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LAND-USE CHANGE MODELLING, SCENARIOS DEVELOPMENT AND IMPACTS ASSESSMENT ON CO_2 AND N_2O EMISSIONS FROM VEGETATION DEGRADATION IN THE DASSARI BASIN, BENIN

By

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IN

CLIMATE CHANGE AND LAND USE

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DECLARATION

I hereby declare that this submission is my own work towards the 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 which has been accepted for the award of any other degree of the University, except where due acknowledgement has been made in the text.

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ABSTRACT

The Kyoto Protocol of the United Nations Framework Convention on Climate Change (UNFCCC) was developed as an attempt to confront and begin to reverse the rising CO_2 concentrations. But in order to set emission reduction targets in AFOLU (Agriculture, Forestry and Other Land Uses) sector, land use scenarios must be developed. The present study addressed this issue in exploring the possible future temporal and spatial impacts on CO_2 and N_2O emissions from vegetation degradation in the Dassari Basin in the NorthWest of Benin. To achieve this objective, the current vegetation carbon and nitrogen stocks were estimated using the highest Tier level recommended by Intergovernmental Panel on Climate Change (IPCC) and scenarios were developed based on the current trend of land use and socio-economic status of the site. The land use cover changes showed a deforestation rate of 1.48 %. The estimated mean carbon stock values and attached standard errors varied from 1.52 ± 0.14 (for the cropland) to 97.83 ± 27.55 (for the plantations) Mg C ha^{-1}. The estimated nitrogen stock varied from 0.0077± 0.0067 (for the cropland) to 0.321±0.088 (for the plantations) Mg ha^{-1} of N. A total of 175,347.75 ± 21,042.48 (CI) and 875.53 ± 101.45 (CI) Mg was found for carbon and nitrogen stocks respectively in 2013 at 95 % (CI). The business as usual scenario or the baseline (LUS1) will contribute to the emissions of 26.70 Gg CO_2 eq. and to a net removal of 21.70 Gg of CO_2 per year over the period 2013-2025. The impact of the policy based food security scenario (LUS2) will contribute to decrease the total emission by up to 29.25 % and will increase the net removal by up to 42.94 % whereas policy based adaptation and mitigation strategy to climate change scenario (LUS3) and food security based mitigation strategy to climate change scenario (LUS4) will respectively contribute to reduce the total emission by up to 13.14 % and 36.47 %. Despite these findings the basin will still be a sink by 2025, but it is time to act and react to strengthen

the resilience of vulnerable communities and contribute to the removal of CO_2 through local project development or project based carbon fund.

RESUME

Le Protocol de Kyoto de la Convention des Nations Unies sur les Changements Climatiques a été ratifié en vue d'essayer d'inverser la concentration de dioxyde de carbone (CO_2) dans l'atmosphère. Mais dans la perspective de cibler la réduction des émissions dans le secteur AFOLU (Agriculture, Foresterie et autres Formes d' Utilisation des Terres et Changement d'Affectation des Terres) les scenarios d'utilisation des terres doivent être développé. La présente étude soulève ces préoccupations en explorant de possibles impacts spatio-temporelles des émissions de dioxyde de carbone et d'oxyde nitreux provenant de la dégradation de la végétation sur le bassin versant de Dassari au Nord-Ouest du Benin. Pour atteindre cet objectif, les stocks de carbone et azote de végétation ont été estimés sur la base du niveau Tier le plus élevé recommandé par le GIEC (Groupe Intergouvernemental des Experts sur l'Evolution du Climat) et les scenarios sont développés en se basant sur la tendance actuelle d'utilisation des terres et les conditions socio-économiques du site. Le taux de déforestation évolue à un rythme de 1.48 % par an. Les moyennes de stock de carbone de végétation et l'erreur standard associée varient de 1.52 ± 0.14 (pour les champs et jachères) à 97.83 ± 27.55 (pour les plantations) Mg $C.ha^{-1}$. Dans le même sens les estimations pour l'azote de végétation donnent 0.0077 ± 0.0067 (pour les champs et jachères) à 0.321 ± 0.088 (pour les plantations) Mg ha^{-1} d'N. Les estimations des stocks de carbone et d'azote en 2013 sont respectivement de 175347,75 ± 21042,48 (IC) et 875,53 ± 101,45 (IC) Mg à 95 % d'intervalle de confiance (IC). Le scenario de base ou pratique actuelle (LUS1) contribuerait aux émissions de 26,70 Gg d'$Eq.CO_2$ (dioxyde de carbone équivalent) et une absorption nette de 21,70 Gg de CO_2 d'ici à l'horizon 2025. Le scenario, politique fondée sur la sécurité alimentaire (LUS2) contribuerait à une réduction de 29,25 % des émissions de CO_2 et une augmentation d'absorption nette de 42,94 % de CO_2 tandis que la tendance actuelle appuyée par la politique d'atténuation et d'adaptation aux changements climatiques (LUS3) et le scenario sécurité alimentaire (LUS4) appuyé par les politiques d'atténuation aux changements climatiques contribueraient respectivement à une réduction des émissions de CO_2 respectivement de 13,14 % et 36,47 d'ici à l'horizon 2025. Au vu des résultats obtenus le bassin demeurerait un puit de carbone d'ici à l'horizon 2025. Toutefois, il est temps d'agir en vue de contribuer à éradiquer la pauvreté en renforçant les capacités d'adaptation des communautés vulnérables aux effets néfastes des changements climatiques et de contribuer à la séquestration du carbone à travers les projets basés sur le fond carbone.

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LIST OF ABBREVIATIONS

AGB	Aboveground biomass
AFOLU	Agriculture, Forestry and Other Land Use
AR or A/R	Afforestation or Reforestation
BEF	Biomass Expansion Factor
BMBF	German Federal Ministry of Education and Research
BEN-LUDAS	Benin - Land Use Dynamic Simulator
CENAGREF	Centre National de Gestion des Réserves de Faune
CDM	Clean Development Mechanism
C	Carbon
CCLU	Climate Change and Land Use
CH_4	Methane
CO_2 eq	Carbon dioxide equivalent
CO_2	Carbon dioxide
COP	Conference Of the Parties to the UNFCCC
DBH	Diameter at breast height
GIEC	Groupe Intergouvernemental d'Experts sur l'Evolution du Climat
GHG	Greenhouse Gas
Eq.CO_2	Equivalent dioxyde de carbone
H	Height
IPCC	Intergovernmental Panel on climate change
KNUST	Kwame Nkrumah University of Science and Technology
LULCC	Land Use Land Cover Changes
LULC	Land Use Land Cover
LUCa	Land Use Category
LUDAS	Land Use Dynamic Simulator
MRV	Monitoring, Reporting and Verifying
N	Nitrogen
NDVI	Normalized Difference Vegetation Index
NO_2	Nitrous oxide
ppm/ppb	parts per million / parts per billion (1 billion = 1,000 million)
REDD	Reducing Emissions from Deforestation and Forest Degradation
REDD+	Reducing Emissions from Deforestation and Forest Degradation, biodiversity conservation, sustainable forest management and enhancement of forest carbon stocks
UNFCCC	United Nations Framework Convention on Climate Change
WASCAL.	West African Science Service Centre on Climate Change and Adapted Land Use

DEDICATION

I dedicate this PhD research work to: ○ My **wife,** Abi-Kabèrou Kawi Annick, who has passed from life to eternity in a very crucial moment of my life. May God accept you in His Kingdom.

- My **daughters,** Chabi Moudoukpè Youssirath Vanessa Adénikè and Chabi Ifè Yèzida Chancelle, for being there for me throughout the entire doctorate programme. May this work be an example for you to follow in your life.
- My **parents,** Leassou Adjaratou and Chabi Agbadje. You never had the opportunity to get profit from the tree (i.e me) you have planted. May God accept you in His Kingdom.

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CHAPTER I: CLIMATE CHANGE AND LAND USE LAND COVER CHANGES (LULCC)

1.1 Background

Motivated by the rapid increase in atmospheric carbon dioxide (CO_2) due to human activities since the Industrial Revolution, several international scientific research programmes have analysed the role of individual components of the Earth system in the global carbon cycle (Falkowski *et al.,* 2000). Land-use change is central to environmental management through its influence on biodiversity, trace gas emissions, carbon cycling and livelihoods (Lambin *et al.*, 2000). Land-use and land-cover changes (LULCC) has effects on carbon dioxide as well as on other trace gases and on both inorganic and biogenic aerosols including dust between vegetation, soils, and the atmosphere (Pielke *et al.,* 2011; Senay, 2008; *Pielke et al.,* 1998; Pielke, 2005; McAlpine *et al.*, 2010; Dirmeyer *et al.*, 2010; Mahmood *et al.*, 2010).

Agricultural expansion and intensification was found as the major drivers of global LULCC (Pielke *et al.,* 2011). Many scientists stressed that LULCC, emerged as a central issue in the broader debate of global change; and that change, has its origins in the concerns for humaninduced impacts on the environment and their implications for climate change (Schneider and Pontius, 2001; Lambin and Geist, 2002), through decrease in vegetation carbon and nitrogen stocks. LULCC has also had a substantial biogeochemical effect on global climate through emission of CO_2 and other greenhouse gases (GHGs), such as CH_4 and N_2O (Denman, 2007). The main greenhouse gas emission /sources removals and process in managed ecosystems are NO_x, CO_2, N_2O, CH_4, CO, NMVOC (IPCC, 2006), (Figure 1.1). The key greenhouse gases of concern for this study are CO_2 and N_2O. According to the Intergovernmental Panel on Climate Change (IPCC, 2006), the use of carbon stocks changes to estimate CO_2 emissions and removals, is based on the fact that changes in ecosystem carbon stocks are predominately (but not exclusively) through CO_2 exchange between the land surface and the atmosphere (i.e. other C transfer processes such as leaching are assumed to be negligible).

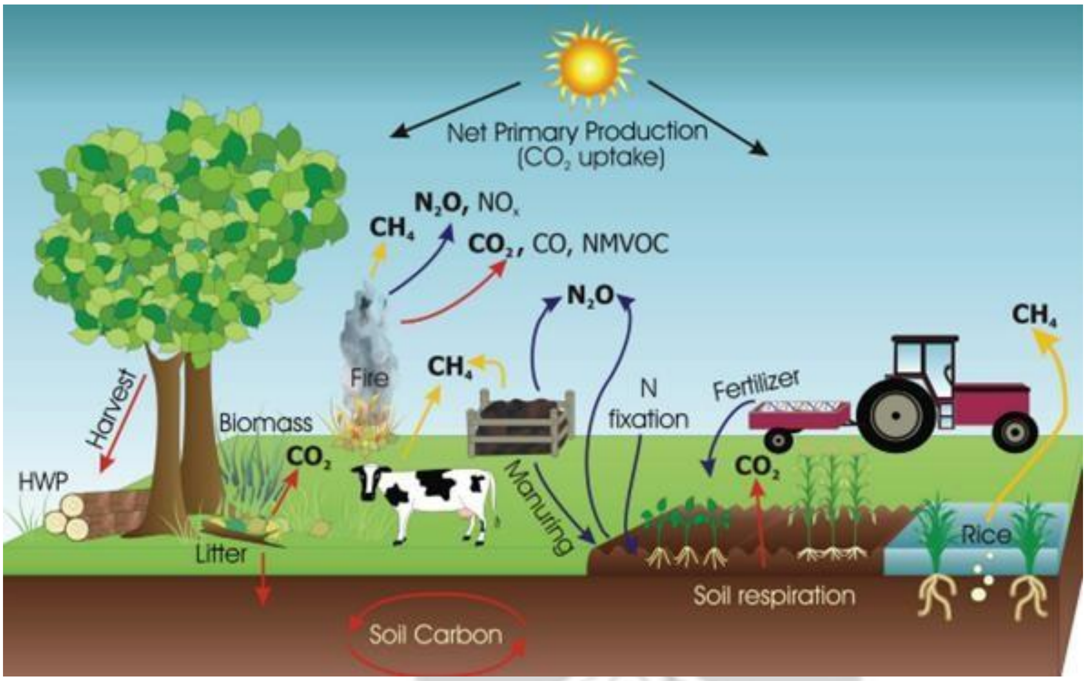


Figure 1. 1 The main greenhouse gas emission /sources removals and process in managed ecosystems (IPCC, 2006)

The carbon sequestered or stored in the forest trees are mostly referred to as the biomass of the tree or forest (Kuyah *et al*., 2012). IPCC (2006) identified five carbon pools of the terrestrial ecosystem involving biomass, namely the aboveground biomass, below-ground biomass, litter, woody debris and soil organic matter. Among all the carbon pools, the aboveground biomass constitutes the major portion of the carbon pool (Hairiah *et al*., 2010; Kuyah *et al*., 2012). Estimating the amount of forest biomass is very crucial for monitoring and estimating the amount of carbon that is lost or emitted during forest or vegetation degradation, and it also gives an idea of the forest's potential to sequester and store carbon in the forest ecosystem (Hairiah *et al*., 2010; GOFC-GOLD, 2013; Kuyah *et al*., 2012).

Estimations of forest carbon stocks are based upon the estimation of forest biomass. Forest's carbon stocks are generally not measured directly. However, many authors assume the carbon content of tree parts to be around 50% of the dry mass. Thus, cutting down trees in the forest or in any land use system means the release of carbon to the atmosphere (Hairiah *et al*., 2010; IPCC, 2013). Carbon stored in the aboveground living biomass of trees is typically the largest pool and the most directly impacted by deforestation and degradation (Hairiah *et al*., 2010).

1.2 Problem statement

In North-West Benin, particularly in Dassari Basin, the demand for land is very crucial for agricultural purpose. The increase of rural population has increased the pressure on the land. Many vegetated areas are converted into agricultural land because of the agricultural practices or the land utilization systems. The current land use practices have resulted in a decrease in vegetation carbon and nitrogen stocks, with the related release of carbon dioxide and nitrous oxide into the atmosphere. Forest lands are cleared and burnt (Picture **1a)** to establish cropland. The background of this picture shows so far the cleared areas with many burned trees meaning in the short terms the decrease of the vegetation carbon and nitrogen stocks. New yams field are established in the area of recent burned trees (Picture **1b)**. The two pictures allow asserting that the process of farming has its impact on the vegetation carbon and nitrogen stocks. Once the tree has been burned or cut, after the forest has been cleared for farming purpose, the amount of carbon and nitrogen held by the burned or cut tree are assumed to be released into the atmosphere in the form of CO_2, N_2O and other gases (Figure 1.1) that are not included in the present research study. Infact, biomass burning includes the combustion of living and dead material in forests, savanna, agricultural wastes and the burning of firewood (Levine, 1994). Under the ideal conditions of complete combustion the burning of biomass material produces carbon dioxide (CO_2) and water vapour

(H_2O), according to the reaction (Levine, 1994).

$$CH_20 + 0_2 \rightarrow CO_2 + H_20 \qquad (1.1)$$

Where CH_2O represents the average composition of biomass material.

Since complete combustion is not achieved under any conditions of biomass burning, other carbon species, including carbon monoxide (CO), methane (CH_4) non-methane hydrocarbons (NMHCs), and particulate carbon, result through the incomplete combustion of biomass material. In addition, nitrogen and sulfur species are produced from the combustion of nitrogen and sulfur in the biomass material. In addition about 90% of the released carbon is in the form of $C0_2$ (Levine, 1994).

Hence the present study could not deal with the uncertainty link to biomass burning under incomplete condition and in addition there is lack information on emission ratio of biomass burning in Africa and particularly in Sudan Savannah environment. We therefore focused on completed emission related to carbon dioxide. Thus, the study focused on carbon dioxide and nitrous oxide which are the main emitted greenhouse gases from biomass burning.

Picture 1. 1 Burned trees explaining impacts of agricultural practices on the vegetation carbon and nitrogen stocks

The research was not to determine how many years the release process will be completed but to underline that once the tree has been burned or cut or the forest land has been cleared for farming, the carbon dioxide uptake stops, and carbon dioxide and nitrous oxide emissions took place IPCC (2006). Reducing emissions from deforestation and forest degradation (REDD+)

policy is based on a core idea: reward individuals, communities, projects and countries that reduce greenhouse gas (GHG) emissions from forests (Angelsen, 2008). For this reason, policy decisions on land use and management should be based on a proper balance between the ecosystem products and services in sustaining human livelihoods and protecting the environment (Le, 2005). Land-use changes simulation models can inform policy-setting and decision-making processes on the use and management of land resources (Le, 2005). The LUDAS (the Land Use Dynamic Simulator) model is useful to unravel the dynamics of land use and project near future land-use trajectories in order to target management decisions (Le, 2005).

The Land Use Dynamic Simulator (LUDAS) model has been recognized (Villamor, 2012; Le, 2005) to be well suited to express the co-evolution of the human and basin systems based on socio-economic, environmental and land use information. Multi-Agent System models like LUDAS allow capturing the complex nature of both spatial interactions and explicit human decision-making on land use, presenting LULCC patterns and associated population dynamics as self-organizing processes emerging from local interactions (Verburg *et al.*, 2004; Parker *et al.*, 2002; Berger and schreimakers, 2006; Deadman and Hare, 2004, Villamor, 2012). The first implementation of LUDAS by Le (2005) in Vietnam was called VNLUDAS. The MAS-LULCC model developed in this study is named BEN-LUDAS (Benin-Land Use Cover Dynamic Simulator). This is the first implementation of the model in the Benin Republic where the socio-economic and environmental context have changed and changes made in the model components and procedures to fit the Benin context. In fitting the model in the Benin context it could be transferred to other West African countries such as Ghana, Nigeria and Togo since the socio-economic situation of these countries are similar. However, LUDAS does not help to determine vegetation carbon and nitrogen stocks. The present study aimed at using BEN-LUDAS for simulating scenarios based on LULCC and socio-economic data and at using field data from forest inventories and allometric models to quantify the vegetation carbon and nitrogen stocks by each type of land use land cover (LULC). The developed allometric equations were integrated into BEN-LUDAS as carbon and nitrogen yield sub-models for the prediction based on each land use change scenario. The study contributes to determine towards the action of the impacts of these land use scenarios for prediction climate in terms of emissions or removal of carbon dioxide and emissions of nitrous oxide. In addition, there are knowledge gaps in biomass allometric equations in the Sudan Savannah environment and the level of emission factors for carbon accounting is unknown. For example Mbow (2013) published allometric equations in the forest ecosystems of Senegal. Sawadogo (2010) published allometric equations for selected tree species in the Sudan Savannah of West Africa. Unfortunately, both equations cannot be applied to estimate the biomass in other land use categories (cropland, grassland and settlement) of the Sudan Savannah environment. This study contribute towards filling these knowledges gaps by providing allometric models in each land use category to estimate the vegetation carbon and nitrogen stocks and at using land use change model (BEN-LUDAS) to monitor and to predict future emissions of carbon dioxide and nitrous oxide for the period 2013-2025.

According to the international agreement under United Nation Framework Convention on Climate change (UNFCCC), countries have an obligation to report their emissions and carbon stocks to assist in the global bookkeeping of emissions and the drivers of climate change. Developing countries that want to participate in other mechanisms of the convention will need to provide such data, as part of global transparency (GOFC-GOLD, 2013). According to IPCC (2006), the use of C stock changes to estimate CO_2 emissions and removals is based on the fact that changes in ecosystem C stocks are predominately (but not exclusively) through CO_2 exchange between the land surface and the atmosphere. Hence, increases in total C stocks over time are equated with a net removal of CO_2 from the atmosphere and decreases in total C stocks (less transfers to other pools such as harvested wood products) are equated with net emission of CO_2 (IPCC, 2006).

This study supports the initiatives of REDD+ and Monitoring, Reporting and Verifying (MRV) (Kyoto Protocol, 1997; IPCC, 2006; Angelsen, 2008; Angelsen *et al.*, 2009; Henry *et al.*, 2011a; Angelsen *et al.*, 2012, GOFC-GOLD, 2013; Hewson *et al.*, 2014). The results address the key message for scientists and decision makers about the ways lands have been used and how each land use decision or land use strategy (scenario) can contribute to the removal or emission of carbon dioxide and nitrous oxide into the atmosphere.

1.3 Hypothesis of the study

h1: The aboveground C and N stocks (stand tree carbon and nitrogen stocks) vary by land use cover type in Dassari Basin; **h2**: The different groups of farmers are driven by socio-economic and environmental factors in land use decision and few farmers adopt mitigation strategies (plantation/agroforestry systems) to reduce emission of carbon dioxide and nitrous oxide due to farming activity; **h3**: The current use of land contributes to the high quantity of carbon dioxide and nitrous oxide emissions into the atmosphere, whereas REDD+ policy based will help to reduce emission of these gases from the basin to the atmosphere.

1.4 Objectives of the research

The main objective of this study was to assess the impacts of land-use changes scenarios on CO_2 and N_2O emissions from the Dassari Basin for the period (2013-2025).

The specific objectives were to:

SO_1: Quantify the vegetation carbon and nitrogen stocks at the basin level based on remote sensing, forest inventory data and allometric models;

SO_2: Determine land use decision drivers and mitigation strategies at the farm level;

SO_3: Assess the land use scenarios impacts on CO_2 and N_2O emissions (2013-2025) at the basin level.

Based on the specific objectives, the following research questions were:

Rq 1: What is currently the amount of vegetation carbon and nitrogen stocks (aboveground biomass of living trees e.g, C and N stocks of living trees) at the basin level?

Rq 2: What are the drivers of environmental degradation and mitigation measures adopted at the farm level in the Dassari Basin?

Rq 3: What will happen up to 2025 in the vegetation carbon and nitrogen stocks and in the CO_2 and N_2O emissions if the current land transformation rate continues i.e. nothing changes in the way of land utilization? Or the policy is:

- Food security based?
- Businesses as usual supported by REDD+?
- Food security and REDD+ based?

1.5 Thesis outline

The study is presented in seven chapters.

- ✓ Chapter One contains the introduction, problem statement related to climate change and LULCC issues. The hypothesis, objectives and research questions of this research are outlined.
- ✓ Chapter Two focuses on the BEN-LUDAS model overview. The context of using the present model is explained. The architecture of the model is summarised and the details of components are described by Le (2005) who developed VN-LUDAS for Vietnam. The chapter lays out a conceptual framework of MAS-LULCC, which is the basis for the application of MAS (Multi-Agent System).

- ✓ Chapter Three is dedicated to the first specific objective. This chapter used many approaches to quantify the vegetation carbon and nitrogen stocks at the basin level. These approaches are based on remote sensing, forest inventory data and allometric equations. Satellite remote sensing forms the basis for characterization of land use pattern and to determine the size of each land use / cover of the total basin. Wood stock, the carbon and nitrogen concentration of the main species of the basin were estimated. The biomass expansion factor useful for the Sudan Savannah environment was established. Finally estimates of the biomass, carbon and nitrogen stock for each LULCC were done and mapped.
- ✓ Chapter Four deals with the second specific objective. In this chapter, land use decision drivers were found out. The level of mitigation strategy at the farmer's field scale was determined and estimates of their willingness to adopt agroforestry and plantation for the future were assessed. The results from the socio-economic data were used as inputs for the BEN-LUDAS model.
- ✓ Chapter Five explains the ecological dynamics of heterogeneous basin agents in the Dassari Basin. The basin variables such as environmental conditions of the basin were used as inputs for the BEN-LUDAS model.
- ✓ Chapter Six deals with the third specific objective. In this chapter land use scenarios were developed based on specific assumptions. The impacts of each scenario were assessed. The assessment was expressed in terms of removal and emission of carbon dioxide and nitrous oxide and their impacts on the livelihood of rural communities.
- ✓ Chapter Seven presents the key conclusions related to the short and long terms of the impact of the scenarios on carbon dioxide and nitrous oxide emission or carbon sequestration. Recommendations were also made for future land use decisions by farmer's household and for authorities at the local, regional and national levels.

CHAPTER II: LAND-USE CHANGE MODELS

2.1 Introduction

Land use changes give rise to series of processes that lead to systematic effects on both local/regional and global climate (Pielke *et al.,* 2011). On a local/regional scale, changes in the radiative properties (albedo), turbulent heat exchanges, water availability, biochemical and trace gases cycles result from the conversion from an ecosystem (e.g. forest) into another that has different functions (e.g. crop or pasture). On a global scale, historical conversion into agriculture affects Net Primary Productivity (NPP), and therefore the storage reservoirs of carbon. Agriculture has therefore altered the global carbon cycle (Bondeau *et al.*, 2007), which in turn modifies the atmospheric CO_2 concentration and thereby, potentially, the global climate. Evidence for a significant effect of LULCC on climate at local scales is therefore convincing (IPCC, 2007; Smith *et al.,* 2014). Where LULCC has been intensive, the regional impact is likely to be at least as important as greenhouse gases and aerosols. The impacts of change on human vulnerability are evident when climate change is realized locally and regionally. LULCC is a significant regional scale driver of climate making it sufficient to require its incorporation into past, present and future climate model simulations. Agarwal *et al.* (2000) have presented a review and assessment of land-use change models (Fitz *et al.,* 1996; Voinov *et al.,* 1999; Veldkamp, 1996; Veldkamp and Fresco, 1996a; Hardie and Parks, 1997; Mertens and Lambin, 1997; Chomitz and Gray, 1996; Gilruth *et al.,* 1995; Wood *et al.*, 1997; Landis 1995; Landis and Zhang, 1998; Berry *et al.*, 1996; Wear and Bolstad, 1998; Swallow *et al.*, 1997). These models of land-use change were compared in terms of scale and complexity, and how well they incorporate space, time, and human decision making. Some of the models captured spatial, temporal and human decision making characteristics. Conversion of Land Use and Its Effects (CLUE) Model, (Veldkamp and Fresco, 1996b) for example applies several human drivers, incorporates collective decision-making levels, from local to national, considers the temporal range of decision making explicitly, in determining the time period for updating changes in land-use types as well as minimum economic age and rotation length of various land-use classes.

Unfortunately, few of the models attempted to incorporate on sight social processes in modelling land-use change, which is the main important aspect of this case study. The coupled human-environment system in modelling land use/cover changes was of concern for the present study. The lack of progress is largely due to the traditional separation of ecological and social sciences (Rosa and Dietz, 1998).

A promising approach to modelling the complex LUCC processes is the multi-agent systems for simulating LULCC (MAS-LUCC) (Le, 2005). The MAS has been recognized as a useful tool for building a sound theoretical framework to deal with the complexity of LULCC (van der Veen and Otter, 2001; Bousquet and Page, 2004) and to more efficiently support environmental decision-making processes (Ligtenberg *et al.*, 2004; Barreteau *et al.*, 2001). Thus, many scientists have attempted to obtain simulation models that describe autonomous individual organisms individual based models (IBM) or agents agent-based models (ABM) (Grimm *et al.*, 2006). ABMs were based on the standard protocol for describing such simulation models, which can make them easy to understand and to avoid duplication. ODD (Overview, Design concepts, and Details) was a first step for establishing a more detailed common format of the description of IBMs and ABMs (Grimm *et al.*, 2006) and has been used for the present case study within the BEN-LUDAS model.

The aim of this chapter is to explore the existing land use/cover change and MAS-LULCC models for the implementation of BEN-LUDAS (Benin - Land Use DynAmics Simulator) in the study area. The specific focus will be on:

- The adoption of the MAS modelling framework of BEN-LUDAS that reflects the organization of the coupled human-environment system of Dassari Basin in an understandable manner and
- The decision-making models for human agents and ecological system for basin (environmental) agents.

2.2 Land-Use Change Models

Land use change models are significant when attempting to understand the dynamics of the environment and how change affects the welfare of the socio-ecological system. LULCC is a widespread, accelerating, and very significant process to humans. LULCC change is both driven by human actions, and, in many cases, it also drives changes that impact humans (Agarwal *et al.*, 2000). Modelling these changes is critical for formulating effective environmental policies and management strategies.

Humans had transformed significant portions of the Earth's land surface. 10–15 % of the Earth's surface is dominated by agricultural crop or urban-industrial areas, whereas 6–8 % is by pasture (Vitousek *et al.*, 1997). These changes in land use have important implications for future changes in the Earth's climate and, in return, great implications for subsequent landuse change (Agarwal *et al.*, 2000). Existing land use/cover change models have been reviewed by Agarwal *et al.* (2000) (See section 2.1) who gives overall setting for these models.

Existing land use/cover changes models were analysed based on the model scale (time step and duration, resolution and extent, agent and domain), model complexity (temporal complexity, spatial complexity, human decision-making complexity) and came to the conclusion that agent-based models are useful to explain changes in land use cover.

2.3 Concept of Multi-Agent System (MAS) model

For the last decade, the challenge has been to develop a new approach focusing more on the interaction between ecological and social components, and taking into account the heterogeneity of these components (Bousquet and Page, 2004). In addition, researchers in the field of ecosystem management can use multi-agent systems (households and patch agents in the present case study) to go beyond the role of the individual and to study more deeply and more effectively the different forms of organization (spatial, networks, hierarchies) and interactions among different organizational levels (Bousquet and Page, 2004). Therefore MAS-LULCC becomes a useful tool for problems integrating social and spatial aspects. ABM represents autonomous entities, each with dynamic behaviour and heterogeneous characteristics. Agents interact with each other and their environment, resulting in emergent outcomes at the macroscale that can be used to quantitatively analyse complex systems (Heckbert and Baynes, 2010).

More information on MAS-LULCC could be found in Le (2005), Bousquet and Page, (2004), Damaceanu (2012), Grimm *et al.* (2010), Heckbert *et al.* (2010), Parker *et al.* (2002), Railsback *et al.* (2006) and Matthews *et al.* (2007). Since BEN-LUDAS is conceived in the setting of agent-based models its selection for understanding the human environmental system is required.

2.4 The BEN-LUDAS model as a Conceptual MAS-LULCC Model

The LUDAS framework (Le *et al.*, 2008) has been used for the BEN-LUDAS conceptual MAS-LUCC. Le *et al.* (2010) described the LUDAS model using the ODD (Overview, Design concept, and Details) protocol, (Grimm *et al.*, 2010). The BEN-LUDAS is applied in the West African context and mainly represents the real world of socio-ecological pattern of the study site. The BEN-LUDAS used the same ODD protocol and focuses on the dynamics of environment based on agricultural activity procedure as the main component of interaction between social and ecological system while VN-LUDAS (Le, 2005) and LB-LUDAS (Villamor, 2012), dealt with logging activity respectively in Vietnam and Indonesia. In addition a procedure was developed based on mitigation strategy to climate change and the related probability of adoption that were not considered in the previous LUDAS.

2.4.1 Purpose

The LUDAS model was primarily designed to support land-use decisions in the forest margins with the following three aims to:

- ✓ explore the magnitude of possible socio-ecological changes over space and time as driven by different land-use policy interventions,
- ✓ identify the most affected components of the system (*what*), locations (*where*) and periods (*when*) with respect to specific policy intervention, and
- ✓ highlight sound policy interventions that likely enhance environmental and socioeconomic benefits efficiently.

For the BEN-LUDAS model development these aims were assumed, but possible impacts of policy intervention on future CO_2 and N_2O emissions from vegetation degradation due to agricultural activity was highlighted. In addition BEN-LUDAS aimed to assess the impacts of the adoption of mitigation strategy to climate change (adoption of agroforestry system and plantation) and socio-economic impacts on the livelihood of households.

With regards to the mentioned assumptions, the structure of BEN-LUDAS is presented in Figure 2.1. In LUDAS, organizations that influenced the ecosystem management in the study area are treated externally. In this way, different scenarios and management settings were pre-defined, and the course of future system development was compared to assess ex-ante impacts of policy interventions.

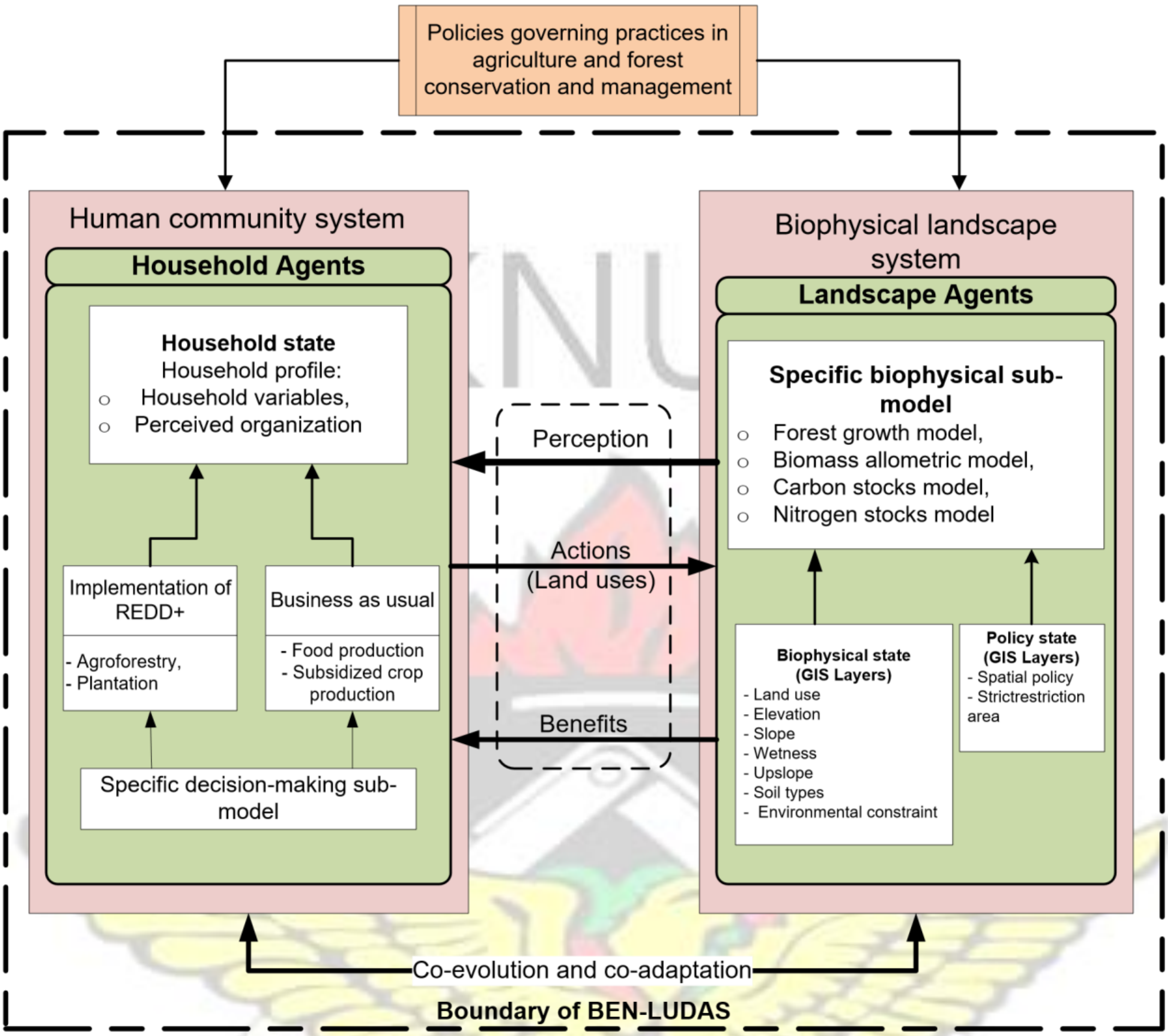


Figure 2. 1 Conceptual framework of BEN-LUDAS model

2.4.2 Entities, Variables and Scales

The BEN-LUDAS Model has human community and environmental systems which consist of household and basin entities (agents), respectively. The variables of basin entities are grid layers of elevation, slope, wetness, upslope, land use and soil that are in units of pixels. The variables of the household entities are listed in Table 2.1. There is one institutional spatialvariable, owner, which relates each pixel of the part of basin a household owns to the household. The model also contains institutional policy variable. The two types of variables in terms of temporal dynamism in the model are as follows:

a. Static variables in the model are owner, elevation, slope, soil suitability, wetness, upslope, household Id, x-coordinate of household house, y-coordinate of household house, household head, educational level, etc. (Table 2.1). For any given head of household these variables are considered fairly constant in the model, within the long term period under consideration i.e. till the household head takes hold, dies and a new head of household is born.

Table 2. 1 Entities and Variables in BEN-LUDAS Model

Entity	Variables	
	Static	Dynamic
Household	Household Id, x-coordinate of household house, y-coordinate of household house, household head, Educational level, Upland Area crop owned by household, Agroforestry area owned by household, plantation area owned by household, household livelihood typology, Fraction of labour for farming or time-labour.	Household size, Age of household head, Household head Leader position, Labour availability: Dependency ratio (persons not in labour force/persons in labour force), Household income, Percapita household income, Access to fertilizer subsidy.
Basin	Owner, Elevation, Slope, Wetness Upslope, Soil, Spatial policy, Strict restriction	Land use, farming (burned), number of years after a farming event (Pt)

b. The dynamic variables are further divided into two groups:

- Dynamic variables driven by natural processes are beyond human control: the age of the household agents and natural forest growth of forested pixels,
- Dynamic variables induced by household decisions or policy interventions are land use type and protection code of land pixel.

One time step represents one year. One grid cell or pixel represents 30 m x 30 m (900 m^2) and the model basin covers 192.57 km^2 (either a total of 213971 pixels).

2.4.3 Overview Process and Scheduling

In the BEN-LUDAS model, neighbourhood interactions are taken into account in land use decisions and land cover transition (see section 5.3.4). Therefore, changes in basin or in community status which gives a feedback to households are pixel-based processes.

2.4.4 Design Concepts

The interface of LUDAS, MAS-HES (Multi Agent System-Human Environment System) model presents simple and essential information (Le, 2005) relating to interaction between human beings and the environment. The BEN-LUDAS uses the same structure like the original one. The coding programmes are simple to build and understand. The design concepts reveal sensing of owner variable as an ownership entity that can influence the use of the land. Interaction among agents causes emergent landscape/community phenomena that lead to landscape and population dynamics (Le, 2005). To observe its internal dynamics as well as its system-level behaviour, the expected outputs of the model needed are, land use cover change area, carbon and nitrogen stocks per land use/cover (LUC) type, biomass stocks per LUC type, annual gross income based on cultivated, annual gross income based on carbon credits, financial return based on carbon credits, Lorenz and Gini information's, size of the income group and households size or population dynamics over the years. These findings have been presented in graphics, maps, files output and data on the households.

The main goal was to explore the use of BEN-LUDAS, MAS-HES model to simulate spatial scenarios based on modelling multi-actor decision-making within a spatial planning process. The model consists of agents representing households involved in rural area activities (farming, subsidized agriculture, etc.). The multi-actor based decision-making is modelled by generating beliefs and preferences of actors about the location of spatial objects and the relation between them. This allows each agent to pursue these beliefs and preferences with their own desires and with that of other agents.

2.4.5 Initialization

The details of BEN-LUDAS consist of three elements namely: initialization, input data and parameters as well as sub-models, and follows the ODD protocol (Grimm *et al.*, 2006). The initial number of columns and rows for the basin grid were 601 and 715, respectively, whereas the maximum patch x coordinate (max-pxcor) and maximum patch y coordinate (max-pycor) were 300 and 357, respectively.

2.4.6 Input Data and Parameters

Inputs for simulations in BEN-LUDAS entail two types: data and parameters. The input data for initial model variables were elevation, slope, wetness, upslope, soil types and land use maps as well as household data. The inputs for model parameters were as follows:

- The strict restricted area, which constrains farmers' decision to farm within the area limited by the soil type (no suitable area for farming activity).
- the policy thresholds, which constrains farmers to farm within the area under legislation.
- the deforestation rate, which drive the overall speed of forest degradation due to farming activity,
- the vision of farmers in farming activity, which determine the location of farming activity based on the position of nearest forest patch,
- the productivity, which determines the crop yield of the study site and the related market price, which define the price of various crops in the market.

- the financial return allowed to define the rate of the budget to be allocated to the farmers if the carbon fund project exists. Mitigation-agroforestry and mitigation plantation with the related probability were applied in the scenarios based mitigation strategy,
- The population growth rate (Table 4.1) and maximum age determined the dynamics of the population.

2.4.7 Sub-Models

Regarding the context of the study area (West African Sudan Savannah zone) the BENLUDAS model used 6 additional sub-models and calculation routines to 13 key sub-models and calculation routines of VN-LUDAS (Le, 2005) (Table 2.2).

Table 2. 2 Main sub-models/ procedures of BEN-LUDAS coded in NetLogo 4.1.3 (modified from Le *et al.*, 2010).

N	Sub-models/ Calculation routines	Functions	Entity involved
1	*Initialization*	Import GIS data and sampled household data, generate remaining population, create household pixels, generate household coefficients, and calculate initial carbon and nitrogen stocks	Household Pixel
2	*REDD+ adoption*	Calculate the willingness to adopt the REDD+ policy of the household (agroforestry and plantation) i.e probability of adoption is applied	Household
3	*Time-Labour-allocation*	Set the time-labour list of the household annually	Household
4	*Financial-return*	Calculate the annual economic return of carbon credit to the farmers	Household
5	*Update-household-state*	Update the changes in household profiles annually	Household
6	*Agent-Categorizer*	Categorize households into similar groups	Household
7	*Generate-household coefficients*	Generate behaviour coefficients of household, allow variants within the group but stabilize behaviour structure of the group	Household
8	*Natural-Transition*	Perform natural succession among vegetation types based on accumulated vegetation growth and ecological edge effects	Pixel
9	*Allometric-model*	Calculate biomass stocks for each land use/cover using allometric equations	Pixel
10	*Calculate-carbon-stocks*	Calculate carbon stocks for each LUC type	Pixel
11	*Calculate-nitrogen stocks*	Calculate vegetation nitrogen stocks for each LUC type	Pixel
12	*Life-cycle*	Create a young new household controlled by an empirical function of population growth	Household

13	*Plot-Graphs*	Draw different graphs of system performance indicators	Household Pixel

The sub-models are:

1) REDD+ adoption, 2) *Calculate biomass-stocks, 3) Calculate-carbon-stocks*, 4) Calculate nitrogen-*stocks* and 5) *Financial-return* 6) *life-cycle* which are briefly described. For detailed descriptions (e.g. model parameters, dimension and reference values) and justification of specific sub-models (see Chapters 3 and 5).

