KWAME NKRUMAH UNIVERSITY OF SCIENCE AND TECHNOLOGY,

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POTENTIAL EFFECTS OF REDD+ POLICY ON LANDUSE/ LAND COVER CHANGES AND ABOVEGROUND CARBON STOCK IN GHANA

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A Thesis submitted to the Department of Civil Engineering, College of Engineering, in partial fulfilment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

In

Climate Change and Land Use

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CERTIFICATION

I hereby declare that this submission is my own work towards the award of PhD in Climate Change and Land Use and that, to the best of my knowledge, it contains no material previously published by another person nor material that has been accepted for the award of any other degree or diploma at Kwame Nkrumah University of Science and Technology, Kumasi or any educational institution, except where due acknowledgement has been made in the thesis.

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DEDICATION

I dedicate this work to my mothers, Gifty Akua Yeboah and Grace Amoako for their dream and push to make my pursuit of higher academic laurels possible, and to my wife Eunice Addo and my three beautiful girls Karin, Karis, and Kailyn Amoako for their unwavering support. I hope that this work spurs my girls on to achieve higher in the academic journey.

ABSTRACT

The Reducing Emissions from Deforestation and Forest Degradation and the Enhancement of Forest Carbon Stocks (REDD+) mechanism promises to address commodity-driven deforestation while encouraging sustainable forest management to reduce greenhouse gas emissions. The wider choices made by farmers on their desire to comply with the tenets of REDD+ program and the carbon dynamics related to changes in land use will determine how well REDD+ works in Ghana. However, there is still a significant knowledge gap on how the implementation of REDD+ influences the dynamics of land use and aboveground carbon change, as well as how farmer choices and participation levels impact the program's performance. Taking the case of Assin South District under the Kakum Hotspot Intervention Area for REDD+, this research analyses the dynamics of aboveground carbon stock under business-as-usual (BAU) and REDD+ scenarios through land use modelling and prediction of future changes between 2019 and 2035 and the socioeconomic factors that influence farmers' choices of farming systems and land decisions and willingness to participate in REDD+. The Terrset Geospatial Monitoring and modelling System (TGMMS) software's Land Change Modeler (LCM) was used for landuse modelling for 2024 and 2035 by applying the multi-layer perceptron (MLP) neural network within the software. The carbon stock between 2019 and 2035 was estimated and valued using the InVEST carbon model.

Above-ground carbon stock in Primary forest was significantly different from other land use at all ages. However, carbon stock in agroforestry at age classes 2 and 3 was not significantly different from secondary at age class 3. Carbon stock under REDD+ could increase by 13 % and 25 % over the BAU scenario in 2024 and 2035, respectively. Land use for crop production could be reduced by 17 – 32% in the same period. Age, years of farming, cocoa income, and distance to road and town have positive influences on the selection of monoculture cocoa farming, whilst marital status, total land holding, and input cost had a negative influence on the same selection. More than 90% of households were willing to participate in all REDD+ activities driven by immediate benefits with major reasons for participation in REDD+ being an increase in yield/income, benefits to be received under the program, sustainability of farms, and environmental reasons respectively. Age, marital status, cost of labour, land holding per capita, livestock income, input cost, distance to the town centre, and distance to the road significantly influenced their decisions. REDD+ project should consider climate-smart practices and the supply of farm inputs that improve the crop yield of farmers. REDD+ actors should promote farm intensification using appropriate technologies for future food security under REDD+. Education on REDD+ should be gender-specific and target factors such as income level (through alternative livelihood), and age.

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LIST OF ABBREVIATIONS AND ACRONYMS

ABM………………...Agent-based model

AFOLU……….......Agriculture, Forestry and Other Land Use

ANN…………………Artificial neural network

ANOVA……………...Analysis of variance

BAU…………........Business as-usual

CA…………………...Cellular automata

CCLU………………...Climate Change and Land Use

ES…………………....Ecosystem Service

ESA…………………..European Space Agency

EUDR………………...European Union Deforestation-Free Union

FC……………………Forestry Commission

GCFRP……………....Ghana Cocoa Forest REDD+ Program

GEE…………………Google Earth Engine

GHG…………………Greenhouse Gas

GIS…………………...Geographical Information Systems

GNDVI…………….....Green Normalized Difference Vegetation Index

GPS…………………...Global Positioning System

HIA……………………Hotspot Intervention Area

IRECI…………………Inverted Red-Edge Chlorophyll Index

KNUST………………..Kwame Nkrumah University of Science and Technology

LCM Land Change Modeler

LUCC………………….Land-use and land-cover change

LULC…………………..Land use Land cover

MLP Multi-layer perceptron neural network

MNDWI………………..Modified Normalized Difference Water Index

MSI……………………Multispectral Instrument

NDBI…………………..Normalized Difference Built-up Index

NDVI…………………..Normalized Difference Vegetation Index

NIR……………………Near infrared bands

REDD+…………….…. Reducing Emissions from Deforestation and Forest Degradation

REIP……………………Red-Edge Inflection Point index

RS………………………Remote sensing

SDG …………………....Sustainable Development Goal

SI……………………….Spectral indices

SNAP…………………...Sentinel Application Platform

SPSS……………………Statistical Package for the Social Sciences

SWIR…………………....Shortwave infrared bands

TGMMS……………….. TerrSet Geospatial Monitoring and Modeling System

TNDVI………………Transformed Normalized Difference Vegetation Index

UNFCCC…………………United Nations Framework Convention on Climate Change

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1. CHAPTER ONE: INTRODUCTION

1.1 Background

The dependency of the human race on land and its resources has been at the centre of many international, regional, and local discussions. The alarming rate at which human alterations to the earth are increasing poses threats to sustainability and this is exacerbated by the high populations of the world and the quest to satisfy their needs.

Tropical ecosystems play a critical role in many ways especially in climate change discourse; biodiversity conservation and global carbon stocks (Edwards et al. 2014), hydrological cycles and soil protection (Stephens et al. 2021), etc. Despite the myriad benefits of tropical ecosystems, it faces considerable threats and degradation through various land use changes from agriculture, settlements, mining, etc. (Laurance et al. 2014). The area of forestland in the world was reduced by 4 percent between 1990 and 2018 with annual average loss of 0.1 percent as cropland areas for permanent crops grew by 25%. Land for agriculture has increased by an average of 0.1% since 1961 (FAO 2020). The landuse changes in terms of forest has seen more loss of tropical forests to agricultural lands as a net loss of forests in the tropics between 1982 and 2016 been recorded (Song et al. 2018). The Goal 15 of the Sustainable Development Goals of the United Nations aims to stop and reverse land degradation and biodiversity loss by safeguarding, restoring, and promoting the sustainable use of terrestrial ecosystems.

But the speed at which landuse and landuse changes are occurring needs to be reduced and reversed if these goals can be achieved. Agricultural driven land use change (expansion and intensification) is essential in providing food to the growing human population and in attaining the Sustainable Development Goals 1 (SDG 1) of zero hunger and finding a balance between forest and agriculture is key (Timko et al. 2018). That notwithstanding, the impact landuse change has on the global carbon emissions is also a challenge if goal 13 of climate action can be attained.

1.1.1 Agriculture forest nexus

The Intergovernmental Panel on Climate Change's Fifth Assessment Report states that, after the energy sector, agriculture, forestry, and other land use (AFOLU) accounts for 20–24% of world emissions (IPCC 2014).

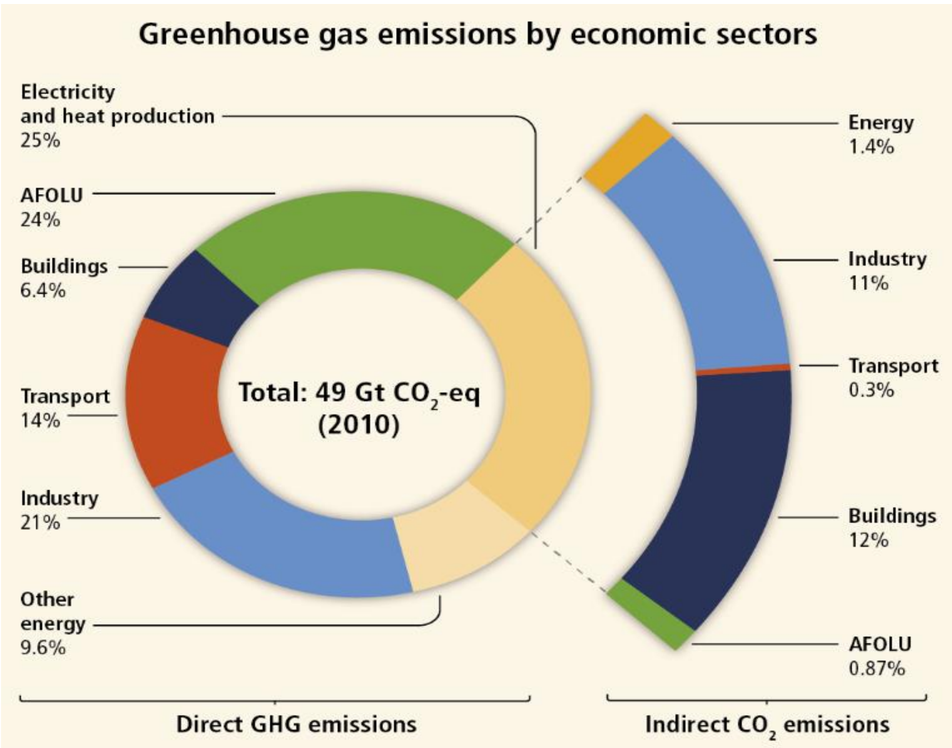


Figure 1.1: Economic sector's share of greenhouse gas emissions (IPCC 2014)

Worldwide, agriculture has been identified as a primary cause of deforestation (Pendrill et al. 2022; V De Sy et al. 2019; Branthomme et al. 2023) contributing to permanent land use changes for the production of commodities, and accounts for 27% of the world's forest loss (Curtis et al. 2018) and destruction of tropical forests for farming and tree plantations releasing 2.6 $GtCO_2$ yr (Pendrill et al. 2022). However, Kan et al. (2023), assert that the threat of losing primary forest landscapes goes beyond international agricultural supply chains, as the ecological value of intact forests is jeopardized by activities which are not related to agriculture such as road clearing, logging and mining, and that are fueled by the demand for non-agricultural products such as wood and minerals .

These non-agricultural activities can also precede and enable agricultural activity, which in turn accelerates forest loss and timber extraction as forest products is a decreasing function of agricultural productivity (Illukpitiya and Yanagida 2010). The agriculture and forest landscape dynamics are driven by the farmers' practices and their management decisions which have implications for landuse changes, ecosystem services, and livelihoods (Ango et al. 2014). The conversion of lowland tropical rainforest into mosaic agricultural landscapes leaves the landscape fragmented with monocultures, settlements, and other mixed cropping systems and patches of forests (Clough et al. 2016), and these deforestation activities drive global emissions. Conversion of forests into land for agriculture and tree plantations in the tropics resulted in the release of annual net emissions of 2.6 Gt of CO_2 (Pendrill et al. 2019). According to Asubonteng et al. (2020) and Tutu Benefoh (2018), Ghana's terrain is incredibly diversified and is composed of tree crops including citrus, cocoa, oil palm, and rubber. Intact canopy forests are usually in the protected forest reserves and secondary forests in off-reserve areas. Agroforestry in different forms have been recommended as a solution to sustainable landscapes. According to van Noordwijk (2020), agroforestry provides opportunity to synchronize efforts across the Sustainable Development Goals (SDGs) and address the unavoidable compromises by integrating forestry and agriculture with rural and peri urban livelihoods and the landscapes. Additionally, Rolo et al. (2021) support combining agroforestry with forests because this practice has a high social value and offers a range of ecosystem services that should be given priority in agricultural landscapes.

1.1.2 Reducing Emissions from Deforestation and Forest Degradation

Under the United Nations Framework Convention on Climate Change (UNFCCC), developing nations were encouraged to pursue good sustainable forest practices, which contribute to mitigation efforts against climate change. This was accomplished through the Reducing Emissions from Deforestation and Forest Degradation and the enhancement of forest carbon stocks (REDD+) mechanism. The main objectives of the agreement were for countries to: i) decrease greenhouse gas emissions (GHG) by reducing, stopping, and reversing the loss and degradation of forests; and ii) increase the removal of GHGs from the earth's atmosphere by conserving, managing, and expanding forests. The success of implementing REDD+ will inure to the benefit of achieving Goals 13 and 15 of the SDGs (ICRAF 2018).

For more than ten years, Ghana has been implementing REDD+ to support sustainable forest management.

The REDD+ strategy of Ghana is developed along agricultural commodities that drive deforestation in the landscape to promote intensification and the incorporation of forest trees in farmlands for emission reductions and other ecosystem services (Forestry Commission of Ghana 2016). Farmers are encouraged to make land-use decisions that have minimal impacts on forest, carbon, biodiversity and adopt climate-smart agricultural practices such as agroforestry. Within the tropical region, the practice of agroforestry presents a win-win solution for humid West Africa capable of addressing environmental issues both at local and global level due to sequestration potential of agroforests of up to 135 Mt CO_2 per year over two decades (Tschora and Cherubini 2020, 1). The capacity for carbon storage in the soil and many plant species of agroforestry, along with its application in reforestation and agricultural areas, make it a valuable technique for sequestering carbon (Montagnini and Nair 2004).

As a results-based incentive mechanism, REDD+ is ideal to safeguard the remaining forest ecosystem by avoiding expansionist agriculture into forest frontiers and improving the agricultural landscape with trees and climate-smart agricultural practices.

The REDD+ scheme is to provide financial incentives to farming communities in addition to their farm incomes. However, this complex mosaic landscape with diverse cash crops that drives the decision of farmers has different incentive mechanisms under the various tree crops systems (out-grower schemes for rubber, available market for cashew and a resilient cocoa board that shields cocoa farmers from the swings of the world cocoa prices and a booming oil palm industry).

The elements that influence participation in REDD+, remain unclear. It is critical to comprehend the ways in which socioeconomic variables impact farmers' decisions about land use and adoption of REDD+. These characteristics include land tenure, gender, income and benefit-sharing (Villamor et al. 2014; Damnyag et al. 2012; Schindler 2009).

The REDD+ principle establishes results-based payments and therefore requires performance indicators that can be measured to determine if the scheme is effective.

1.2Problem statement and Justification

Within the southwestern area of Ghana, enormous portions of the high forest of Ghana holds important biodiversity hotspots including the Upper Guinean forests of West Africa, which is of global significance for biodiversity (Forestry Commission of Ghana 2016). This is the same area dominated by cocoa production for which the premier emission reduction (ER) program of Ghana along the cocoa commodity was formed out of the REDD+ Strategy of Ghana dubbed the Ghana Cocoa Forest REDD+ Program (GCFRP).

The change of land use from forests to cropland has been highlighted as the principal driver of deforestation. With an annual rate of 3.2%, Ghana is one of the top deforesting countries in Africa (Forestry Commission of Ghana 2017a). The expansion of cocoa was responsible for more than a quarter of agriculture conversion, making it the primary commodity driving deforestation in the program area according to the analysis of the Forest Reference level for the (Forestry Commission of Ghana 2017b; Forestry Commission of Ghana 2017a). Implemented over an area extent of 5.9 million hectares, the GCFRP is the first ER program targeting cocoa as a commodity to help improve yield of farmers through intensification activities and also produce in a climate responsible and sustainable way thereby reducing the emissions from the cocoa sector (Forestry Commission of Ghana 2016; Forestry Commission of Ghana 2017b). This resonates well with the overall aim of the 20-year REDD+ Strategy which seeks to create a climate-smart and responsible farming and green landscapes by improving primary tree crops and commodities and NTFPs production (Forestry Commission of Ghana 2016).

Through bringing multiple stakeholders to the table to leverage on their investment and resources and encouraging community participation, the GCFRP approaches landscape governance with communities at the centre to promote agroforestry and nature based solutions for their livelihood and sustainable cocoa production and sourcing (FCPF 2024).

Land-use change processes are more complicated as a result of interactions between the factors with the interrelationships shaped by underlying policies and institutions (Amadou et al. 2015). The research in this field have evolved over the years from geographers and natural scientist using only spatially explicit models, whereas social scientists used the human behavioural models to understand landuse changes (Irwin and Geoghegan 2001).

Numerous studies have shown how people's decisions about how to use their land are influenced by the economic opportunities and restrictions that are created by markets and policies and through institutions mediated (Lambin et al. 2003).

Few studies have been done to understand how land use and land cover changes over time using remote sensing and geographic information systems through analysis of images (Asubonteng et al. 2018; Sassen et al. 2022; Tutu Benefoh et al. 2018). Less research has been done to understand carbon stocks dynamics in Ghana's cocoa landscape and how tree diversity are impacted with landuse changes ((Dawoe et al. 2016; Mohammed et al. 2016),

Despite gaining momentum with the implementation of REDD+ interventions under the Ghana Cocoa Forest REDD+ Program leading to the achievement of emission reductions and subsequent receipt of the first payment from the World Bank as the second country in Africa under the REDD+ scheme, our knowledge of how the implementation of REDD+ contribute to changes in carbon stocks and land use, as well as how farmer decisions and participation levels impact the program's success, is still severely lacking. Existing literature focused on institutional innovations (van der Haar et al. 2023), tradeoffs considered when expanding farms (Adanu et al. 2023), landuse use change under policy reforms (Braimoh 2009), how land tenure influences the investment people make in inputs used for production within the cocoa sector of Ghana (Donkor et al. 2023). Malek et al. (2019)found that about 90% of landuse decisions happen at the household level with economic, political and demographic factors being the major driving forces at the global level. An (2012), posits that agents make rational choices that are bounded by imperfect resources and when making pertinent judgments, people frequently aim for adequate instead of optimal utility (Kulik and Baker, 2008).

It is against this background that this study using the case of Assin South District under the Kakum Hotspot Intervention Area for REDD+, seeks to analyze the dynamics of carbon stock changes under business-as-usual (BAU) and REDD+ scenarios through land use modeling and prediction of future changes between 2019 and 2035 and the socioeconomic factors that influence farmers' choices of farming systems and land decisions and willingness to participate in REDD+. It is expected that the results will contribute to filling the knowledge gap and support decision making on REDD+ planning and forest and agricultural landscape management.

1.3 Specific Objectives

1. To estimate above-ground carbon and floristics diversity of different land uses at various growth stages
2. To model landuse dynamics on aboveground carbon stock for 2024 and 2035 under business-as-usual (BAU) and REDD+ scenarios.
3. To assess the socioeconomic factors that influence the decision of farmers on landuse choices.
4. To assess farmers' willingness to participate in REDD+ activities and the factors influencing their choice of participation.

1.4 Research Questions

In order to accomplish the aforementioned objectives, the following research inquiries were looked at;

- How do carbon stocks differ in different landuses of various growth stages?
- How do REDD+ interventions differ in carbon storage and sequestration compared to business-as-usual for the cocoa and forest landscape?
- What socioeconomic factors influence the landuse choices of farmers?
- What factors influence the willingness-to-participate in REDD+ scheme in Ghana?

1.5 Outline of thesis

The thesis has been structured under different chapters in presenting the various parts of the research as follows:

Chapter 1 focuses on background in terms of land use changes and climate change under the agriculture and forestry nexus. The problem definition, the specific objectives and research questions are also articulated under this section;

Chapter 2 focuses on the various state-of the-art and existing literature on the complexities of land use change dynamics and the modeling tool adopted to understand the complexities, REDD+ and the cocoa industry of Ghana and factors influencing farmers' landuse choices;

Under Chapter 3, aboveground carbon stocks of different landuses and age classes, biodiversity assessments are presented;

In order to evaluate the effectiveness of REDD+ in advancing the climate change mitigation agenda, Chapter 4 simulates how land cover in the research area changes between 2015, 2019, 2024 and 2035. It proceeds to compare the dynamics of aboveground carbon stocks under the BAU and REDD+ scenarios under study.

Chapter 5 examines factors influencing decisions of farmers in the cocoa landscape whereas chapter 6 analyzes the factors that affect how willing farmers are to participate in the REDD+ scheme. The general conclusions of the study and recommendations are finally provided under chapter 7.

2.0 CHAPTER TWO: LITERATURE REVIEW AND SUMMARY METHODOLOGY

2.1 Climate and climate change

2.1.1 Definition and causes of climate change

The term "Climate" is a multifaceted term with a range of meanings and applications. It is defined by da Cunha & Ricardo (2011) as the long-term average atmospheric condition of a place or region. These long-term patterns have been altered over the years leading to a global change in climate. According to Dietz et al. (2020) the current climate change is causing both changes in long-term averages and an increase in fluctuations around them, with an increase in the frequency of extreme events, like heat waves, torrential downpours, continuing sea rise, and droughts. Climate change is a complex phenomenon driven by both natural and anthropogenic factors (Chand 2021; Abayechaw 2023). Findings from detection and attribution studies proves that human activity is increasing the frequency and severity of these extreme climate events more rapidly than it has ever done in the history of modern civilization (Dietz et al., 2020; Ming et al., n.d.; (Zhou and Qian 2021)). The latest report from the Intergovernmental Panel on Climate Change (IPCC), thus, the Sixth Assessment Report (AR6) confirms that the influence of human activities has warmed the atmosphere, ocean and land, since 1980, the previous four decades have all been progressively warmer than the decades before them (IPCC 2022; Intergovernmental Panel on Climate Change 2023).

In the last hundreds to thousands of years, there have been rapid, intensifying, and unparalleled changes (Notz 2020; Wolff et al. 2015)

Although, the earth's climate has always been dynamic, present-day changes are so significant and swift that they could overwhelm adaptive capacity leading to drastically disruptive patterns in both the climate and biosphere (Dietz et al., 2020). Since the middle of the 20th century, human activity has increased atmospheric concentrations of greenhouse gases (GHGs) such as CO_2, methane, nitrous oxides, and chlorofluorocarbons while simultaneously lowering the Earth's surface's albedo, or reflectivity (Dietz et al., 2020; IPCC, 2022). The impact of land use on climate change is heterogeneous (Jia et al. 2022) . Changes in land use, especially in the areas of agriculture and deforestation, have a substantial impact on climate change because they modify carbon emissions, surface energy fluxes, and hydrological effects (Scott 2020). Deforestation and other changes in human land use have been found to cause a relative cooling in Arctic regions, which aggravates polar amplification (Lott et al., 2020). Deforestation, which is usually caused by such as small-scale agriculture, construction, and charcoal production (Ryan et al. 2014) increases atmospheric CO_2 and modifies surface energy and mass balances, all of which have a substantial impact on climate change (Longobardi et al. 2016)

2.1.2 Effects of climate change

The emissions of greenhouse gases from human activities has also increased global surface temperature, reaching 1.1°C above 1850-1900 in 2011-2020 (IPCC, 2022; Ming et al., n.d.; T. Zhou, 2021). The AR6 shows that global mean surface air temperature would reach 1.5℃ or even beyond it (Zhou et al., 2021). Depending on where deforestation and afforestation occurs, the impact of changing land use on biophysical and biochemical interactions at regional and global scales can balance each other out and change the global mean temperature (Devaraju et al. 2015). Climate change, a major ecological and socioeconomic challenge on the twenty-first century (Dietz et al., 2020), poses significant challenges for developing countries, affecting their economic growth and sustainable development (Arndt et al. 2015).

Climate change is having a significant impact on Africa's economy, with a 1°C increase in temperature reducing GDP growth by 0.67% points (Abidoye and Odusola 2015). This is especially true for the agricultural sector, where unpredictable rainfall patterns and high temperatures are threatening food security (Girvetz et al. 2019). Although precipitation is a major component of food security, the effects of temperature are less evident, with extremely high or low temperatures having a detrimental short-term impact (Pickson and Boateng 2022). The planting boundaries of crops in temperate regions and middle latitudes have moved to high latitudes and high elevations due to climate change (Duan et al., 2022). According to Agbongiarhuoyi et al. (2013), in the near and long term, it is anticipated that changes in climate and weather patterns will have a significant detrimental influence on natural resources, food security, and food production. They added that development of pathogens, insect pests, and cocoa pods is altered by climate change, which results in reduced crop yields and affects farm income.

2.1.3 Adaptation and mitigation strategies

As global warming continues, these alterations will intensify and have lasting, irreversible consequences, especially with regard to the rise in sea level (Intergovernmental Panel on Climate Change, 2023). To address these climate change challenges, there is a need for better climate data and projections, as well as the promotion of climate-smart agriculture practices (Girvetz et al., 2019). The interrelationship between climate change and forests is complex (Khaine and Woo 2015), the removal of large quantities of CO_2 and storing carbon (Moomaw et al. 2019) is an important mitigation function that intact forests contribute to towards the fight against climate change. Fawzy et al. (2020) emphasizes the necessity of supplemental measures to traditional mitigation efforts, such as biogenic-based sequestration. The harsh impacts of climate change can be reduced through sustainable and smart cities as highlighted by urban development theories (Blagojević et al. 2020). Smallholder farmers in Ghana have been found to employ diverse adaptation strategies to climate change. These consist of planting early-maturing crops and applying weedicide (Asare-Nuamah and Amungwa 2021) in addition to using mulching, drought-resistant crops, and agroforestry techniques (Fagariba et al. 2018). Along with coping mechanisms like crop and soil management, cocoa farmers have also used adaptation mechanisms like behavioral and technological changes (Afriyie-Kraft et al. 2020; Denkyirah et al. 2017). Farmers have implemented various strategies to fight climate change, including utilizing improved varieties, predicting the weather, altering cropping patterns and agroforestry, reducing soil erosion, and applying fertilizer (Agbongiarhuoyi et al. 2013).

2.2 Land Use and Land Cover (LULC) and LULC changes

2.2.1 Concepts of Land use land cover

Land is a vital resource that provides a variety of ecosystem services (Purswani et al. 2019). “Land use” and “land cover” are not synonymous terms (Briassoulis, 2020). Land use is a multifaceted process affected by technical, natural, socio-economic, and environmental factors (Ovchinnikova et al., 2021). It is a broad concept that encompasses a variety of human activities and arrangements aimed at maximizing the value of terrestrial ecosystem services (Erb 2015). atr and Berberolu (2012) also defines land use as the human activities that take place on the land. Land use can be characterized into agricultural and non-agricultural uses, with the latter including residential, industrial, and recreational areas (Rondhi et al. 2019) . On the other hand, the term “land cover” is defined by Lambin (2000) as the attributes of a specific area, which includes biota, topography, and human structures. Ghana has a complex mosaic of various landcover types and ecosystems, including semi-deciduous forests, food-crop lands, coastal wetlands, and cash crops such cocoa plantations, oil palm estates, cashew, and rubber plantations (Asubonteng et al., 2018). A large variety of flora and fauna species are supported by these varied habitats, which add to the high biodiversity of the area. The way these ecosystems interact and how human activity affects them both play a critical function in shaping the landscape (Torquebiau et al. 2013). Changes in land use such as transformation of natural forest land into cultivated land and settlements is one of the many factors influencing this landscape (Antwi et al. 2014).

2.2.2 Land use and land cover changes

Research suggests that landuse changes are driven by both natural and anthropogenic factors (Sewnet 2015; Sewnet 2016).Land use land cover change, which is both a cause as well as an effect of biophysical and socioeconomic changes, is a global phenomenon that has come into view in the research agenda on environmental changes (Liu et al., 2016). At the most basic level, land use and land cover change refers to changes in the areal extent (increases or decreases) of a specific type of land use or land cover, thus, the conversion of one land use or land cover to another (Briassoulis, 2020). There is a close relationship between land cover and land use change, with modifications to land use practices often times resulting in changes in land cover (Rawat & Kumar, 2015).

Key drivers of changes in land use and land cover have been identified by a variety of studies. Both Yirsaw et al. (2017) and Belay & Mengistu (2019) emphasize the importance of socioeconomic factors such as population growth, economic development, and urbanization that influence changes in land use and land cover. Allan et al. (2022) underlines the significance of policy and regulation, economic and financial factors, and the accessibility of transportation. Land-use cover changes are not necessarily evil, as humans need to raise more buildings for shelter and industrialization due to the ever-growing human population and produce food to cater for human needs and enjoy other ecosystem services necessary for the survival of humans (Foley et al., 2005). However, the exploitation of the environment and these ecosystem services provided by the land and its ecosystem can be detrimental to the environment, especially when not properly managed (Van Asselen & Verburg, 2013). In tropical agroforestry, adaptation strategies include the preservation of shade trees, but conversion of shaded to unshaded systems is now a common practice to increase short-term yield (Tscharntke et al., 2011).

2.2.3 Agricultural expansion as driver of land use land cover change

Agriculture involves activities such as crop cultivation, livestock rearing and the management of natural resources to support food production (Zawiła-nied, 2023). Agricultural expansion, on the other hand refers to the increase in agricultural activities such as the expansion of farmland, the adoption of new agricultural technologies, and the intensification of agricultural practices to meet the growing demand for food and other agricultural products (Barbier, 2020). It often involves the conversion of natural habitats into agricultural land and the use of modern techniques to enhance productivity. Agricultural expansion plays a crucial role in meeting the needs of a growing population (Meyfroidt, 2021).

Agriculture is expanding all over the world, particularly in areas with high conservation value (Scharlemann et al., 2004). This trend has continued into the twenty-first century, with increased global cropland and primary production, particularly in Africa and South America (D’Amour et al. 2017). Tropical forests were the primary source of new agricultural land in the 1980s and 1990s, with significant environmental consequences (Gibbs et al. 2010). Agriculture in Ghana is expanding rapidly, owing to a variety of factors. This expansion is also characterized by an increase in cultivated land area, particularly by medium- and large-scale farmers (Chapoto et al. 2013). In Ghana, agriculture plays a vital role in the country's economy, employing a large portion of the population and helping to reduce poverty (Darfour and Rosentrater 2016). However, there is rising concern about how agricultural practices, like deforestation and soil degradation, affect environmental sustainability (Adomako and Ampadu 2015).

Tropical frontiers have recently seen an increase in agriculture, which has been accompanied by widespread deforestation and the resulting loss of biodiversity, carbon emissions, soil erosion, disturbance of hydrological regulation and other ecosystem services, habitat fragmentation, land conflicts, and the marginalization of Indigenous and rural communities. (Barbier, 2020; Emmerson et al., 2016). This can negatively impacts biodiversity by reducing the available habitat for many plants and animal species (Emmerson et al., 2016). Loss of biodiversity can disrupt ecological balance and affect the overall functioning of ecosystems. Agricultural expansion should consider the conservation of biodiversity. Implementing sustainable agricultural practices such as agroforestry, crop rotation, and integrated pest management, can help minimize negative impacts on biodiversity while maintaining agricultural productivity (Knauer et al., 2017).

It is worth noting that agricultural expansion can contribute to improved food security by increasing the availability of food within the local community (Stavert et al., 2018). When local farmers produce a diverse range of crops, it reduces reliance on imported food and ensures a more stable and accessible food supply (Graesser et al., 2015). However, agricultural expansion can also lead to land conflicts and displacement of local communities, especially when large scale commercial farming encroaches on traditional lands or displaces indigenous communities (Stavert et al., 2018). One of the main drivers of expansion is Population Growth. As the global population continues to increase, there is a greater demand for food and agricultural products. This drives the need for agricultural expansion to meet the growing food needs (Jellason et al., 2021). Also, Economic development is a driver of agricultural expansion. Economic growth often leads to increased urbanisation and changes in dietary preferences (Seto et al., 2020). This, in turn, drives the expansion of agriculture to produce more diverse crops and livestock to meet changing consumer demands. Another driver of agricultural expansion is global trade and market demand (Emmerson et al., 2016). International trade and market demand for agricultural products can drive expansion. Countries may seek to increase their agricultural production to meet export demands and take advantage of economic opportunities (Knauer et al., 2017).

Climate change and food security also drive expansion. Climate change impacts such as changing rainfall patterns and increased frequency of extreme weather events can affect agricultural productivity and food security (An et al., 2019). To mitigate these risks and ensure food security, agricultural expansion may be pursued. Government policies, subsidies, and incentives can influence agricultural expansion. Policies that support agricultural development, provide access to credit, or promote land use changes can encourage expansion. Advances in agricultural technology such as improved crop varieties, precision farming techniques, and mechanization, can increase productivity and efficiency. These advancements can incentivize agricultural expansion to capitalize on the benefits of new technologies.

2.3 Remote sensing (RS) and GIS techniques in LULC change analysis

2.3.1 Land use modelling

Land use and land cover change models have evolved in response to the need for more accurate and comprehensive representations of socio-ecological processes (Verburg et al. 2019). Land use and land cover models are crucial for understanding and predicting changes in these areas. As demonstrated in studies on urban expansion in Arak, the combination of Markov chain and Cellular Automata Markov models is particularly effective in predicting land use/cover changes (Nadoushan et al., 2015) and deforestation in the Doon Valley (Mukhopadhaya, 2016). These models have been improved further by incorporating geographic information systems (GIS) and identifying key drivers such as road density and distance to settlements (Widiawaty et al., 2020). In predicting land cover changes, models such as Agent- Based Modelling (ABM), land change modeller (LCM) in TerrSet, Cellular Automata, artificial neural network (ANN) analysis in LCM, Multi-Layer Perceptron Markov Neural Network (MLP-NN), and Markov Chain (MC) have been explored and adopted by several researchers who have sought to tell the future of the landscape of a given area (Anand & Oinam, 2020; Binutha & Somashekar, 2014; Khawaldah, 2016).

2.3.2 Future land use land cover change predictions

The Earth's land cover is changing dramatically as a result of both natural and man-made interventions (Binutha & Somashekar, 2014). Land use change information is crucial for natural resource planning, monitoring, and management. Usually, the use of machine learning models to analyse changes in land cover is limited to identifying changes in categorical land cover data, or data that is classified (Patil et al., 2017). However, spatial land use dynamics can both be monitored and predicted by modelling (Nganro et al., 2021). Projecting future land cover (LC) changes is a vital step in sustainable land use planning and management (Khoshnood Motlagh et al., 2021). According to Mahamud et al. (2019), aside future land cover predictions, predicted land use land cover patterns can also be used in other models to further assess the impact of land use and land cover changes on environment, agricultural, ecosystem, and water resources. Several studies all over the world have, therefore, sought to extend the use of such models to predict the spectral band information of satellite images.

A study by Nguyen et al. (2020) employed data from Landsat images to analyze and predict the spatial dynamics of land use and land cover categories in Dak Nong province, Vietnam. In their study, 10 distinct land use and land cover classes were classified using the Random Forest (RF) algorithm of image classification. Additionally, based on the change detection over the previous years, the integration of Markov Chain (MC) and Multi-Layer Perceptron Markov Neural Network (MLP-NN) was applied to predict the future LULC changes in the region. Images from Landsat 5-TM and Landsat

8-OLI were also used in a different study by Khawaldah (2016) to explore the land use and land covers of Amman, the capital city of Jordan, and the resulted maps were used to predict the future landscape based on Markov Model. Also, the land covers of the Hable-Rud River basin, Iran, were extracted from corrected Landsat satellite images to predict the future land covers of the basin using the land change modeler (LCM) (Khoshnood Motlagh et al. 2021) . Based upon Markov and Cellular Automata, a Land Transformation Model (LTM) was developed and used to generate the future scenario of Devikulam Taluk, India (Binutha and Somashekar 2014).

Furthermore, Anand and Oinam (2020) monitored and predicted the future land use land cover of Manipur River basin, India, using land change modeller (LCM) in TerrSet. The study produced a projected land use land cover map of the area using Markov Chain and artificial neural network (ANN) analysis in LCM based on the land use land cover maps produced from the Landsat satellite images for previous years. Using an integrated GIS Cellular Automata - Markov model, Mahamud et al. (2019) predicted a future LULC scenario of Kelantan, Malaysia. Nganro et al. (2021) used population growth as a parameter to predict the land use change of Makassar in 2050 based on 2017 land use classification map as the start of the prediction by adopting the NetLogo software, which is integrated with Agent- Based Modeling (ABM). Finally, a research by Patil et al. (2017) used topographic and historical climatic variables as input to predict the spectral band values of high-resolution satellite imagery across New Mexico and Washington in the United States. The study adopted the use of the Random Forests (RF)-based machine learning model in the scikit-learn machine learning package that is implemented in Python® programming language. At the prediction stage, the RF model uses the future climate and the topographic variables as model inputs. The output of the model was used to acquire a true colour photorealistic image and an image showing the normalized difference vegetation index values. They then used the trained model to explore what the land cover might look like for a climate change scenario during the 2061–2080 period.

Remote sensing and GIS techniques have also been used in a number of studies to forecast future changes in land cover in different parts of Ghana. Koranteng et al. (2020) conducted a comprehensive analysis using integrated approach of geospatial procedures like remote sending and GIS of past, current, and future land use land cover from satellite images of Ghana's Ashanti regional capital (Kumasi) and surrounding districts. After mapping five major land use land cover categories of the area for 1990, 2000, and 2020, the study employed the use of Markov Cellular Automata modelling to predict the probable land use land cover changes for 2040. A study by Akubia et al. (2020) also applied multi-layer perception (MLP) neural network and Markov chain to project the 2030 land cover of the Greater Accra Metropolitan Area, Ghana. Another studies (Aduah et al. 2018; Aduah and Mantey 2020) have been conducted in the Bonsa catchment and Sekondi-Takoradi metropolitan area to model the possible future of land use land cover patterns by using the Dyna-CLUE model, Markov chain, and logistic regression. The Markov chain was used to estimate two-year land use demands, the Dyna-CLUE model was used to dynamically model the spatial patterns of multiple land uses, and the land use change driving factors and land use types were quantified using the logistic regression model. The Cellular Automata and Markov Chain (Cellular Automata-Markov) have also been used by Koranteng & Zawila-Niedzwiecki (2015) to predict the future land use land cover in the lower half of the Ashanti Region of Ghana for 2020 and 2030. Using the Markov Chain and Multi-Layer Perceptron neural network, along with drivers that represent proximity, biophysical, and socioeconomic variables, the urban extent of the region was forecasted for 2025 in a study by (Addae and Oppelt 2019).

2.4 Cocoa and cocoa production in Ghana

2.4.1 General overview of cocoa production

Cocoa farms are mostly found in the tropical regions because cocoa trees can only grow within about 20 degrees north or south of the equator where the climate and soil conditions are suitable for its cultivation (Aneani et al., 2017). They take about 3-5 years to start producing their first cocoa pods and each cocoa tree produces around 20-30 pods which can continue to bear fruit for about 30 years. Cocoa trees need shade to grow, and this is why many farmers plant other trees, to provide shade for the cocoa trees (Avane et al., 2022). The demand for ethically sourced and sustainable produced cocoa is increasing, with consumers becoming more conscious of the social and environmental impacts of their purchases (Verter & Becvarova, 2014). The drivers of cocoa expansion can vary depending on the region and the specific circumstances. According to Vigneri (2008), economic incentives drive cocoa expansion. Cocoa farming can be financially rewarding for farmers, especially in regions where cocoa prices are high and demand is strong (Kenfack Essougong et al., 2020). The potential for income generation motivates farmers to expand their cocoa cultivation.

Favorable climate and soil conditions also drive cocoa expansion (Abdulai et al., 2018). Cocoa requires specific climatic conditions, such as stable temperature range, sufficient rainfall, and well-drained soil (Alho et al., 2021). Areas with these favorable conditions are more likely to see cocoa expansion. Government policies and initiatives that promote cocoa cultivation, provide subsidies, or offer technical assistance can incentivize farmers to expand their cocoa production (Abman et al., 2020). Also, the demand for cocoa and cocoa-based products, such as chocolate, drives the need for increased cocoa production (Barbier, 2020). As consumer preferences and global demand grow, farmers may expand their cocoa cultivation to meet market needs. Access to resources and technology is a major cause of cocoa expansion. Availability of resources like land, labour, and capital, as well as access to improved farming techniques and technology, can encourage farmers to expand their cocoa production (Akrofi-Atitianti et al., 2018). Cocoa has been expanding over the years due to increased demand for chocolate and other cocoa-based products. Farmers are cultivating more cocoa trees and exploring new regions for cultivation (Akrofi-Atitianti et al., 2018). People are moving into cocoa production because it can be a profitable and sustainable agricultural venture. Cocoa is in high demand, especially for chocolate production, so farmers see it as a lucrative opportunity (Delgado-Ospina et al., 2021). Plus, cocoa farming can provide a stable source of income for many communities.

