieilledent *et al*., 2016). There is no doubt, forests serve two purposes: 1. Sequestration of carbon through biomass accumulation and 2. Emission of carbon through anthropogenic activities (burning and clear falling of trees for farming, energy generation etc) carried out within the forest ecosystem. These activities are said to be triggered by the Millennium Development Goals (MDGs) which focus on eradicating extreme hunger and poverty (FAO, 2010). These activities must be carried out in a sustainable manner, so as to achieve the set goals (tackle hunger and poverty) while ensuring that sustainable forest ecosystems are maintained, as the forest is mostly at the receiving end when the agricultural revolution is not practiced sustainably.

The results of aboveground biomass from Buru community forest will also serve as baseline information on the forest's carbon status, being the first time of its estimation. Furthermore, this can help in onward regular monitoring and reporting of the AGTB estimates of the forest in line with the IPCC (2007) which supported the periodic estimation of AGTB in a forest to be made known or updated with the amount of AGTB in stock. Also, the estimated carbon stock can now promote carbon credits of Buru community forest in contributing towards offsetting greenhouse gas emissions, thereby making it relevant among other forests. This is in line with Sullivan *et al*. (2017) who asserted the facts that tropical and subtropical forests are carbon banks that need to be parts of carbon credits.

Aboveground tree biomass which is known for its role in carbon offsetting had over time greatly contributed to ameliorating climate change. It is now known how much role Buru community forest plays in climate change as the outcome of the AGTB is obtained. This can further determine the trend and rate at which carbon in Buru community forest is responding to climate change, as well as it's potential for resource conservation. This is in agreement with the findings of Borokini (2010) who asserted that aboveground biomass has a strong relationship with biodiversity conservation and climate change mitigation in Nigeria.

Remote sensing applications became an imperative tool as this information has to be obtained and reported at consistent and regular intervals. Moreover, Nath *et al*. (2019) affirmed that studies on Biomass/Carbon are gaining global attention as man's activities in forest environments intensify.

Furthermore, the forest has good numbers of smaller trees to succeed the older ones. This can be seen in the greater numbers of trees on the smaller to medium diameter from the stand. This is evident, that the forest is still productive and should be approached with a good management plan to maximize this potential. This could be as the result of the difficult terrain which makes accessibility difficult for loggers and limited farming activities which are major threats to the forest.

5.2 Effect of Seasonal Variation of Landsat Data on Aboveground Tree Biomass Estimation of Buru Community Forest

The outcome from the two major seasons examined revealed that, remote sensing data obtained through Landsat imageries in the month of July (Equation 4.1), best account for the variation in AGTB within the study area. This is the period of intense raining season in Buru community forest, where draught related stress is somewhat absence neither were there shedding of leaves by the forest vegetation. Also, chlorophyll and chloroplast which are the major plant chemical components that interact (transmission, absorption, and reflection) with the incoming electromagnetic radiation are at their peak of functions. Similar studies carried out by Sheikh *et al.* (2017) affirmed that photosynthetic activities in green plants are driven by chlorophyll, a green colour pigment that resulted in the increase, growth, and general well-being of biological and chemical components of the plants tends to fluctuate with season. The chlorophyll is greatly influenced by several factors, ranging from the amount of moisture contents, temperature, and precipitation among others. Since the variation in the amount of these factors in the forest environment across the seasons (dry and wet) varies, they may affect the amount of the incoming solar radiation absorbed and reflected which invariably determine the contents of the satellite images obtained across the season as well. Similarly, Zhu and Liu (2015) applied seasonal Landsat NDVI in eleven study sites in Southeast Ohio, where it was revealed that NDVI in summer correlated more with AGB than that in the winter as this was able to reduce error due to saturation. However, the present findings looked into the combination of several indices as the predictor variables unlike Zhu and Liu (2014) who utilized only NDVI. In this finding, the model consists of Band 5 (Near Infrared), the ratio of Band 6 (Shortwave Infrared 1) and Band 4 (Red), and Normalize difference of Band 7 (Shortwave Infrared 2) and Band 4 as the best predictors of AGTB in Buru community forest. These variables indicate vegetation greenness and quantity, also they are key predictors of AGTB in previous studies in tropical forests that used Landsat sensors. Lu *et al.* (2005, 2012) found the Near Infrared (NIR) band to be the best predictor of AGTB in a tropical forest in Brazil. In like manner, Barbosa *et al.* (2014) found the Shortwave Infrared 1 (SWIR1) band to be the best predictor of AGTB in a tropical forest in Brazil. The combination of NIR and SWIR1 bands were found to be the key variable for predicting AGTB in Indonesia by Wijaya *et al*. (2010). Also, Avitabile *et al.* (2012) found SWIR bands to have provided an adequate contribution to the prediction of AGTB in a tropical forest in Uganda. On the other hand, some studies have affirmed NDVI (Patel and Majumdar 2010; Das and Singh 2012; Gizachew et al., 2016), SAVI (Patel and Majumdar 2010; Vicharnakorn et al. 2014) and GNDVI (Patel and Majumdar 2010) to be key predictors of AGTB in tropical forests. Jensen (2007), also affirm that the R.S data obtained across the long and short wavelengths depend on the contents of the chlorophyll and some biophysical components of the plant (Biomass, leaf tissue, and water contents).

The outcome from the two seasons observed (wet and dry), revealed the remote sensing data obtained through Landsat imageries in the months of July to be better off in terms of AGTB estimation. This could be a result of the state of chlorophyll, chloroplast, and moisture content, of trees in the forests community that might be at their peak of activities which could have best accounted for the variation in AGTB estimation within the study area (RMSE = 444.12, R^2_{adj} = 94.94, AIC = 246.59, BIC = 21.02 and C.V =3094.57) as compared to the data obtained in the dry season (month of December). The selection was stronger on the outcome of the 5-fold Cross Validation (C.V) based on the sample size used.

Furthermore, this could have emanated from the fact that the peak of wet season (July) of the forest could have greatly influenced the reflectability of the spectral variable thereby giving it an age over that of December in estimating AGTB of Buru community forest. In like manner, July AGTB took similar trends of decline from 1988 to 2018 which is in line with the LULCC of Buru community forest unlike that of December.

5.3 Land Use Land Cover Change of Buru Community Forest

The classification of Buru community forest led to six (6) classes namely: less disturbed forest; disturbed forest; grasses, shrubs, and farmland; water body; bare land; and built-up area as the major components of the forest. The selection of classes varies from location to location and is based on the objectives of the researcher. Alo *et al.* (2020) classified Shasha Forest into forest, shrubs, and built-Up areas. Oluwajuwon *et al.* (2021) classified Ogbese Forest Reserve, Ekiti State in Southwestern Nigeria into forest, plantation, farmland, grassland, and bare land.

The classified LULC from 1988 to 2018 revealed a consistent decline of the less disturbed forest (1255.41 ha to 864.72 ha), while disturbed forest on the other hand was consistently increasing (501.75 ha to 846.45 ha). However, the trends of the increase and decrease varies across the study periods (1988, 2000, 2008, and 2018), as 1988 to 2000 experienced the greatest loss of 342.27 ha to other LULC, though majorly gained by disturbed forest, and grasses, shrubs, and farmland. After this period, there was a drastic reduction in the decreasing pattern of less disturbed forests where only 48.43 ha were loss from 2000 to 2018 as compared to 342.27 lost from 1988 to 2000. The trend of decline in the less disturbed forest in the study area could be the result of the impact of the Participatory Forest Management Project (PFMP) which was carried out for five years (2005-2010) by the Nigerian Conservation Foundation (NCF) in partnership with the Royal Society for Protection of Birds (RSPB) in Buru Community Forest. The project was implemented through a series of environmental awareness campaigns, training workshops, lectures, seminars, stakeholder meetings, a literacy programme, forest patrol, and monitoring. The volunteer guards were sourced from across the communities around the forest and the incentives given to them were partly from the fine obtained from trespassers and also donors. However, the NCF still hosts a sensitization programme with the communities from time to time after the elapsed of the participatory forest management project in 2010.

However, the less disturbed forest area is also in a difficult terrain which might have contributed to its natural protection as well. The finding corroborates with Oluwajuwon *et al.* (2021) who experienced a consistent decline in the amount of forest land with an increase in the farm land from 1998 to 2018 within Ogbese Forest Reserve, in Southwestern Nigeria. Similarly, Alo and Nwatu (2018) experienced a consistent decline in the green area of the Ibadan metropolitan during the LULC classification from 1985 to 2018. Most of the green areas were lost to built-up as it increased from 6.25 % to 21.77 % while green areas decreased from 85.36 % to 67.88 % from the year 1985 to 2018. It could be that forest area is diminished by human activities to meet up with their economic and social needs, which has led to polarising the forest environment thereby altering the ecological balance within the ecosystem.