Model calibration and validation details are outlined in Section 6.4.1.

2.5 Conclusions

The evolution of ABM platforms over the past ten or more years has been fascinating. The goal of developing this model is to explore alternative scenarios to improve livelihoods of rural communities at the local scale and mitigate climate change. The model specification, module-by-module and object-by-object, clearly shows an explicit and fully parameterized architecture, which accounts for the evolution of the coupled human-environment systems. The proposed agent-based architecture (BEN-LUDAS) allows integrating diverse personal, environmental and policy-related factors into upland farmers' decision-making about land use and the subsequent accumulated outcomes in terms of spatially explicit patterns of the natural basin and population. The model is useful in explaining the dynamics of human and environment system and to perceive the changes of both over time and how these changes affect the livelihood and the future impacts on CO_2 and N_2O emissions from vegetation degradation.

CHAPTER III: ASSESSMENT OF CURRENT VEGETATION CARBON AND NITROGEN STOCKS OF THE WEST AFRICAN SUDAN SAVANNAH BASIN

3.1 Introduction

The sources and sinks of carbon from LULCC are significant elements in the global carbon budget (Houghton *et al.*, 2012). Current challenges of forest management are related to verifiable, reliable, accurate and cost-effective methods to adequately document forest resources dynamics (GOFC-GOLD, 2013).

The accuracy of carbon stock by each land use cover type depends on the availability of reliable allometric models to infer oven-dry aboveground biomass of trees from tree census data (Chave *et al.*, 2015). However, large uncertainties in emission estimates arise from inadequate data on the carbon stock of forests and the regional rates of deforestation (Baccini *et al.*, 2012; Houghton *et al.*, 2012). These uncertainties in turn compromise the estimation of terrestrial carbon emissions (DeFries *et al.*, 2002; Houghton 2005; Grassi *et al.*, 2008; Pelletier *et al.*, 2011) and the required knowledge on biomass or carbon stocks. Infact, uncertainty related to the estimation of carbon stock is the related standard error.

A number of comprehensive allometric models for biomass estimation have previously been developed for the major tree species in Europe, America and Asia (Ter-Mikaelian and Korzukim, 1997; Jose *et al.*, 1998, Moura-Costa and Stuart, 1999; Nelson *et al.*, 1999; Clark and Clark, 2000, Eamus *et al.*, 2000; Grierson *et al.*, 2000; Keith *et al.*, 2000; Keller *et al.*, 2001; Fleurant *et al.*, 2004; Jenkins *et al.*, 2004; Chave *et al.*, 2005; Zianis and Mencuccini, 2005; Domke *et al.*, 2012; Chave *et al.*, 2015). In Sub-Saharan Africa most of the estimation of the total carbon stocks in Africa, and especially West-African countries focused on the use of allometric models together with forest inventory data (Chave *et al.*, 2005; Akindele and Lemay, 2006; Dossa *et al.*, 2008; Mbaekwe and Mackenzie, 2008; Djomo *et al.*, 2010;

Djuikouo *et al.*, 2010; Sawadogo *et al.*, 2010; Henry *et al.*, 2011b; Rasmussen *et al.*, 2011; Shirima *et al.*, 2011; Bakayoko *et al.*, 2012; Kuyah *et al.*, 2012; Mbow *et al.*, 2013; Ngomanda *et al.*, 2014). The majority of studies have so far focused on forest ecosystems, specific tree species or plantations for the estimation of aboveground biomass and carbon stocks (Daolan *et al.*, 2004; Akindele and Lemay, 2006; Li and Xiao, 2007; Basuki *et al.*, 2009; Fonton *et al.*, 2009; Djomo *et al.*, 2010; Djuikouo *et al.*, 2010; José 2010; Henry *et al.*, 2011b; Návar-Chaidez 2011; Rasmussen *et al.*, 2011; García *et al.*, 2012; Guendehou *et al.*, 2012; Aholoukpe *et al.*, 2013; Hunter *et al.*, 2013; Ngomanda *et al.*, 2014; Chave *et al.*, 2015; Montagnoli *et al.*, 2015). Very few studies have focused on the estimation of aboveground biomass in the agricultural landscape (Kuyah *et al.*, 2012).

Attempts to estimate aboveground biomass at the basin level requires typically remote sensing derived land use/land cover information as well as allometric models from each land use/cover category (LUCa). The data for allometric models for estimating biomass in woody vegetation comes either from destructive or from non-destructive methods. Destructive methods are based on the harvest of the living trees together with measurements of DBH (diameter at breast height) or girth, stem and total height as well as the dry mass of stem, foliage and branches. The collected variables are then used as input for estimating tree volume and biomass for selected trees species (Chave *et al.*, 2005; Litton and Kauffman, 2008; Basuki *et al.*, 2009; José 2010; Mbow *et al.*, 2013). The application of destructive methods is labour intensive and time consuming Djomo *et al.* (2010). This method is therefore restricted to small trees at small scales (Ketterings *et al.*, 2001; Li and Xiao, 2007). Additionally, harvesting trees requires in general special authorization which is often not easy to acquire, especially when the study region involves protected areas.

Recent assessments have switched to the use of non-destructive methods (Montes *et al.*, 2000; Lehtonen *et al.*, 2004; Flombaum and Sala, 2007; Nogueira *et al.*, 2007; Tackenberg

2007; Chen *et al.*, 2008; Henry *et al.*, 2010; Guendehou *et al.*, 2012). The tools and approaches used thereby varied considerably between regions. A biomass expansion factor and wood stock were the key parameter/variable used by allometric models based on nondestructive methods for the assessment of total biomass of living trees. Wood stock is the third variable that contributes to reduce uncertainty in estimating tree biomass using allometric model. The importance of wood stock for estimating forest biomass and greenhouse-gas emissions from LULCC change has been stressed by Nogueira *et al.* (2007). A variety of different approaches has been applied. Montes *et al.* (2000), for instance, estimated the biomass of *Thuriferous juniper* woodland in Morocco based on component volumes estimated from two orthogonal-view photographs and the stock of each component. This approach is not well suited to estimate biomass in natural environments (*Thuriferous juniper* woodland), especially when the environment is subject to degradation by human use and wood supply to the local populations is at stake. Lehtonen *et al.* (2004) developed expansion factors conditional on stand age and dominant tree species to estimate total biomass of pine trees in Norway. Flombaum and Sala (2007) presented an approach for the calibration of a fast non-destructive method to estimate aboveground plant biomass by double-sampling vegetation cover and aboveground biomass in the Patagonian steppe. They fitted linear regression models to describe the relationship between vegetation cover and biomass for the dominant species and life forms. Tackenberg (2007) presented a nondestructive method based on scaled digital images analysis of the plants silhouettes, addressing not only aboveground fresh biomass and oven-dried biomass, but also vertical biomass distribution as well as dry matter content and growth rates. The method used by Tackenberg (2007) is time and cost effective compared with the destructive method, especially if development or growth rates are to be measured repeatedly.

Two problems hinder the transfer of the currently used non-destructive methods in the WestAfrican context: first, biomass expansion factors are not available for most relevant local tree species and the devices used are costly and very complex to use. In the southern part of the Republic of Benin, Guendehou *et al.* (2012) assessed stem biomass based on stem volume for selected tropical tree species using an increment borer as the device of stem wood sample extraction and wood stock of selected species. Unfortunately, the obtained biomass expansion factor (BEF) could not be applied in the context of the current study since the study was undertaken under the tropical forest conditions in that are different from the conditions in the study region which is in Sudan Savannah zone. The work by Guendehou (2012) needed therefore to be expanded to reflect conditions and tree species in different land use systems to allow a more precise estimation of the relevance of African trees for carbon stocks.

In order to reduce the uncertainty in estimates of carbon emissions resulting from deforestation and forest degradation, more complete and higher quality information on the spatial distribution of carbon stocks is needed. The estimation of the total carbon stocks at the basin level is the most complex and requires the most fineness methods for many reasons. Firstly, at the basin or catchment scale the vegetation pattern is changed from one land use/cover to another and the tree species distribution varied gradually in size and species composition. Secondly, there is a need for reliable methods that are applicable to target species in the region of interest (Henry *et al.,* 2010). The accurate estimation of the vegetation carbon and nitrogen stocks is based on Tier three approach recommended by IPCC (2006). Remote sensing data is needed for mapping carbon distributed along the basin using the obtained forest inventory data, developed allometric equations and the carbon and nitrogen content of the main species of the region to considerably reduce uncertainty.

The aim of this chapter is to quantify the vegetation carbon and nitrogen stocks at the basin level using current land use/cover (2013-2014), ground truth data, allometric equations and carbon and nitrogen fraction of the main species of the site, which belongs to the Sudan Savannah environment.

3.2 Methodology

Schematic presented in the methodology is given in Figure 3.1. The main steps were:

- ✓ Acquisition of data from four sources (MODIS NDVI, field work, high resolution images and Landsat 8 images),
- ✓ First Field work to conduct forest inventory for analysis based on Importance Value Index (IVI) for the selection of the main species of the basin,

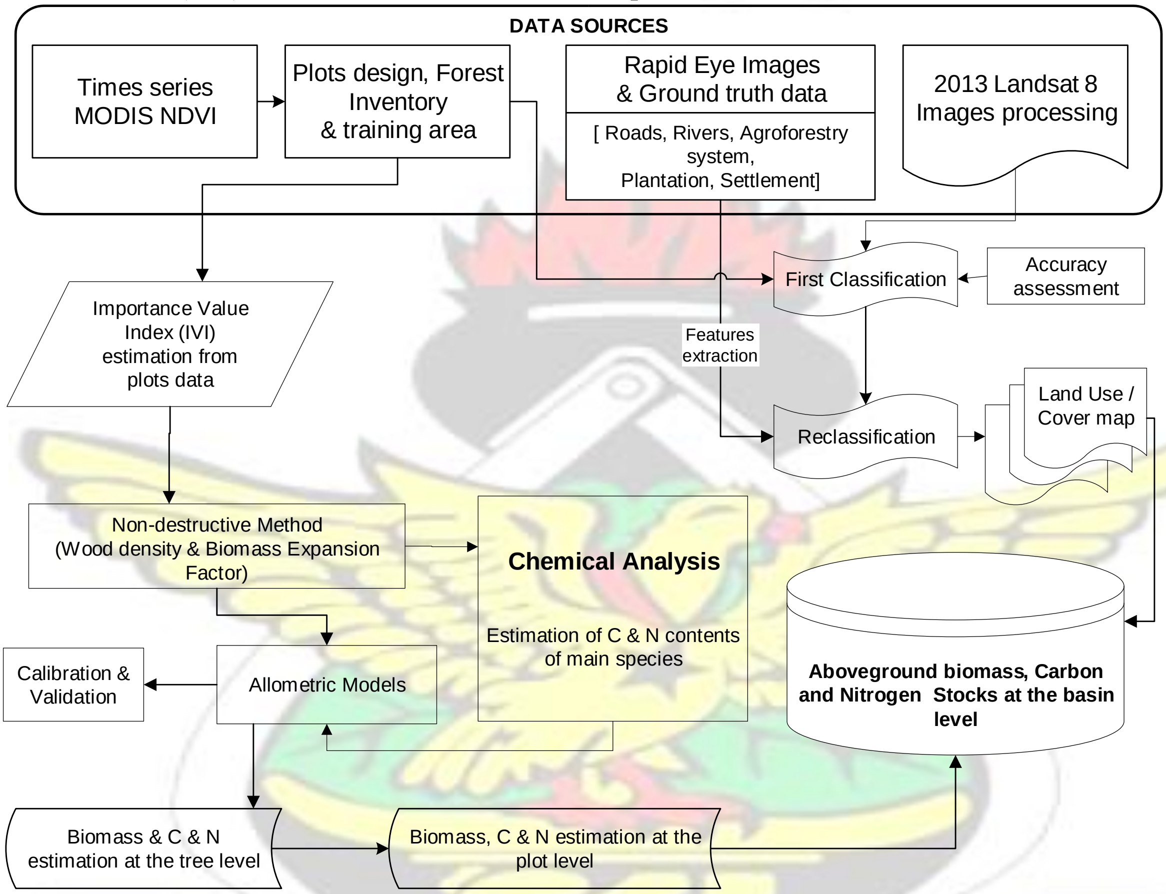


Figure 3. 1 Flowchart showing main steps of the aboveground biomass, carbon and nitrogen stocks assessment

- ✓ Images classification, accuracy assessment and reclassification,
- ✓ Second field work and surveys of the individual main tree species,
- ✓ Non-destructive method assessment,
- ✓ Chemical analysis for the estimation of C and N of the wood samples,

- ✓ Development of allometric models based on three predictors (DBH, height and wood density),
- ✓ Biomass, carbon and nitrogen content assessment at the tree level and plots level based on allometric models and C and N content previously estimated,
- ✓ Mapping the aboveground biomass, carbon and nitrogen stocks at the basin level using ArcGIS 10.1.

3.2.1 Data Collection

a. Land Use/Cover Classification

Data Sources for Images Classification

The Landsat data product used for this study was derived from the Landsat Data Continuity Mission (LDCM), (http://glovis.usgs.gov). The Level 1 Terrain (L1T) data products (data type) used consist of Level 1 Radiometric (L1R) data products with systematic geometric corrections. The data were also terrain corrected for relief displacement. Two scenes of

Landsat 8 were used for land use/cover classification. The acquisition dates were 13 October 2013 and 29 October 2013 both with path-row 193-53 with 30 m spatial resolution. Many reasons explain the choice of this moment. Firstly, from June to September clouds are the main constraints for a good quality of images acquisition because this period falls in the rainy season. During October the maximum photosynthetic activity can be reached for any land use/cover. In addition, crops are easily discriminated from other land use/cover such as vegetation and the cloud cover percentage is quasi-null. From November to January, fire patterns disturbed the quality of the images and crops are harvested by farmers and this can lead to the soil surface response (bare soil) in the acquired images. The characteristics of the four used bands in each scene are presented in Table 3.1.

Table 3. 1 Landsat 8 bands identification for land use/cover classification

Band Reference Number	Band Description	Band Centre (nm)
Band 2	Blue (Operational Land Imager (OLI))	482
Band 3	Green (OLI)	562
Band 4	Red (OLI)	655
Band 5	Near-Infrared (NIR) (OLI)	865

State of the art for land use/cover classification

The land use/cover classification was first based on the observed classes in the study area. The approaches to identify these land use/cover (LULC) classes were based on field campaign and contact with resource persons from CENAGREF ("Centre National de Gestion des Réserves de Faune", National Centre of Fauna Reserve Management) institution. The results of investigations from CENAGREF enabled Dassari Basin to be classified into three strata. The first stratum is the local community site where farming activity are carried out without any restriction. The second stratum is a narrow band of 3 to 4 km qualified as controlled land use zone (Zone d'Occupation Contrôlée) according to CENAGREF. In this stratum farming activity can be carried out when it is allocated. The third zone is a protected area or national Park, where farming activity is not allowed.

The classification scheme adopted was fitted to the regional classification described in the West African region. This regional concept for LULC classification was based on Aubreville (1956) classification, which was reviewed and underlined in Table 3.2.

Eleven LULC classes were used, seven of which reflected the dominant land use classes in the case study region. These are riparian forest and woodland, savanna woodland, shrub savanna, cropland and fallow, settlements, agroforestry and plantation. Agroforestry and tree plantation were separated from cropland since an increase of agroforestry and plantation could be a mitigation strategy to climate change.

Table 3. 2 Description of LULC types identified in Dassari Basin

N	Land-use/cover (LULC) types	Description	Data sources
1	Riparian forest and woodland	Forest along the river bank and woodland in the mountainous zone. Both are area of land covered with mature trees and other plants growing close together with (cover trees > 70 %).	Landsat 8
2	Savanna woodland	Area covered by few grass with big and small trees.	Landsat 8
3	Shrub savanna	Area covered by grassland and small trees (trees with DBH < 20 cm and 5 m in height) but sometimes with scattered big trees	Landsat 8
4	Grass savanna	Area covered by 80 % of grass and very scattered trees	Landsat 8
5	Cropland and Fallow	Area covered by crops (maize, sorghum, millet, bean, yam, cotton, rice, etc.). Fallow are areas of abandoned farms within 2 to 5 years old.	Landsat 8
6	Bare land	Bare area,	Landsat 8
7	Settlements	Areas that have been populated with permanent residents or covered with scanty grass and exposed rock, and bare lands. According to IPCC (2006), the land-use category settlements includes soils, herbaceous perennial vegetation, such as turf grass and garden plants, trees in rural settlements, homestead gardens and urban areas.	Landsat 8 + Rapid Eye (0.5 to 2m resolution)
8	Agroforestry	Agroforestry is non timber trees-based system (cashew) or fruit based system. Cashew plantations were extracted by digitizing Rapid Eye images in ArcGIS 10.1	Rapid Eye + Ground truthing data
9	Plantation	A plantation is timber trees-based system (Eucalyptus, teak, mango, etc.). Plantations were extracted by digitizing Rapid Eye images in ArcGIS 10.1	Rapid Eye + Ground truthing data
10	Stream and rivers	Areas covered with water such as small reservoirs and rivers	Landsat 8 + ASTER (30m resolution)
11	Road	Bitumen and main laterite roads	Rapid Eye +

Each land use/cover type has been classified within IPCC (2006) land use categories as shown in Table 3.3.

AFOLU consists of Agriculture, Forestry and Other Land Use (IPCC, 2006). Land use categories (LUCa) are forest land, cropland, grassland, wetland, settlements and other land.

For this study wetland is not taken into account as land use type in Dassari Basin for two main reasons.

The first reason was that, according to IPCC (2006) wetlands include any land that is covered or saturated by water for all or part of the year, and that does not fall into the forest land (FL), cropland (CL), or grassland (GL) categories. Emissions from unmanaged wetlands are not estimated. The second reason was based on the fact that the study focused on the change in the vegetation pattern that could affects carbon and nitrogen stocks or carbon dioxide and nitrous oxide emission through stand trees degradation.

Table 3. 3. AFOLU sector and land use/cover classes of Dassari Basin

Land use/cover categories (IPCC, 2006)					
Forest land	Grassland	Cropland	Wetland	Settlements	Others land
Riparian forest and woodland, Savanna woodland, Shrub savanna	Grass savannah	Crop, Fallow	-	Settlements (hamlet, tarred road, homestead gardens)	Bare (bare area laterite road), water (small Reservoir, rivers).

b. Forest inventory approach

Establishment of gridded vegetation index map using MODIS data

Clusters of land use based on time series were derived using Normalized Difference Vegetation Index (NDVI) of Moderate-resolution Imaging Spectro-radiometer (MODIS).

MODIS data was used with 500 m resolution and 0 % cloud cover from August 2013 to November 2013 (https://lpdaac.usgs.gov/products/modis_products_table) (Table 3.4). NDVI (Eq. 3.1), mean NDVI (Eq. 3.2) and the sample variance (Eq. 3.3) were calculated per pixel across time. The mean NDVI was used as input in the k-mean cluster analysis. The numbers of retained clusters were based on the number of LUCa.

Table 3. 4 Downloaded 500 m Resolution MODIS Images

N°	Julian day	Acquisition date
1	225	13-8-2013
2	241	29-8-2013
3	257	14-9-2013
4	273	30-9-2013
5	289	16-10-2013
6	305	1-11-2013

These clusters were then used for a stratified random sample creation in ArcGIS 10.1. The centroids of the selected pixels were used to establish plots at which ground training area information was derived for the classification (Figures 3.2). The gridded vegetation index map was edited for the installation of plots for forest inventory within each land cover and land use system. For any given pixel, model builder component of ERDAS imagine 10 software was used to calculate the mean NDVI and its variance based on Equations 3.1, 3. 2 and 3.3, by using these six time series dataset based on the built models (equations) in this software. The formulae of these equations are:

$$\mathrm{NDVI}_i = \frac{\mathrm{NIR}_i - Red_i}{\mathrm{NIR}_i + \mathrm{Red}_i} \tag{3.1}$$

$$\mathrm{Mean}_{\mathrm{NDVI_i}} = \frac{\sum_{i=1}^{N} (NDVI_{(x,y)} i)}{N} \tag{3.2}$$

The unbiased sample variance was expressed as:

$$s^2 = 1/(N-1) \sum_{i=1}^{N} [NDVI_i - MeanNDVI_i]^2 \tag{3.3}$$

$$standardized\ \mathrm{Mean}_{\mathrm{NDVI_i}} = \left[(\mathrm{Mean}_{\mathrm{NDVI_i}} - NDVI_{min})/(NDVI_{max} - NDVI_{min})\right] x\ (2^8 - 1) \tag{3.4}$$

Where,

NDVI = Normalized Difference Vegetation Index

NIR = Near-Infrared band of MODIS Red

= Red band of MODIS

i = pixel position (i.e. pixel i) in the scene

N = number of scenes or elements x =

longitude coordinate of pixel i y = latitude

coordinate of pixel i s^2 = variance of pixel i

$Mean_{NDVI}$ (i) = Mean NDVI of pixel i

Min = Minimum value of Mean NDVI of all pixels

Max = Maximum value of Mean NDVI of all pixels

NDVI was rescaled from range [-1; 1] to [0; 255] using logarithmic function (Eq. 3.4) in ERDAS Imagine 10 to avoid negative values in data manipulation and visualization (Figure 3.2).

Cluster analysis of the vegetation index and plots installation

The Lloyd (1982) and MacQueen (1967) algorithms were used for k-mean cluster in R software to fit with the number of LUCa (forest land, cropland, savannah grassland, settlement and other land use). Secondly, a number of candidate pixels that had large homogenous patches on the initial MODIS cluster image were selected randomly based on the previous estimated variance of pixels. Finally, if the patch (pixel) shown on the map (Fig. 3.2) was indeed relatively homogeneous and large enough when visited on the ground, a field measurement plot was selected for forest inventory in the mid-point of this MODIS pixel at

30 m x 30 m scale for forest land, grassland and cropland, and 100 m x 100 m for settlement. The size of plots was 30 m x 30 m for forest land, grassland and cropland, 100 m x 100 m for settlements and 10 m x 20 m for agroforestry and plantation. The total plots of 250 (Figure 3.2 and Table 3.5) cover a total area of 27.26 ha.

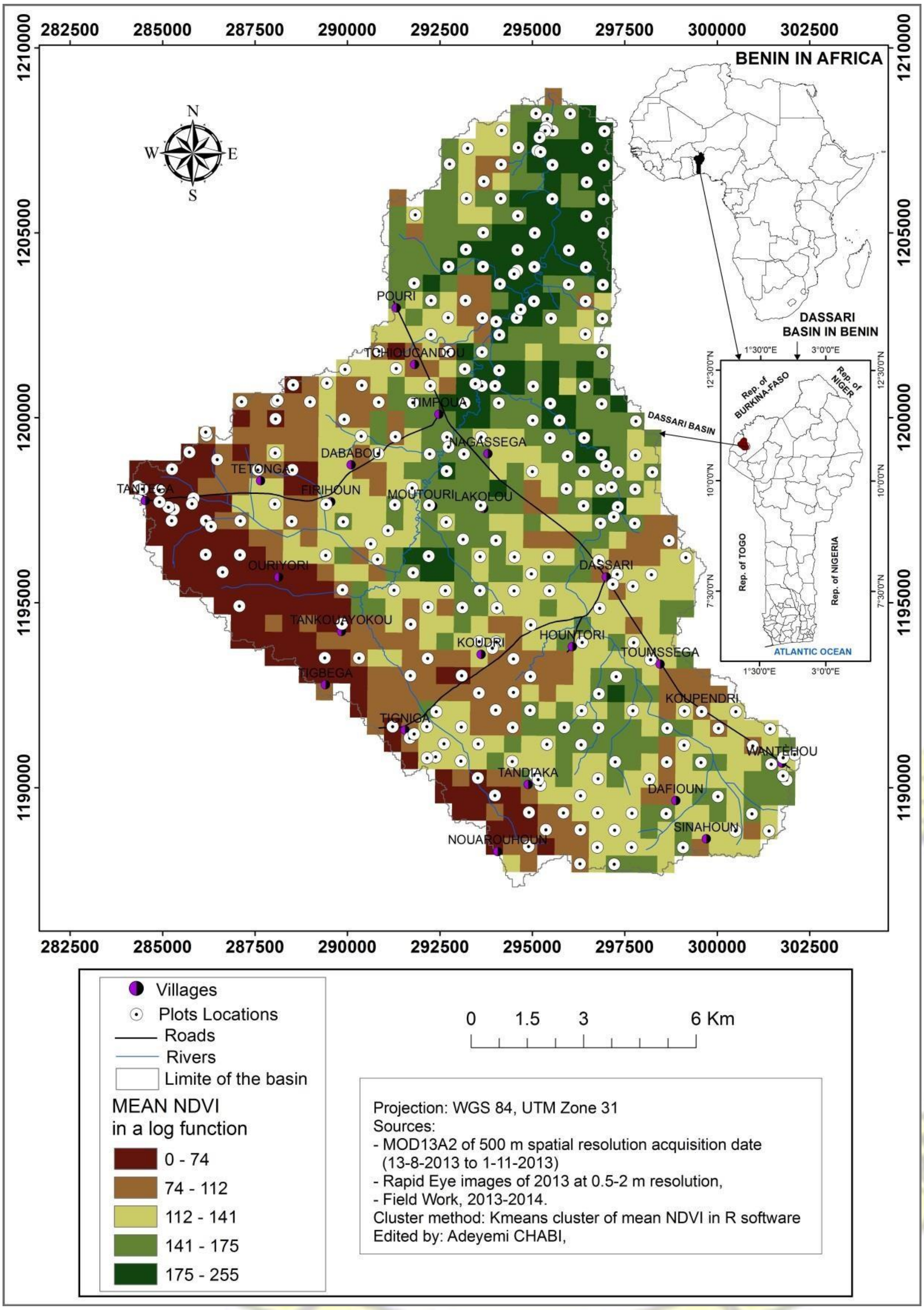


Figure 3. 2 Gridded vegetation index map with plots location data

Community analysis was carried out during six months (from April to September of 2014). In every land use/cover system, plots were installed randomly proportionally to their size (Table 3.5) using the gridded vegetation index map (Fig. 3.2).

Table 3. 5 Land use/cover (LUC) classes and number of installed plots.

LUCa/ LULCC	Area (ha)	Percentage (%) in the basin	Area sampled (ha)	Number of installed plots
Forestland				
RFW	320.4	1.66	0.81	9
SW	5447.79	28.29	2.43	27
SS	4241.88	22.03	5.04	56
Grassland GL				
	96.48	0.5	3.06	34
Cropland CPF				
	8031.15	41.7	7.2	80
Settlement SL				
	486.72	2.53	8	8
Other land use				
AGF	20.7	0.11	0.26	13
PLT	16.74	0.09	0.46	23

Note: RFW: Riparian forest and woodland; SW: Savanna Woodland; SS: Shrub Savanna; GL: Grassland; CPF: Cropland and Fallow; SL: Settlement; AGF: Agroforestry; PLT: Plantation
NB: Agroforestry and plantation were seen as mitigation strategies to climate change, they were therefore discriminated from cropland.

c. Tree community analysis

Total number of tree species identifies during plots survey was 84. Three variables namely diameter at breast height (dbh), stem and total height were measured on all trees with dbh greater than or equal to 5 cm.

Similarity index analysis

Similarity indices estimation was a basis for determining the LULC types that might be combined for further importance value index and specific allometric model establishment. According to Anne *et al.* (2005), the classic Jaccard index depend on the number of species shared by two assemblages and the number of species unique. In the case of this study Jaccard index (Table 3.6) has been used to determine the level of similarity of the main

LULC types at basin scale.

Access 2010 software was used to establish the database. Once the tabulation has been carried out, query language was used to count species according to their distribution in different land use/cover type.

Table 3. 6 Jaccard index (%) for diverse LULC types

	Riparian forest and woodland	Savanna woodland	Shrub savanna	Grass savanna	Cropland and	Settlement fallow
Riparian forest and woodland		61.7	46.2	17	45.9	8.6
Savanna woodland			53.8	17.6	51.6	6.3
Shrub savanna				16	48.4	4.8
Grass savanna					20.9	13
Cropland and fallow						15.4
Settlement						

The Jaccard coefficient measures similarity between finite sample sets, and is defined as the size of the intersection divided by the size of the union of the sample sets (Eq. 3.5):

$$Jclas = \frac{A}{\mathrm{A + B + C}} \qquad (3.5)$$

Where
A and B represent two communities
J_{clas} = Jaccard index,
A = Common species from 2 LULC types,
B = Species from LULC type 1,
C = Species from LULC type 2

The results show that the level of similarity was high between LULC types of forest land: 61.7 % between riparian forest and woodland; 53.8 % between savanna woodland and shrub savanna (Table 3.6). The level of similarity was high with forest land and cropland and fallow. This was based on the fact that the forest land (riparian forest and woodland, savanna woodland and shrub savanna) was converted to cropland and fallow for farming activities.

The importance value index (IVI) was used to determine the main species that can contribute to the vegetation carbon and nitrogen stocks in each LULC type of the basin.

Importance Value Index (IVI) analysis

Importance value index was used for the first time by Curtis (1956) to determine the overall importance of each species in the trees community structure. The IVI is calculated in summing up the percentage values of the relative frequency, relative density and relative dominance of the species (Table 3.7). Density (D), frequency (F), Dominance (Dom), relative density (RD %), relative frequency (RF %), relative dominance (RDom %)) and Importance Value Index (IVI) were calculated for each species in each LUCa based on IPCC (2006) classification (Table 3.3) from the count data in Access 2010 (Table 3.6). The various parameters were obtained as:

Density (D):

$$D = \frac{Number\ of\ species\ \mathrm{A_i}}{Area\ sampled} \qquad (3.6)$$

Frequency (F):

$$F = \frac{Number\ of\ plots\ in\ which\ species\ \mathrm{A_i}\ occurs}{Total\ no.\ of\ plots\ sampled} \qquad (3.7)$$

Dominance (Dom):

$$Dom = \frac{Total\ cover\ or\ basal\ area\ of\ species\ \mathrm{A_i}}{Area\ sampled} \qquad (3.8)$$

Relative density (RD %):

$$RD = \frac{Density\ of\ species\ \mathrm{A_i}}{Total\ density\ for\ all\ species} X\ 100 \qquad (3.9)$$

Relative frequency (RF %):

$$RF = \frac{Frequency\ value\ for\ species\ \mathrm{A_i}}{Total\ frequency\ values\ for\ all\ Species} X\ 100 \qquad (3.10)$$

Relative dominance (RDom %):

$$RDom = \frac{Dominance\ for\ species\ \mathrm{A_i}}{Total\ Dominance\ for\ all\ species} x\ 100 \qquad (3.11)$$

Importance Value Index (IVI):

$$IVI(A_i) = \sum(RD + RF + RDom) \qquad (3.12)$$

Where,
IVI (A_i) = Importance Value Index of species Ai with i varied from 1 to N (here N equal to 81)
RD = relative density of each specie expressed in percentage (%)
RF = relative frequency of each specie expressed in percentage (%)
RDom = relative dominance of each specie expressed in percentage (%)
Total density for all species = sum of density from each species
Total frequency values for all Species = Sum of frequency from each species Total
Dominance for all species = Sum of dominance from each species

The retained species for performed measurements on individual trees were presented in each LUCa and had high IVI (Table 3.7). These main species of the basin belonged to these LUCa and respectively represented 80.5 %, 82.75 %, 79.55 % and 76.8 %, for forestland, grassland, cropland and settlement. From these retained main trees species; analysis was performed to define the validity domain of size class distribution for each LUCa.

Table 3. 7 IVI of main species in each LUCa

Species name	**IVI index**			
	Forestland	Grassland	Cropland and fallow	Settlement
Terminalia genus	42.57	125.85	19.23	-
Acacia genus	33.18	24.39	21.01	-
Combretum genus	31.13	-	5.99	-
Pterocarpus erinaceus	25.55	-	6.02	-
Anogeisus leiocarpus	24.09	-	-	-
Mitragyna inermis	18.22	-	-	-
Lannea genus	16.06	-	44.97	28.25
Ficus genus	8.79	32.28	28.84	42.08
Crosopteryx febrifuga	8.01	-	-	-
Entada Africana	7.32	22.27	-	-
Parkia biglobosa	-	42.14	65.50	-
Vitelaria paradoxa	-	-	21.28	-
Azadirachta indica	-	-	15.92	96.63

Defining validity domain of size class distributions for different land use categories

The validity domain of size class distribution is a basis for defining the validity domain of further established allometric equations. Table 3.8 shows the proportion of surveyed trees by two ranges of DBH size classes.

The DBH of the main species ranged between two size class distributions. The two size class's distributions on DBH are 5 to 45 cm and 45 excluded to 100 cm. The results provided from the 250 plots data revealed the size class distribution of these main species according to the DBH range in Table 3.8. The species belonged to the first class in each LUCa represented 98.6 %, 87.5 %, 99.3 % and 91.9 % respectively for forestland, grassland, cropland and fallow, and settlement. From the tabulation of plots data, the DBH of the second class (45 excluded to 100 cm) the trees have their DBH scattered for all LUCa. Most tree species have their DBH within the first class for each LUCa and these classes were retained for further developed allometric equations in each LUCa.

Table 3. 8 Range of DBH (cm) of trees species and their proportion in each LUCa

	Range of DBH (cm) and their proportion in (%)	
	First range	Second range
Forestland	5-45 (98.6)	45-100 (1.4)
Grassland	5-45 (87.5)	45-100 (12.5)
Cropland and fallow	5-65 (99.3)	65-100 (0.8)
Settlement	5-55 (91.9)	55-100 (8.1)

Note: ( ) represents the proportion in percent of trees species within DBH range.

Special considerations for stem diameter, stem and tree height measurements

Stem diameter (or girth), total tree height and wood stock are three main variables accounted for aboveground biomass assessment at the basin level. To avoid unbiased measurements, tree shape and stem height were taken into account. Statistical analysis was done for all species (Table 3.9) to define the number of diameters to be measured along the stem (Figure 3.3). The result of stem height analysis of these retained species according to IVI index, helped to estimate the number of this diameter stem measurements based on the proportion of tree species in two ranges of stem height (Table 3.9).

Table 3. 9 Proportion in percent of trees species stem height within two ranges of height

Species	Proportion in (%) of trees species stem height	
	Trees stem height = < 2.3 m	Trees stem height > 2.3 m
Terminalia genus	95.85	4.15
Acacia genus	91.57	8.43
Combretum genus	91.5	8.5
Pterocarpus erinaceus	74.86	25.14
Anogeisus leiocarpus	72.29	27.71
Mitragyna inermis	87.79	12.21
Lannea genus	94.81	7.02
Ficus genus	88.63	11.37
Crosopteryx febrifuga	93.13	6.87
Entada Africana	98.01	1.99
Parkia biglobosa	93.1	6.9
Vitelaria paradoxa	97.05	2.95
Azadirachta indica	79.2	20.8

Most trees species (from 72 % to 98%) have stem height less or equal to 2.3 m (Table 3.9). The conclusion was that most stem trees height was less or equal to 2.3 m in this West African Sudan Savannah zone. 4 to 20 % of trees species have their stem height higher or equal to 2.3 m. Based on these considerations, three measurements (G_1, G_2 and $G_{\_crown}$), (Figure 3.3), of stem diameter were considered for the performed measurements on individual tree species. The first measurement was done at 1.3 m, the second at 2.3 m, the third at the crown base (Figure 3.3). This approach helped to avoid unbiased stem volume and stem biomass estimation.

Size classes distribution of selected species

The results from Table 3.7 and 3.8 led to the establishment of diameter of each tree species within the basin. Once the number of each tree species has been distributed along its size class distribution with 5 cm interval, proportion rate was applied and the number of trees was estimated for survey detailed measurements on individual trees (Table 3.10).

Table 3. 10 The number of sampled trees within divers LUCa

Species	N	Range of DBH (cm)	Range of stem height (m)	Range of total tree height (m)
Terminalia genus	24	5.0 – 50.1	1.1 – 8.5	1.5 – 12.5
Acacia genus	18	5.0 – 39.2	1.2 – 6.0	1.7 – 12.4
Combretum genus	11	5.0 – 36.1	1.2 – 6.3	2.0 – 9.0
Pterocarpus erinaceus	16	5.2 – 96.5	1.3 – 7.0	2.1 – 15.0
Anogeisus leiocarpus	16	5.0 – 82.0	1.2 – 7.0	2.0 – 14.0
Mitragyna inermis	14	5.0 – 65.0	1.3 – 6.0	2.0 – 12.0
Lannea genus	23	5.4 – 68.9	1.1 – 5.5	1.3 – 12.8
Ficus genus	15	5.0 – 75.3	1.3 – 4.8	2.0 – 8.8
Crosopteryx febrifuga	08	5.5 – 40.4	1.3 – 4.3	2.0 – 10.8
Entada Africana	07	5.0 – 25.6	1.2 – 4.0	1.8 – 7.5
Parkia biglobosa	17	5.5 – 104	1.3 – 6.2	2.0 – 14.0
Vitelaria paradoxa	08	5.3 – 54.3	1.1 – 4.5	2.0 – 12.5
Azadirachta indica	19	5.3 – 80.0	1.3 – 4.8	2.5 – 10.6

Note: The range of DBH at 1.3 m aboveground for each species in the entire basin was expressed in cm. The range of stem and total height of each species in the entire basin were expressed in metres. N= Number of selected trees in different size classes by species. In addition trees were surveyed in agroforestry system and plantation.

d. A non-destructive method for estimating aboveground biomass

Tree variables measurements

The criterion for selecting trees from each species was that stem height should lower or equal to 2.3 m. Many conditions were considered when choosing sample trees in the field. The sample tree should be supposed none deformed. The selected sample trees should be straight and without nodules. Figure 3.3 shows the various variables collected within a sample tree in this basin. A total of 270 trees were non-destructively sampled be considering all the main tree species (Table 3.10). In the previous of this non-destructive survey the destructive approach was applied to the 13 tree species, belonging to 7 species. Advantage was taken of rural electrification project along the road from Dassari to Tigniga (Figure 4.1). Trees along this road were to be logged to give way to electrification extension. Negotiations were done with the project officers for the release of 13 individual from these seven selected species namely *Terminalia macroptera, Ficus sp, Acacia seyal, Entanda Africana, Combretum glutinosum, Crosopteryx febrifuga* and *Anogeisus leiocarpus* for destructive and nondestructive measurements. Only tree species commenced for logging and fall within the species of interest (Table 3.10) were destructively measured. These were used for the establishment of Biomass Expansion Factor (BEF) function as well as for assessment of the uncertainties. For the non-destructive method, the following were carried out on individual

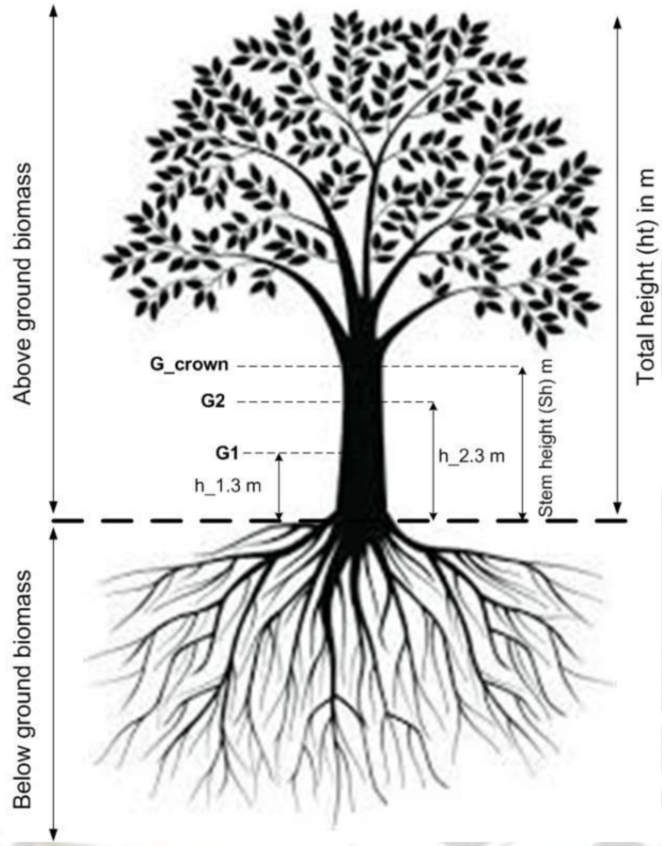
trees.

i. Measurement of stem girth at 1.3 m, 2.3 m and crown base, and stem height (Picture 3.1); ii. Extraction of stem wood sample of the tree at 1.3 m above ground using the increment borer (Picture 3.2); iii. Oven-drying the wood sample obtained with the increment borer and estimation of the wood density of the surveyed tree; iv. Estimation of stem-dry mass of the tree species using Eqs. 3.16 to 3.19.