2.4.2 Ghana cocoa industry

Ghana is a major cocoa-producing country (Kongor et al., 2018). In recent years, Ghana has consistently produced around 800,000 to 900,000 metric tons of cocoa beans annually which contributes to Ghana's position as one of the top cocoa producers in the world (Takyi et al., 2019). The cocoa industry plays a crucial role in Ghana's economy and provides livelihoods for many farmers in the country (Delgado-Ospina et al., 2021). Ghana has the perfect climate and soil conditions for cocoa cultivation, which is why it thrives here (Akrofi-Atitianti et al., 2018). The cocoa beans are harvested from the cocoa trees, and then they go through a process of fermentation and drying to develop their unique flavor (Cilas & Bastide, 2020). After that, the cocoa beans are sold to local cooperatives or companies, who then export them to chocolate manufacturers around the world (Cilas & Bastide, 2020). Ghanaian cocoa is known for its high quality and rich taste, making it a favorite among chocolate lovers. Cocoa farming also provides livelihoods for many farmers and their families in Ghana (Delgado-Ospina et al., 2021). It's an important source of income and employment in rural areas. The government of Ghana has implemented various initiatives to support cocoa farmers and ensure sustainable cocoa production (Delgado-Ospina et al., 2021). Ivory Coast produces the most cocoa in the world. It is the largest cocoa-producing country, followed by Ghana (Wainaina et al., 2021). Together these two countries account for a significant portion of global cocoa production. Cocoa farming is a vital part of their economies and cultures (Gateau-Rey et al., 2018). The cocoa industry faces sustainability challenges, including deforestation, child labor and low farmer incomes (Alho et al., 2021).

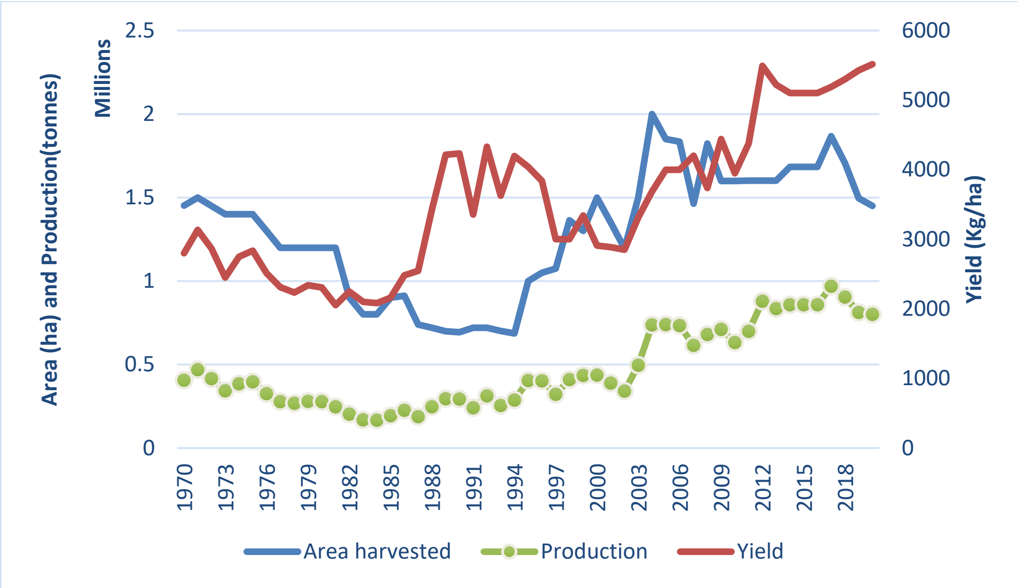


Figure 2.1 Trends of cocoa production (tonnes), area harvested (ha) and yields (kg/ha) in Ghana based on FAOSTAT, 2023

2.4.3 Cocoa expansion as a driver of deforestation

The West African Guinean rain forest (GRF), identified over 20 years ago as a global biodiversity hotspot, had shrunk to 113,000 km2 at the turn of the millennium, accounting for 18% of its original area (Gockowski & Sonwa, 2011). The expansion of extensive smallholder agriculture, predominantly cash crops such as cocoa, has been the primary driver of this environmental change (Gockowski & Sonwa, 2011; Saj et al., 2017). The global efforts to reduce climate change are negatively impacted by the expansion of cocoa into forests (Critchley et al., 2022). West Africa no longer has any frontier forests for future generations to exploit (Gockowski & Sonwa, 2011). Ghana's tropical rainforests store some of the most carbon of any ecosystem type, and when they are converted to cocoa, a significant amount of CO2 is released into the atmosphere (Critchley et al., 2022). Strategies in West Africa to reduce deforestation and conserve biodiversity must focus on shifting agricultural practices from traditional to modern science-based methods (Gockowski & Sonwa, 2011). Ghana's economy and the livelihoods of millions of smallholder farmers depend heavily on cocoa. Nevertheless, in the nation's High Forest Zone, including Forest Reserves, cocoa is a significant contributor to forest loss (Critchley et al., 2022).

2.4.4 Cocoa production systems

Cocoa production, which mostly in the forest regions in forest fragments (Mohammed et al., 2016), has traditionally been small scale and labor-intensive in Ghana, and native timber trees provide some shade. In Ghana and other West African countries, cocoa growing systems are made up of a variety of tree species and densities (Asare & Ræbild, 2016). Cocoa production is mainly in two different systems, based on the presence of shade trees. It comprises the monoculture cocoa production system (full-sun cocoa) and agroforestry cocoa production system (shaded cocoa). The monoculture cocoa system is a system for producing cocoa with little to no shade coverage (Critchley et al., 2022). In West Africa, true monocultures are uncommon because most cocoa fields contain a few other tree species. Cocoa hybrids that thrive in low- or no tree canopy coverage are necessary for monoculture systems when soil nutrients and pesticide (fungicide and insecticide) application are not constraints. High pest densities can be caused by physiological stress in unshaded cacao as well as the larger cacao area planted (Tscharntke et al., 2011).

On the other hand, agroforestry cocoa system is a system of production that include non-cocoa tree species and keep them healthy on the same land as cocoa (Critchley et al., 2022). These give cocoa trees shade, serve as a home for beneficial organisms, and give farmers access to additional resources. Given that the recommended practice for moving cocoa production toward a climate-smart path is agroforestry (Adams et al., 2021), the practice of incorporating valuable and appropriate trees into cocoa growing systems is common in smallholder cocoa farms (Asare & Ræbild, 2016). In Central Africa, the majority of cacao is still grown in low-input agroforests where cacao-related trees are traditionally valued by farmers (Saj et al., 2017). The ability of shaded-cocoa systems to capture atmospheric carbon dioxide (CO2) and store the carbon (C) in cocoa (*Theobroma cacao*) trees and soil, relative to other agricultural practices, has led to a significant increase in the role of these systems for mitigating and adapting to climate change (Acheampong & Dawoe, 2014). Shade, however, is only required for young cacao trees and is less important in older cacao plantations (Tscharntke et al., 2011).

There is no one model for their design and implementation; instead, local factors (like climate), historical extension service influences, and farmer needs and goals determine the species and planting density of shade trees (Critchley et al., 2022). A survey by Acheampong & Dawoe (2014) shows that farmers typically prefer shade trees with extra advantages, such as fruit and timber trees that bring in additional revenue, and those that improve their soil health and fertility. However, though trees like *Ceiba pentandra* (Onyina) are deep tap rooted and draw ground water, which benefits the cocoa, it was reported to promote “akate” (Capsids) in cocoa farms and are self-pruning, which can sometimes destroy the cocoa (Acheampong & Dawoe, 2014). Cocoa trees have shallow rooting system, and when growing cash crops like cocoa in agroforestry systems as compared to monocultures, farmers anticipate a decrease in yield because of competition for resources like water and nutrients (Niether et al., 2019). Niether et al. (2019) concluded that cocoa yield in agroforestry systems are lower than in monoculture systems due to the below-ground competition of soil nutrients between cocoa trees and shade trees, since the roots of the shade trees were located in the same soil space of the cocoa roots. Contrastingly, a research by Asare et al. (2019) shows that as the canopy cover of shade trees increased, yields dramatically increased as well. Comparing the medium shade level of cocoa agroforestry to the full sun, low shade, and heavy shade levels, the results of Nunoo et al. (2014) showed that the medium shade level uses less agrochemicals, supports biodiversity, and has a sustainable yield of about 500 $kgha^{-1}$ for over 70 years.

2.4.4 Ecological and economic importance of shade trees

Shade trees play a crucial role in both ecological and economic aspects. In agroforestry, these systems are long-term sustainable, contributing to biodiversity conservation and carbon storage (Saj et al., 2017). Agroforestry shade trees improve functional biodiversity, carbon sequestration, soil fertility, drought resistance, and weed and biological pest control (Franzen & Borgerhoff Mulder, 2007; Tscharntke et al., 2011). Also, they contribute to the conservation of biodiversity and ecosystem services, such as maintaining crop pollinators and reducing pest incidence (Barrios et al., 2018). In addition to increasing the amount of organic matter in the soil, preventing erosion, and controlling weeds, the application of shade tree leaves as mulch can enhance crop yields and quality (Heckman et al., 2022). Agroforestry techniques have the potential to reduce emissions associated with the carbon footprint (Ortiz-Rodríguez et al., 2016). Therefore, the presence and management of shade trees in agriculture are essential for both ecological sustainability and economic viability.

2.4.5 REDD+ Mechanism and relation with emission reduction and biodiversity

In addition to sequestering carbon, forests are hotspots for a wide variety of plant and animal species, exhibiting remarkable biodiversity (Buotte et al. 2020; Brockerhoff et al. 2017). Significant threats to biodiversity are posed by deforestation and degradation, which also contribute to habitat loss, species extinction, and fragmentation (Dennis 2018). While REDD+'s potential advantages are well acknowledged, questions have been raised about how well it will work to simultaneously advance biodiversity and climate change objectives. According to Busch et al. (2011), there exists a possibility for substantial co-benefits for biodiversity conservation via the REDD+ mechanism, which aims to decrease emissions caused by deforestation and forest degradation. Implementing REDD+ can reduce climate change while simultaneously protecting biodiversity (Harvey et al. 2010; Peterson et al. 2012). A framework that incorporates biodiversity data into strategic planning and evaluates biodiversity changes after REDD+ implementation is recommended by Gardner et al. (2012) as a means of incorporating biodiversity concerns into national REDD+ initiatives. This proposition is supported by van Asselt (2017) who emphasizes the significance of taking biodiversity concerns into account when developing REDD regulations under the UNFCCC, as well as the function of national and international regulations in guaranteeing that REDD helps to conserve biodiversity.

2.4.6 REDD+ in Ghana

With the goal of reducing or stopping carbon emissions from forests in the Global South, the growing global initiative known as Reducing Emissions from Deforestation and Forest Degradation (REDD+) was launched (Bayrak & Marafa, 2016; Lund et al., 2017). The program is founded on the idea of paying for environmental services, according to which forests' capacity to sequester carbon has a marketable value that can be covered by grants and other financial instruments (Santosa et al., 2015). Ghana began exploring REDD+ as a concept arising from international climate change discussions in the early stages of the concept. Ghana is a pioneer in the REDD+ initiative in West Africa, having been involved with it since 2008 when the country was enlisted to the REDD+ Readiness Program by the Forest Carbon Partnership Facility (FCPF) of the World Bank (Asiyanbi et al. 2017; Johnson 2021).

Ghana was able to secure funding from the FCPF to support the implementation of readiness activities starting in 2012 thanks to the submission and approval of a Readiness Plan Idea Note (R-PIN) and the subsequent approval of Ghana's REDD+ Readiness Preparation Proposal (R-PP), which serves as a blueprint for REDD+ readiness implementation and outlines the key processes, systems, and frameworks in 2010. The funding received for readiness preparation helped Ghana to set in place systems such as the National REDD+ Strategy, forest reference level, and safeguards information system while further work on National Forest Monitoring systems exist.

Ghana has chosen to implement REDD+ using a nested method, focusing first on the High Forest Zone and then scaling up to include the other three primary ecological zones of the nation, such as the Savanna Zone, through a phased programming approach. The suggested policies and initiatives aimed at tackling the causes of deforestation and forest degradation are bounded by distinct ecological boundaries and connected to the production and supply chains of important commodities. The National REDD+ Strategy which was launched in 2016 by the Ministry of Lands and Natural Resources through the Forestry Commission is meant to serve as a guide and framework for achieving REDD+ in a well-coordinated manner by pursuing a broad set of actions to tackle deforestation and forest degradation at the landscape level.

Asiyanbi et al. (2017) claims that the initial design of Ghana's REDD+ program outlined strategies to encourage and compensate independent demonstration and piloting efforts to a range of local stakeholders and non-state players. Nevertheless, supporters of the REDD+ program altered this approach in the finalized national strategy at the end of 2015. It was decided to use a landscape strategy instead of individual-based pilots.

Nukpezah and Alemagi (2020) point out that despite some obstacles in the areas of legislation and policy and institutional arrangement, progress has been made in the areas of Monitoring, Reporting and Verification (MRV) and audit, benefit sharing, finance, as well as demonstrations and pilots.

REDD+ not only helps combat climate change by reducing emissions but also contribute to the preservation of biodiversity (Angelsen, 2017).

2.4.6.1 Ghana Cocoa Forest REDD+ program

REDD+ initiatives often involve measures to preserve and restore biodiversity, ensuring that the rich natural heritage of Ghana is conserved (Newton et al., 2016). It provides incentives for countries like Ghana to protect their forests and prevent deforestation and forest degradation (Panfil & Harvey, 2016). This is done through various activities like sustainable land management, reforestation, and promoting alternative livelihoods for communities that depend on forests (Magnago et al., 2015). The implementation and development of REDD+ in Southwest Ghana have been significantly influenced by local players and global-local intermediaries, who have integrated aspects of pre-existing practices (den Besten et al., 2019). The Ghana Cocoa-Forest REDD+ program, the premier program under the REDD+ Strategy of Ghana seeks to significantly improve cocoa yields through the adoption of environmentally sound climate-smart practices to curb deforestation and forest degradation in cocoa landscapes whilst addressing other drivers of deforestation and forest degradation in Ghana's High Forest Zone (Forestry Commission of Ghana 2017a; Forestry Commission of Ghana 2016). It leverages the efforts of community members and farmers to desist from expanding into forest frontiers, illegal felling of trees, and other activities that contribute to deforestation of forest degradation. The program promotes cocoa agroforestry by the incorporation of trees on farms.

REDD+ brings several benefits to local communities in Ghana. Firstly, it helps to protect the livelihoods of communities that depend on forests by promoting sustainable land management practices. This ensures that they can continue to benefit from the resources provided by the forests, such as timber, non-timber forest products, and ecosystem services (Angelsen et al. 2012); Angelsen, 2017).

Secondly, REDD+ encourages the involvement of local communities in decision-making processes. This means that their voices are heard and their traditional knowledge and practices are taken into account when it comes to forest management (Palomo et al., 2019). It helps empower communities and promotes their active participation in conservation efforts (Gateau-Rey et al., 2018). REDD+ initiatives often include capacity-building programs and provide opportunities for sustainable economic development (Bayrak and Marafa, 2016). This can include training on sustainable farming practices, alternating income generating activities, and support for eco-tourism initiatives (Johnson, 2021). These efforts help to improve the quality of life for local communities while also conserving the forests.

Some examples of livelihoods promoted by REDD+ include sustainable agricultural practices, agroforestry and ecotourism (Palomo et al., 2019). These activities provide local communities with alternative sources of income that are environmentally friendly and help reduce the pressure on forests. Ghana's successful reforestation initiatives have highlighted the value of real local involvement and capacity building, offering possible models for REDD+ initiatives (Appiah et al., 2015). Ghana received its first results-based emission reduction payment under the Ghana Cocoa Forest REDD+ Program in 2023 from the Forest Carbon Partnership Facility of the World Bank (FCPF 2024). This was after the country had submitted a monitoring report and gone through validation and verification of the emission reductions with a third-party verifier. This achievement kicked started the benefit-sharing arrangement where the received funds needed to be equitably distributed to the various Hotspot Intervention Areas and beneficiaries such as the traditional authorities, community members, and the state agencies involved in the implementation of the program.

2.4.6.2 Benefit sharing arrangements and Social and environmental safeguards

It has been demonstrated that payments for environmental services, decentralized forest management, participatory management, and other forest partnerships help local communities while advancing the REDD+ goal (Behr et al., 2012). A range of studies have explored benefit sharing arrangements for REDD+. Achieving the proper incentives for all parties involved is also essential to the success of REDD+. This includes implementing policy measures like local forest use regulations and rights to forest lands (Behr et al., 2012). The significance of local partners is acknowledged by non-governmental organizations and international development partners, who continuously urge governments to incorporate equitable distribution of benefits and equity into their readiness preparation plans. According to the meta-analysis of Weatherley-Singh and Gupta (2015), most national and international indirect drivers of deforestation and forest degradation are not being targeted by specific REDD+ interventions and related benefit-sharing mechanisms at the project level, but a small number of local, direct drivers and a few regional indirect drivers are. They draw the conclusion that, as of yet, the expanding body of scholarly analyses of REDD+ projects do not provide compelling theories of change; that is, there is a dearth of attention to the ways in which the benefits of REDD+ could revolutionize the way that drivers act as catalysts.

Effective benefit-sharing mechanisms cannot be designed until the goals of REDD+ and benefit sharing are well defined, with a clear definition of "benefit" in place, given the diverse range of interests and rationales at play (Luttrell et al., 2013). Protecting against the detrimental effects on society and the environment that result from placing too much emphasis on these kinds of financial incentives has become necessary. A number of organizations have made voluntary efforts (initiatives) to develop principles, criteria, indicators, and guidelines in the context of safeguards in addition to the UNFCCC's official efforts (Iwanaga et al., 2017). Benefit-sharing is a crucial component of social safeguards, and further discussions are required to improve programs.

2.4.7 Factors influencing farmer adoption of climate mitigation interventions

Climate-smart agriculture is the adoption of sustainable and resilient practices in farming to address the challenges posed by climate change (Zabel et al., 2019). It involves implementing techniques that reduces greenhouse gas emissions, enhance productivity and promote adaptation and resilience (Stavert et al., 2018). Climate-smart agriculture focuses on practices such as agricultural conservation, agroforestry, efficient water management, soil conservation, and the use of climate-resilient crop varieties (Kenfack Essougong et al., 2020). By adopting these practices, farmers can mitigate climate risks, improve their livelihoods, and contribute to global efforts to combat climate change (Gateau-Rey et al., 2018).

Climate smart cocoa production refers to the implementation of sustainable and adaptive practices in cocoa farming to mitigate the impacts of climate change. It involves techniques that promote environmental stewardship, and ensure long term viability of cocoa farming (Takyi et al., 2019). The practices, as indicated earlier on, include agroforestry, water management, soil conservation, integrated pest management, and diversification. By adopting climate smart cocoa production, farmers can mitigate climate risks, improve productivity, and contribute to a more sustainable cocoa industry (Wainaina et al., 2021). Farmers are increasingly willing to adopt climate-smart cocoa production practices because they recognize the importance of sustainability and the need to adapt to changing climate conditions (Avane et al., 2022).

Planting shade trees alongside cocoa trees helps regulate temperature, conserve soil moisture and provide habitat for beneficial insects (Seto et al., 2020). Implementing efficient irrigation systems and water conservation techniques can help cope with changing rainfall patterns and reduce water usage (Zawiła-nied, 2023). Practices like mulching, cover cropping, and terracing help prevent soil erosion, improve soil fertility and retain moisture (Emmerson et al., 2016). Integrated Pest Management (IPM) is the process of using natural pest control methods, such as biological controls and pheromone traps, to reduce the need for chemical pesticides (Kenfack Essougong et al., 2020). Diversification is planting other crops alongside cocoa, like fruits or vegetables, to provide additional income sources and to reduce dependence on a single crop (Kenfack Essougong et al., 2020). These practices contribute to sustainable cocoa farming and help farmers adapt to the challenges posed by climate change.

2.5 Theoretical approach and Conceptual framework

2.5.1 Theory of land use change

The theoretical literature concerning land use change encompasses a diverse array of theories that explicitly focus on land use as the primary subject of theoretical inquiry (Briassoulis, 2020). Alterations in land use signify how households react to evolving needs and objectives, as well as how they adjust to shifting environmental, socioeconomic, and political conditions (Lambin et al., 2001). According to Briassoulis (2020) three major groups theories exist for landuse:

a. the urban and regional economics theorization tradition

b. the sociological (and political economy) theorization tradition, and

c. the nature-society (or, human-nature) theorization tradition.

On the basis of their representational approach, these groups are further differentiated. While the sociological tradition is interested in both the economic and social drivers of land use change, with differing degrees of emphasis on the two, the urban and regional economics theorization tradition is almost exclusively focused on the economic determinants of land use change. The lineage of nature-society theorization offers more thorough explanations of a range of drivers, while the relative emphasis varies according to the specific theoretical framework's chosen direction. Swift shifts in the pace or trajectory of land use change may arise from alterations in political, institutional, and economic conditions (Lambin, 2000). Land use change analysis, being inherently interdisciplinary, has led to the development of numerous analytical frameworks that integrate diverse theoretical and methodological approaches (Irwin and Geoghegan, 2001; Rindfuss et al., 2008).

This study adopts a realist standpoint, acknowledging that theories can shed light on both historical and current contexts and offer insights into future trends. Nonetheless, realism does not endorse the idea of a universal theory capable of predicting the future. In taking this perspective, this study associates with the Social Sciences-based theories under the Nature- Society Theorization tradition by Briassoulis (2020).

2.5.2 Conceptual framework

The relationship between human society and land use results in several dynamics that can be beneficial or detrimental to the environment. It is prudent to understand these dynamics which can inform policies, and actions and also provide reliable predictions. However, this is a difficult task because the relationship that exists between humans and their environment is complicated (Amadou, 2015). There are several systems that have been developed to understand these dynamics.

Land use decisions may have a significant impact on reducing greenhouse gas emissions in the atmosphere and assisting in the adaptation of climate change. By modifying the reflectance of the land surface, the effectiveness of evapotranspiration, and the release of biogenic gases into the atmosphere, changes in land cover can have an impact on climate. Cocoa cultivation has been responsible for the loss of millions of hectares of primary and secondary forests in recent decades, resulting in increased greenhouse gas emissions (Gockowski and Sonwa, 2011). This work associates with the framework as by Coral and Bokelmann (2017) in Figure 2.2 as it posits that decisions are strongly shaped by social constructions, values, and the individual history of each decision-maker. The actions and decisions at present could, in turn, impact the environment and its biophysical features, consequently influencing future decisions and system dynamics.

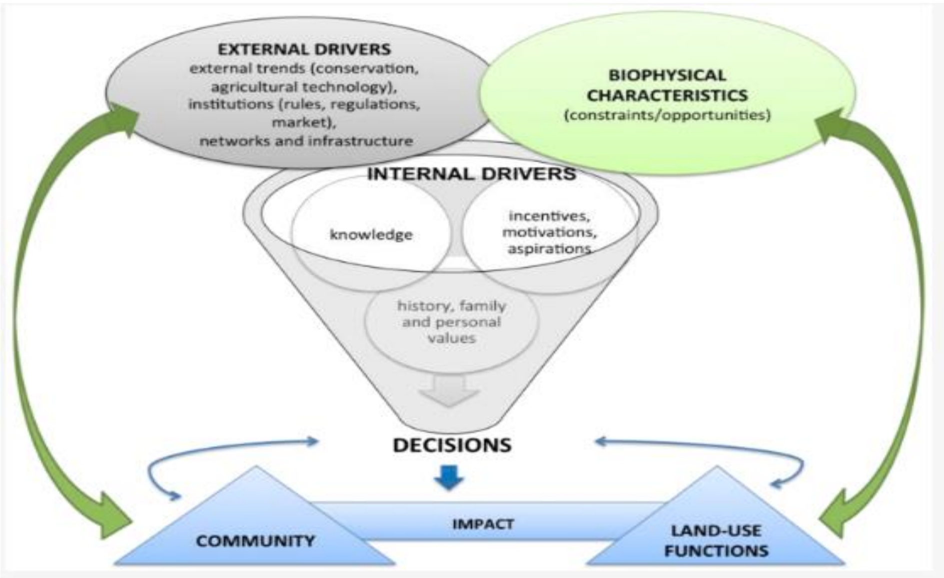


Figure 2.2: Framework for Analysis of Drivers and Dynamics of Historical Land-Use Changes (Source: (Coral and Bokelmann 2017)

Forests function as carbon sinks because of the biomass buildup in their stems, roots, and mature soils, which removes carbon from the atmosphere. Changes in forest cover, such as clearing forests for agriculture and bushfires, can release carbon into the atmosphere and turn forests into sources of emissions (Rhemtulla et al., 2009). Land use transformation from one landcover type with different levels of carbon stock to another land use emits the carbon stored in trees, vegetation and soil into the atmosphere and affects biodiversity and ecosystem services (Sedjo and Sohngen, 2012).

The concept for this study is associated with the land-use transition curve and carbon stock presented in Figure 2.3, that the agricultural landscape presents an opportunity to increase carbon stocks and biodiversity that in the long run will mimic the primary forest but only when the people in the landscape are willingness and incentivized to participate in the program.

The land use transition curve has generally mirrored shifts in demographic patterns and economic progress. Understanding the relative significance of actions for forest conservation and restoration in various places is made easier with the use of the forest transition model (Chazdon et al. 2017). Diverse pathways along the curve can result in less-than-ideal outcomes for rural communities and societal resilience. Tree cover loss, in particular, can lead to shortcomings in forest-based livelihoods and the delivery of environmental services. The change in land use reflects the decline of natural habitats in preceding years.

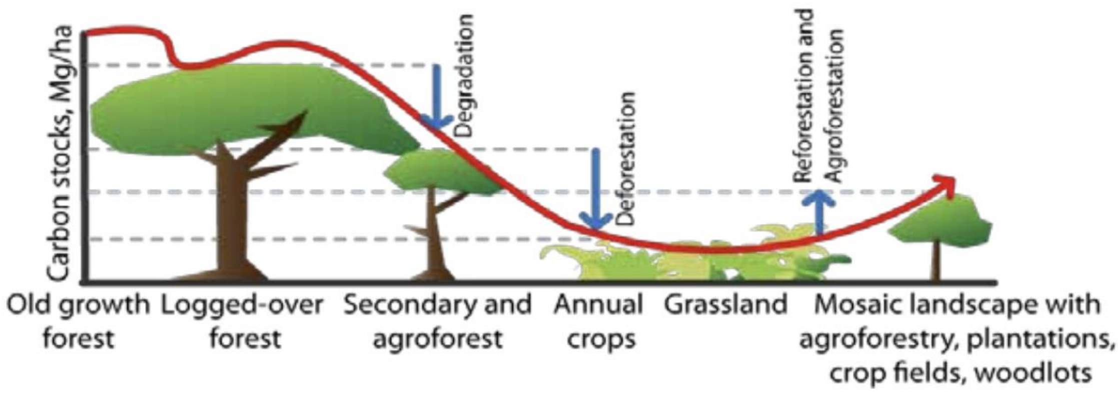


Figure 2.3: The Forest/ Land use transition curve

Source: (CIFOR, ICRAF, CGIAR, Biodiversity and CIAT 2011 2011)

The systems found in the initial phase of the curve, also known as old growth, climax, or pristine forest, are usually found in isolated locations. The state claims these forests for industrial forestry or biodiversity preservation. Secondary forests are created when these forests are degraded due to human needs for building materials, firewood, and agricultural land. These forests may also be beneficial for actively sequestering carbon. Their protection requires specific policies, governance solutions, and incentives (benefit-sharing arrangements).

The implementation of agroforestry techniques presents a chance to enhance biodiversity and carbon sequestration on previously agriculturally converted land. Studies conducted in the cocoa sector indicate that increased biodiversity and shade levels lead to better yields. Under REDD+, Ghana's mosaic cocoa forest ecosystem offers a promising chance to boost carbon sequestration while sustaining agricultural productivity and livelihoods. The Reducing Emissions from Deforestation and Forest Degradation (REDD+) mechanism has brought increased attention to the role of forests as sinks and sources of emissions. In essence, it is a performance-based system that offers incentives to forest users and owners to raise carbon removal rates and lower emissions. Concerns regarding the strategy of forest management for carbon sequestration at the expense of numerous benefits of forests, including biodiversity. This has given rise to the importance of safeguard mechanisms and principles for REDD+ projects. Reducing deforestation and forest degradation, along with the conservation of mature or pristine forests, however, would maintain higher carbon stocks and biodiversity. Restoration of deforested or degraded land can also enhance active carbon sequestration

Farmers' adoption of climate-smart agriculture (CSA) is a major factor in agricultural growth sustainability in terms of economic, environmental, and social development. Farmers' decisions regarding production systems and the incorporation of agroforestry cocoa systems, including the addition of trees on farms for carbon sequestration, are influenced by various factors. According to Kifle et al. (2022), the adoption of climate-smart agriculture (CSA) practices is affected by factors such as farming system, farm size, access to irrigated farms, access to extension services, distance to marketplaces, and access to weather information.

After more than a decade of REDD+ journey in Ghana, an assessment of the potential transformation under REDD+ compared to Business-As-Usual scenarios is necessary to ascertain the impact of REDD+ in improving carbon stocks and biodiversity and the willingness of the forest fringe communities in the landscape to support the initiative going forward under the premier REDD+ program dubbed the Ghana Cocoa Forest REDD+ Program.

2.6 Materials and Method

2.6.1 Research approach

Iterative steps from the project proposal stage, fieldwork, thesis writing, and defense comprised the research workflow. A detailed evaluation of the scientific literature covering the five primary topics of the study was the first step in the process. Spatial methodologies for mapping land use, the cocoa business in Ghana, cocoa production systems, national REDD+ policies, carbon stocks and emissions, biodiversity, and agroforestry systems were among the subjects considered in the literature review. Based on the significant research gaps identified by the literature assessment, the research problem and objectives were established. A study area that permits all aspects of the research subject to be studied was chosen following the pre-site selection assessment. The fieldwork took place between January to July 2021 in the Assin South and Kakum National Park area. Permission was sought and granted by the Wildlife Division of the Forestry Commission for entry into the National Park which is a strictly prohibited area for line cutting and plot demarcation in an attempt not to open the Park up for easy access and poaching activities. Wildlife officers accompanied the research team to the National Park during data collection to ensure our safety. Logistics for the fieldwork included a vehicle, linear tapes and a compass, base maps from unsupervised classification, Global Positioning System (GPS), diameter tapes, a hypsometer, etc. Data entry and cleaning followed after the field data collection to enhance accuracy and get all data in their right formats for analysis. Species not identified in the field were also worked on with the help of the herbarium created during the fieldwork which was sent to the Forestry Research Institute of Ghana and the Forestry Commission Resource Management Support Centre for identification. Spatial analysis on land use maps, carbon and biodiversity analysis and socio-economic analysis followed after the data cleaning.

2.6.2 Study area

The study was conducted in the Assin South district of Ghana. It forms part of the Kakum Hotspot Intervention Area (HIA) as one of the nine earmarked HIAs for the Ghana Cocoa Forest REDD+ Program (GCFRP) implementation in the high forest zone of the country. The Kakum HIA which is situated in the Central Region of Ghana is composed of two administrative districts, namely Assin North and Assin South and contributes to 3.7% of the total land area of the GCFRP.

Selection of research areas

Brahabebome, Assin Adiembra and Assin Kruwa communities were selected for the study based on three considerations. Firstly, the distributions of these communities around the Kakum national park. To obtain a fair representation of the outcomes, the communities were selected at the North West (Brahabebome), Northern (Assin Adiembra), and the South West (Assin

Kruwa) of the National park. Secondly, the evidence of implementation of REDD+ through both the government and private sector partners of REDD+ was considered for the communities. The third element of consideration was the size of the community for the distribution of the samples to represent each community. Stratified random sampling was applied in this case where a community is selected on the stratification of geographical location in relation to the National Park, the size of the community and the evidence of engagement on REDD+.

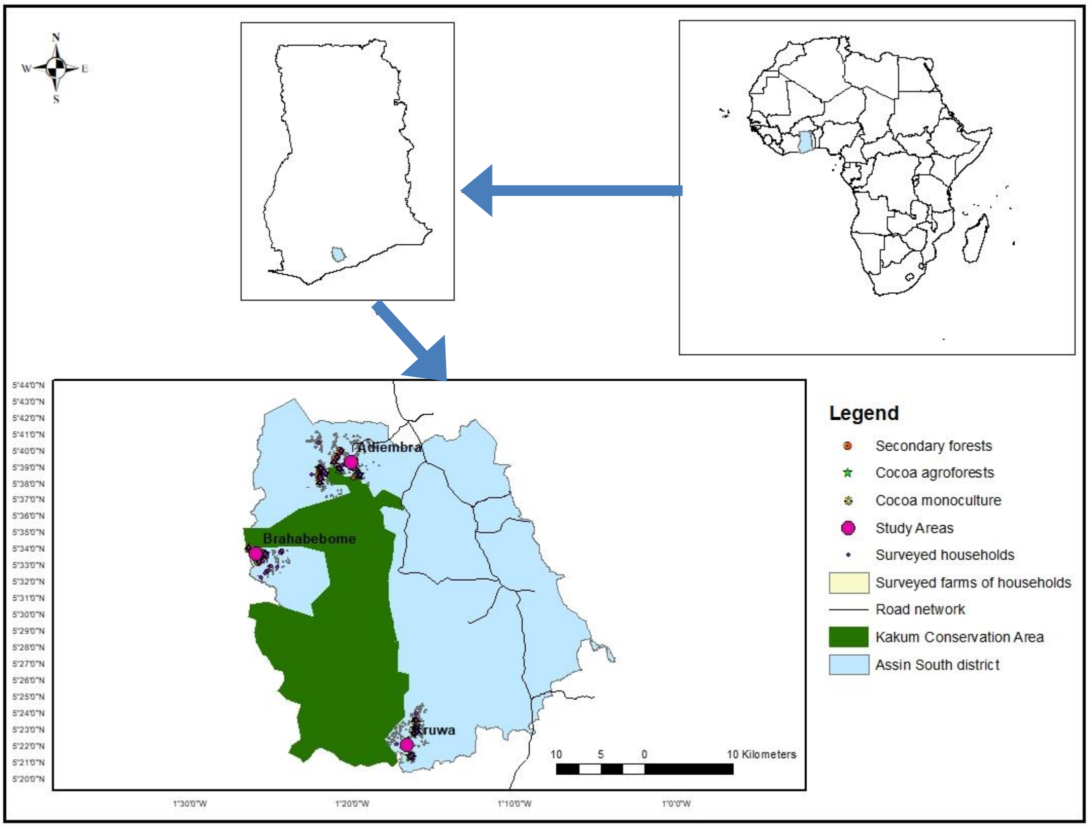


Figure 2.4. Map of Study Area

The sizes considered small community, medium community and large community based on the 2010 census data for the district. The sizes were considered because it was assumed that diversity in income activities increases as the size of the community increases.

Climate

The Assin South district falls within the moist evergreen and semi-deciduous forest zone experiencing a bi-modal rainfall pattern, with the major rainy season beginning in April and lasting until July, and the minor rainy season beginning in September and lasting until November. The average monthly rainfall between 1960 and 2019 peaks in June with 266 mm in the major rainy season with an average of 17 days of rain according to rainfall data recorded at the Birimso-Kakum Meteorological station of Ghana.

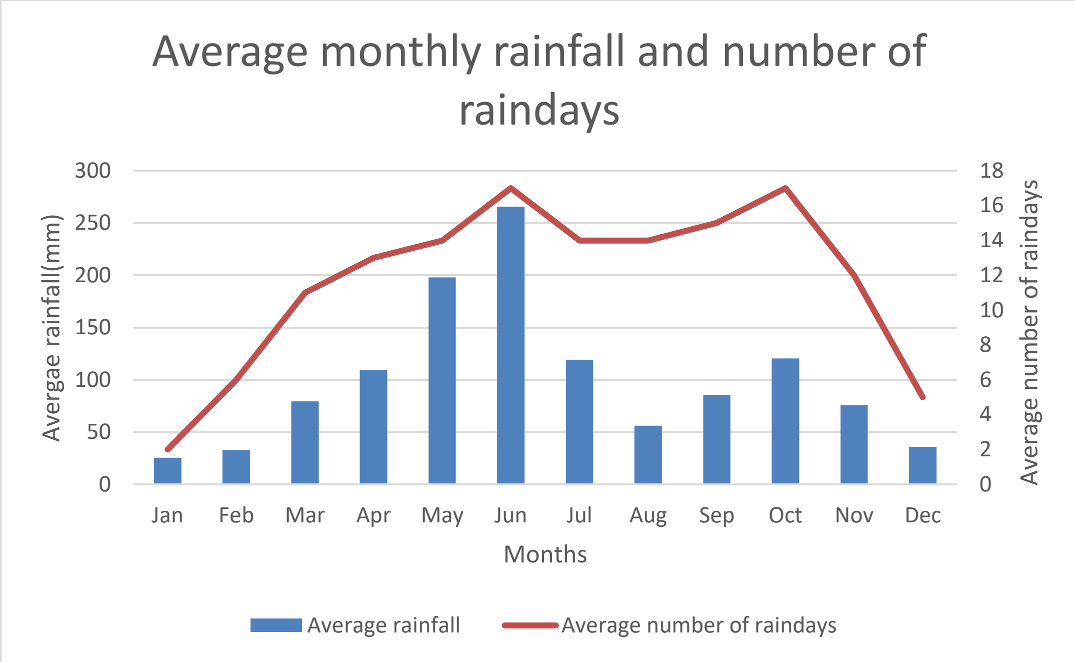


Figure 2.5: Average monthly rainfall and number of rain days (Source: Ecolimits 2020)

Average temperature is observed to be highest between February and May in the period between June 2014 to March 2018 as recorded by Ecolimits 2020

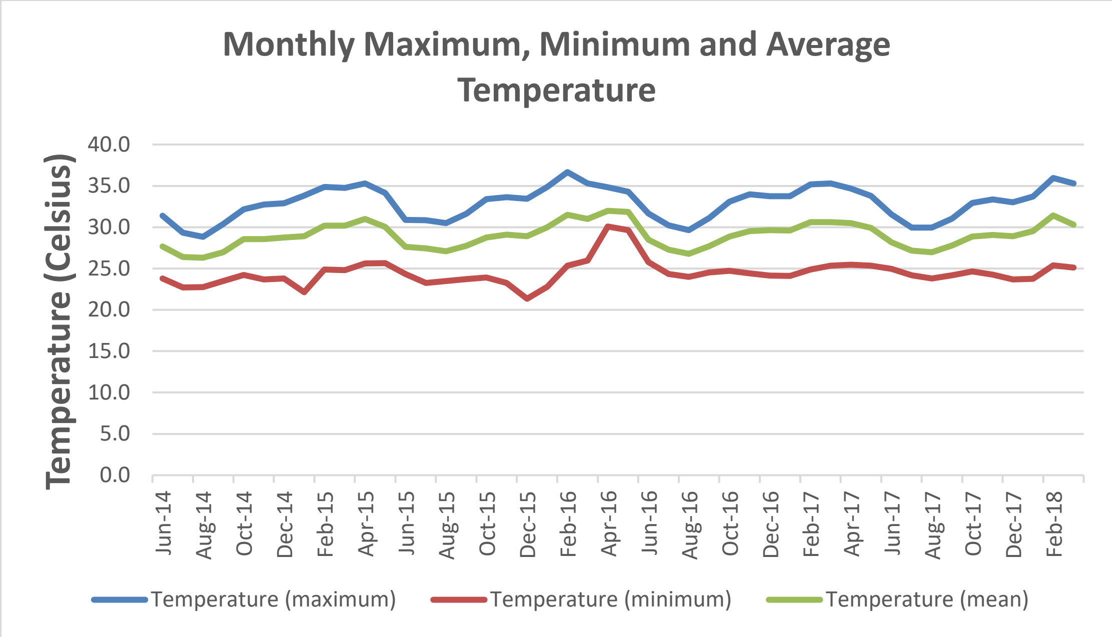


Figure 2.6: Monthly maximum and average of temperature in study area (Source: Ecolimits 2020)

Soils

The soils of the Kakum conservation area is predominantly Lixisols with a higher clay content in the subsoil than in the topsoil as a result of pedogenetic processes leading to an argic subsoil which has a cation exchange capacity of less than 24 cmol(+) kg-1 clay at least in some part of the B horizon and a base saturation of more than 50% (Food and Agriculture Organization of the United Nations 1988). Silt from alluvial erosion processes, clayey soils, and loamy soils make up the majority of soil types. Numerous mineral resources that could be developed are present in the district. Rock and stone deposits, as well as gold deposits, are found in the district. Adiembra, Bosomadwe Camp, Ongwa, and other places have quarry deposits (Ghana Statistical Service 2014).

Relief and drainage

The geography of the area is undulating, with an average height of 200 meters above sea level. Numerous rivers and streams, including the Kakum, Wanko, Ochi, and Kyina, drain the territory. Swamps are also abundant in the area, offering opportunities for dry-season vegetable and fish production (Ghana Statistical Service 2014).

Vegetation cover

In the majority of the forest reserves are lush, evergreen vegetation cover with tree species such as Wawa, Mahogany, and Odum. Raffia and bamboo are the primary vegetation in the swampy areas of the district. Ayensua, Krotoa, Apeminim, Atendansu are the forest reserves in the district while Kakum is a national park managed by the Wildlife Division of the Forestry Commission of Ghana.