The classification accuracy obtained from this study which ranged between 93.04 % to 95.41 % is more or less similar to that of Liping *et al*. (2018) who classified LULCC of Jiangle area in China and obtained an overall accuracy of 94.94 %, 92.12 %, and 92.33 % in 1992, 2003 and 2014, respectively. Similarly, Alo and Nwatu, (2018) obtained an overall accuracy of 87.75 % to 88.75 % when they classified land use land cover of urban green space of Ibadan metropolis. Alo *et al.* (2020) also observed a classification accuracy range of 78.50 % to 86.55 % in modelling forest cover dynamics in Shasha forest reserve, Osun State, Nigeria. There is no doubt, that the overall classification accuracy obtained from this study is of high precision i.e there is a high chance that most of the features within Buru community forest were rightfully classified into their respective classes.

The fluctuation in the water body (1.69%, 5.96 %, 4.04 %, and 1.51 %) over the study period could be the result of the massive exploitation that took place between 1988 and 2000 which might have exposed the waterway to erosion and flooding. This fluctuation in water body is contrary to that of Liping *et al.* (2018) where waterbody was the largest (45.34 %) with an increment of 6.25 km^2 between 2003 and 2014. Though the increase was as a result of the managerial action that took place in the country annals, for sustainability and posterity's purpose. Similarly, bare land experienced a consistent increase from 1.88 % in 1988 to 4.61 in 2008 with exception of 2018 (3.26 %) where it began to reduce. This might not be far from human activities as Akinsoji (2013) earlier stated that the major threat to Buru community forest is anthropogenic activities. Similar scenario was observed by Rajan *et al.* (2016), where a consistent increase in bare land from 11.14 % to 24.41 % between 2009 and 2016 in the Dalma wildlife sanctuary in Jamshedpur, India.

The area statistics indicated a strong correlation between the built-up and the less disturbed forest area. The built-up increased from 7.02 ha to 22.41 ha and the less disturbed area on the contrary, decreased from 1255.41 ha to 913.14 ha between 1988 and 2000, which is a strong indication that human activities are major drivers of deforestation within the study area. This also implies that every slight increase in population or built-up could lead to greater loss of the forests. This was further buttressed by the sharp decrease in the less disturbed forest from 869.58 ha to 864.72 ha as built up continue to decline from 13.23 ha to 7.38 ha in year 2008 to 2018. This finding is in agreement with Liping *et al.* (2018) who found that human activities were the cause of obvious changes in the Jiangle area of China, from 1992 to 2014. Also, Ogundele *et al*. (2016) observed that in a quest to meet up with Man's needs, Nigerian forest resources have been put under pressure.

The LULCC of Buru community forest (less disturbed forest; disturbed forest; Grasses, shrubs, and farmland; water body; bare land and built-up) all experienced losses, unchanged, and gains within some portion of their respective classes. However, the greatest loss (482.49 ha) and unchanged area (772.92 ha) were more pronounced in a less disturbed forest area with the disturbed forest area having the highest gain (517.95 ha) from 1988 to 2018. On the other hand, the least loss (6.57 ha), unchanged (0.45 ha), and gains (6.93 ha) were observed in the built-up area. This indicates that Buru Community Forest lost 16.08ha of her less disturbed forest on average majorly to a disturbed forest area as shown in table 4.9 which was the result of the presence of human activities like farming and logging over time by the locals. The area of unchanged less disturbed forest was an indication that the forest has the potential resilient against deforestation. However, it was observed that the unchanged area is more or less mountainous/difficult terrain which might be a contributing factor to the remaining unchanged area of less disturbed forest in the study area. Also, the highest gain observed in disturbed forest areas is an indication of the fact that most of the lost area of less disturbed was actually transited to disturbed forest areas which can easily be converted to farmland if not protected. This is similar to the findings of Kayet and Pathak (2015) who reported that the Very Dense Forest (VDF) of Saranda forest, Jharkhand reduced to 8.61% and Open Forest (OF) increased to 7.03% between the years 1992 and 2014 due to an increase in the built-up area and mining activity. This loss observed in the less disturbed forest is in support of Li *et al*. (2016) who stated that people's demand can directly lead to LULCC.

Conclusively, every hectare of Buru community forest degraded will lead to the loss of 205.61 t to 317.62 t of aboveground tree biomass. The ripple effect of this will be the loss of flora and fauna species within Buru community forest, and consequently environmental degradation.

5.4 Prediction of Land Used Land Cover Change of Buru Community Forest for 2028 and 2040

Haven projected for the first and third decades (2028 and 2048); it was obvious that less disturbed forests will be on a slow decline in the first decade thereby leading to an increase in the less disturbed forest area in the third decades. Also, from the projected maps for 2028 and 2048, the less disturbed area with an area of 775.62 ha and 1068.21 ha accounted for 37.75 % and 51.99 % of the total area respectively, while 905.85 ha and 638.55 ha accounted for 44.09 % and 31.08 % of the disturbed area respectively. This revealed less disturbed forest areas to be on the increase in the 3rd decade from 2018. This could be as a result of the decrease in pressure on Buru community forest during and after the activities of NCF and RSBP that were carried out from 2006 to 2010. The outcome from the prediction is in agreement with Ranjan *et al*. (2016) who observe that by analysing prior and examining certain locations or positions, it can be predicted that forest area is diminished by human influences to fulfil their needs. This is an indication that if human perception towards forest can be changed, the forest is likely going to regain its status while servicing the environment sustainably. The decline in the first decades of less disturbed forest is similar to the findings of Alo *et al.* (2020) when they predicted the forest cover of Shasha forest reserves from 2017 to 2034 and observed a decline in the forest cover, which was at the rate of about 478.7

ha per annum. Also, grasses, shrubs, and farmland were on the increase as well by 2028 and 2048. While water will relatively experience minimum change with a decrease in bare land and a slit increase in built-up in 2028 and 2040. The trend of change in Buru community forest is not far from the FAO (2011) report that Nigeria lost 55.7% of its total primary forest between 2000 and 2005, and the rate of forest change increased by 3.12% per annum. However, the projection is subject to the trends of activities around the Buru community forest from 2008 to 2018 which can go otherwise if these activities changes trends.

CHAPTER SIX

SUMMARY, CONCLUSION, AND RECOMMENDATIONS

6.1 Summary

The aboveground tree biomass of Buru community forest was estimated, thus revealing the state of its contribution to carbon cycling, reducing greenhouse gas emissions, and mitigating the impact of global warming.

The effect of seasonal variation on remote sensing data for assessing Aboveground Tree Biomass in Buru Community Forest, Taraba State was accessed. The ideal period for remote sensing data acquisition for biomass estimation should be from a clear atmospheric weather condition, in the period of the wet season (preferably in July). Various vegetation indices, simple bands ratio, image transformations, and processed bands acquired from the month of July and December were used as explanatory variables for accounting for the AGTB within the forest. The remote sensing data obtained from the peak of the rainy season was proven to be better predictors of AGTB within the study area, which can now be used to estimate AGTB of Buru community forest.

The community forest was classified into six (6) LULC change classes. The statistics of each class were obtained for quantitative and planning purposes. Also, the probability matrix of LULC transfer from the period of 2018 to 2028 and 2048 was derived. The unchanged areas across the six classified classes were identified, with less disturbed forests having the highest proportion compared to others as presented in Table 4.9.

6.2 Conclusion

In conclusion, the aboveground tree carbons stock within Buru community forest was obtained with the optimum season for remote sensing data acquisition and classification of land use/cover change which was further used to predict LULC for 2028 and 2048 for effective management plans.

Results of this study show that the appropriate period of remote sensing data acquisition for AGTB estimation in Buru community forest should be from clear images of the month of July which is during raining season. However, most studies chose clear images from the dry season which spans from October to May.

On the contrary, the spectral reflectance indices in the month of July have a stronger correlation with AGTB compared to that of December which is dry season in the study area. The study, therefore, demonstrates the potential of seasonal data effects on the accurate estimation of AGTB in Buru Community Forest of Taraba State, Nigeria.

6.3 Recommendations

Based on the outcome of this study, the following recommendations are made:

1. The ideal period for remote sensing data acquisition for biomass estimation, in Buru community forest should be from a clear weather conditions of the rainy season (July).
2. There is a need for further research on the following spectral variables: index (ND74), band (band5), and bands ratio (OLI6/4) which happened to be exceptional among other spectral variables used in relating to Biomass.
3. Furthermore, urgent attention is needed as the buffer zone if being depleted by farming activities. This could exert pressure on Buru community forest.
4. Finally, there is an urgent need for the State Government to Gazzate the forest to salvage some highly economic species such as *Garcinia cola* and *Irvingiawombolu* which Buru Community forest serves as a one of the repository to these species among others.