The destructive approach consisted of the following steps:

i. Logging of the tree species by rural electrification project officers, ii. Weighting of fresh mass of stem, branches and foliage using weighing score; iii. Oven-drying of fresh wood samples selected from stem, branches and foliage at 75ºC for 2 to 3 days to constant weight; iv. Estimation of dry mass of stem, branches and foliage of the tree using Eq. 3.20,

v. Calculation of BEF based on dry mass of stem, branches and foliage using Eq. 3.21, vi. Modelling BEF as a function of stem dry mass, vii. Comparison of the non-destructive method to the destructive method based on predictive total biomass by BEF function.



G_1 = stem Girth at breast height (at 1.3 m),

G_2 = stem Girth of tree at 2.3 m height,

G_crown = stem Girth of tree at crown base,

NB: The below ground biomass is not considered in this study.

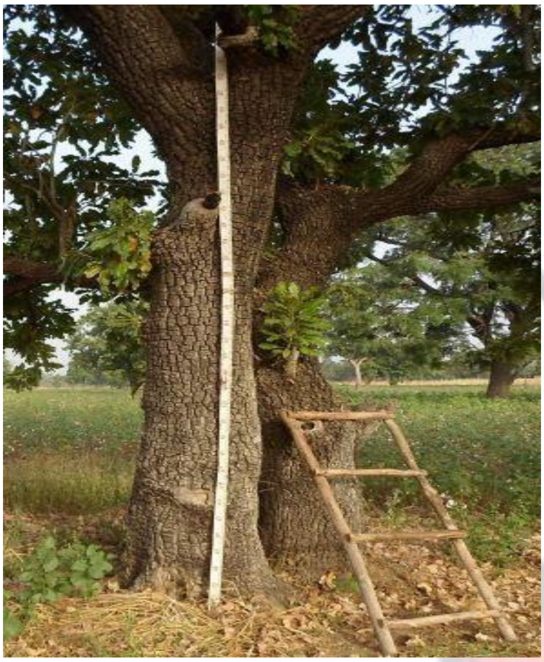
Figure 3. 3 Tree design showing detailed measurement of diameters and heights on individual sample tree

Collecting wood samples in the field

Samples of wood were extracted from the tree using an increment borer. The wood samples were extracted at 1.3 m above the ground.

The inner diameter of the bit of this device was 0.5 cm, indicating the diameter of the core sample extracted to be 0.5 cm.

Once the wood was extracted, its length L was measured and expressed in centimetres. An example of wood sample is presented in Picture 3.3.



Picture 3.1 Techniques of trees measurement in the field. (CHABI, 2014)

Picture 3. 2 Techniques of extraction of wood sample using increment borer. (CHABI, 2014)

1= Increment borer

2= Wood sample

Picture. CHABI, October 2014

Picture 3. 3 Fresh wood sample obtained from increment borer

Estimation of basic wood density

The extracted core wood from each selected tree species was oven-dried at 75º C for 48 to 72 hours depending on water content of the wood sample constant weight. The oven dry density (ρ) in terms of dry mass per fresh volume was estimated for each wood sample as in (Eq.3.16).

$$\rho = \frac{4\mathrm{dMS_i}}{\pi d^2 L_i} \quad (3.16)$$

Where: ρ = wood density in $g.cm^{-3}$
dMS_i = Dry mass of wood sample i expressed (g)
d = diameter of the core wood (0.5 cm) L_i = length of the sample i expressed (cm)

Estimation of stem volume and stem biomass

The stem volume of measured trees was measured by section according to Figure 3.3. The truncated cone function was used to estimate stem volume (Eq. 3.17):

$$V_{stemi} = Sh_i \text{ x } \frac{1}{12\pi} \; x \; (\; {C_{1i}}^2 + \; {C_{2i}}^2 + \; C_{1i} \; \cdot C_{2i}) \quad (3.17)$$

Where:
Sh_i = height (m) of section i of the tree stem,
C_{1i} = the greater girth of the section i of the tree stem,
C_{2i} = the smaller girth of the section i of tree stem,
V_{stemi} = Volume (cm^3) of section i of the tree stem,

Stem mass were estimated based on wood density and stem volume values of the sections of the tree stem (Eq. 3.18). Total mass of the tree stem is calculated as the sum of all sections (Eq. 3.19):

$$B_{stemi} = (\rho \; x \; V_{stemi})/1000 \quad (3.18)$$

$$TB_{stem} = \sum_{i=1}^{n} \; B_{stemi} \quad (3.19)$$

Where:
V_{stemi} = Volume (cm^3) of section i of stem,
B_{stemi} = Biomass (Kg) of section i of stem,
TB_{stem} = Total mass of tree stem (Kg) n = Number of the stem section of the tree

In the next step, dry mass of stem, branches and foliage (total biomass) were derived by the destructive approach for the same trees:

$$B_{tot} = \sum_{j=1}^{m} \frac{fM_j * dmS_j}{fmS_j} \quad (3.20)$$

Where:
B_{tot} = Total mass of a tree (sum of dry mass of stem, branches and foliage) (Kg)
fM = Fresh mass of stem, branches or foliage (Kg), fmS = Fresh mass of sample of stem branches or foliage (g). dmS = Dry mass of wood sample of stem branches or foliage(g), j = index of the

different components (stem, branches and foliages) m= number of components of the various 3 organs

For the following step, the Biomass Expansion Factor (BEF) per tree for the 13 individual trees was calculated using Eq. 3.21.

$$BEF = \frac{\mathrm{B_{tot}}}{\mathrm{B_{stem}}} \qquad (3.21)$$

Where:

B_{tot} = Total mass of a tree (sum of dry mass of stem, branches and foliage) (Kg),
B_{stem} = Stem dry mass (kg)
BEF = Biomass Expansion Factor

Equations 3.16 to 3.19 were applied to the non-destructive method concerning 270 tree species whereas Equations 3.16 to 3.21 were applied to the 13 trees species using both the destructive and non-destructive approaches for comparison.

Once the BEF has been modelled based on the 13 trees, the total mass of the 270 individual trees were estimated then using the BEF model.

Modelling BEF as a function of stem dry mass

The calculation of the 13 destructively sampled trees was correlated to stem dry mass and the linear regression model was applied. Stem dry biomass was log-transformed to provide a more even spread of the data.

$$\mathrm{BEF} = \beta_0 + \beta_1 \ln\left(B_{stem}\right) + \varepsilon \qquad (3.22)$$

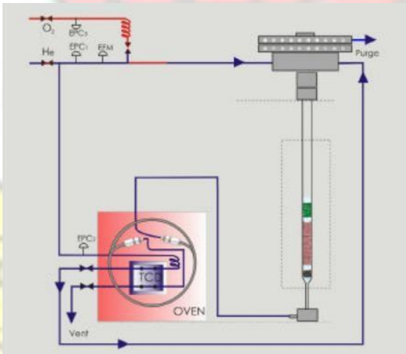
Where β_0 and $\beta 1$ are model parameters

Chemical analysis for the estimation of carbon and nitrogen content of wood samples The samples from Eucalyptus trees (7 samples) were added to the samples obtained from the main species (245 samples) of the natural vegetation, cashew (25 samples). Total number of wood samples was 277 obtained from 18 tree species (Picture 3.4-3.5). Initial assignment for the chemical analysis was the grinding of 277 wood samples obtained from 18 tree species. The samples were first re-dried (because it was dry when estimating wood density) to avoid any water content. The weighing process followed the grinding.

Picture 3. 4 Example of grinding sample in the small bottle

Picture 3. 5 Total number of ground wood samples in the small bottles

Picture 3. 6 Euro EA 3000



Picture 3. 7 The analytical circuit

Picture 3. 8 Output presented in the screen of the computer

Chemical analysis was done at the Institute of Crop Science and Resource Conservation, within the laboratory of the Department of Plant Nutrition in Germany (Bonn) using the EA3000 model CHNS-O Elemental Analyser (http://www.eurovector.it/) (Picture 3.6-3.8).

3.2.2 Data analysis

a. Random forest (RF) algorithm for image classification

The images classification in R software was based on the following steps:

1. Importing co-registered images into R;
2. Spectral Bands and Indices;

3. Preparing Data for Random Forest;
4. Running Random Forest;
5. Recursive Partitioning and Regression Trees (Rpart).

The variables used for random forest (RF) were bands 2, 3, 4, 5 (Table 3.1), NDVI (Normalized Difference Vegetation Index) of Landsat 8 satellite images.

b. Accuracy assessment of the supervised classification

According to Gómez and Montero (2011), any supervised classification is not complete until an assessment of its accuracy has been performed. The classification accuracy is a measure of the degree to which the derived image classification agrees with reality or conforms to the 'truth' (Campbell, 1996; Janssen and Van der, 1994; Maling, 1989; Smits *et al.*, 1999). Generally an error matrix known as confusion matrix is used to compare information based expert judgement and the classifier. Let $A_1, \ldots A_k$ be the set of crisp classes under consideration, the error matrix N is defined as a frequency matrix, where each element (*nij)* represents the number of pixels that the expert classified as pixel in land use type i but the classifier did in land use type j, (Gómez and Montero, 2011; Foody, 2002). In the case of this study two types of accuracy indices (overall accuracy and Kappa index) were used. The following formula characterized each type of indices:

Given the error matrix N = n_{ij}, the overall accuracy is defined as:

$$O^c = \sum_{i=1}^{k} n_{ij} / |T| \quad (3.23)$$

Where |T| is the number of pixels being tested.

Given the error matrix N = (n_{ij}) the Kappa statistic is defined as:

$$K = (O^c - pe)/(1 - pe) \quad (3.24)$$

Where pe represents the percentage of items that have been classified correctly by chance, that is:

$$\text{pe} = \frac{1}{n} \sum_{i} n_i . n_i \quad (3.25)$$

By applying these equations for the confusion matrix of the classification results, overall accuracy and Kappa index were 0.75 and 0.69 respectively.

The performance evaluation of kappa stress that it does not quantifies the level of agreement between two datasets. It represents the level of agreement of two dataset corrected by chance.

c. Method for the establishment of biomass allometric equations at the basin level

The sample size consisted of 270 individual trees that have been non-destructively surveyed (Table 3.12). For each tree of that sample, the BEF was applied to calculate the aboveground biomass (AGB). The AGB was then used as the response which we tried to predict with generalized linear models (GLM) (McCullagh and Nelder, 1989) using predictors easily measured in the field. The models were fitted using **(1) just on DBH, (2) DBH and H, (3) and a combination of the three predictors.** Based on the properties of the residuals we decided on a Gamma GLM with a log link. For each level of complexity we started with a model that contained the interactions between all involved predictors as well as the main effects (conditional on the interactions). The model structure was simplified on the small sample size corrected Aikaike Information Criteria (AICc) (Sugiura 1978, Burnham and Anderson, 2004). Quadratic effects were not considered since their inclusion led to unrealistic model behaviour for higher response values that were interpreted as overfitting of the model. Models were fitted for each land use category (LUCa) – i.e. data were sub-set by LUCa before fitting. Effects of species on the model fit as well as on the structure of the residuals were tested but effects were small. We used the following LUCa to fit the models: forest land (the combination of riparian forest, savanna woodland and shrub savanna), savanna grassland (grassland), settlement, cropland (cropland and fallow). The sample size differed by LUCa: agroforestry: 25, forest: 181, cropland: 178, settlements: 63, grassland: 90. We did not fit models for the land use category plantation but applied published equations. Aboveground biomass from plots plantations of *Tectona grandis* and *Eucalyptus grandis* were obtained using published allometric equations from Guendehou *et al.* (2012) and Montagu *et al.* (2005) respectively whereas the generic equation (Table 3.15) was applied to estimate aboveground biomass of *Azadirachta indica* and *Gmelina arborea*.

We further compared model predictions with the observed aboveground biomass at the tree level based on the average deviation (Cairns *et al.*, 2003, Chave *et al.*, 2005, Basuki *et al.*, 2009). The average deviation is calculated as follows:

$$\delta(\%) = \frac{100}{n}\sum_{i=1}^{n}\frac{\acute{Y} - Y_i}{Y_i} \qquad (3.27)$$

Where δ is the average absolute deviation in percent, Y_i = the observed dry weight, Ý the predicted dry weight, n = number of observations.

d. Method for the estimation of aboveground biomass, carbon and nitrogen stocks Biomass stock map was generated using the best specific equation for each LUCa especially equation type III which involved the three predictors. Biomass stock of each plot was estimated in two steps when *Phoenix reclinata* and *Borassus flabellifer* were seen in the plot data. These species were retrieved from each plot data and their biomass estimated using equation from Schoroth *et al.* (2002) developed for the estimation of aboveground biomass of coconut. In the second step we applied specific equations for the concerned plots and we summed up together the two results to obtain the total biomass of the plot.

The estimation of carbon and nitrogen was first based on the results of biomass data at the tree level. The mean carbon and nitrogen content were applied to each species of the plots.

The results of chemical analysis for carbon and nitrogen content were the input (Table 3.18).

The mean biomass, carbon and nitrogen stock maps were edited in ArcGIS 10.1. The total aboveground biomass, carbon and nitrogen stocks of each LUC class were estimated as the product of the mean biomass stock ($Mg.ha^{-1}$) or mean carbon stock ($Mg\ C\ ha^{-1}$) or mean nitrogen stock ($Mg.ha^{-1}$ of N) value per hectare and the size (expressed in hectare) of the LUC type.

3.3 Results and discussions

3.3.1 Land use/cover types of Dassari Basin in 2013

The land use cover map of the study area spread as a baseline for estimating vegetation carbon and nitrogen stocks at the basin level (Figure 3.4). Three main land use/cover types i.e cropland and fallow, savanna woodland and shrub savanna characterized the Dassari Basin. These land use/cover types respectively represented 41.70 %, 28.29 %, and 22.03 % of the total area.

Table 3.11. Area (ha) and proportion (%) of each LUC type in Dassari Basin

N	LUC types	Area (ha)	Proportion in %
1	Riparian forest and woodland	320.4	1.66
2	Savanna woodland	5447.79	28.29
3	Shrub savanna	4241.88	22.03
4	Grass savanna	96.48	0.50
5	Cropland and Fallow	8031.15	41.70
6	Bare land	107.91	0.56
7	Settlements	486.72	2.53
8	Agroforestry	20.7	0.11
9	Plantation	16.74	0.09
10	Stream and rivers	348.57	1.81
11	Roads	139.05	0.72
	TOTAL	**19257.39**	**100.00**

The high proportion of cropland and fallow proved that the vegetation degradation due to farming activity was very crucial in the Dassari Basin and this could lead to the loss of high proportion of vegetation carbon and nitrogen stocks, thus more emission of CO_2 and N_2O. Agroforestry system and plantation respectively covered only 0.11 % and 0.09 % of the total area of the basin. These low proportions configure the assertion that mitigation strategies to climate change based on the adoption of agroforestry systems and plantations were little known by farmers of these villages.

At some instances in the text we refer to forest land that incorporates the LUCa (Land use category) riparian forest and woodland, savanna woodland and shrub savanna. Agroforestry and plantation were separated from cropland since an increase of agroforestry and plantation could be a mitigation strategy to climate change.

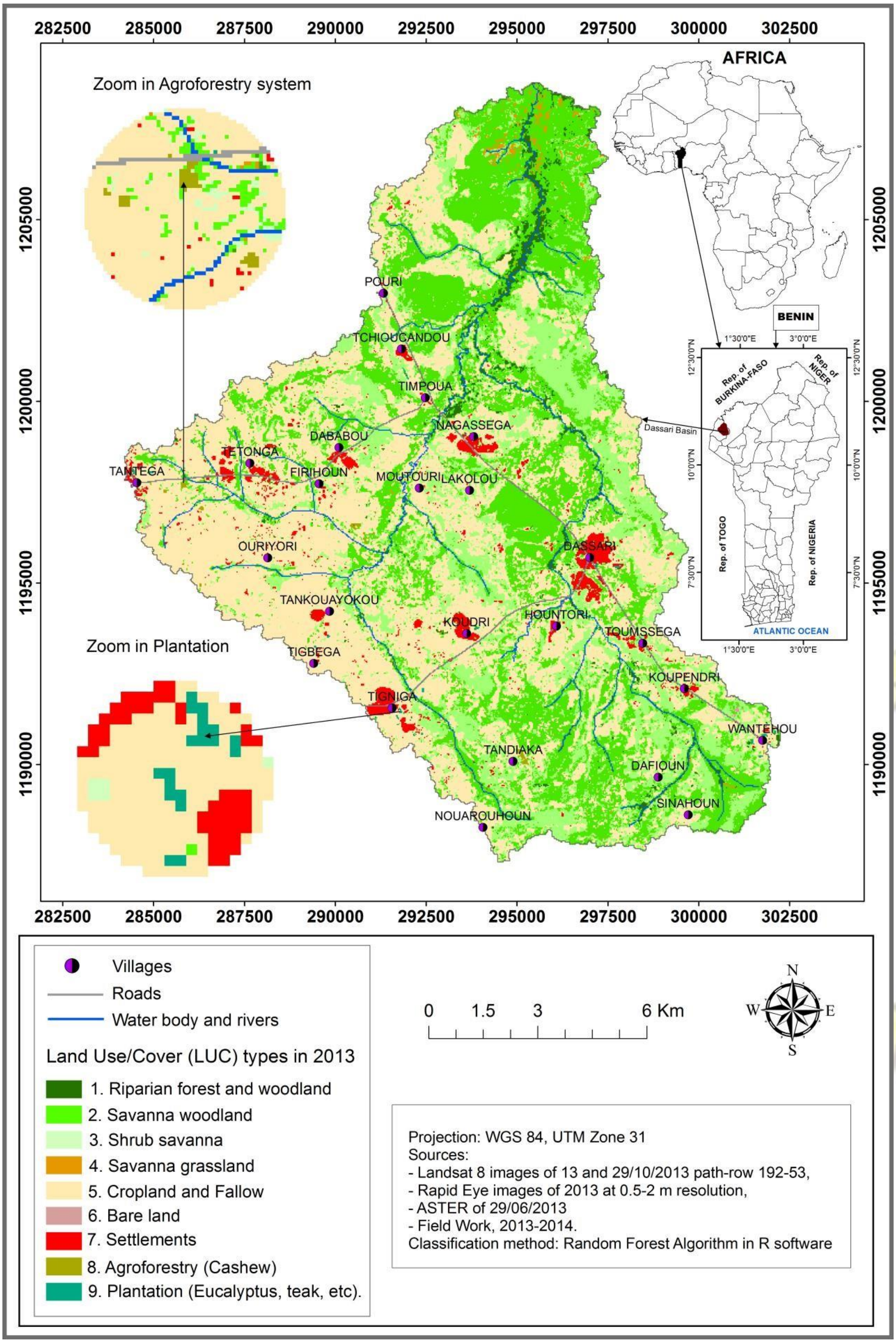


Figure 3. 4 Land Use/Cover types of Dassari Basin in 2013

3.3.2 Basic wood density of the main species

Estimated basic wood density of the main species in the study area is presented in Table 3.12. The species *Anogeisus leiocarpus, Combretum glutinosum, Terminalia macroptera, Vitelaria paradoxa, Pterocarpus erinaceus, Azadirachta indica, Acacia seyal, and Crosopteryx febrifuga* were characterized by a high mean wood density. The low mean density observed for *Lannea microcrapa* and *Ficus sp* was in line with the high water content of the species which is lost during the drying process. The threshold for this low was 0.500 $g.cm^{-3}$.

Table 3. 12 The Basic wood density ($g.cm^{-3}$) of the main tree species

Trees species	N	Basic wood density min	Basic wood density max	Mean (SE)	DBH (cm) min	DBH (cm) max	**Previous studies** ρ ($g.cm^{-3}$)
Terminalia macroptera	19	0.740	0.893	0.821 (0.010)	9.3	40.7	0.768[1*]; 0.870[2*]
Acacia seyal	16	0.669	0.909	0.751 (0.015)	7.6	34.4	-
Combretum glutinosum	11	0.827	0.962	0.877 (0.013)	7.9	31.9	0.900[2*]
Pterocarpus erinaceus	21	0.671	0.973	0.826 (0.015)	6.9	44.7	0.740[1*]
Anogeisus leiocarpus	16	0.813	0.977	0.889 (0.012)	6.9	32.4	-
Mitragyna inermis	18	0.579	0.687	0.631 (0.008)	7.0	34.5	-
Lannea microcrapa	22	0.472	0.648	0.546 (0.011)	7.0	50.6	-
Lannea acida	06	0.504	0.676	0.573 (0.027)	10.8	35.9	-
Ficus sp	21	0.440	0.607	0.528 (0.010)	8.6	52.7	-
Crosopteryx febrifuga	18	0.518	0.778	0.704 (0.016)	5.6	30.5	-
Entada africana	15	0.556	0.688	0.631 (0.010)	8.4	27.6	-
Parkia biglobosa	23	0.566	0.689	0.630 (0.006)	8.6	62.4	0.525[3*]
Vitelaria paradoxa	23	0.608	0.950	0.838 (0.016)	8.0	53.8	-
Azadirachta indica	16	0.619	0.886	0.763 (0.018)	8.8	50.5	0.660[4*] ; 0.620[5*]
Anacardium occidentale	25	0.512	0.625	0.569 (0.006)	9.2	57.9	0.431[3*]; 0.500[5*]

Note: N=Number of trees selected. The stem wood samples of selected trees were extracted at 1.3 m of the ground. DBH range = Range of diameter at breast height of sampled species. Figures in bracket represent the standard error.

References of previous studies:

[1*] Sallenave, P. 1955, 1964

[2*] von Maydell, HJ, 1983
[3*] Carsan et al., 2012
[4*] Oey, et al., 1951
[5*] Little and Wadesworth, 1964

Standard error of the measurements were very low for all species and confirmed thereby the accuracy of the measurements as well as the relative low importance of confounding factors which influence density variation per species as described by Chave *et al.* (2006).

Measurements on basic wood density were in line with results from previous studies (Oey, 1951; Sallenave 1955, 1964; Little and Wadesworth, 1964; Von, 1983; Carsan *et al.*, 2012).

3.3.3 Biomass Expansion Factor (BEF)

The biomass expansion factor increased significantly with the log of stem dry mass (Table 3.13 and Figure 3.5). The BEF as a function of stem dry mass varied between 1.46 and 1.88, with a mean of 1.67 ± 0.08 (95 % confidence interval). The BEF of *Terminalia macroptera,* which is the main species of the study site ranged from 1.55 to 1.88, with a mean value of 1.73. The model explained 69 % of the variance in the data.

Table 3. 13 Coefficients for the BEF – stem dry biomass relationship fitted

	Coefficient	Standard error	p-value
Intercept	1.24155	0.09253	3.66×10^{-8}
ln(stem dry biomass)	0.14701	0.02968	0.000434

Note: 13 trees belonging to 7 species were available for the comparison of destructive method to the nondestructive assessment for BEF modelling

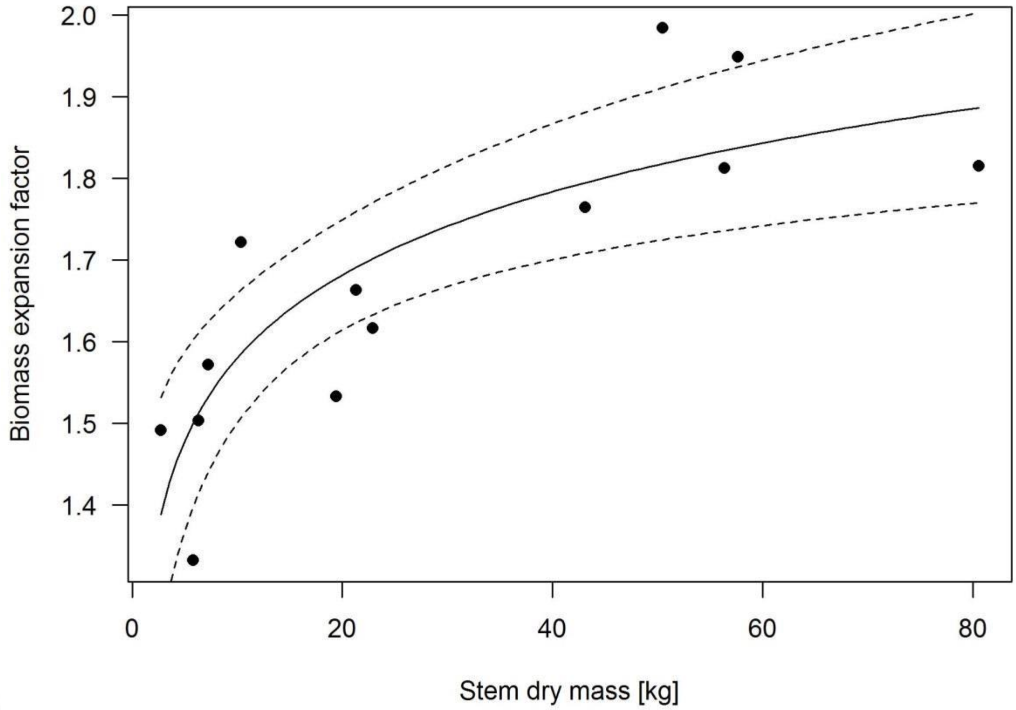


Figure 3. 5 Estimated relationships between stem dry biomass and biomass expansion factor

Note: The model used 13 trees that were available for the analysis by the destructive approach. The dashed lines represent the 95% confidence band.

Total mass obtained by the destructive sampling (observed values from 13 trees) and the total biomasses estimated by the non-destructive method (predicted values from these trees using the estimated BEF – stem dry mass relationship) were very similar (Figure 3.6, Pearson correlation coefficient of 0.99).

Given the small sample size (13 individual trees from seven species) and the limited range of DBH (less than 25 cm) care should be taken not to extrapolate results. However, the sampled trees represent the common size distribution of trees in the human influenced ecosystems of the study region. Therefore, the results can be assumed to provide a good estimate for biomass expansion factor assessments in the region.

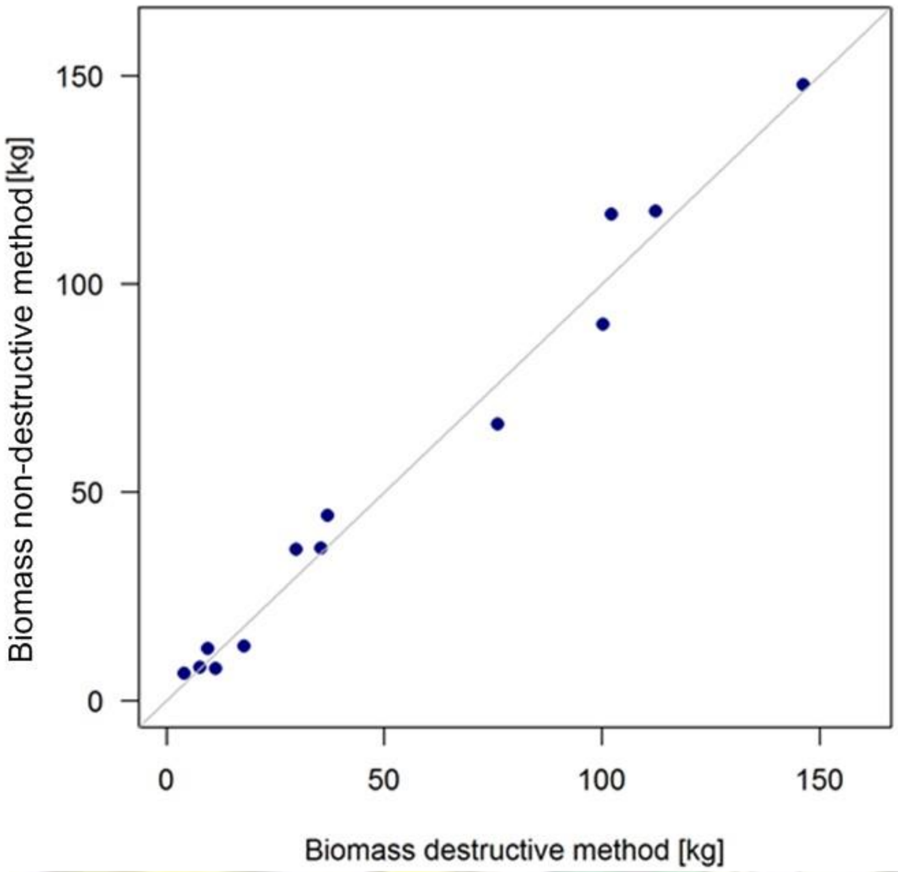


Figure 3. 6 Comparison between total biomass derived by the destructive and the nondestructive method

Note: The grey line represents the 1:1 line to aid interpretation.

Segura *et al.* (2005) used a similar approach based on an estimated biomass expansion factor function for the per-humid premontane transitional forest zone in Costa Rica. In contrast to our findings, BEF decreased with stem biomass. While the Costa Rican study underestimated total biomass of trees on average by 17.31 %, the study results overestimate total biomass slightly by 1.82 % when applying the Segura (2005) equation to the data. Levy *et al.* (2004) estimated biomass expansion of coniferous species in Great Britain. Levy's BEF was a function of tree height of stand tree. Levy's BEF overestimated the total biomass of our sampled tree species on average by 4.46 %. Magalhães and Seifert (2015) used BEF as a function of DBH when estimating aboveground biomass of *Androstachys johnsonii* in Mozambique. The BEF of

Magalhães and Seifert (2015) underestimates the total biomass on average by 62.54 % of the samples tree species.

The BEF can also be estimated based on dbh of the 13 trees assessed by the destructive approach (Figure 3.7).

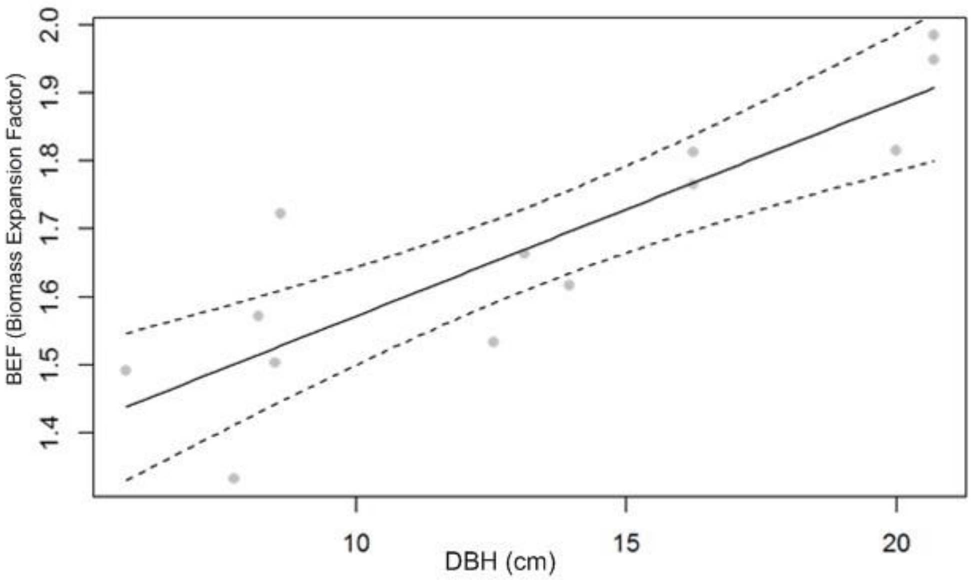


Figure 3. 7 Estimated relationships between DBH and biomass expansion factor

Note: The model used 13 trees that were available for the analysis by the destructive approach. The dashed lines represent the 95% confidence band.

The model based on dbh was slightly superior to the model based on stem dry biomass if compared by means of the small sample size corrected AIC (AICc) or a likelihood ratio test and explained 75% of the variance in the BEF (Table 3.14).

Table 3. 14 Coefficients for the BEF – DBH relationship fitted

	Coefficient	Standard error	p-value
Intercept	1.25801	0.07697	4.61×10^{-9}
DBH	0.0314	0.00543	0.000122

Note: The analysis was based on the 13 destructively sampled trees and non-destructive assessment

If this model was used to predict total biomass, the values derived by the destructive approach were overestimated on average by 2.27 % - a bit higher compared to the model based on stem dry mass. We therefore stuck to the estimation based on stem dry biomass.

3.3.4 Allometric model at the basin level

All models indicated a high goodness of fit expressed by the explained deviance as well as by the pseudo-R^2 by Nagelkerke (1991). While the AICc clearly favoured the more complex models (Table 3.15), even the models using only dbh as a predictor provided a high goodness of fit. While analyses of the effect of land use categories as an additional predictor on all sample points indicated significant differences between the coefficients across land use categories the effect of size is relatively low. A notable exception is the land use class of agroforestry, which was clearly distinct from the other models. Effect of plots indicate, however, that even the small differences between coefficients across the land use categories led to important changes in prediction. Within a model class, coefficients always had the same sign and of the same order of magnitude. For models of type II, the inclusion of the interaction between dbh and total height always was selected based on the lower AICc. For the other categories wood density was included in the models in addition to the other two main effects and the interaction between dbh and total height. For forest land and grassland, the interaction between dbh and wood density was also selected based on AICc.

The basic wood density (ρ) was not a good predictor for the estimation of AGB in agroforestry system (cashew plantation). In cashew plantations, big trees i.e cashew trees over 45 years old tend to lose their wood ignition followed by the observed decrease of wood density for bigger cashew trees. In the available 25 cashew trees, wood density was high for cashew trees with an age of 10 to 20 years.

Table 3. 15 Parameters and expressions of the allometric models generated using dbh (cm), height H (m) and ρ (g.cm^{-3})

Models	LUCa	Intercept	DBH	H	DBH:H	ρ	DBH:ρ	AIC	Expl. Dev.	Nagelkerke
	Coefficients	β_0	β_1	β_2	β_3	β_4	β_5			
I		$\dot{\beta}_0$ +	$\dot{\beta}_1(DBH)$							
	Forest land	2.391980*** (0.082228)	0.111911*** (0.003528)					1921.3	0.82	0.89
	Grassland	2.219779*** (0.092797)	0.114745*** (0.004002)					895.75	0.90	0.94
	Cropland	2.751514*** (0.072229)	0.091492*** (0.002608)					1981.3	0.84	0.91
	Settlements	2.454958*** (0.091445)	0.091898*** (0.003292)					636.64	0.91	0.95
	Agroforestry	2.563685*** (0.137175)	0.077676*** (0.004729)					241.67	0.92	0.95
II	$ln\,(AGB) =$	β_0 +	$\beta_1(DBH)$ +	$\beta_2(H)$ +	$\beta_3(DBHxH)$					
	Forest land	-0.051323 (0.178402)	0.160755*** (0.009200)	0.456829*** (0.029571)	-0.011051*** (0.001321)			1745.9	0.93	0.96
	Grassland	-0.115578 (0.227236)	0.177817*** (0.010732)	0.439903*** (0.040451)	-0.012521*** (0.001474)			821.11	0.96	0.98
	Cropland	0.0871685 (0.1495242)	0.1549490*** (0.0062096)	0.4660558*** (0.0251691)	-0.0113066*** (0.0007811)			1818.4	0.94	0.97
	Settlements	0.570740* (0.257908)	0.153706*** (0.011535)	0.329399*** (0.043811)	-0.010279*** (0.001639)			607.38	0.95	0.97
	Agroforestry	0.361587 (0.444254)	0.136600*** (0.015331)	0.403086*** (0.085069)	-0.010145*** (0.002141)			226.77	0.96	0.98
III	$ln\,(AGB) =$	β_0 +	$\beta_1(DBH)$ +	$\beta_2(H)$ +	$\beta_3(DBHxH)$ +	$\beta_4(\rho)$ +	$\beta_5(DBHx\rho)$			
	Generic	-0.7654108*** (0.1091666)	0.1573235*** (0.0042834)	0.4238142*** (0.0155108)	-0.0108973*** (0.0005404)	1.3500342*** (0.1004703)		2300.2		
	Agroforestry	Model reduced to the type II model								
	Forest land	-0.529352* (0.218806)	0.153447*** (0.009621)	0.421777*** (0.022671)	-0.011862*** (0.001007)	0.838169** (0.285044)	0.024398* (0.011265)	1645.1	0.96	0.98

Grassland	-0.406853 (0.276970)	0.146300*** (0.013038)	0.418648*** (0.028276)	-0.011198*** (0.001026)	0.729644* (0.366277)	0.027054° (0.015229)	757.26	0.98	0.99
Cropland	-0.7272044*** (0.1278645)	0.1501417*** (0.0045440)	0.4212572 *** (0.0185620)	-0.0103647*** (0.0005729)	1.4462214*** (0.1095952)		1709.1	0.97	0.98

Settlements -0.031603 0.150500*** 0.341267*** -0.010006*** 0.938432*** 597.9 0.96 0.98 (0.284948) (0.010299) (0.039210) (0.001463) (0.260039)

Note: The coefficients are provided at the link scale. The log-link was used for fitting the gamma glm. The ':' operator represents the interaction between both involved variables. Standard error is provided in parenthesis. The sample size differed by land use category: agroforestry: 25, forest: 181, cropland: 178, settlements: 63, grassland: 90. AGB = Aboveground biomass based on dry weight (kg/tree). The statistical analyses are significant at 95% confidence interval. ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; and non-significant, °$p > 0.05$.

3.3.5 Comparing the equations to previously published equations

We could only compare our allometric models for forest lands with previous published allometric equations due to lack of allometric equations for cropland, grassland and settlements. We therefore compared only the models for forest land and the generic model with results from Brown *et al.* (1997), Chave *et al.* (2005), Chave *et al.* (2015) and Jose (2010). Equations developed by these authors were chosen in the global dry forest region for comparison. The results were in line with all mentioned equations in terms of mean deviation of the observed aboveground biomass at the stand tree level (Table 3.16).

Table 3. 16 The average deviation of various models compared to the models type of the present study in each LUCa

LUCa	Previous studies				Present study		
	Brown *et al.* (1997)	Chave *et al.* (2005)	Jose (2010)	Chave *et* (2015)	Models type *al.* I	II	III
	Average deviation δ (%)						
Forest land	25.02	9.04	26.41	14.87	21.67	8.64	4.77
Grassland	34.23	6.54	35.73	12.69	11.88	5.00	2.34
Cropland	29.30	10.21	30.77	14.74	24.50	10.06	5.26
Agroforestry	-	-	-	-	8.00	3.75	-
Settlements	60.93	9.70	62.77	15.46	12.40	7.30	6.35
Generic	-	9.00	-	14.19	-	-	5.34

Note: Model type I is function of dbh, model II is function of dbh and height and the model type III is function of dbh, height and wood stock.

The model type I, which was only based on dbh revealed an average deviation of 21.67 % for forest land whereas equations based on dbh for Brown *et al.* (1997) and Jose (2010) showed respectively 25.02 and 26.41 % of the average deviation from the observed above ground biomass. The same analysis was done with the model type II and III in comparison with the previous studies when dbh was not the only predictor. Model type III revealed an average deviation of 4.77 % for forest land whereas Chave *et al.* (2005) and Chave *et al.* (2015)

respectively presented 9.04 and 14.78 %. This confirmed the good performance of the model that could be used to estimate aboveground biomass at the stand tree level in the Sudan Savannah ecosystems in West Africa.

3.3.6 Aboveground biomass stock at the basin level

The mean biomass stock and attached standard error varied from 3.28 ± 0.31 to 204.92 ± 57.69 $Mg.ha^{-1}$ at 95 % confidence interval with the low ($Mg.ha^{-1}$) biomass stock within the cropland and the highest ($Mg.ha^{-1}$) biomass stock in plantation emphasizing the importance of mitigation strategy in the climate change debate. The large uncertainty of plantations can be explained by the differences in age structure as explained already. Since the land use data classification used could not separate between young and old cashew tree plantations we unfortunately have to deal with this high uncertainty. The biomass stock map was generated from the best equations obtained for each LUCa. The map in Figure 3.8 shows the LUC types and the biomass stock at the basin level. Information on uncertainty for biomass stock can be found in Table 3.17.