3.0 CHAPTER THREE: CARBON STOCKS DYNAMICS AND SPECIES DIVERSITIES IN COCOA LANDSCAPES

3.1 Introduction

Climate shifts are caused by changes in land usage (Jakovac et al., 2023; Steffen et al., 2015). A few of the human-driven activities causing these changes in land use are mining, urbanization, and agriculture. Due to the greenhouse gases (GHGs) released into the atmosphere as a result of these activities, our ecosystem becomes unbalanced, leading to global warming and a change in climate, a major concern on the political agenda worldwide (IPCC, 2014, Olorunfemi et al., 2019, 2020).

In light of this, most studies on carbon stocks, such as Mesa-Sierra et al. (2022) and Soto-Navarro et al. (2020), have confirmed that the trend of carbon stocks is negative. It is disheartening that this trend is driven by human demands. As the adoption of strategies to help mitigate these global issues increases, the quantification of biomass and carbon being held in different landscapes is challenging, but very informative and also urgently needed so that their contribution can be accurately assessed (Calderón-Balcázar et al., 2023; Mesa-Sierra et al., 2022). This has pushed governments and businesses at the local and international levels to commit to generating policy mechanisms and funding for climate change initiatives like forest-based natural climate solutions (REDD+ and carbon sequestration payments) (Mesa-Sierra et al., 2022).

Most of these global agreements, recognized by multiple countries, have established goals that require the participation of terrestrial ecosystems

(Anderegg et al., 2020; Soto-Navarro et al., 2020). These endeavours are aimed at these ecosystems because they currently absorb approximately 30% of human-generated carbon emissions each year. Forests, in particular, play a crucial role in this absorption, accounting for an estimated 8.8 Pg CO2e per year out of a total land carbon uptake of 9.5 Pg CO2e per year between 2000 and 2007 (Anderegg et al., 2020; Friedlingstein et al., 2022; Pugh et al., 2019). Additionally, many forest-based approaches are expected to offer significant benefits for biodiversity, ecosystem services, and conservation (Anderegg et al., 2020; Griscom et al., 2020).

Land use transitions not only impact carbon stock change but also negatively affect the variety of species of the land. Human activities have led to significant depletion and degradation of high biodiversity areas such as forests and wetlands (Appiah-Badu et al., 2022; Bentsi-Enchill et al., 2022; Ganivet & Bloomberg, 2019). Forests are crucial as they host a substantial proportion of the world's biodiversity (Appiah-Badu et al., 2022; Davies et al., 2021; Ganivet and Bloomberg, 2019; Gatti et al., 2017). Studies reveal that intact forests exhibit greater species diversity compared to degraded forests and transitioned forests, including those transformed into plantations (Gatti et al., 2017; Ifo et al., 2016; Watson et al., 2018). This implies that the greater the diversity of tree species in a forest, the better it is at sequestering carbon and mitigating greenhouse gases in the atmosphere. In other words, a decrease in biodiversity can significantly impair a forest's ability to withstand the effects of climate change. As a consequence, REDD+ projects can be severely affected, and their effectiveness can be significantly reduced. (Hinsley et al., 2015).

Extensive research has revealed that human activities have had a detrimental impact on the Earth's many landscapes and carbon-sequestering abilities, particularly within tropical forests (Mesa-Sierra et al., 2022). In Ghana, deforestation caused by cocoa production has occurred at an alarming rate, leading to a decrease in carbon storage and biodiversity (Kouassi et al., 2023; Kroeger et al., 2017; Slavin, 2023). To combat this issue, the government, REDD+ stakeholders, European Union Deforestation-free Regulation (EUDR), and other interest groups are working together to devise strategies to reduce the impact of deforestation, not solely driven by cocoa, but in general. Their goal is to improve the carbon stock capabilities of the landscape and simultaneously enhance its species diversity (Ashiagbor et al., 2022; Earthworm, 2023). One of the strategies currently being considered is the Forest Investment Program. The program aims to restore forest cover and contribute to carbon enhancement, regreening, and reducing emissions in the forest-savanna transitional zone of Ghana (African Development Bank, 2016; Kumeh et al., 2019). Sustainable land-use practices, such as plantation forestry, are being promoted under this program. However, despite these efforts, forest restoration activities through the promotion of forest plantations have yet to achieve their goal of reforesting the landscape and hence enhancing carbon stocks and improving or even maintaining the biodiversity of the area (Appiah et al., 2015).

In Ghana, there has been exploration of the potential benefits of agroforestry systems for carbon mitigation, much like in the case of forest plantation development and tree crops. By converting lower carbon stock land uses or covers to higher carbon stock alternatives, agroforestry has shown promise in enhancing carbon storage (Dawoe et al., 2016; Asante et al., 2017). Studies have revealed that planting trees intermittently with crops can facilitate this process (Apuri et al., 2018; Asante et al., 2017; Wade et al., 2010). As such, the adoption of cocoa agroforestry by farmers in Ghana could play a significant role in boosting carbon stocks and supporting the implementation of REDD+ (Asante et al., 2017).

These interventions in addition to various land use changes have birthed a very heterogeneous landscape with different carbon stock potentials. The mosaic of the cocoa landscape has several different land uses that have different carbon stock values. Precisely gauging and quantifying changes in carbon storage is critical for evaluating the consequences of land-use changes and land-cover changes. Environmental factors that may be impacted by climate change, such as temperature, precipitation, soil moisture, and pH, can significantly affect carbon sequestration and should be considered in climate change mitigation assessments (Mesa-Sierra et al., 2022). However, continuously monitoring carbon storage over time is essential for developing effective landscape management plans and conservation strategies that boost carbon sequestration in human-altered landscapes.

Numerous studies have delved into the intricacies of carbon stock dynamics both within and beyond the cocoa landscape. The majority of these studies have honed in on the sequestration potential of agroforestry systems, specifically aboveground carbon stocks in trees, tree crops, and other crops (Afele et al. 2021; Asase and Tetteh 2010; Asigbaase et al. 2021; Dawoe et al. 2016; Mohammed et al. 2016). Of all tree crops, cocoa has received the most attention (Afele et al. 2021; Asase and Tetteh 2010; Asigbaase et al. 2021;

Dawoe et al. 2016; Mohammed et al. 2016). However, Ashiagbor et al. (2022) have recently explored how land-use conversions related to cashew lead to carbon accumulation in the forest-savannah transitional zone. While carbon stock dynamics have also been scrutinized in other land use and cover types such as tropical woodlands (Aabeyir et al. 2020); old plantations, secondary and primary forests (Brown et al., 2020); and teak plantations (Kumi et al., 2021), no studies have yet compared the sequestration potentials of the different land use and cover forms in the landscape. The study will further establish correlations between tree parameters and carbon storage.

Efforts to mitigate climate change largely involve discovering methods to augment carbon sequestration. Unfortunately, there is limited understanding of the varying capacities of different land use systems in sequestering carbon through biomass accumulation in Ghana's cocoa landscape. This lack of information on the accumulation and reduction of biomass due to land use change hinders the reliable and precise estimation of biomass carbon stocks (Olorunfemi et al., 2019). The study aimed to examine the species diversity and carbon sequestration levels in the agricultural landscape of the GCFRP.

Specifically, the objectives are to:

1. Analyse the species diversity of primary forests, cocoa agroforests, and secondary forests.

2. Estimate the aboveground carbon stocks of four landuse types – cocoa monoculture, cocoa agroforest, secondary forest, and primary forest

3. Estimate Trees on Cocoa farms' contribution to the basal area and carbon stocks of cocoa agroforests

3.2 Methodology

This research was conducted in the Assin South district of Ghana in the Kakum hotspot intervention area of the Ghana Cocoa Forest REDD+ Program which houses the Kakum National Park and has the other landuses of interest. The National park was used as the reference point to distribute sample plots representatively (North, East and South, the west side of the Park was not considered as that falls outside the study area). The landuse were classified based on their level of growth or maturity (old representing 20 years plus, matured representing 11-20 years and young representing 3-10 years of growth) with the exception of the Primary forest. In all, 75 plots were used for the study as described I Table 3.1.

Table 3.1 Sample plots per land-use type and age

Land use	Category	Age (years)	Number of plots
Cocoa agroforest	Young cocoa farm	3 to 10	9
	Mature cocoa farm	11 to 20	9
	Old cocoa farm	20 +	9
Cocoa monoculture	Young cocoa farm	3 to 10	9
	Mature cocoa farm	11 to 20	9
	Old cocoa farm	20 +	9
Fallow/ Secondary forest	Young growth	3 to 10	6
	Matured	11 to 20	6
	Old (sacred groves)	20 +	6
Primary forest (Ka-kum National Park)	Old natural forest		3
Total			**75**

3.2.1 Plot selection for biomass data collection

Selection criteria was based on farmers/landowner's willingness to support research, landowner's knowledge of the secondary forest and farm age and an appropriate distribution and representativeness of ages. The information on age was cross-validated using important historical events and through triangulation via interviews with a number of community members in each village or community. Only stands with similar topography, drainage was included.

3.2.1.1 Plot layout

Plot sizes of 100 m x 100 m were laid in the primary forests, secondary forest, and cocoa agroforests within which trees with diameter at breast height greater than 5 cm were measured and the various species enumerated. A nested plot of 25 m x25 m was laid within the 100 m x 100 m to measure all cocoa trees within the cocoa agroforests. For cocoa monoculture plots, only the 25 m x25 m was laid for measuring the cocoa trees.

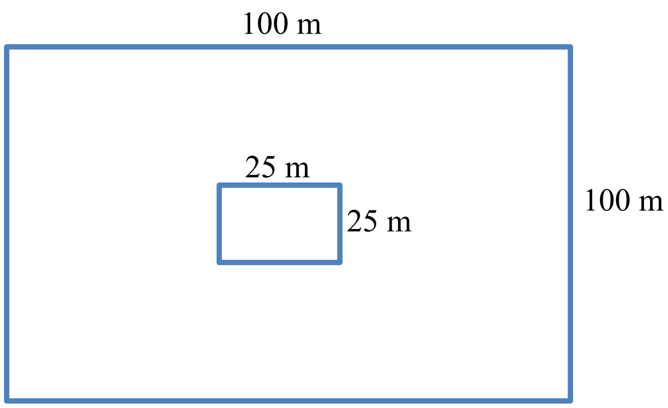


Figure 3.1: Plot layout for tree measurement

3.2.1.2 Data collection

Shade trees within cocoa farms were measured on the main plots with cocoa stems measured in the sub-plot. Identification of species was done by using the exudates of the tree, smell or colour of bark by the experienced botanist from Forestry Commission.

Within each plot, the Nikon Forestry Pro laser rangefinder was used to measure the height of trees and diameter tapes were used for measuring diameter at breast height (DBH) of trees ≥5cm and Spiegel Relaskop for buttressed trees. Lianas and shrubs were excluded from diameter and height measurements.

3.3 Data Analysis

3.3.1 Tree diversity analysis

Species and family importance value index were calculated for the various species identified. This was done as according to Addo-Fordjour et al. (2009) by adding the relative density of each tree and species and their respective relative frequency and relative basal area.

To estimate the diversity of the different landuses under study, the Shannon-Wiener species diversity index which considers the evenness and abundance of the occurring individual species was used (Spellerberg and Fedor 2003).

The formula for the Shannon-Weiner diversity index (H') used is as below (Equation 3.1):

$$H = -\sum_{i=1}^{S} p_i \ln p_i \qquad \text{……………………………………………………… 3.1}$$

Where

H= the Shannon-Wiener index;

pi= the proportion of individuals belonging to species I;

ln=the natural log (i.e., 2.718);

S= total number of species in the community (richness).

To compare the similarity between the different plots and land uses, the Jaccard's index of similarity (*I*) was calculated for each age class and land use type (Real and Vargas 1996)

The equation for the Jaccard index is as below (Equation 3.2);

$I = (a/ a + U_x + U_y)$………………………………………….. 3.2

Where

a = number of species shared by plot X and Y;

U_x= number of species exclusive to plot X;

U_y= number of species exclusive to plot Y.

The degree of species composition similarity between the various landuse categories was also evaluated and compared pairwise using Sørensen's Similarity Index (SSI) equation (Equation 3.3):

SSI = 2 M/ (2 M + N)……………….. 3.3

where M = number of species common to both plots under comparison and N is the sum of the exclusive species to the plots under comparison.

The Genetic Heat Index (GHI) was utilized to evaluate the conservation value of the trees found in the forests and cocoa agroforests (Abu-Juam and Hawthorne 1995)

Each plot's GHI was determined using the formula below (Equation 3.4):

GHI = [((BK × BK weight) + (GD × GD weight) + (BU × BU weight) + (RD × RD weight) + (GN × GN weight))/ (BK + GD + BU + RD + GN)] × 100 ……………………… 3.4

Where:

BK = number of black star species;

GD = number of gold star species;

BU = number of blue star species;

GN = number of green star species;

RD = number of red, scarlet, and pink star species.

An area with a high genetic diversity index (GHI) is considered particularly rich in uncommon species, meaning that any loss or deterioration of the area may result in a substantial loss of genetic resources (Brown et al. 2022). For the different conservation classes, the GHI values are as follows: low conservation value (50 < GHI <100), moderate conservation value (100 ≥ GHI <150), very high conservation value for GHI > 200, high conservation value (150 ≥ GHI <200), and very low conservation value (GHI < 50) (Hawthorne 1996). The species' star ratings were used to calculate the GHI (every species is given a star category according to how uncommon it is both locally and globally, with additional weights taken into account for the taxonomy and ecology of the species) (Brown et al. 2022).

Table 3.2: Index for Genetic heat of the various star categories of species

Star category	Weight for GHI	Remarks
Black (BK)	27	Species that are either near-endemic or native to Ghana. Seldom seen worldwide, and scarce in Ghana at the very least. Population conservation needs to be given urgent attention.
Gold (GD)	9	Quite uncommon both locally and globally. Endangered and rare forest endemics in Guinea and the Guineo-Congo. It is inevitable that Ghana will have some responsibility for preserving these species.
Blue (BU)	3	Forest endemics from Guinea and the Guineo-Congo, which are common elsewhere but uncommon in Ghana, or vice versa. Ghana might benefit from focusing on the preservation of some of these species. .
Scarlet (SC)	1	Common, but severely threatened by over-exploitation. Reducing exploitation is necessary to ensure the sustainability of consumption. Protection is essential on all fronts.
Red (RD)	1	Prevalent, but under threat from extensive exploitation. Require cautious management, some tree-by-tree, and area protection.
Pink (PK)	1	Common and moderately exploited.
Green (GN)	0	Widely distributed, undisturbed species of tropical, pantropical, and Guineo-Congolian Africa. Not especially concerned with conservation.

Source: adapted from (Brown et al. 2022; Abu-Juam and Hawthorne 1995)

3.3.2 Aboveground biomass and Carbon Stock Estimation

Estimation of the above-ground biomass (AGB) was based on three variables, namely DBH, tree height, and wood density, using the allometric equation of the pantropical model by Chave et al. (2014):

The formula (Equation 3.5) for calculating above-ground biomass(kg) is

$$\mathrm{AGB} = 0.0673 \times (\rho \mathrm{D}^2\mathrm{H})^{0.976} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ 3.5$$

Where

D = diameter at breast height (cm),

H = tree height (m), and

ρ = wood density (g cm^{-3}).

The global Wood Density database of the World Agroforestry Centre provided the specific wood densities of the various tree species (Zanne et al. 2009).The dry matter conversion from AGB to carbon was made possible by using the carbon fraction of 0.465 as recommended by (Martin et al. 2018).

Basal Area

The stand basal area (m^2 ha^{-1}) for each plot was calculated through the addition of the cross-sectional area of the individual trees per plot. The mean for the land use per age class was determined through the average of the different plots per age class for the particular land use.

The Basal Area (*BA*, m^2 ha^{-1}) is given as (Equation 3.6);

$$BA = \sum_1^n \frac{\pi D_i^2}{4} \times \frac{10000}{A} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ 3.6$$

Where

D is DBH,

A (m^2) is the area of the plot,

n is the number of trees in the plot.

Timber volume

Timber volume was calculated following the method as described in Brown et al. (2020) and as calculated by the Forestry Commission of Ghana. Before volume computations, the buttress height of 0.5 m was deducted from the merchantable height (Equation 3.7)

$$Timber\ volume = (0.00007857\ x\ DBH\ ^{2})x\ Hm\ x\ 0.6093 \quad \ldots\ldots\ldots\ldots.. 3.7$$

where

DBH = diameter at breast height and

Hm = merchantable height

3.3.3 Statistical analysis

The Silva metricus software, Microsoft Excel 2010, the R statistical package version 3.0.3, were used for all data analysis.

In order to determine if the means of the variables for the basal area (BA, $m^2\ ha^{-1}$), tree density (N/ha), and aboveground carbon (AGC) were significant, two-way analysis of variance (ANOVA) tests were performed. The independent variables were land usage and age.

3.4 Results

3.4.1 Stand structure

The recorded number tree stems per hectare for the various age classes per landuse showed a reduction in the number of trees per hectare as a landuse ages from class 1 through to class 3.

Table 3.3 Number of tree stems per hectare (N/ha) for the different land uses and age classes

Landuse	Cocoa agroforests			Cocoa monoculture			Secondary Forest			Primary forest
Variable/Age class	1	2	3	1	2	3	1	2	3	3
Max	1537	1693	1710	2464	2080	2272	1552	1200	864	833
Min	872	797	716	896	800	640	192	304	480	672
Mean	1295	1257	1138	1429	1340	1063	843	797	627	774
Standard deviation	202	304	372	547	354	471	500	312	149	89

Stem density was significantly different among the landuse but was not significant between age class.

3.4.2 Basal Area

Basal area was significant across landuses and age. Though the primary forest stem density was low between 672 to 833 compared to higher ranges of number of stems for cocoa monoculture, cocoa agroforests and secondary forest, it still had higher basal areas than the above landuses.

The basal area for both cocoa agroforest and secondary forest increased significantly with age but the differences of basal area in monoculture cocoa was very marginal with the range between 11.98 m^2ha^{-1} and 13.5 m^2ha^{-1} from age class 1 to age class 2. With a mean basal area of 39 m^2ha^{-1}, the primary forest recorded the highest amongst the landuses. The cocoa agroforest had basal area ranging from 13.42 m^2ha^{-1} for the young agroforest to 20.6 m^2ha^{-1} for the old cocoa agroforest. Secondary forests had basal areas of 6.8 m^2ha^{-1} and 17.8 m^2ha^{-1} for young and old forests respectively.

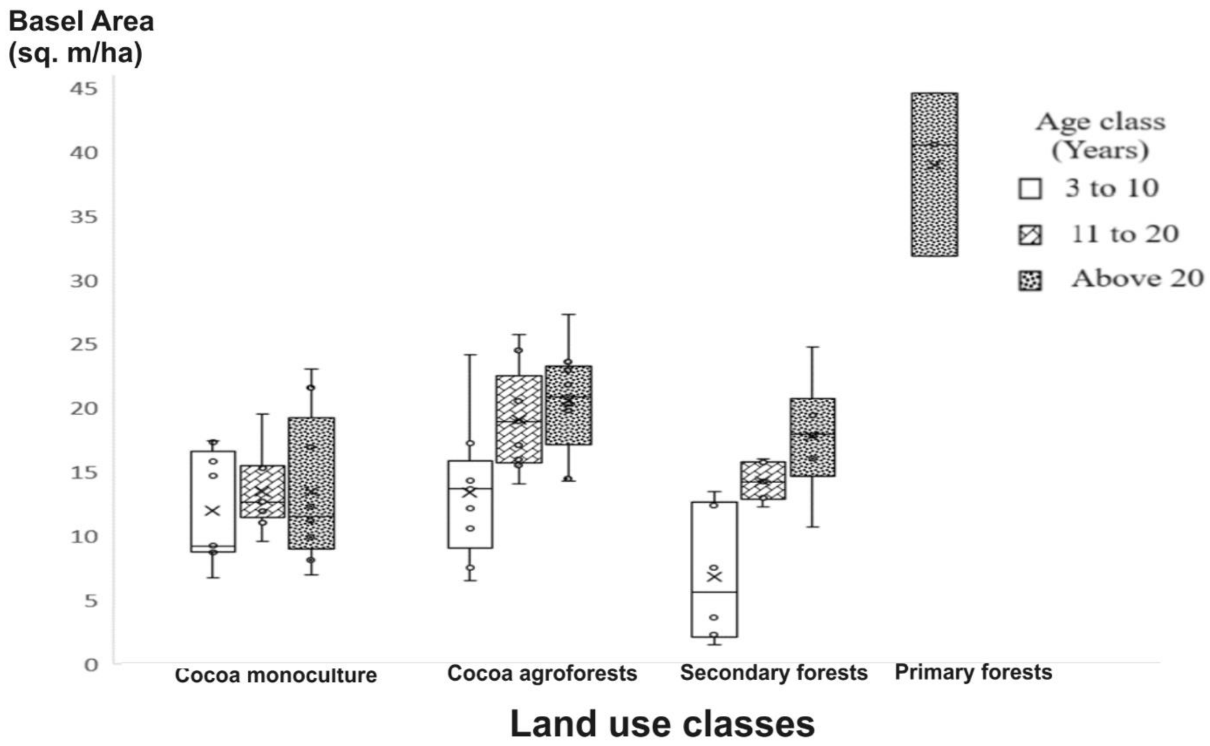


Figure 3.2 Basal area for the different land uses

3.4.3 Aboveground Carbon stocks per landuse

The results obtained showed that mean carbon stocks in the primary forest is higher (154.78 $MgCha^{-1}$) than in cocoa monoculture (11.23 $MgCha^{-1}$), cocoa agroforest (29.01 $MgCha^{-1}$), and secondary forest (30.95 $MgCha^{-1}$).

Table 3.4 Aboveground carbon $MgCha^{-1}$ for the different land uses and age classes

Land use	Cocoa agroforests			Cocoa monoculture			Secondary Forest			Primary forest
Variable	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**	**3**
Max	32.12	51.06	73.55	15.24	17.62	20.36	35.20	50.48	70.17	176.93
Min	7.66	19.20	14.76	5.49	7.71	5.54	2.98	21.90	19.36	133.17
Mean ($MgCha^{-1}$)	18.70	30.57	37.78	10.07	11.57	12.05	15.00	33.55	44.31	154.77
Standard deviation	8.88	10.19	17.65	3.91	3.14	5.51	13.46	12.30	16.56	21.89

The aboveground carbon within cocoa monoculture were mostly similar between plots of same age category with lower standard deviation. Also, standard deviations were high within age category 3 of both cocoa agroforests and secondary forests as the minimum stocks were less than 20 $MgCha^{-1}$ with maximum stock recorded on some plots going above 70 $MgCha^{-1}$. This is presented below in Figure 3.3.

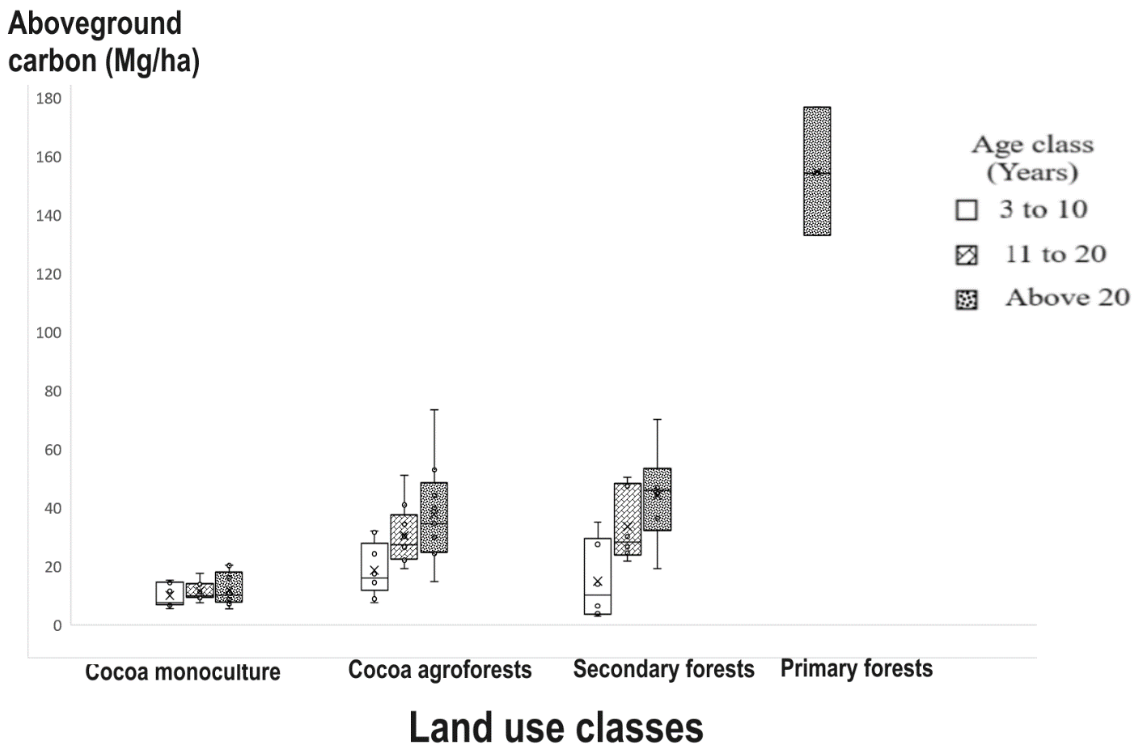


Figure 3.3 Aboveground carbon per land use and age class

A two-way analysis of variance test was carried out to ascertain the significant level of effect of age and landuse as well as the interaction effect of age and landuse on aboveground carbon stocks. The ANOVA was done for aboveground carbon, basal area and timber volume and the number of stems per plot.

The results from the ANOVA show significant difference between land use (cocoa monoculture, cocoa agroforests, secondary forest, and primary forest) for above-ground carbon stocks, basal area, number of stems, and timber volume. The effect of age was also significant for all the dependent variables except for stocking density (treesha^{-1}).

Table 3.5: Summary of Analysis of Variance for aboveground carbon stock, basal area, timber volume and number of stems for landuse and age classes

Dependent variable	Sum of squares	df	Mean square	F-statistic	P- value
Aboveground Carbon stocks (MgC/ha)					
Land use	55991.16	3	18663.72	144.63	0.00
Age	2848.68	2	1424.34	11.034	0.00
Land use: Age	1479.46	4	369.87	2.87	0.03
Basal area (m^2/ha)					
Land use	2070.55	3	690.18	34.42	0.00
Age	470.28	2	235.14	11.73	0.00
Land use: Age	177.78	4	44.45	2.22	0.08
Timber Volume (m^3/ha)					
Land use	1004967	3	334989.1	131.39	0.00
Age	38257.33	2	19128.66	7.50	0.00
Land use: Age	29678.86	4	7419.72	2.91	0.03
Number of stems(trees/ha)					
Land use	3744711	3	1248237	8.81	0.00
Age	822020.2	2	411010.1	2.90	0.06
Land use: Age	111642	4	27910.49	0.19	0.94

The age of landuse was significant for aboveground carbon stock in a landuse with the exception of the monoculture. The Primary forest had only one age category, hence no comparison of means was done. Compared to matured and recent plantations, older cocoa plantations and secondary forests often have higher carbon storage capacities.

To further test for interaction effect the analysis of variance also did a pairwise comparison of different age classes interacting within and across land uses.

The was no significance difference in aboveground carbon stocks in cocoa agroforest in age class 1 and age class 2 and also compared with all age classes of cocoa monoculture. Interestingly, there was no significance difference in aboveground carbon of secondary forest of age class two and cocoa agroforest of age class 2 or age class 3. Similar findings was found for a secondary forest of over 20 years having no significance compared to cocoa agroforest between 11 and 20 years or over 20 years old. This goes to show how greening cocoa landscapes with trees on farm can increase sequestration and carbon storage in agricultural landscape while preserving those stored in secondary forests. Aboveground carbon in primary forest were however significant compared to all landuses of varied age classes. This means, the conversion of primary forest to other landuse comes at a significant cost of carbon loss.

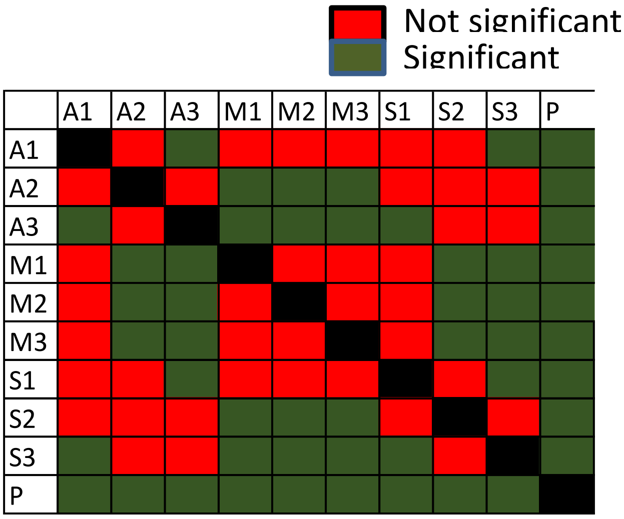


Figure 3.4: Landuse age interaction effect on the significance of carbon stocks (A-Cocoa Agroforest, M- Cocoa Monoculture, S- Secondary forest, P- Primary forest)

3.4.4 Timber volume

The timber volume for both cocoa agroforest and secondary forest increased significantly with age. The timber volume for the monoculture cocoa farms was not assessed as the studies was limited to shade trees and not cocoa stems. The primary forest had the highest mean basal area of 597.61 m^3ha^{-1}. The cocoa agroforest had timber volume ranging from 42.23 m^3ha^{-1} for the young agroforest to 107 m^3ha^{-1} for the old cocoa agroforest. Secondary forests had timber volumes of 51.87 m^3ha^{-1} and 177.6 m^3ha^{-1} for young and old forests respectively.

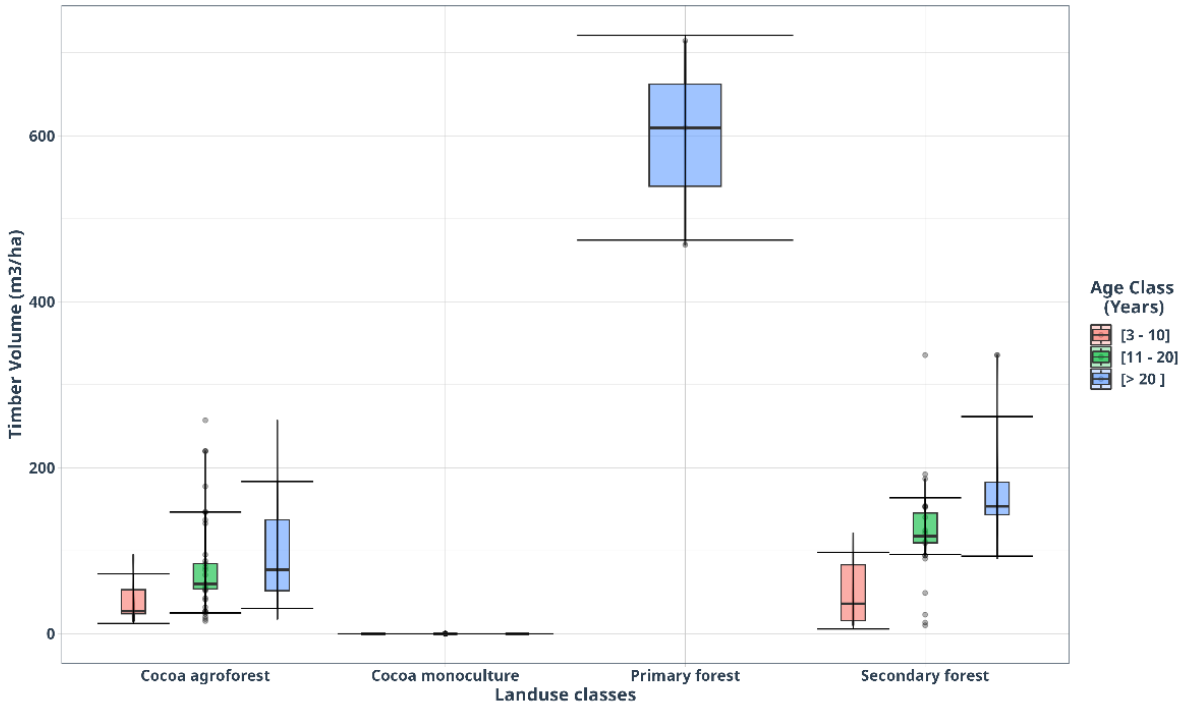


Figure 3.5: Timber volumes for landuse and age classes

Relative contribution of trees on farm to stand parameters in cocoa agroforest plantations

With a p-value of 0.72, there was no significance between cocoa agroforests and cocoa monoculture when only the cocoa trees are used for the estimation of aboveground carbon. With trees on farm added, however, the carbon stocks were significant. Trees on farm contributed 53%, 58.9%, and 60% for cocoa agroforests of age class 1,2 and 3 respectively

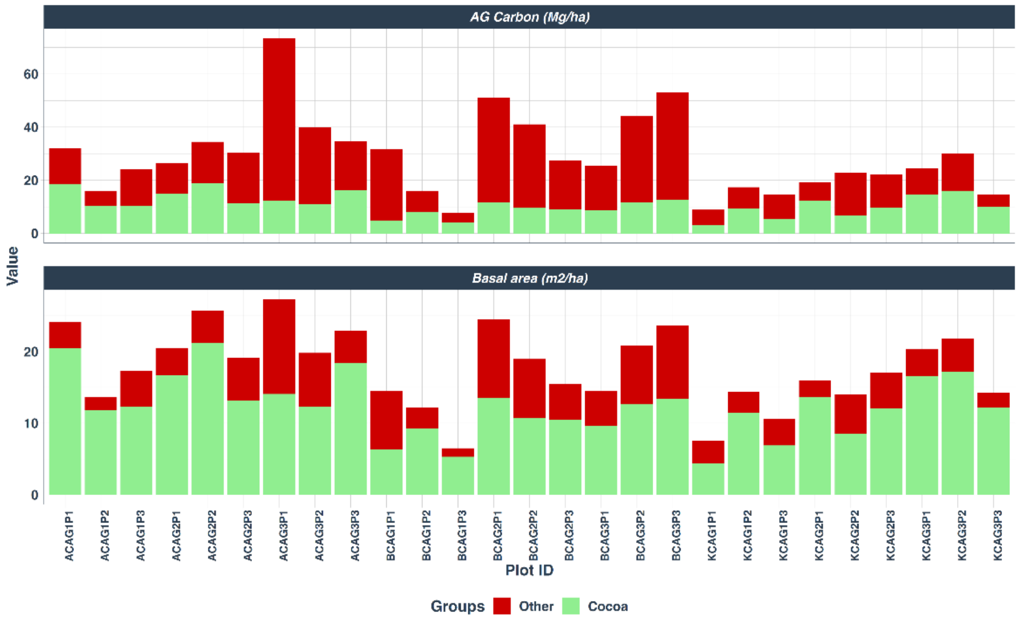


Figure 3.6: Trees on farm contribution to aboveground carbon and basal area of cocoa agroforests

A student t-test was carried out to evaluate the contribution of trees within carbon farm to the overall aboveground carbon stocks. This was done for all the age categories. With only cocoa stems between the monoculture and the agroforests, there was no significant difference in the aboveground carbon stored across all ages. The introduction of the carbon stocks in the trees on farms to the analysis brought the significance difference for both age class 1 and 3 at 95% confidence interval.

Table 3.6 Student t-test of trees on farm contribution to aboveground carbon within cocoa agroforests

Age Class	P-value
Monoculture vs cocoa agroforests cocoa stems	
1	0.37
2	0.99
3	0.97
Trees on farm contribution to carbon	
1	0.01
2	0.07
3	0.00

3.5 Tree diversity

3.5.1 Abundance and floristic composition

We identified and measured 8654 individuals with about 48% being *Theobroma cacao* and the remaining 4506 individual shade trees occurring in cocoa agroforests, secondary forests, and the primary forest (Kakum National Park). Aside the *Theobroma cacao* which occurs only within the cocoa farming system (monoculture and cocoa agroforests), *Albizia zygia* had the highest relative frequency of 41% occurring across 31 sampled plots. *Morinda lucida* had the most importance index with 458 individuals occurring across 29 of the sampled plots (Figure 3.7)

In total, 95 different species were enumerated within 75 plots. Ten (10) species occurred across all age classes of cocoa agroforest, secondary forests and the primary forests. These are; *Antiaris toxicaria*, *Daniellia ogea, Ficus capensis, Funtumia elastica, Hannoa klaineana, Macaranga barteri, Milicia* *excelsa, Pycnanthus angolensis, Terminalia ivorensis* and *Trichilia monadelpha*

Within cocoa agroforests, 35 species were present across all age classes while only 18 species occurred across all age classes of secondary forests. Cocoa agroforests had 54, 45 and 51 species recorded for age class 1, 2 and 3 respectively. For secondary forests, 33, 39 and 45 species were recorded for age class 1, 2 and 3 respectively.

Twelve (12) of the sampled species (*Bussea occidentalis, Annickia polycarpa, Microdesmis keayana, Bosqueia angolensis, Albizia glaberrima, Microdesmis puberula, Cylicodiscus gabonensis, Irvingia gabonensis, Treculia Africana, Drypetes aubrevillei, Trema orientalis and Solanum erianthum*) occurred in only one plot.

Table 3.7 Occurrence of species across different age classes and different land uses

Species	Cocoa agroforest			Secondary forest			Primary forest
	Age class						
	1	2	3	1	2	3	3
Albizia adianthifolia	x		x	x	x		
Albizia glaberrima		x					
Albizia ferruginea	x		x	x	x		x
Albizia zygia	x	x	x	x	x		x
Alstonia boonei	x	x	x		x	x	x
Amphimas pterocarpoides	x	x	x		x	x	x
Anthocleista nobilis				x	x	x	
Annickia polycarpa							x
Antiaris toxicaria	x	x	x	x	x	x	x
Aulacocalyx jasminflora							x
Baphia nitida				x	x	x	x
Blighia sapida	x		x	x	x	x	x
Bombax buonopozense	x	x			x	x	x
Bosqueia angolensis	x						
Bridelia atroviridis	x	x		x	x	x	x
Bussea occidentalis						x	
Canarium schweinfurthii	x						x
Carapa procera	x					x	x
Ceiba pentandra	x	x	x	x		x	x
Celtis mildbraedii	x	x	x			x	x
Citrus sinensis	x	x	x				
Cleistopholis patens					x		
Cola gigantea						x	x
Cola nitida			x	x		x	x
Cylicodiscus gabonensis							x
Dacryodes klaineana							x
Daniellia ogea	x	x	x	x	x	x	x
Dialium guineense	x		x				
Diospyros kamerunensis	x	x	x	x			x
Diospyros sanza-minika						x	x
Distemonanthus benthamianus	x	x	x		x		x
Drypetes aubrevillei							x
Duguetia staudtii							x
Entandrophragma angolense	x	x	x			x	x
Entandrophragma candollei							x
Ficus capensis	x	x	x	x	x	x	x
Ficus exasperata	x	x	x	x	x	x	

Funtumia elastica	x	x	x	x	x	x	x
Guarea cedrata							x
Hannoa klaineana	x	x	x	x	x	x	x
Harungana madagascariense			x	x	x		x
Holarrhena floribunda	x	x	x				x
Homalium letestui							x
Irvingia gabonensis							x
Khaya ivorensis			x				x
Lannea welwitschii	x	x	x	x	x		x
Macaranga barteri	x	x	x	x	x	x	x
Mangifera indica	x	x	x				
Mareya micrantha	x	x			x	x	x
Margaritaria discoidea	x				x	x	x
Microdesmis keayana							x
Microdesmis puberula							x
Milicia excelsa	x	x	x	x	x	x	x
Morinda lucida	x	x	x	x	x		x
Musanga cecropioides	x	x	x		x		x
Myrianthus libericus	x				x	x	x
Napoleonaea vogelii					x	x	x
Nauclea diderrichii			x				x
Nesogordonia papaverifera	x	x	x			x	x
Newbouldia laevis	x	x	x	x		x	x
Okoubaka aubrevillei	x	x					
Ongokea gore		x					x
Panda oleosa	x			x			x
Parkia bicolor			x			x	x
Persea americana	x	x	x				
Petersianthus macrocarpus	x	x	x		x		x
Piptadeniastrum africanum							x
Pouteria altissima	x	x	x				x
Psidium guajava	x			x			
Psydrax subcordata				x	x	x	x
Pycnanthus angolensis	x	x	x	x	x	x	x
Rauvolfia vomitoria	x	x	x	x	x	x	
Ricinodendron heudelotti			x			x	x
Solanum erianthum	x						
Spathodea campanulata	x	x	x		x	x	
Spondias mombin	x	x	x	x			x
Sterculia oblonga			x				x
Sterculia rhinopetala			x			x	x
Sterculia tragacantha			x	x	x	x	

Strombosia pustulata		x	x			x	x
Terminalia ivorensis	x	x	x	x	x	x	x
Terminalia superba	x	x	x	x			x
Tetrapleura tetraptera	x					x	x
Tetrorchidium didy-mostemon			x		x	x	x
Trema orientalis	x						
Treculia africana							x
Trichilia monadelpha	x	x	x	x	x	x	x
Trichilia prieuriana						x	x
Trichilia tessmannii		x	x				x
Triplochiton scleroxylon	x	x				x	x
Vitex doniana					x		x
Voacanga africana		x			x		x
Xylia evansii				x			x
Zanthoxylum gilletii	x	x	x			x	x

x- shows presence of species in the age group. Cells without x has no presence of the species

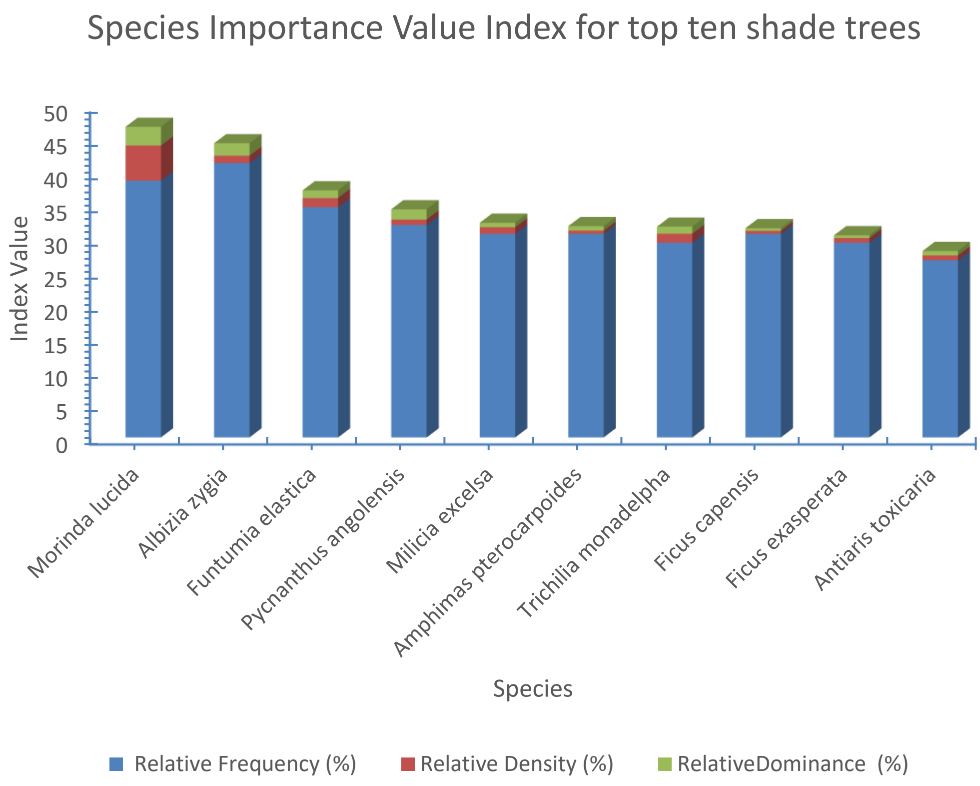


Figure 3.7: Species importance Value Index for top ten shade trees for all land uses

For family importance value, Malvaceae came top with 4213 individuals belong to 5 species. However, Meliaceae and Mimosaceae families had 8 species each and Euphorbiaceae with 7 species. Sixteen families had only one species in the family. Figure 3.8 presents the importance value index for the top ten families.