6.4 Contributions to Knowledge

This study has contributed to knowledge in the following ways:

1. The study provides information on the suitable month of remote sensing data acquisition for Aboveground tree Biomass estimation,
2. Information on various land used/cover changes in Buru Community Forest for thirty years (1988-2018) were provided,
3. Accurate prediction of land use/cover changes for 30 years (2018-2048) in Buru Community Forest was achieved, while the probability level at which these changes are likely to take place was determined using remote sensing techniques.

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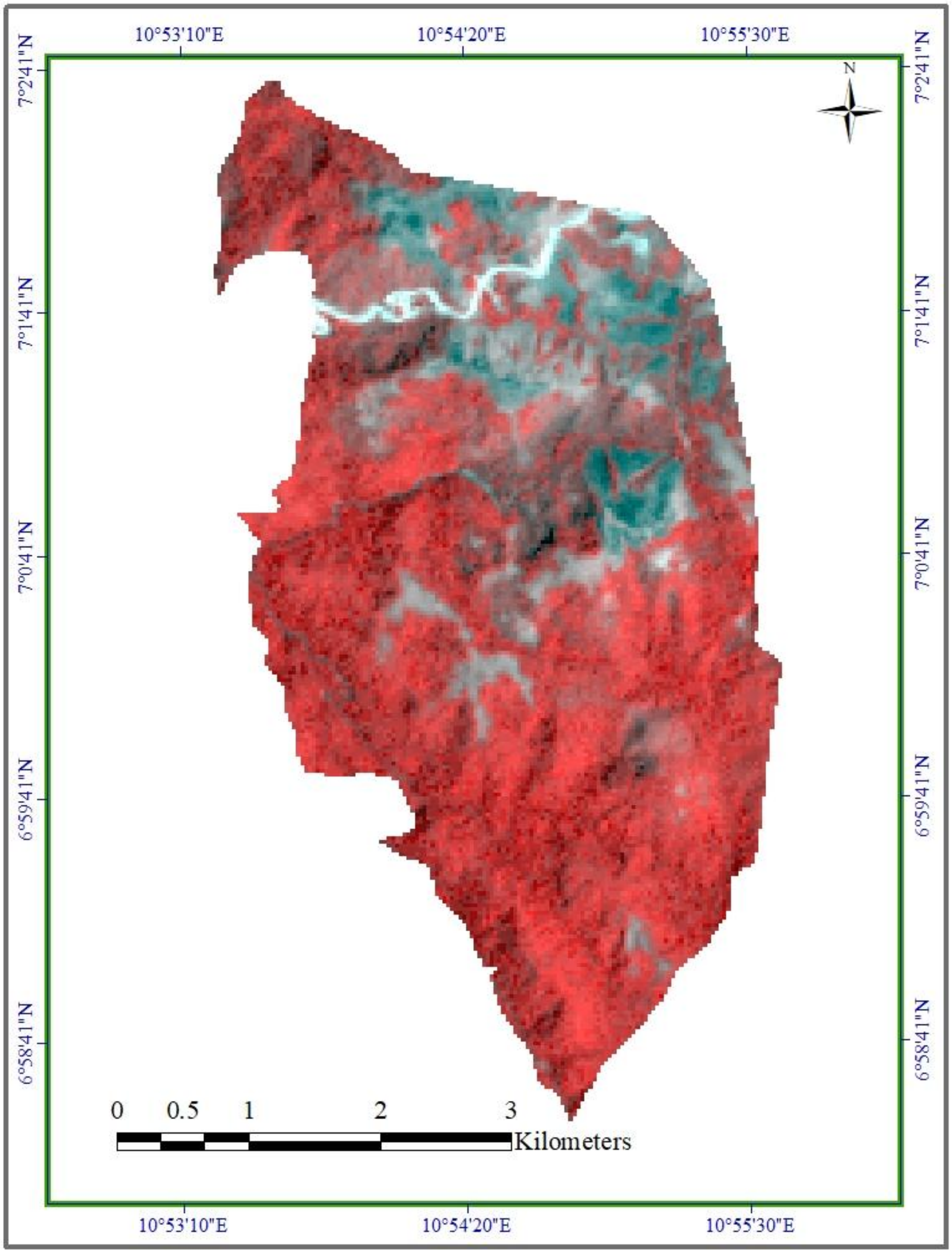
APPENDIX

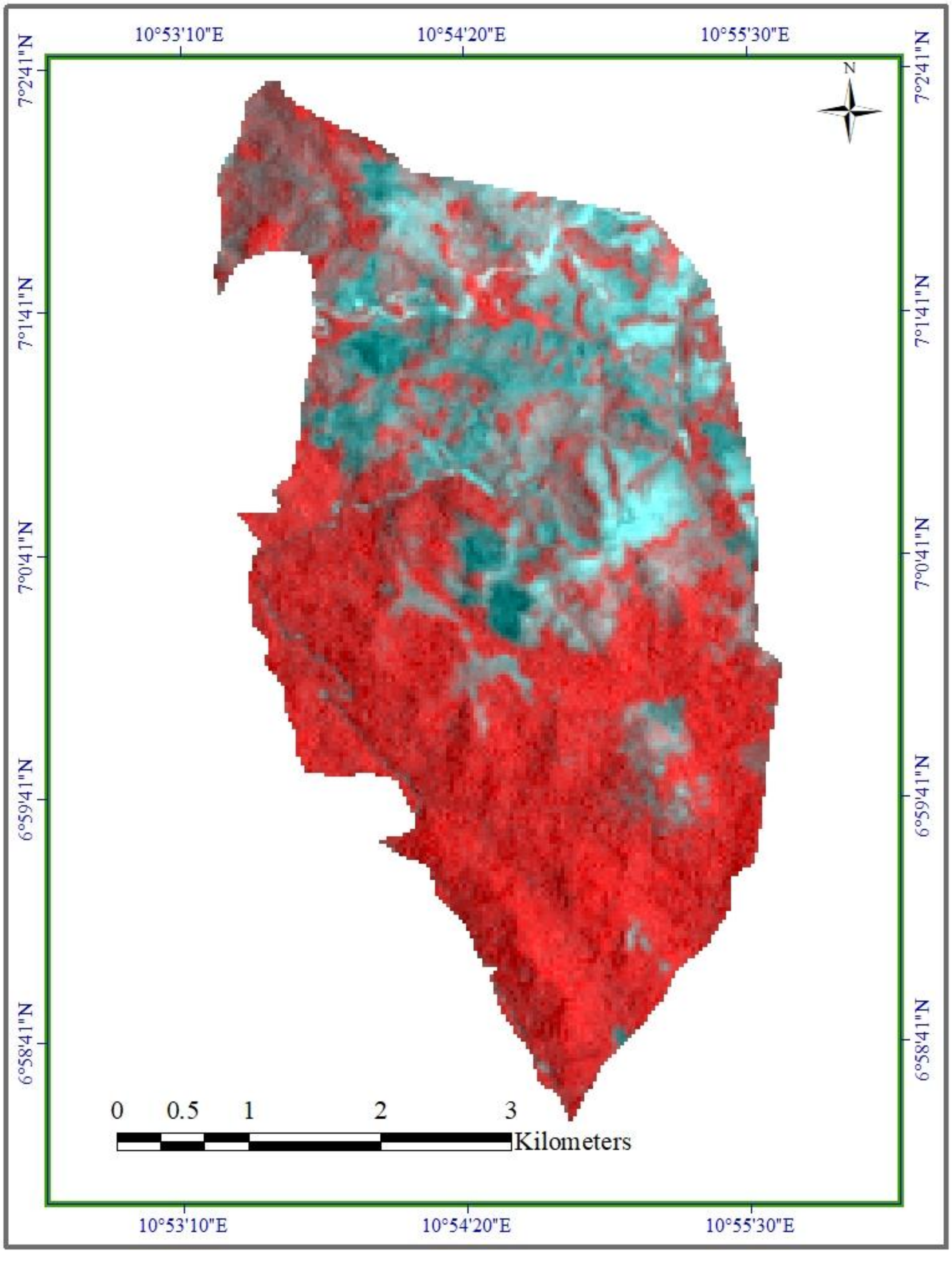
Appendix 1: The Stand Variable of Buru community forest

Plot	Dq	N/ha	Gha	Hd
1	30.10	432	30.68	27.70
2	27.00	396	22.70	24.10
3	27.50	408	24.21	28.00
4	28.10	368	22.75	25.60
5	29.80	445	27.26	27.90
6	27.30	347	19.17	24.70
7	20.80	616	20.96	24.00
8	30.30	328	23.60	28.80
9	27.60	480	28.78	28.40
10	27.00	324	18.61	22.90
11	28.50	364	23.14	24.50
12	28.70	336	20.92	21.60
13	28.60	480	30.85	25.20
14	27.70	392	23.64	22.70
15	31.40	400	31.05	26.70
16	25.50	424	21.66	20.20
17	25.70	328	17.06	18.30
18	26.70	372	20.87	25.70
19	28.90	420	27.49	29.80
20	27.80	468	28.39	25.90