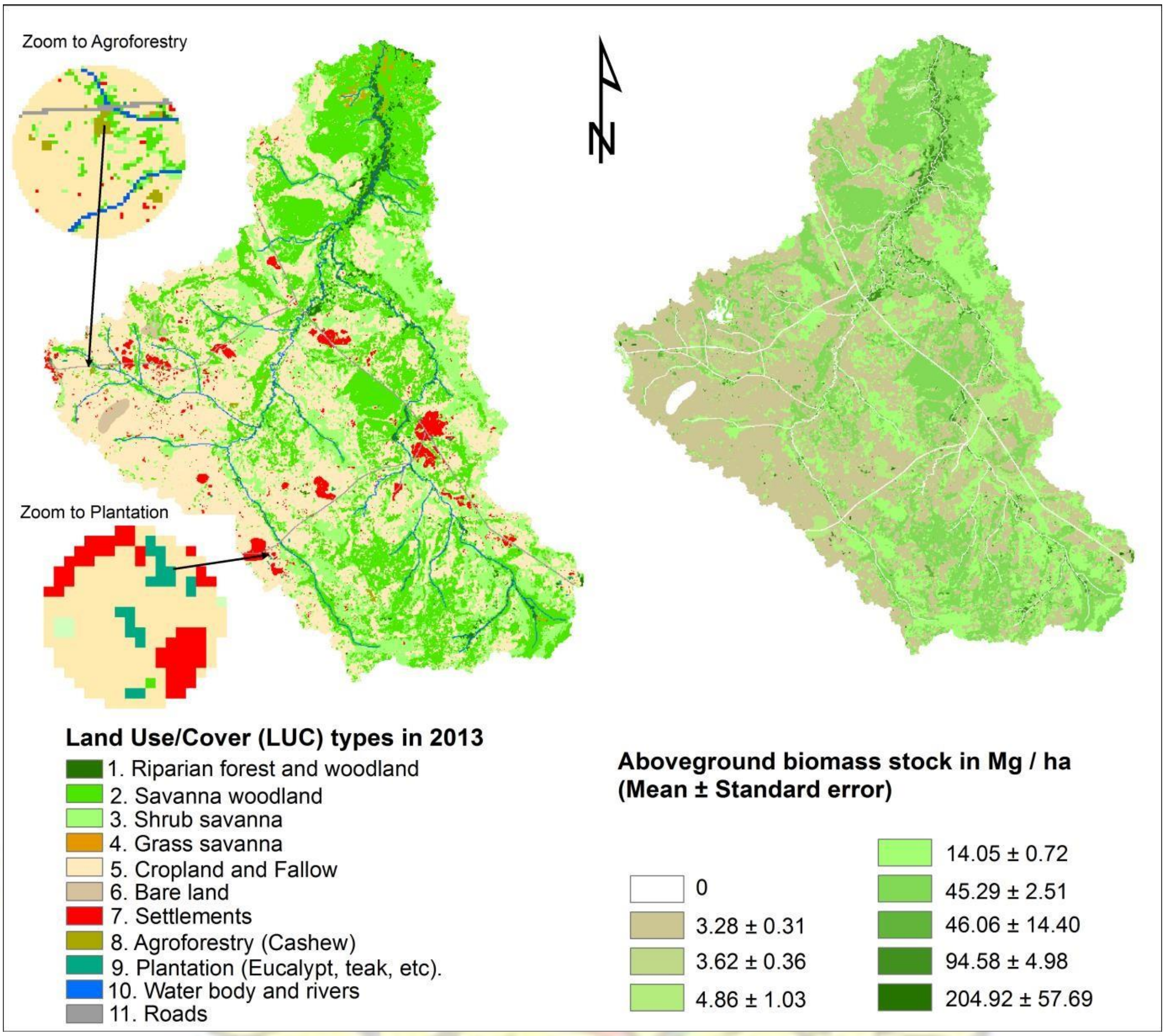


Figure 3. 8 The land use/cover classes and biomass stock at the basin level

Note: The mean biomass stock was expressed in $Mg.ha^{-1}$. The total biomass stock in each LUC is presented in Table 3.17

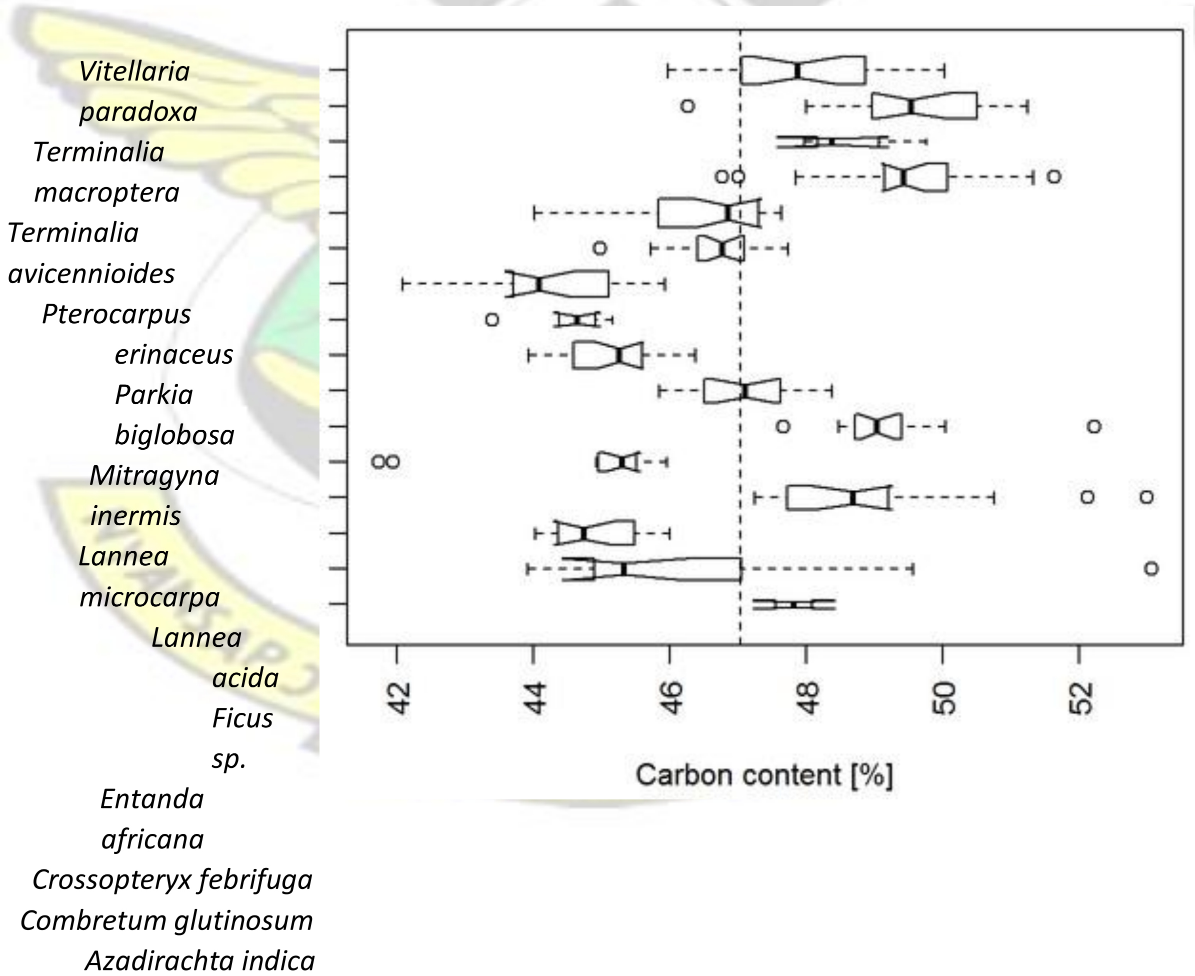
Table 3. 17 Aboveground mean biomass stock ($Mg.ha^{-1}$) and total biomass stock (Mg) with the sample plot data and attached uncertainty

LUC / LUCa	Range of Biomass stock ($Mg.ha^{-1}$) min	max	Mean biomass stock in $Mg.ha^{-1}$ and (S.E.)	Percentage error (% error)	Total biomass stocks (Mg)
		Forest land			**340534.70 ±36445.4**
Riparian forest and woodland	76.29	120.22	94.58 (4.98)	(10.33)	32271.87±334.74
Savanna Woodland	27.22	69.84	45.29 (2.51)	(10.89)	248050.22±27019.98
Shrub Savanna	6.47	25.14	14.05 (0.72)	(10.11)	60212.61±6090.67
		Grassland			**349.66±68.81**
Savanna grassland	0.06	9.20	3.62 (0.36)	(19.68)	349.66±68.81
		Cropland			**26409.82±5024.04**
Cropland and Fallow	0.07	9.32	3.28 (0.31)	(19.02)	26409.82±5024.04
		Settlements			**2375.84±988.13**
Settlements	0.86	9.60	4.86 (1.03)	(41.59)	2375.84±988.13
		Agroforestry			**1132.73±584.46**
Cashew plantation	10.74	211.19	46.06 (14.40)	(61.28)	1132.73±584.46
		Plantation			**3138.20±1777.35**
Eucalyptus grandis	7.69	695.20	204.92 (57.69)	(55.17)	2819.78±1556.44
Tectona grandis	32.41	232.75	162.00 (64.88)	(78.50)	145.80±114.46
Azadirachta indica	64.45	240.53	179.62 (57.61)	(62.86)	129.33±81.30
Gmelina arborea	10.39	34.39	25.17 (7.46)	(58.09)	43.29±25.14

Note: The minimum (min) and maximum (max), the mean biomass stock and its stand error (SE), the confidence interval (CI) at 95 % with its percent error and the total biomass at each LUC type / LUCa were illustrated. The age of plantations and agroforestry system varied from 5 to 45 years old which explained the large percentage error obtained from their plots data. The area of each LUC was provided in Table 3.11

3.3.7 Carbon and nitrogen contents of dry matter of the main wood tree species

The results of the carbon and nitrogen content of the stem wood samples of the main species of the basin in this Sudan Savannah environment are presented in Table 3.18. The species which had the high mean carbon fraction of dry matter and related standard error were *Terminalia macroptera* (49.43±0.24), *Pterocarpus erinaceus* (49.43±0.27), and *Crosopteryx febrifuga* (49.17±0.21). The species that exhibited the least carbon fraction was *Combretum glutinosum* (41.73 %) and the highest value was obtained with *Acacia seyal* (53.07 %). The estimated mean with attached standard error varied from 44.28±0.209 to 49.43±0.27. The overall mean or the mean of mean of the stem wood samples was 47.01±0.28 %. The obtained mean value is comparable to the IPCC (2006) default value of 47 %, when dealing with the Tier 1 approach.



Anogeissus leiocarpa
Acacia seyal
Acacia gourmaensis

Figure 3. 9 Boxplot showing the distribution of carbon content by tree species However, our results revealed that some species have their carbon higher than 47 % and some carbon content lower than 47 % (Table 3.18 and Figure 3.9) and confirmed the relevance of using higher Tier for carbon accounting. This default IPCC (2006) values might over or under estimate the carbon stocks of the ecosystem or any land use category (LUCa).

The main question to be asked was which default value to use 0.47 or 0.5 when using Tier 1 for carbon accounting? The use of local data (Tier 3) in this study resulted in greater accuracy level (see Table 3.19 for uncertainty) in estimating carbon stock. In addition the greater number of samples size (277) for the estimation of carbon content helped to discover the uncertainty level of each default value applied for the mean biomass stock in each LUC type. The application of the default carbon content value of 0.5 to convert the mean biomass stock into the mean carbon stock for each LUC type, overestimated the mean carbon stock for all LUC types. The use of the default value of 0.5 resulted in overestimation of the mean biomass stock to the mean carbon stock by 5.52 % (for riparian forest and woodland), 6.54 % (for savanna woodland), 6.41 % (for shrub savanna), 8.21 % (for grassland), 7.6 % (for cropland and fallow), 5.53 % (for settlements), 7.65 % (for agroforestry system) and 4.72 % (for plantation). The application of the coefficient 0.47 to convert the mean biomass stock to the mean carbon stock slightly overestimated biomass stock by 0.15 % (for savanna woodland), 0.54 % (for shrub savanna), 1.72 % (for grassland), 1.14 % (for cropland and fallow), and 1.19 % (for agroforestry) and underestimated by 0.81 % (for riparian forest and woodland), 0.80 % (for settlements) and 1.55 % (for plantation).

It can be concluded that the coefficient 0.47 despite it could not reach the higher level of accuracy in estimating carbon stock like the present case study can be used in the absence of the information about the carbon content of the *in situ* data from the main species of the region. Despite the fact that tree species varied considerably from one region to another for the previous studies the obtained carbon content ranged in the same order with other authors (Guendehou *et al.*, 2012; Hughes *et al.*, 1999; Andreae and Merlet., 2001; Lasco and Pulhin, 2003; Feldpausch *et al.*, 2004; McGroddy *et al.*, 2004).

The nitrogen content of the main species varied from 0.08 % to 0.58 %. The mean fraction of nitrogen in dry matter varied from 0.128±0.012 (SE) to 0.357±0.016 % (SE). The mean of mean fraction of dry matter nitrogen content was estimated to be 0.229±0.016 %. The species with high nitrogen content are *Acacia seyal*, *Acacia gourmensis*, *Ficus sp*, *Entanda africana* and *Lannea microcarpa*. The impact of human disturbance on these tree species could contribute to the high level of N_2O emissions into the atmosphere explaining the high Global Warming Potential of this gas which is 298 times that of CO_2.

The C/N ratio ranged from 80.71 (minimum) to 570.05 (maximum). The mean C/N ratio for these species and related standard error ranged from 135.97±6.75 to 386.52±28.28. The C/N ratio was high for all tree species and confirmed thereby their terrestrial origin. C/N ratios in the range 4-10:1 are usually from marine sources, whereas higher ratios are likely to come from a terrestrial source (Gray and Biddlestone, 1973). Therefore, the C/N ratio serves as a tool for understanding the sources of sedimentary organic matter, which can lead to information about the ecology, climate and ocean circulation at different times in the Earth's history (Ishiwatari and Uzaki, 1987).

Table 3. 18 Carbon (C) and nitrogen (N) content of dry matter of stem wood of the main species of the basin

	n	Carbon (C) contents (% dm)			Nitrogen (N) contents (% dm)			DBH (cm)		C/N ratio		
Trees species		min	max	Mean (SE)	min	max	Mean (SE)	min	Max	min	max	Mean (SE)
Terminalia macroptera	19	46.267	51.241	49.474 (0.266)	0.108	0.303	0.192 (0.013)	9.3	40.7	160.50	428.39	281.81 (18.33)
Terminalia avicennioides	03	47.971	49.759	48.70 (0.53)	0.155	0.181	0.168 (0.007)	16.6	24	265.03	312.16	289.96 (13.67)
Acacia seyal	14	43.928	53.071	46. 50 (0.684)	0.13	0.583	0.290 (0.037)	7.6	34.4	80.71	357.6	194.24 (21.72)
Acacia gourmaensis	02	47.55	48.09	47.824 (0.269)	0.297	0.349	0.323 (0.025)	13.4	19	160.11	137.80	148.95 (11.15)
Combretum glutinosum	11	41.737	45.959	44.72 (0.438)	0.14	0.358	0.241 (0.020)	8	32	125.94	320.95	201.36 (19.15)
Pterocarpus erinaceus	21	46.779	51.645	49.438 (0.278)	0.164	0.427	0.242 (0.014)	6.9	44.7	110.09	295.09	216.28 (10.63)
Anogeisus leiocarpus	16	44.037	46.003	44.917 (0.167)	0.08	0.273	0.128 (0.012)	6.9	32.4	161.30	570.05	386.52 (28.28)
Mitragyna inermis	18	44.978	47.74	46.724 (0.174)	0.177	0.354	0.243 (0.011)	7	34.5	129.46	262.19	199.40 (9.23)
Lannea microcrapa	20	42.091	45.938	44.282 (0.209)	0.148	0.405	0.273 (0.015)	7	50.3	110.95	306.08	173.47 (11.14)
Lannea acida	6	43.408	45.164	44.526 (0.248)	0.14	0.386	0.265 (0.035)	10.8	36	115.60	320.80	186.92 (30.61)
Ficus sp	21	43.931	46.38	45.153 (0.139)	0.16	0.427	0.294 (0.015)	8.6	52.7	105.3	286.90	163.14 (9.83)
Crosopteryx febrifuga	18	47.662	52.229	49.172 (0.217)	0.118	0.306	0.182 (0.014)	5.6	30.6	161.14	417.54	295.68 (20.50)
Entada africana	15	45.852	48.377	47.098 (0.191)	0.242	0.475	0.357 (0.016)	8.4	27.6	100.09	196.18	135.97 (6.75)
Parkia biglobosa	23	44.02	47.636	46.516 (0.214)	0.127	0.396	0.201 (0.013)	8.6	62.4	119.40	358.43	247.85 (12.35)
Vitelaria paradoxa	22	45.972	50.032	47.942 (0.228)	0.13	0.337	0.228 (0.010)	8	60	136.41	367.23	220.11 (11.37)
Azadirachta indica	16	47.253	52.999	49.005 (0.413)	0.104	0.302	0.177 (0.014)	8.8	50.5	162.43	474.64	302.38 (22.53)
Anacardium occidentale	25	44.928	47.693	46.446 (0.138)	0.103	0.32	0.161 (0.011)	9.2	57.9	146	441.34	375.79 (17.58)
Eucalyptus grandis	7	47.018	49.031	47.744 (0.350)	0.125	0.191	0.157 (0.011)	5.7	29.2	247.25	376.14	310.57 (21.94)

Note: % dm = percentage of C and N in dry matter. n = Number of trees selected. The stem wood samples of selected trees were extracted at 1.3 m of the ground. DBH range = Range of diameter at breast height of sampled tree species. Figures in bracket represent the standard error (SE) of the mean

3.3. 8 Carbon and nitrogen stock at the basin level in 2013

The results of this study found respectively a total of 175347.75 ± 21042.48 (CI) and 875.53 ± 101.45 (CI) Mg of carbon and nitrogen stocks in 2013 at 95 % confidence interval. The mean carbon stock in Mg $C.ha^{-1}$ and its standard error were 44.81±2.38 (riparian forest and woodland), 21.35±1.16 (savanna woodland), 6.57±0.35 (shrub savanna), 1.67±0.15 (savanna grassland), 1.52±0.14 (cropland and fallow), 2.30±0.48 (settlement), 21.39±6.68 (agroforestry system) and 97.83±27.55 (plantation). The carbon stock was higher in settlements than in cropland and savanna grasslands and confirms our observation in the field which tested that people aimed at planting trees within settlements. This human action confirmed the importance of the mitigation strategy to climate change in line with the implementation of Kyoto protocol. The analysis of the carbon stock in each LUC revealed that the carbon stock in riparian forest and woodland was higher than that obtained in the agroforestry system based cashew plantation. In fact despite the fraction of dry matter of stem wood of cashew plantation (*Anacardium occidentale*) which ranged from 44.928 to 47.693 % with a mean fraction of dry matter and its standard error of 46.446 ± 0.138 % its stock is lower than the riparian forest and woodland explaining the tree spacing within the cashew plantation which was an example of mixing crops and trees. The tree stock per hectare in cashew plantation was estimated at 300 trees whereas it was 1397 trees per hectare in riparian forest and woodland. The amount of carbon lost when a patch of riparian forest and woodland was cleared for farming activity cannot unfortunately be completely compensated during the growth period of cashew plantation even if it has reached the climax. We evaluated this loss to be 23.42 Mg $C.ha^{-1}$. Despite the loss, it is important to adopt agroforestry after riparian forest has been cleared to the detriment of cropland because in the absence of cropland the carbon stock lost is equal to a carbon stock of 44.81±2.38 Mg $C.ha^{-1}$.

Figure 3.10 shows the spatial distribution of carbon and nitrogen stock at the basin level.

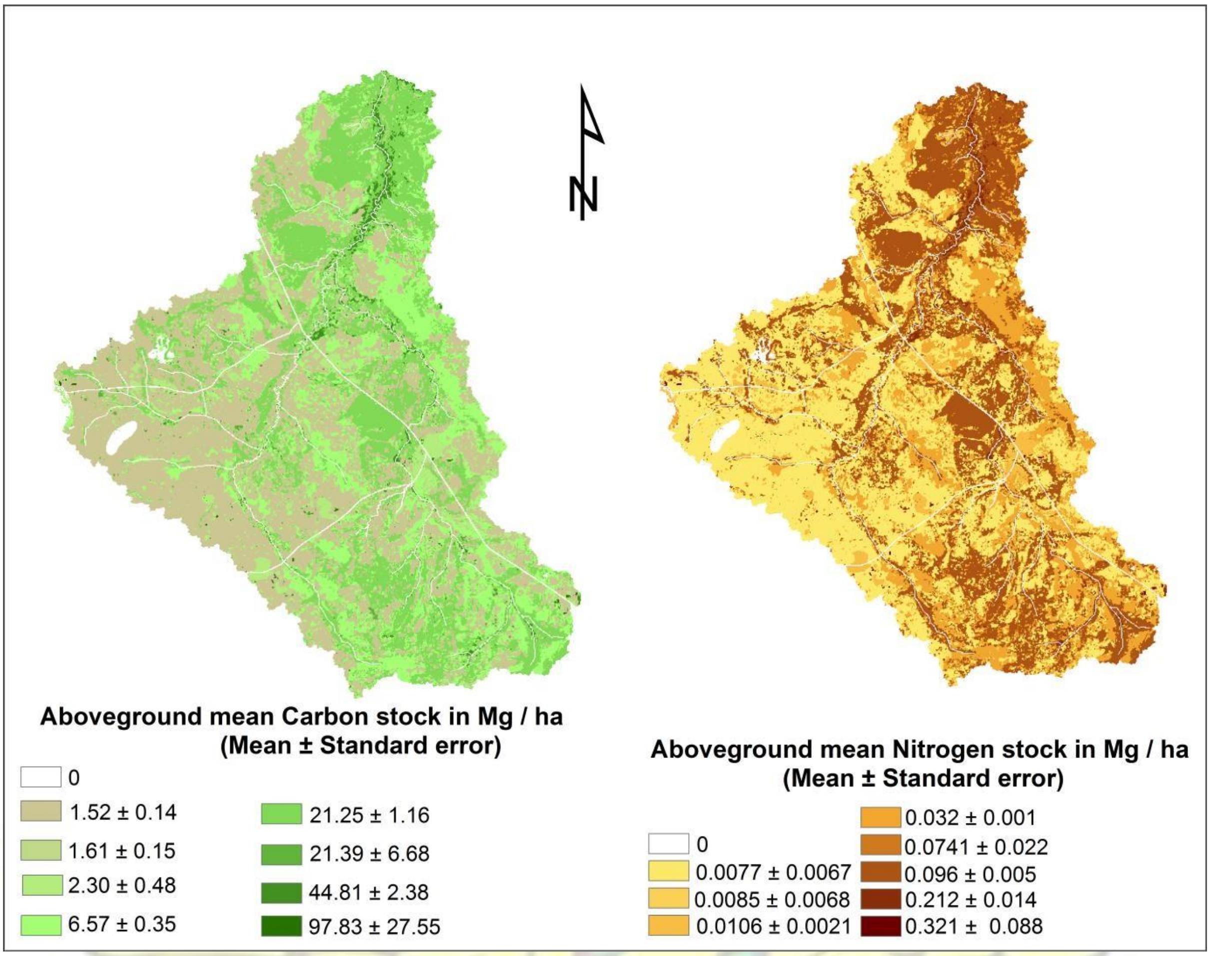


Figure 3. 10 Carbon and nitrogen stock at the basin level in 2013

The analysis of the same results from Table 3.20 showed the mean nitrogen stock and related standard error ranged from 0.007±0.0067 (cropland) to 0.321±0.088 (plantation) $Mg.ha^{-1}$ of N.

Table 3. 19 Mean Carbon stock (Mg C.ha^{-1}) and total carbon stocks (Mg) with the sample plot data and attached uncertainty

LUC / LUCa	Descriptive statistic				
	Range of carbon stock (Mg C.ha^{-1})		Mean carbon stock (Mg C.ha^{-1}) (S.E.)	Percentage error (% error)	Total carbon stocks (Mg)
	min	max			
		Forest land			**159841.01±17094.11**
Riparian forest and woodland	35.46	57.27	44.81 (2.38)	(10.42)	15291.86±1593.81
Savanna Woodland	12.50	31.90	21.25 (1.16)	(10.77)	116401.70±12539.08
Shrub Savanna	2.76	12.22	6.57 (0.35)	(10.52)	28147.43±2961.21
		Grassland			**161.55±29.86**
Savanna grassland	0.03	2.98	1.67 (0.15)	(18.48)	161.55±29.86
		Cropland			**12272.24±2326.92**
Cropland and Fallow	0.03	4.33	1.52 (0.14)	(18.96)	12272.24±2326.92
		Settlements			**1125.66±466.99**
Settlements	0.41	4.57	2.30 (0.48)	(41.48)	1125.66±466.99
		Agroforestry			**442.91±271.41**
Cashew plantation	4.99	98.08	21.39 (6.68)	(61.28)	442.91±271.41
		Plantation			**1504.36±853.17**
Eucalyptus grandis	3.67	331.91	97.83 (27.55)	(55.19)	1346.27±743.14
Tectona grandis	16.52	108.70	82.62 (33.09)	(78.50)	74.36±58.37
Azadirachta indica	31.58	117.87	88.02 (28.23)	(62.86)	63.37±39.84
Gmelina arborea	4.88	16.16	11.82 (3.50)	(58.06)	20.34±11.81

Note: The minimum (min) and maximum (max), the mean carbon stock or emission factor and its stand error (S.E.), the confidence interval at 95 % with its percent error and the total carbon stocks at each LUC type / LUCa or activity data were illustrated. The age of plantations and agroforestry system varied from 5 to 45 years which explained the large percentage error obtained from their plots data. The area of each LUC was provided in the Table 3.11

Table 3. 20 Mean Nitrogen stock (Mg N.ha^{-1}) and total nitrogen stocks (Mg) with the sample plot data and attached uncertainty

LUC / LUCa	Descriptive statistic: Range of nitrogen stock (Mg.ha^{-1} of N) min	max	Mean nitrogen stock (Mg.ha^{-1} of N) (S.E.)	Percentage error (% error)	Total nitrogen stocks (Mg)
		Forest land			**740.37±85.05**
Riparian forest and woodland	0.170	0.285	0.212 (0.014)	(13.23)	72.41±9.58
Savanna Woodland	0.045	0.160	0.096 (0.005)	(11.67)	530.79±61.97
Shrub Savanna	0.008	0.064	0.032 (0.001)	(9.81)	137.16±13.46
		Grassland			**0.825±0.12**
Savanna grassland	0.0001	0.0178	0.0085 (0.0068)	(15.73)	0.825±0.12
		Cropland			**62.57±10.57**
Cropland and Fallow	0.00018	0.0252	0.0077 (0.0067)	(16.90)	62.57±10.57
		Settlements			**5.20±2.03**
Settlements	0.0017	0.0201	0.0106 (0.0021)	(38.99)	5.20±2.03
		Agroforestry			**1.53±0.90**
Cashew plantation	0.017	0.340	0.0741 (0.022)	(58.63)	1.53±0.90
		Plantation			**5.01±2.79**

Eucalyptus grandis	0.012	1.091	0.321 (0.088)	(54.06)	4.42±2.39
Tectona grandis	0.058	0.418	0.291 (0.115)	(77.61)	0.26±0.20
Azadirachta indica	0.114	0.425	0.317 (0.101)	(62.64)	0.23±0.14
Gmelina arborea	0.024	0.079	0.058 (0.017)	(58.05)	0.10±0.05

Note: The minimum (min) and maximum (max), the mean nitrogen stock or emission factor and its stand error (S.E.), the confidence interval at 95 % with its percent error and the total nitrogen stocks at each LUC type / LUCa or activity data were illustrated. The age of plantations and agroforestry system varied from 5 to 45 years which explained the large percentage error obtained from their plots data. The area of each LUC was provided in the Table 3.11

3.4 Conclusions

The results from this study help to close the existing knowledge gap with respect to biomass, carbon and nitrogen stocks in the Sudan Savannah environment. The fitted generalized linear model equations fitted on local data can be useful for future scientific works in the Sudan Savannah environment generally populated by the determined main species in the present study. The estimation of above ground biomass, carbon and nitrogen stock in each land use cover category are of great importance for carbon balance calculations in the Sudan Savannah in West Africa. The work also provides a database in wood density of the main species of the Sudan Savannah zone, the related biomass expansion factor, the biomass, carbon and nitrogen stock in each land use cover class that would be an indispensable information tool for carbon accounting programme related to the implementation of the Kyoto Protocol and

REDD+ initiatives in the Sudan Savannah environment.

CHAPTER IV: DRIVERS OF LAND USE CHANGE AND MITIGATION STRATEGIES

4.1 Introduction

Rural households pursue a wide range of livelihood strategies in developing countries (Fang Haiyang, 2012). Some households diversify their livelihood strategies while others rely on one or more activities. The sustainable livelihood assets (SLA) framework first established by the Department for International Development (DFID) of the United Kingdom has been adopted by many domestic organizations and scholars since 2000. The concept of sustainable livelihoods is increasingly important in research about local and regional development, poverty alleviation, rural agriculture development and resource management. However, the level and degree of reliance on livelihood capital differ across households (Bebbington, 1999) and the impact on the environment is perceived differently. According to Fang and Haiyang (2012) livelihood stability would force the related policy to act co-ordinately while eradicating poverty and promoting resource sustainability. Factors that contribute to the economic reliance of households on a particular economic activity in general and on livelihood capital in particular may vary depending upon the type of resource endowment, household demographic and economic characteristics, as well as exogenous factors such as markets, prices, policies and technologies (Brown *et al.,* 2006). In this regard, understanding factors that determine variations in choice in relation to household activity and, particularly, understanding the reliance of these choices on livelihood capital is essential for both conservation and development-targeted policies (Jonathan, 2000).

The security and quality of the livelihood of farmers is of paramount concern in rural areas of Benin and especially in the Dassari Basin. Land use scenarios development and impact assessment on the future emissions of carbon dioxide and nitrous oxide cannot be well understood without any particular attention on the livelihood of farmer's communities of Dassari Basin who mostly depend on land resources.

This chapter characterizes household's agents based on factors that influence a household's decision making and identifies the level of the mitigation strategy to climate change. In addition, the findings of the characterization were linked to the BEN-LUDAS model and used to parametrize the model.

4.2 Geographic location and boundary of the study area

Dassari Basin is situated in the North-West of Benin (Figure 4.1) and covers an area of 192.57 km^2. The site is located between latitudes 10°44'08'' and 10° 55' 42'' North and longitudes 1° 01' 32'' and 1°11'30'' East.

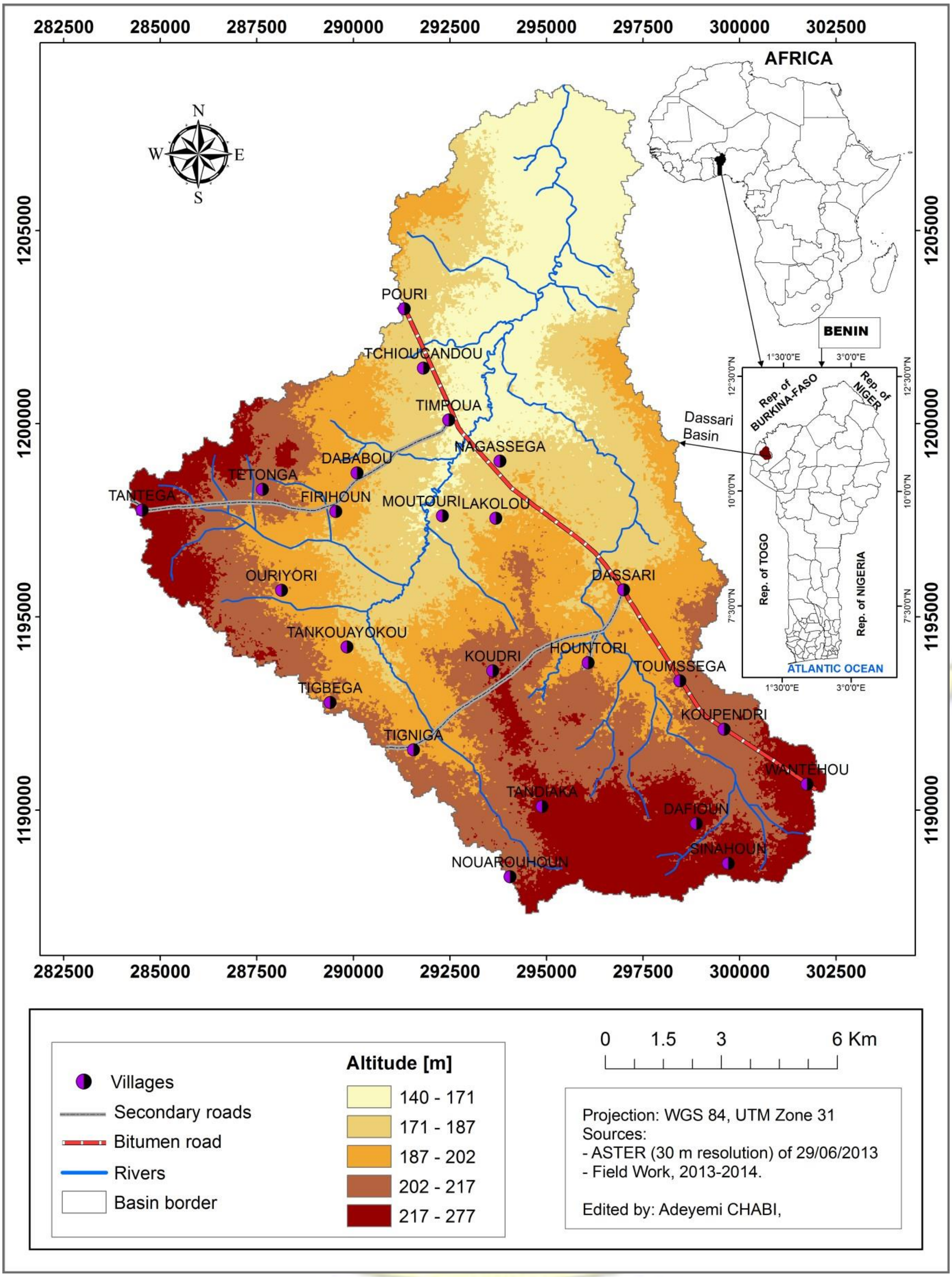


Figure 4. 1 Geographic location of Dassari Basin in North-West of Benin (Field work, 2014)

4.3 Socio-economic setting of the study site

Benin Republic has 77 municipalities (administrative units). The West Atacora is part of North–West Benin with four municipalities, namely Materi, Tanguieta, Boukoumbe and Cobly. The Dassari site (Figure 4.1) got the name from Dassari village, which is one subcommune of Materi commune. This Dassari sub-commune comprises of more than 10 villages and hamlets. The villages that belong to the catchment were taken into account for the socio-economic field investigation. Pattern of the population size of these four communes is presented in Table 4.1. Analysis of the population revealed an increment in population since the first assessment of the population in 1979 and the last one in 2013. According to INSAE (2013) the population growth rate of Materi commune was 1.69 per year, increase to 3.65 % and then decrease to 2.54 % during the periods 1972-1992, 1992-2002 and 2002-2013 per year respectively. This situation can be explained by migration as underlined by Sow *et al.* (2014).

Table 4. 1 Population of West Atacora commune in Benin

West Atacora Municipality	**Population of**				**Population growth rate (%)**		
	1979	1992	2002	2013	1979-1992	1992-2002	2002-2013
Materi	46274	58516	83721	111003	1.69	3.65	2.54
Tanguieta	27242	40430	54719	73731	2.86	3.07	2.69
Boukoumbe	47049	58196	60568	83147	1.53	0.4	2.86
Cobly	26796	38382	46660	68955	2.6	1.97	3.53

Source: INSAE (2003; 2013)

The analysis of the population growth of these communes from 1979 to 2013 shows an exponential increase (Figure 4.2). This population growth can have a negative impact on the socio-ecological system of the Dassari Basin such as the pressure on forest land, decrease of soil fertility and an increase of poverty.

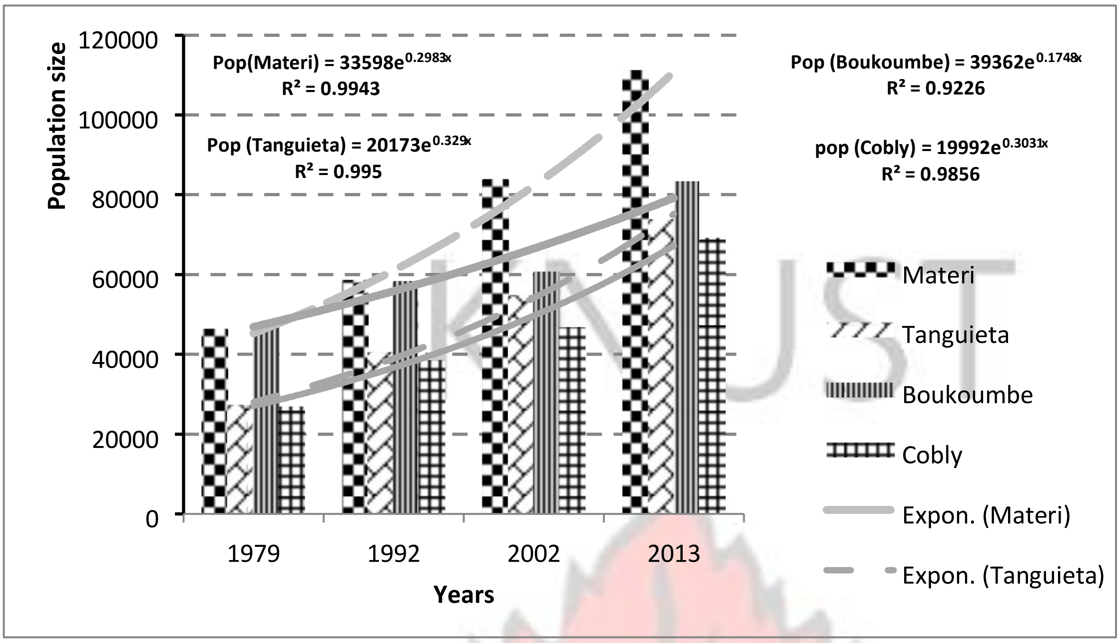


Figure 4. 2 Population trends of West Atacora from 1979 to 2013 Table 4. 2 Projection of the population to 2,025

Municipality	Population in 2013	Population growth rate (Tx in %) 2002-2013	Population trend equations	Projection in 2025 based on equations	Projection based on Tx for 2025
Materi	111,003	2.54	$33{,}598e^{0.2983x}$	149,301	149,987
Tanguieta	73,731	2.69	$20{,}173e^{0.329x}$	104,517	101,388
Boukoumbe	83,147	2.86	$39{,}362e^{0.1748x}$	94,330	116,629
Cobly	68,955	3.53	$19{,}992e^{0.3031x}$	90,998	104,559

X =1 time scale equal to 10 years

Sources: INSAE (2013) provided raw data (Population in 2013 and population growth rate)

The main activities in this area are agriculture and livestock. Farmer's households represented 98 % (RGPH, 2003) in the rural area, especially in the Dassari Basin. Regarding farming, women were involved in all the value chain of this activity, from ploughing to harvesting, i.e. women thus performed labour in all the processes of farming.

4.4 Methodology

The socio-economic data collection and analysis is illustrated through the flowchart (Figure 4.3). The households' agent's characterization helped to determine the level of human impacts on the environment. The methodological approach is outlined as follows:

- ✓ Systematic sampling (Sample size estimation, sample selection),

- ✓ Questionnaire administration,
- ✓ Socioeconomic data collection and analysis,
- ✓ PCA for the determination of the main factors affecting households agents,
- ✓ Data analysis based hierarchical cluster following by K-mean cluster for the determination of the number of households group evolving in the farming in the basin using PCA scores,
- ✓ Analysis based binary logistic model to estimate factors affecting adoption of agroforestry and plantation by households.

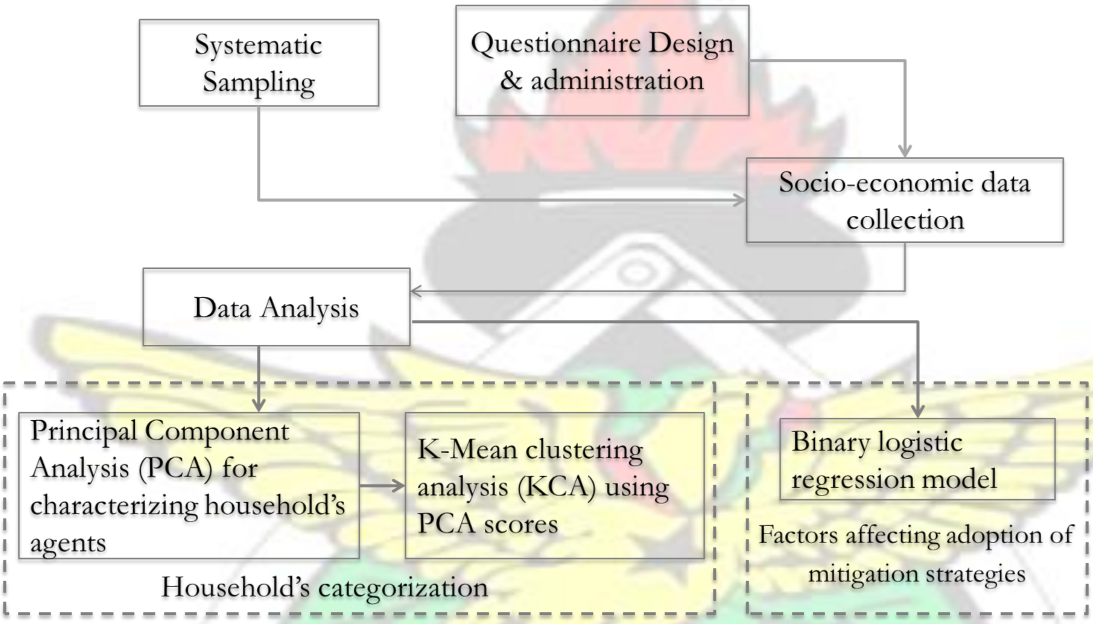


Figure 4. 3 Flowchart showing the approach used for socio-economic data collection and analysis

4.4.1 Households sampling techniques

This section is focused on the sampling design. The households sampling techniques was first based on the analysis of the population trend of Materi (Figure 4.2) commune on which Dassari (the pilot site) is one of the sub-communes. According to INSAE (2013) the proportion of the farmer's households represented 98 % of the total households of the commune with a mean of 7.4 persons per household. Based on this consideration this proportion was used to determine the required number of households to be chosen for investigation or questionnaire administration.