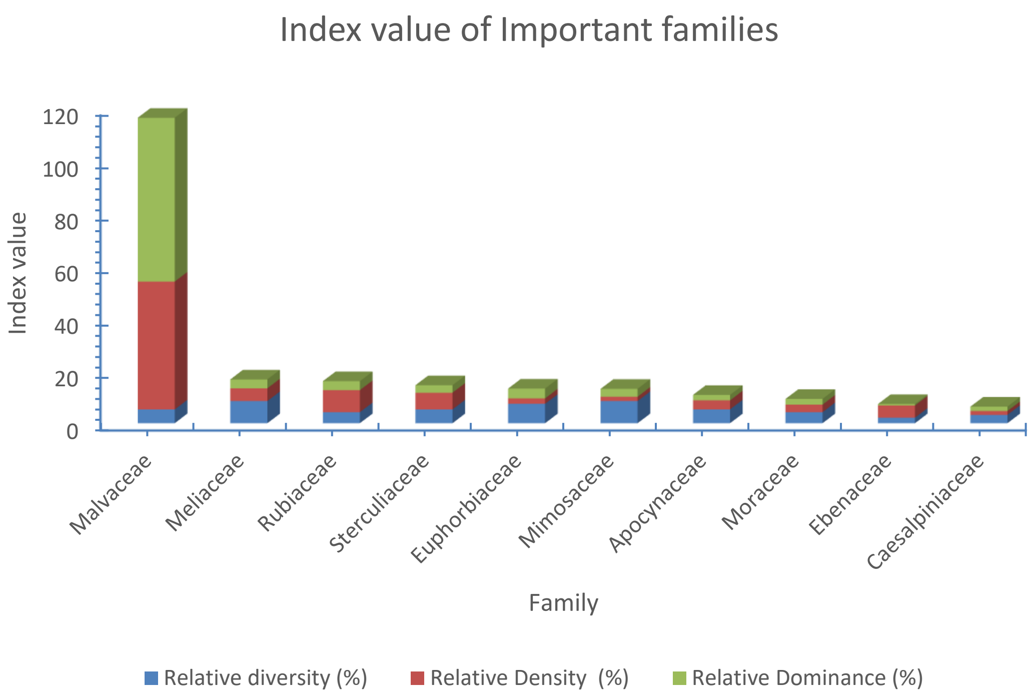


Figure 3.8: Index value of important families

3.5.2 Species diversity indices

The Shannon Weiner diversity index, which has values ranging from 0 to 5, is the most often used diversity index in ecological research for evaluating diversity across different environments (Clarke and Warwick, 2001). Typically, the values fall between 1.5 and 3.5.

The index increased with age across all land uses with the Primary forest recording the highest Shannon Weiner diversity of 2.99, with species richness of 76, followed by secondary forest with Shannon index of 2.43, though with a lower species richness of 63 compared to the cocoa agroforest with 69 species richness.

Table 3.8: Diversity indices of the different landuse and age classes

Landuse	AC	SF	PF	AC	SF	PF	AC	SF	PF	AC	SF	PF
Age class/ indices	Margalef			Menhinick			Simpson			Shannon-Wiener		
1	2.86	2.67		1.28	1.64		0.43	0.22		1.44	1.82	
2	3.03	3.98		1.44	2.27		0.48	0.15		1.34	2.34	
3	3.28	4.10	8.47	1.61	2.62	2.07	0.44	0.12	0.09	1.48	2.43	2.99

AC- Agroforest Cocoa, SF – Secondary Forest, PF – Primary Forest

3.5.2.1 Species accumulation

With three (3) plots, the species accumulation curve for Primary Forest is rapid and had all species observed without a curve in the total of the 3-ha plot cumulatively. The cocoa agroforests and secondary forest had 27 plots each of 100 m x 100 m with a cumulative total land area of 27 ha each. Identification of new species per added plot was quicker in the secondary forest compared to the cocoa agroforests.

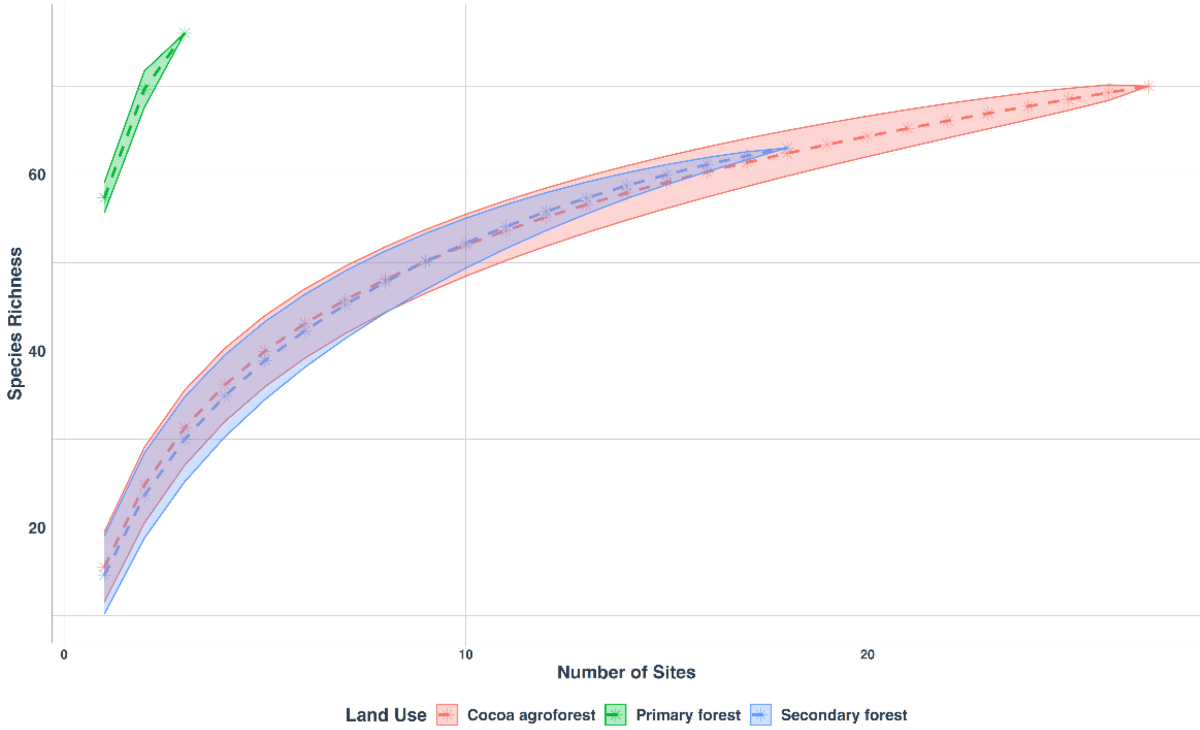


Figure 3.9: Species accumulation curves for Primary forests, secondary forest and cocoa agroforest 3ha plot total

3.5.2.2 Succession stage of species and landuses

There were much more shade-bearers in the primary forest than in the cocoa agroforest or secondary forests, (Figure 3.10). In comparison to the other two landuses, the secondary forest had a larger percentage of pioneers, followed by the cocoa agroforests. The proportions of the non-pioneer light demanders were relatively similar between the landuse types.

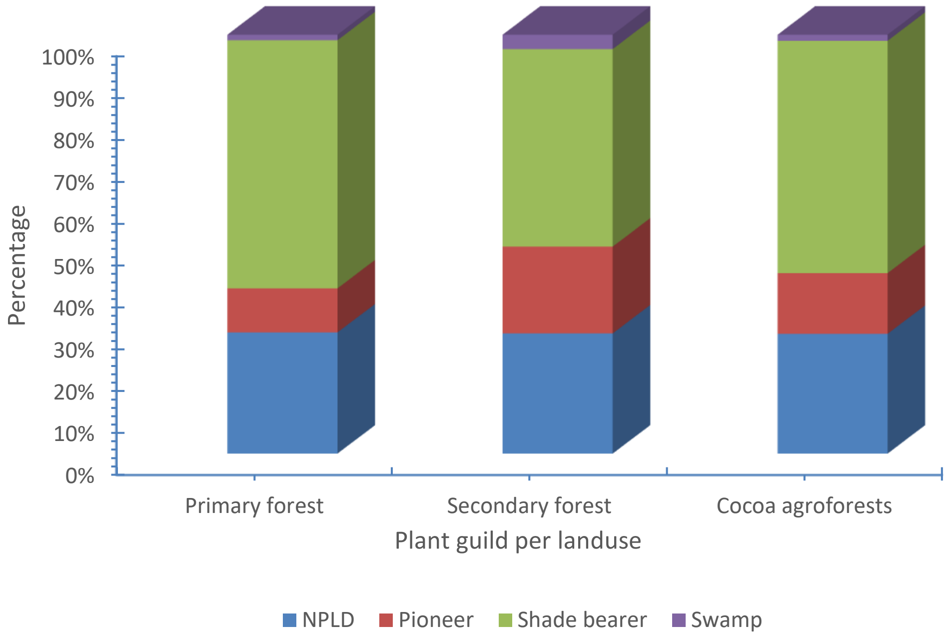


Figure 3.10: Distribution of the different successional groups identified for the study

3.5.3 Species Similarity

Figure 3.11 presents the number of species shared by primary forest with the cocoa agroforest (54) and the secondary forest (54). Forty-five (45) species were common to all landuses. The primary forest however, had 13 species that were exclusive to it followed by cocoa agroforest with 9 species and secondary forest having only 3 species exclusive to it.

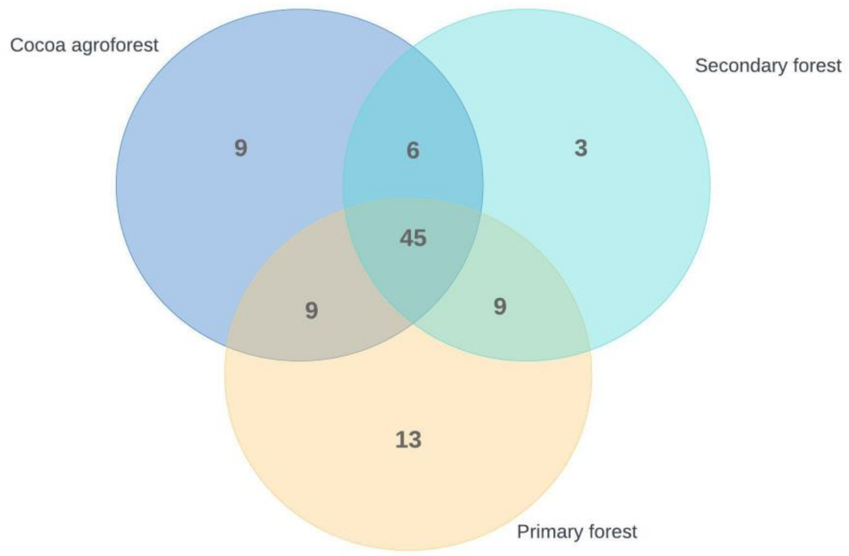


Figure 3.11: Distribution of species for all landuses indicating shared and mutually exclusive species between landuse

When comparing age groups, mature secondary forests and old secondary forests share more species (28), whereas young secondary forests only share 22. Nineteen species were common to all age classes of secondary forests. However, the shared species between the age class 1 and age class 2 was higher (24). The exclusive species for an age class was also higher for the old secondary forest (15) with both the young and matured secondary forest having 6 species exclusive to them Figure 3.123.12.

A different pattern was observed for the age classes in the cocoa agroforests with 42 species shared between the old cocoa agroforest and young cocoa agroforest whereas only 39 species are shared between the matured and old agroforests. Thirty-seven (37) species were common to all age classes of cocoa agroforest. The young cocoa agroforest also has the highest exclusive species (10), followed by the old cocoa agroforest (9) and matured agroforest with just 3 species.

Figure 3.12: Distribution of species showing shared species for age classes for secondary forest (a) and cocoa agroforests (b)

According to Table 3.93.9, primary × secondary, primary × cocoa agroforest, and secondary forest × cocoa agroforest revealed Sørensen's similarity index values over 0.5 reflecting 77%, 71%, and 81% of mutually comparable species, respectively.

Table 3.9: Comparison of Sørensen's Similarity Index (SSI) and Jaccard Similarity Index (JSI) for the landuses.

Paired Land use Type	Jaccard Similarity Index	Sørensen similarity index
Primary x secondary	0.77	0.87
Primary x cocoa agroforest	0.71	0.83
Secondary x cocoa agroforest	0.81	0.89

3.5.4 Conservation Value

With a conservation value of 393, the primary forest had the highest value, followed by the cocoa agroforest, which had a value of 241, and the secondary forest, which had a value of 84, which was the lowest.

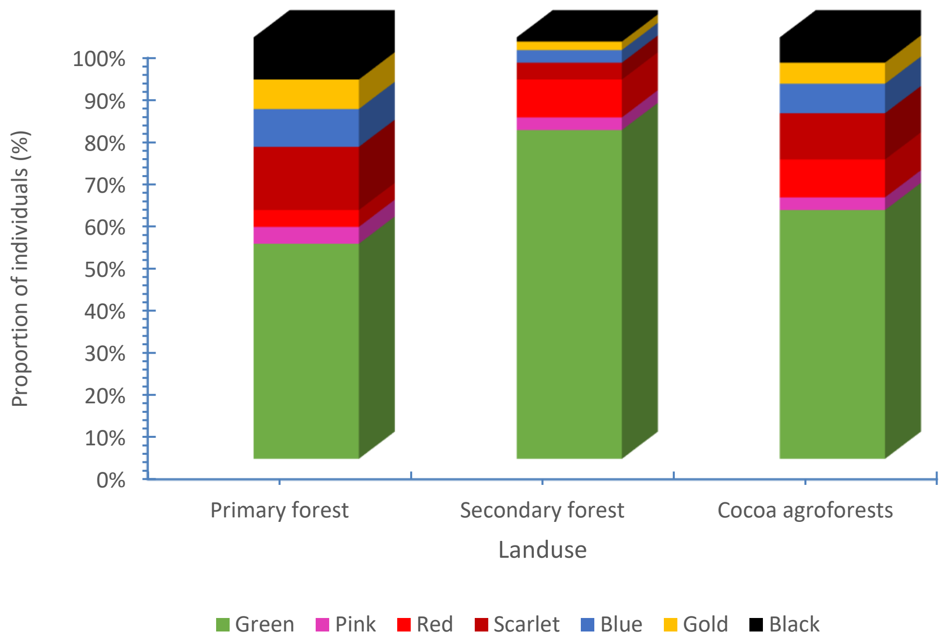


Figure 3.13: Conservation status of species for each landuse

As anticipated, green star species dominated the star species categories across different land-use types (Figure 3.13). Among these, the primary forest exhibited the highest percentage of high conservation species (black, gold, blue), totalling 20 species. In comparison, the cocoa agroforest featured 12 such species, while the secondary forest had only 4 species classified as high conservation status. In terms of the most abundant economic timber species (scarlet, red, pink), the distribution of these species is nearly identical in both the primary forest and cocoa agroforest, with 17 and 16 species, respectively. The secondary forest, on the other hand, featured 10 economic timber species.

3.6 Discussion

3.6.1 Carbon stocks, basal area and tree volumes

The average basal area of cocoa trees in our study surpasses the reported figure of 8.1 $m^2\ ha^{-1}$ in Cameroon by Jagoret et al. (2017). Additionally, their findings of the mean total basal area for on-farm trees at 17.6 $m^2\ ha^{-1}$ contrasts with the 23.21 $m^2\ ha^{-1}$ observed in our examined agroforests in Ghana

Brown et al. (2020) similarly observed higher basal area and aboveground carbon in primary forests in comparison to secondary forests, aligning with the results of our study. Our identification of an increase in carbon stocks with the age of cocoa farms is in harmony with the research by Mohammed et al. (2016), where they established a positive relationship between cocoa farm age and carbon stocks.

He also found unshaded cocoa to have less carbon stocks (16.7 ± 2.2 Mg C/ha) compared to shaded cocoa (31.3 ± 2.2 Mg) C/ha corroborating the findings of this study. The lager diameter trees and higher heights of trees within the primary forest could be attributed to the higher carbon stocks.

The study conducted by Asigbaase et al. (2021) strengthens the assertion that shade trees on cocoa farms significantly contribute to the total carbon stocks. According to their research, these shade trees on both conventional and organic cocoa plantations stored more than 70% of the farm's carbon stocks.

On tree volumes, Brown et al. (2020) found plantation forest to have more volume compared to primary forest though primary forest volume was higher than the secondary forest. This could be due to the planting distance used for tree plantations and the number of stems that can be found per plot compared to the primary forest. This result is different from that of this study though plantation forest was not studied in this work.

3.6.2 Species Diversity

The higher species richness of the primary forest confirms earlier studies in Ghana (Brown et al. 2022). The study of Nero (2021) also found primary forests to have higher abundance and richness compared to reclaim mined site in south-western Ghana.

The high floristic diversity of cocoa agroforest presents a case to support transitioning of monoculture to agroforest to conserve as suggested by the findings of Zequeira-Larios et al. (2021) that agroecosystems' broad floristic diversity contributes to the preservation of local plant species and may encourage the growth of agroforestry plantations linked to the production of cocoa.

The reported Shannon index of average 1.42 for cocoa agroforest is lower compared to cocoa agroforests in Cameroon of 2.42 reported by Jagoret et al. (2014). Our findings align with the results of Ansah et al. (2023), who noted that protected forests exhibited a higher Shannon index (2.74) compared to cocoa agroforests.

As reported for this studies, Dawoe et al. (2016) also found the following families of importance value to the cocoa landscape Meliaceae and Mimosaceae with 8 species each to the family and lower Shannon index for cocoa agroforest with the maximum of 1.69.

3.6.3 Conservation status

As expected, the primary forest contained the highest number of high conservation status and timber species. Owusu et al. (2022) also reported of the evidence of the high conservation importance of the Ankasa Conservation area reserve, which is also a Wildlife Protected Park. The results is consistent with the findings of Brown et al. (2022) who found primary forest having higher numbers of high conservation value species compared to other landuses. This could be due to the protection status of the National Park as access and felling rights are curtailed by forest protection laws.

The higher proportion of trees of high conservation status in the cocoa agroforests can be attributed to the intentional tending natural regeneration (Asare and Anders 2016) of trees and protection of desirable and timber species by farmers on their cocoa farms with the intention to utilize for building project in the future or serving medicinal purposes. These results demonstrate how cocoa agroforests are a good substitute landscape for restoring native tree species, making agricultural landscapes greener, and preserving biodiversity. Remarkably, within the cocoa agroforests, some black star species were identified, suggesting that, with appropriate support and tree tenure arrangements, farmers could play a role in safeguarding species that are on the verge of extinction.

Following the World Bank Safeguard Policy on Natural Habitats and forests, it is imperative for REDD+ programs to guarantee that forest restoration projects preserve or improve biodiversity and ecosystem functionality (Forestry Commission of Ghana 2018). These results presents hope for the Ghana Cocoa Forest REDD+ program to meet these set safeguards.

3.7 Conclusion

The research has showcased the capability of cocoa agroforests to offer ecosystem services, including carbon sequestration, biodiversity, and timber, resembling both primary and secondary forests. The outcomes of this study contribute to the reinforcement of existing literature. These findings present both hope and challenges that need to be handled well to maximize emission reductions.

On one front, when farmers tend naturally occurring trees on farm or add new ones through planting, carbon stocks will increase in cocoa landscapes. However, the conversion of fallow lands/secondary forests and primary forests will lead to emissions in carbon stocks as seen from the differences in the carbon in these different land uses. Not only does this affect carbon but also on floristic diversity in these landscapes. These two scenarios can either positively or negatively impact on the REDD+ mechanism.

One of the main conclusions from our research is that secondary forests and cocoa may both protect rare and endangered species (black stars) as well as primary forest plant species with high conservation value.

The age of the landuse was found to have significant effect on the carbon stock distribution, thus, old cocoa agroforests and cocoa monoculture farms and secondary forest tend to store more carbon than young ones.

CHAPTER 4: PREDICTION OF LAND USE LAND COVER CHANGE AND CARBON EMISSIONS DYNAMICS IN COCOA LANDSCAPE OF GHANA UNDER REDD+

4.1 Introduction

Land use Land cover (LULC) change has become an area of prominence among environmentalists and land use planners. Throughout the past centuries, people have affected nearly 75% (seventy-five percent) of the Earth's surface (Winkler et al., 2021). These changes have posed profound challenges such as global and local climate change, urbanization, agricultural expansion, deforestation, and other environmental issues. The Kakum area stands as a unique and ecologically diverse landscape, characterized by a delicate balance between pristine natural ecosystems and human activities (Addo-Fordjour et al. 2009; Ansah et al. 2023). Over recent decades, the patterns of land use and land cover in this region have witnessed notable transformations, influenced by an interplay of socioeconomic, environmental, and climatic factors. Understanding these changes is imperative making informed decisions, implementing sustainable resource management practices, and safeguarding the ecological integrity of Kakum.

About 20% of carbon emissions resulting in climate change is caused by deforestation and forest degradation (Van Der werf, 2009; Stocker et al., 2013). An estimated 18 percent of greenhouse gases released into the atmosphere are produced by tropical forests. This is as a result of forest being cleared for agriculture and other purposes that compromise the forest’s integrity (IPCC

2007). Farmers are known to be one of the forefronts of deforestation and carbon emissions. In Ghana, with about 350,000 farmers involved in cocoa farming, cocoa expansion has been identified as the main cause of deforestation (Antoh et al., 2017). In most cocoa growing areas, poverty persist resulting in the clearing of forests for subsistence agriculture, increasing the rate of environmental degradation and accumulation of carbon in the atmosphere. As a result, using a cocoa intensification strategy, the Ghanaian government hopes to lower carbon emissions from the forest sector (Nasser et al., 2020). Reducing carbon emissions from forests is critical to mitigating the harmful effects of deforestation and climate change. To reduce deforestation and climate change, the world community implemented REDD+ (Reducing Emissions from Deforestation and Forest Degradation Plus)(Agbefu, 2014). This system will enable Ghanaian smallholder cocoa farmers to generate additional revenue through carbon mitigation programs associated with REDD+ (Reduced Emissions from Deforestation and Forest Degradation). The main goal of REDD+ is to raise farmer incomes and cocoa yields without significantly increasing the amount of land available for agriculture. Rising income levels are projected to lessen the need for farm expansion and forest intrusion, resulting in less deforestation (Antoh et al., 2017).

Recently, research has been undertaken to assess the extent, pace, and trends of change in the Kakum Conservation Area from 1991 to 2015, employing supervised classification and post-classification change detection techniques on Landsat satellite imagery (Doe et al., 2018).

Kankam et al. (2022) investigated the consequences of spatio-temporal LULC changes on the provision of ecosystem services. The research further delved into the influence of social and environmental factors driving LULCC on the potential supply of ecosystem services in the landscape. Nyatuame et al. (2023) utilized the cellular automata-Markov model integrated into IDRIS 17 software to evaluate the prospective Land Use and Land Cover (LULC) changes in the Tordzie watershed in Ghana for the years 2030 and 2050. Likewise, Koranteng and Zawila-Niedzwiecki (2015) employed Markov Chain analysis and Cellular Automaton to simulate forest loss and various dynamics in land use changes within the Ashanti Region of Ghana. They projected a potential Land Use and Land Cover (LULC) map for the years 2020 and 2030.

However, these studies focussed on business-as-usual scenarios and did not look at how the dynamics of landuse change also drives carbon stocks in the landscape and the possible scenarios of climate mitigation interventions on the changes. The objective of this research is to simulate alterations in land cover within the study area for the years 2019, 2024, and 2036. Additionally, the study aims to assess and analyze variations in carbon stocks during these periods under various intervention scenarios.

4.2 Methodology

4.2.1 Study area

The Study was carried out in the Assin South district of Ghana.

4.2.2 Data collection

Sentinel 2 Level 1C data, reference data from the field, shapefiles of forest reserves, national parks, existing landcover maps and regional boundaries were used to generate landcover, validate and perform accuracy assessment of the landcover map. The Sentinel data was obtained from the Copernicus Open Access Hub (https://scihub.copernicus.eu/dhus/#/home) while the shapefiles of the forest reserves, existing landcover maps and national parks were obtained from the Forestry Commission of Ghana and the regional boundaries from the Ghana Survey Department. To avoid geometric error associated with different coordinate system all the data were projected to Universal Transverse Mercator coordinate system (Zone 30 N).

Sentinel 2 Data

Sentinel 2 images with cloud cover of less than 15% were downloaded for the study period (2015, 2019 and 2022). The level 1C data are organized in tiles (the spectral bands at a fixed size) and each tile is identified by a unique value (tile ID) (ESA, 2015). Two Sentinel 2 tiles cover the study area and their IDs were T30NXM and T30NYM. The tile IDs are useful for image selection. The Sentinel 2 level 1C is a multispectral image with 13 bands and different spatial resolutions of 10, 20 and 60 meters. The 10 (B2, B3, B4 and B8) and 20 (B5, B6, B7, B8A, B11 and B12) meters spatial resolutions bands were used for this study. Bands 2, 3 and 4 make up the visible bands whilst 5, 6, 7 make up the red-edge bands (Lillesand et al., 2015). The near infrared bands (NIR) are made up of 8 and 8A and the shortwave infrared bands (SWIR) made up of 11 and 12 (Lillesand et al., 2015). Table 4.1 gives details of the acquisition dates for the tiles used.

Table 4.1: Sentinel satellite images used for the study

Satellite	Acquisition Date
Sentinel 2	December 24, 2015
Sentinel 2	January 7, 2020
Sentinel 2	January 26, 2022

4.2.3 Pre-Processing of Sentinel 2 L1C Data

The Sentinel 2 tiles were pre-processed to correct errors associated with their acquisition and initial processing and also prepare them for further processing and analysis. The pre-processing operations that were performed were atmospheric correction (cloud masking), cloud free mosaicking, tile seamless mosaicking, image compositing and sub setting. These pre-processing operations were done in ENVI 5.3.

4.2.3.1 Cloud Masking

The improved Function of Mask 4.0 (Fmask) algorithm was used for cloud and cloud shadow detection and removal. Thematic raster layer showing clouds, cloud shadow, snow and clear land was developed from each tile in mini conda 3 (python code editor). The thematic layer was reclassified to extract only the cloud and cloud shadow pixels. The reclassified thematic layer was used to mask out all cloud and cloud shadow pixels for all the bands for each tile.

4.2.3.2 Cloud Free Mosaicking

After masking out cloud and cloud shadow pixels for each tile, the respective bands for each tile and year were mosaicked. This was to address nodata values created as a result of the cloud masking and also to ensure all the bands for each tile are complete. Thus, the cloud free mosaicking was to fill in "spaces" created by the cloud masking in the bands of the respective tiles.

4.2.3.3 Seamless Mosaicking

The cloud free mosaicked bands were mosaicked using the seamless mosaic workflow with histogram matching technique in ENVI 5.3. The respective bands for the two tiles were mosaicked for each epoch (2015, 2019 and 2022). The seamless mosaicking was to address differences in color and tone caused by illumination conditions since the tiles were produced on different dates.

4.2.3 Developing Spectral Indices

Six (6) spectral indices (SI) were developed from the pre-processed Sentinel 2 tiles for each epoch (2015, 2019 and 2022). The seamless mosaicked bands for each epoch were used as inputs in generating the spectral indices. The formulae for all the spectral indices were obtained from the European Space Agency (ESA) Sentinel Application Platform (SNAP) help menu. The spectral indices were Normalized Difference Vegetation Index (NDVI), Red-Edge Inflection Point index (REIP), Transformed Normalized Difference Vegetation Index (TNDVI), Green Normalized Difference Vegetation Index

(GNDVI), Inverted Red-Edge Chlorophyll Index (IRECI), Modified Normalized Difference Water Index (MNDWI) and Normalized Difference Built-up Index (NDBI). The spectral indices were made up of vegetation indices (NDVI, REIP, TNDVI, GNDVI and IRECI). The SIs which includes vegetation indices have the ability to characterize different foliage attributes at the canopy level, detect changes in different forest types and differentiate non-vegetation classes such as water and built-up (Barati et al., 2011; Zarco-Tejada et al., 2018). All the spectral indices were developed in ENVI 5.3 using the band math tool.

4.2.3.1 Developing Image Ratios

The NIR band (B8) of the seamless mosaicked bands for the 3 epochs were ratioed. This was done by dividing the B8 of the current epoch over the previous epoch. This temporal image ratioing was used to spectrally detect changes that occurred within the study area over the study period. Values from the ratioed B8 that tend toward 1 indicate areas of no change whilst higher or lower ratio values indicate change. The ratioed images were reclassified into two classes; change and no-change. The reclassified ratioed images were used as preliminary change detection maps to identify areas of change, collect reference data and used it for both training and validation.

4.2.4 Image Compositing

The outputs from the seamless mosaicking operation and the spectral indices were stacked to generate image composites. All the raster data (seamless mosaicked bands and spectral indices) were resampled to 10 m before stacking. This was to ensure that all the raster layers have same spatial resolution. Three (3) composites were generated with one for each epoch.

4.2.4.1 Subsetting

The image composites extend beyond the boundary of the study area. Since the interest of this work was within the study area the clip tool in ArcGIS 10.5 was utilized to extract the relevant portions of the image composites within that boundary. This was done for each epoch and the outputs were used for the supervised image classification process.

4.3.1 Reference Data Collection

The field data collection was carried out in the dry season to ensure the data collected corresponds to the acquisition period of the satellite data to avoid the effect of seasonal variation in analyzing the satellite images. The field data collection was carried out between January 2021 and March 2021.

At each location, the geographic coordinates, landcover types, landcover changes and description of adjoining landscape were recorded and photos taken to assist classification.

With the assistance of farmers and indigenes, age of cocoa and other tree crop plantations and other vegetation classes were obtained. This information was used as reference data to train and validate the historical landcover maps (2015 and 2019).

A total of 747 coordinates were collected from the field exercise and converted to 243 polygons. Extra 87 polygons were collected from Google Earth through onscreen digitization making the total 330 polygons for analysis. Of the 330 polygons, 231 representing 70% was used for the training of the images and 30% used for post classification accuracy assessment.

4.3.1.2 Selection of prediction dates and assumptions

The year 2024 was selected because the Ghana Cocoa Forest REDD+ program which is the basis of the study is envisaged to be concluded by 2024 with the Forest Carbon Partnership Facility of the World Bank and as such the interest in knowing how the implementation of the program has affected the carbon stocks and sequestration for achievement of emission reductions under the program for carbon finance. The year 2035 marks a year to the end of the REDD+ strategy and is studied to understand how the landscape in the Assin South will be transformed based on the implementation of interventions under the strategy.

The assumptions for the study are that under business-as-usual scenarios, the drivers of deforestation and forest degradation such as expanding cocoa into forest areas, illegal logging and mining activities, will continue unabated and emissions will rise as forest cover losses continue. Under the REDD+ scenario, it is assumed that forest areas will be protected and while farmers will be encouraged to incorporate trees on farm to improve on forest cover and biodiversity in agricultural landscape. As such, carbon stocks and sequestration will be improved leading to achievemnent of emission reductions for carbon finance.

4 .3.2 .1 Landuse/landcover classes

The study considered eight classes for the analysis and creation of the landuse/landcover maps. These have been described further in Table 4.2Table 4.2: LULC classes description.

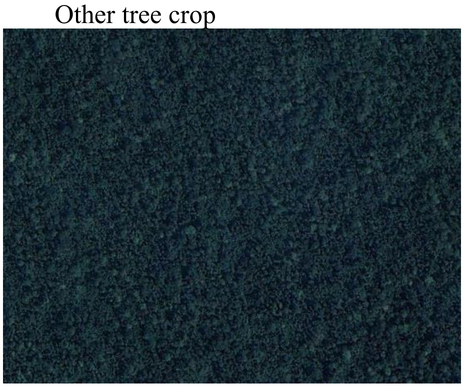
Table 4.2: LULC classes description.

Land Use Classes	Description
Closed forest	Land with a minimum mapping unit of 1m of woody vegetation with a crown canopy that is over 60% and a maximum height of 5m.
Open forest	Open forests have canopy cover between 15% and 60%.
Water body	Represents all surface water bodies mainly the rivers and the ponds in the landscape.
Grassland	Represents all grasses, bushes, bamboos and shrubs in the landscape
Settlement / Bare Surface	Represents places where people have settled or built structures such as houses, roads, etc
Monoculture cocoa	Cocoa plantation with no or very little natural or planted trees to form enough canopy shade to protect the plantation from direct sunlight
Agroforest cocoa	Cocoa plantation with natural or planted trees and forms enough canopy shade to protect the plantation from direct sunlight
Other tree crops	These include regions of the landscape that are primarily covered with palm trees and cocoa.
Food crop	Food crop comprises all lands covered with agricultural crops such as plantain, cassava, and maize.

Settlement / Bare Surface

Other tree crop

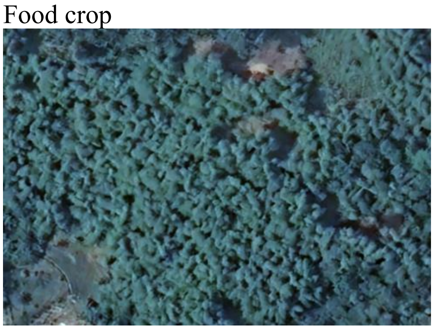
Closed forest



Open forest

Food crop

Agroforest Cocoa



Monoculture Cocoa

Figure 4.14: Samples of landuse as taken from Google Earth

4.3.2 Supervised Classification

Supervised classification was conducted utilizing 70% of the reference data as training data. Following the training of composite images and the derivation of spectral signatures for each class, the supervised image classification was implemented using the maximum likelihood (ML) algorithm. The training of the composite images, signature development and the classification were done in ENVI 5.3 using the classification workflow. The selection of the ML classifier was based on its consideration of not only the cluster center but also its shape, size, and orientation. This is accomplished by computing a statistical distance that relies on the mean values and covariance matrix of the clusters (Wim H. Bakker et al., 2004). This makes this classifier very useful in the classification of heterogeneous landscape (Scheres, 2010) such as exist in the study area. The supervised classification was run separately for each epoch.

4.4 Accuracy assessment

The accuracy assessments were conducted using 30% of the reference data to generate a confusion matrix and kappa statistics analysis report (Lillesand et al., 2015).

Accuracy assessment of the generated maps was also subjected to community validation and expert review following the recommendation of Ashiagbor et al 2023 that implementing an expert review on classified maps is expected to result in a LULC map that more accurately represents the landscape, regardless of the classification algorithm classification algorithm used and the accuracies it generated. This was to improve on both producer and user accuracies. Review comments necessitated visits to particular area of interests to confirm what landuse were in such areas. Google Earth was used to augment the validation process. Reclassification of misclassified areas improved the map accuracies from 85.3 to 91.6% for the 2022 map based on the changes in reported areas for certain classes.

4.5 Change Detection

The change detection on the land cover maps was conducted using the "matrix union" tool in Erdas Imagine 2018. This tool employs pixel-by-pixel change detection, comparing each pixel in the old land use map with the corresponding pixel in the new land use map.

4.6 Spatial variable collection and preparation

Researchers focus primarily on the physical and socioeconomic variables that cause LULC changes due to their greater impact on LULC change mechanism. For the purpose of this study, five physical variables were employed for the prediction to identify changes over the years to help in accurate modeling. The variables used include the digital elevation model (DEM), slope, topographical wetness index, distance from major rivers, distance from major roads, and distance from communities. The DEM with a 30m spatial resolution was obtained from the Earth Explorer online data platform (https://earthexplorer.usgs.gov), and the slope was derived from the DEM. The rivers, roads, and communities datasets were obtained as secondary data from the Resource Management Support Centre (RMSC) of the Forestry Commission of Ghana. Using the Euclidean distance method in ArcGIS, the distance from major rivers, distance from major roads, and distance from communities were calculated. After developing the variables, all the variables were subjected to geometry matching to ensure consistency and accuracy in the prediction. This involved configuring the cell size, data extent, No Data value, and coordinate reference system. The cell size was set to 30 m, the No Data value to 255, and the coordinate reference system to WGS_1984_UTM_Zone_30N for all the spatial variables.

4.7 LULC change Prediction

The forecasting was carried out utilizing the Land Change Modeler (LCM) integrated into the TerrSet Geospatial Monitoring and Modeling System (TGMMS) software. The LCM produces a relative number of transitions by assessing how variables influence future LULC change and the extent of land cover transformation between earlier and subsequent LULC states (Leta & Demissie, 2021). Gains and losses describe LULC transitions for every LULC category in the model. The LCM predicted maps are generated in two forms, known as the soft projection and hard projection. In hard predictions, each pixel is assigned to a particular land use category on a simulated map created for the prediction year (Ayele et al., 2019).

To generate a soft prediction, a projected map is crafted to illustrate vulnerability, with each pixel being allocated a value ranging from 0 to 1. A lower number signifies a lower susceptibility to change, whereas a higher number indicates a heightened vulnerability to change (Ayele et al., 2019).

To predict future years, the trend fluctuations in LULC changes for the years 2015, 2019, and 2022 were examined. Based on historical land use data, current trends, and expected future changes, the future land use scenarios were created. Based on the distinct sub-models and related explanatory variables, the LCM module supports three different methods to generate maps of transition potential: logistic regression, a similarity-weighted instance-based machine learning tool (SimWeight), and multi-layer perceptron (MLP) neural network (Eastman, 2016). For the purpose of this study, multi-layer perceptron (MLP) neural network was used. Compared to the others, the multi-layer perceptron (MLP) neural network is more dynamic and flexible when several transition types are modeled. Once more, it accurately predicts the land that is expected to undergo change from the image of a later date to the specified simulation date, relying on the projection. (Eastman, 2016).