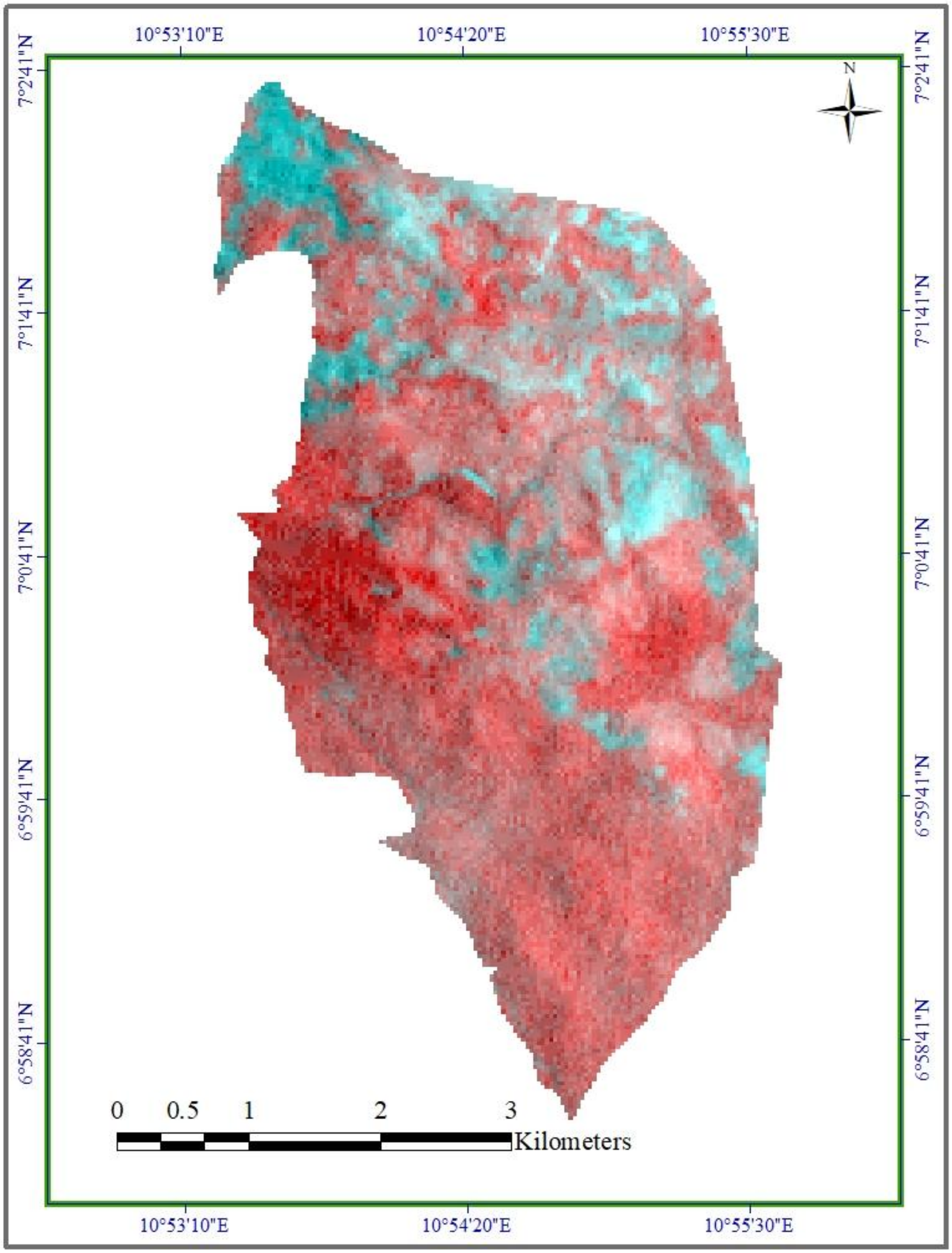
Dq= quadratic mean, N/ha=number per hactar, Gha= Basal area per hectar, Hd= Dominant height



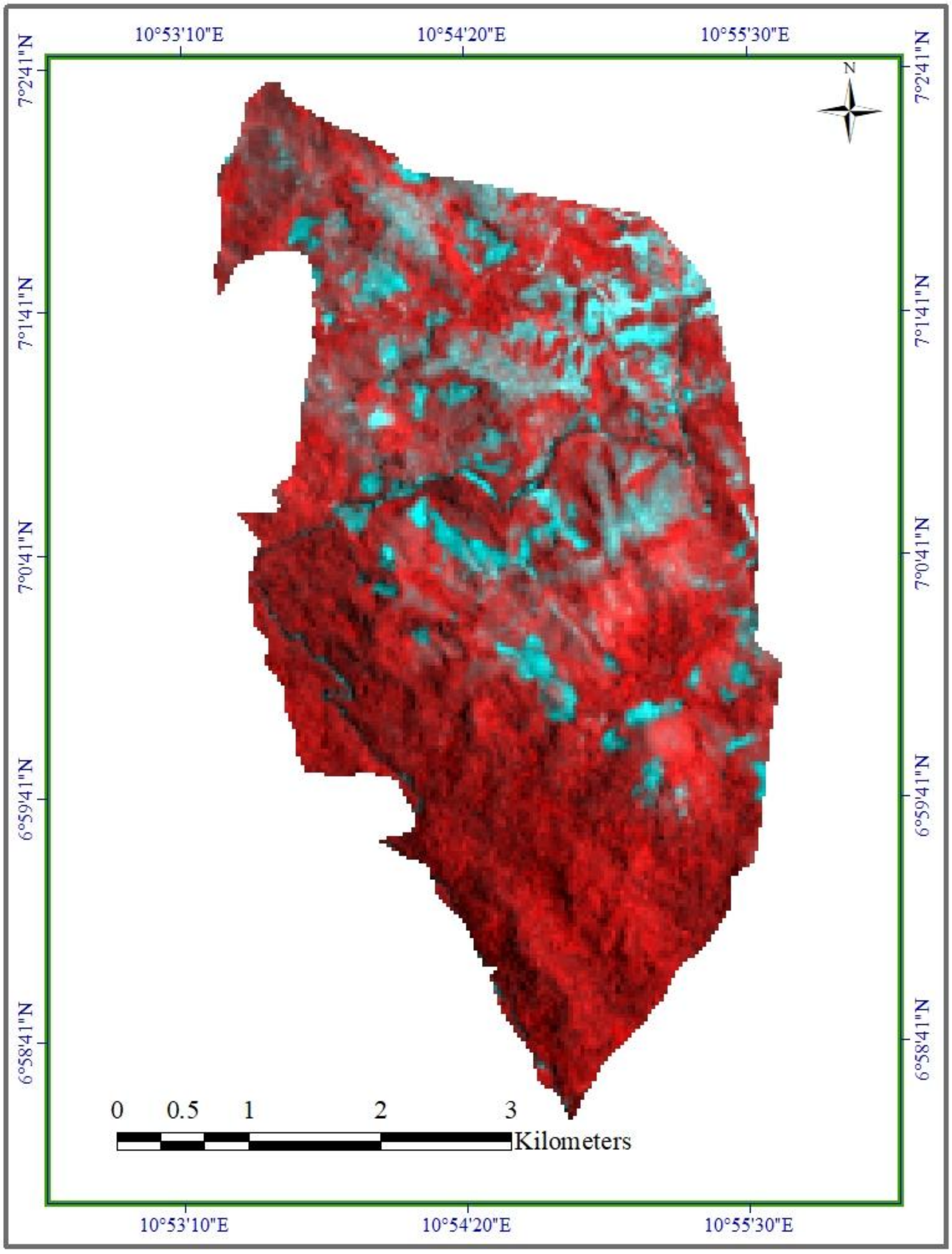
Appendix 2: False colour composite Imagery of Buru Community Forest 1988