The following formula (Eq. 4.1) (United Nations, 2005) was used for the estimation of households sample size:

$$Nh = \frac{(z_{1-\alpha/2})^2 .\ p\ (1-p)}{d^2} \qquad (4.1)$$

Where:
Nh is the parameter to be calculated and is the sample size in terms of number of households to be selected; $z_{1-\alpha/2}$ is the statistic that defines the level of confidence desired; here at 5% type I error ($p<0.05$) it is 1.96 p is the proportion of the total population accounted for by the target population ($p=0.98$); d is absolute error or precision (has to be decided by the researcher). 0.02 (2%) was chosen for d.

Finally a total of 188 households were estimated based on the Eq 4.1. The entire questionnaire was administrated to 187 households. The list of farmers was obtained from the local institution for agricultural development. This list accounted for 510 farmers. The sampling interval was determined based on Eq 4.2.

$$k = \frac{\mathrm{N}}{\mathrm{n}} \qquad (4.2)$$

Where,
k = Sampling interval,
N = The total number of the farmers obtained from the list, (510 farmers) n = The sample size (188)

The estimation of k was equal to 2.71 or 3. The starting point was determined by choosing a random number between 1 and 3. The random obtained was 2. Thus the first selected number in this list was 2, the second 5 and so on till the full selection of the 187 farmers or head of households. These 187 households were selected in 10 villages within 24 villages and hamlets of the basin. The plots of households were surveyed and georeferenced using GPS (Global Position System). A GIS database of upland crops, agroforestry systems and plantations was constructed and mapped (Figure 4.4).

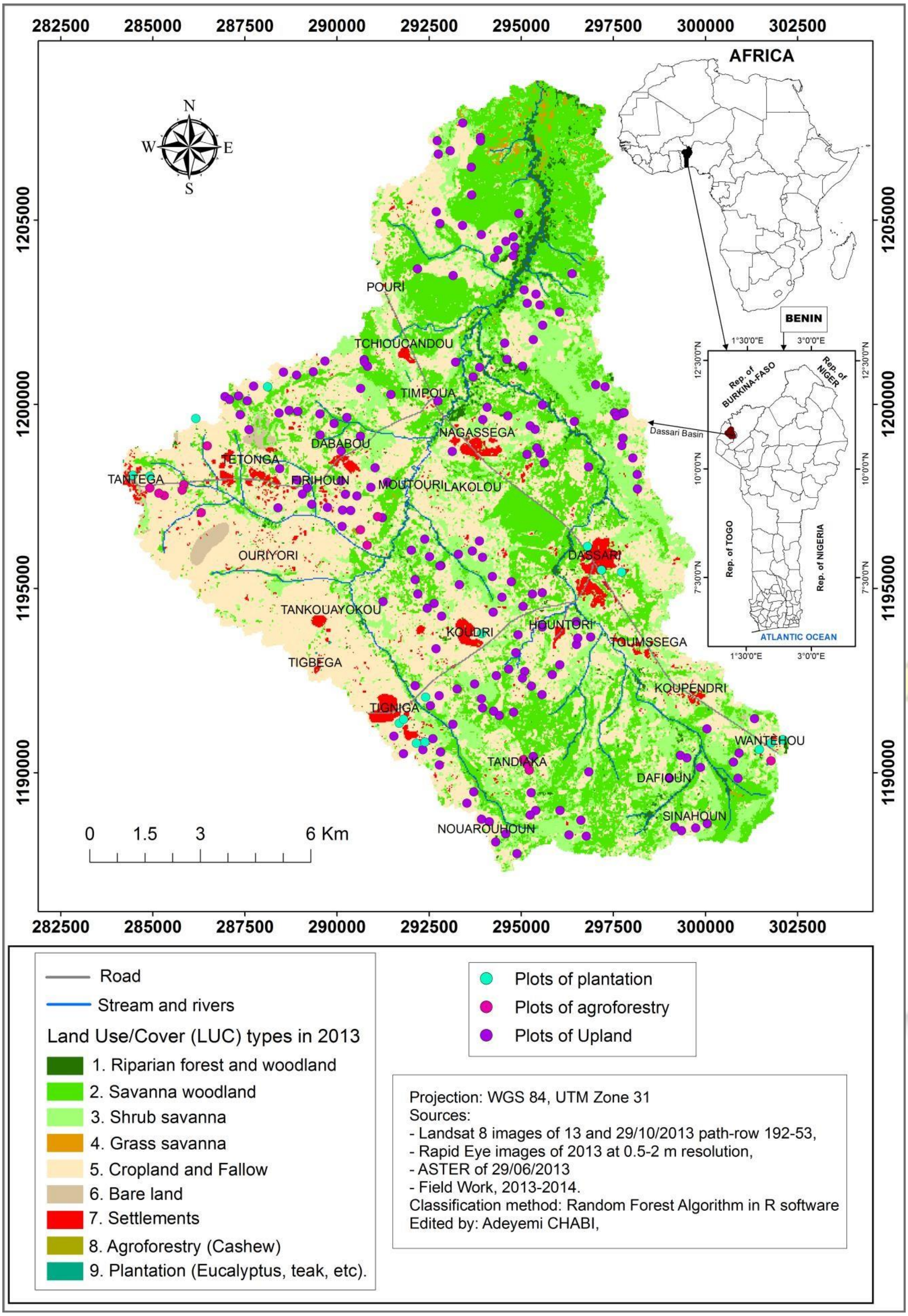


Figure 4. 4 Locations of surveyed holding plots in the study area

4.4.2 Methods for categorizing household agents

a. Concept of sustainable livelihoods framework

According to DFID (Department for International Development) (2000) livelihood strategies comprise the range and combination of activities and choices that people make/undertake in order to achieve their livelihood goals. It should be understood as a dynamic process in which people combine activities to meet their various needs at different times. In the past most efforts have been geared towards application of the sustainable livelihood framework in diverse geographical and sectoral settings (Ellis *et al.,* 2003; Ellis and Biggs, 2000; Hussein, 2002; Bebbington, 1999; Baumann, 2000; Beall and Kanji, 1999; Turton, 2000; Hobley and Shields, 2000).

The livelihood framework includes five core asset categories: human, social, financial, natural and physical capital (DFID, 2000; Campbell *et al.*, 2001). Odero (2002) proposed an extension to the sustainable livelihoods framework by introducing a sixth asset, information capital which was not assessed in the present study.

Within these assets, human capital is perhaps the most important factor (Chivaura and Mararike, 1998; Odero 2002) for the fact that people are both object and subject of development. A feedback loop to the household's organization in the Dassari Basin confirms this assertion. A new household generates the value of two persons for labour availability (household head and wife) at the time of marriage and this number is increasing as soon as the household head gets children or an additional wife. Thus, the livelihood approach states that the type of activity undertaken and the amount of income earned by a household is a function of the assets at its disposal (Barrett *et al.,* 2005; Brown *et al.,* 2006; Fang and Haiyang, 2012).

b. Statistical analyses for discovering grouping criteria and agent groups

Principle Component Analysis (PCA) for characterizing household's agents

Principal component analysis is a powerful tool for reducing a number of observed variables into a smaller number of artificial variables that account for most of the variance in the data set (Kim and Mueller, 1978; Cattell, 1966; Stevens, 1986). With a large number of variables, the dispersion matrix may be too large to study and interpret properly. There would be too many pairwise correlations between the variables to consider. Thus, graphical display of data may also not be of particular help with the obtained 19 variables. To interpret the data in a more meaningful form, it is therefore necessary to reduce the number of variables (19) to a few, interpretable linear combinations of the data assuming that the relation between variables is linear. The variable were centred and scaled prior to the PCA.

The general form for the formula to compute scores on the first component extracted (created) in a principal component analysis was as followed:

$$PC_1 = b_1X_1 + b_2X_2 + \cdots \dots \dots +. b_PX_P \qquad (4.3)$$

Where:
PC1 = the subject's score on principal component 1 (the first component extracted)
b_1 …. b_p = the regression coefficient (or weight) for observed variable p, as used in creating principal component 1
Xp = the subject's score on observed variable, X_i. is i = 1, …., p.

Each linear combination corresponded to a principal component.

Four criteria were used to determine the number of meaningful components for interpretation: the eigenvalue-one criterion, the scree-test, the proportion of variance accounted for and the interpretability criterion. The eigenvalue-one criterion, also known as the Kaiser criterion (Kaiser, 1960) was used to retain and interpret any component with an eigenvalue greater than 1.00. The first six retained component have their eigenvalue higher than 1.00.

With the scree-test (Cattell, 1966) approach the eigenvalue associated with each component was plotted and a "break" between the components with relatively large eigenvalues and those with small eigenvalues were observed. The components that appear before the break are assumed to be meaningful and are retained for rotation; those appearing after the break are assumed to be unimportant and are not retained. According to the proportion of variance accounted for; the cumulative percent of variance of components accounted for at least 70 % were retained. Once the components were selected based on the three outlined criteria, we now observed each component and found if:

- Each of them used the minimum of three variables with meaningful loadings,
- The variables that load on a given component shared the same conceptual meaning,
- The variables that load on different components measured different constructs?
- The rotated factor pattern demonstrated "simple structure".

K-Mean clustering analysis (KCA) using PCA

The cluster analysis (Duda *et al.*, 2000; Hastie *et al.*, 2001; Jain and Dubes, 1998) attempts to pass through data quickly to gain first order knowledge by partitioning data points into disjoint groups such that data points belonging to same cluster are similar while data points belonging to different clusters are dissimilar. One of the most popular and efficient clustering methods is the K-means method (Chris and Xiaofeng, 2004; Hartigan and Wong, 1979; Lloyd, 1957; MacQueen, 1967; Jain and Dubes, 1998; Wallace, 1989) which uses prototypes (centroids) to represent clusters by optimizing the squared error function. They are determined by minimizing the sum of squared errors (Chris and Xiaofeng, 2004).

The cluster analysis was run using the five factors identified in the PCA in the aim to avoid collinearity. Thus, hierarchical cluster was first run using the five factors of the PCA as input.

The results from hierarchical cluster were used to run k-mean cluster. The number of clusters determine in the hierarchical cluster is equal to k in k-mean cluster.

When running k-mean cluster the k means the household's agents groups.

Equation 4.3 was used to determine household agent groups based on the PCA results:

$$\text{Jk} = \sum_{k=1}^{k} \sum_{i \epsilon Ck} (x_i - m_k)^2 \qquad (4.4)$$

Where (x_1, · · ·, xn) = X is the data matrix and mk = Pi∈Ck xi/nk is the centroid of cluster Ck and nk is the number of points in Ck.

From the 28 variable collected within the households, some of them revealed that there are household which were only focused on food production, most of them used cotton production as financial option and in other ways some farmers applied agroforestry or plantation in their plots.

4.4.3 Binary logistic regression model to estimate the likelihood of adoption of mitigation strategies

The willingness to adopt mitigation strategy to climate change by households was estimated based on binary logistic regression model analysis. The model was constructed by an iterative maximum likelihood procedure using SPSS 17 package.

$$\log\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k \qquad (4.5)$$

Where *i* denotes the *i*-th observation in the sample, *Pi* is the predicted probability of adoption, which is coded with 1 (willingness to adopt) or with 0 (not to adopt), $ß_i$ is the intercept term, and $ß_1$, $ß_2$, ..., $ß_k$ are the coefficients associated with each explanatory variable X_1, X_2, ...X_k.

4.5 Results and discussion

4.5.1 Land use decision drivers, model of farmers decision making and mitigation strategies at the farmer's field scale

Conceptual model of farmers decision making and drivers of land use change

The results from questionnaire administration were used to establish the farmers' decision making. The main driving forces outlined from this survey revealed some drivers of land use in the basin. The broad categories of driving forces have been identified (Figure 4.5) using the combination of answers provided from farmers and experts from local agricultural development programmes. These driving forces allowed the determination of the demographic change which was a function of population growth explained by an increase of natality and an increase of the size of households. The demographic change was also explained by migration of young households who moved sometimes from the Materi commune to Nigeria (neighbouring country).

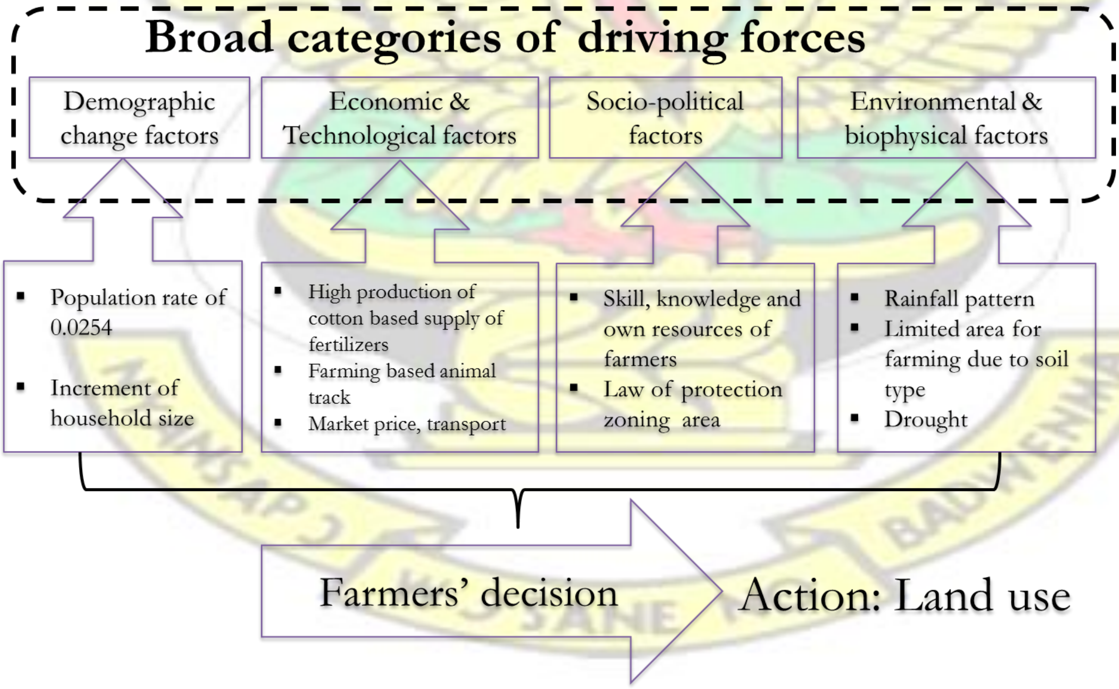


Figure 4. 5 Flowchart showing drivers of land use and model of farmers' decision making

4.5.2 Identification of typological agent groups

a. PCA (Principal Component Analysis) for discovering household agents group The results of PCA for deriving the households typology showed five components with initial eigenvalues higher than 1.0 (Table 4.3). The five components which were used to determine the household agents group explained 75.083 % of the total variance of original variables. The rotated Component Matrix (i.e. loadings or the regression coefficient **b** or weight for observed variable) using Varimax rotation method and Kaiser Normalization of first five principal components allowed a better understanding of what each component meant. The first component is strongly related to holding cotton (b = 0.970), subsidy fertilizer (b=0.970) and income (b = 0.728).

Table 4. 3 Total variance explained by extracted components, using Principal Component Analysis (PCA) as the extraction method

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.457	34.106	34.106	5.457	34.106	34.106	3.103	19.393	19.393
2	2.449	15.304	49.410	2.449	15.304	49.410	2.986	18.665	38.058
3	1.747	10.920	60.330	1.747	10.920	60.330	2.904	18.150	56.208
4	1.346	8.413	68.742	1.346	8.413	68.742	1.624	10.153	66.361
5	1.014	6.340	75.083	1.014	6.340	75.083	1.395	8.722	75.083
6	0.960	5.998	81.081						
7	0.927	5.793	86.874						
8	0.643	4.021	90.895						
9	0.540	3.373	94.268						
10	0.427	2.666	96.934						
11	0.332	2.074	99.008						
12	0.134	0.837	99.845						
13	0.025	0.155	100						
14	0.000	0.000	100						
15	0.000	0.000	100						
16	0.000	0.000	100						

This component had a contribution of 34.10 % for the total variance of the original dataset and confirms the importance of cotton production in the site. Infact, the results from interview revealed that cotton production was mostly used by the farmers of the basin. Infact, this crop contributed to the high pressure on the land and lead to the high deforestation rate. The component was named holding cotton.

The second component (PC2) is most weighted by upland crop (b=0.927), income from upland crop (b=0.921) and total holding (b=0.745). We choose to call this component holding upland crop factor which has 15.3% of the total variance of the variables.

Table 4. 4 Rotated Component Matrix (i.e., loadings) using Varimax rotation method and Kaiser Normalization of first five principal components

Variables	**Principal Components**				
	Holding cotton factor (34.1%)	Holding up crop factor (15.3%)	Labour factor (10.92%)	Mitigation factor (8.41%)	Education factor (6.34%)
	1	2	3	4	5
Household age (Hage)	-0.172	0.070	0.430	0.253	**-0.582**
Household size (Hsize)	0.131	0.184	**0.819**	-0.010	-0.031
Household Education (Hedu)	0.126	0.019	-0.163	0.068	**0.776**
Household sex (Hsex)	0.472	0.387	0.052	-0.011	0.196
Household leader (Hlead)	-0.086	0.177	-0.325	-0.274	**-0.419**
Household labour (Hlabour)	0.137	0.157	**0.926**	0.027	-0.104
Household holding (Hhold)	0.540	**0.745**	0.207	0.271	0.018
Household income (Hincome)	**0.728**	0.590	0.207	0.131	0.013
Household subsidy (Hsub)	**0.970**	0.073	0.124	0.064	0.089
Household hold cotton (Hcot)	**0.970**	0.073	0.124	0.064	0.089
Household hold upcrop (Hupcrop)	0.072	**0.927**	0.193	0.136	-0.068
Household hold agroforestry (Hagro)	0.052	0.252	-0.038	**0.705**	-0.008
Household hold plantation (Hplant)	-0.048	0.171	0.147	**0.768**	0.315
Household income from crop (Hincrop)	0.116	**0.921**	0.149	0.115	-0.072
Household income from livestocks (Hliv)	0.137	0.157	**0.926**	0.027	-0.104
Households income from other activities (Hoth)	-0.214	0.053	0.023	-0.511	0.304

Notes: - Numbers in parenthesis are percentages of total variance of original variable set explained by the principal components. **-** Bold numbers are the high loadings, indicating most important original variables representing the principal components.

The component 3 (PC3) is weighted by labour (b=0.926), income from livestock (b =0.926) and household size (b=0.819). The component represented 10.92 % of the variance of all variables and was named labour factor.

The principal component 4 (PC4) is linked to the variable holding plantation (b = 0.768) and holding agroforestry system (b=0.705). This component explained 8.41 % for the variance of the original dataset. The component is named mitigation strategies.

The component 5 (PC5) is weighted by the variables education (b = 0.776) and age (b = 0.582) with a contribution of 6.34% to the variance of the original dataset. This component was called education factor.

The statistics of the key categorical variables were used to determine the pattern of each household group using the most variables characterized by various factors. (Table 4.5).

b. Livelihood typologies of household agents

Three types of households were determined based on the results from hierarchical and kmean clustering procedures.

Household type 1: Group of farmers with cotton production based

The first group (I) of farmers was identified based on holding cotton factors and education. This group of farmers is characterized by the variables income, holding cotton, subsidy, education, age and leadership. The group (Table 4.5) was characterized by the mean holding cotton of 2.73 ha with 1 and 7 ha for minimum and maximum respectively. The mean holding cotton of this group is 1.16 and 3.69 times higher than the mean holding cotton of group II and group III respectively. In contrast, the labour availability of group I was 1.24 and 1.07 times lower than the labour availability of group II and group III respectively. We can conclude that this group have the revenue for farming activity and doesn't only rely on labour availability. This group of farmers used mechanization for ploughing their holdings. The group represented 46 % of the whole population.

Household type 2: Mitigation and multi crop production group of farmers

The group II or the group of famers with multi crop production represented only 5.34 % the total number of the households. The farmers of this group have the ability to adopt mitigation strategies to climate change.

Household type 3: Group of poor farmers

This group is the most important in the basin. It represented 48.66% of the total number of the farmers. The mean upland crop is equal to 3.32 ha whereas the lower upland crop is less than 1 ha. The households of this group had developed livelihood based food production rather than cotton production.

Table 4. 5 Descriptive statistics for 5 key categorizing variables for each classified agent group

Categorizing variable	Households groups	N	Mean	*S.E.*	*min*	*max*
Labour availability (H_{labor})	I	86	4.89	0.30	2	18
	II	10	6.1	0.86	4	12
	III	91	5.25	0.28	2	14
Holding cotton (H_{cotton}) in ha	I	86	2.73	0.14	1	7
	II	10	2.35	0.31	1	4
	III	91	0.74	0.08	0	3
Holding upland crop (H_{upcrop}) in ha	I	86	3.48	0.19	0.75	10.5
	II	10	5.47	1.09	1	12
	III	91	3.32	0.22	0.65	11.5
Holding agroforestry (H_{agro}) in ha	I	86	0.03	0.01	0	1

	II	10	1.17	0.24	0	2
	III	91	0.02	0.1	0	1
Holding plantation (H_{plant}) in ha	I	86	0.02	0.009	0	0.5
	II	10	0.72	0.18	0	1.7
	III	91	0.008	0.006	0	0.5
Annual gross income in (1000 CFA)	I	86	507.821	27.321	101.250	1234.000
	II	10	1062.688	169.593	392.500	2207.000
	III	91	920.582	48.581	281.395	2382.000

Note: N = The number of households, the mean of the variable, the related standard Error (S.E.), the minimum and the maximum in each agent group

4.5.3 Mitigation strategy at the farm level

The farmers of Dassari Basin still have little knowledge on the mitigation strategy to climate change. The analysis of the socio-economic and field investigation revealed that only 7.48 % of farmers adopted agroforestry system (cashew plantation) in combination with cropping system in their holding. The size of agroforestry system varied from 0.2 (minimum) to 9.9 (maximum) ha with a mean of 1.57 ha.

Plantation, mainly Eucalyptus plantations was planted by 8.55 % of farmers. The mean size of plantation was 2.26 ha. In contrast to the adoption of agroforestry, Eucalyptus plantation was planted between 1988 and 1992 as a result of a project which involved farmers. Thus, the age of Eucalyptus ranged from 20 to 25 years. The Eucalyptus plantation represented 97.89 % of the total area of plantations of the basin. The remaining plantations were mango trees (about 35 years), teak or *Tectona grandis* (about 18 years) and *Gmelina arborea* (about 5 years). Due to the high proportion of Eucalyptus plantations, future analysis focused on its carbon sequestration for developed scenarios. Thus the carbon and nitrogen content, and the carbon stock of this plantation were estimated to assess the impact of mitigation based plantation to climate change at the basin level.

The investigation to test the level of the adoption of mitigation strategies to climate change (Table 4.6) showed that 17.6% of farmers have no intention to adopt neither agroforestry nor plantation in their farm land whereas 66.4% would rather adopt agroforestry than plantation. In the same order 15.5 % would like to adopt plantation than agroforestry system. **Table 4. 6 Statistics on the adoption of mitigation strategies**

		Adoption of plantation (%)	
		No	Yes
Adoption of agroforestry (%)	No	17.6	15.5
	Yes	66.4	0.5

Table 4. 7 Estimated parameters of factors affecting agroforestry adoption

Variables	Annotation	Coefficient	Standard error	Wald statistic	Significance.
Constant	β_0	1.56	0.66	5.52	0.02
Age	X_{1i}	-0.01	0.01	0.80	0.37
Size	X_{2i}	0.02	0.05	0.20	0.66
Education	X_{3i}	-0.61	0.38	2.61	0.11
Sex	X_{4i}	-0.04	0.45	0.01	0.92
Labour	X_{5i}	0.03	0.09	0.12	0.73
Total Holding	X_{6i}	1.39	1.05	1.76	0.19
Holding cotton	X_{7i}	-1.35	1.06	1.64	0.20
Holding cropland	X_{8i}	-1.50	1.06	1.99	0.16
Holding agroforestry	X_{9i}	-2.66	1.42	3.53	0.06

Chi -square (df = 8) = 8.360
(-2) Log likelihood = 221.724
Accuracy of prediction overall (%) = 72.2
Nagelkerke R^2 = 0.12

The positively significant coefficient of total holding indicates its positive influence on agroforestry adoption which was as presumed. The coefficient of holding agroforestry was negatively significant, which implies that the older the farmers, the less the probability of adopting agroforestry. The level of the adoption of agroforestry is also functional linked to the land tenure or total holding (Table 4.7) and the previous status of holding agroforestry.

Farmers who have high value holding tend to devote a piece of their land to agroforestry.

Table 4. 8 Estimated parameters of factors affecting plantation adoption

Variables	Annotation	Coefficient	Standard error	Wald statistic	Significance
Constant	β_0	-1.28	0.84	2.35	0.13
Age	X_{1i}	-0.01	0.02	0.44	0.51
Size	X_{2i}	0.03	0.07	0.21	0.65
Education	X_{3i}	0.78	0.48	2.61	0.11
Sex	X_{4i}	-0.36	0.57	0.40	0.53
Labour	X_{5i}	-0.01	0.11	0.01	0.90
Total holding	X_{6i}	0.04	0.71	0.00	0.96
Holding cotton	X_{7i}	-0.24	0.74	0.10	0.75
Holding cropland	X_{8i}	-0.08	0.73	0.01	0.91
Holding plantation	X_{9i}	-0.66	1.95	0.11	0.74

Chi -square (df = 8) = 7.83
(-2) Log likelihood = 159.146
Accuracy of prediction overall (%) = 84
Nagelkerke R^2 = 0.05

In the same order, subsistence oriented small farmers are highly risk averse to adopt plantation (Table 4.8) due to limited holding. The model was able to explain 12 percent relationship between the variables and the adoption probability and 72 percent of the sample cases correctly (Table 4.7) in adopting agroforestry system. Educated farmers tend to adopt plantation than non-educated farmers (Table 4.8).

In general, farmers were more willing to adopt agroforestry than plantation because it was possible to combine crop and agroforestry based cashew plantation in the same land during a time scale of 10 years.

4.6 Conclusions

The households of the Dassari Basin are driven by a broad range of factors which compromise their livelihoods and impacted environmental conditions. The main factors which involved the farmers’ decision making are population growth, high production of cotton based subsidy with fertilizers, farming based mechanization, the protection zoning area, the variability in rainfall pattern and drought with dry skew and soil suitability. Population growth can lead to pressure on the land if the trend continues and the rate of migration doesn't change.

CHAPTER V: ECOLOGICAL DYNAMICS OF HETEROGENEOUS LANDSCAPE AGENTS IN THE DASSARI BASIN

5.1 Introduction

The role of land-use in global environmental change requires historical reconstruction of past land-cover conversions and/or projection of likely future changes (Stéphenne and Lambin, 2001), with component processes and stated variables that may change rapidly in space and time (Beven and Kirkby, 1979). In the context of human ecological system modelling, the priority should be given to formulate and approve ecological processes that play important roles in building human-environment relationships (Le, 2005). Therefore, modelling the dynamics of ecosystem through forest yields and forest conversion due to natural and human disturbance becomes relevant to the representation of the complexity of the LULCC process. According to Le (2005) the major assumption of ecological dynamics of heterogeneous landscape agents is that different landscape patches have different potential productivities (forest yields) in response to natural conditions and human interventions.

This chapter attempts to explain the complexity of the basin and the related environmental and biophysical characteristics through the following specific objectives:

1. Estimate the historical rate of changes and trajectory in LULC of the basin,

2. Characterize the heterogeneity and biophysical characteristics of landscape agents and,
3. Formulate and calibrate ecological sub-models (i.e. forest yield and natural transition) of landscape agents.

5.2 Bio-physical characteristics

5.2.1 Climate

Long-term (1952-2010) minimum temperature of Natitingou station located 50 km from the site showed daily minimum temperature range from 15.25 to 25.08 ºC, with an average of 20.53 ºC. In the same order, the observed daily maximum temperature ranged from 26.63 to 39.27 ºC, with a mean temperature of 32.59 ºC. The observed trend line of these minimum and maximum temperatures during this period showed a positive slope of 0.0017 and 0.0023, respectively.

Long-term (1971-2013) mean monthly precipitation for Tanguieta station (15-20 km from the study area) is 87.5 mm.

The standardized precipitation index (SPI), developed by McKee and Kleist (1993), showed two periods, 1978-1979 and 1985-1986 of extreme drought with some years of moderate to severe droughts during the 42 years of observation.

5.2.2 Soil types

The basin is characterized by six soil types (Figure 5.1). These soil types are namely hydromorphic ferruginous soil on plate schist, ferruginous indurate soil on colluvium material, ferruginous indurate soil on tablet schist, hydromorphic mineral soil, brute mineral soil on breastplate and little developed soil on alluvium-colluvium material.

GIS tools were used to sum the area of all polygons that belonged to a soil class by estimating the area of these soils type. The ferruginous indurate soil on tablet schist covered a total of 75.43 % of the total area of the basin. The maximum cropping area was growing within this soil type.

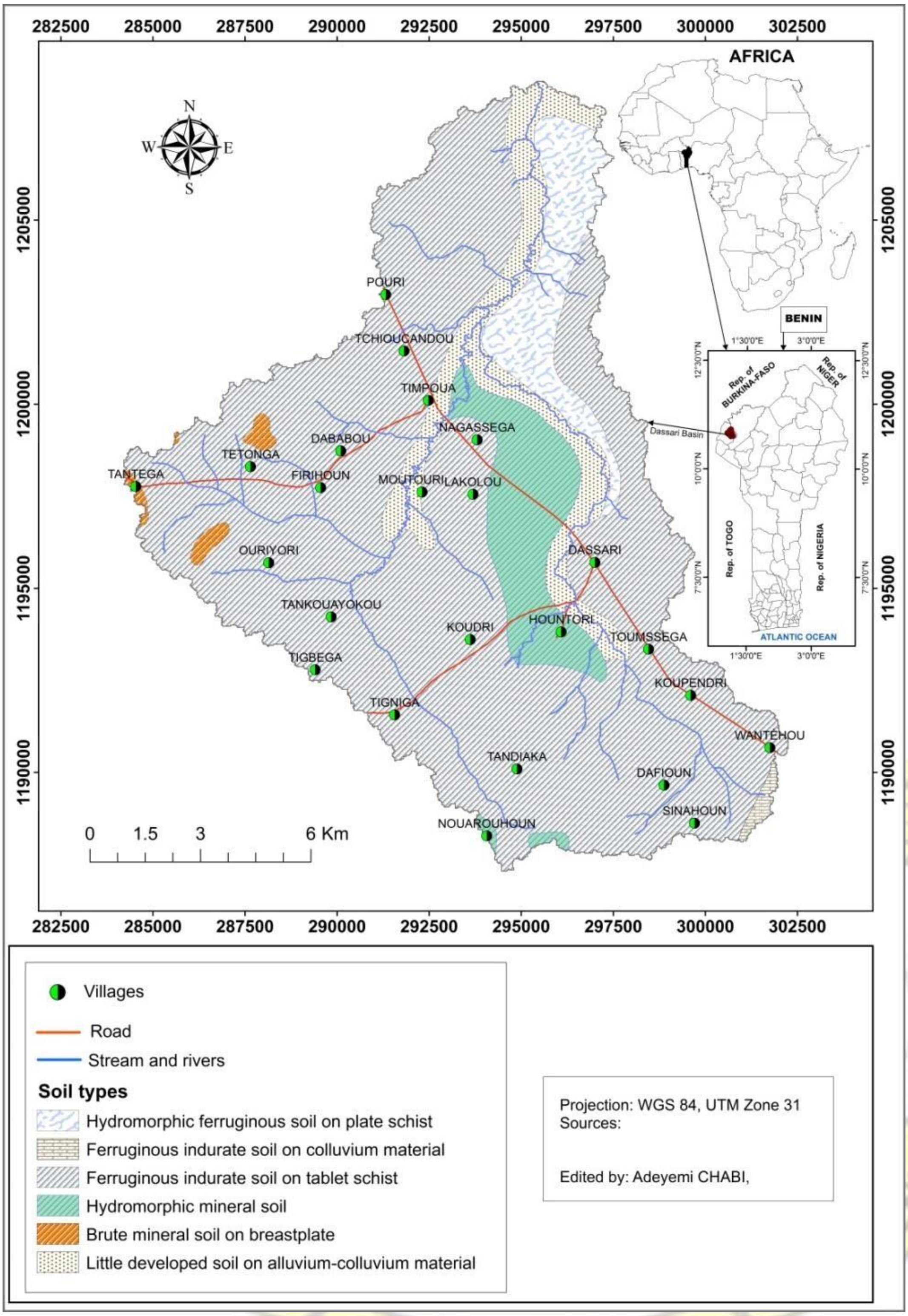


Figure 5. 1 Soil types of the study area

5.3 Methodology

The ecological dynamics of the basin involves its complexity related to environmental and biophysical characteristics. The Landsat ETM+ was used to estimate deforestation rate from 2001 to 2013. The deforestation rate is the main important input for simulating land use/cover change between two periods. In addition to the land use map, the biophysical characteristics of the basin (dealt in this chapter) and the sub-models from the chapter 3 were integrated in the BEN-LUDAS model.

5.3.1 Methods for the classification of Landsat ETM+ of 2001

a. Data source

The Landsat 7 ETM + (Enhanced Thematic Mapper plus) was downloaded from http://glcf.umd.edu/index.shtml. The path-row 193-52 scene of 2001/10/20 was used based on the criterion defined in Section 3.2.1.1.

b. Classification based Landsat 7 ETM+ key interpretation

The classification of the scenes was mainly based on the key interpretation of Landsat 7 ETM+. Utility of each important selected band (1, 2, 3, 4 and 5) for this study is presented in Table 5.1.

The analyses of colour composite based on these criteria identified some features within the others (Figure 5.1). Thus:

✓ For the true colour rendition, band 1 was displayed in the blue colour, band 2 was displayed in the green colour and band 3 was displayed in the red colour. The resulting image was fairly close to realistic and there was little contrast and features in the image, which were hard to distinguish;

✓ For the false colour, band 2 was displayed in blue, band 3 was displayed in green, and band 4 was displayed in red. This rendition looks rather strange vegetation, which jumps out as a bright red because green vegetation readily reflects infrared light energy;

Table 5. 1 Application domain of each selected band for images classification of 2001

Bands	Electro magnetic Spectrum (EMS) And Band width (λ, µm)	Application domain
1	Blue light (0.45-0.515)	This band penetrates clear water better than other colours. It is absorbed by chlorophyll, so plants not show up very brightly in this band; useful for soil/vegetation discrimination, forest type mapping, and identifying man-made features
2	Green light (0.525-0.605)	This band reflects more green light than any other visible colour; man-made features are still visible
3	Red light (0.63-0.69)	It has limited water penetration; reflects well from dead foliage, but not well from live foliage with chlorophyll; useful for identifying vegetation types, soils and urban (city and town) features
4	Near IR (NIR) (0.75-0.90)	A good band for mapping shorelines and biomass content; very good at detecting and analysing vegetation
5	Shortwave IR (SWIR) (1.55-1.75)	This band provides a good contrast between different types of vegetation; useful for measuring the moisture content of soil and vegetation

Source: Landsat 7 ETM+ handbook (images were downloaded via GLCF: http://www.landcover.org/index.shtml)

In the pseudo natural colour, band 2 was displayed in blue, band 4 was displayed in green, and band 5 was displayed in red. This rendition looks like a jazzed up true colour rendition - one with more striking colours.

Different features presented various patterns from one colour composite to another. The crossing of information lead to the discrimination of two to three features (Table 5.2). In addition, four main criteria were defined and added to perform the analysis. These criteria were based on the mountainous area, the rivers, restricted areas like private area under protection (farm of ostrich in Dassari) and the specific location of tree species like *Terminalia macroptera*. The discrimination of various land cover such as riparian forest and woodland, savanna woodland, shrub savanna and grassland was based on the use of gradient colour (from high to fairly). During the forest inventory, the field observations revealed the location of *Terminalia macroptera* in the area with high soil moisture content. To confirm the observation plots coordinates where 100% of this species appeared were selected and projected and recognized as woodland or wetland vegetation (Table 5.2) if dark red colour appeared when using false colour composite.

Table 5. 2 Criterion for discriminating different land use / cover of 2001 in the study area

Ground Cover Type	In Natural Colour (3,2,1), appears:	In False Colour: (4,3,2), appears:	In Pseudo Natural Colour (5,4,2), appears:
Trees and bushes	Olive Green	Red	Shades of green
Crops	Medium to light green	Pink to red	Shades of green
Wetland Vegetation	Dark green to black	Dark red	Shades of green
Water	Shades of blue and green	Shades of blue	Black to dark blue
Urban areas	White to light blue	Blue to gray	Lavender
Bare soil	White to light gray	Blue to gray	Magenta, Lavender, or pale pink

Source: Landsat 7 ETM+ handbook. The information from this table provided keys indicators for the classification of the images for this work.

In summary, a visual inspection of natural colour, false colour and pseudo natural colour (Table 5.2) representation of the Landsat scene has been used to identify training areas of each feature (land use/cover class) in these colour composites. The training area was finally generated using the previous approaches. The supervised classification using maximum likelihood classification was performed.

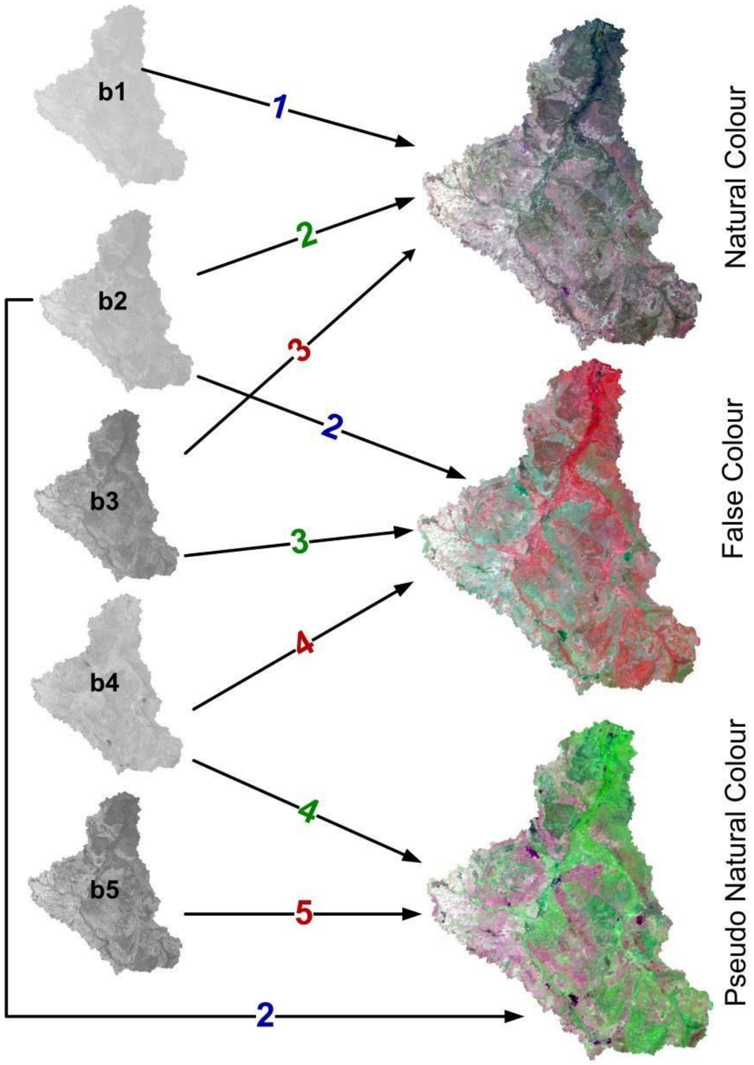


Figure 5. 2 Colour composite of Landsat 7 ETM+ bands

c. Accuracy assessment of land use map of 2001

The accuracy assessment indices used were described in Section 3.2.2.1. The selected sample points for accuracy assessment were historical google earth images (2006) based. The points from land use classes such as riparian forest and woodland, savanna woodland, shrub savanna and grassland savanna were located in the specific areas such as mountains and strict protected zone for the fact that the classified Landsat ETM+ was from 2001 and the available high resolution google earth pro images was for 2006. In addition, we assumed that in terms of ecological dynamics of the ecosystem in the mountainous area there is no significant change between 2001 and 2006 in the Sudan Savannah environment. The cropland was easily discriminated using the colour composite approach (Figure 5.1) and band 5 of Landsat ETM+. The chosen settlement points were based on the socio-economic information, i.e coupled information between the building date of churches and schools of the site and the overpassing date of satellite sensor. The overall accuracy and kappa index (Gómez and Montero, 2011) have respectively shown 0.75 and 0.70 acceptable to retain the results of the classification.

d. Reclassification of land use/cover map

The reclassification of the land use map used the same approach for 2013 in Section 3.2.2.2. However, the area of roads has been enlarged from 2001 to 2013. The socio-economic information gathered in the field revealed an increase of the size of the roads due to the development of the main roads. For example the main road from Benin-Burkina Faso was not bitumenous in 2001. To overcome this constraint, buffer zone of 12 m was applied as default to delineate the size of this road along Wantehou and Pouri villages (Figure 4.1). The overlay of agroforestry and plantation that were surveyed during the field work (2013) to the classified map was based on the historical planting date. Infact, when each agroforestry and plantation was surveyed with GPS and sometimes with the support of Rapid Eye high resolution image (0.5 -2 m resolution) the planting date was given by the owner of this agroforestry or plantation. The chosen layers from these agroforestry and plantation was based on the assumption that the tree must have a minimum of 5 years before the passing date of Landsat ETM+ sensor, i.e a minimum of 17 years in 2013. The agroforestry and plantation that responded to this query were extracted and overlaid to the land use map of 2001. We also assumed that plantations less than 5 years old do not contribute so much to the carbon sequestration.

e. Change detection method

A number of the image analysis approaches to change detection can be referred to as linear techniques, meaning that land cover change at each image location is associated with some linear transformation of a bi-temporal spectral vector (Collins and Woodcock, 1996). Classified maps for 2001 and 2013 were compared quantitatively by change matrix and also qualitatively by evaluation of spatial change map. The image difference rows calculated for each class was obtained from Eq. 5.1 (Erener *et al.*, 2012):

$$Idfr = \frac{\text{FCT} - \text{ICT}}{\text{ICT}} \tag{5.1}$$

Where;
Idfr is image difference rows for each class, FCT is the final class total in pixel count, ICT is the initial class total in pixel count.