To develop a multivariate function in MLP modeling for anticipating LULC transitions, Cramer's V value was employed as the weighting factor for the driver variables. When comparing explanatory factors to land cover categories, LCM automatically computes Cramer's V and shows the degree of connection. Higher values indicate that a variable is more significant than a lower number. Cramer's V values of ≥ 0.4 and ≥ 0.15 are regarded as helpful and good, respectively. For this study, the overall Cramer's V was 0.6222. Appendix 2 displays the possible land use class transition map for the years 2019 through 2035. Appendix 3 shows the parameters and performance metrics of the MLP model. The skill measure and accuracy rate were found to be 0.99 and 98.5 %, respectively, while two calibration stopping requirements were maintained: RMS = 0.01 and iterations = 5,000.

4.7.1 Model validation

Validation was done to evaluate the predicted LULC map's quality in comparison to the reference map. In the validation process, the 2015 and 2019 Sentinel 2 images were employed to model the 2022 LULC image. After the simulation, a comparison between the actual 2022 LULC map and the simulated 2022 LULC map was done. The value of the Kappa-index ranges from +1 to -1, where a positive value denotes better agreement and a negative value denotes inadequate agreement. The performance of projection for the reference (2022) and simulated map (2022) is analyzed using the $K_{location}$, K_{no}, $K_{location\ stratum}$, and $K_{standard}$ parameters.

Numerous researches indicate that for LULC modeling, the predictive model's acceptable accuracy must be ≥ 0.70 (Armenteras et al. 2019; Verma et al. 2024). The actual and projected LULC are 72 % identical, according to the K-indices of agreement for this study, which are $K_{location}$ =0.69, K_{no}=0.74, $K_{location\ strata}$ = 0.72, and $K_{standard}$ = 0.71. The average value of 0.72 is greater than 0.70. Armenteras et al. (2019) obtained Cramer's V = 0.7833 and a Kappa total = 0.9704.

The LULC data for the years 2015 and 2019 were supplied for calibrating the LCM. The model's validation was then conducted by simulating the current LULC map for 2022. Having achieved satisfactory results in the model validation for the 2022 timeframe, the prediction process was reiterated to extend projections to the maps of 2024 and 2035. This involved utilizing the classified maps from 2015, 2019, and the actual 2022.

4.8 Estimation of carbon storage

Carbon storage values for the land cover classes, with the exception of grassland and settlement were sourced from field data measurement (Table 4.3). The aboveground biomass carbon for grassland, settlement, belowground biomass carbon, soil carbon, and dead wood carbon were put to zero for the carbon analysis. This is because the study focused on only the values from the field data measurement. For estimating carbon stock in the study landscape, the InVEST Carbon Storage and Sequestration model software, developed by the Natural Capital Project (www.naturalcapitalproject.org), was employed. The InVEST carbon model tracks the carbon cycle by summing up the carbon pool values assigned to each Land Use and Land Cover (LULC) type. Ultimately, it calculates the total amount of carbon stored in the entire study region (Piyathilake et al., 2022).

In the carbon storage and sequestration process the business as usual and REDD+ LULC maps for the year 2024 were provided. The current LULC map (2019 LULC map was used because of the start year of the Ghana Cocoa Forest REDD+ Project), the carbon pools data (CSV format), price of carbon (5 dollar/t), based on the current price negotiated with the Forest

Carbon Participants of the WorldBank, annual market discount rate (0.07), and annual price change (0.05) were also provided as required by InVEST 3.14.1 Workbench. To convert the carbon pool data to CSV format, Microsoft Excel was used. From the current and future output maps from the carbon storage and sequestration process, the carbon storage in 2019 and expected carbon storage in 2024 (for both business-as-usual and REDD+ scenario) were determined using the zonal statistics as table in ArcGIS 10.7.1. The same process was done to determine the expected business as usual and REDD+ scenario carbon storage for the year 2035.

Table 4.3: Carbon stocks in aboveground, belowground, soil, and dead wood across each land cover class

LULC class	Aboveground biomass carbon(tC/ha)	Belowground biomass carbon(tC/ha)	Soil carbon(tC/ha)	Dead wood carbon (tC/ha)
Closed Forest	154.78	0	0	0
Open Forest	30.95	0	0	0
Grassland	0	0	0	0
Settlement	0	0	0	0
Monoculture Cocoa	11.23	0	0	0
Agroforestry Cocoa	29.01	0	0	0
Other Tree Crops	0	0	0	0
Food Crops	0	1	0	0

4.9 Results

4.9.1 Accuracy assessment

Closed forest, open forest, grassland, settlement, monoculture cocoa, agroforestry cocoa, other tree crops, and food crops are the eight different classes the study area has been classified into. Table 4. displays the Overall Accuracy (OA), User's Accuracy (UA), and Producer's Accuracy (PA) for the Land Use and Land Cover (LULC) maps of 2015, 2019, and 2022. The 2015 LULC map achieved an Overall Accuracy (OA) of 97.8% and a kappa value of 0.97, indicating a high level of agreement. The 2019 and 2022 LULC maps exhibited Overall Accuracy values of 94.9% and 91.6%, with corresponding kappa values of 0.94 and 0.89, respectively.

The producer accuracy for the 2015 image classification ranges from 81.7% to 99.7%, with both monoculture cocoa and other tree crops having the highest producer accuracy. The user accuracy also ranges from 86.8% to 100%. For the 2019 image classification, the producer accuracy ranges from 79.6% to 99.6%, where monoculture cocoa and other tree crops still recorded the highest of 99.6%. Closed forest had the highest user accuracy of 100%. The producer accuracy for the 2022 image classification was 89.5%, 98.8%, 95.8%, 80.9%, 98.9%, 77.8%, 97.5%, and 97.8% for closed forest, open forest, grassland, settlement, monoculture cocoa, agroforestry cocoa, other tree crops, and food crops, respectively. Again, the user accuracy ranges from 63.3% to 100%, with closed forest recording the highest and open forest recording the lowest.

Table 4.4: Classification accuracy for the 2015, 2019, and 2022 land cover maps

LULC class	2015 PA (%)	UA (%)	2019 PA (%)	UA (%)	2022 PA (%)	UA (%)
Closed Forest	94.9	100	94.3	100	89.5	100
Open Forest	98.7	86.8	98.8	83.4	98.8	63.3
Grassland	99.5	97.4	96.6	97.7	95.8	93.6
Settlement	81.7	100	79.6	100	80.9	100
Monoculture Cocoa	99.7	96.1	99.6	84.7	98.9	78.9
Agroforestry Cocoa	99.8	99.0	84.3	99.0	77.8	96.8
Other Tree Crops	99.7	98.9	99.6	97.8	97.5	96.6
Food Crops	97.3	98.6	97.5	98.3	97.8	96.0
Overall accuracy	97.8		94.9		91.6	
Kappa	0.97		0.94		0.89	

4.9.2 Transitions in land use land cover of Assin South from 2015 to 2022

Land use land cover change map for Assin South was created for 2015, 2019, and 2022. The results show that between 2015 and 2019, closed forest was the major class of land cover in the area, covering 33672.81 ha (30.57%). Monoculture cocoa was the next most dominant landcover in the area, occupying a span of 24482.31 ha corresponding to 22.23%. Agroforestry cocoa and other tree crops in a close range, covered 14645.35 ha (13.30%) and 14407.72 ha (13.08%) of the landscape respectively. Next was food crops which occupied 8321.62 ha (7.55%) followed by grassland occupying 7614.65 ha (6.91%). The open forest and settlement took up 6333.67 ha (5.75%) and 667.36 ha (0.61%) of the landscape respectively. Between 2019 and 2022, Closed Forest remained the most dominant land cover, taking up 33,281.1ha (30.21%) of the landscape. Monoculture cocoa tagged on as the next dominant landscape covering 23,377.79 ha (21.22%) of the total landscape. Agroforestry cocoa 17,783.43ha (16.14%) and other tree crops 15637ha (14.20%) followed as the next dominant landcover respectively.

Table 4.5: LULC classes area for the years 2015, 2019, and 2022 (area unit = Hectares)

LULC class	2015	%	2019	%	2022	%
Closed Forest	33,672.81	30.57	33,281.10	30.21	32,585.25	29.58
Open Forest	6,333.67	5.75	5,934.19	5.39	5,589.01	5.07
Grassland	7,614.65	6.91	5,992.85	5.44	5,472.11	4.97
Settlement	667.36	0.61	1,148.98	1.04	1,191.73	1.08
Monoculture	24,482.31	22.23	23,377.79		22,560.60	
Cocoa				21.22		20.48
Agroforestry	14,645.35	13.30	17,783.43		19,065.04	
Cocoa				16.14		17.31
Other Tree Crops	14,407.72	13.08	15,637.00	14.20	17,463.38	15.85
Food Crops	8,321.62	7.55	6,996.96	6.35	6,225.19	5.65
Total	110152.34	100.00	110152.34	100.00	110152.34	100.00

Table 4.6a: LULC change matrix from 2015 to 2019 (area unit = Hectares)

LULC class	Closed Forest	Open Forest	Grassland	Settlement	Monoculture Cocoa	Agroforestry Cocoa	Other Tree Crops	Food Crops	Total
				2015 - 2019					
Closed Forest	33,209.39	402.46	6.99	0.03	10.47	16.85	26.26	0.36	33,672.81
Open Forest	67.30	5,531.65	0	9.66	456.26	40.08	227.90	0.81	6,333.67
Grassland	2.82	0	5,807.82	360.55	859.34	35.97	457.06	91.09	7,614.65
Settlement	0	0.08	0.53	662.92	0.09	3.24	0.03	0.47	667.36
Monoculture Cocoa	0.05	0	0	6.45	20,937.79	2,776.34	707.15	54.53	24,482.31
Agroforestry Cocoa	0.82	0	0	0	0	14,643.38	0	1.15	14,645.35
Other Tree Crops	0.65	0	174.35	8.23	0	163.00	14,053.04	8.45	14,407.72
Food Crops	0.07	0	0	97.87	1,113.66	104.54	165.35	6,840.10	8,321.62
Total	33,281.10	5,934.19	5,992.85	1,148.98	23,377.79	17,783.43	15,637.00	6,996.96	110152.34

The matrix for 2019-2022 is presented below;

Table 4.6b: LULC change matrix from 2019 to 2022 (area unit = Hectares)

2019 - 2022									
LULC class	Closed Forest	Open Forest	Grassland	Settle-ment	Monoculture Cocoa	Agrofo-restry Co-coa	Other Tree Crops	Food Crops	Total
Closed Forest	32,423.55	820.57	1.13	0.24	5.42	20.31	8.96	0.92	33,281.10
Open Forest	111.03	4,599.78	14.5	7.12	623.03	224.15	189.27	165.31	5,934.19
Grassland	0.98	36.65	5,189.17	25.98	211.47	81.73	157.77	289.1	5,992.85
Settlement	6.17	5.72	15.99	1,072.68	11.34	4.28	6.89	25.89	1,148.98
Monoculture Cocoa	9.39	83.34	0	20.97	20,863.82	1,299.21	380.39	720.67	23,377.79
Agroforestry Cocoa	8.09	7.88	76.03	6.8	168.47	17,411.61	42.95	61.6	17,783.43
Other Tree Crops	13.59	1.21	10.04	5.07	256.89	13.31	15,259.88	77.01	15,637.00
Food Crops	12.44	33.86	165.25	52.85	420.16	10.43	1,417.27	4,884.69	6,996.96
Total	32,585.25	5,589.01	5,472.11	1,191.73	22,560.60	19,065.04	17,463.38	6,225.19	110152.34

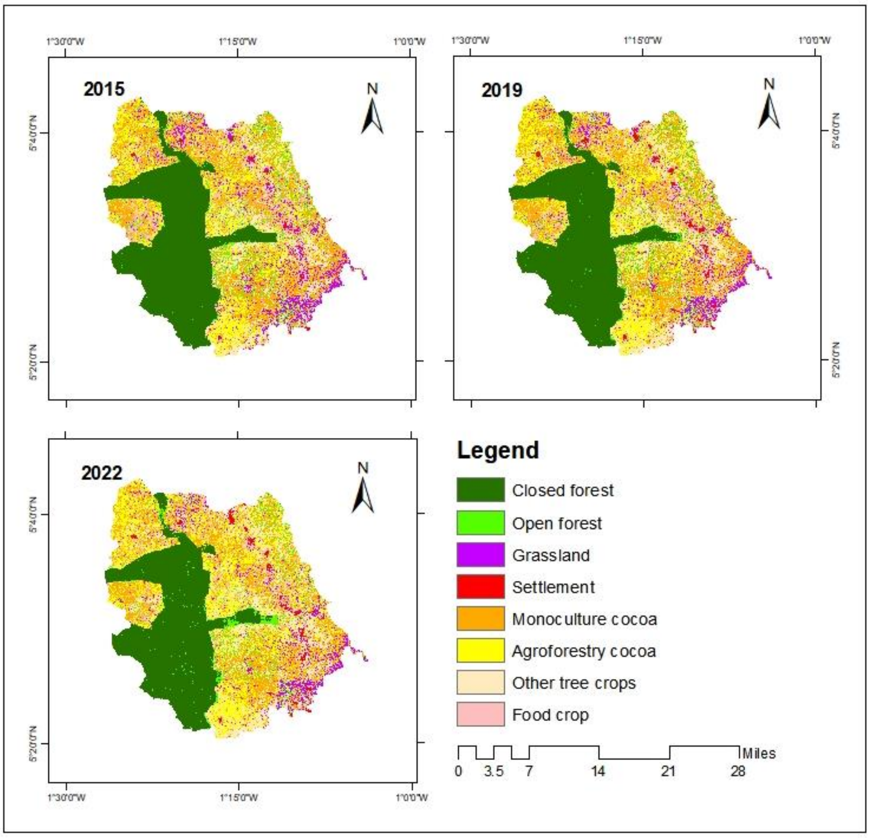


Figure 4.215: Land use land cover maps of the Assin South landscape for 2015, 2019, and 2022

4.9.3 Business as usual (BUA) Predicted land use land cover maps of Assin South

According to the simulation results, closed forest, the dominant land cover class is expected to decrease from 33281.1 ha to 32789.16 ha (29.76 %) between 2019 and 2024. Open forest and Grassland will also decrease to 5634.96 ha and 4361.42 ha. Settlement, monoculture cocoa, agroforestry cocoa, and other tree crops will rather increase to 1502.5 ha (1.36 %), 23856.65 ha (21.65 %), 18665.15 ha (16.94 %), and 16345.54 ha (14.84 %), respectively.

From the 2035 prediction area and percentage coverage results, it is expected that closed forest will occupy a total area of 31996.45 ha (29.04 %), indicating

1284.65 ha decrease of closed forest cover from 2019. There will also be a decrease of open forest, grassland, and monoculture cocoa by 559.69 ha, 3323.66 ha, and 641.08 ha, respectively. Settlement is expected to increase to 1943.04 ha, agroforestry cocoa to 21006.69 ha, and other tree crops to 17428.76 ha.

4.9.4 REDD+ Predicted land use land cover maps of Assin South

Between 2019 and 2024, both closed forest and open forest will maintain their total area without losing to other classes based on the REDD+ scenario projection results. Closed forest and open forest is expected to cover an area of 33,281.1 ha (30.21 %) and 5,934.19 ha (5.38 %) . Aside closed forest and open forest maintaining their total area in the study landscape, settlement will also maintain its total area coverage of 1148.98 ha. Agroforestry cocoa and other tree crops will increase to 21,063.33 ha (19.12 %) and 16,081.05 ha (14.59 %). The remaining area of the study landscape is expected to be covered by grassland (4,715.24 ha), monoculture cocoa (22,085.99 ha), and food crop (5,842.46 ha).

From the projection results between 2019 and 2035, closed forest, open forest, and settlement will still maintain the same expected coverage area in 2024. Grassland, monoculture cocoa, and food crop is expected to decrease to 3463.33 ha, 18,504.63 ha, and 4,785.24 ha, respectively. Agroforestry cocoa and other tree crops will rather increase to 26,344.35 ha and 16,690.52ha.

Table 4.7: Area and percentage coverage of LULC classes for the business as usual (BAU) and REDD+ predicted years 2024 and 2035 (area unit = Hectares)

LULC class	2024 (BAU)	%	2024 (REDD+)	%	2035 (BAU)	%	2035 (REDD+)	%
Closed Forest	32789.16	29.76	33281.1	30.21	31996.45	29.04	33281.1	30.21
Open Forest	5634.96	5.12	5934.19	5.38	5374.5	4.87	5934.19	5.38
Grassland	4361.42	3.95	4715.24	4.28	2669.23	2.42	3463.33	3.14
Settlement	1502.5	1.36	1148.98	1.04	1943.04	1.76	1148.98	1.04
Monoculture Cocoa	23856.65	21.65	22085.99	20.05	22736.71	20.64	18504.63	16.79
Agroforestry Cocoa	18665.15	16.94	21063.33	19.12	21006.69	19.07	26344.35	23.92
Other Tree Crops	16345.54	14.84	16081.05	14.59	17428.76	15.82	16690.52	15.15
Food Crops	6996.96	6.35	5842.46	5.30	6996.96	6.35	4785.24	4.34
Total	110152.34	100.00	110152.34	100.00	110152.34	100.00	110152.34	100.00

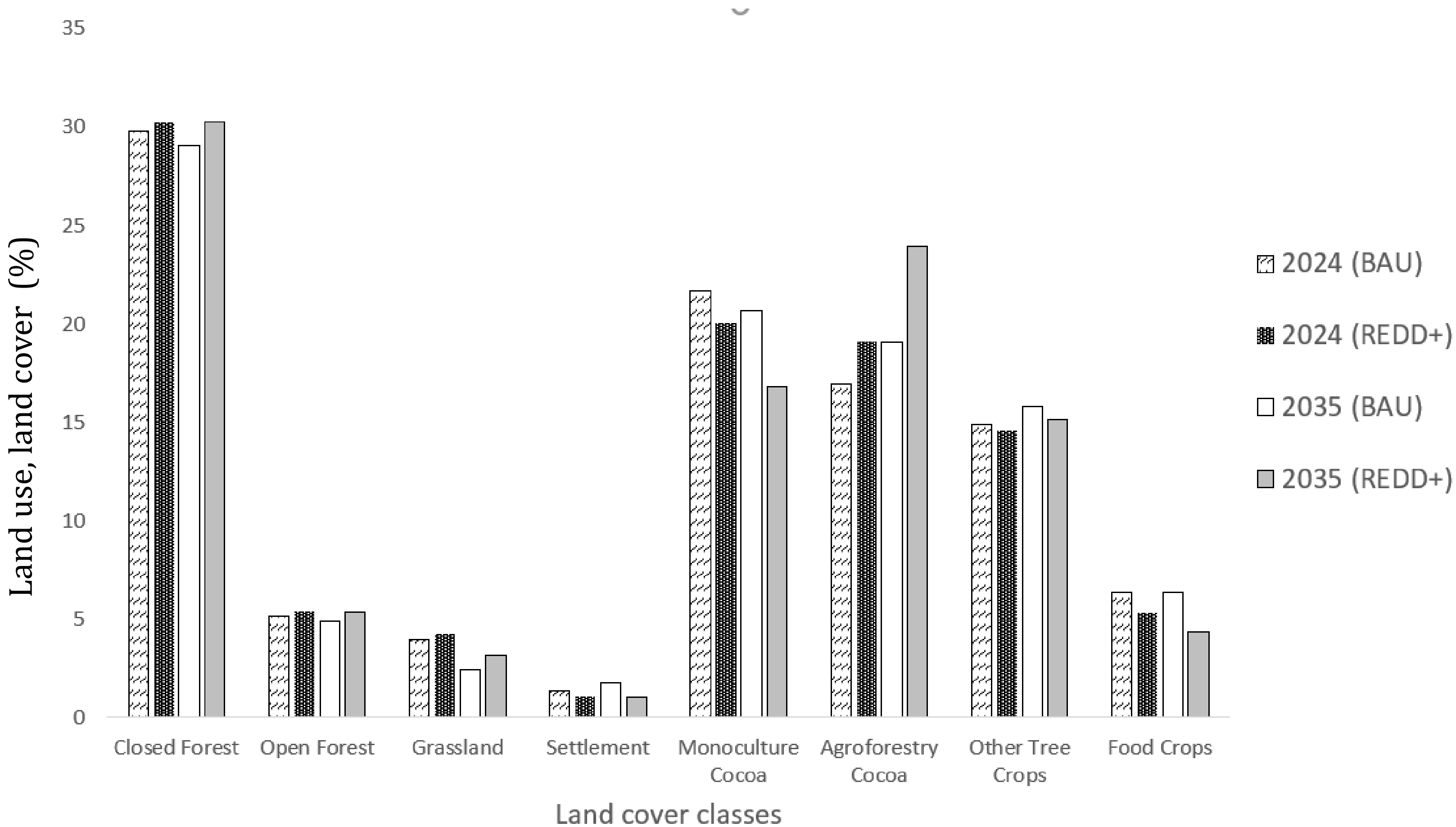


Figure 4.16: LULC classes coverage for the business as usual (BAU) and REDD+ predicted years 2024 and 2035

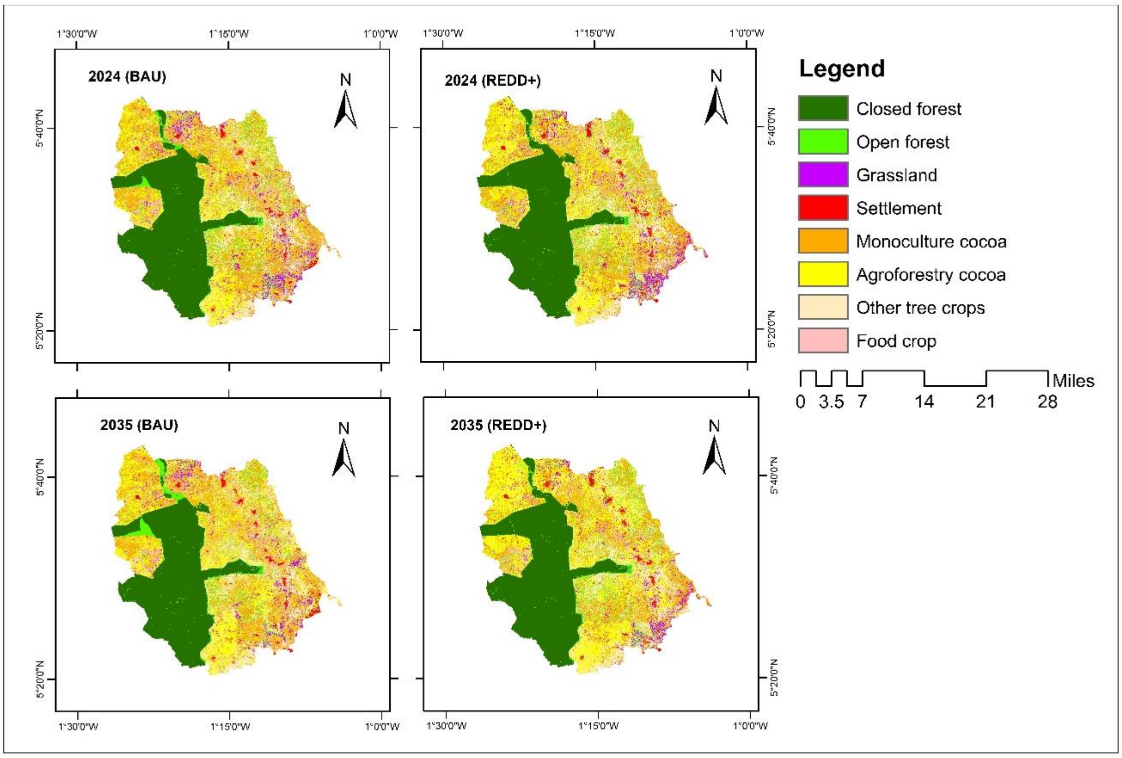


Figure 4.417: Predicted land use land cover maps of the Assin South landscape for 2024 (BAU), 2024 (REDD+), 2035 (BAU), and 2035 (REDD+)

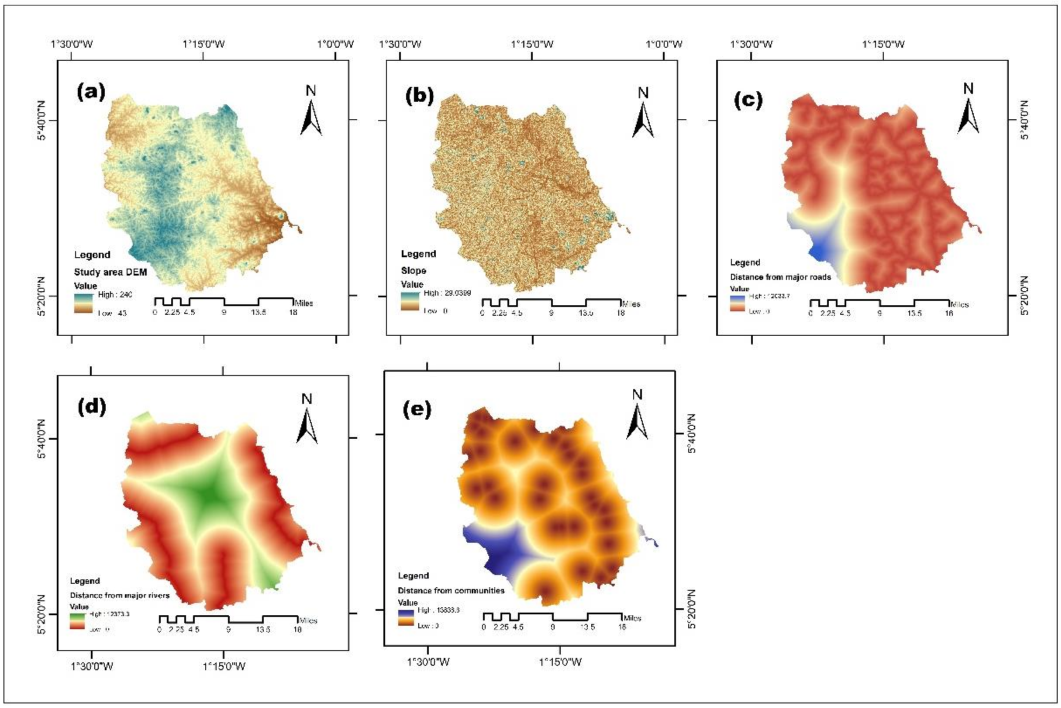


Figure 4.518: Spatial variables: (a) study area DEM (b) slope (c) distance from major roads (d) distance from major rivers (e) distance from communities

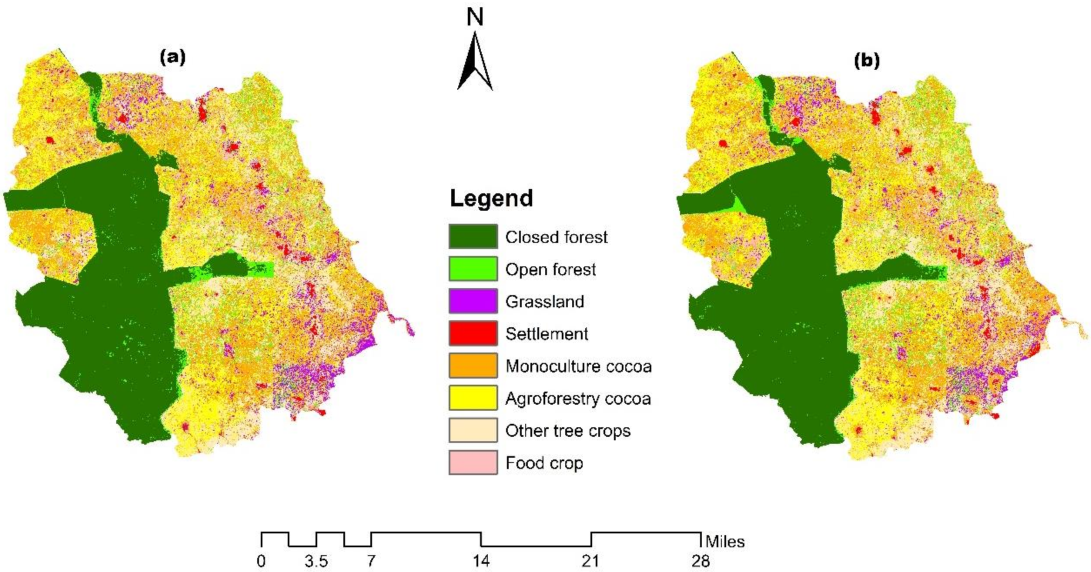


Figure 4.6: a) Actual map and (b) Projected map for 2022

4.8. 5 Results of carbon prediction

From the carbon storage under BAU scenario table, the continuous decline in the forest areas from 2019 through 2024 to 2036 and relatively slower adoption of cocoa agroforest contributed to a decline in the total carbon stock of the study area. Between 2019 and 2024, the area lost 2% of the carbon stock with a further 2% (cumulative 4%) by 2036. The gain in carbon stock under the BAU scenario from cocoa agroforestry was 5% and 18% for the periods 2024 and 2036 respectively.

Table 4.8: Carbon storage in the different land use land cover for BAU scenario -2019

Landuse type	AREA	Total C (million t)	C in each LULC (%)
		2019	
Closed Forest	33,281.10	6,681,882.04	84.23
Open Forest	5,934.19	272,693.99	3.44
Grassland	0	0	0
Settlement	0	0	0
Monoculture Cocoa	23,377.79	356,011.21	4.49
Agroforestry Cocoa	17,783.43	622,681.96	7.85
Other Tree Crops	0	0	0
Food Crops	0	0	0

The 2024 and 2035 BAU scenarios are presented below;

Table 4.9 Carbon storage in the different land use land cover for BAU scenario (2024 and 2035

	2024		
Closed Forest	32,789.16	6,583,114.72	83.77
Open Forest	5,634.96	258,943.47	3.29
Grassland	0	0	0
Settlement	0	0	0
Monoculture Cocoa	23,856.65	363,303.58	4.62
Agroforestry Cocoa	18,665.15	653,555.14	8.32
Other Tree Crops	0	0	0
Food Crops	0	0	0
	2035		
Closed Forest	31,996.45	6,423,961.49	82.86
Open Forest	5,374.50	246,974.54	3.19
Grassland	0	0	0
Settlement	0	0	0
Monoculture Cocoa	22,736.71	346,248.45	4.47
Agroforestry Cocoa	21,006.69	735,543.53	9.49
Other Tree Crops	0	0	0
Food Crops	0	0	0

The carbon situation from REDD+ scenario is however different compared to BAU scenario. With the intervention of REDD+, the forest areas in both closed and open forests are protected and conserved through the time epochs. The agroforestry situation of the landscape also improved with 18% increase of carbon sequestration in cocoa agroforests between 2019 and 2024. There is a significant increase in the 2019-2036 timeline with a major 48% increase in carbon sequestration from cocoa agroforestry.

Table 4.10: Carbon storage in the difference land use land cover for REDD+ scenario (2024 and 2035)

Landuse type	AREA	Total C (million t)	C in each LULC (%)
		2024	
Closed Forest	33,281.10	6,681,882.04	83.23
Open Forest	5,934.19	272,693.99	3.40
Grassland	0	0	0
Settlement	0	0	0
Monoculture Cocoa	22,085.99	336,338.89	4.19
Agroforestry Cocoa	21,063.33	737,526.76	9.19
Other Tree Crops	0	0	0
Food Crops	0	0	0
		2035	
Closed Forest	33,281.10	6,681,882.04	81.90
Open Forest	5,934.19	272,693.99	3.34
Grassland	0	0	0
Settlement	0	0	0
Monoculture Cocoa	18,504.63	281,799.76	3.45
Agroforestry Cocoa	26,344.35	922,440.24	11.31
Other Tree Crops	0	0	0
Food Crops	0	0	0

4.8 .6 Net Present Value of landscape

The declining NPV trend suggests significant economic losses by 2035 as a result of the ongoing decline in the estimated amount of forest cover under the BAU scenario, which will raise the cost of C. In terms of carbon trading, the state suffers a financial loss as a result. However, because of the sequestration in protected forests and the rise in carbon value from cocoa agroforests, the REDD+ scenario offers a positive net present value (NPV) as presented in Table 4..

Table 4.11: Net Present Value (USD) for BAU Scenario and REDD+ Scenario

LULC map	MIN	MAX	RANGE	MEAN	STD	SUM
2024 (BAU)	(7.72)	0.99	8.71	(0.03)	0.54	(322029.51)
2035 (BAU)	(7.67)	0.98	8.65	(0.07)	0.87	(771585.99)
2024 (REDD+)	0	0.99	0.99	0.05	0.20	499335.85
2035 (REDD+)	0	0.98	0.98	0.11	0.29	1178524.07

4.9 Discussion

4.91 Forest cover in Assin South from 2015 to 2022

Between 2015 and 2022, forest cover in the study landscape (both closed forest and open forest) decreased by 1832.22 ha. This finding is corroborated by similar research done by Tsai et al. (2019), which stated that forest cover decreased in southern Ghana by 625 km^2 (68%). Another related study conducted by Owusu and Essandoh-Yeddu, (2018) also stated the forest cover in Ghana's Forest Savannah Transitional Zone precisely Brong Ahafo Region decreased from 169700.85 ha to 98574.21 ha between 1990 and 2000. From Agariga et al. (2021) research finding, forest cover in the Asutifi North District of Ahafo Region also reduced from 63% to about 32% between 1986 and 2020. Both the primary forest and secondary forest in the Wassa West District has also reduced according to Kusimi, 2008.

From the numerous studies conducted in Ghana and beyond, area of forest has been reducing due to several anthropogenic activities. Forest cover in Ghana has reduced because of human activities such as lumbering, cocoa farming and mining (Kusimi, 2008). Aside human activities, natural occurrences such as wildfire is said to be a driver of forest loss (Ankomah et al., 2020). Misuse of forest resources due to weak forest management policies and conventional logging operations using unplanned-selective logging method are also major drivers of forest loss in Ghana (Owusu-prempeh, 2017). Again, human need for settlement space and the higher demand for fuelwood for cooking are often stated as the cause of forest cover loss or deforestation (Amoah and Korle, 2020). Changes in climatic factors, such as humidity change as a results of unstable temperature and precipitation is likely to affect water use by forest plants. This process affects forest growth and health, leading to the reduction in forest cover (Amoah and Korle, 2020).

4.9.2 Extent of monoculture cocoa and agroforestry cocoa between 2015 and 2022

Over the seven-year period, monoculture cocoa decreased by 1921.71 ha in the study landscape. Agroforestry cocoa on the other hand increased by 4419.69 ha. There are numerous similar research studies which supports this finding. For instance, Batame (2023) research finding made it clear that monoculture cocoa decreased from 514.04 km^2 to 407.27 km^2, whiles agroforestry cocoa increased from 69.12 km^2 to 307.41 km^2 between 1999 and 2022 in the Bia West District. Reduction in monoculture cocoa could be as a results of direct exposure to sunlight, causing some of them to die eventually (Andres et al., 2016; Batame, 2023). Again, large areas of monoculture was transitioned to agroforestry cocoa, other tree crops, and food crops in the study landscape. The increase in agroforestry cocoa could also be attributed to large areas suitables for growing cocoa, the social prestige associated to growing cocoa as an asset for future generations, and the numerous government benefits for cocoa farming (Batame, 2023).

4.9.3 Future extent of LULC change in Assin South District under BAU and REDD+ scenarios

For the BAU scenario, forest cover is expected to decrease by 791.17 ha between 2019 and 2024. Between 2019 and 2035, forest cover will decrease by 1844.34 ha. These findings are similar to Nyamari and Cabral (2021) research finding conducted in Kenya. From their research study, forest decreased from 39407.9 km^2 in 2016 to 10638.2 km^2 in 2028.

Under REDD+ scenarios, forest are protected with a slower or no deforestation. This is confirmed by the studies of Simonet et al. (2019)who found out that 4.0 ha of forest were saved from deforestation by participating farmers in a REDD+ project in the Brazilian Amazon. Cocoa agroforests are expected to increase with the conversion of monoculture cocoa to agroforests. Nyamari and Cabral (2021) also found forest areas to improve under REDD+ scenarios

Armenteras et al. (2019) found out that under Business as usual scenarios, there will be fragmentation and decreased connectivity of the northern part of NW Amazon in Columbia with a forest cover loss of 7.92% but slower when climate change intervention

The situation of land area available for food crops production observed as reducing under REDD+ scenario is similar to findings of Tabeau et al. (2017) that in certain less developed nations, the agri-food industry is impacted by REDD+ regulations if more than 15% of the potential for agriculture is kept from being destroyed by deforestation.

The intact forests protected under the REDD+ Scenario and the increase in canopy cover within the cocoa agricultural landscapes may improve landscape connectivity under the REDD+ scenario for the movement of species within the study area. Studies by Oliveira-Junior et al. (2020) observed that fragmented landscapes encourage the seclusion of forests encircled by a matrix that obstructs or impedes species migration, impacting their range and endangering their preservation and that connectivity of landscapes should be promoted.

4.9.4 Carbon Dynamics and NPV under BAU and REDD+ Scenarios

Our findings of loss of forest cover and negative NPV under BAU scenario is confirmed by many studies (Avtar et al. 2022; Verma et al. 2024; Adelisardou et al. 2022). For Viti Levu Island, Fiji, a possible loss in carbon of −7.959 Mt C is projected in the next 20 years if the business-as-usual scenario does not change anytime soon (Avtar et al. 2022). Iran faces the potential loss of 2,624,113 metric tons of stored carbon in its plains, experiencing an average annual sequestration decline of -475,547 metric tons if the historical trend persists under the business-as-usual (BAU) scenario. This could result in substantial social costs (Adelisardou et al. 2022). Nyamari and Cabral (2021) predict the positive change in carbon stocks under REDD+ intervention.

4.10 Conclusion

The main objective of this study was to investigate the costs and spatiotemporal impacts of varying intensities of land use and cover changes on carbon sequestration and storage. The results underscore the importance of government initiatives, particularly in areas with accessible road networks, to establish provisions for the conservation of forested landscapes. The north western block of the Kakum National Park faces the threat of encroachment and degradation under the business as usual scenario for both 2024 and 2036. Forest loss is ongoing at the business-as-usual rate in the Assin South district.

Various scenarios were considered for a dynamic analysis of the potential for storing or removing carbon by different landuse. Our findings reveal that alterations in land cover and use can exert a substantial influence on the enduring spatial pattern of carbon sequestration and storage.

We can conclude that a country has significant economic losses when its forest cover declines. Also carbon stocks increase through cocoa agroforests and the protection of forests under the REDD+ scenario.

The study concludes that carbon stock under REDD+ could increase by 13 % and 25 % over the BAU scenario in 2024 and 2035, respectively. However, landuse for crop production could be reduced by 17 – 32% in the same period

CHAPTER 5:

CAPTURING LAND-USE DECISION MAKING FACTORS FOR FARMERS: CASE STUDY OF ASSIN SOUTH DISTRICT, CENTRAL REGION, GHANA

5.1Introduction

As economies grow, socioeconomic and environmental variables are increasingly important for the long-term viability of farming practices (Wadduwage 2021), results indicate that farmers make land use decisions influenced by diverse factors, including livelihood conditions, weather discrepancies, and the physical-economic conditions of their localities. (Nguyen et al. 2017). One of the various factors is unpredictable rainfall patterns that alter the availability of fodder and longer growing seasons brought about by global change that opens up new land use opportunities (Zhumanova et al. 2016). Land use adoption by farmers is also contingent upon several socio-economic and farm-related factors (Nigussie et al. 2017). Due to their poor knowledge of environmental issues and the current state of the economy, farmers are primarily focused on increasing their income (Goibov et al. 2012). The lack of resources and tools for adaptation can also be a hindrance caused by poverty which influences their choice in land use practices (Obayelu et al. 2014). Villamor et al. (2014) evaluated gender's role in decision-making and predicted increased women's participation to raise emissions from localized deforestation and forest degradation and complicate efforts to cut those emissions. The elements that influence participation in REDD+, remain unclear. It is critical to comprehend the ways in which socioeconomic variables impact farmers' decisions about land use and adoption of REDD+. These characteristics include land tenure, gender, income and benefit-sharing (Villamor et al. 2014; Damnyag et al. 2012; Schindler 2009).

The REDD+ principle establishes results-based payments and therefore requires performance indicators that can be measured to determine if the scheme is effective.

In capturing factors influencing farmers in land-use decision making in Assin South district, the focus was to;

- Determine the socio-economic characteristics that influence the choice of farming system.
- Assess the determinants of future farming decision given financial support.