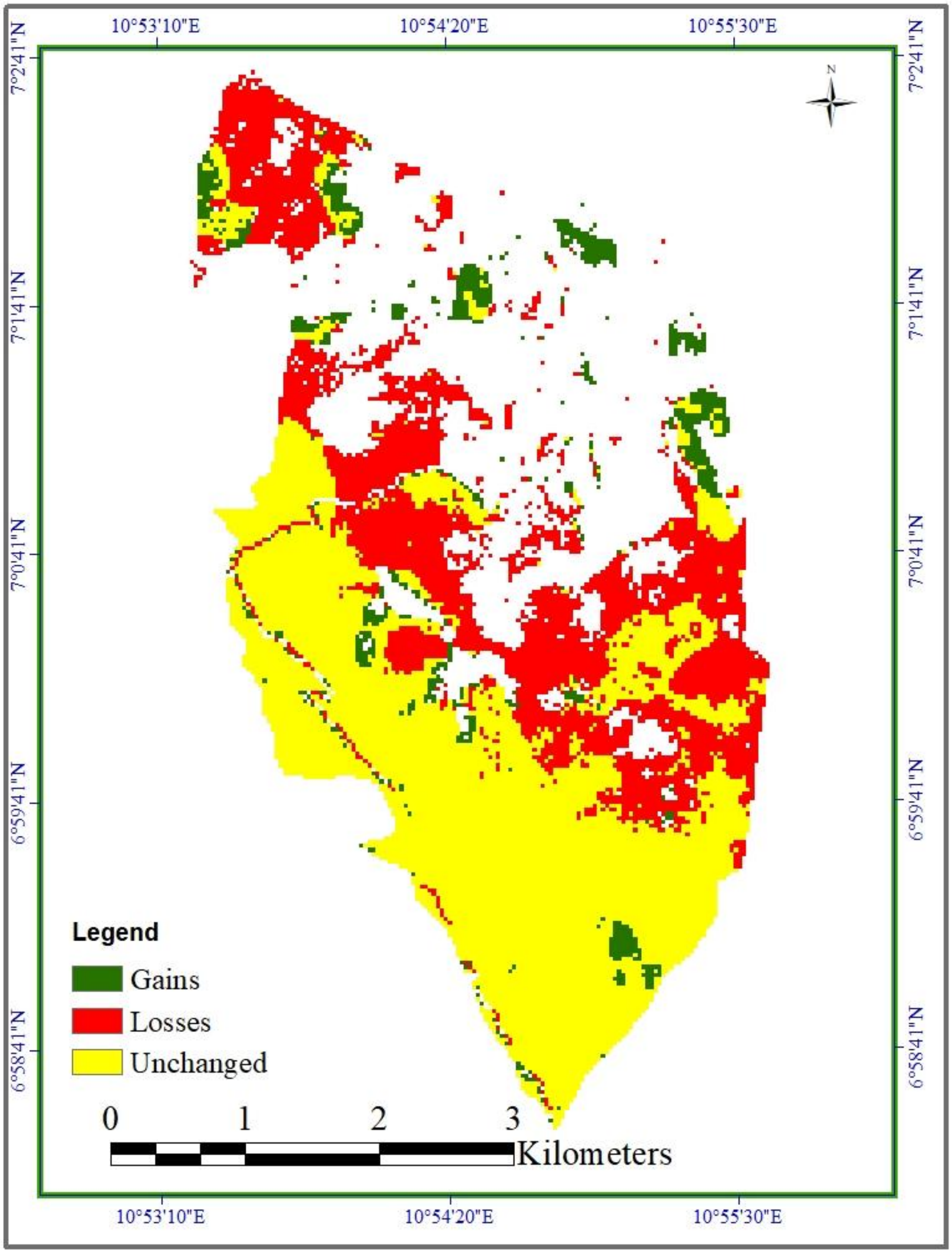
Appendix 3: False colour composite Imagery of Buru Community Forest 2000



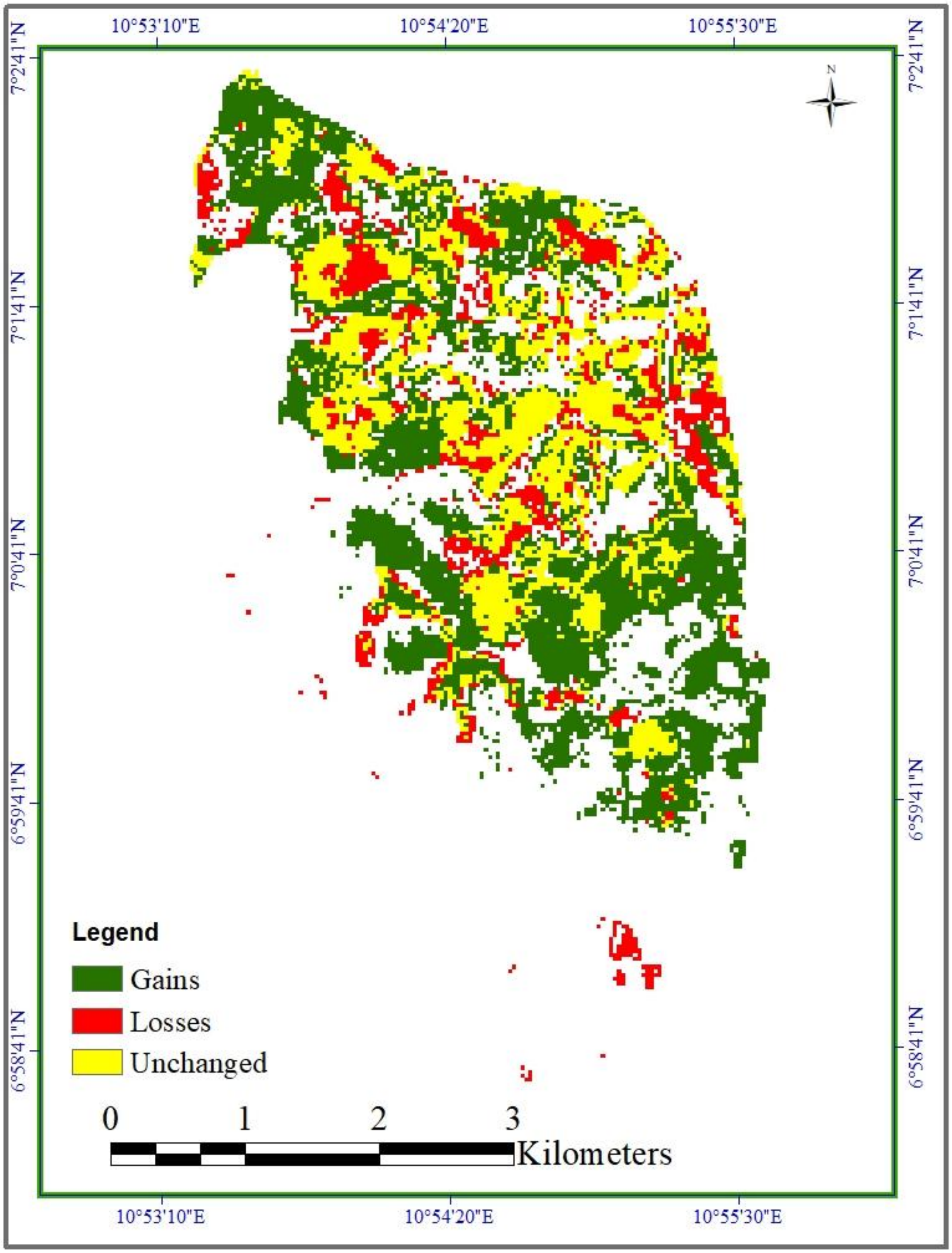
Appendix 4: False colour composite Imagery of Buru Community Forest 2008



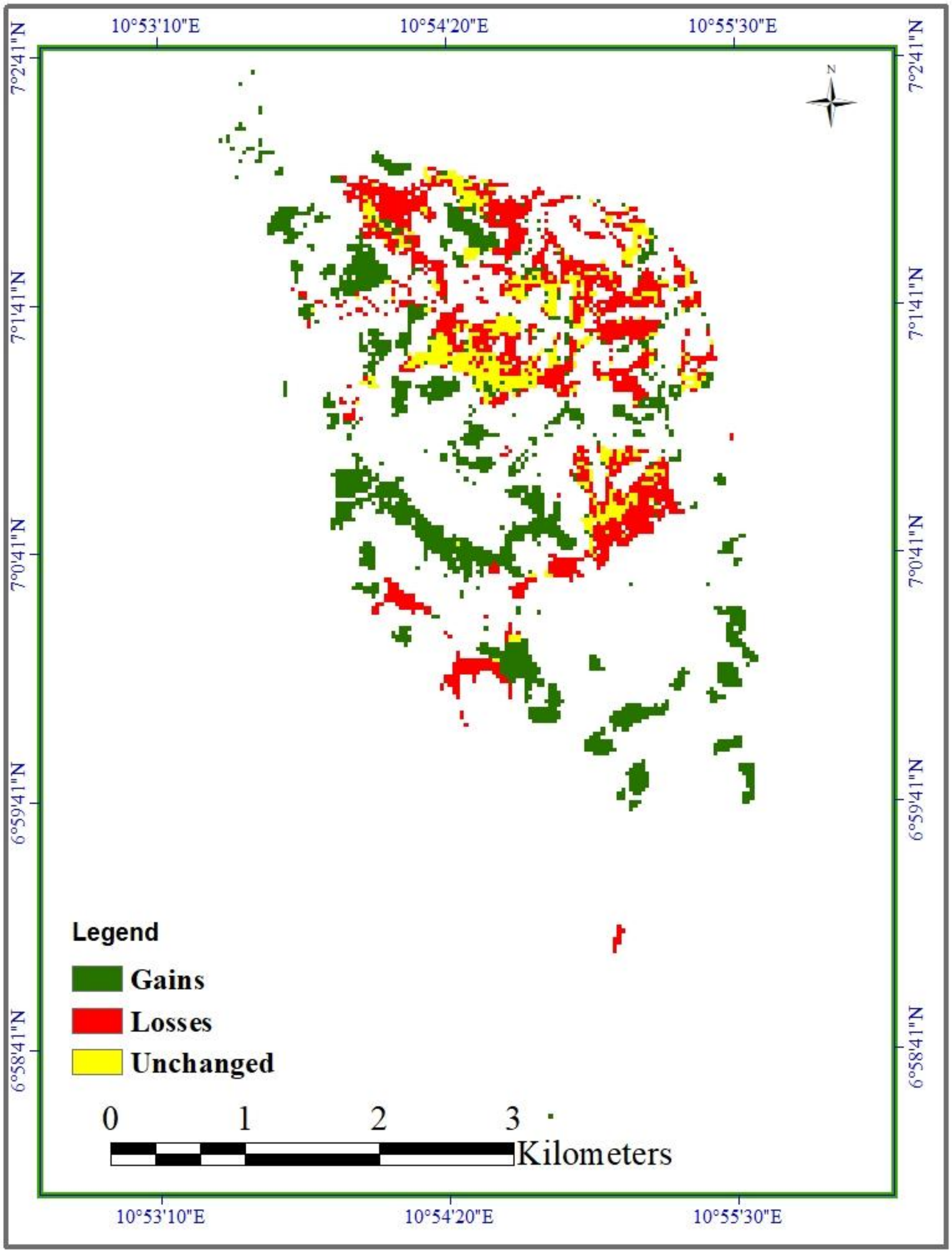
Appendix 5: False colour composite Imagery of Buru Community Forest 2018