5.3.2 Methods of landscape characterization

The bio-physical characteristics of the study site are the main inputs into the BEN-LUDAS model. These bio-physical characteristics nourish the dynamics of ecosystems within the basin. The upslope contribution area for the patch is a proxy for soil nutrient accumulation. The elevation (m) at the patch location is used to derive surface slope (degree) at the patch location. This index is a profound indicator for soil erosion risk. The wetness index (a positive coefficient) at the patch location is a good proxy for indicating soil moisture content (Sørensen *et al.*, 2006; Wilson and Gallant, 2000).

a. Upslope contributing area

Upslope area (P_{As}), is defined as the total catchment area above a point or short length of contour (Moore *et al.*, 1991; Tarboton 1997). It is a distributed quantity that has important hydrological, geomorphological, and geological significance (Costa-Cabral and Burges, 1994). Upslope area is commonly used for the automatic demarcation of channels relying on the notion of a critical support area (O'Callaghan and Mark, 1984; Jenson and Domingue, 1998;

Morris and Heerdegen, 1988; Lammers and Band, 1990; Tarboton *et al.*, 1992; Martz and Garbrecht, 1992).

For a grid cell *i* of a DEM, P_{As} is computed from the grid cells from which the water flows into the cell i:

$$PAs = \left(\frac{1}{\mathrm{b}}\right)\sum_{i=1}^{n} \rho i.Ai \qquad (5.2)$$

Where, *Ai* is the area of the grid cell *i*, n is the number of cells draining into the cell *i*, *ρi* is the weight depending on the runoff generation mechanism, and *b* is the contour width approximated by the cell size.

The mapping of upslope contributing area in ArcGIS 10.1 software was first based on the delineation of flow direction as input for flow accumulation. Once the flow accumulation was known the upslope was derived.

b. Soil suitability index for agriculture

The soil suitability for agriculture influences the farmer's decision choice in the basin. Within the six soil types of the catchment, the level of their suitability to agriculture varies each from other. To express this constraint as the variable, which characterize the basin based suitability index, the logarithmic function of the suitability based on expert judgment was calculated. The level of suitability was classified (from 1 not suitable, to 6 highly suitable to agriculture).

c. Topographical wetness index

Topographic wetness index (P_{wet}) can quantify the control of local topography on hydrological processes and indicate the spatial distribution of soil moisture and surface saturation (Quinn *et al.*, 1995). The distribution of the index may be calculated for any catchment and is used as a basis for the prediction of source areas, saturation excess overland flow and subsurface flows.

The index has the form:

$$Pwet = Ln\left(\frac{a}{tan\beta}\right) \qquad (5.3)$$

Where, in terms of a raster DEM, *a* = the upslope area, per unit contour length, contributing flow to *a* pixel; *tanß* = the local slope angle acting on a cell (this is taken to approximate the local hydraulic gradient under steadystate conditions)

5.3.3 Method to specify forest yield function: (the Forest Yield Dynamics sub-model)

a. Basal area of forest stand

Basal area is the cross-sectional area of a tree trunk at breast height. The stand basal area was estimated using Eq. 5.4.

$$BA = \frac{1}{A}\sum_{i=1}^{n} \mathrm{CSA} \qquad (5.4)$$

Where BA is the basal area of the plot in $m^2.ha^{-1}$, A the area sampled in ha, *n* the number of the trees in the plot and CSA the tree cross sectional area in m^2.

According to Le (2005), BA indicates not only the forest yield, but also the stock of a forest stand, which is strongly correlated with the competition status that is important for the growth of forest trees. In forestry practice, the amount of timber logged is often expressed in terms of basal area (Le, 2005).

The basal area was first estimated for each plot of each land use / cover system. Thus, the average forest yield (variable *p_yieldforest*) (Y_{LUC}) and its uncertainty range [Y_{LUC} - CI_{LUC}, Y_{LUC} + CI_{LUC}] where CI_{LUC} is the confidence interval of Y_{LUC}. At the confidence level of 95 %:

CI_{LUC} = 1.96 x Sdt_{LUC}/sqrt (N_{LUC}) where Sdt_{LUC} = standard deviation of Y_{LUC}, and N_{LUC} the number of plots surveyed in each land use / cover system.

b. Forest growth model

The forest yield model developed in this study was previously developed in VN-LUDAS model (Le, 2005). The yield function can be expressed either by the integration of the growth function along elapsed time (i.e., ${}^{t}P_{Gr} = \int {}^{t}Z_{G}.dt$), or by the previous residual stock (${}^{t-1}P_{Gr}$) plus the instant growth rate (i.e., ${}^{t}P_{Gr} = {}^{t-1}PGr + {}^{t-1}Z_{G}$). Thus the relationship of these concepts can be numerically expressed as follows:

$${}^{t}P_{Gr} = ({}^{t-1}P_{Gr} + {}^{t-1}Z_{G}) - G_{removals} \qquad (5.5)$$

Where ${}^{t}P_{Gr}$ is the basal area at time t, ${}^{t-1}PGr$ is the previous residual stock, ${}^{t-1}Z_{G}$ is the instant growth rate; and $G_{removals}$ is the harvested basal area.

Accordingly like Le (2005), we used residual basal area ${}^{t}P_{Gr}$ as the response variable to represent forest dynamics.

Z_G expresses the theoretical basal area growth (Vanclay, 1994) of a forest stand as a whole and can be calculated as:

$$Z_G = a(P_G)^{\varepsilon} - b(P_G) \qquad (5.6)$$

Where, P_G is stand basal area, *a* and *b* are the constants, and ε is a coefficient of very small value (ε -------> 0).

However, when empirical data are available, it is still difficult to fit the equation of this nonlinear form with the data (Le, 2005; Vanclay, 1994).

To determine the parameters *a* and *b* of Eq. 5.6, the following was assumed:

1- The stand growth rate Z_G is asymptotically zero in the equilibrium state (${}^{eq}P_G$).
2- The derivative of the growth function Z_G is zero when it reaches the maximum (${}_{max}Z_G$).
3- ${}^{eq}P_G$ is constant over space since there is no evidence to correlate this parameter with location variables.

Accordingly, the ${}^{eq}PG$ and ${}^{max}ZG$ are settable either by forestry experts or review of literature on tropical forests (Havel, 1980; Vanclay, 1994).

Assuming that the parameters ε, ${}^{eq}P_G$ and ${}^{max}Z_G$ are known, the following equations determined the parameters *a* and *b*:

$$a = {}^{max}Z_G / [({}^{eq}P_G)^{\varepsilon} (\varepsilon^{\varepsilon/(1-\varepsilon)} - \varepsilon^{1/(1-\varepsilon)})] \quad (5.7)$$

$$b = {}^{max}Z_G / [{}^{eq}P_G (\varepsilon^{\varepsilon/(1-\varepsilon)} - \varepsilon^{1/(1-\varepsilon)})] \quad (5.8)$$

Where, ${}^{max}Z_G$ is the value that can be approximated from the projected outputs of empirical growth models, ${}^{eq}P_G$ is the high value of the plot basal area of the surveyed plots in the riparian forest and woodland, savanna woodland, shrub savanna and savanna grassland ε is fixed by setting a very small value (i.e., $\varepsilon = 10^{-6}$).

In the case of the present study area we used reference from Jean-Louis (1997) to estimate ${}^{max}Z_G$. The author presented the basal area increment of some species in the region where the the rainfall is about 900 to 1000 mm per year in the West of Burkina-Faso. The region presents similar characteristics in rainfall pattern and specific species like our study site. For this reason, the mean increment basal area of species such as *Entada Africana, Terminalia avicinoides, Lannea acida, Combretum glutinosum, Stereospermum kunthianum* and *Parkia biglobosa* respectively showed 6.76, 2.13, 1.64, 6.20, 11.06 and 6.43 % of the mean increment basal area for Jean-Louis (1997) study. Thus the overall mean increment basal area was set to be 5.7 %. We used this mean increment for the present case study and assume that for any given tree species of stand basal area BA, its increment within the year is equal to 5.7 times BA divided by 100.

The ${}^{max}Z_G$ was then estimated for each LUC class of our plots data and the results were used as input into the BEN-LUDAS Model. The following steps were used before the integration into the BEN-LUDAS model:

- Estimation of the individual cross sectional area of trees based on the plots data obtained from each land use/cover system,
- Calculation of the average basal area of all trees for each LUC,
- Applying 5.7 % to this average and considered the obtained value as ${}^{max}ZG$ for each

LUC.

The ${}^{max}ZG$ increment for each LUC were 1.04 (riparian forest and woodland), 0.42 (savanna woodland), 0.16 (Shrub savanna), 0.23 (savanna grassland), and 0.03 (cropland and fallow).

c. Special consideration for overcoming $G_{removals}$ for farming activity

The main human activity in the Dassari Basin is farming. Increases of agricultural land are of the expense of removal of tree cover in riparian forest and woodland, savanna woodland and shrub savanna and in a few cases in savanna grassland. Removals of tree cover were done by farmers through: logging of the small trees and burning of the big ones. It is assumed that burning and logging both contributed to the mortality of the tree, hence to the decrease of vegetation carbon and nitrogen stocks. Direct count of the number of logged and burned trees in the field are considered not realistic especially when the establishment of the farm to the detriment of natural vegetation took place over a certain number of years and in addition the residual trees were converted into firewood consumption or into charcoal production. To overcome this constraint, the amount logged or burned trees were approximated as the observed difference between basal area of forest and farm land. The following steps were used based on available plots data.

- Calculation of the difference between the mean basal area of natural vegetation (riparian forest and woodland, savanna woodland, shrub savanna and grassland) and farm land,
- Estimation of the difference of mean tree stock between natural vegetation and farm land,
- Estimation of the mean logged cross sectional area for a single tree.
- Estimation of the amount logged, which was equal to the mean difference of basal area (or mean trees stock times mean logged/burned basal area) between forest land and farm land.

5.3.4 Method for modelling natural transition among land-cover types: the Natural Transition sub-model

Two type of conversion govern forest ecosystem: natural conversion and human induced conversion. The natural conversion occurred in forest when trees grow in a normal way and stand basal area of the forest patch is higher than the threshold (Eq. 5.11) of LUC. The land use transition occurred in the case of N1 to N3 (normal transition routine) (Figure 5.3). Three categories of human induced conversion occurred in the basin. The first category is the conversion due to logging activity, which occurred through the transition rule from riparian forest to savanna woodland, savanna woodland to shrub savanna and shrub savanna to grassland (decision rule H1, Eq.5.5 and 5.11).

The second category of conversion occurred during the farming activity when the forest patch is transformed to the farm (decision rules H2 to H5, Eq. 5.5 and Section 5.3.3.3). The third category of conversion occurred when farmers' decision was motivated by the implementation of REDD+. The first type of REDD+ is the initiative based regeneration of degraded land without human disturbance (decision rule H5, explained as the transition from cropland to grassland and to other forest land during long period).

The second REDD+ initiative is the mitigation strategy to climate change based (decision rule H6 to H7).

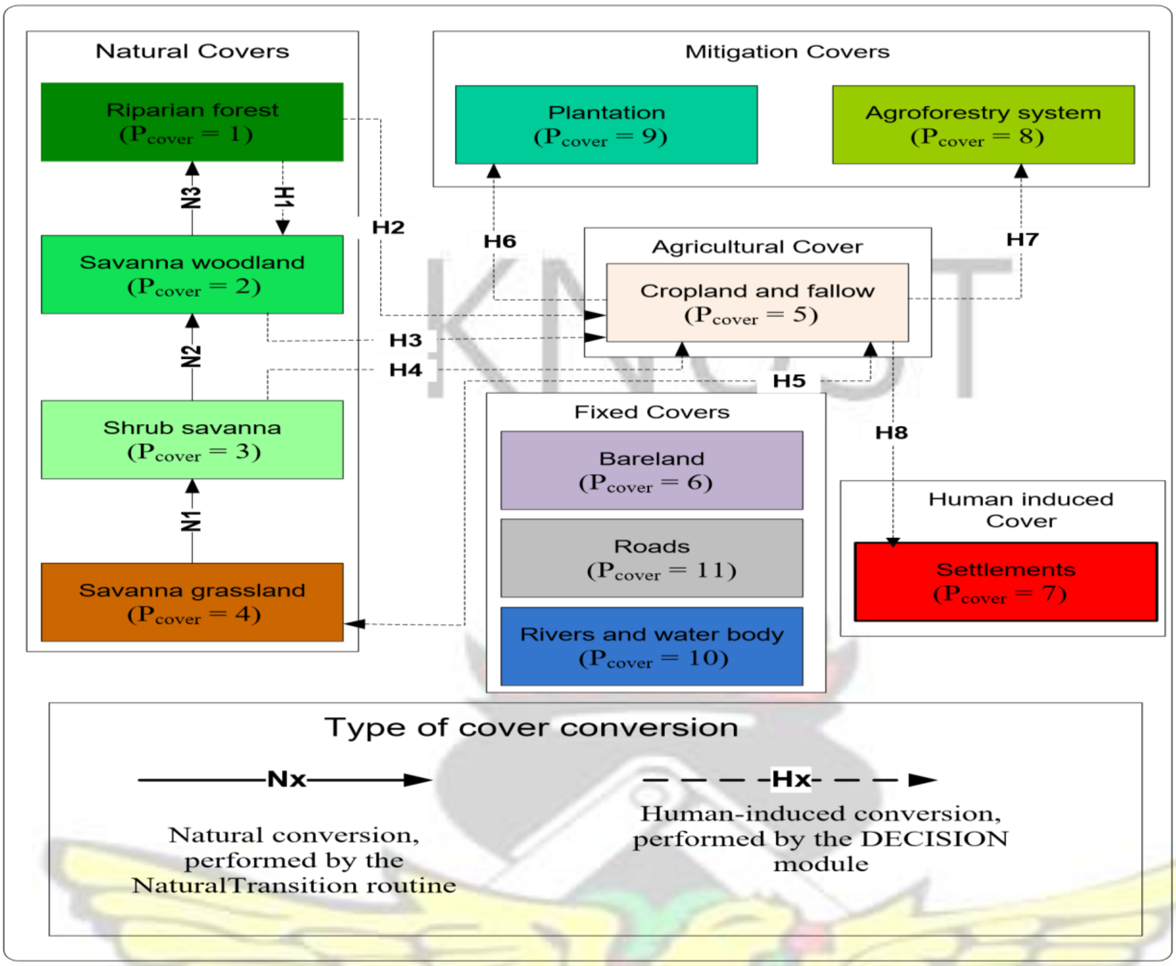


Figure 5. 3 Land use/cover transition in BEN-LUDAS: combination of human-induced transition (influenced by DECISION module) and natural transition (viz. Natural Transition sub-model)

This type of conversation, which leads to the transition from cropland to plantation and agroforestry system is due to farmers' decision motivated by farmers' skills or the external action based carbon fund project. Other type of conversion occurred when the surrounding area in the settlements or the garden were converted to settlements (decision rule H8). These areas are naturally farm lands.

The human induced conversion is the consequence of deforestation and forest degradation which required appropriate tools to estimate the deforestation rate.

5.3.5 Estimation of the deforestation rate based algorithms

The deforestation rate was applied between 2001 and 2013 using the results of land use maps from the two periods. Deforestation rate was estimated (Eq. 5.9) following AguilarAmuchastegui *et al.* 2014 and Puyravaud, (2003) as,.

$$r = \frac{1}{t_2 - t_1} ln \frac{A_2}{A_1} \tag{5.9}$$

In addition to Eq. 5.9 another equation from FAO, (1995) for comparison Eq. 5.10. The following equation is given as (FAO cited by Orekan, 2007):

$$r = \left[\left(\frac{A_2}{A_1} \right)^{\left(\frac{1}{t_2 - t_1} \right)} \right] - 1 \tag{5.10}$$

Where, r is the deforestation rate in decimals, t_2-t_1 is the difference between the years of the forest cover area assessments (the assessment period), A_1 is the forest area at t_1 and A_2 is the corresponding area at t_2

When comparing the results obtained from the two equations, the difference in magnitude was of the order of 0.0, which is not significant. For that reason, the equation Eq. 5.9 which is easier to manipulate was selected.

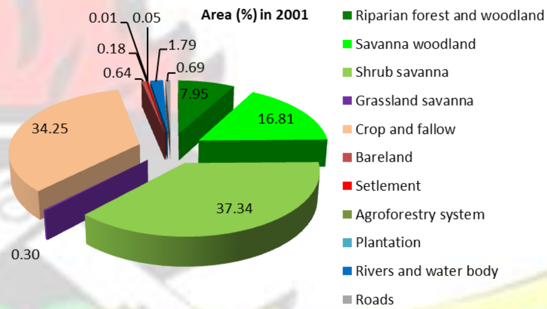
5.4 Results and discussion

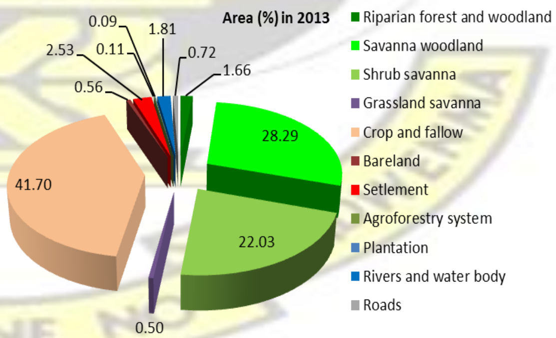
5.4.1 Land use cover change analysis (2001-2013)

The land use/cover maps showed on increment in the area of cropland by 21.76 % between 2001 and 2013 indicating most cropland expended at the expense of other land cover classes. The total area of cropland covered 34.25 % in 2001 (Table 5.3 and Figure 5.4) was increased to 41.70 % in 2013 (Table 5.3 and Figure 5.5). The forest land while comprised of riparian forest and woodland, savanna woodland and shrub savanna covered 62.11 % in 2001 and was decreased to cover 51.98 % of the total area of the basin. In 2013, the rate of decease in forest cover within the period was therefore 1.48 % per year. The rate of increase in cropland cover was estimated to be 1.8 % per year.

Table 5. 3 Statistics of land use/cover in 2001 and 2013

Land use cover classes	Area in ha		Area in percentage
	2001	2013	
Riparian forest and woodland	1531.35	320.4	
Savanna woodland	3238.02	5447.79	
Shrub savanna	7190.55	4241.88	
Grassland savanna	57.33	96.48	
Crop and fallow	6595.83	8031.15	
Bare land	122.4	107.91	
Settlements	33.75	486.72	
Agroforestry system	2.07	20.7	
Plantation	9	16.74	
Rivers and water body	344.61	348.57	





Roads	132.48	139.05

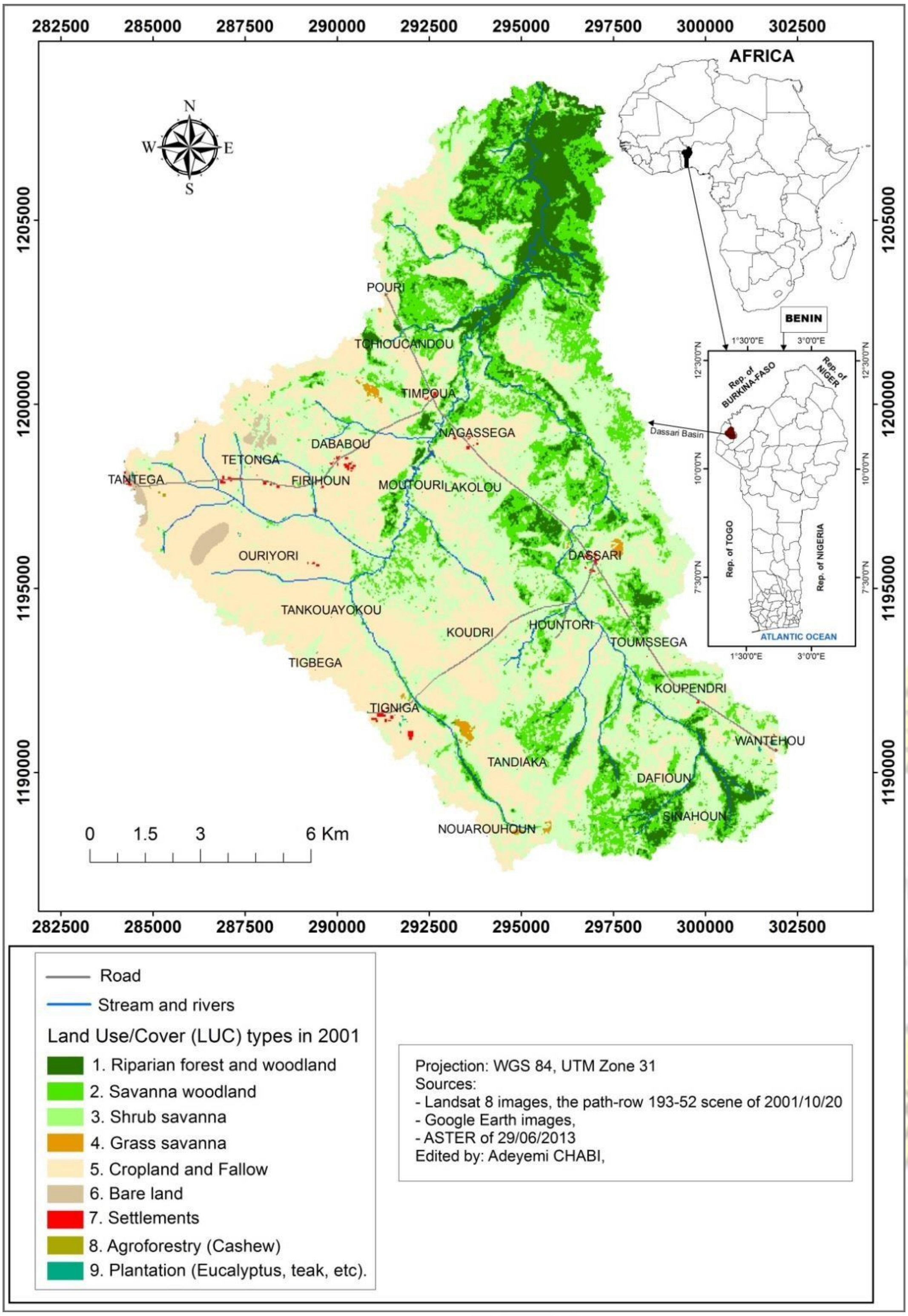


Figure 5. 4 Land use/cover map of 2001 in the Dassari basin

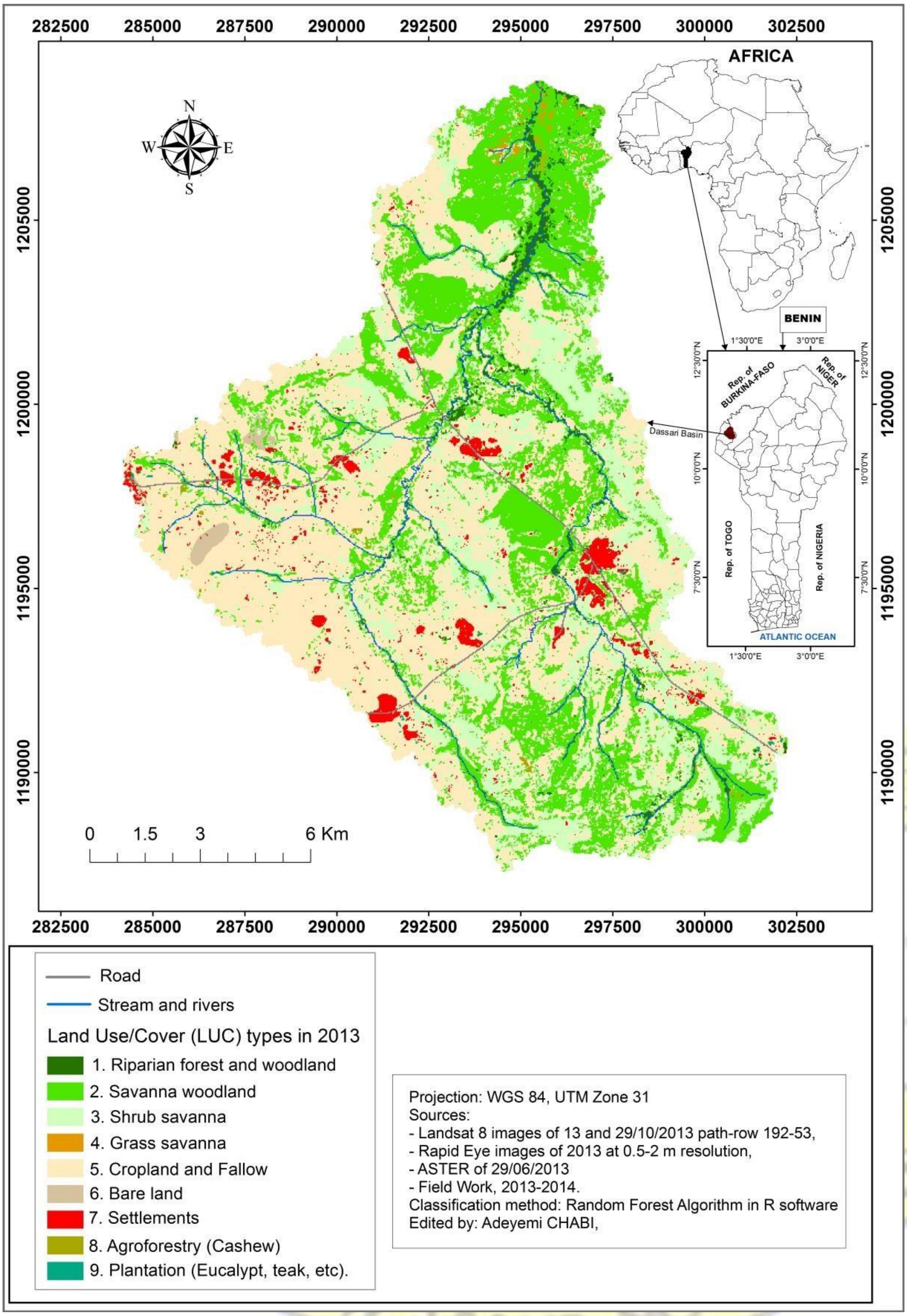


Figure 5. 5 Land use/cover map of 2013 in the Dassari Basin

5.4.2 Basin characterization

The biophysical variables of the basin (Figure 5.6) were determined by the natural growth of the forest. Four main bio-physical variables based on statistical and GIS analysis were utilised. These variables were the elevation, slope, upslope contribution area and the wetness index.

The basin was characterized by two reliefs (upland and mountainous zones) with range of elevation from 140 m to 277 m above mean sea level. The mountainous zone is covered by the same type of plant species seen in the upland zone. The mountainous area could be seen around Wantehou and Firihou villages. This elevation determined the slope gradient observed in the basin. The slope was expressed as a good indicator for erodibility (Le, 2005) and varied from 0 to 0.34 radius or 2.44 to 4.83 °. When the slope is high in the area of high pressure on the land it contributed to the loss of the productivity in farm land. We use this indicator as an input for modelling the dynamics of the ecosystem. We used upslope contribution area as a proxy for soil nutrient accumulation (see Section 5.3.2.1). The nutrient accumulation helps to determine area of good vegetation and area of potential yield for cropping system. The upslope contribution area which was $\log_{10}$ transformed, varied from 30 to 62.10^6 with high value along the rivers and water body indicating the water flow accumulation. This variable was used to map biomass, carbon and nitrogen stocks following Gaussian distribution for each land use cover type. The wetness index is a good proxy for indicating soil moisture content (see Section 5.3.2.3). The wetness index showed high pattern along the river and within the lowlands with the value ranging between 4.44 and 22.54. These biophysical factors for basin characterization were used as input in the BEN-LUDAS model to determine the dynamics of the ecosystem.

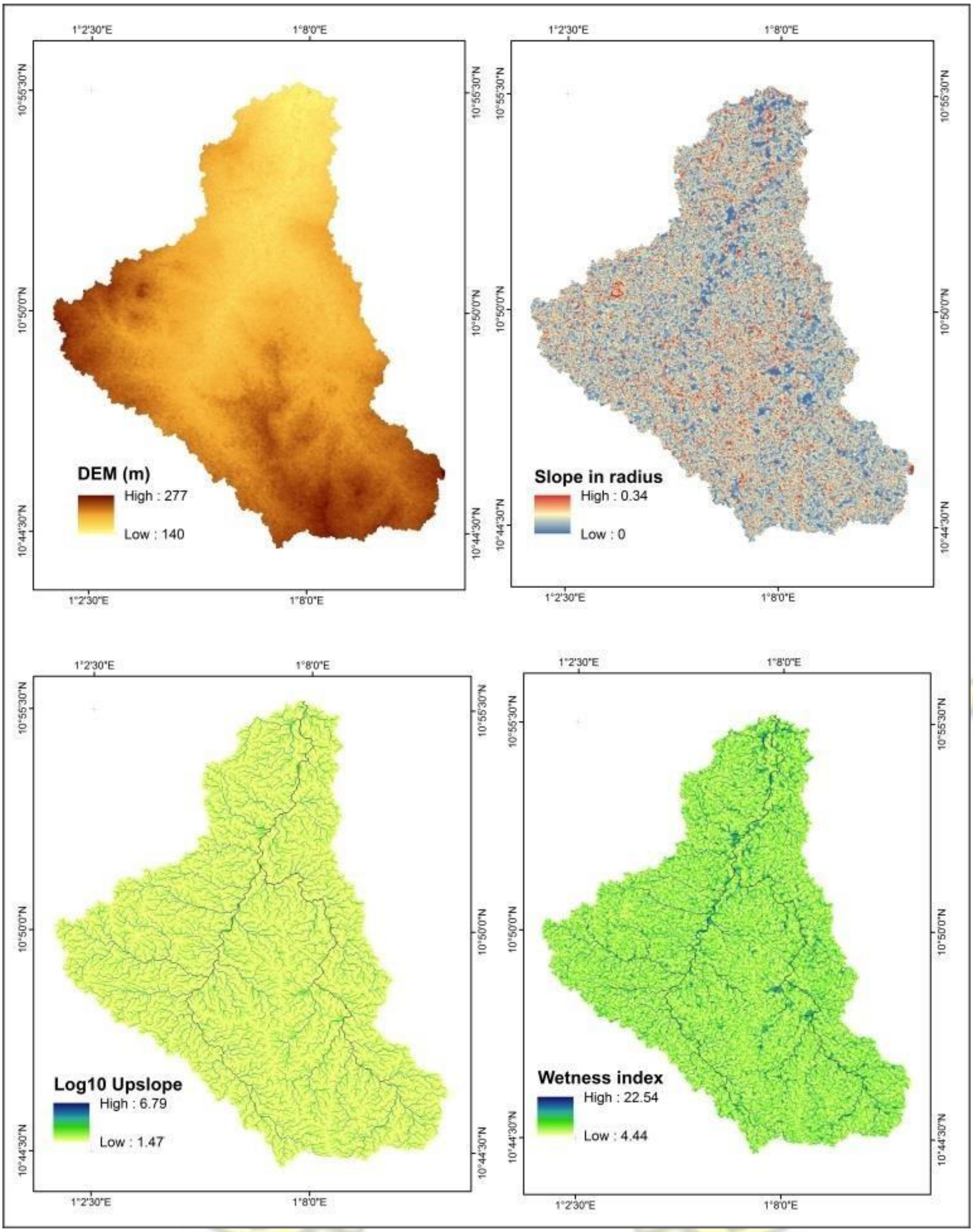


Figure 5. 6 Raster images of a) elevation (m), b) slope gradient (radius), c) upslope contributing area (m^2/m) (log10 transformation), and d) wetness index in Dassari basin

5.4.3 Modelling the dynamics of stand basal area

The stand basal area is the key factor which has been applied to model farming activity in the Dassari Basin. It was assumed that when a forest patch is cleared and the land is sown for cropland purpose, its state changed by losing some amount of yield forest. The current state of each land use cover type within its uncertainty ranged is expressed in Eq. 5.11.

$$
{}^{2013}P_{Gr\,(j)} \begin{cases}
19.12 + \textit{random}\ (11.18) & \textit{if}\ \ {}^{2013}P_{cover\,(j)} = 1 \\
07.915 + \textit{random}\ (2.57) & \textit{if}\ \ {}^{20132013}PP_{cover\,(j)cover\,(j)} == 23 \\
03.1 + \textit{random}\ (0.66) & \textit{if} \\
2.85 + \textit{random}\ (3) & \textit{if}\ \ {}^{2013}P_{cover\,(j)} = 4 \\
1.35 + \textit{random}\ (0.72) & \textit{if}\ \ {}^{2013}P_{cover\,(j)} = 5 \\
0.91 + \textit{random}\ (1.08) & \textit{if}\ \ {}^{2013}P_{cover\,(j)} = 7 \\
12.91 + \textit{random}\ (7.4) & \textit{if}\ \ {}^{2013}P \quad \notin \\
17.0 + \textit{random}\ (33) & \textit{if}\ \ {}^{2013}P_{cover\,(j)cover\,(j)} == 89 \\
0 & \textit{if}\ \ {}^{2013}P_{cover\,(j)}\ [6, 10, 11]
\end{cases} \qquad (5.11)
$$

Table 5. 4 Stand basal area in each land use/cover type (LUC)

LUC	Descriptive statistic		
	Mean Y_{LUC}, (m^2ha^{-1})	SE (Standard Error)	CI_{LUC} at 95 %
Riparian forest and woodland	24.71	4.36	5.59
Savanna woodland	9.20	2.06	1.285
Shrub savanna	3.43	0.64	0.33
Savanna grassland	2.85	0.38	1.50
Cropland and fallow	2.48	0.43	0.36
Settlement	1.45	0.41	0.54
Agroforestry (Cashew)	16.61*	1.8	3.7
Plantation (Eucalypt)	32**	3.44	15

Note: *The socio-economic information revealed the age of this agroforestry system (cashew) ranged from 7 to 16 years old. ** The socio-economic information revealed the age of this plantation (eucalyptus) ranged from 5 to 35 years old. The plots from other plantations (10 plots) such as *Gmelina arborea*, *Azadirachta indica*, *Tectona grandis and Mangifera indica* were not involved in estimating stand basal area for the fact that their area are very small in the catchment.

The yield lost is a function of the initial state of the patch. A patch from the riparian forest and woodland, which has 24.71±5.59 (SE) m^2ha^{-1} (Table 5.4), will be converted to cropland with the final yield of 2.48±0.36 (SE) $m^2.ha^{-1}$ (decision rule H2) during the life-span of the cropland or when the farmers decided to let it as fallow for a long time. The cropland can change the state and converted to grassland (decision rule H5) by increasing its yield from 2.48±0.36 (SE) $m^2.ha^{-1}$ to 2.85±1.50 (SE) $m^2.ha^{-1}$ if the cropland became not productive and it was abandoned by farmers. The recovery process of the patch can be started by gaining yield (regeneration) which was one of REDD+ implementation option. In the same order a farmer can decide to devote the degraded land to either agroforestry system or plantation (decision rule H7 and H6, Figure 5.3). When a cropland patch was devoted to agroforestry system and plantation its yield changed and respectively become 16.61±3.7 (SE) m^2ha^{-1} and 32±15 (SE) m^2ha^{-1}.

5.5 Conclusions

A better understanding of the biophysical environment of any territory is a key factor for the evidence of the decision making. The current state of the socio-ecological system of the Dassari Basin could help to project for the future dynamic of the environment. The degradation rate of 1.48 % per year in the basin is significant information to predict the future impacts on CO_2 and N_2O emissions from vegetation degradation under various policies setting or scenarios. The biophysical characteristics of the site can also be useful as input for BEN-LUDAS model. Forest yield and natural transition rule were the key factors which determined the dynamics of the site. The flexibility of BEN-LUDAS model allowed the integration of these parameters in the model procedures.

CHAPTER VI: IMPACTS ASSESSMENT OF LAND USE SCENARIOS

6.1 Introduction

The Kyoto Protocol (http://unfccc.int/kyoto_protocol/items/2830.php) of the United Nations Framework Convention on Climate Change (UNFCCC) was developed as an attempt to confront and begin to reverse the rising CO_2 concentrations. Emissions of CO_2 from land use and land-use change represent up to 20 % of current CO_2 emissions from burning fossil fuels (Dixon *et al.*, 1994; Smit *et al.*, 2014; Brown *et al.*, 1996). According to the Kyoto protocol, changes in land-use can positively impact atmospheric CO_2 concentrations by either:

i) Decreasing emissions that would occur without intervention, or ii) Sequestering CO_2 from the atmosphere into vegetation and the associated soil. The Kyoto Protocol recognised the role that changes in the land use such as deforestation and afforestation, have on the global carbon cycle. Possible mitigation strategies to sequester carbon are planting trees, changing agricultural tillage or cropping practices, or reestablishing grasslands. In addition, the Protocol includes a mechanism by which industrialised (Annex I) nations can offset some of their emissions by investing in projects in non-industrialised (non-Annex I) nations in line with the clean development mechanism (CDM, Article 12).

The purpose of the clean development mechanism is to assist Parties not included in Annex I in achieving sustainable development and in contributing to the ultimate objective of the convention, and to assist parties included in Annex I in achieving compliance with their quantified limitation and reduction commitments.

In the context of this study the land use scenarios are the different policies that could be adopted to change the way the land is used for agricultural purpose. In other terms, scenarios define the new approaches for agricultural practices with the aim to reduce the impacts of the current practice in the environment and to alleviate poverty at the household level. These scenarios or policies are characterized by the improvement of socio-economic and agronomic conditions of the site at different levels. These scenario need to be developed with the aim to set emission reduction target. These scenarios have a baseline or counterfactual with the aim to estimate what would have happened in the absence of a policy or project. It is required so that the mitigation impact of a project or policy can be quantified. In the forestry sector, the baseline is particularly important in attempts to reduce emissions from deforestation and degradation (Bond *et al.*, 2009).

The developed land use scenarios will help countries with historically high rates of deforestation to adjust their policy in term of land use management and to unfold the future impact of the defined policies. The present chapter addresses this issue in developing four land use scenarios based on the change of land use pattern between 2001 and 2013 and the socio-economic situation of the study site.

The aim was to compare scenarios based mitigation strategy to climate change as an issue of contributing for carbon and nitrogen sequestration, and the condition financial investment' as an economic development pathway, and to explore the possible future temporal and spatial impacts on vegetation carbon/nitrogen stocks or CO_2 and N_2O emissions.

6.2 International agreements for climate change mitigation strategy in AFOLU sector

Kyoto Protocol

The Kyoto Protocol (1997) was adopted in Kyoto on 11th December 1997. The Protocol is the set of 28 Articles and the Parties to this Protocol being Parties to the UNFCCC. The Kyoto Protocol recognized that some GHGs such as Carbon dioxide (CO_2), Methane (CH_4), Nitrous oxide (N_2O), Hydrofluorocarbon (HFCs), Perfluorocarbons (PFCs), Sulphur hexafluoride (SF_6) destroy ozone layer and contribute to the global environmental change.

Safeguards in REDD plus under the Cancun Agreement

UNFCCC Cancun and Durban Agreements (Decision 1/CP.16 and Decision 12/CP.17) define safeguards as policies and measures that aim to address both direct and indirect impacts of REDD + in communities and ecosystems (UNFCCC, 2013). The safeguards comprise three levels (governance, social and environment) and are underlined as follows:

- That actions complement or are consistent with the objectives of national forest programmes and relevant international conventions and agreements;
- Transparent and effective national forest governance structures, taking into account national legislation and sovereignty;
- Respect for the knowledge and rights of indigenous peoples and members of local communities, by taking into account relevant international obligations, national circumstances and laws.
- The full and effective participation of relevant stakeholders, in particular indigenous peoples and local communities,
- That actions are consistent with the conservation of natural forests and biological diversity, ensuring that the actions referred to in paragraph 70 of this decision are not used for the conversion of natural forests, but are instead used to incentivize the protection and conservation of natural forests and their ecosystem services, and to enhance other social and environmental benefits,

- Actions to address the risks of reversals;
- Actions to reduce displacement of emissions.

In line with the Cancun Agreement, Paris Agreement was approved by Parties in 2015.