5.2 Methodology

5.2.1 Study Area

Brahabebome, Assin Adiembra and Assin Kruwa communities were selected for the study based on three considerations. Firstly, the distributions of these communities around the Kakum national park. To obtain a fair representation of the outcomes, the communities were selected at the North West (Brahabebome), Northern (Assin Adiembra), and the South West (Assin Kruwa) of the National park. Secondly, the evidence of implementation of REDD+ through both the government and private sector partners of REDD+ was considered for the communities. The third element of consideration was the size of the community for the distribution of the samples to represent each community.

The sizes considered small community, medium community and large community based on the 2010 census data for the district. The sizes were considered because it was assumed that diversity in income activities increases as the size of the community increases.

5.2.1.1 Sample size calculation

The sample size for the survey is calculated using the formula below (Equation 5.1);

$$n' = \frac{n}{1+\frac{z^2 * \hat{p}(1-\hat{p})}{\varepsilon^2 N}} \quad \text{.......................................} \; 5.1$$

Where z is the z score, ε is the margin of error, N is the population size, and $\hat{p}$ is the population proportion.
The tables below present the total households per community and the selected number of households for the research.

Table 5.1: Population distribution of case study area

Community Name	Population			Number of households	Category of community*	REDD+ level*
	Both Sexes	Male	Female			
Assin Adiembra	3,701	1,810	1,891	746	Large	Low
Kruwa	2,847	1,469	1,378	674	Medium	High
Brahabebome	1,599	809	790	311	Small	Medium

Source:(Ghana Statistical Service 2014) *Researcher's own classification

Table 5.2: Sample distribution of case study area

Community Name	Number of households sampled for the study
Assin Adiembra	143
Kruwa	128
Brahabebome	62
Total	333

5.2.1.2 Sampling technique for social survey

Simple random sampling was employed in the selection of households for the socio-economic survey. The administration of the questionnaire was with either the household head (in the instance where the household head was fit and could sit through the time for the questions or was present during the house visit) or a respondent (someone within the household responding to the questions on the directive of the household head or when the household head was not available to answer the questions)

5.2.1. 3 Socio-economic settings

The Assin South District has a housing stock of about 18,938 representing 5.5 percent of the total number of houses in the Central region of Ghana. Household averaged 5.4 members. Agriculture is practiced by 81.1% of families in the district. Crop farming is practiced by the majority of households in the district (98.1%). Poultry (chicken) is the most commonly raised animal in the district (Ghana Statistical Service 2014). Access to main market centers remains a challenge as the road network is mostly in a deplorable state. There are currently ongoing efforts in constructing roads for some of the main connecting roads, trunk roads under the Cocoa Roads rehabilitation project by the government. Both Kruwa and Assin Adiembra had access to the national grid for electricity whereas Brahabebome did not have electricity. The community is now being provided with solar-powered light poles in the main street and community center. The landscape is dominated by the Kakum National Park and cocoa farm with most farmers in the study areas being cocoa farmers. Other tree crops such as rubber (*Hevea brasiliensis*) and oil palm (*Elaeis guineensis*) and citrus can also be found in the landscape with patches of fallow lands (secondary forests) and other annual crops.

5.2.1.4 Land tenure and inheritance

The Central region and for that matter, most people of the Akan tribe follow the matrilineal inheritance system. However, since the farming landscape of especially cocoa is known for the influx of migrant farmers, the lineage for inheritance was established for the study. Individuals either belong to the matrilineal or the patrilineal inheritance system though an individual could belong to both systems when the mum and dad belong to these two systems separately.

Smallholder farms with a variety of food crops and perennials under various land tenure patterns define the Assin South district. Share-cropping system, family ownership, single ownership and rented/lease systems of land tenure exist in the study area.

Under the share-cropping arrangements, the caretaker farmer does tend the farm and all farm related activities with financial support or none from the actual landowner. The yields from the farm are then shared under an agreed arrangement either into two parts (Abuno) or three parts (Abusa). The Abuno is the common form of the share-cropping in the Assin South with 27.9% and Abusa with 7.2%.

Famers who were actual single landowners of their farms formed 52.6% with family ownership forming 10.8%. Rent/Leasehold is not a common practice within that enclave with only 1.5% of the households under that system.

5.3 Model Estimation

5.3.1 Decision on Farming system

Binomial Logistic regression model for the choice of farming system

The binomial logistic regression is utilized to pinpoint the factors that impact the choice of farming system by agent groups. This model relies on the random utility model and it is specified in a functional form as (Equation 5.2);

$$y = \frac{e^{(b_0+b_1x)}}{1+e^{(b_0+b_1x)}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 5.2$$

Here, x = input value, y = predicted output, b_0 = bias or intercept and b_1 = the coefficient for input x. The equation above could resemble a linear regression, in which weights or coefficient values are used to predict an output value by combining input values linearly. However, the difference is that, the output value of the logistic model is a binary value (0 or 1) instead of a numeric value as in the case of a linear regression model. Using STATA, the log likelihood technique is used to estimate the vectors or parameters based on the data set of each household agent.

Specification of Variables

Dependent variable

Farming system $y_{(0,1)}$ denotes the dependent variable of the logistic regression model. The two types of farming systems include, cocoa agroforestry (0) and cocoa monoculture (1).

Explanatory variables

On the decision of a farming system, respondents have the independent variables that may affect their decision. These variables are categorized into household agents' characteristics and others. The other characteristics include; income components, physical components, asset components, and cost components.

Table 5.3: Variable description

Variables	Description
Farming Systems	The farming system engaged in by respondent , Cocoa Agroforestry and Cocoa Monoculture (0= Cocoa Agroforestry, 1= Cocoa Monoculture)
Marital Status	Whether one is single or married (0= Single, 1= Married)
Education	The education status, Whether one has had a formal education or not (0= no formal education, 1= formal education)
Gender	The gender of respondent, male and female (0= Male, 1= Female)
Age	The age of respondent
Animal	Whether the respondent owns livestock or not (0= Yes, , 1 = No)
Years of farming	The number of years engaged in farming
Total Land holdings (ha)	Hectares of land owned
Cocoa Income	Income from cocoa produced in Ghana Cedis (Gh¢)
Income from off-farm activity	Income from off-farm activities in Ghana Cedis (Gh¢)
Distance to town center (m)	The plot distance to town center in meters
Distance to road side (m)	The plot distance to the road side meters
Input cost	The cost of input for farming activities

Household Agent Characteristics

The household agent characteristics here are the variables that describe the respondent or the representative of the household. These include; age, marital status, gender, and education. Age here, implies the age of the respondent in years. Marital status explains whether one is single or married. The gender depicts the gender status of the individual namely, male and female. The levels include; males and females respectively. The education status variable also describes the educational level of the respondent. There are 2 levels, the no formal education level, and formal education level. Finally, years of farming shows the number of years one has been farming.

Other characteristics

Concerning the other characteristic, the component variables include, income, cost, asset and physical. The income components comprise, cocoa income, and income from off-farm activities. Cocoa income is explained as income earned from cocoa produced, and income from off-farm activity is also explained as income from off-farm activities. With the asset component, the variables encompass animal, and total land holdings in hectares. Animals here describe whether the respondent has livestock or not. Then the total land holdings variable gives in hectares the total land owned.

The physical component comprises the variables as distance to town centre, and distance to road. The distance to town depicts the plot distance to the town centre in meters while distance to road shows in meters the plot distance to the road side. Furthermore, the cost component includes the input cost. The input cost implies the total cost incurred by households as far as production is concerned.

5.3.2 Decision on land use continuity

Binomial Logistic regression model for the choice between continuing with cocoa farming or changing to new crop or investment given financial support in the next 5 to 20 years

The binomial logistic regression is utilized to pinpoint the factors that influence the decision to choose between continuing with cocoa farming and changing to a new crop or investment by agent groups in the next 5 to 20 years if households are given financial support. This model is relies on the random utility model and it is specified in a functional form as (Equation 5.3);

$$y = \frac{e^{(b_0+b_1x)}}{1+e^{(b_0+b_1x)}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots \; 5.3$$

Where, x = input value, y = predicted output, b_0 = bias or intercept and b_1 = the coefficient for input x. The equation above may be analogous to that of a linear regression that uses weights or coefficient values to predict an output value by combining input values in a linear fashion. However, the difference is that, the output value of the logistic model is a binary value (0 or 1) instead of a numeric value as in the case of a linear regression model. Using STATA, the log likelihood technique is used to estimate the vectors or parameters based on the data set of each household agent.

Specification of Variables

Dependent variable

Future choice $y_{(0,1)}$ denotes the dependent variable of the Logistic regression model. The two groups of systems include, continuing with cocoa farming (0) and changing to a new crop investment.

Explanatory variables

For the choice between continuing with cocoa farming or changing to new crop or investment, respondents have the independent variables that may affect their choice. These variables are categorized into household agents' characteristics and other characteristics. The other characteristics include; income component, physical component, cost component and system component.

Table 5.4: Variable Description for future choice of landuse

Variables	Description
Next 5 to 20 years	Whether respondent is willing to continue with cocoa farming or change to a new crop if given financial assistance (0= change to new crop 1= continue with cocoa farming
Age	The age of respondent
Education	The education status, Whether one has had a formal education or not (0= no formal education, 1= formal education)
Gender	The gender of respondent, male and female (0= Male, 1= Female)
Farming system	The farming system engaged in by respondent , Cocoa Agroforestry and Cocoa Monoculture (0= Cocoa Agroforestry, 1= Cocoa Monoculture)
Livestock income	Income earned from rearing livestock
Land holdings per capita	Per capita from land holdings
Cocoa Income	Income from cocoa produced in Ghana Cedis
Income from off-farm activity	Income from off-farm activities in Ghana Cedis
Distance to town (m)	The plot distance to town in meters
Distance to house (m)	The plot distance to the house in meters
Cost of labor	The cost of labor involved in the farming activities
Input cost	The cost of input for farming activities

Household Agent Characteristics

The household agent characteristics here are the variables that describe the respondent or the representative of the household. These include; age, marital status, gender, and education. Age here, implies the age of the respondent in years. Marital status explains whether one is single or married. The gender depicts the gender status of the individual namely, male and female. The levels include; males and females respectively. The education status variable also describes the educational level of the respondent. There are 2 levels, the no formal education level, and formal education level. Finally, years of farming shows the number of years one has been farming.

Other characteristics

Concerning the other characteristic, the component variables include, income, cost, physical and system. The income components comprise, cocoa income, income from off-farm activities and land holdings per capita and livestock income. Cocoa income is explained as income from cocoa produced while income from off-farm activity is explained as income from off-farm activities. Land holdings per capita as the per capita income from land holdings as livestock income is the income earned from rearing livestock.

Moving on to the physical component, the variables comprise the distance to town center, distance to road. The distance to town depicts the plot distance to town in meters while distance to road shows in meters the plot distance to the road side. Also, the cost component includes, input cost while the system component includes farming system. Input cost depicts the cost of input in involved in production and farming system described the type of farming system one engages in; cocoa monoculture or cocoa agroforestry.

5.3.3 Household agents' behavior estimation regarding land-use choices

Multi-nomial logistic regression for land-use choices

The factors influencing the land-use decisions made by household agent groups are determined using the multi-nomial logistic model (M-logit). The multi-nomial logistic regression is also based on the random utility model and its functional form is shown as (Equation 5.4);

$$p(y_i = k) = \frac{\exp(X_i \beta_k)}{1+\sum_{j-1}^{j} \exp(X_i \beta_j)} \text{ .... } 5.4$$

In this model, the dependent variable categories, denoted as k=0,1,...,J, are employed to forecast the probability (p) of selecting a particular land use (y_i) as the observed outcome for the i-th observation on the dependent variable. Here, X_i represents a vector of explanatory variables for the i-th observation, and (β_j) signifies a vector of regression coefficients in the j-th regression. Utilizing STATA, the log-likelihood technique is employed to estimate the parameter vectors based on the dataset for each household agent.

Specification of Variables

Dependent Variable

The M-logit model's dependent variable is households' land-use choice (P_use). The available options encompass cocoa, oil palm, rubber, and other alternatives.

Explanatory variables

In determining future land-use options, independent variables are interacting with the dependent variable, potentially influencing the decision-making process. These variables are categorized into characteristics of household agents and other relevant factors. The other characteristics include; income component, physical component, asset component, cost component, and system component.

Table 5.5: Variable description for landuse choice

Variables	Description
Land-use choices	The choice of land use, cocoa farming, oil palm farming, rubber farming, other land-use options (0= cocoa farming, 1= oil palm farming, 2= rubber farming, 3= other land-use options)
Gender	Whether the respondent is a male or female (0= male, 1= female)
Education Status	The education status, whether one has had a formal education or not (0= no formal education, 1= formal education)
Age	The education status, whether one has had a formal education or not (0= no formal education, 1= formal education)
Next 5 to 20 years	Whether respondent is willing to continue with cocoa farming or change to a new crop if given financial assistance (0= change to new crop 1= continue with cocoa farming
Livestock income	Income earned from rearing livestock in Ghana Cedis
Cocoa income	Income earned from cocoa production in Ghana Cedis
Total land holdings (ha)	Total land owned in hectares
Land holding per capita	Per capita from land holdings of respondent
Income from off farm activities	Income from off farm activities households engage in
Distance to town center (m)	Plot distance to town center in meters
Distance to road (m)	Plot distance to road side in meters
Input cost	The cost of all inputs (in Ghana Cedis)

Household agent characteristics

The household agent characteristics here are the variables that describe the respondent or the representative of the household. These include; age, marital status, gender, and education. Age here, implies the age of the respondent in years. Marital status explains whether one is single or married. The gender depicts the gender status of the individual namely, male and female. The levels included; males and females. The education status variable also describes the educational level of the respondent. There are 2 levels, the no formal education level, and formal education level. Finally, years of farming shows the number of years one has been farming.

Other characteristics

Concerning the other characteristic, the component variables include, income, asset cost, physical and system components. The income components comprise, cocoa income, livestock income, and income from off farm activities. Cocoa income shows the income earned from cocoa production as livestock income depicts the income earned from rearing livestock. Off farm activities also cover the income earned from off farm activities.

Moving on to the asset component, the variable, total land holding in hectares explains the land in hectares one owns. The physical component comprises the variables as plot distance to town centre, and distance to road. The distance to town depicts the plot distance in meters to the town centre while the plot distance to road also shows the plot distance in meters to the road side.

Furthermore, the cost component includes the input cost. The input cost implies the input cost of production. Finally, the system component involves the variable, next 5 to 10 years. The next 5 to 10 years variables also presents a choice between continuing with cocoa farming in the next 5 to 10 years or invest in another crop production given financial support.

Prior to the logistic regression the explanatory variables were checked for the presence of multicollinearity. The Variable Inflation Factors (VIF) was employed for the testing of multi-collinearity. In Ordinary Least Square regression analysis, there exist the problem of multicollinearity when there is a linear relationship between two or more independent variables thus, the VIF shows the severity of multicollinearity.

The VIF can be calculated as (Equation 5.5);

$$VIF_i = \frac{1}{1-R_i^2} = \frac{1}{Tolerance} \qquad \text{……………………………..} \; 5.5$$

where R_i^2 is the unadjusted coefficient of determination for regressing the i^{th} independent variable on the remaining ones. The Tolerance is the reciprocal of VIF and either the Tolerance or the VIF can be used to detect multicollinearity. Usually, a VIF above 4 or Tolerance below 0.25 shows the possibility of the presence of multi collinearity and hence needs to be investigated further.

5.4 Results and Discussion

To start with, a multi-collinearity test was carried out to know the collinearity between the variables before the major regressions. For this study, the Variable Inflation Factors (VIF) method of multi-collinearity testing was employed. The VIF determines the strength of the correlation between the independent variables. By regressing the variables against one another, the VIF is predicted. The VIF test shows the non-existence of multicollinearity. The results of the multi-collinearity tests are shown in the Table 5.6

Table 5.6: Result multi-collinearity test (VIF)

Variables	VIF	1/VIF
Cocoa Income	1.470	0.678
Education	1.330	0.754
Input Cost	1.220	0.818
Gender	1.200	0.836
Age	1.200	0.836
Land holding	1.190	0.839
Income from off farm activities	1.170	0.858
Marital Status	1.160	0.860
Livestock Income	1.130	0.887
Farming System	1.130	0.888
Distance to town center	1.120	0.893
Years of farming	1.110	0.898
Distance to road	1.040	0.964
Mean VIF	1.190	

5.4.1 Modeling the choice of farming system

Factors affecting the choice of farming system

A logistic regression analysis was performed of the factors affecting the choice of farming system among the households. The choice is between cocoa monoculture and cocoa agroforestry. Here, cocoa agroforestry was chosen as the base and the average marginal effects were recorded. The average marginal effects give an effect on the probability. Thus, the average change in probability when an explanatory variable change by one unit. Analysis was done for all respondents put together irrespective of gender and an analysis where both genders are separated was also carried out. For the variable, gender the base is male therefore the analysis is made in terms of females as compared to males. Also, marital status has single as the base so the analysis is made in terms married people compared to those who are single.

Table 5.7: Logit estimation of choice of farming system

Variable	Marginal effect/Standard Errors	Marginal effect/Standard Errors (Males)	Marginals effect/Standard Errors (Females)
Farming System			
age	0.001	0.003	-0.006*
	(0.002)	(0.002)	(0.004)
Gender	0.048	-	-
	(0.052)	-	-
Marital Stats	-0.126**	-0.139*	-0.131
	(0.064)	(0.079)	(0.103)
Education	-0.039	0.031	-0.137
	(0.054)	(0.073)	(0.086)
Years of farmland	0.004	0.004*	0.005
	(0.002)	(0.003)	(0.005)
Total land holding (ha)	-0.025**	-0.035***	0.002
	(0.012)	(0.013)	(0.027)
Animal	0.012	0.073	-0.098
	(0.048)	(0.056)	(0.091)
Cocoa Income	0.000**	0.000**	-0.000
	(0.000)	(0.000)	(0.000)
Income from off farm activity	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Input Cost	-0.000**	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)
Distance to Road (m)	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Distance to Town center (m)	0.000*	0.000***	-0.000
	(0.000)	(0.000)	(0.000)
Observation	333	222	111

Notes: *Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Cocoa Agroforestry is the base.*

From the results, involving all respondents put together, the significant variables include, marital status, total land holding in hectares, cocoa income, income from off farm activity, input cost, distance to road and distance to town center.

The results show that married people are more inclined to engage in cocoa agroforestry than single people which can be attributed to cheap labour that comes with getting married Denkyirah et al. (2017), the idea of using cheap labour is consistent with Armengot et al. (2016) who reported that agroforestry farms requires more labour hours than monoculture farms. Respondents declared that they are more willing to engage in agroforestry when there is an increase in their total land holdings as they will have space to include shade trees on their farms without necessarily affecting their total yield output. Interesting findings show that an increase in cocoa income and increase in input cost do not affect a farmer's decision to engage in coco monoculture or agroforestry. Denkyirah et al. (2017) affirms this result as cocoa farmers are more inclined to use their farm income for non-farm activities hence will not use that as basis to engage in cocoa monoculture or cocoa agroforestry. Finally, farmer's choice of cocoa monoculture or cocoa agroforestry is affected by the distance of their farms to the road or town centre.

With gender specific, the significant variables for the males are not different from when both genders are put together. However, for the females only two significant variables, age and distance to road found to be significant. Hence, as a female age, she is likely to engage in cocoa agroforestry. Male and female responses to agroforestry practices and other investment opportunities reflect different risk exposure and perceptions (Villamor et al., 2014). Moreover, as distance to road increase, the probability that one chooses cocoa monoculture over cocoa agroforestry is not affected. Comparing these different scenarios, it can be inferred that for the choice of farming systems, males have more significant effects as compared to females. These findings were not surprising as they align with the findings of Obeng and Weber (2016) that socioeconomic factors such as level of education, age, income, years of farming experience, and household farm labour, are factors that influence farmers' choice in adopting a cocoa production system. Furthermore, access to a road, access to non-farm income sources, and membership in farmer groups were all important factors in the adoption of farm practices that are climate-smart (Bate et al., 2019)

5.4.1.1 Future landuse choice under the scenario of available funds to support

Respondents choice of farming system under scenario where they had financial support in the near future was assessed. Both men and women selected cocoa agroforests as the future crop they will be interested in investing in with more financial support. Women were more inclined to cocoa farming compared to taking up new investments in other tree crops such as oil palm, rubber and citrus. Thirty percent of men were interested in going into other tree crops with 19% opting for oil palm, 5% for rubber, 4% for citrus and 3 % for coconut.

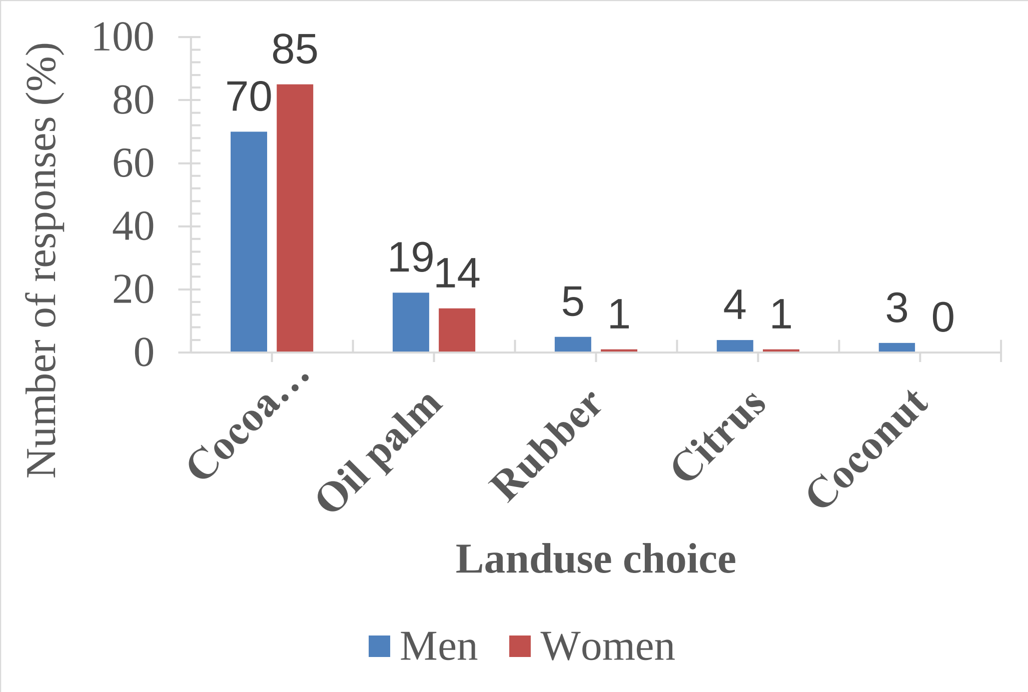


Figure 5.1: Future land use decisions in the scenario of available funds/support

5.4.2 Modelling scenario of continuity given financial support

Factors affecting the choice between continuing with cocoa farming or changing to a new crop or investment

Will the farmer maintain existing cocoa farm or change to a new crop when financial support is provided?

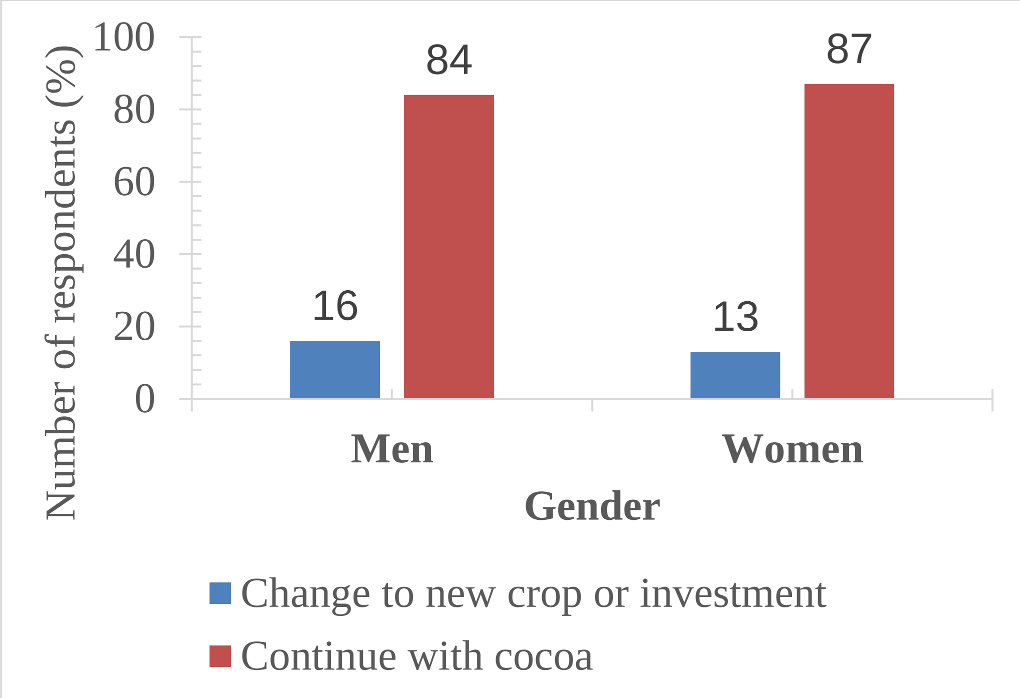


Figure 5.2: Gender-segregated future decision on investment in farming

As indicated by the chart, both men and women are more inclined to maintaining their investment in cocoa farming compared to changing to new crop or investment.

Changing to new crop was chosen as the base for comparison and the average marginal effects were recorded. The average marginal effects give an effect on the probability. Two analyses were made with one putting all respondents together irrespective of gender and another where gender was separated. The variable gender has male as the base, therefore the analysis was made in terms of females. For the variable farming system, the base was cocoa agroforestry hence, the analysis is made in terms cocoa monoculture as compared to cocoa agroforestry.

Table 5.8: Logit estimation of choice continuing with cocoa farming or changing to a new crop or investment

Variables	Marginal effects/Standard error	Marginal effects/Standard Errors (Males)	Marginal effects/Standard Errors (Females
Next 5 to 10 years			
age	-0.001	-0.003	-0.003
	(0.002)	(0.002)	(0.002)
Marital Status	-0.144**	-0.197***	-0.197
	(0.062)	(0.076)	(0.076)
Education	0.006	-0.008	-0.008
	(0.049)	0.067	(0.067)
Gender	0.060	-	-
	(0.046)	-	-
Years of farming	0.005**	0.007**	0.007
	(0.003)	(0.003)	(0.003)
Livestock Income	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Cocoa Income	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Land holding per capita	-0.020	-0.032	-0.032
	0.043	(0.052)	(0.052)
Income from off farm activity	-0.000*	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)
Input Cost	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Distance to Town center (m)	0.000	0.000*	0.000
	(0.000)	(0.000)	(0.000)
Distance to Road (m)	0.000*	0.000***	0.000
	(0.000)	(0.000)	(0.000)
Farming System	-0.109**	-0.163***	-0.163
	(0.045)	(0.059)	(0.059)
Observation	333	222	111

*Notes: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*
Changing to new crop is the base.

From the results involving all respondents put together, the significant variables include; marital status, years of farming, income from off farm activities, distance to road and farming system. The results revealed that a married couple with access to finance is more likely to invest in new crops such as rubber rather than cocoa farming. However, an increase in years of farming increases a farmer's willingness to continue cocoa farming given financial support which can be attributed to a number of factors such as ready market and income security (Hashmiu et al. 2022). Other interesting findings reveal that cocoa farmers in the Assin area are not influenced to change from cocoa farming to other crops when their income from off-farm activities decrease. More so, roads do not play any significant role to a farmer's decision. However, as the decision to engage in cocoa monoculture as compared to cocoa agroforestry increases, the probability of a farmer to choose to continue with cocoa farming given financial support decreases by 10.9%. Obeng & Weber (2016) also suggests that crop diversification is a rural household's weather-shock coping strategy.

Now moving on to the gender specific analysis, the variables that are significant in the males' analysis are the same as those that were significant when both all genders were put together. However, for the females' analysis, none of the variables were found significant. Once again, comparing these different cases, it can be inferred that, the effect of the overall regression is from the females in comparison with the males.

Modeling land-use choices of farming options in the future.

Factors affecting land-use choices of "farming options"

The choice is between cocoa farming, oil palm production, rubber production and other options. Here, cocoa farming was chosen as the base and the average marginal effects were recorded.

Landuse choices under consideration are;

1._predict: Pr (Land Use Choices==0), (pr outcome (cocoa farming))

2._predict: Pr (Land Use Choices==1), (pr outcome (oil palm farming))

3._predict: Pr (Land Use Choices==2), (pr outcome (rubber farming))

4._predict: Pr (Land Use Choices==3), (pr outcome (other options))

Table 5.9a: M logit estimation of land-use choices

Land Use Choice	Marginal effect	Standard deviation	Marginal effect (Males)	Stand-ard devia-tion	Marginal effect (Females)	Standard deviation
age						
1	0	0.002	-0.002	0.002	0.002	0.002
2	-0.001	0.001	0	0.002	-0.002	0.002
3	0.001	0.001	0.001	0.001	0	0
4	0.001	0.001	0.001	0.001	0	0
Gender						
1	0.167***	0.049	-	-	-	-
2	-0.022	0.046	-	-	-	-
3	-0.070*	0.037	-	-	-	-
4	-0.075*	0.042	-	-	-	-
Marital Status						
1	0.004	0.05	0.012	0.072	-0.066	0.077
2	-0.016	0.047	-0.054	0.065	0.066	0.077
3	-0.029	0.03	-0.051	0.043	0	0
4	0.041	0.035	0.094	0.063	0	0
Education						
1	0.089**	0.045	0.134**	0.062	-0.015	0.061
2	-0.025	0.045	-0.069	0.062	0.015	0.061
3	-0.021	0.022	-0.016	0.032	0	0
4	-0.043	0.029	-0.049	0.041	0	0
FutureNext5to20						
1	0.447***	0.04	0.463***	0.053	0.239***	0.05
2	-0.322***	0.035	-0.320***	0.046	-0.239***	0.05
3	-0.055***	0.019	-0.053*	0.028	0	0
4	-0.071***	0.019	-0.090***	0.027	0	0
Cocoa Income						
1	0	0	0	0	0	0
2	0	0	0	0	0	0
3	-0.000*	0	-0.000*	0	0	0
4	0.000**	0	0.000**	0	0	0
Livestock Income						
1	0	0	0.000*	0	0	0
2	0	0	0	0	0	0
3	0	0	0	0	0	0
4	0	0	0	0	0	0

*Notes: *** p<0.01, ** p<0.05, * p<0.1*
Cocoa farming was selected as the base case for comparison.

From the results, the analysis for all genders put together have the variables, gender, education, the choice of farming decision in the next 5 to 10 years, cocoa income, total land holding, input cost, distance to town center and distance to road. Thus, a unit increase in females as compared to males increases the probability of choosing rubber farming as compared to cocoa farming decreases by 7%.

Table 5.10b: M logit estimation of land-use choices

Land Use Choice	Marginal effect	Standard deviation	Marginal effect (Males)	Standard deviation	Marginal effect (Females)	Standard deviation
Income from off farm activity						
1	0	0	-0.000*	0	0	0
2	0	0	0	0	0	0
3	0	0	0	0	0	0
4	0	0	0	0	0	0
Total land holding (ha)						
1	-0.018**	0.008	-0.018	0.011	-0.01	0.017
2	0.013*	0.008	0.021**	0.01	0.01	0.017
3	0.004	0.006	0.004	0.009	0	0
4	0.001	0.005	-0.007	0.009	0	0
Input Cost						
1	0	0	0	0	0	0
2	0	0	0	0	0	0
3	0.000**	0	0.000**	0	0	0
4	0	0	0	0	0	0
Distance to Town center (m)						
1	0.000***	0	0.000***	0	0	0
2	0	0	0	0	0	0
3	-0.000*	0	-0.000*	0	0	0
4	-0.000*	0	-0.000*	0	0	0
Distance to Road (m)						
1	0.000**	0	0.000**	0	0	0
2	-0.000**	0	-0.000**	0	0	0
3	0	0	0	0	0	0
4	0	0	0	0	0	0

Again, a unit increase in females as compared to males increases the probability of choosing other farming option as compared to cocoa farming decreases by 7.5%. According to Ahimbisibwe et al. (2019), gender-based decision-making is clearly split between husbands and wives. It is also individualistic, with husbands dominating the process and wives and other family members participating less.

Prior to making decisions, households take into account diverse factors, including market prices for both annual and perennial crops and previous season yields for tree-crop management. The association between gender and land use change is pronounced in lowland areas, whereas conservation awareness is more important in the uplands for the preservation of rubber agroforests.

Also, a unit increase in the decision to continue with cocoa farming in the next 5 to 20 years as compared to changing to a new crop decreases the probability of choosing oil palm production by 32.2% as compared to cocoa farming. In the same light, a unit increase in the decision to continue with cocoa farming in the next 5 to 20 years as compared to changing to a new crop decreases the probability of choosing rubber farming by 5.5%. Similarly, a unit increase in the decision to continue with cocoa farming in the next 5 to 20 years as compared to changing to a new crop decreases the probability of choosing other farming options by 7.1%.

For the cocoa income variable, a unit increase in cocoa income decreases the probability of the choice of rubber farming by approximately 0% however, a unit increase in cocoa income increases the probability of choosing other farming options by approximately 0%. Here the magnitude of the probability of change is similar but the direction of change varies. Furthermore, a unit increase in the total land holdings in hectares increases the probability of the choice of oil palm by 1.3% as compared to the cocoa farming option. Surprisingly, a unit increase in input cost increases the probability of choosing rubber farming option as compared to cocoa farming. However, the probability is approximately 0%. More so, a unit increase in the distance to town center decreases the probability of choosing rubber farming land use option as compared to cocoa farming land use option. In the same way, a unit increase in the distance to town center decreases the probability of choosing other farming option of land use as compared to cocoa farming land use option. Finally, a unit increase in the distance to road decreases the probability of choosing oil palm farming option of land use as compared to cocoa farming land use option.

In the case of the gender specific analyses, significant variables in the males' analysis are similar to the analysis involving both all genders put together. However, for the females' analysis, only the choice of farming decision in the next 5 to 10 years variable is significant. Thus, a unit increase in the decision to continue with cocoa farming in the next 5 to 20 years as compared to changing to a new crop decreases the probability of choosing oil palm production by 23.9% in comparison to cocoa farming option. Again, comparing these different cases, it can be inferred that, the effect of the overall regression is from the females in comparison with the males. Ahimbisibwe et al. (2019) asserts that increased participation of women in decision-making at the landscape level is anticipated to lead to increased emissions from deforestation and forest degradation in the region, posing additional challenges to endeavors aimed at reducing such emissions.. Michalscheck et al. (2020) argues that though the husband, who is mostly the household head, is the principal decision-maker and strategic gatekeeper in a funnel-like process, he is greatly influenced by his wife and son's choices regarding "his decision," or the outcome of the household-level negotiations.

5.5 Conclusion

This study aimed to find out diversity in land-use decision-making. The specific objectives sought to determine the factors that affect the choice of farming system, the factors which influence the choice between continuing with cocoa or changing to a new crop or investment in the next 5 to 20 years given financial support and the determinants of the choice of land-use types. Considering the gender specific scenarios and the various results obtained, it can be inferred that there is a level of heterogeneity among the different genders.

In the situation of the factors that influence the choice of farming system, the significant variables for all genders include; marital status, total land holding in hectares, cocoa income, income from off farm activity, input cost, distance to road and distance to town centre. The results are not different in the males' analysis in the terms of the variables that are significant and the direction of change however, for the females' analysis only age and distance to road are statistically significant.

Also, in the situation of the factors that determine the choice between continuing with cocoa and changing to new crop or investment the variables that are significant in the case where all genders were put together include; marital status, years of farming, income from off farm activities, distance to road and farming system. The results not different in the males' analysis in terms of the variables that are significant and the direction of change however, for the females' analysis, none of the variables is significant.

Moreover, for the situation of the determinants of the land-use choices, for the results of the analysis involving all genders put together, gender, education, the choice of farming decision in the next 5 to 10 years, cocoa income, total land holding, input cost, distance to town center and distance to road have significant effects. The results from the males' analysis are not similar to when both genders are put together however, the females' analysis only have 2 significant variables.

Despite these findings, it is admirable to identify the role of REDD+ implementation in encouraging farmers to adopt cocoa agroforestry as a mitigation and adaptation measure towards the exacerbating effects of climate change on crops. The study area falls under the Ghana Cocoa Forest REDD+ Programme landscape and is also a key part of the five Hotspot Intervention Areas (i.e Kakum HIA). There is constant sensitization of farmers to maintain beneficial trees on their cocoa farms whilst planting new seedlings with guidance from Agriculture Extension Officers in the landscape. These tree seedlings are provided to farmers as part of the GCFRP. Farmers who have adopted agroforestry are continually motivated from the benefits they have started accruing through carbon and non-carbon payments (Forestry Commission of Ghana 2020).

The study concludes that;

Age, years of farming, cocoa income, and distance to road and town have positive influences on the selection of monoculture cocoa farming, whilst marital status, total land holding, and input cost had a negative influence on the same selection.

- ❖ Men dominate decision-making in cocoa farming and have more significance for the factors than women.
- ❖ Gender differences in choices reflect different risk exposure and perceptions of investment opportunities
- ❖ Agroforestry adoption increases with total land holdings.

CHAPTER 6

EXAMINING THE FACTORS THAT AFFECT THE PARTICIPATION IN REDD+

6.1 Introduction

The emission of various greenhouses such as carbon dioxide, methane and nitrous oxide is consistently rising globally (Arto and Dietzenbacher 2014). The concentration of these gases in the atmosphere is increasing, leading to implications for climate (Malhi et al. 2021; Stokes et al. 2014). This increase is primarily due to anthropogenic-induced activities like the burning of fossil fuels, deforestation and forest degradation, agriculture, industrial processes and transportation (Lamb et al. 2021). The conversion of forests to agriculture and grassland, an increase in animal populations, the burning of biomass in wildfires, crop production, fertilizer use, and other related emissions have all contributed to the rising gas emissions (Smith et al. 2016; Tubiello et al. 2021).

Agriculture-related emissions are mostly produced by developing nations worldwide, and they are also predicted to increase at the highest rate in these regions (Smith et al. 2014). Developing countries account for 70% of the potential climate change mitigation through land use in agriculture (Boateng et al. 2017). Over 80% of agricultural land is managed by smallholder farmers in developing countries (Lee 2017). These activities particularly deforestation and agriculture are driven by farmers (Doggart et al. 2020). Farmers clear forests for agriculture, contributing to 20% of global carbon dioxide emissions (World Bank,

2017) and agricultural activities in general amount to 21% as stated by FAO in 2016 (Kwakwa et al. 2022).

The farmer's adapted agricultural practices like deforestation, unbalanced soil nutrient content, slash-and-burn agriculture, and increased reliance on the production of agro-chemicals (such as herbicides, insecticides, vaccines and biotechnology) contribute to high carbon emissions in the atmosphere facilitating climate change (Adomako and Ampadu 2015). Farmers' incomes and livelihoods, their health, and the ecosystem as a whole are all negatively impacted by the climate's disastrous effects on agricultural productivity (Adomako and Ampadu 2015). Several initiatives have been introduced to address the increasing effects of gas emissions (Gillingham and Stock 2018).

Many factors influence a household's willingness to adopt REDD+ (Van Khuc et al. 2021). A study revealed that gender is a factor in farmers' willingness to participate in REDD+, with females having less information about REDD+-related design and those that are aware supporting the initiative more strongly (UNDP 2016). Other factors are the socio-economic status (Sanou et al. 2019), education (Komba and Muchapondwa 2017), age of the head of the household (Rakatama et al. 2018), the size of the household (Musthafa and Youn 2022), awareness of the project's objectives (Appiah et al. 2016), the number of years the household has been in its current location (Van Khuc et al. 2021).

In Tanzania, households were prepared to take part in the REDD+ program if they were given at least 2074 USD annually, even if doing so meant missing out on direct benefits from forest resources (Komba and Muchapondwa 2017). In Eastern Brazilian, findings revealed that only 31% of the households interviewed knew enough about the project to accurately describe it and of those, the majority hoped that the project would increase their income, while 33% thought it would increase their agricultural production and 26% thought it would help protect the forests (Cromberg et al. 2014). Pandit (2018) considered 9 communities in the watershed of Nepal and found that most households were unaware of the REDD+ implementation and only a few showed interest after forest rules restricted access According to a survey conducted in Nigeria, some farmers expressed their willingness to protect the forest, primarily due to their childhood memories of the place (Isyaku 2021). However, a significant number of farmers were indifferent towards protecting the forest, unless they received compensation for it and a few farmers were willing to donate a portion of their income to support forest conservation efforts (Isyaku 2021).

Israel et al. (2020) stated that farmers are unlikely to participate in REDD because every farming household is involved in at least one emission activity. Some farmers were concerned that the REDD+ program's increase in the value of natural forests may spark a resource grab, in which the government would reassert its authority over forest tenure which would be leased by wealthy private sector interests, keeping out residents in the process (Blomley et al. 2017).