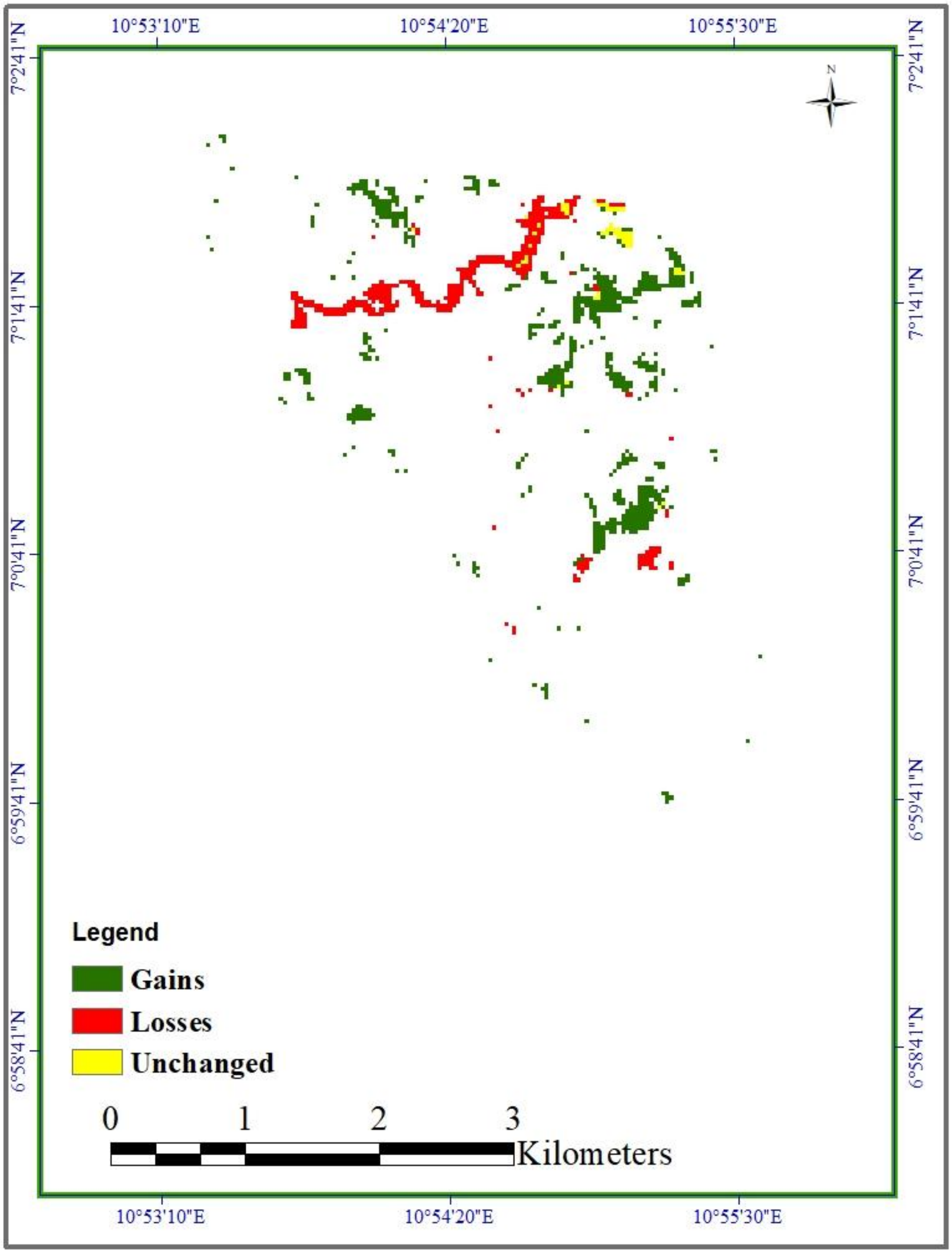
Appendix 6: Iincreases, decreases and Unchanged in Less Disturbed Forest from 1988 to 2018



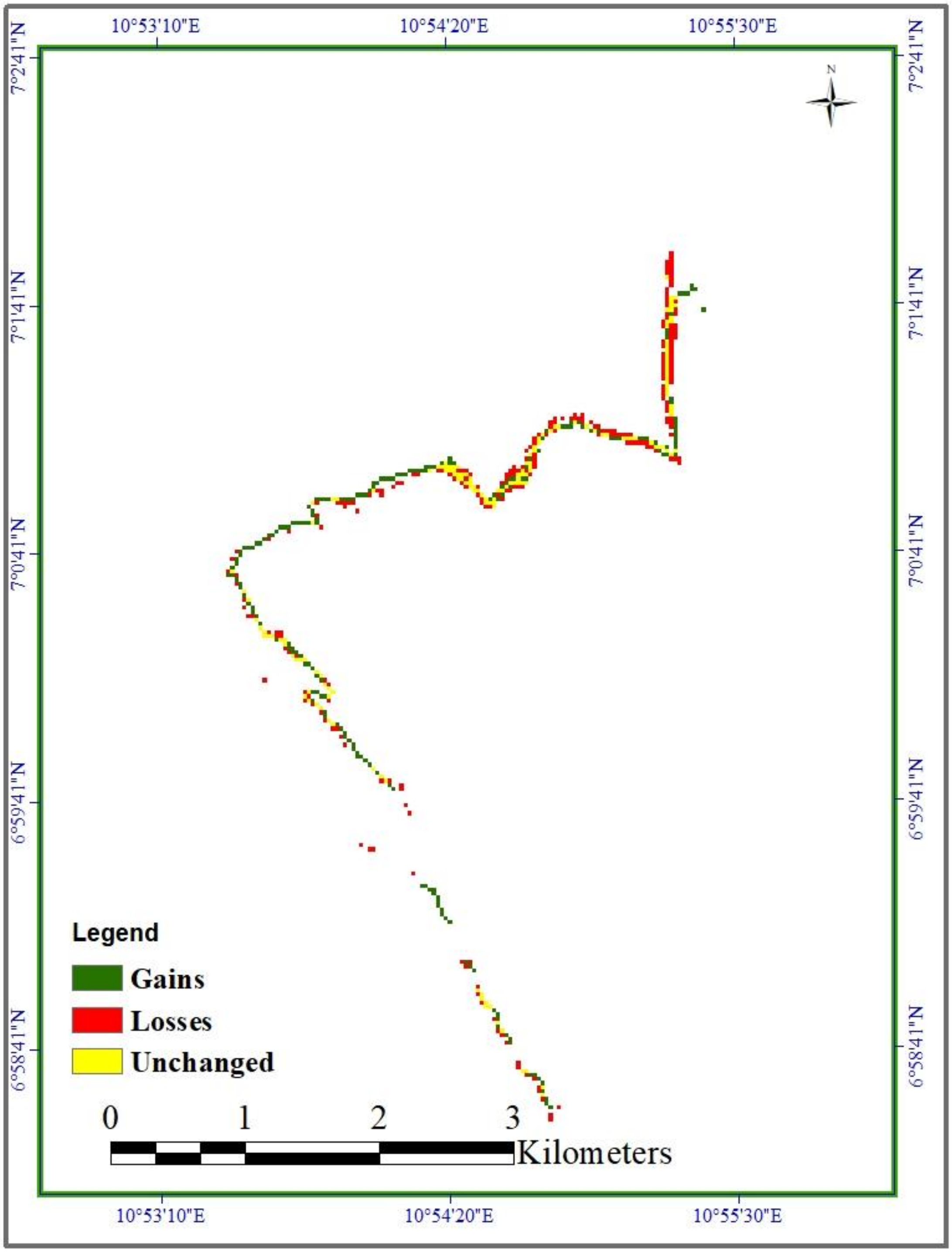
Appendix 7: Iincreases, decreases and Unchanged in Disturbed Forest from 1988 to 2018