Paris Agreement (COP 21)

The adoption of the Paris Agreement is recalling:

- decision 1/CP.17 on the establishment of the Ad Hoc Working Group on the Durban Platform for Enhanced Action,
- Articles 2, 3 and 4 of the Convention,
- relevant decisions of the Conference of the Parties, including decisions 1/CP.16, 2/CP.18, 1/CP.19 and 1/CP.20,

The Paris Agreement is based on the key goal: "**Transforming our world: the 2030 Agenda for Sustainable Development**". In accordance with this goal the main important retained resolution which fit with the present research study are:

- The Conference of the Parties recognize that climate change represents an urgent and potentially irreversible threat to human societies and the planet and thus requires the widest possible cooperation by all countries, and their participation in an effective and appropriate international response, with a view to accelerating the reduction of global greenhouse gas emissions,
- The Conference of the Parties notes with concern that the estimated aggregate greenhouse gas emission levels in **2025** and **2030** resulting from the intended nationally determined contributions do not fall within least-cost 2 ˚C scenarios but rather lead to a projected level of 55 gigatonnes in 2030, and also notes that much greater emission reduction efforts will be required than those associated with the intended nationally determined contributions in order to hold the increase in the global average temperature to below 2 ˚C above pre-industrial levels by reducing emissions to 40 gigatonnes or to 1.5 ˚C.

The developed scenarios in the case of this research study were simulated from 2013 to 2025 with the aim of determining the impact of each scenario in terms of emissions of carbon dioxide (CO_2) and nitrous oxide (N_2O) due to vegetation degradation in the basin and in addition to assess their future impacts in terms of emissions reduction and net removal of carbon dioxide.

6.3 National circumstance

Benin is a West African country located between latitude 6º 30' and 12º 30' North and longitude 1º and 3º 40' East with an area of 114,763 km^2 (DCN, 2011). Regarding the agricultural sector, the country produces cash crops mainly cotton with the emergence of pineapple and cashew (DCN, 2011). The most important food crops are maize, cassava and sorghum. Farming is still influenced by traditional practices.

Brief analysis of the national inventory of GHGs emissions revealed the need for the country to build an effective climate change action and defines options for mitigating climate change. The country also provides a basis to participate in the flexibility mechanisms associated with the United Nations Framework Convention on Climate Change (UNFCCC), focusing on REDD+ with regards to these actions, the methodological approach for the national GHGs inventory was based on the IPCC Tier 1 method. The DCN (2011) revealed that in the year 2000 the agricultural and energy sectors were the main sources of the total emissions, with 68 and 30 %, respectively.

In the agricultural sector, climate scenarios were used for the horizon 2015 and 2025 with the analysis of the magnitude of the impacts on crops yield in the different agro-ecological zones of Benin. In the forestry sector, the scenario were used for the horizon 2050 and 2100 with the analysis of the increase of the temperature on the ecosystem in terms of water stress or heat that could cause tree mortality.

Despite these actions to mitigate climate change in the AFOLU sector more effort are needs to be done. Infact, the country still uses the Tier 1 method for the GHGs inventory. In addition there is the lack of data provided from modelling land use/cover changes and its future impacts on the GHGs emissions in the AFOLU sector. The results provided by this research work will contribute towards closing these gaps for this part of the country (Sudan Savannah zone) and also contribute towards decision making at the national level.

6.4 Methodology

6.4.1 BEN-LUDAS model calibration and validation process

The calibration and validation of the BEN-LUDAS model was based on socio-economic information, two time series land use cover maps and the deforestation rate (Figure 6.1) using the sub-model Time-Labour-allocation previously defined in Table 2.2.

The model calibration was based on the livelihoods strategy of farming. The human asset of the livelihoods strategy defines the percentage of time and the labour allocated to agriculture practices by the farmers. Time-Labour-Allocation sub-model was used through labour-spent procedure developed within the BEN-LUDAS model. Infact, the change of land use during the time and space is a function of the quantum time-labour (percentage of time devoted to farming) and the number of persons who farm. The sub-model Time-Labour-allocation (Table 2.2) expressed the time-labour (in % times persons) allocated to farm a piece of land (at the pixel scale or patch level) during a time scale of one year or unit of simulation. For this purpose, farming is a function of the time allocated to the agricultural practice and the number of persons or the number of workers within the household. The deforestation rate is inversely proportional to the time-labour, i.e. high is the time-labour allocated to sow a patch of land, low is the deforestation rate. The Time-Labour-Allocation sub-model was constructed by simulating the model several times (11) using land use map of 2013. We run the model at the time scale of 12 years and we used the output to estimate the deforestation rate using Eq. 5.9. The log-transformation Time-Labour-Allocation sub-model was generated using SPSS 17 packages. The sub-model was then expressed in the form of **ln (TimeLabour) = -1.023 x ln (deforestation rate) + ln (38.924)** function (Figure 6.1 and Table 6.1) with R^2 = 0.9999. The sub-model was finally transformed in the exponential function (Eq.

6.1) as follows:

Time-labour [%] = exp [-1.023 x ln (deforestation rate) + ln (38.924)]   (6.1)

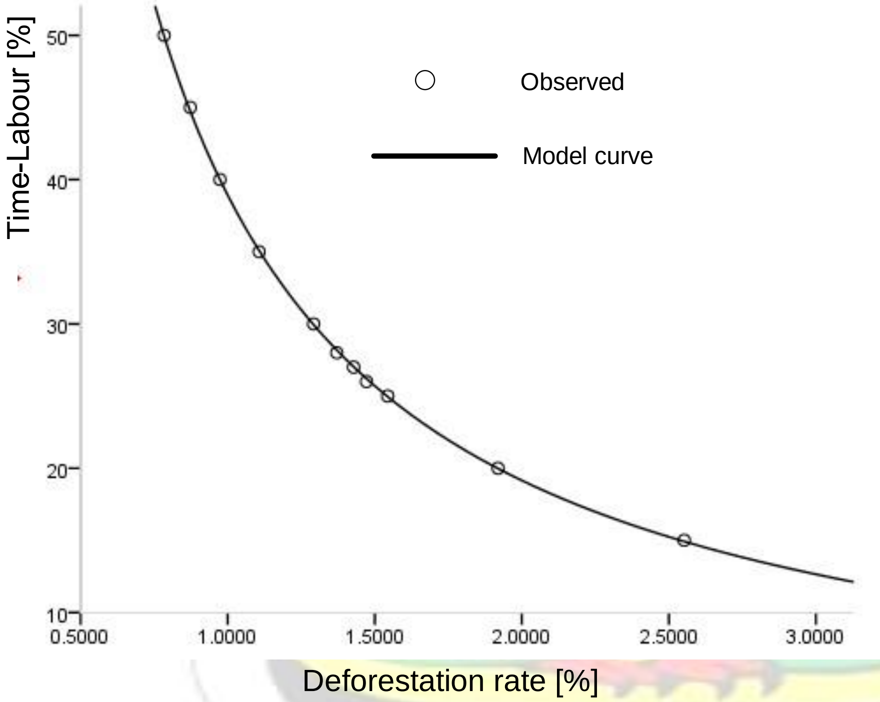


Figure 6. 1 Time-labour as a function of deforestation rate

The Time-Labour-allocation sub-model was integrated into the BEN-LUDAS model for validation and for simulating LULCC of developed scenarios.

Table 6. 1 Parameters of Time-Labour-Allocation sub-model

	Coefficient	**Standard error**	**Sig.**
Intercept	38.924	0.069	0.000
ln (deforestation rate (%))	-1.023	0.004	0.000

Note: The independent variable is ln (Time-Labour (%))

The model validation was based on the following steps:

- ✓ Estimation of the deforestation rate using Eq. 5.9,
- ✓ Integration of the land use map of 2001 into the BEN-LUDAS model,
- ✓ Simulating land use map of 2001 using the estimated deforestation rate from land use cover maps of 2001 and 2013,
- ✓ Comparing (Table 6.2) 12 years simulated (2013), (the outputs of the model) to the classified land use map of 2013,
- ✓ Estimating the difference between the classified map and the simulated one using Eq. 6.2 as follows:

$$Difference = \left[\frac{\text{LUC 2013} - \text{Simulated (2001–2013)}}{\text{LUC 2013}}\right] X\ 100 \qquad (6.2)$$

Where:
LUC 2013 is the classified land use/cover map of 2013 and simulated 2013 is the output of the classified land/cover 2001 simulating for 12 years under BEN-LUDAS.

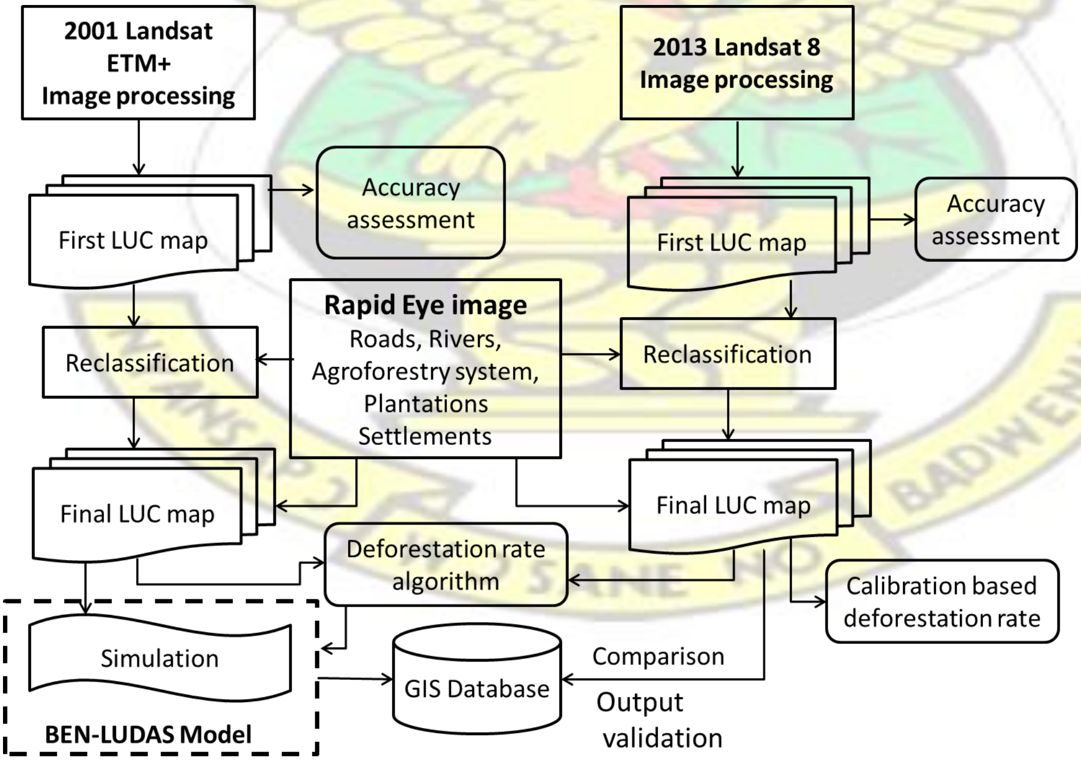


Figure 6. 2 Flowchart showing the calibration and validation process of BEN-LUDAS

The 12 years' timeline simulated 2013 shows (Table 6.2) the order of difference with the magnitude of 0.09 % for forest land whereas the difference was estimated to be 0.46 % for cropland and fallow. The low difference estimated between the observed and the predicted confirms that the model mimics well the reality and can be used for simulating land use/cover changes under developed scenarios.

Table 6. 2 Model validation (simulated 2013 versus classified land use cover maps of 2013)

LUCa	Area in (ha)			Difference (%)
	LUC 2001	LUC 2013	Simulated LUC 2013	
Forest land	11959.92	10010.25	10019.16	0.09
Cropland and fallow	6595.83	8031.15	8068.59	0.46

6.4.2 Land use scenarios

a. Business as Usual Scenario

The business as usual (BAU) scenario (LUS1) was based on the farmer's practices. The farming activity comprises the logging and burning of plant biomass. The main crops were maize, sorghum, millet, yam, rice, and beans as food crops and cotton as industrial crop. The assumptions for the business as usual scenario were the population growth rate of 2.54 %, a deforestation rate of 1.48 % and the present mean crop yield of 0.7 $t.ha^{-1}$. The observed deforestation rate of 1.48 % explained an increase of cropping area to 21.76 % from 2001 to 2013.

The assumptions of this scenario assumes that an increase of agricultural area without any AFOLU (Agriculture, Forestry and Other Land Use) initiative affects vegetation carbon and nitrogen storage at the basin level and this leads to the emission of carbon dioxide and nitrous oxide into the atmosphere due to farming activity.

b. Food security scenario

The food security scenario (LUS2) aims to contribute to the policy enhancement in farming activity. The cotton production is perceived as one of land use change drivers which leads to the increment of farm land and does not significantly contribute to alleviate poverty of rural population (according to our investigations from different stakeholders). The policy based food security that will lead to the increment of crop yield by 2.5 $t.ha^{-1}$ and the abandonment of cotton production in this part of the country is needed. Thus, this policy will help to decrease farm land size from 2013 to 2025 and to maintain the deforestation at the rate of 0.97. To estimate the deforestation rate of 0.97 % we first assumed that this rate was obtained under only food security between 2001 and 2013 i.e. assuming that cotton was not produced between 2001 and 2013. Infact, the forest land decreases to 1949.85 ha between 2001 and 2013 meaning an increment of cropland to 23.02 %. The socio-economic information revealed that cotton represents 32.27 % to the total crop. To calculate deforestation rate without cotton 32.27 % of 1949.85 was first estimated. This was then added to the area of forest land in 2013 and obtained 10639.32 ha. This value was used to calculate the deforestation rate, which is without cotton, and we obtained a rate of 0.97%. This rate was used for food security scenario. In addition to these inputs, the population growth rate of
2.54% was assumed.

c. Business as usual based adaptation and mitigation strategy scenario

This scenario (LUS3) assumed that farmer's households are conscious of the fact that their environment or weather is changing. It is assumed the farmers believe that there is a relationship between rainfall patterns and natural vegetation and that they decide as a result to devote a piece of their land for planting trees or adopt agroforestry systems to respond to the carbon market project and adaptation option to climate change. The mitigation strategy to climate change support farmers to adopt agroforestry systems and plantations at the farmer's fields and adaptation options (cropping systems strategies used to increase productivity at the farmer's field scale) contribute to increased resilience of farmers due to climate effect. To implement this scenario, input of LUS1 were considered and previous probability of 70 % and 65 % respectively for agroforestry system and plantation estimated were applied. In addition, the adaptation options to climate change assumed to increase the crop yield from 0.7 to 2.5 t/ha.

The policy based on the assumptions of this scenarios support REDD+ initiatives. This includes activities related to: Afforestation, Reforestation and Vegetation (ARR),

Agricultural Land Management (ALM), Improved Forest Management (IFM) and Reduced Emissions from Deforestation and Degradation (REDD). The assumptions for each scenario are outlined in Table 6.3.

Table 6. 3 Main assumptions of the land use scenarios based on land use change between 2001 and 2013 and on the socio-economic condition of the site

LUS_1: BUA (business as usual)	LUS_2: Food security	LUS_3: BUA based Adaptation and Mitigation strategy to climate change	LUS_4: Food security based Mitigation strategy to climate change
Population growth rate of 0.0254	Population growth rate of 0.0254	Probability of agroforestry system adoption is 70 %	Probability of agroforestry system adoption is 70 %

Deforestation rate of 1.48 % (Increment of cropland based cotton production to 23. 02 %)	Deforestation rate of 0.97 % (Increment of cropland to 15 %)	Probability of plantation adoption is 65 %	Probability of plantation adoption is 65 %
Productivity does not change (Mean Yield equal to 0.7 T / ha)	Policy enhancement in agricultural practices (yield improvement i.e from 0.7 to 2.5 t/ha)	Policy based adaptation strategy to climate change (yield improvement based adaptation option i.e from 0.7 to 2.5 t/ha)	Policy enhancement in agricultural practices (yield improvement i.e from 0.7 to 2.5 t/ha)

d. Food security based mitigation strategy scenario

The food security based mitigation strategy to climate change scenario (LUS4) used in addition to the assumptions of food security scenario the probability to adopt agroforestry system and plantation by farmers. Probability of 70 % (for agroforestry system) and 65 % (for plantation) were applied for this scenario.

6.4.3 Approach for estimating carbon stocks change (Emission-Removal of CO_2)

In the context of this study, the key activity data requirement for modelling carbon dynamics are area of forest land remaining forest land, forest area affected by disturbance, land afforested derived from cropland and land converted to forest through plantation or natural regeneration. For land use, the IPCC recognizes two methods to estimate carbon emissions: the Stock-Change method and the Gain-Loss method (IPCC, 2006). The Stock-change method estimates emissions by identifying the changes in carbon stocks at the beginning and end of the period over an entire monitoring area. The Gain-Loss method estimates emissions by identifying the area of change from one cover type to another and the difference in stocks between those two types per unit area (Angelsen, 2008). Hewson *et al.* (2014) provides a more detailed explanation and assert that for the Gain-Loss method, the field inventory is conducted to obtain an estimate of mean stock-per-unit-area for each cover class. These stocks per-unit-area estimates can then be assumed to be constant, and land use is monitored to estimate the areas of change between pairs of classes. In this case, the data on the difference in stocks associated with a change between two classes over time are called Emission Factors (EFs), and the areas of change are called Activity Data. These are multiplied to estimate the emissions associated with each type of land-use change.

We applied the stock-change approach (Eq. 6.3) in the case study to estimate emission and removals of carbon and nitrogen during 12 years simulations (2013-2025) for all scenarios. Land use transition rule based change detection approach (Section 5.3.15) was applied to determine area of change between the two periods and the carbon and nitrogen stock was assumed to be constant. This change detection approach used the two land use maps: the map of 2013 and the output of one of the scenarios. The net losses in total ecosystem carbon stocks were used to estimate CO_2 emissions to the atmosphere, and net gains in total ecosystem carbon stocks were used to estimate removal of CO_2 from the atmosphere (IPCC, 2006).

Equation 6.3 was used to express this removal/emission for each LUC class:

$$\Delta C = \frac{C_{t2} - C_{t1}}{t_2 - t_1} \qquad (6.3)$$

Where:
ΔC = annual carbon stock change in the pool, Gg C yr^{-1}
C_{t1}= carbon stock in the pool at time t_1, Gg C
C_{t2}= carbon stock in the pool at time t_2, Gg C

The conversion from the biomass to carbon and from the carbon to the carbon dioxide at the tree level was based on the Eq 6.4 as follow:

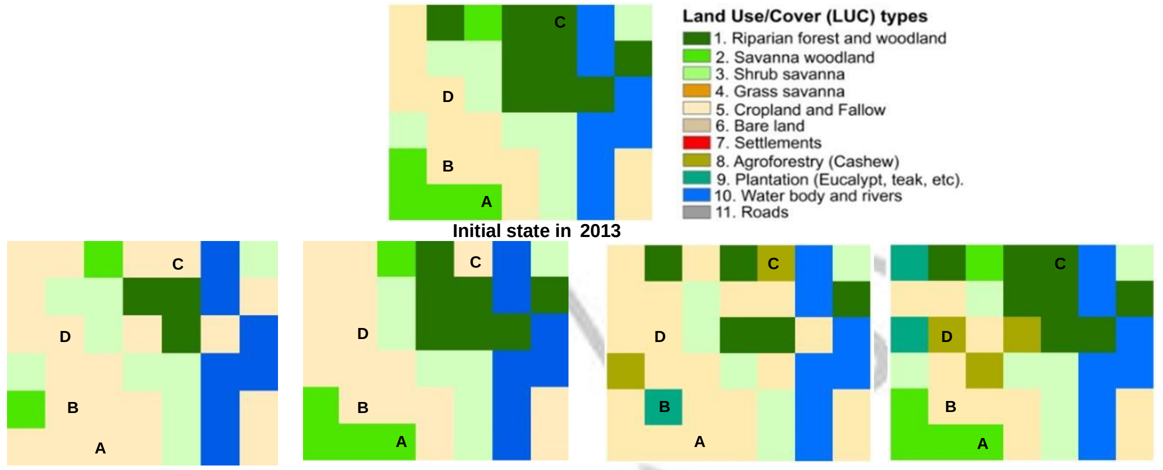
$$CO_{2\,(emission)} = AGB_{(allometric\ model)}\ x\ C\%_{(carbon\ content)}\ x\ \frac{44}{12} \qquad (6.4)$$

Where:
CO_2 = Carbon dioxide emission
AGB = Aboveground biomass at the tree level using allometric equation C%
= carbon content (%) of the tree species

6.4.4 Illustration of the emission/removal process based on the zoom in the specific areas

The specific area was zoomed with few pixels to explain the process of land use transition matrix and its implication in the estimation of carbon dioxide emissions and removal from land use cover changes. It was first assumed that the mean carbon stock previously estimated for each LUC class in the Table 3.19 was constant over the year. In fact, the mean carbon stock or emission factors (EFs), which is agro-ecological zone based for each country, is the key input for carbon accounting recommended by IPCC (2006). At the pixel level for example, the decision rules of land use transition from Figure 5.3 and the mean carbon stock from Table 3.19 can be applied to estimate emission or removal of carbon dioxide `during two periods. The removal and emission process during two periods (2013 and 2025) are explained in Figure 6.3. The process of land use transition and its implication in the removal /emission process were explained in the four scenarios as an example and which mimic the real world. These cases are as followed:

1. The pixel A (Figure 6.2) was savanna woodland in 2013 and has changed to cropland under the scenarios LUS1. Thus, the named pixel holds the mean carbon stock of 21.35±1.16 $Mg.ha^{-1}$ which has become 1.52±0.14 $Mg.ha^{-1}$ over 12 years timeline because of farming activity or shifting cultivation. Thus, the estimation of emission/removal factor was based on the difference between two mean carbon stocks from two LUC class. The lost was equal to 19.53 $Mg.ha^{-1}$ meaning the difference of: 21.35 $Mg.ha^{-1}$ – 1.52 $Mg.ha^{-1}$. For this given pixel of the size 0.09 ha which represented the activity data (AD) it will release 1.75 Mg of carbon or 6.45 Mg of carbon dioxide during the change of its state from savanna woodland to cropland.



LUS1: Business as usual scenario

LUS2: Food security based adaptation and mitigation strategy to climate change scenario

LUS3: Business as usual based mitigation strategy to climate change scenario

LUS4: Food security scenario

Figure 6. 3 Land use transition scheme and its implication in the removal/emission process

2. The pixel B was cropland in 2013 and has changed the state to become plantation under the scenario LUS3. Thus, it can be said that the owner of the land decided to adopt mitigation based plantation. This mitigation action to climate change lead to a reduction of (1.52 $Mg.ha^{-1}$ - 97.83 $Mg.ha^{-1}$. x 0.09 ha) of carbon from the atmosphere equals the removal of 31.81 Mg of carbon dioxide from the atmosphere.

3. The pixel C was riparian forest and woodland in 2013 and has changed the state to become agroforestry under the scenario LUS3. This context means that during the 12 years simulation it was assumed that the farmers aim to first convert the forest land to agricultural land for crop production during a certain number of years before they decide to transform that land to either agroforestry or plantation. In the present case, the final state is concerned despite we could say there is first emission before that emission was reduced due to agroforestry system. The emission was estimated to be 2.10 Mg of C or 7.73 Mg of CO_2 despite agroforestry has been established after cropland. In the absence of agroforestry 3.89 Mg of C or 14.29 Mg of CO_2 will be emitted. It was previously explained in Section 3.3.8 that agroforestry cannot help to compensate the total amount of carbon loss from riparian forest when it is converted to cropland.

4. The pixel D was cropland in 2013 and has changed to agroforestry under the scenario LUS4 indicating the removal of 1.78 Mg of C or 6.56 Mg of CO_2 from the atmosphere.

6.5 Results and discussion

6.5.1 Impact assessment of land use cover change on CO_2 and N_2O emission (2001-2013)

The assessment of LULCC on CO_2 and N_2O emission from 2001 to 2013 was based on the results of mean carbon stock used to estimate emission factors (Table 3.19). The mean carbon stocks were assumed to be constant over time during 2001 and 2013.

Table 6. 4 Emission of CO_2 and N_2O in Gg per year during 2001-2013

Period	CO_2 emission	CO_2 removal	N_2O	Net removal	Emission CO_2eq.
2001-2013	12.04	-36.62	0.03	-24.58	21.34

The total of 21.34 CO_2 eq Gg of carbon dioxide was emitted per year during 2001 and 2013 due to farming activity. This trend will continue if there is no policy to mitigate the effect of change or to reduce emission from the vegetation degradation.

6.5.2 BEN-LUDAS as a tool for visualizing and testing the impacts of land-use scenario

BEN-LUDAS graphic user interface (GUI) is presented in 3 main parts as follows:

✓ The button of importation of spatial data, the button that enable user to generate basal area, biomass, carbon and nitrogen stocks and the button for the importation of the households data. All these buttons were executed under the command procedure based submodels (number 1 of part 1). The set of number 2 buttons in part 1 deal with the spatial attributes such as elevation, slope, upslope, spatial policy, restricted area, wetness index, land use, soil type. These spatial attributes can also be visualized several times as soon as the buttons of the biomass, carbon and nitrogen content. The setup button allows clearing all data in the screen.

The number 3 presented the GIS raster, simulation button and output exportation button (Figure 6.3).

✓ Part 2 (numbers 4, 5 and 6) describe the global parameters and the parameters for land use scenarios development. The set of number 4 button dealt with the times scale of the simulation, the global parameters such as spatial policy related to protected zone area, the deforestation rate, the vision of the farmer or its sphere of influence, the productivity parameters, the markets price input and the counter of population dynamic. User will find the parameters of mitigation setting of the set of buttons in number 5. This set of buttons show the on/off buttons for adoption or not of mitigation strategy (adoption or not of agroforestry and plantation) during the scenario running and their defined probability. The set of buttons in number 6 show the population dynamic sub-model. This population dynamic sub-model was built based on the assumption of birth and death and the rates associated.

✓ The part 3 (numbers 7 to 18) show respectively the Lorenz curve, the financial return to the farmers if mitigation strategy was applied during the implementation of carbon fund project in scenarios based mitigation, the size of different groups of household during the simulation process, the curve of household growth (or population growth), the Gini index, the annual gross income based carbon credit curve, the annual gross income based cultivated area, the area in hectares of each LUC, the biomass, carbon and nitrogen stocks and finally the area of mitigation strategy.

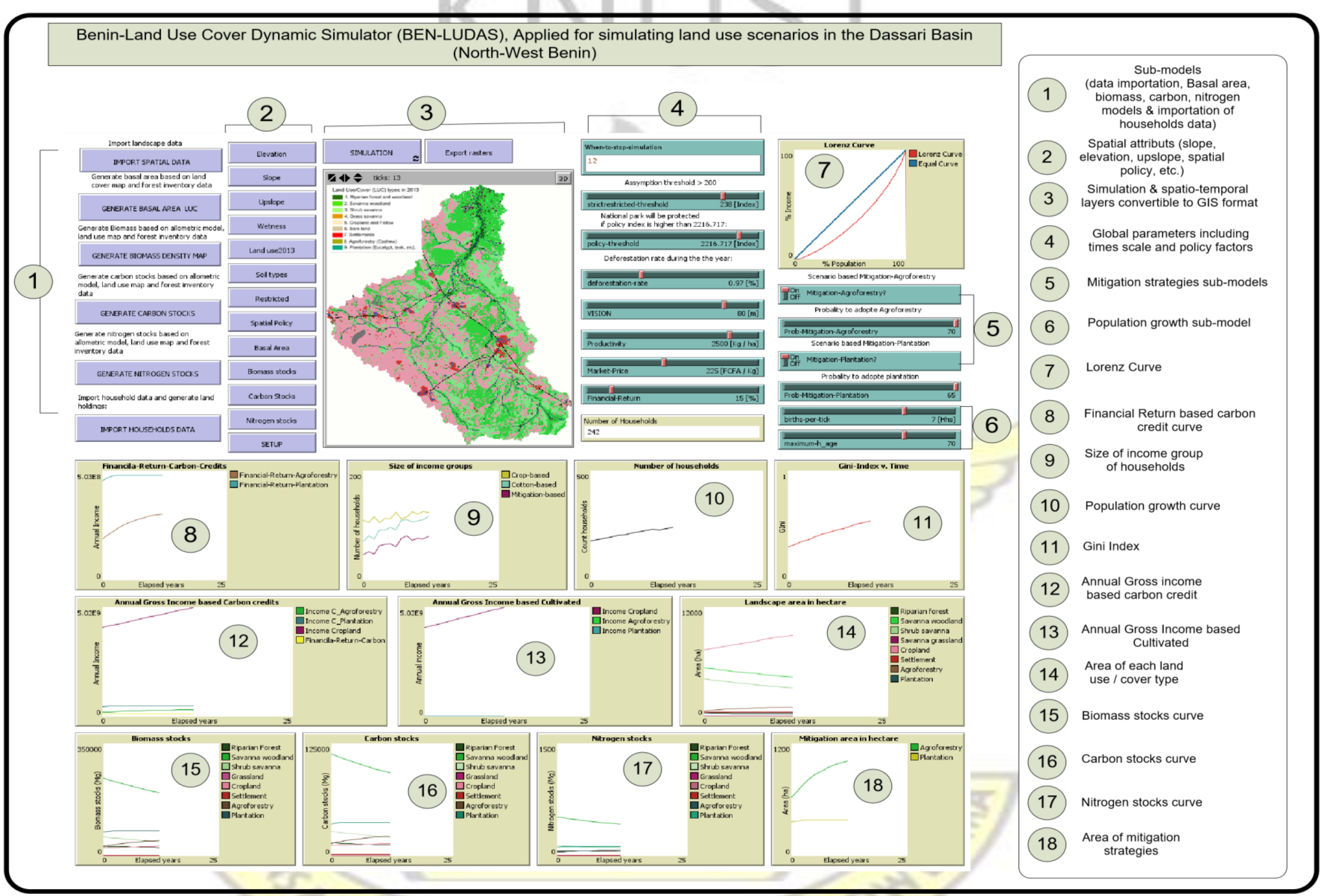

Benin-Land Use Cover Dynamic Simulator (BEN-LUDAS), Applied for simulating land use scenarios in the Dassari Basin (North-West Benin)
Import landscape data
IMPORT SPATIAL DATA
Generate basal area based on land cover map and forest inventory data
GENERATE BASAL AREA LUC
Generate Biomass based on allometric model, land use map and forest inventory data
GENERATE BIOMASS DENSITY MAP
Generate carbon stocks based on allometric model, land use map and forest inventory data
GENERATE CARBON STOCKS
Generate nitrogen stocks based on allometric model, land use map and forest inventory data
GENERATE NITROGEN STOCKS
Import household data and generate land holdings:
IMPORT HOUSEHOLDS DATA
Elevation
Slope
Upslope
Wetness
Land use2013
Soil types
Restricted
Spatial Policy
Basal Area
Biomass stocks
Carbon Stocks
Nitrogen stocks
SETUP
SIMULATION
Export rasters
ticks: 13
When-to-stop-simulation
12
Assymption threshold > 200
strictrestricted-threshold 238 [Index]
National park will be protected if policy index is higher than 2216.717:
policy-threshold 2216.717 [Index]
Deforestation rate during the the year:
deforestation-rate 0.97 [%]
VISION 80 [m]
Productivity 2500 [kg / ha]
Market-Price 225 [FCFA / kg]
Financial-Return 15 [%]
Number of Households
242
Lorenz Curve
Lorenz Curve
Equal Curve
% Income
% Population
Scenario based Mitigation-Agroforestry
Mitigation-Agroforestry?
Probality to adopte Agroforestry
Prob-Mitigation-Agroforestry 70
Scenario based Mitigation-Plantation
Mitigation-Plantation?
Probality to adopte plantation
Prob-Mitigation-Plantation 65
births-per-tick 7 [Hhs]
maximum-h_age 70
Financila-Return-Carbon-Credits
Financial-Return-Agroforestry
Financial-Return-Plantation
Size of income groups
Crop-based
Cotton-based
Mitigation-based
Number of households
Gini-Index v. Time
Annual Gross Income based Carbon credits
Income C_Agroforestry
Income C_Plantation
Income Cropland
Financila-Return-Carbon
Annual Gross Income based Cultivated
Income Cropland
Income Agroforestry
Income Plantation
Landscape area in hectare
Riparian forest
Savanna woodland
Shrub savanna
Savanna grassland
Cropland
Settlement
Agroforestry
Plantation
Biomass stocks
Carbon stocks
Nitrogen stocks
Mitigation area in hectare
Elapsed years
1 Sub-models (data importation, Basal area, biomass, carbon, nitrogen models & importation of households data)
2 Spatial attributs (slope, elevation, upslope, spatial policy, etc.)
3 Simulation & spatio-temporal layers convertible to GIS format
4 Global parameters including times scale and policy factors
5 Mitigation strategies sub-models
6 Population growth sub-model
7 Lorenz Curve
8 Financial Return based carbon credit curve
9 Size of income group of households
10 Population growth curve
11 Gini Index
12 Annual Gross income based carbon credit
13 Annual Gross Income based Cultivated
14 Area of each land use / cover type
15 Biomass stocks curve
16 Carbon stocks curve
17 Nitrogen stocks curve
18 Area of mitigation strategies

Figure 6. 4 The BEN-LUDAS's graphic-user interface enables users to visualize and test impacts of land-use scenarios

6.5.3 Impact assessment of developed land use scenarios

a. Impacts of developed land use scenarios on LULCC

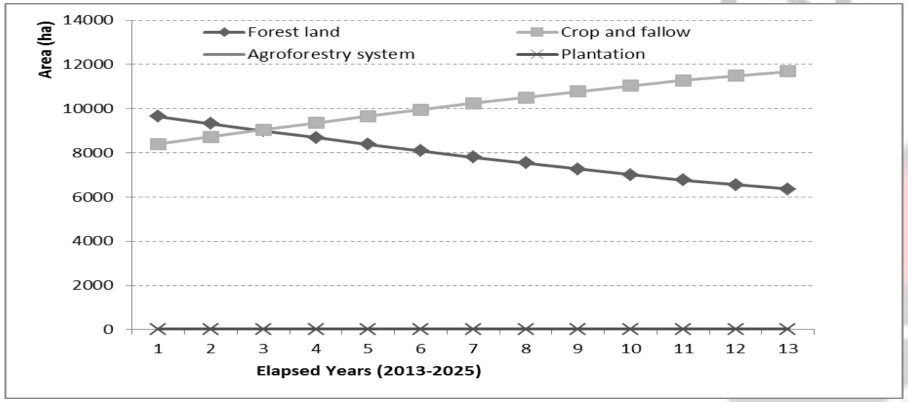
The business as usual scenario is based on the continuation of observed trends in land use practise and livelihood of rural communities known as business-as-usual scenario. The deforestation rate was 1.48 % per year for the business-as-usual scenario. The business-asusual scenario (LUS1 in Figure 6.5) in this context will contribute to the increment of cropland by 3.79 % per year by 2025, whereas the area of forest land (riparian forest, savanna woodland and shrub savanna) will decrease by 3.03 % per year if the trends continue without any policy change. The current way of using the land will lead to the abandonment of much farm lands as fallows. This situation can be explained by the decrease of productivity from 2013 to 2025 because some land will be over-exploited due to the high pressure on the land as a result of lack of forested area for farming in the future.

The policy intervention actions under the food security scenario are the improvement of the productivity at the farmer's field scale and on a legislation declares the West-Atacora on which the study area as not suitable for cotton production. Infact, these actions aim to restore the degraded land by limiting the impact of human pressure in the forest land. The effects of these actions tested under food security scenario (LUS2 in Figure 6.5) will contribute to the increment of cropland by 2.12 % per year and the decrease of forest land by 2.65 % per year. The productivity improvement could strengthen the resilience of rural communities and alleviate poverty at the household scale.

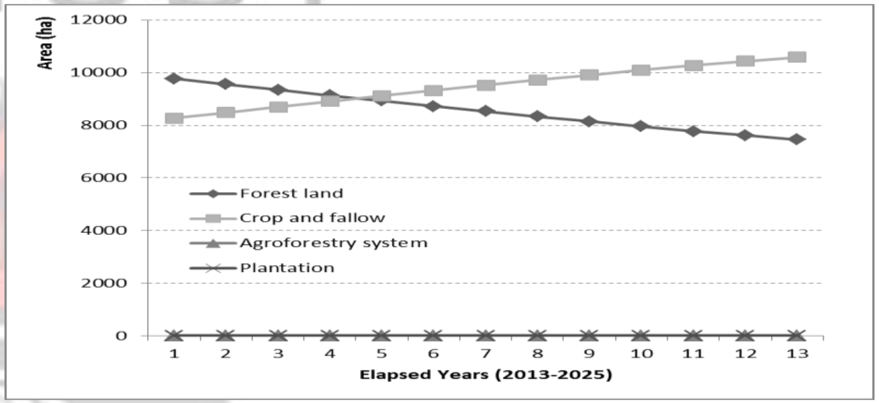
The scenario based adaptation and mitigation strategy to climate change (LUS3 in Figure 6.4) was built to change policy setting of business as usual by adopting agroforestry and planting tree in the devoted land by farmers and by improving crop based adaptation options (different cropping systems used at the farm scale to improve productivity). The adaptation options to climate change will be applied to strengthen the resilience of farm land thus, of rural communities who are dependent on the productivity of the land. This scenario will lead to an increment of agroforestry system by 481.52 % per year and increment of the plantation area by 191.93 % per year. The increment of cropland was estimated to be 1.64 % per year and the decrease of forest land by 2.62 % per year, which is in contrast to the developments under LUS1.

The food security scenarios based mitigation strategy to climate change will lead to an increment of cropland by 0.94 % per year from 2013 to 2025 whereas the area of forest land will decrease by 1.89 % per year and area of agroforestry and plantation will respectively increase by 401.88 % and 182.66 % per year if mitigation strategies are adopted at the farmer's field scale within the degraded land.

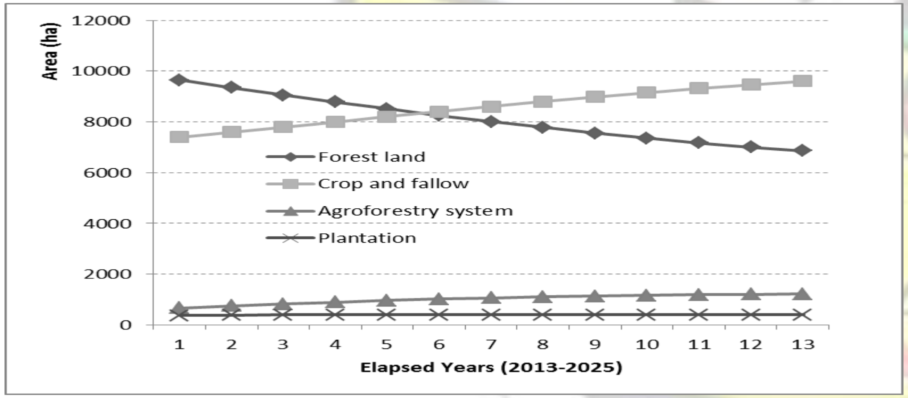
The future spatial pattern (2013-2025) of land use/cover for these scenarios is illustrated in Figure 6.6. The observation of land use cover trajectory of LUS1 revealed that except for the villages of Wantehou and Koupendry (Figure 4.1) the pressure on the land will increase in the areas of the remaining villages and the national park which was protected is at risk and may be an object of conflict between farmers and the authority in charge of the protection of this zone regarding the trajectory of change for all scenarios. In the other way, in the absence of land for farming, households may be constrained to migrate. Infact, the land use trajectory has shown the area of change between the two periods for all scenarios. The outputs provided is an important tool for decision making in the setting of land and forest management to mitigate climate change. The trajectory of change between 2013 and all scenarios is in line with the past trend (2001-2013) (Figures 5.4 and 5.5).