Despite the studies above, there remains a gap on the barriers, drivers of voluntary participation and awareness of REDD+ initiatives. Current research has not identified the primary driver of voluntary participation among farmers in Ghana. It is essential to identify the most effective ways to fully convince farmers to engage in the goals of the REDD+ initiative as their participation is necessary for achieving the initiative's objectives of reducing greenhouse gas emissions and conserving forests while promoting sustainable livelihoods for forest-dependent communities. This research explores the drivers, barriers, and motivators of voluntary participation among farmers and provides insights into effective strategies to increase their involvement in the initiative.

In examining the factors that affect the participation in REDD+, the focus is to;

i. Analyse the factors affecting the reasons for participation in REDD+
ii. Assess the willingness to accept premium cash for the participation in REDD+.

6.2 Methodology

Study area and sample size are as described in Chapter 5 in this study

6.2.1 Household agents' behavior estimation of participation in REDD+

Multi-nomial logistic regression for reasons for participation in REDD+

Specification of Variables

Dependent Variable

Reasons for REDD+ participation ($P_{reasons}$) by households is the dependent variable of the M-logit model. The categories of choice include; 0 Increase yield/income Environmental reasons, REDD+ benefit, Sustainability of farm (0=Environmental reasons, 1=Increase yield/Income, 2=REDD+ benefits, sustainability of farms.

Explanatory variables

For the willingness to accept options, there are independent variables that are being interacted with the dependent variable ($P_{reasons}$) that affect their decision or choice. These variables are grouped into household agents' characteristics and other characteristics. The other characteristics include; income component, physical component, asset component, cost component, and system component.

Table 6.1: Variable Description for REDD+ participation

Variables	Description
Reasons for REDD+ participation	The reasons for the participation in REDD+; Increase yield/income Environmental reasons, REDD+ benefit, Sustainability of farm (0=Environmental reasons, 1=Increase yield/Income, 2=REDD+ benefits, sustainability of farms.
Age	The age of respondent
Gender	The gender of respondent, male and female (0= Male, 1= Female)
Years of farming	The number of years of farming
Marital Status	Whether the respondent is single or married (0= single, 1=married)
Education Status	The education status of respondent, no formal education, and formal education (0= no formal education, 1= formal education
Education REDD+	Whether respondent has had any education on REDD+, Yes or No (0=No, 1=Yes)
Cocoa income	Income earned from cocoa farming
Land holdings per capita	Per capita from land holdings of respondent
Livestock Income	Income earned from livestock farming
Income from off-farm activity	Income from off-farm activities in Ghana Cedis
Cost of labor	The cost of labor involved in the farming activities
Input cost	The cost of input for farming activities
Distance to town center	Plot distance to town center
Distance to road	Plot distance to road side

Household agent characteristics

The household agent characteristics are the variables that describe the respondent or the representative of the household. These include age, gender, household size, marital status, educational statistics, and years of farming. Age here, implies the age of the respondent in years. The gender variable also gives a definition of the gender of the respondent (whether male or female). The household size tells of the people in a household and marital status also shows if the respondent is married or not. The initial levels were single, married separated, separated and divorced. These were later simply groped into two, namely single and married. Thus, both separated and divorced respondents were added to the initial single respondents. Education status variable also describes the educational level of the respondent. There are two levels of no formal education and formal education.

Other characteristics

Concerning the other characteristic, the component variables include, income, cost, and system components. The income components comprise of, land holding per capita, livestock income, and income from off farm activities. Land holding per capita income can be explained as the per capita income from the total land holdings of households. Income from off farm activity cover the income earned from off farm activities. Moving on to the physical component, the variables encompass distance to town centre, and distance to road side. Distance to town centre refers to the plot distance to town centre and distance to road gives the plot distance to the road side.

Furthermore, the cost component includes the input cost and the labour cost. The total input cost implies the total cost incurred by households as far as production is concerned. The labour cost also depicts the total cost involved in the farming or the production process. The system component involves REDD+ education and the REDD+ education variable shows whether the household has received any education on REDD+ or not.

6.2.2 Household agents' behavior estimation of acceptance of premium (Cash)

Multi-nomial logistic regression for willingness to accept premium

Specification of Variables

Dependent Variable

Willingness to accept cash (P_{WTA}) by households is the dependent variable of the M-logit model. The categories of choice include; 0-150, 151-300, 301-450, 451-600, and 601-750.

Explanatory variables

For the willingness to accept options, there are independent variables that are being interacted with the dependent variable (WTA) that may influence their decision or choice. These variables are grouped into household agents' characteristics and other characteristics. The other characteristics include; income component, physical component, asset component, cost component, and system component.

Table 6.2: Variable description for willingness to accept premium

Variables	Description
Willingness to accept	The range in cash respondents are willing to accept in order to participate in REDD+; 0-150, 151-300, 301-450, 451-600, 601-750 (0=0-150, 1=151-300, 2=301-450, 3=451-600, 4=601-750)
Age	The age of respondent
Household Size	The number of people in the household
Marital Status	Whether the respondent is single or married (0= single, 1= Married)
Education	The education status of respondent, no formal education and formal education (0= no formal education, 1= formal education)
Years of farming	The number of years of farming
Animal	Whether respondent owns any livestock or not (0= No, 1= Yes
Education REDD+	Whether respondent has had any education on REDD+, Yes or No (0=No, 1=Yes)
Cocoa Income	Income earned from cocoa farming
Land holdings per capita	Per capita from land holdings of respondent
Income from off-farm activity	Income from off-farm activities in Ghana Cedis
Distance to town (m)	The plot distance to town in meters
Distance to house (m)	The plot distance to the house in meters
Cost of labor	The cost of labor involved in the farming activities
Input cost	The cost of input for farming activities

Household agent characteristics

The household agent characteristics are the variables that describe the respondent or the representative of the household. These include age in years, household size, education and years of farming. The household size tells of the people in a household. Education variable describes the educational level of the respondent. There are two levels of no formal education and formal education. The years of farming variable shows the number of years one has been farming.

Other characteristics

Concerning the other characteristic, the component variables include, asset, income, cost, physical and system components. Asset component identified here is the animal variable depicting whether one owns any livestock or not. The income components comprise, land holding per capita, cocoa income, and income from off farm activities. Land holding per capita income can be explained as the per capita income from the total land holdings of households. Cocoa income is the income earned from cocoa production. Income from off farm activity covers the income earned from off farm activities.

The physical component comprises the distance to house variable. The distance to house depicts the plot distance in meters to house. The cost component includes the input cost and the labor cost. The total input cost implies the total cost incurred by households as far as production is concerned. The labor cost depicts the total cost involved in the farming or the production process. The system component encompasses the REDD+ education variable, and the REDD+ education variable shows whether the household has received any education on REDD+ or not.

6.3 Results and Discussion

A multi-collinearity test was carried out to know the collinearity between the variables before the major regressions. For this study, the Variable Inflation Factors (VIF) method of multi-collinearity testing was employed. The VIF determines the strength of the correlation between the independent variables. By regressing the variables against one another, the VIF is predicted. The VIF test shows the non-existence of multicollinearity. The results of the multi-collinearity tests are shown in the Table 6.3.

Table 6.3: Result of multi-collinearity test (VIF)

Variables	VIF	1/VIF
Cocoa Income	1.930	0.517
Cost of Labor	1.900	0.527
Education	1.320	0.760
Marital Status	1.250	0.798
Input Cost	1.250	0.801
Land holding per capita	1.210	0.823
Gender	1.200	0.833
Age	1.190	0.837
Income from off-farm activities	1.170	0.855
REDD+ Education	1.160	0.863
Livestock Income	1.150	0.867
Distance to town center	1.140	0.879
Years of farming	1.110	0.902
Distance to road	1.030	0.973
Mean VIF	1.290	

6.3.1 Willingness to participate in REDD+ activities

The willingness to participate in REDD+ was assessed by asking questions relating to activities that contribute to achieving the objectives of REDD+ such as incorporating trees in cocoa farms, adopting climate smart cocoa production activities and farm intensification. Also, governance requirements for easy control and payment of benefits to REDD+ beneficiaries require the registration of farmers, this was also tested to ascertain the willingness to participate and also whether there are gender differences in the participation. Overall, there was over 90% willingness to participate in all REDD+ activities with registration under a Hotspot Intervention Area and adoption of climate smart practices recording 97% willingness.

Chi-square test reveal only significance difference for registration under an HIA structure for male and female respondents with a p-value of 0.04.

Table 6.4 Willingness to participate in various REDD+ activities

Willingness to Participate in REDD+ activities	Gender	Yes	No	Total	Chi-Square test(p-value)
Willing to incorporate trees on farms	Male	208	14	222	0.54
	female	102	9	111	
	Total	310	23	333	
		Yes	No	Total	
Register under an HIA structure	Male	213	9	222	0.04
	female	111	0	111	
	Total	324	9	333	
		Yes	No	Total	
Adopt climate smart practices	Male	215	7	222	0.47
	female	109	2	111	
	Total	324	9	333	
		Yes	No	Total	
Adopt farm intensification	Male	200	22	222	1
	female	100	11	111	
	Total	300	33	333	

6.3 1Modeling the reasons for participation in REDD+

The graph depicts gender segregated reasons for choosing to participate in REDD+. From the graph, it can be observed that the highest reason for participation for households is increase in yield/income, followed by REDD+ benefits, sustainability of farm and finally environmental reasons. Thus, people place more importance on increasing yields and income as far as participation in

REDD+ is concerned and the least in importance is having the environment in mind.

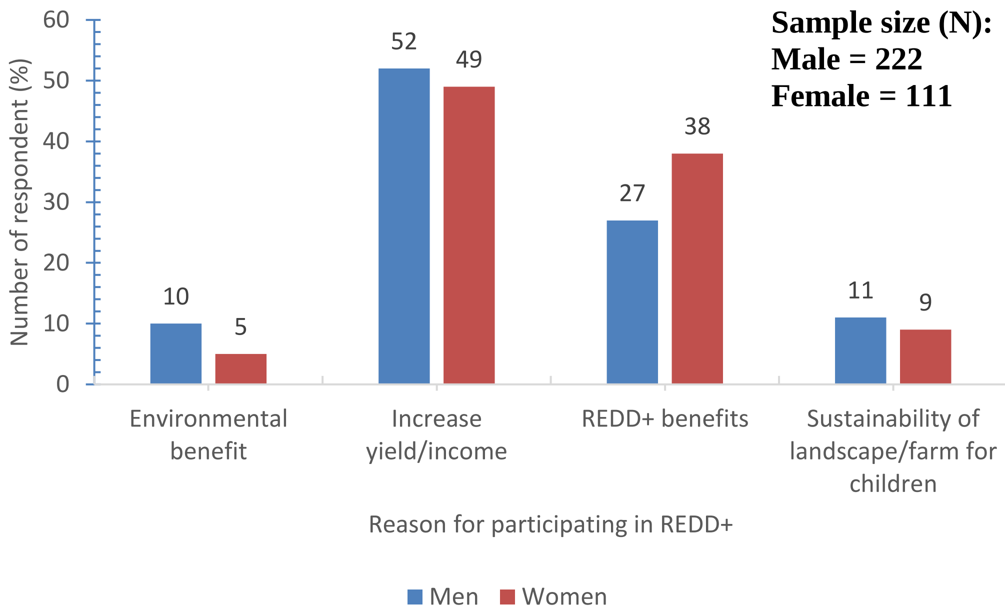


Figure 6.1 Reasons for participating in REDD+

6.3.1.1 Factors affecting the reasons for participation in REDD+

A multinomial logistic regression analysis was performed of the factors affecting the reasons for participation in REDD+. The reasons for participation include; environmental reasons, increase in yield and income, REDD+ benefits and sustainability of landscape or farm for children. This finding corresponds with the findings of Komba & Muchapondwa (2017)which shows that households would participate in REDD+ if the programme would give them some REDD+ benefits like a compensation of an average of US$ 2072 per year. Their findings indicate that household participation was more likely when households were aware of the REDD+ financial incentives, that deforestation and forest degradation are bad for the environment, and that spending more time gathering the most significant forest products. According to (Van Khuc et al., 2021) there is a direct correlation between the amount of money received and the rate at which locals agreed to participate in the REDD+ project. In this current study, the variable, gender the base is male therefore the analysis is made in terms of females as compared to males. Also, marital status has single as the base so the analysis is made in terms married people compared to those who are single.

Notedly, increase in yield/income reason for participation variable remains the reference variable in this regression. Therefore, the influence of the factors on the various reasons listed in the table are made in comparison to the increase yield/income reason variable. Among the factors that influence the environmental reason for REDD+ participation, the variables that are significant include; age, REDD+ Education, Cost of labour, Land holdings per capita, Livestock income and distance to town. Thus, as one ages the probability of participating in REDD+ because of environmental reasons as compared to increase in yield and income decreases by 0.3%.

An unexpected result relates to awareness and education on REDD+ that, the more one receives education on REDD+, the probability of participating in REDD+ due to environmental reasons reduce by 9.4%. This goes a long way to explain the low value that is placed on protecting the environment. Also, as the cost labour increases, the probability that one chooses to participate in REDD+ because of environmental reasons reduces. Furthermore, as land holding per capita and livestock income increase, the probability that one participates in REDD+ for environmental reasons also increases. However, as the distance town centre increases the probability of participating in REDD+ because of environmental reasons decreases.

Moving on to the reason of the REDD+ benefits, 7 of the explanatory variables are significant. The variables include; gender, marital status, REDD+ education, cost of labour, input cost, land holding per capita, distance to road. As the number of females as compared to males increase, the probability that one participates in REDD+ because of REDD+ benefits increase by about 13%. Unlike the situation of environmental reason, the increase in REDD+ education increases the probability of participating in REDD+ because of REDD+ benefits. Similar factors such as bid level of the carbon price, the respondent's age, sex, the labour force, the amount of forest land areas, the respondent's awareness of REDD+, and the income from non-timber forest products were also identified in a study by Tien (2017).

As the farm plot distance to the road widens, the probability of participating in REDD+ because of the REDD+ benefits decreased. With marriage, there is a higher probability of engaging in REDD+ because of the REDD+ benefits. Again, as land holding per capita increases, the probability of participating in REDD+ because of REDD+ benefits increased. Furthermore, it was anticipated that poor households would be more interested in this project to mitigate climate change than their non-poor counterparts, as Van Khuc et al. (2021) indicated that they placed a higher value on forests. Other studies have also assessed and found several factors that influence the adoption of other climate-smart agricultural practices and reported similar findings (Deressa et al., 2009; Obeng, E., A. Weber, 2016; Yegbemey et al., 2013).

Table 6.5: M-logit estimation of reasons for REDD+ participation

Variable	Marginal effect (Environmental)	Marginal effect (REDD+ Benefits)	Marginal effect (Sustainability)
Reasons for participating in REDD+			
Age	-0.003*	0.003	0.002
	(0.001)	(0.002)	(0.001)
Gender	-0.066	0.130**	-0.031
	(0.038)	(0.053)	(0.040)
Years of farming	0.000	0.002	0.000
	(0.001)	(0.003)	(0.002)
Marital Status	-0.005	0.137**	-0.042
	(0.041)	(0.073)	(0.041)
Education	-0.018	-0.012	-0.011
	(0.037)	(0.068)	(0.043)
REDD+ Education	-0.094**	0.102**	-0.089**
	(0.038)	(0.048)	(0.042)
Cocoa Income	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Cost of Labor	-0.000***	0.000**	0.000**
	(0.000)	(0.000)	(0.000)
Input cost	-0.000	0.000***	-0.000
	(0.000)	(0.000)	(0.000)
Land holding per capita	0.059*	0.105*	0.009
Livestock Income	0.000***	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Income from off-farm activity	-0.000	0.000	0.000*
	(0.000)	(0.000)	(0.000)
Distance to town center	-0.000**	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Distance to Road	0.000	-0.000**	-0.000
	(0.000)	(0.000)	(0.000)

[i]Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
[ii]Reference reason is Increase yield/income

With regards to participation because of sustainability of farm, 3 explanatory variables namely; REDD+ education, cost of labor and income from off-farm activity are significant. Thus, more REDD+ education decreases the sustainability reason of participating in REDD+. Also, as cost of labor increases, the probability of a household to participate in REDD+ because of the sustainability of their farm is high. The probability of participating in REDD+

because of sustainability of farm increase as the income from off-farm activity increases. Results from a comparable study suggest that while impoverished households exhibit greater awareness of the significance of forests and the REDD+ project, households not in poverty are more inclined to engage in the project across all subsidy levels (Van Khuc et al., 2021). However, Tien (2017) recommends that local people should be trained and given more education about REDD+ in order to increase the participation of farmers in the REDD+ programme.

6.3.2 Modelling the willingness to accept premium

Figure 6.2 depicts the reasons to register for REDD+. The various reasons include; farm group benefit, non-monetary, other incentive, farm registration, receiving extension service, farm intensification and premium. Each of the reason has two levels; yes and no.

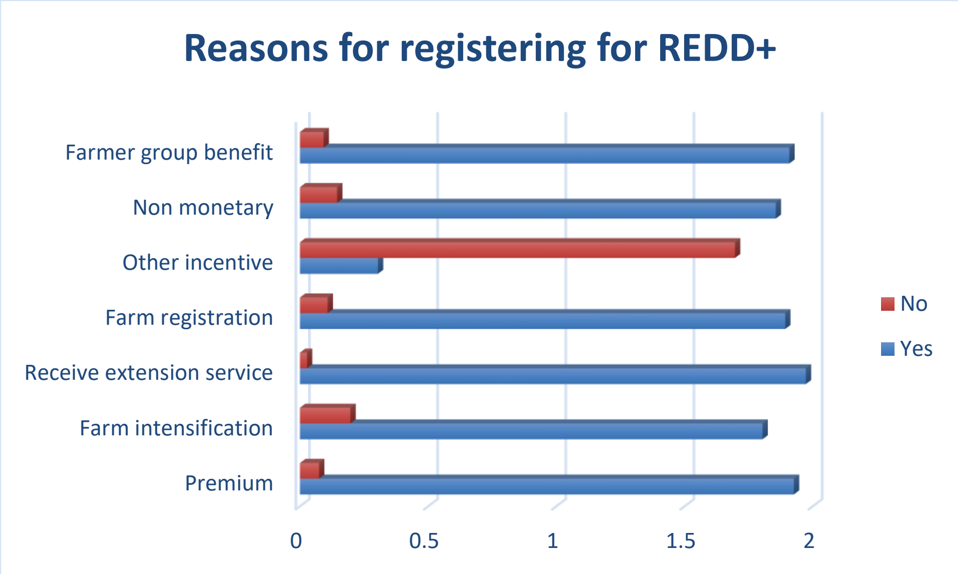


Figure 6.2: Reasons for registering for REDD+

For yes response, receiving extension service is the highest followed by premium, then farm group benefit, and non-monetary benefit. Other incentive recorded the lowest yes followed by farm registration, and farm intensification in ascending order

A multi-collinearity test was carried out to know the collinearity between the variables before the major regressions. For this study, the Variable Inflation Factors (VIF) method of multi-collinearity testing was employed. The VIF determines the strength of the correlation between the independent variables. By regressing the variables against one another, the VIF is predicted. The VIF test shows the non-existence of multicollinearity. The results of the multi-collinearity tests are shown in the Table 6.6.

Table 6.6: Result multi-collinearity test (VIF

Variables	VIF	1/VIF
Cocoa Income	1.900	0.526
Cost of labor	1.800	0.555
Land holding per capita	1.470	0.679
Household size	1.440	0.696
Input cost	1.270	0.788
age	1.240	0.807
Education	1.190	0.843
Animal	1.150	0.872
Income from off-farm activity	1.150	0.873
REDD+ Education	1.140	0.879
Distance to house	1.120	0.892
Years of Farming	1.110	0.899
Mean	1.330	

6.3.3 Factors affecting the willingness to accept premium

A multinomial logistic regression analysis was performed of the factors affecting the willingness to accept premium for the participation of REDD+. Here, the levels/ranges include; 0-150, 151-300, 301-450, 451-600, and 601-750. Notedly, the reference premium acceptance range remains 451-600 range (3) therefore the analyses on the influence on the other ranges listed in the table are made in comparison to the reference. In a study by Nielsen et al. (2018), all the farmers interviewed were willing to engage in REDD+ contracts when given compensation.

With regards to the range (0-150), two explanatory variables namely, age, and REDD+ education and are significant. Thus, the probability of accepting premium cash in the range (0-150) decrease as one ages compared to the reference range. Again, having received an education on REDD+ increases the probability of accepting a premium cash within the range 0-150. For 151-300, only an explanatory variable (REDD+ education) has significant influence. Thus, having received an education on REDD+ decreases the probability of accepting a premium cash within the range 151-300.

Years of farming is the only significant variable for the 451-600 range. Having more experience in farming increases the probability of receiving a premium within the range 451-600 compared to the reference range. For the 601-750 range, the distance to house variable is significant. This implies that the probability of accepting a premium within 601-750 increases when the plot distance to house is nearer. Komba & Muchapondwa (2017) asserts that, upon becoming aware of the program and its incentives, households choosing to participate tended to request lower compensation. In contrast, the findings of Shrestha & Shrestha (2017) suggest that socioeconomic factors like education, family size, agricultural land holdings, and biophysical factors such as the distance between the respondent's household and the affiliated community forest are more influential in determining participation in community forest management than the economic incentives offered by the REDD+ pilot project.

With years of farming experience increase, farmers are willing to receive a premium payment of between 301-450 Ghana Cedis on bag of cocoa sold to participate in REDD+ whereas when farmers are well educated on both the carbon and non-carbon benefits of REDD+, they are willing to participate in REDD+ for cash premium within the range 0-150 Ghana cedis on bag of cocoa sold

Table 6.7:M-logit estimation of willingness to accept premium cash in order to participate in REDD+

Variable	Marginal effects			
Willingness to accept	**(0-150)**	**(151-300)**	**(301-450)**	**(601-750)**
Age	-0.004*	0.002	-0.001	0.000
	(0.002)	(0.002)	(0.001)	(0.001)
Household size	0.013	-0.010	-0.005	-0.003
	(0.010)	(0.009)	(0.006)	(0.004)
Education	0.001	0.012	-0.009	0.020
	(0.063)	(0.053)	(0.035)	0.019
Years of farming	-0.001	-0.000	0.003**	0.001
	(0.003)	(0.003)	(0.001)	0(.001)
Animal	0.014	-0.017	0.024	0.021
	(0.057)	(0.048)	(0.032)	(0.019)
Cocoa income	0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Land holding per capita	0.076	-0.076	0.024	-0.083
	(0.082)	(0.073)	(0.034)	(0.065)
Income from off-farm activity	0.000	0.000	-.0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Cost of labor	0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Input cost	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Distance to house	0.000	-0.000	0.000	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Redd+Education	0.117**	-0.098*	0.009	-0.030
	(0.058)	(0.050)	(0.031)	(0.023)

[i]Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. [ii]Reference range, 451-600

6.4 Conclusion

The study set out to examine the factors that affect the participation in REDD+ across different household types. The specific objectives sought the analyse the factors the reasons for the participation in REDD+ and also to assess the determinants of the willingness to accept premiums for the participation in REDD+. For the factors that affect the reasons for the participation in REDD+, the significant explanatory variables include; age, marital status, cost of labour cost of input, REDD+ education, Land holding per capita, livestock income, distance to town centre and distance to road

The determinants of the willingness to accept premiums for the participation in REDD+, the significant explanatory variables include; age, REDD+ education, years of farming and distance to house. Several socio-economic factors influence their reasons for their participation, but the significant factors were age, marital status, REDD+ education, cost of labour, land holding per capita, livestock income, input cost, distance to town centre, and distance to road. As farmers age, the probability of participating in REDD+ because of environmental reasons decreases. Farmers and landowners make the decision to use their land for agriculture or for other purposes, particularly in off-reserve agricultural areas. Since farmers are logical people, they will use their property for projects that will benefit them and give them the most reliable source of revenue now and in the future. It is essential to raise the value of forests (by informing farmers and land users of the full range of the goods and services they provide) above competing options in order to ensure that forests and trees will play a significant role in future landscapes and support government projects and ambitions to reduce emissions from deforestation and forest degradation. In this way, forests will fulfill their many goals, which include maintaining water services, sequestering carbon, and protecting biodiversity.

The study concludes that more than 90% of households were willing to participate in all REDD+ activities driven by immediate benefits. Age, marital status, cost of labor, land holding per capita, livestock income, input cost, distance to the town center, and distance to the road significantly influenced their decisions.

CHAPTER 7: CONCLUSIONS AND RECOMMENDATIONS

7.1 General conclusions

This research focused on answering four research questions to examine the impact of landuse changes on carbon dynamics in the Assin South district of Ghana which is part of the Kakum Hotspot Intervention Area under the Ghana Cocoa Forest REDD+ program, the premier program of the Ghana REDD+ Strategy.

By examining the dynamics of carbon stock changes under business-as-usual and REDD+ scenarios through landuse modeling and prediction of future changes and the socioeconomic factors that influence farmers' choices of farming systems and land decisions and willingness to participate in REDD+, the study sheds light on how the ongoing REDD+ mechanism implementation can be structured to achieve maximum emission reductions.

In answering the research objective,

- **How do carbon stocks differ in different landuses of various growth stages?**

  The carbon stored in the above ground biomass of various ages of growth of different landuses (cocoa monoculture, cocoa agroforest, primary forest, secondary forest) was assessed with the associated floristic diversity of the landuses. The species diversity of the three landuse types were characterized and compared, the carbon stocks of the four landuse types were estimated, and the contribution of Trees on Cocoa farms to carbon stocks and basal area of cocoa agroforests were assessed.

Objective 1: To estimate carbon stored in the above ground biomass of various ages of growth of different landuses (cocoa monoculture, cocoa agroforest, primary forest, secondary forest) and assess the associated floristic diversity of the landuses

The following conclusions were reached for Objective 1;

- The study found that total carbon stocks in the primary forest were higher than in cocoa monoculture, cocoa agroforest, and secondary forest respectively for all ages combined.
- Above-ground carbon stock in Primary forest was significantly different from other land use at all ages. However, carbon stock in agroforestry at age classes 2 and 3 was not significantly different from secondary at age class 3.
- Primary forest recording the highest Shannon Weiner diversity of 2.99, with species richness of 76, followed by secondary forest with Shannon index of 2.43, though with a lower species richness of 63 compared to the cocoa agroforest with 69 species richness.
- Trees on farm contributed significantly to total carbon stock of cocoa agroforests.

In answering the research objective 2,

- ❖ How does REDD+ interventions differ in carbon storage and sequestration compared to business-as-usual for the cocoa and forest landscape?

  The study analyzed landuse change dynamics and its impact on carbon stock between 2019 and 2036 under business-as-usual and REDD+ scenarios by assessing LULC changes in the study area, and by predicting the future LULC of the landscape. The prediction was done using the LCM (Land Change Modeler) embedded in the TerrSet Geospatial Monitoring and Modeling System (TGMMS) software with the embedded multi-layer perceptron (MLP) neural network used. To estimate the carbon stock in the study landscape, the InVEST carbon storage and sequestration model software which has been originally developed by the Natural Capital Project

Objective 2: To analyze landuse change dynamics and its impact on carbon stock between 2019 and 2036 under business-as-usual and REDD+ scenarios

The following conclusions were reached for Objective 2;

- Carbon stock under REDD+ could increase by 13 % and 25 % over the BAU scenario in 2024 and 2035, respectively. However, landuse for crop production could be reduced by 17 – 32% in the same period.
- The areas of land covered by closed and open forest is expected to keep decreasing in 2024 and 2035 based on the business as usual scenarios. However, under the REDD+ scenario, closed and open forest areas are maintained.
- Also, agroforestry cocoa will continue to increase under both scenarios through the future predicted years but at a slower pace under the BAU scenario

- Monoculture cocoa will experience some rise and fall under the BAU scenarios and a constant decrease over the predicted years based on the REDD+ scenario projection.

In answering the objective 3,

- ❖ What socioeconomic factors influence the landuse choices of farmers?

Objective 3: To assess the socioeconomic factors that influence the decision of farmers on landuse choices

The third objective sought to capture the heterogeneity in land-use decisions by determining the socio-economic characteristics that influence the choice of farming system, assessing the determinants of future farming decision given financial support, and identifying the various factors influencing household decision making on land-use choices.

The following conclusions were reached for Objective 3;

- Age, years of farming, cocoa income, and distance to road and town have positive influences on the selection of monoculture cocoa farming, whilst marital status, total land holding, and input cost had a negative influence on the same selection.

- Increase in years of farming increases a farmer’s willingness to continue cocoa farming given financial support which can be attributed to a number of factors such as ready market and income security
- Also, there was a significant negative relationship between the choice between continuing with cocoa farming or changing to a new crop or

investment and marital status, income from off farm activity, and farming system.

- A significant positive relationship existed between the choice between continuing with cocoa farming or changing to a new crop or investment and their years of farming and the distance to road.

In answering the objective 4,

- ❖ What factors influence the willingness-to-participate in REDD+ scheme in Ghana?

This study assessed the willingness-to-participate in REDD+ scheme in Ghana by farmers and the different factors influencing their choice of participation.

Objective 4: To assess the willingness-to-participate in REDD+ scheme in Ghana by farmers and the different factors influencing their choice of participation

The following conclusions were reached for Objective 4;

- More than 90% of households were willing to participate in all REDD+ activities driven by immediate benefits. The results of this study showed that the major reasons for participation in REDD+ for households are increase in yield/income, REDD+ benefits, sustainability of farm, and environmental reasons. People place more importance on increasing yields and income as far as participation in REDD+ is concerned and the least in importance is having the environment in mind.
- Age, marital status, cost of labor, land holding per capita, livestock income, input cost, distance to the town center, and distance to the road significantly influenced their decisions.

7.2 Limitations of the study

- The major limitation of the study was that only the above ground carbon stocks of the land-use types were taken into considering, without capturing the entire carbon stocks of the land-uses which include below ground, soil and deadwood carbon. Also, only carbon stocks data generated from this research was used, putting the other landuse classes that were not of interest to zero. This does not present a full description of the carbon dynamics in the landscape especially with transitions within classes not studied and how it will affect the carbon dynamics.
- Also, owing to insufficient funding and limited timeframe, the study was limited to a single cocoa-growing region, specifically the Central Region of Ghana. To compare the outcomes, it would be best to have gathered more information from a different cocoa-growing region.

7.3 Recommendations

7.3.1 Recommendations for further research

- The study recommends that future studies should consider all carbon pools (aboveground, belowground, soil, litter, and deadwood stocks) to fully understand and appreciate the effect of land use change on carbon dynamics under the two scenarios.

7.3.2 Policy Implications and recommendations

- The National REDD+ Secretariat should promote farm intensification using appropriate technologies for future food security under REDD+ as the scenario has an implication on land area available for farming.
- REDD+ actors should strive to replace secondary forest loss with cocoa agroforestry for effective tree cover.

- Education on REDD+ should be gender-specific and target factors such as income level (through alternative livelihood), age and total land holdings of farmers
- From the study, Cocoa agroforests and secondary forests stores considerable carbon and contributes well to the REDD+ agenda pursued by Ghana towards climate change mitigation and the receipt of results-based payments for emission reduction. Trees in the agricultural landscape would need safeguarding against factors contributing to forest degradation such as illegal logging and mining to protect the biodiversity and carbon stored in them. This will require strengthening existing tree tenure and giving much benefits and control of trees within off-reserve areas to farmers and landowners.
- The results showed that a REDD + scenario will bring more carbon stocks especially in protecting existing forest cover and enhancing carbon stocks through agroforestry systems leading to higher net present value of the landscape and emission reduction payments. The BAU scenario in the study showed the loss of forest over the time period. These findings provide forest managers and the implementing authority of the REDD+ program in Ghana to pay attention to enforcement of protected forest laws in preventing encroachment and illegal entry into forest reserves and enhancing forest patrols.
- It also gives hope that agroforestry can work in improving the biodiversity and carbon sequestration potential of agricultural landscape. Endemic and scarce species found within the agroforest with diversity comparable to the primary forest also gives REDD+ implementers and forest managers the indication that to educate farmers and community members on the need to tend trees on farm while protecting those in their secondary forest landscapes.
- The findings of the study suggest that farmers place more importance on increasing yields and income as far as participation in REDD+ is concerned and the least in importance is having the environment in

mind. Implementers of the REDD+ project should therefore consider climate smart practices and the supply of farm inputs that improves crop yield and consequently bumper harvest and income.

- Education on benefit to REDD+ participation should also be coined in language such as how the microclimate when improved by agroforestry practice will inure to their benefit of having rains to sustain their farms and support cocoa productivity.

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Appendix 1: HOUSEHOLD QUESTIONNAIRE

Code for GPS:

Research title:

ASSESSING THE IMPACT OF LAND USE/ LAND COVER CHANGES ON CARBON STOCK DYNAMICS ON IMPLEMENTATION OF REDD+ POLICY IN GHANA

Overall objective

This questionnaire aims to collect data for understanding the decision-making of farmers on livelihood options, adoption of REDD+, and its impacts of the land-use of the Assin South District of Ghana.

Information to be collected from this questionnaire:

General Household data; farm characteristics and land tenure; off farm jobs; crop production for last season; livestock production; labour availability and allocation; farm inputs; agricultural extension; REDD+ awareness and participation.

Your responses will be anonymous

Village: ……………………… Compound No: ………………………… Coordinates: ………………………………/……………………………

Name of the respondents: ……………………………………………………………… Are you household head?: Yes [ ] or No [ ] Phone no.: ………………………

Date of the interview: ……/……/2021/ Time start: ………………………Time end: ………………………

*Village centre coordinates

**Distance to Main town road.......

What main town do you access for goods and services?.....................

**indicated for reference: will be determined in GIS environment from the farm and house coordinates

SECTION ONE: DEMOGRAPHIC STRUCTURE AND INFORMATION ON THE HOUSEHOLD

1.1 Household size ___________

1.2 Household characteristics

	1.2.1	1.2.2	1.2.3	1.2.4	1.2.5	1.2.6
	Gender	Age	Marital status	Educational level (years)	Farm occupation	Off-farm activities occupation
1						
2						
3						
4						
5						
6						

7						
8						
9						
10						
11						
12						
HH- household head **W- Wife** **C-Child** **R-Respondent** **N-Nephew/niece** **A-Aunt** **G- Grandparent**	1. **Male** 2. **Female**		**1.Maried 2.Divorced 3.Separated** **4.Widow 5.Single** **6.Young member less than 16 years**		**1.Yes 2.Non**	**1.Yes 2.Non**

1.3 Ethnic group of the household head? _......................._______________________

1.4 Religion of the household head?________(**Use the key : 1. Muslim 2. Christian 3.Non believer. 4.Animist 5.Others (to specify**)

1.5 Does the household have access to the electricity? ___________________ (**1.Yes** **2. No**)

1.6 What is the dependency ratio of the household (how many people depend on the household income or head for subsistence)……………….?

1.6 What is the lineage of land inheritance in the community? Matrilineal or patrilineal?...

1.8: Occupation			All questions concerned the last 12 months

1.8.1	1.8.2	1.8.3	1.8.4	1.8.5	1.8.6	1.8.7
The main activity of the household head	Further activities of the household head	Number of days/week allocated to the main activity	Number of months allocated to the main activity during the last 12 months	Number of days/week allocated to the secondary activity	Number of months allocated to the secondary activity during the last 12 months	Number of days lost due to the disease during the last 12 months
1.Agiculture 2.Trader 3.Teaching 4. Artisan 5.Office job 6.Off farm work 7.Student 8.Unemployed 9.Other to specify		Please check the definition of one day of work = 6-8 hours of work		Please check the definition of one day of work = 6-8 hours of work		

2.0 Do you belong to any cooperative? Yes [ ]

SECTION TWO: PLOT SPECIFIC INFORMATION (FARM

No [ ]

2.1 How many farms are under cultivation by the household?_______

2.2

Farm	*current crop cultivated	**Previous crop on the land(landuse)	Area of the farm (Farmer estimation)	Farm area (measured)
1				
2				
3				
4				
5				

6				

*crop cultivated 1. Cocoa agroforest 2. Cocoa monoculture 3. Rubber 4. Oil palm 5. Citrus
** previous landuse 1. fallow land 2. Rubber 3. Forest 4. Food crop (like cassava, maize plantain etc.) 5. Cocoa farm 6. Coconut farm

2.3 Why are you into the cocoa farming (or the crop planted) either than the other tree crops?

i. Previous crop was not doing well [ ]
ii. Not getting enough money from the previous crop [ ]
iii. Financial and technical assistance from cocoa board and partners [ ]
iv. Land is not good for the other crops [ ]
v. Influence from other neighboring farmers [ ]
vi. Availability of market for the produce [ ]

2.4 Do you have other food crops within your farm? …………………………………………..

a. Yes [ ] b. No [ ]

2.5 Is the size of your farm the same as you started or it changed along the way?

a. Increased b. [ ] decreased [ ] c. remained same [ ]

2.5.1 Do you intend to clear more land(forests) for farm?

a. Yes [ ] b. No

2.5.2 What other land use in this community is competing with the cocoa?

……..

2.5.3 What is causing this competition?

a. Good market for the other crop or landuse [ ] b. Financial incentive for the other landuse or crop [ ] c. other (specify)……………………………………

2.5.4 Aside your current farmland, do you own other lands or houses for rent both in this community or elsewhere?

a. Yes [ ] b. No [ ] size ……………….?

2.6 Answer the questions on the land referring to the total area and the farming system type implemented by the household members

	2.6a	2.6b	2.6c	2.6d
Number of parcels	Crop cultivated (as in 2.2)	Land tenure of the cultivated parcel	During how many years you cultivated this parcel?	Fees by year if the parcel is rented (Ghc)
1				
2				
3				
4				
5				

Key for 2.6b 1. Landowner 2. Family land 3. Rented/lease 4. Community land 5. Sharing of farm produce Abuno (into 2) 6.Sharing of farm produce abusa (into 3)

2.7 Other household assets

2.7.1 Livestock and Poultry

Do you have animals? 2. No (**If No, then go**
__________ 1. Yes **to the next section**)

Type of animal	Number owned	Number born the last 12 months	Number bought the last 12 months	Price of each bought animal	Number of month during which you fed the animals			Number sold the last 12 months	Price of each sold animal
					On community land	On household land	In the bush		
1.Sheep									
2.Goat									
3.Cow									
4.Pig									
5.Poultry									
6.Other									

2.7.2 Livestock Products

Household livestock Products	Quantity used by the household (kg/year)	Quantity sold (kg/year)	Price per unit
1.Milk products			
2.Meat			
3.			
4.			
5.			

2.8 Activities' division: estimation of the number of persons and days on each parcel according to the labour type

Season and activity type per parcel		Total number of employed labours and total number of work days (per activity and per season) (1 day = 6 – 8 hours of labour)													
		Household labour						Rented labour						Communal labour	
		Male adult		Female adult		Young (< 16yrs)		Male adult		Female Adult		Young (< 16 yrs)		All participants	
		No	Days	No	Days	No	Days	No	Days	No	Days	No	Days	No	Days
Parcel 1	Land clearing/preparation														
	Pruning														
	Weeding														
	Pesticide, fertilizers, etc														
	Harvesting														
Parcel 2	Land clearing/preparation														
	Pruning														
	Weeding														
	Pesticide, fertilizers, etc														
	Harvesting														

Parcel 3	Land clearing/preparation														
	Pruning														
	Weeding														
	Pesticide, fertilizers, etc														
	Harvesting														
Parcel 4	Land clearing/preparation														
	Pruning														
	Weeding														
	Pesticide, fertilizers, etc														
	Harvesting														
Total number of days															

2.9 Farm remuneration

Farm remuneration rate	Rented labour Ghc			Communal labour (Ghc)
	Male adult	Female adult	Young	Money spent by the household for one day of work
Weeding Harvesting Fertilizer/pesticide application Pruning				

2.10 Other farm input cost

Item type	**Quantity used per parcel of land**	**Unit price**
Fertilizer		
Pesticide		
Cocoa seedlings		
Farm tools • cutlass		

• sprayer • working gear • pruning tools		

2.11 Details on crop productivity and sale for these last 12 months?

Parcel number	Crop type	Amount harvested (kg)bags	Amount lost because of disease (kg)	Amount sold (kg)	Cost of kg bag of sold product	To whom the production has been sold
1						
2						
3						
4						

[*note: income and productivity should be after Abunu/Abusa sharing arrangement, probe further to understand if income/productivity is correct and match with each other*]

2.12Off-farm income

Self-employment (store, driving etc)	Renting of land or house	Remittance/pension

SECTION THREE: REDD+ AND WILLINGNESS TO PARTICIPATE

3.1.0 Next 5 to 20 years, do you still see yourself planting this cocoa or may change to another tree crop or other investment?
a. Change to new crop or investment [ ] b. continue with cocoa [ ]

3.1.1 if there is financial support, will you clear new area to establish more farm? What crop will you plant?
Yes [ ] No [ ] …………………………………………..