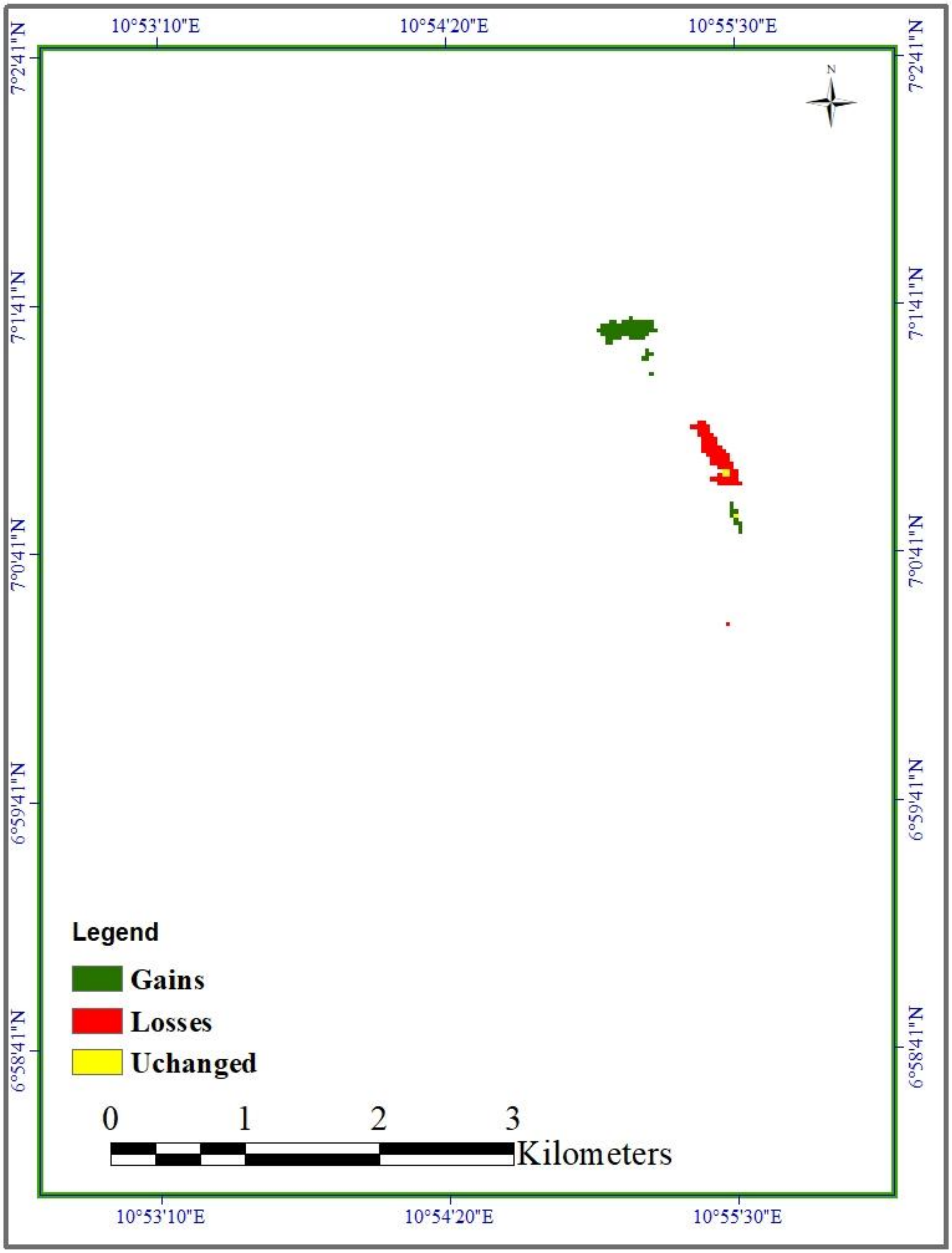
Appendix 8: Iincreases, decreases and Unchanged in Grasses, Shrubs and farm land from 1988 to 2018



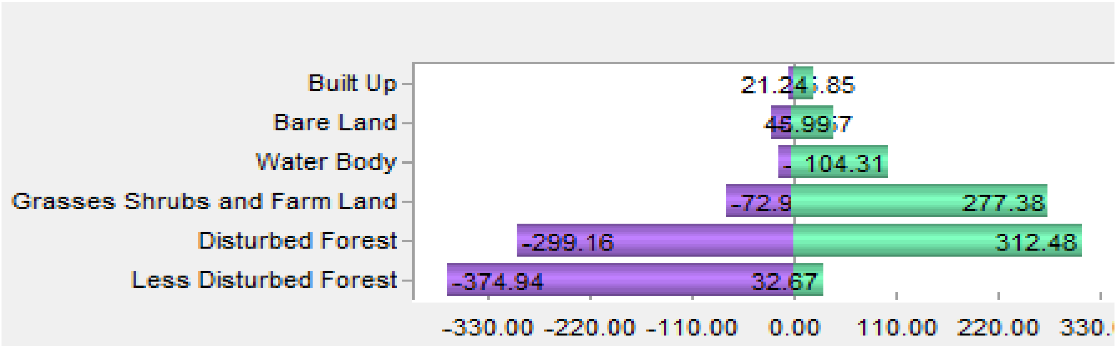
Appendix 9: Iincreases, decreases and Unchanged in Bare Land from 1988 to 2018



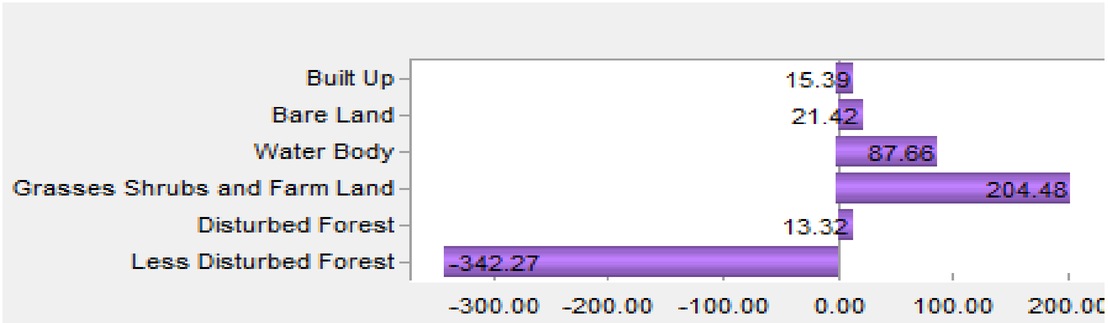
Appendix 9: Iincreases, decreases and Unchanged Water body from 1988 to 2018



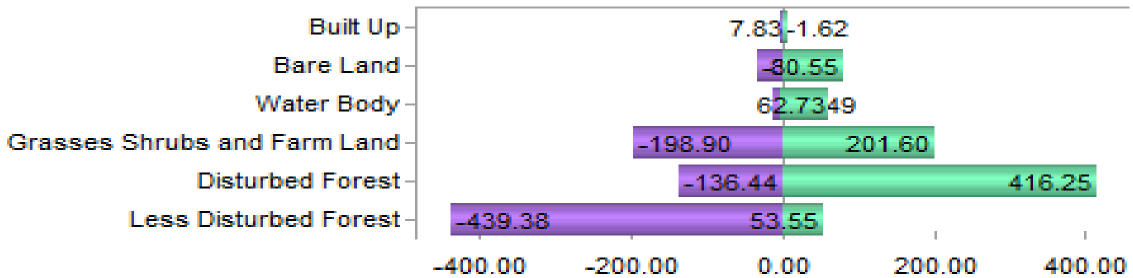
Appendix 11: Iincreases, decreases and Unchanged in Built-up Land use types from 1988 to 2018



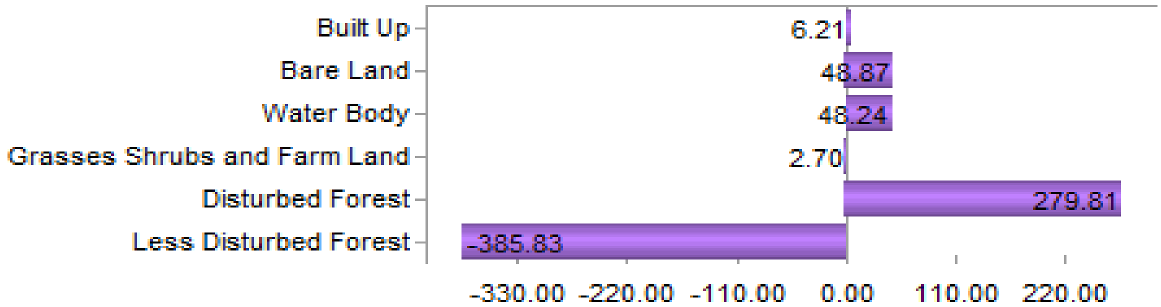
Appendix 12: Gains and Losses between 1988 and 2000



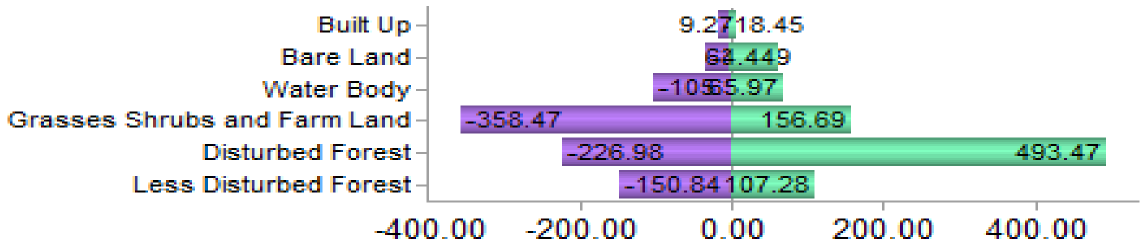
Appendix 13: Net Change between 1988 and 2000



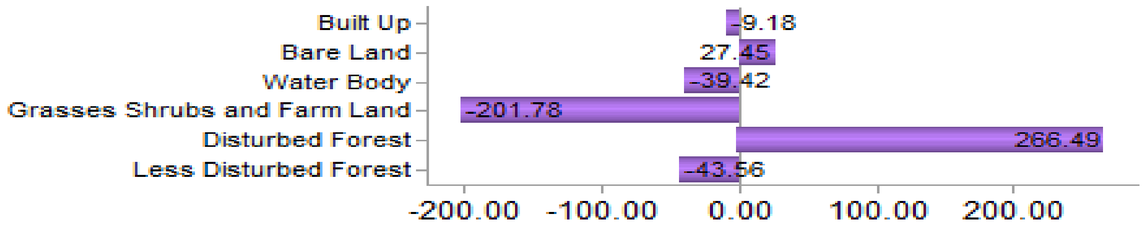
Appendix 14: Gains and Losses between 1988 and 2008.



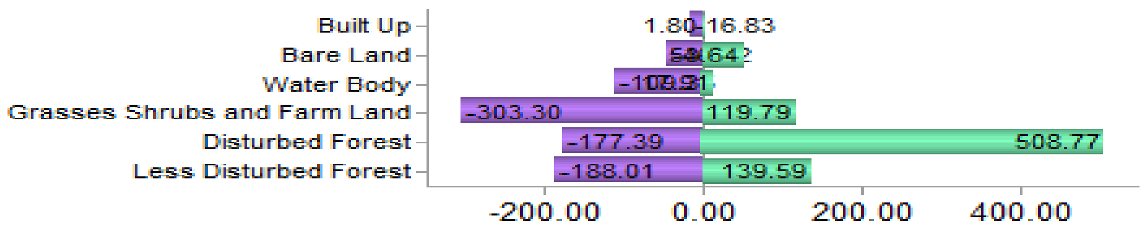
Appendix 15: Net Change between 1988 and 2008



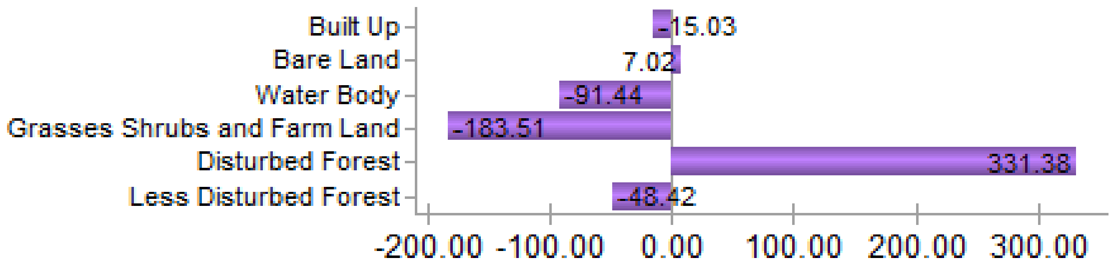
Appendix 16: Gains and Losses between 2000 and 2008



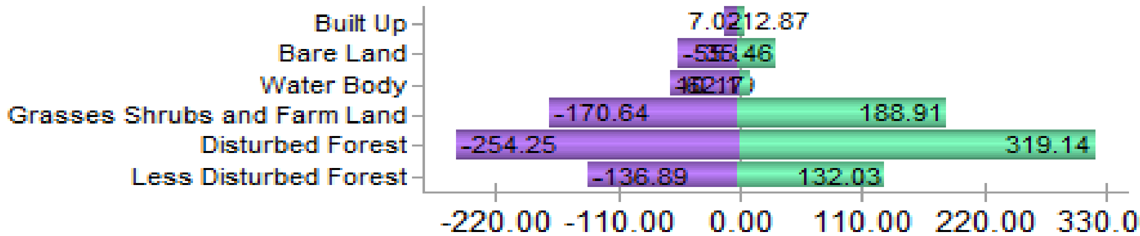
Appendix 17: Net Change between 2000 and 2008



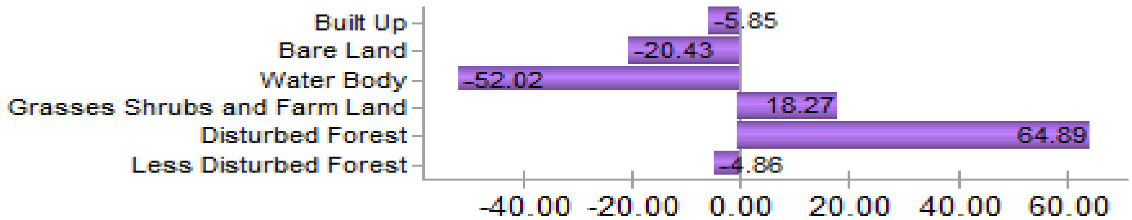
Appendix 18: Gains and Losses between 2000 and 2018



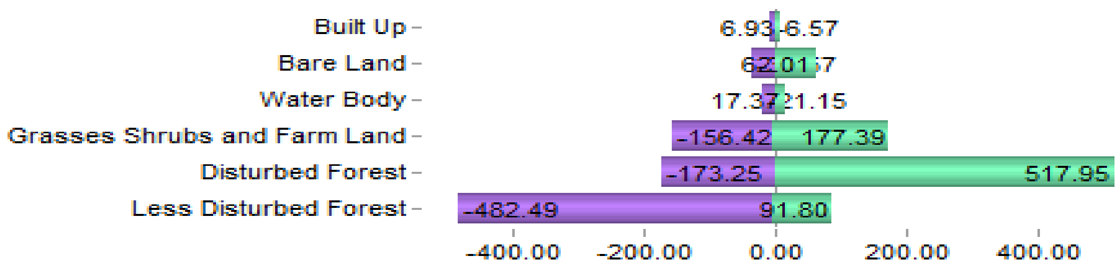
Appendix 19: Net Change between 2000 and 2018



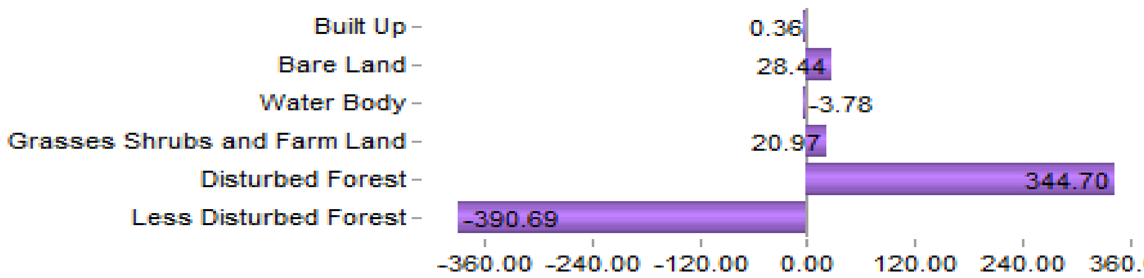
Appendix 20: Gains and Losses between 2008 and 2018



Appendix 21: Net Change between 2008 and 2018



Appendix 22: Gains and Losses between 1988 and 2018



Appendix 23: Net Change between 1988 and 2018