3.1.2 If rubber, oil palm or another cash crop were to grow here, would you consider that as an option over cocoa agroforest?
Yes [ ] No [ ]

3.1.3 i. Do you have trees on your farm and can you quantify the number?
a. Yes [ ] b. No [ ]

ii. If yes, were these trees on the land before you started the farm?
……
……………………………

iii. If no, do you intentionally plant trees on your farm?

……
…………………………

3.1.4 Have you had any engagement from COCOBOD, FC or other private sector on REDD+ (its objectives) and climate smart cocoa production? [Note: let respondent provide details on the answer?

a. Yes [ ] b. No [ ]

3.1.5 Are you benefitting from any cocoa projects, training, extension or other type of activities in the HIA? (e.g. seedlings, farm inputs, training from cocoa company, NGO or Cocobod) (0=No; 1=Yes) [*note: needs probing. Take interviewee through different interventions*]

a. Yes [ ] b. No [ ]

3.1.6 Do you perceive that the cocoa agroforest (trees providing shade for the cocoa) is a contributing factor for the yield of the cocoa? [Note: let respondent provide details on the answer]
a. Yes [ ] b. No [ ]
………
………………………………

3.1.7 Do you perceive that your income from the farm can be improved if you adopt good agronomic practices that are climate friendly? [Note: let respondent provide details on the answer]
a. Yes [ ] b. No [ ]

3.2 Policy and governance

a. Tree tenure and land system and REDD+

3.2 .1 What do you know about the tenure of trees on your land and in your farm?

………
……………………………

3.2.2. i. Have you ever had any conflict over the ownership of trees on your farm? (1). Yes [ ] (2). No [ ] (**if No, jump to 3.2.7**)
ii. If yes, what was it? …………………………………………………………………………………………………… ……………
…………………………………………………………………………

3.2.3. i. Was it resolved? (1). Yes [ ] (2). No [ ]
ii. If yes, how was it resolved? ………………………………………………………………………………………………… …
……………………………………………………………………………

iii. Did you like the outcome? (1). Yes [ ] (2). No [ ]
iv. Based on the outcome, would you continue to plant and or maintain trees on your farm? Yes [ ] (2).No[ ]
…….
…………………………

3.2.4 Are you limited by your land tenure in incorporating trees on your farmland? (1). Yes [ ] (2). No [ ]
………
…………………………

3.3 Willingness to participate in REDD+
3.3.1 Have you had any education on the benefit sharing agreement under REDD+?
(1) Yes [ ] (2). No [ ]

3.3.2 Are you willing to incorporate trees on your farms to increase shade for better yield or manage already existing trees for shade on your farm?
(1) Yes [ ] (2). No [ ]

3.3.3 Are you willing to participate in climate smart agriculture which follows directives under the REDD+?
(1) Yes [ ] (2). No [ ]

3.3.4 Would you participate in climate smart cocoa under REDD+ if your other farmers show increase yield and income?
(1) Yes [ ] (2). No [ ]

3.3.5 If you would be able to harvest the timber once the trees had reached an appropriate size and sell it by existing formal procedures and regulations, will you participate in the REDD+ scheme?
(1) Yes [ ] (2). No [ ]

3.3.6 Are you willing to participate in a REDD+ scheme if the consortium partners would compensate you with non-monetary benefits such as fertilizers, pesticides, farm inputs etc. and also improve the yield of your farm?

Benefit	Yes/No	Explanation
fertilizer		
Pesticides		
hybrid cocoa seedlings		
shade tree seedlings		
farming tools (machete, scythe, wellington boots, tricycle mechanized sprayer)		
other inputs to support CSC		

3.3.7 a. if there was a premium payment for cocoa from agroforest system under REDD+, will you participate in it?
Yes [ ] No [ ]
3.3.7 b. Would you prefer the benefits be made in cash if you are willing to participate in REDD+?
(1) Yes [ ] (2). No [ ]

3.3.8a if you were to estimate, what will be your package of benefit (in cash) you will accept to participate in a REDD+ ?
…………………………………………………………………..Ghc

3.3.8 b. Would you still participate in REDD+ if the benefits are paid as non-monetary benefit through farmer group?
(1) Yes [ ] (2). No [ ]

3.3.9 What are your reasons or incentives to participate in REDD+?

i.	Environment	[ ]
ii.	REDD+ benefits	[ ]
iii.	Increase yield/ income	[ ]
iv.	Sustainability of landscape/farm for children/family	[ ]

3.3.10 Are you willing to register under a farmer group that is managed for productive landscape under REDD+ so that you can receive non-monetary benefits such as fertilizer and farm inputs?
(1) Yes [ ] (2). No [ ]

3.3.11 Are you willing to intensify cocoa production on your current piece (s) of land by adopting climate-smart agriculture of REDD+ rather than cultivating new areas for farms?
(1) Yes [ ] (2). No [ ]

3.3.12 Are you willing to participate in REDD+ if you will receive extension services from the consortium partners?
(1) Yes [ ] (2). No [ ]

3.3.14 If you were to get other incentive packages that are monetary rewards for your adoption of climate-smart practices, would you leave REDD+ practices to join that?
(1) Yes [ ] (2). No [ ]

Appendix 2: Index value for important families

IVI range	Botanical family	Number of species	Total number of individuals	Total basal area in m2	Relative diversity (%)	Density relative (%)	Dominance relative (%)	IVI family (%)
1	Malvaceae	5	4213	734.8843	5.2632	48.6827	62.3699	116.3157
2	Meliaceae	8	420	39.9525	8.4211	4.8532	3.3908	16.6651
3	Rubiaceae	4	725	40.2997	4.2105	8.3776	3.4202	16.0084
4	Sterculiaceae	5	549	33.7075	5.2632	6.3439	2.8608	14.4678
5	Euphorbiaceae	7	179	44.1314	7.3684	2.0684	3.7454	13.1823
6	Mimosaceae	8	143	35.5439	8.4211	1.6524	3.0166	13.0901
7	Apocynaceae	5	297	24.4499	5.2632	3.4319	2.0751	10.7702
8	Moraceae	4	247	25.6944	4.2105	2.8542	2.1807	9.2454
9	Ebenaceae	2	403	6.2627	2.1053	4.6568	0.5315	7.2936
10	Caesalpiniaceae	3	128	19.7385	3.1579	1.4791	1.6752	6.3122
11	Pandaceae	4	72	9.3605	4.2105	0.832	0.7944	5.8369
12	Lecythidaceae	3	112	13.5853	3.1579	1.2942	1.153	5.6051
13	Combretaceae	2	98	25.2419	2.1053	1.1324	2.1423	5.38
14	Urticaceae	2	80	19.9412	2.1053	0.9244	1.6924	4.7221
15	Anacardiaceae	3	42	4.4058	3.1579	0.4853	0.3739	4.0171
16	Ulmaceae	1	172	10.8939	1.0526	1.9875	0.9246	3.9647
17	Olacaceae	2	130	3.0257	2.1053	1.5022	0.2568	3.8643
18	Fabaceae	3	19	3.9713	3.1579	0.2196	0.337	3.7145
19	Simaroubaceae	1	112	15.271	1.0526	1.2942	1.2961	3.6429
20	Annonaceae	3	26	1.2527	3.1579	0.3004	0.1063	3.5647
21	Rutaceae	2	71	7.1182	2.1053	0.8204	0.6041	3.5298
22	Myristicaceae	1	70	18.258	1.0526	0.8089	1.5496	3.4111
23	Guttiferae	2	27	10.9896	2.1053	0.312	0.9327	3.3499
24	Papilionaceae	1	111	4.3134	1.0526	1.2826	0.3661	2.7014
25	Burseraceae	2	21	1.6028	2.1053	0.2427	0.136	2.484
26	Lauraceae	1	54	2.9146	1.0526	0.624	0.2474	1.924

27	Bignoniaceae	1	23	6.0396	1.0526	0.2658	0.5126	1.831
28	Sapotaceae	1	20	5.7936	1.0526	0.2311	0.4917	1.7754
29	Sapindaceae	1	23	3.0786	1.0526	0.2658	0.2613	1.5797
30	Bombacaceae	1	11	4.0275	1.0526	0.1271	0.3418	1.5216
31	Lamiaceae	1	28	0.1947	1.0526	0.3235	0.0165	1.3927
32	Loganiaceae	1	9	1.8309	1.0526	0.104	0.1554	1.312
33	Santalaceae	1	7	0.1949	1.0526	0.0809	0.0165	1.1501
34	Cecropiaceae	1	6	0.2037	1.0526	0.0693	0.0173	1.1392
35	Flacourtiaceae	1	3	0.0293	1.0526	0.0347	0.0025	1.0898
36	Myrtaceae	1	2	0.0598	1.0526	0.0231	0.0051	1.0808
37	Solanaceae	1	1	0.005	1.0526	0.0116	0.0004	1.0646
	Total	95	8654	1178.2684	100	100	100	300

Appendix 3: Species Importance Value Index

IVI range	Species code	Scientific name	Common names	[Plot] where the species are present	Total number of individuals	Total basal area in m 2	Frequency relative (%)	Density relative (%)	Dominance relative (%)	IVI species (%)
1	000085	Theobroma cacao	Cocoa	54	4148	685.3845	72	47.9316	58.1688	178.1004
2	000054	Morinda lucida	Konkroma	29	458	33.2164	38.6667	5.2924	2.8191	46.7781
3	000004	Albizia zygia	Okoro	31	95	22.1075	41.3333	1.0978	1.8763	44.3074
4	000038	Funtumia elastica	Funtum	26	120	13.604	34.6667	1.3866	1.1546	37.2079
5	000071	Pycnanthus angolensis	Otie	24	70	18.258	32	0.8089	1.5496	34.3584
6	000053	Milicia excelsa	Odum	23	85	8.0124	30.6667	0.9822	0.68	32.3289
7	000006	Amphimas pterocarpoides	Begyewoba	23	42	7.8979	30.6667	0.4853	0.6703	31.8223
8	000088	Trichilia monadelpha	Tanuro	22	116	12.5453	29.3333	1.3404	1.0647	31.7385
9	000036	Ficus capensis	Odoma	23	38	4.8358	30.6667	0.4391	0.4104	31.5162
10	000037	Ficus exasperata	Nyankyerene	22	60	4.9316	29.3333	0.6933	0.4185	30.4452
11	000009	Antiaris toxicaria	KyenKyen	20	64	7.9146	26.6667	0.7395	0.6717	28.0779

12	000082	Terminalia superba	Ofram	19	74	19.4119	25.3333	0.8551	1.6475	27.8359
13	000072	Rauvolfia vomitoria	Kakapenpen	19	105	6.2034	25.3333	1.2133	0.5265	27.0731
14	000027	Daniellia ogea	Hyedua	19	79	9.3914	25.3333	0.9129	0.7971	27.0433
15	000047	Macaranga barteri	Opam	16	115	34.0496	21.3333	1.3289	2.8898	25.552
16	000040	Hannoa klaineana	Fotie	17	112	15.271	22.6667	1.2942	1.2961	25.2569
17	000059	Nesogordonia papaverifera	Danta	17	102	10.6004	22.6667	1.1786	0.8997	24.745
18	000021	Citrus sinensis	Citrus	17	56	4.4644	22.6667	0.6471	0.3789	23.6927
19	000081	Terminalia ivorensis	Emire	17	24	5.83	22.6667	0.2773	0.4948	23.4388
20	000079	Sterculia tragacantha	Foto	16	74	10.7544	21.3333	0.8551	0.9127	23.1012
21	000065	Persea americana	Pear	16	54	2.9146	21.3333	0.624	0.2474	22.2047
22	000066	Petersianthus macrocarpus	Esia	14	45	12.6092	18.6667	0.52	1.0701	20.2568
23	000034	Entandrophragma angolense	Edinam	14	60	7.4965	18.6667	0.6933	0.6362	19.9962
24	000005	Alstonia boonei	Nyamedua	14	20	10.7918	18.6667	0.2311	0.9159	19.8137
25	000060	Newbouldia laevis	Sesemasa	14	20	3.2335	18.6667	0.2311	0.2744	19.1722
26	000075	Spathodea campanulata	Akuakuo-Ninsuo	13	23	6.0396	17.3333	0.2658	0.5126	18.1117
27	000056	Myrianthus libericus	Nyankomanini	12	64	14.709	16	0.7395	1.2484	17.9879
28	000019	Ceiba pentandra	Onyina	12	15	17.1203	16	0.1733	1.453	17.6263
29	000020	Celtis mildbraedii	Esa	11	172	10.8939	14.6667	1.9875	0.9246	17.5788
30	000012	Blighia sapida	Akyi	12	23	3.0786	16	0.2658	0.2613	16.5271
31	000046	Lannea welwitschii	Kumanini	12	16	2.3088	16	0.1849	0.196	16.3808
32	000011	Baphia nitida	Edwen	11	111	4.3134	14.6667	1.2826	0.3661	16.3154
33	000049	Mareya micrantha	Edubrafo	11	20	0.754	14.6667	0.2311	0.064	14.9618
34	000091	Triplochiton scleroxylon	Wawa	9	23	30.0562	12	0.2658	2.5509	14.8166
35	000068	Pouteria altissima	Asanfena	10	20	5.7936	13.3333	0.2311	0.4917	14.0561
36	000031	Distemonanthus benthamianus	Kotreamfo	10	14	3.619	13.3333	0.1618	0.3071	13.8023
37	000095	Zanthoxylum gilletii	Okuo	10	15	2.6538	13.3333	0.1733	0.2252	13.7319
38	000015	Bridelia atroviridis	Opam kotokro	9	15	1.9467	12	0.1733	0.1652	12.3385
39	000055	Musanga cecropioides	Odwema	8	16	5.2322	10.6667	0.1849	0.4441	11.2956
40	000013	Bombax buonopozense	Akata	8	11	4.0275	10.6667	0.1271	0.3418	11.1356
41	000029	Diospyros kamerunensis	Omena	8	32	0.6326	10.6667	0.3698	0.0537	11.0901
42	000023	Cola gigantea	Wapuo	5	344	4.4752	6.6667	3.975	0.3798	11.0215
43	000080	Strombosia pustulata	Afena	7	109	2.2879	9.3333	1.2595	0.1942	10.787

44	000018	Carapa procera	Kokuia-bese	7	68	3.9202	9.3333	0.7858	0.3327	10.4518
45	000030	Diospyros sanza-minika	Ensoafe	4	371	5.6301	5.3333	4.287	0.4778	10.0982
46	000008	Anthocleista nobilis	Wodefo?kete	7	9	1.8309	9.3333	0.104	0.1554	9.5927
47	000002	Albizia ferruginea	Awiea-fosa-mena	7	11	1.4066	9.3333	0.1271	0.1194	9.5798
48	000070	Psydrax subcordata	Nte-teadupon	7	11	1.3785	9.3333	0.1271	0.117	9.5774
49	000089	Trichilia prieuriana	Kaekae-dokro	5	136	13.7181	6.6667	1.5715	1.1643	9.4025
50	000024	Cola nitida	Bese	6	28	7.5853	8	0.3235	0.6438	8.9673
51	000050	Margaritaria discoidea	Papiaa	6	10	7.3901	8	0.1156	0.6272	8.7428
52	000073	Ricinodendron heudelotti	Wama	6	13	5.0379	8	0.1502	0.4276	8.5778
53	000076	Spondias mombin	Atoa	6	21	1.0579	8	0.2427	0.0898	8.3324
54	000042	Holarrhena floribunda	Sese	6	13	0.2686	8	0.1502	0.0228	8.173
55	000057	Napoleonaea vogelii	Obuayaa	5	66	0.9683	6.6667	0.7627	0.0822	7.5115
56	000063	Panda oleosa	Baman	5	50	1.8523	6.6667	0.5778	0.1572	7.4016
57	000093	Voacanga africana	Badaa	5	39	1.1405	6.6667	0.4507	0.0968	7.2141
58	000010	Aulacocalyx jasminflora	Asaben	3	249	2.5398	4	2.8773	0.2156	7.0928
59	000078	Sterculia rhinopetala	Wawa-bima	5	18	2.1119	6.6667	0.208	0.1792	7.0539
60	000083	Tetrapleura tetraptera	Prekese	5	7	1.4755	6.6667	0.0809	0.1252	6.8728
61	000041	Harungana madagascariense	Kosoa	5	7	0.1978	6.6667	0.0809	0.0168	6.7643
62	000067	Piptadeniastrum africanum	Dahoma	4	13	7.387	5.3333	0.1502	0.6269	6.1105
63	000084	Tetrorchidium didymostemon	Fiankra	4	13	2.1823	5.3333	0.1502	0.1852	5.6688
64	000062	Ongokea gore	Bo dwi (otwe adwe)	4	21	0.7378	5.3333	0.2427	0.0626	5.6386
65	000045	Khaya ivorensis	Mahog-any	4	16	0.8789	5.3333	0.1849	0.0746	5.5928
66	000001	Albizia adianthifolia	Pampena	4	6	0.656	5.3333	0.0693	0.0557	5.4583
67	000058	Nauclea diderrichii	Kusia	3	7	3.165	4	0.0809	0.2686	4.3495
68	000092	Vitex doniana	Afoa	3	28	0.1947	4	0.3235	0.0165	4.3401
69	000026	Dacryodes klaineana	Adwea	3	17	1.285	4	0.1964	0.1091	4.3055
70	000039	Guarea cedrata	Kaebohro	3	12	0.2272	4	0.1387	0.0193	4.1579
71	000035	Entandrophragma candollei	Cedar	3	6	0.9333	4	0.0693	0.0792	4.1485
72	000048	Mangifera indica	Mango	3	5	1.0391	4	0.0578	0.0882	4.146
73	000077	Sterculia oblonga	Ohaa	3	9	0.2114	4	0.104	0.0179	4.1219
74	000090	Trichilia tessmannii	Tanuro nini	3	6	0.233	4	0.0693	0.0198	4.0891

75	000017	Canarium schweinfurthii	Bediuonua	3	4	0.3178	4	0.0462	0.027	4.0732
76	000028	Dialium guineense	Osran(yo oyi)	3	3	0.1335	4	0.0347	0.0113	4.046
77	000043	Homalium letestui	Eso-nana-koroma	3	3	0.0293	4	0.0347	0.0025	4.0372
78	000064	Parkia bicolor	Asoma	2	7	1.8532	2.6667	0.0809	0.1573	2.9048
79	000033	Duguetia staudtii	Adua wusa	2	7	0.4684	2.6667	0.0809	0.0398	2.7873
80	000061	Okoubaka aubrevillei	D Ball	2	7	0.1949	2.6667	0.0809	0.0165	2.7641
81	000022	Cleistopholis patens	Ngo ne ngyen	2	2	0.4587	2.6667	0.0231	0.0389	2.7287
82	000094	Xylia evansii	Semantha	2	3	0.1427	2.6667	0.0347	0.0121	2.7134
83	000069	Psidium guajava	Guava	2	2	0.0598	2.6667	0.0231	0.0051	2.6948
84	000016	Bussea occidentalis	Samanta	1	7	2.4492	1.3333	0.0809	0.2079	1.6221
85	000007	Annickia polycarpa	Adua sika	1	17	0.3256	1.3333	0.1964	0.0276	1.5574
86	000051	Microdesmis keayana	Ofema	1	8	0.0879	1.3333	0.0924	0.0075	1.4332
87	000014	Bosqueia angolensis	Okure	1	6	0.2037	1.3333	0.0693	0.0173	1.4199
88	000003	Albizia glaberrima	Okoronini(atwere)	1	1	0.5153	1.3333	0.0116	0.0437	1.3886
89	000052	Microdesmis puberula	Finwa	1	4	0.0302	1.3333	0.0462	0.0026	1.3821
90	000025	Cylicodiscus gabonensis	Danya	1	2	0.2187	1.3333	0.0231	0.0186	1.375
91	000044	Irvingia gabonensis	Besebuo	1	1	0.2922	1.3333	0.0116	0.0248	1.3697
92	000086	Treculia africana	Ototim	1	2	0.1531	1.3333	0.0231	0.013	1.3694
93	000032	Drypetes aubrevillei	Duamako	1	1	0.0079	1.3333	0.0116	0.0007	1.3456
94	000087	Trema orientalis	Sesia	1	1	0.0079	1.3333	0.0116	0.0007	1.3456
95	000074	Solanum erianthum	Pepedeawuo	1	1	0.005	1.3333	0.0116	0.0004	1.3453
	Totals			75	8654	1178.2684	100	100	100	300

Appendix 4: Total Carbon (Mg/ha) by Species and DBH Classes

Specie	DBH in Classes of 10 cm										Total
	0 - 9.99	10 - 19.99	20 - 29.99	30 - 39.99	40 - 49.99	50 - 59.99	60 - 69.99	70 - 79.99	80 - 89.99	90 +	
Albizia adianthifolia	0.1624	0.6489			0.7369						0.4682

Albizia ferruginea	0.0347	0.1791	0.1644	0.2328	0.7434	1.0985			2.9232		0.8476
Albizia glaberrima									3.3325		3.3325
Albizia zygia	0.1691	0.6197	1.1456	2.1634	3.1088	6.6785	1.5467				2.1407
Alstonia boonei	0.0948	0.2884	0.6322			0.5914		1.4979	2.2183	8.9655	3.1391
Amphimas pterocarpoides	0.1977	0.1592	0.2484	0.5951	0.8004	1.1739	2.3743		4.6821	7.4910	2.4167
Annickia polycarpa	0.0360	0.3663	0.7258								1.1280
Anthocleista nobilis	0.1517	0.6812	1.8313								0.7159
Antiaris toxicaria	0.0466	0.1690	0.2211	0.5203	0.6259	0.9808				10.6429	1.6788
Aulacocalyx jasminflora	0.5528	1.7116	0.6128	0.3866	0.8046						3.0701
Baphia nitida	0.9059	0.1908									0.9753
Blighia sapida	0.2236	0.6473	2.0019		1.2283	3.7730					1.2751
Bombax buonopozense	0.0072	0.2738	0.0740	2.1566	0.4310		0.9770		2.2158	3.5427	1.5675
Bosqueia angolensis		0.0150	0.5630								0.5781
Bridelia atroviridis	0.2418	0.6372	0.1623	0.2522		1.1411					0.6783
Bussea occidentalis	0.5182	3.6793	6.9058								11.1033
Canarium schweinfurthii		0.0185	0.1038	0.4202	0.5055						0.3493

Carapa procera	0.0963	0.5696	1.9670	0.3696	0.7036						2.1681
Ceiba pentandra	0.0554	0.3487	0.0702	3.9145	5.2141	0.5382	0.8517			9.0843	4.7593
Celtis mildbraedii	0.1190	0.9791	2.4335	2.3275	2.2092	2.3351	1.9016	2.4645			4.3968
Citrus sinensis	0.0221	0.1407	0.4424	0.7510	0.8295					14.5740	1.6225
Cleistopholis patens		0.4084									0.4084
Cola gigantea	0.5559	2.4245	1.6883	0.5895	0.7807						2.8194
Cola nitida	0.0122	0.3634	0.5526	2.3270	12.6012						5.7674
Cylicodiscus gabonensis			0.2663		1.2291						1.4953
Dacryodes klaineana	0.0112	0.0712	0.4043	2.3528	1.7057	1.4376					2.8598
Daniellia ogea	0.1717	0.5388	1.2956	0.4138	0.5228		1.8550			6.0311	1.6301
Dialium guineense		0.0414	0.1461	0.5670							0.2515
Diospyros kamerunensis	0.0540	0.2685	0.1738			1.4651					0.4230
Diospyros sanza-minika	0.9945	2.8576	1.0012	2.0371				3.0484	5.1078		7.6606
Distemonanthus benthamianus	0.0135	0.0614	0.9821	0.4261						18.3312	2.4367
Drypetes aubrevillei		0.0367									0.0367
Duguetia staudtii		0.1211		1.1933	1.0874						1.2615

Entandrophragma angolense	0.068	0.2658	1.0481	0.6515	0.7778	0.8986	1.5437	1.9687	3.1469	8.5470	2.2965
Entandrophragma candollei	0.055	0.0484	0.2665		0.8103				3.5523		1.8311
Ficus capensis	0.0811	0.1956	0.1276			0.8665				7.2256	0.5385
Ficus exasperata	0.1521	0.2494	0.2564	0.3418	0.4310	0.6158					0.4762
Funtumia elastica	0.3248	1.1055	0.6418	0.4029	0.6046	1.3073					1.3233
Guarea cedrata	0.0191	0.1881	0.2094								0.2714
Hannoa klaineana	0.0272	0.6955	0.7327	0.3675	0.4691	0.8367	1.4811	1.3328	1.8984	4.2153	2.5671
Harungana madagascariense	0.0931	0.0475									0.0840
Holarrhena floribunda	0.0109	0.0347	0.1133	0.4466							0.1426
Homalium letestui	0.0172	0.0910									0.0418
Irvingia gabonensis							2.2707				2.2707
Khaya ivorensis	0.0091	0.1085	0.2162	0.2808	0.7267	0.9129					0.7713
Lannea welwitschii		0.1854	0.3780	0.4329	0.7139		1.4841				0.6505
Macaranga barteri	0.5199	2.4367	2.2083	9.3701	4.7291		1.2172				5.5429
Mangifera indica		0.0263			1.4041		1.8682	2.3136			1.8707
Mareya micrantha	0.1066	0.1465	0.1694								0.1462

Margaritaria discoidea	0.0215	0.0580	2.7513	8.0334	0.8586	1.7194	30.3752				7.7711
Microdesmis keayana	0.0487	0.2656									0.3142
Microdesmis puberula	0.0155	0.0822									0.0977
Milicia excelsa	0.2923	0.3647	0.4793	1.0025	1.0453	1.2015	1.6512	3.1642	4.5921		1.5676
Morinda lucida	0.1900	0.7851	1.7039	1.3900	1.4854	4.2707	3.1697	3.1489	3.3022	7.8480	4.5336
Musanga cecropioides	0.0117	0.2947	0.6656	3.0050		0.8271				2.4004	1.2440
Myrianthus libericus	0.3590	0.6989	1.7683	5.5000	7.3718	6.3466					3.6600
Napoleonaea vogelii	0.1679	0.5759	0.3340	0.5240							0.7666
Nauclea diderrichii		0.0541		0.4088	0.7668	1.7180			3.7130	16.3740	8.2509
Nesogordonia papaverifera	0.2313	0.9044	1.3744	0.6851	1.4073	1.4174	2.1406	2.9696	3.8934	5.9993	3.3001
Newbouldia laevis	0.0101	0.0969	0.2190	1.7770		1.1551	1.8137				0.8246
Okoubaka aubrevillei		0.4827		0.3896							0.4361
Ongokea gore	0.0311	0.2957	0.2436	0.4689	0.7905	1.9642					1.1119
Panda oleosa	0.1691	0.2769	0.6305	0.9063	0.8179		1.5167				1.6020
Parkia bicolor	0.0155	0.2122	0.0760							10.2265	5.2651
Persea americana		0.0630	0.3957	0.6476	0.5246	1.9690					0.6421

Petersianthus macrocarpus	0.0063	0.3254	0.2990	1.0922	0.8799	1.9522	2.7218	4.1919	4.0534	10.9697	6.4590
Piptadeniastrum africanum		0.0372	1.2757	0.4984	0.9767					46.4669	13.0762
Pouteria altissima	0.0083	0.1130	0.1948	0.3730		1.0258				15.7984	3.4244
Psidium guajava	0.0826	0.0868									0.0847
Psydrax subcordata	0.1860	1.2849									0.6835
Pycnanthus angolensis	0.1526	0.6442	1.2077	1.5286	1.0672	0.9212	4.3673	1.7382	3.2758	3.4487	2.6013
Rauvolfia vomitoria	0.2925	0.6631	0.1967								0.7339
Ricinodendron heudelotti		0.1406	0.3655	1.1694				1.1515	1.4593	5.8142	2.0470
Solanum erianthum	0.0072										0.0072
Spathodea campanulata	0.0242	0.1868	0.0832	0.1606	0.3606		1.2166	1.3710	1.8313	4.2942	1.2576
Spondias mombin	0.1511	0.1236	0.3152	0.2828			1.1757				0.5142
Sterculia oblonga	0.0203	0.1398			0.6376						0.3125
Sterculia rhinopetala	0.0189	0.7779	0.7374		0.9415		2.4314				2.2702
Sterculia tragacantha	0.6495	2.8586	1.8081	1.4086	0.6446	1.5407	1.7109	2.6343			2.4255
Strombosia pustulata	0.2100	1.5657	1.8962	0.4482	0.8458	1.4680					1.7602
Terminalia ivorensis	0.0202	0.4636	1.1984	0.3043	0.4659			2.4777	2.5998	6.2172	1.3191

Terminalia superba	0.0237	0.0901	0.2416	1.1813	1.2588	1.2459	1.4088	2.2821		21.0663	5.7443
Tetrapleura tetraptera		0.4573	1.3375	0.4297	0.7602						1.0474
Tetrorchidium didymostemon	0.0757	0.0502	1.7205	0.3048	0.6313						1.5874
Theobroma cacao	3.0363	10.4676	3.3055	3.3417							15.2825
Treculia africana		0.0303			0.8345						0.8649
Trema orientalis		0.0126									0.0126
Trichilia monadelpha	0.3691	1.0698	1.5444	1.5933		1.3650					1.7870
Trichilia prieuriana	0.2087	3.6929	5.0708	2.3670	1.8201						11.5940
Trichilia tessmannii		0.2021		0.3130							0.2760
Triplochiton scleroxylon	0.0064	0.2162	0.1313	0.1743		0.7779	1.2808	1.7819	2.1833	27.2139	13.2436
Vitex doniana	0.0720	0.1124									0.1470
Voacanga africana	0.2884	0.3460	0.0784	0.3096							0.5159
Xylia evansii	0.5416	0.0521									0.2968
Zanthoxylum gilletii	0.0572	0.1111	0.3075	2.5136		1.8353	2.8463		5.9495		1.9177
Total	**3.1054**	**11.0353**	**6.5554**	**5.2961**	**5.1788**	**4.6813**	**6.0103**	**4.0514**	**5.4716**	**31.7430**	**37.2711**

Appendix 5: Land Change Modeler MLP Model Results

a. General Model Information

1) Input Files

Independent variable 1	EvL200haT
Independent variable 2	DEM
Independent variable 3	Community
Independent variable 4	River
Independent variable 5	Road
Independent variable 6	Slope
Independent variable 7	EvL_REDD+35
Training site file	REDD_Train_Anthropogenic

2) Parameters and Performance

Input layer neurons	7
Hidden layer neurons	7
Output layer neurons	7
Requested samples per class	2500
Final learning rate	0.0001
Momentum factor	0.5
Sigmoid constant	1
Acceptable RMS	0.01
Iterations	5000
Training RMS	0.1418
Testing RMS	0.1422
Accuracy rate	98.50%
Skill measure	0.9825

3) Model Skill Breakdown by Transition & Persistence

Class	Skill measure
Transition : Grassland to Monoculture Cocoa	0.9281
Transition : Grassland to Other Tree Crops	0.9869
Transition : Monoculture Cocoa to Agroforestry Cocoa	1.0000
Transition : Food Crops to Monoculture Cocoa	0.9683
Persistence : Grassland	0.9981

Persistence : Monoculture Cocoa	1.0000
Persistence : Food Crops	0.9963

b. Weights Information of Neurons across Layers

1) Weights between Input Layer Neurons and Hidden Layer Neurons

Neuron	h-Neuron 1	h-Neuron 2	h-Neuron 3	h-Neuron 4	h-Neuron 5	h-Neuron 6	h-Neuron 7
i-Neuron 1	10.1522	3.0572	4.3660	12.8464	-5.3582	-17.9824	-11.7890
i-Neuron 2	0.3941	-0.6873	0.1955	-0.5986	1.1012	1.8285	0.6090
i-Neuron 3	0.1107	-1.9207	0.7061	-0.6250	0.8548	0.2920	0.7344
i-Neuron 4	-0.2116	-0.6472	0.2039	-0.4309	0.7185	0.4490	0.4437
i-Neuron 5	-0.5364	-1.9080	-0.4939	-2.8243	2.1965	4.0535	1.2049
i-Neuron 6	-0.3381	-1.3224	0.1973	0.1899	-0.5136	0.4482	0.0667
i-Neuron 7	-14.2147	11.6963	0.8503	1.1984	-4.4849	-3.4616	7.4030

2) Weights between Hidden Layer Neurons and Output Layer Neurons

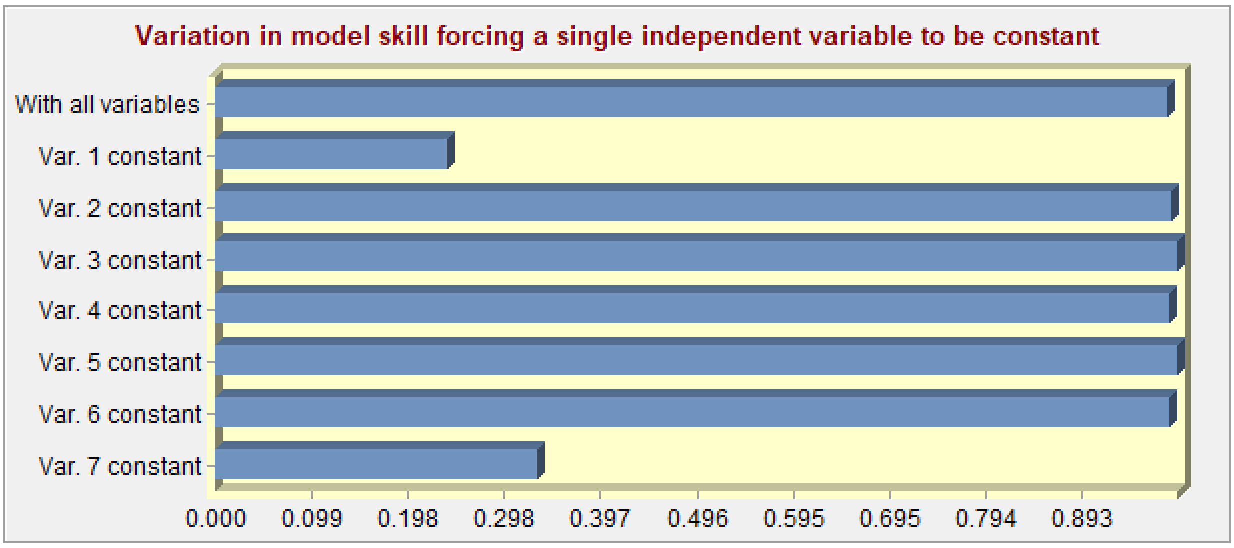
Neuron	o-Neuron 1	o-Neuron 2	o-Neuron 3	o-Neuron 4	o-Neuron 5	o-Neuron 6	o-Neuron 7
h-Neuron 1	-4.1869	-9.7980	-9.8375	-10.6002	9.7129	8.3219	0.8944
h-Neuron 2	-6.1741	0.6110	4.0636	2.6666	-11.2177	-3.3126	-5.3670

h-Neuron 3	0.7378	-4.4141	-0.4743	-2.3049	-2.6316	-2.6477	-5.2709
h-Neuron 4	3.6199	-9.3975	3.2882	0.0495	0.1823	1.0852	-10.1127
h-Neuron 5	0.7327	2.4211	-5.8153	-4.3152	1.0996	-4.3925	4.2800
h-Neuron 6	-6.1655	8.8307	-7.4887	-9.2744	-4.7888	-7.2686	9.4395
h-Neuron 7	1.4423	6.8907	-4.4164	6.4367	-8.4205	-7.8425	2.6803

C. Sensitivity of Model to Forcing Independent Variables to be Constant

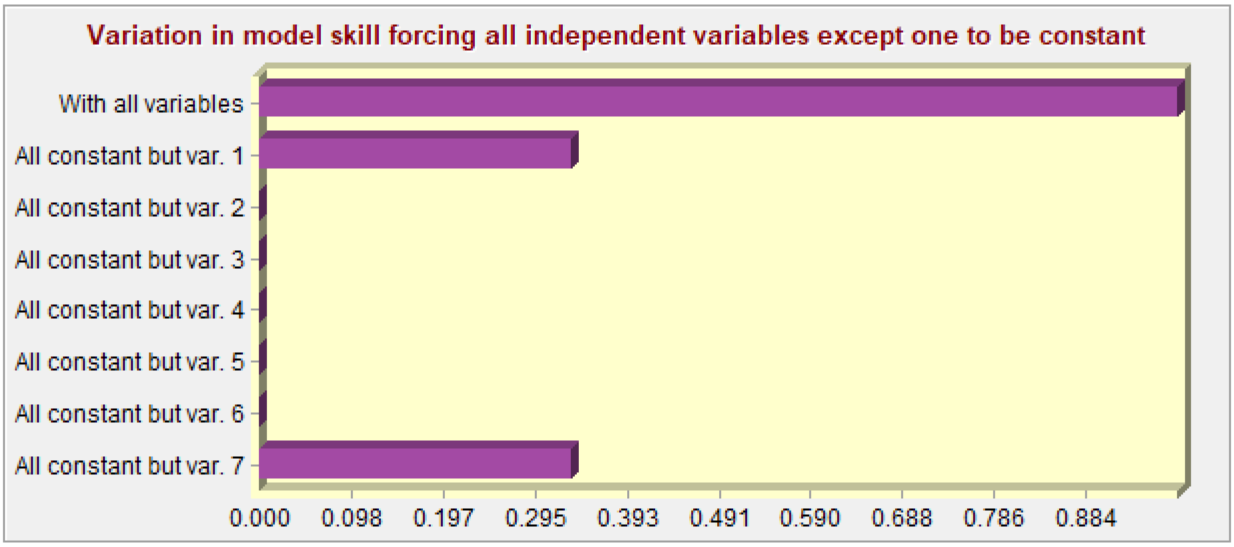
1) Forcing a Single Independent Variable to be Constant

Model	Accuracy (%)	Skill measure	Influence order
With all variables	98.50	0.9825	N/A
Var. 1 constant	34.75	0.2388	1 (most influential)
Var. 2 constant	98.76	0.9856	5
Var. 3 constant	99.35	0.9924	7 (least influential)
Var. 4 constant	98.59	0.9836	3
Var. 5 constant	99.32	0.9921	6
Var. 6 constant	98.63	0.9840	4
Var. 7 constant	42.79	0.3325	2



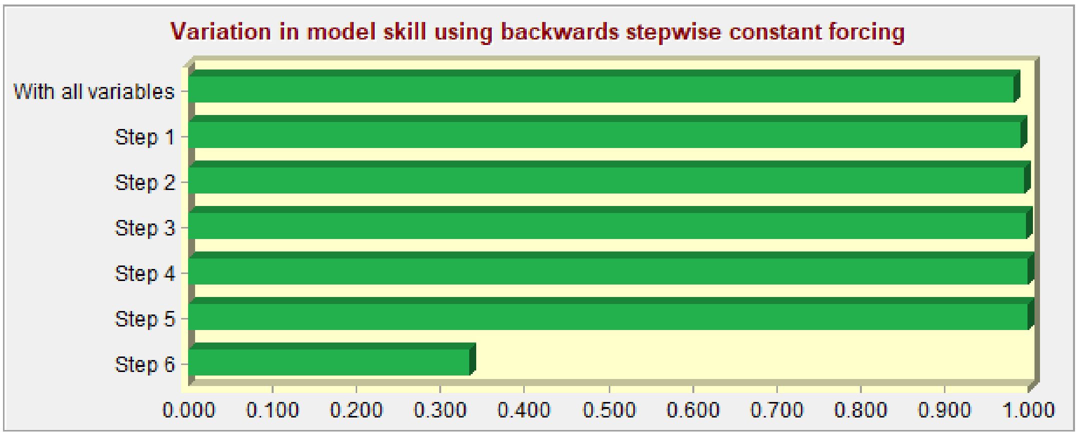
2) Forcing All Independent Variables Except One to be Constant

Model	Accuracy (%)	Skill measure
With all variables	98.50	0.9825
All constant but var. 1	42.85	0.3333
All constant but var. 2	14.30	0.0002
All constant but var. 3	14.32	0.0003
All constant but var. 4	14.30	0.0002
All constant but var. 5	14.28	-0.0001
All constant but var. 6	14.30	0.0002
All constant but var. 7	42.91	0.3340



3) Backwards Stepwise Constant Forcing

Model	Variables included	Accuracy (%)	Skill measure
With all variables	All variables	98.50	0.9825
Step 1: var.[3] constant	[1,2,4,5,6,7]	99.35	0.9924
Step 2: var.[3,6] constant	[1,2,4,5,7]	99.57	0.9949
Step 3: var.[3,6,2] constant	[1,4,5,7]	99.75	0.9971
Step 4: var.[3,6,2,5] constant	[1,4,7]	99.97	0.9996
Step 5: var.[3,6,2,5,4] constant	[1,7]	100.00	1.0000
Step 6: var.[3,6,2,5,4,1] constant	[7]	42.91	0.3340



Appendix 6: Cramer Values