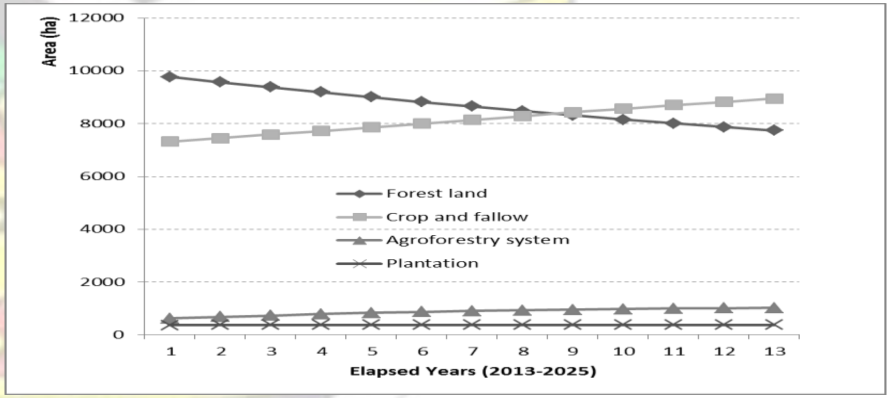
LUS1: Business as usual scenario



LUS2: Food security scenario



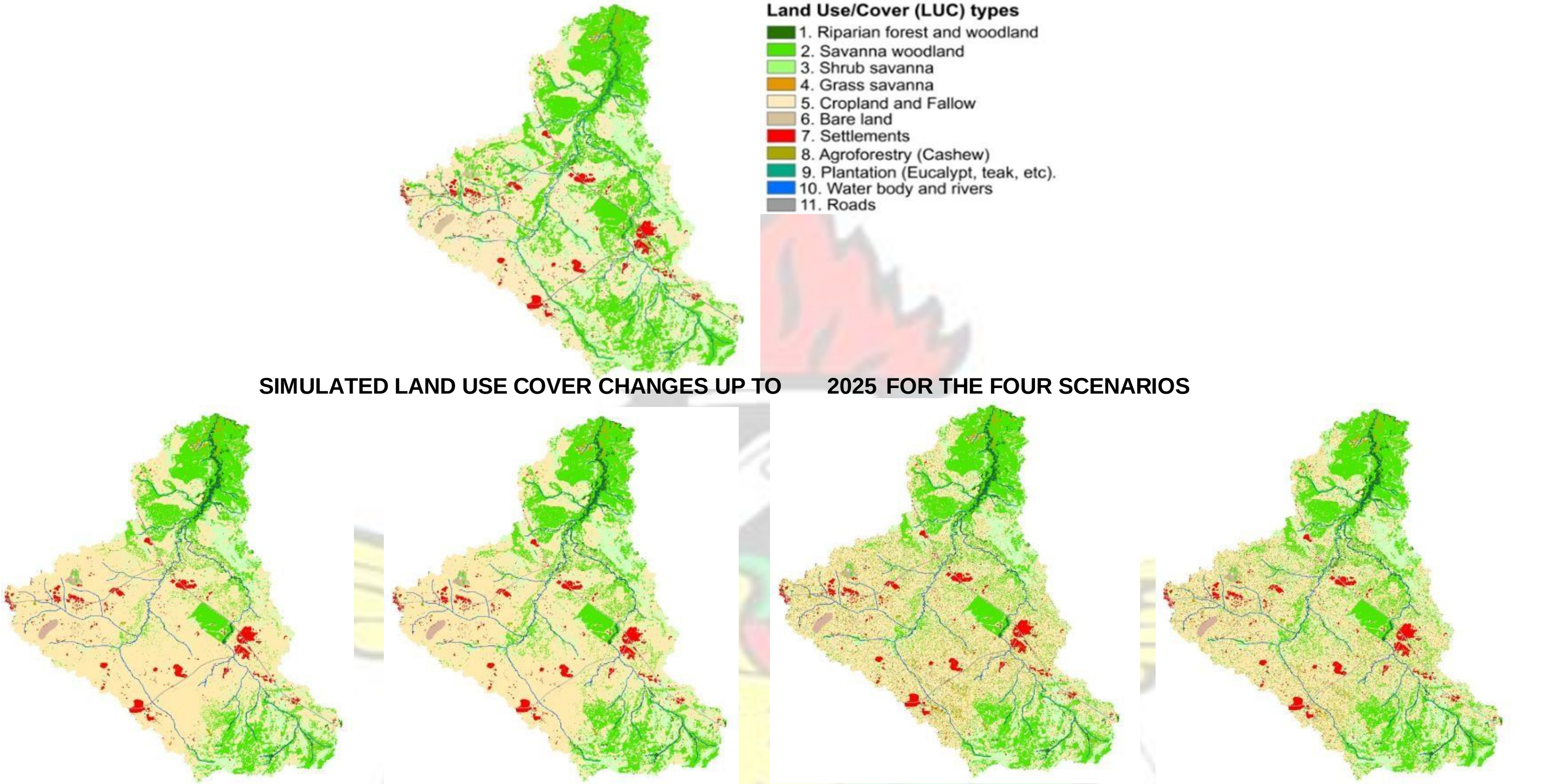
LUS3: Business as usual based adaptation and mitigation strategy to climate change scenario



LUS4: Food security based mitigation strategy to climate change scenario

Figure 6. 5 Simulated areas of land-uses /cover changes for developed scenarios between 2013 and 2025 Source: Data exported from BEN-LUDAS

LUC IN 2013



LUS1: Business as usual scenario

LUS2: Food security scenario

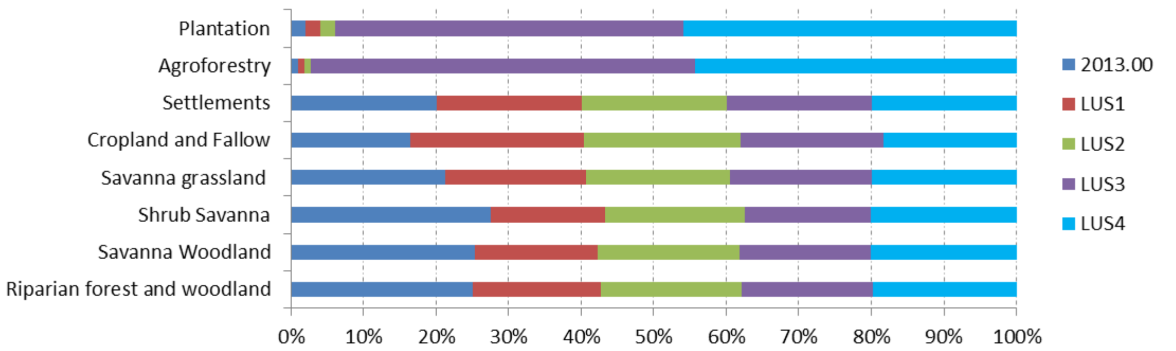
LUS3: Business as usual based adaptation and mitigation climate strategy to climate change scenario

LUS4: Food security based mitigation strategy to change scenario

Figure 6. 6 Simulated land-uses/cover changes for developed scenarios between 2013 and 2025 Source: Data exported from BEN-LUDAS

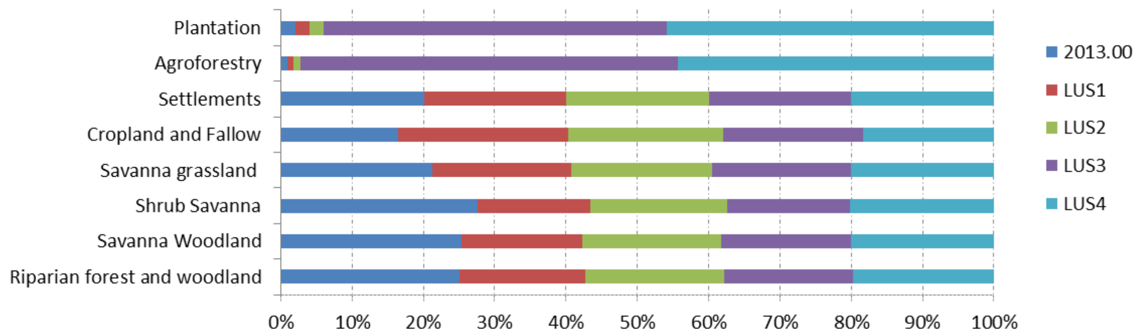
b. Impacts of developed land use scenarios on the vegetation carbon and nitrogen stocks

The research in Chapter 3 determined respectively a total storage of 175347.75 ± 21042.48 (CI) and 875.53 ± 101.45 (CI) Mg of carbon and nitrogen stocks in 2013 at 95 % confidence interval. The analysis of the scenarios revealed that LUS1 and LUS2 scenarios will respectively contribute to the decrease of carbon stocks by 2.34 and 1.66 %, and nitrogen stocks by 2.31 and 1.64 % per year. In contrast, the scenarios LUS3 and LUS4 will respectively help to uptake carbon by 0.85 % and 1.12 % per year and sequestered nitrogen into the vegetation by 0.03 and 0.37 % per year.



	Riparian forest and woodland	Savanna Woodland	Shrub Savanna	Savanna grassland	Cropland and Fallow	Settlements	Agroforestry	Plantation
2013.00	15291.86	116401.71	28147.44	161.56	12272.24	1125.66	442.91	1646.64
LUS1	10870.90	77838.98	16133.43	148.01	17833.42	1121.93	442.91	1637.84
LUS2	11847.06	89463.85	19625.24	150.87	16152.74	1121.93	442.91	1637.84
LUS3	11088.72	83315.70	17670.82	148.01	14663.18	1121.93	26035.54	39360.97
LUS4	12089.08	92258.64	20555.72	152.07	13644.14	1121.93	21802.84	37538.21

Figure 6. 7 Simulated stocks of carbon (in Mg) for developed scenarios between 2013 and 2025 in each LUC Source: Data exported from BEN-LUDAS



	Riparian forest and woodland	Savanna Woodland	Shrub Savanna	Savanna grassland	Cropland and Fallow	Settlements	Agroforestry	Plantation
2013.00	72.42	530.79	137.16	0.83	62.58	5.21	1.54	5.41
LUS1	51.48	354.95	78.62	0.76	90.94	5.19	1.54	5.39
LUS2	56.10	407.95	95.63	0.77	82.37	5.19	1.54	5.39
LUS3	52.51	379.92	86.11	0.76	74.77	5.19	90.25	129.43
LUS4	57.25	420.70	100.17	0.78	69.58	5.19	75.58	123.44

Figure 6. 8 Simulated stocks of nitrogen (in Mg) for developed scenarios between 2013 and 2025 Source: Data exported from BEN-LUDAS

The amount of carbon and nitrogen sequestered within the forest land will decrease whereas the carbon sequestration of cropland will increase under scenarios LUS1 and LUS2 (Figures 6.7 & 6.8). This will lead to the emission of CO_2 and N_2O into the atmosphere and contribute to global warming for the future climate.

c. Impacts of developed land use scenarios on future emissions of CO_2 and N_2O

The business as usual scenario or the baseline (LUS1) will contribute to the emissions of 16.805 Gg of CO_2 and 0.033 Gg of N_2O, to the net removal of 21.70 Gg of CO_2 and to the total emissions of 26.70 Gg of CO_2 eq. per year over the period 2013-2025 (Table 6.5). The impact of the policy under food security (LUS2) scenario will contribute to decrease the total emission by 29.25 % and will increase the net removal by 42.94 % whereas policy based adaptation and mitigation strategy to climate change (LUS3) and food security based mitigation strategy to climate change (LUS4) will respectively contribute to reduce the total emission by 13.14 % and 36.47 %. The scenarios LUS3 and LUS4 will also respectively contribute to increase the net removal by 105.05 % and 131.11 % per year from 2013 to 2025. To reach the objectives of the policy behind the baseline motivated by the adaptation and mitigation strategy to climate change scenario (LUS3) which is built to support REDD+ and MRV initiatives, 101.4 ha and 32.13 ha respectively for agroforestry system (mixed crops and fruit based trees) and plantation (timber based trees) will be adopted per year from 2013 to 2025. This action means the conversion 1.4 % of cropland to agroforestry and plantation per year. In the same time for the food security motivated by the mitigation strategy to climate change, 84.91 ha of agroforestry and 31.97 ha of plantation will be adopted per year by the households of the basin meaning conversion of 1.3 % of cropland to agroforestry and plantation. The analyses of the results (Table 6.5) allow asserting that the basin will still be a sink for the next 12 years (up to 2025). Despite this, it is time to act and react with the aim to strengthen resilience of farmers and contribute to carbon sequestration through local project development or project based carbon fund.

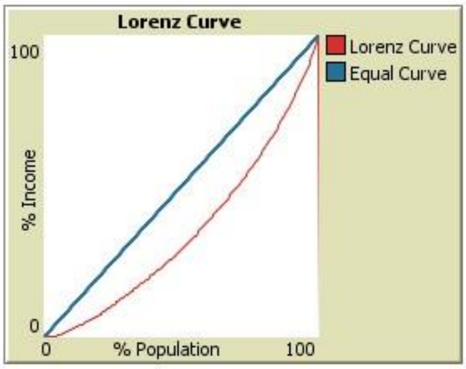
Table 6. 5 Results of simulated CO_2 and N_2O emission in Gg per year from 2013 to 2025

Scenarios	CO_2 emission	CO_2 removal	N_2O emission	Net removal	Emission of CO_2 eq.
LUS_1	16.80	-38.50	0.033	-21.70	26.70
LUS_2	11.88	-42.91	0.024	-31.02	18.89
LUS_3	14.59	-59.09	0.029	-44.50	23.19
LUS_4	10.67	-60.85	0.021	-50.17	16.96

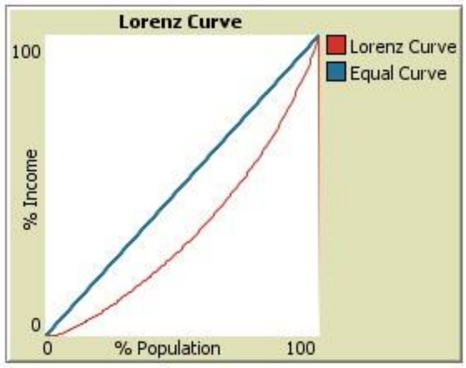
In the context of this study, we analysed the net removal that could occur due to the adaptation and mitigation to climate change for the scenarios LUS3 and estimated this to be 44.5 Gg of CO_2 eq per year. In the same line, the net removal that could occur in applying LUS4 was estimated to be 50.17 Gg of CO_2 eq per year.

d. Impacts of developed land use scenarios on the socio-economic status of households

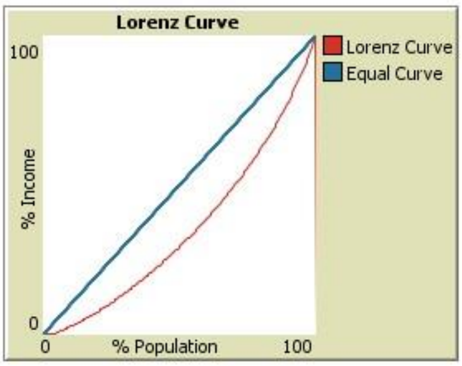
Lorenz curve was used to measure the income distribution of households when simulating various land use scenarios. The Lorenz curve is shown in Figure 6.9 for each scenario. The Gini index (Figures 6.10) is a measure of the inequality of a distribution. A value of 0 expressed total equality and a value of 1 explained the maximal inequality. Given the Lorenz Curve plot, the Gini coefficient was computed as a function of socio-economic status of households under developed land use scenarios using NetLogo 4.1.3.



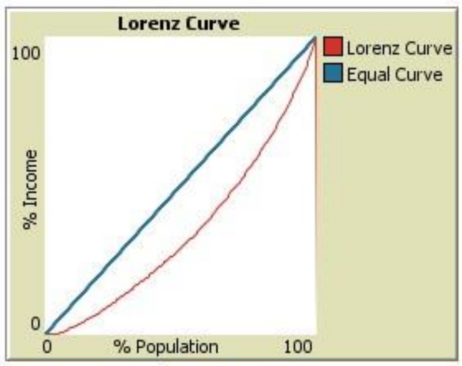
Lorenz curve for LUS 1



Lorenz curve for LUS2



Lorenz curve for LUS3



Lorenz curve for LUS4

Figure 6. 9 Graphical outputs of Lorenz Curve under the four scenarios Source: Data exported from BEN-LUDAS

The Gini values showed significant trends after 6 years of simulation. The difference of Gini values of 0.01 within the same year between two scenarios can explain the significant difference in term of livelihood of population as Gini varies from 0 to 1.

The Gini index increased during the 12 years simulation of LUS1 and tested that the population will be poorest for the coming years due to the high pressure on the land and its lack and mainly due to the low productivity obtained at the farmer's plots. The other scenarios showed increasing trends but with a moderate slope and tested the importance of the improvement of crop yield at the farmer's plots level and in addition the adoption of agroforestry systems and financial returns for farmers as an issue of mitigation strategy to climate change. The Gini values for each scenario during 12 years simulation were presented in appendix 1 and Table 9.2.

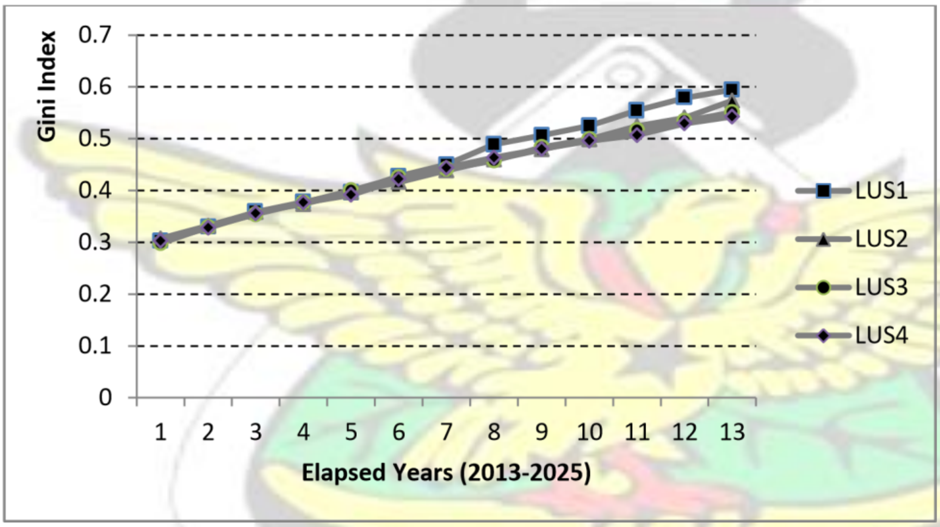


Figure 6. 10 Graphical outputs of Gini index showing the simulated income distribution of the households Source: Data exported from BEN-LUDAS

6.6 Conclusions

The impacts of developed land use scenarios on CO_2 and N_2O emission revealed an increment of the amount of CO_2 and N_2O into the atmosphere if the present trend of land disturbance would continue for the next 12 years (from 2013 to 2025). The business as usual scenario or the baseline (LUS1) will contribute to the emissions of 16.805 Gg of CO_2, 0.033 Gg of N_2O, to the net removal of 21.70 Gg of CO_2 and to the total emissions of 26.70 Gg of CO_2 eq. per year over the period 2013-2025. The impact of food security (LUS2) based policy action would lead to reduction of the total emissions by 29.25 % and would increase the net removal by 42.94 % whereas policy based adaptation and mitigation strategy to climate change (LUS3) and food security based mitigation strategy to climate change (LUS4) would respectively contribute to reduce the total emissions by 13.14 % and 36.47 %. The scenarios LUS3 and LUS4 would also respectively contribute to increase the net removal by 105.05 % and 131.11 % per year from 2013 to 2025.

CHAPETR VII: CONCLUSIONS AND RECOMMENDATIONS

7.1 Introduction

The present research was conducted to support REDD and MRV initiatives and to inform policy makers about the current status of land use and the future impacts of various policy setting on carbon dioxide and nitrous oxide emissions from vegetation degradation in the

Dassari Basin. The key conclusions and recommendations are focused on the impacts of policy settings tested under business as usual, food security, business as usual motivated by adaptation and mitigation strategy to climate change and food security based mitigation strategy to climate change scenarios.

7.2 Conclusions

The results from this study help to close the existing knowledge gap with respect to vegetation carbon and nitrogen estimation in the Sudan Savannah environment. The generalized linear models, equations fitted on local data can be useful for future scientific works in the Sudan Savannah environment generally populated by the determined main species in the present study. The estimation of carbon and nitrogen stock and aboveground biomass in each land use cover category are of great importance for carbon balance calculations in the Sudan Savanna in West Africa.

The work has provided indispensable information on wood density of the main species of the Sudan Savannah zone, the related biomass expansion factor, the carbon and nitrogen content of the main tree species, the biomass, carbon and nitrogen stocks in each land use cover category that will be an important tool for carbon accounting programme related to the implementation of REDD+ in the Sudan Savanna environment.

The impacts of developed land use scenarios predicted an increment of the emission of CO_2 and N_2O into the atmosphere if the present trend of land disturbance is continued for the horizon 2025. The business as usual scenario or the baseline (LUS1) will contribute to the emissions of 16.805 Gg of CO_2, 0.033 Gg of N_2O, to the net removal of 21.70 Gg of CO_2 and to the total emissions of 26.70 Gg of CO_2 eq. per year over the period 2013-2025. The impact of the policy based food security (LUS2) will contribute to decrease the total emission by 29.25 % and will increase the net removal by 42.94 % whereas policy based adaptation and mitigation strategy to climate change (LUS3) and food security based mitigation strategy to climate change (LUS4) will respectively contribute to reduce the total emission by 13.14 % and 36.47 %. The scenarios LUS3 and LUS4 will also respectively contribute to increase the net removal by 105.05 % and 131.11 % per year by 2025.

The main factors which involved the farmers' decision making are population growth, high production of cotton based subsidy with fertilizers, the farming based mechanization, the protection zoning area, the variability in rainfall pattern and drought with dry spells and the soil suitability. The farmers of Dassari basin still have little knowledge on the adaptation strategies to climate change and there is no significant factor affecting adoption of these strategies at the farm level.

Despite that, the basin will still be a sink up to 2025. It is time to act and react with the aim to strengthen the resilience of farmers and contribute to carbon sequestration through local project development or project based carbon fund.

7.3 Limitations

The study presented some few limitations in the evolving global carbon budget. We did not parameterize this component and we stuck to the forest growth sub-model which used the basal area as increment of the tree species of the basin to illustrate the dynamic of the ecosystem. Indeed, the increment of stand basal area is a function of the rainfall pattern and other climatic and biophysical environment. Except for the rainfall pattern which could define climate variability, our model involved biophysical parameters in the BEN-LUDAS procedures. The study mainly focused on Net Ecosystem Productivity (NEP) which can be assessed as a time-averaged C stocks of the system (Hairiah *et al.*, 2010; IPCC, 2006) using the forest yield dynamic sub-model. Another limitation could be the miss validation using current land use cover map of 2015 or 2016 which was not available. Further research need to focus on other carbon pools which were not taken into account by the present research study. In addition, the current research study focuses only on CO_2 and N_2O. Further research on the ratio of emitted GHGs from biomass burning is recommended.

7.4 Research outlook

The World Bank's BioCarbon Fund provides carbon finances for projects that sequester or conserve greenhouse gases in forest, agroecosystems and other ecosystems. The BioCarbon Fund aims to "test and demonstrate how land use, land-use changes and forestry activities can generate high-quality emission reductions with environmental and livelihood benefits that can be measured, monitored and certified and stand the test of time" (GOFC-GOLD, 2013).

Each BioCarbon Fund project is expected to deliver between 400,000 and 800,000 tonnes of CO_2 equivalents (CO_2eq) over a period of 10 to 15 years. In return, a typical project will receive about US$2-3 million in payments (GOFC-GOLD, 2013). It is hoped that the finding of this study can convert the LUS3 or LUS4 as a project acceptable in the BioCarbon Fund. The implementation of one or two of these scenarios can support the baseline by the adaptation and mitigation strategy to climate change which can receive a minimum of US$ 2 million in payment.

In addition the project will involve some other relevant scientific researches that were not a part of this work. The additional research aspect will involve for example the remaining carbon pools and other parameters in the BEN-LUDAS model.

7.5 Recommendations for policy and research

The research findings are important decision making tools for environmental management when attempting to alleviate poverty and contribute to the implementation of the Kyoto Protocol and REDD+ initiatives. The policy tested under baseline motivated by adaptation and mitigation strategy to climate change scenario can be a useful strategy to reduce the emission of carbon dioxide from the basin into the atmosphere while maintaining economic growth.

For scientists, the present research needs to be completed by taking into account other carbon pools.

8 REFERENCES

Agarwal, C., Green, G.L., Grove, M., Evans, T., and Schweik, C. (2000). *A Review and Assessment of Land-Use Change Models Dynamics of Space, Time, and Human Choice*. Indiana University 408 North Indiana Avenue.

Aguilar-Amuchastegui, N., Riveros, J.C., and Forrest, J.L. (2014). Identifying areas of deforestation risk for REDD+ using a species modeling tool. *Carbon Balance and Management,, 9:10*.

Aholoukpe, H.B., Flori, A., Deleporte, P., Amadji, G., Chotte, J.L., and Blavet, D. (2013). Estimating aboveground biomass of oil palm: Allometric equations for estimating frond biomass. *Forest Ecology and Management,, 292*, 122-129.

Akindele, S.O., and Lemay, V.M. (2006). Development of tree volume equations for common timber species in the tropical rain forest area of Nigeria. *Forest Ecology and Management,, 226*(1-3), 41-48. doi: 10.1016/j.foreco.2006.01.022

Andreae, M.O., and Merlet, P. (2001). Emission of trace gases and aerosols from biomass burning. *Global Biogeochemical Cycles 15*, 955-966.

Angelsen, A. (2008). *Moving ahead with REDD: Issues, options and implications* Indonesia: CIFOR, Bogor.

Angelsen, A., Brockhaus, M., Kanninen, M., Sills, E., Sunderlin, W.D., and Wertz-Kanounnikoff, S. (2009). *Realising REDD+: national strategy and policy options*. Bogor, Indonesia: Center for International Forestry Research (CIFOR).

Angelsen, A., Brockhaus, M., Sunderlin, W.D., and Verchot, L.V. (2012). *2012 Analysing REDD+: Challenges and choices.*

Anne, C., Chazdon, R.L, Colwell, R.K., and Shen, T.J. (2005). Abundance-Based Similarity Indices and Their Estimation When There Are Unseen Species in Samples. *Biometrics 62,* , 361-371. doi: 10.1111/j.1541-0420.2005.00489.x

Aubreville, A. (1956). Accord a Yangambi sur la nomenclacture des types Africains de vegetation. *Revue bois et forets des tropiques,, 51*, 27.

Baccini, A., Goetz, S.J., Walker, W.S., Laporte, N.T., Sun, M., and Sulla-Menashe, D. (2012). Estimated carbon dioxide emissions from tropical deforestation improved by carbon-density maps. *Nature Climate Change,, 2*, 182-185. doi: 10.1038/NCLIMATE1354

Bakayoko, O., Assa, A.M., Coulibaly, B., and N'guessan, K.A. (2012). Stockage de Carbone Dans des Peuplements de Cedrela odorataet de Gmelina arboreaen Côte D'ivoire. *European Journal of Scientific Research,, 75 No.4* 490-501

Barreteau, O., Bousquet, F., and Attonaty, J. (2001). Role-playing games for opening the black box of multi-agent systems: method and lessons of its application to Senegal River Valley irrigated systems. *Journal of Artificial Societies and Social Simulation,, 4 (2)*.

Barrett, C.B., Bezuneh, M., Clay, D.C., and Reardon, T. (2005). Heterogeneous constraints, incentives and income diversification strategies in rural Africa. *Quarterly Journal of International Agriculture,, 44(1)*, 37-60.

Basuki, T.M., Van, P.E., Skidmore, A.K, and Hussin, Y.A. (2009). Allometric equations for estimating the above-ground biomass in tropical lowland Dipterocarp forests. *Forest Ecology and Management,, 257*(8), 1684-1694. doi: 10.1016/j.foreco.2009.01.027

Baumann, P. (2000). "Sustainable Livelihoods and Political Capital: Arguments and Evidence form Decentralization and Natural Resource Management in India," London: Overseas Development Institute,.

Beall, J., and Kanji, N. (1999.). "Households, Livelihoods and Urban Poverty." Background paper for the ESCOR commissioned research on Urban Development, Urban Governance, Partnership and

Poverty In Social Policy and Administration (Ed.), (pp. 38). London School of Economics and Political Science, .

Bebbington, A. (1999). “Capitals and Capabilities: A Framework for Analyzing Peasant Viability, Rural Livelihoods and Poverty.” *World Development 27, No. 12,*, 23.

Berger, T., and Schreinemachers, P. (2006). Creating agents and landscapes for multiagent systems from random samples *Ecology and Society, , 11(2)*, 19.

Berry, M.W, Hazen, B.C., MacIntyre, R.L., and Flamm, R.O. (1996). LUCAS: A System for Modeling Land-Use Change. *IEEE Computational Science and Engineering 3(1)*, 24.

Beven, K.J., and Kirkby, M.J. (1979). A physical based, variables contribution area model of basin hydrology. *Hydrological science, 24*, 43-66.

Bond, I.G., Wertz-Kanounnikoff, S., Hazlewood, P., Wunder, S., and Angelsen, A. (2009). Incentives to sustain forest ecosystem services: A review and lessons for REDD. Natural Resource Issues No. 16. International Institute for Environment and Development, London, UK, with CIFOR, Bogor, Indonesia, and World Resources Institute, Washington D.C., USA.

Bondeau, A., Smith, P.C., Zaehle, S., Schaphoff S, L.W, and Cramer, W. (2007). Modelling the role of agriculture for the 20th century global terrestrial carbon balance. *Global Change Biology,, 13*, 679-706.

Bousquet, F., and Page, C.L. (2004). Multi-agent simulations and ecosystem management: a review. *Ecological Modelling,, 176* 313-332. doi: 10.1016/j.ecolmodel.2004.01.011

Brown, D.R., Stephens, E.C., Ouma, J.O., Murithid, F.M., and Barrette, C.B. (2006). Livelihood strategies in the rural Kenyan highlands. *African Journal of Agricultural and Resource Economics, , 25 (1)*, 21-36.

Brown, S. (1997). Estimating biomass and biomass change in tropical forests: a primer. *FAO, Forestry Paper 134, Rome, ,* 87.

Brown, S., Sathaye, J., Cannell, M., and Kauppi, P. (1996). Management of forests for mitigation of greenhouse gas emissions. Chapter 24 in RT Watson, MC Zinyowera, and RH Moss (eds.), *Climate Change 1995: Impacts, Adaptations and Mitigation of Climate Change: ScientificTechnical Analyses. Contribution of Working Group II to the Second Assessment Report of the Intergovernmental Panel on Climate Change* Cambridge, UK, and New York, USA.: Cambridge University Press,.

Burnham, K.P., and Anderson, D.R. (2004). Multimodel inference: understanding AIC and BIC in model selectionn. *Sociological Methods and Research,, 33,* , 261-304.

Cairns, M.A., Olmsted, I., Granados, J., and Argaez, J. (2003). Composition and aboveground tree biomass of a dry semi-evergreen forest on Mexico’s Yucatan Peninsula. *Forest Ecology and Management,, 186*, 125–132.

Campbell, B., Sayer, J.A., Frost, P., Vermeulen, S., Ruiz, Pérez, M., Cunningham, A., and Prabhu, R. (2001). Assessing the performance of natural resource systems. *Conservation Ecology,, 5 (2)*, 22.

Campbell, J.B. (1996). Introduction to remote sensing (2nd ed.). In Taylor and Francis (Ed.), (pp. 84). London.

Carsan, S., Orwa, C., Harwood, C., Kindt, R., Stroebel, A., Neufeldt, H., and Jamnadass, R. (2012). *African Wood Density Database*.

Cattell, R.B. (1966). The scree test for the number of factors. . *Multivariate Behavioral Research, 1,*, 245-276.

Chave, J., Andalo, C., Brown, S., Cairns, M.A., Chambers, J.Q, Eamus, D., Yamakura, T. (2005). Tree allometry and improved estimation of carbon stocks and balance in tropical forests. *Ecosystem Ecology,, 145*. doi: 10.1007/s00442-0050100-x

Chave, J., Muller-Landau, H., Baker, T.R., Easdale, T.A., Teege, H.T., and Webb, C.O. (2006). Regional and phylogenetic variation of wood density across 2456 neotropical tree species. *Ecological Applications, 2006,, 16(6)*, 2356-2367.

Chave, J., Rejou-Mechain, M., Burquez, A., Chidumayo, E., Colgan, M.S., Delitti, W.B., Vieilledent, G. (2015). Improved allometric models to estimate the aboveground biomass of tropical trees. [Research Support, Non-U.S. Gov't]. *Glob Chang Biol,, 20*(10), 3177-3190. doi: 10.1111/gcb.12629

Chen, W., Li, J., Zhang, Y., Zhou, F., Koehler, K., Leblanc, S., and Wang, J. (2008). Relating Biomass and Leaf Area Index to Non-destructive Measurements in Order to Monitor Changes in Arctic Vegetation. *ARCTIC,, 62*, 281-294.

Chivaura, V.G., and Mararike, C.G. (1998.). The Human Factor Approach to Development in Africa, . Harare: University of Zimbabwe Publications, .

Chomitz, K., and Gray, M.D.A. (1996). Roads, Land Use, and Deforestation: A Spatial Model Applied to Belize. *World Bank Economic Review,, 10(3)*, 487-512.

Chris, D., and Xiaofeng, H. (2004). *K-means Clustering via Principal Component Analysis.* Paper presented at the Appearing in Proceedings of the 21 st International Conference on Machine Learning,, Banff, Canada, .

Clark, D.B., and Clark, D.A. (2000). Landscape-scale variation in forest structure and biomass in a tropical rain forest *Forest Ecology Management, , 137*, 185-198.

Collins, J.B., and Woodcock, C.E. (1996). An Assessment of Several Linear Change Detection Techniques for Mapping Forest Mortality Using Multitemporal Landsat TM Data. *REMOTE SENS. ENVIRON.*, 56:66-77.

Costa-Cabral, M., and Burges, S.J. (1994). Digital elevation model networks (DEMON): A model of flow over hillslopes for computation of contributing and dispersal areas *Water resources research, 30(6)* 1681-1692.

Curtis, J.T. (1956). The use of distance measures in phytosociological sampling *Ecology,, 37, No 3*, 451-461.

Damaceanu, R.C. (2012). An Agent-based Computational Study of Wealth Distribution in Function of Technological Progress Using Netlogo. *American Journal of Economics,, 1*(1), 15-20. doi: 10.5923/j.economics.20110101.02

DCN. (2011). Deuxième communication nationale de la République du Bénin sur les changements climatiques (pp. 165). BENIN: MEHU, DGE.

Deadman, P., and Hare, M. (2004). Further towards a taxonomy of agent-based simulation models in environmental management. *Mathematics and Computers in Simulation,, 64* 25-40. doi: 10.1016/S0378-4754(03)00118-6

DeFries, R.S., Houghton, R.A., Hansen, M.C., Field, C.B., Skole, D., and Townshend, J. (2002). Carbon emissions from tropical deforestation and regrowth based on satellite observations for the 1980s and 1990s. *Proc. Natl Acad. Sci. USA 99*, 14256-14261.

Denman, K.L. (2007). *Couplings between changes in the climate system and biogeochemistry*. Cambridge University Press.

DFID. (2000). Sustainable Livelihoods Guidance Sheets. Department for International Development.

Dirmeyer, P.A., Niyogi, D., de Noblet-Ducoudr, N., Dick- inson, R.E., and Snyder, P.K. (2010). Impacts of land use change on climate *Int J Climatol, 30*, 1905–1907. doi: doi: 10.1002/joc.2157

Dixon, R.K., Brown, S., Houghton, R.A., Solomon, A.M., Trexler, M.C., and Wisniewski, J. (1994). Carbon pools and flux of global forest ecosystems *Science 263*, 185-190.

Djomo, A.N., Ibrahima, A., Saborowski, J., and Gravenhorst, G. (2010). Allometric equations for biomass estimations in Cameroon and pan moist tropical equations including biomass data from Africa. *Forest Ecology and Management,, 260 (10)*, 1873–1885.

Djuikouo, M.N.K., Doucet, J-L., Nguembou, C.K., Lewis, S.L., and Sonké, B. (2010). Diversity and aboveground biomass in three tropical forest types in the Dja Biosphere Reserve, Cameroon. *Afr. J. Ecol,, 48*, 1053–1063

Domke, G.M., Woodall, C.W., Smith, J.E., Westfall, J.A., and McRoberts, R.E. (2012). Consequences of alternative tree-level biomass estimation procedures on U.S. forest carbon stock estimates. *Forest Ecology and Management,, 270*, 108-116. doi: 10.1016/j.foreco.2012.01.022

Dossa, E.L., Fernandes, E.C.M., Reid, W.S., and Ezui, K. (2008). Above- and belowground biomass, nutrient and carbon stocks contrasting an open-grown and a shaded coffee plantation. *Agroforest Syst, , 72*, 103–115.

Duda, R.O., Hart, P.E., and Stork, D.G. (2000). *Pattern classification*. 2nd ed. Wiley.

Eamus, D., McGuinness, K., and Burrows, W. (2000). Review of allometric relationships for estimating woody biomass for Queensland, the Northern Territory and Western Australia. In N. C. A. S. T. R. 5A (Ed.), *National Carbon Accounting System technical report no.5a* (pp. 64). Environment Australia Cataloguing-in-Publication: Canberra: Australian Greenhouse Office.

Ellis, F., and Biggs, S. (2000). "Evolving Themes in Rural Development 1950s-2000s,". *Development Policy Review, 19 2001*(4,), 437-448.

Ellis, F., Kutengule, M., and Nyasulu, A. (2003). "Livelihoods and Rural Poverty Reduction in Malawi," *World Development, , 31,* (9,), 1495-1510.

Erener, A., Düzgün, S., and Yalciner, A.C. (2012). Evaluating land use/cover change with temporal satellite data and information systems. *Procedia Technology,, 1*, 385-389. doi: 10.1016/j.protcy.2012.02.079

Falkowski, P., Scholes, R.J., Boyle, E., Canadell, J., Canfield, D., Elser, J., Steffen, W. (2000). The Global Carbon Cycle: A Test of Our Knowledge of Earth as a System. *SCIENCE' S COMPASS, 290*, 291296.

Fang, S., and HaiYang, S. (2012). Relationship analysis between livelihood assets and livelihood strategies: A Heihe River Basin example. *Sciences in Cold and Arid Regions, 4(3):*, 0265-0274. doi: 10.3724/SP.J.1226.2012.00265

FAO. (1995). *Food and Agriculture Organization of the United Nations (FAO): Forest Resources Assessment 1990*. Rome: FAO.

Feldpausch, T.R., Rondon, M.A., Fernandes, E.C.M, and Riha, S.J. (2004). Carbon and nutrient accumulation in secondary forests regenerating on pastures in central Amazonia. *Ecological Applications, 14*, S164-S176.

Fitz, H.C., DeBellevue, R., Costanza, R., Boumans, T., Maxwell, L.W., and Sklar, F.H. (1996). Development of a General Ecosystem Model for a Range of Scales and Ecosystems. *Ecological Modelling,, 88*, 263-295.

Fleurant, C., Duchesne, J., and Raimbault, P. (2004). An allometric model for trees. *J Theor Biol, , 227*, 137-147.

Flombaum, P., and Sala, O.E. (2007). A non-destructive and rapid method to estimate biomass and aboveground net primary production in arid-environments. *Journal of Arid Environments,, 69* 352–358. doi: 10.1016/j.jaridenv.2006.09.008

Fonton, H.N., Dah-Dovono, J.Z., Adoko, F.K., and Dotchamou, T. (2009). Modélisation du volume du fût d'arbre pour une gestion durable des écosystèmes forestiers soudaniens. *Bois et Forêts des Tropiques,, 300(2)* 95-100. .

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

García, M.F.A, López, S.F.R, Andrés, M., Rubio, E., González, J.J.L, and de las Heras, J. (2012). Allometries, biomass stocks and biomass allocation in the thermophilic Spanish juniper woodlands of Southern Spain. *Forest Ecology and Management,, 270*, 85-93. doi: 10.1016/j.foreco.2012.01.007

Gilruth, P.T., Marsh, S.E., and Itami, R. (1995). A Dynamic Spatial Model of Shifting Cultivation in the Highlands of Guinea, West Africa *Ecological Modelling, , 79*, 179-197.

GOFC-GOLD. (2013). *A sourcebook of methods and procedures for monitoring and reporting anthropogenic greenhouse gas emissions and removals associated with deforestation, gains and losses of carbon stocks in forests remaining forests, and forestation*. The Netherlands: Wageningen University.

Gómez, D., & Montero, J. (2011). Determining the accuracy in image supervised classification problems. *EUSFLAT-LFA 2011*, 342-349.

Grassi, G., Monni, S., Federici, S., Achard, F., and Mollicone, D. (2008). Applying the conservativeness principle to REDD to deal with the uncertainties of the estimates. *Environ. Res. Lett,, 3, 035005*

Gray, K.R., and Biddlestone, A.J. (1973). Composting - process parameters. *The Chemical Engineer*, 71-76.

Gregg, M., Roger, A.P., Mike, A.S., Roni, A., Richard, A., and Bettse, K. (2002). The climatic impacts of land surface change and carbon management, and the implications for climate-change mitigation policy. [Journal]. *Science Direct, 3* 149–157. doi: 10.1016/S1469-3062(03)00028-7

Grierson, P.F., Williams, K., and Adams, M.A. (2000). Review of unpublished biomass-related information: Western Australia, South Australia, New South Wales and Queensland. National Carbon Accounting. In S. T. R. n. C. A. G. Office. (Ed.), (pp. 96).

Grimm, V., Berger, U., Bastiansen, F., Eliassen, S., Ginot, V., Giske, J., DeAngelis. D.L. (2006). A standard protocol for describing individual-based and agent-based models. *Ecological modelling 198*, 115-126. doi: 10.1016/j.ecolmodel.2006.04.023

Grimm, V.B. U., DeAngelis, D.L., Polhill, J.G., Giske, J., Railsback, S.F. (2010). The ODD protocol: A review and first update. *Ecological Modelling, 221*(23), 2760-2768. doi: 10.1016/j.ecolmodel.2010.08.019

Guendehou, G.H.S., Lehtonen, A., Moudachirou, M., Mäkipää, R., and Sinsin, B. (2012). Stem biomass and volume models of selected tropical tree species in West Africa. *Southern Forests, , 74(2),* , 77-88.

Hairiah, K., Dewi, S., Agus, F., Velarde, S., Ekadinata, A., Rahayu, S., and van Noordwijk, M. (2010). *Measuring Carbon Stocks Across Land Use Systems: A Manual*. Bogor, Indonesia. : World Agroforestry Centre (ICRAF), SEA Regional Office, .

Hardie, I.W., and Parks, P.J. (1997). Land Use with Heterogeneous Land Quality: An Application of an Area Base Model. . *American Journal of Agricultural Economics,, 79(2)*, 299-310.

Hartigan, J.A., and Wong, M.A. (1979). A K-means clustering algorithm. *Applied Statistics, 28*, 100– 108.

Hastie, T., Tibshirani, R., and Friedman, J. (2001). Elements of statistical learning. *Springer Verlag.*

Havel, J.J. (1980). Application of fundamental synecological knowledge to practical problems in forest management I: theory and methods. . *Forest Ecology and Management 3*, 1-29.

Heckbert, S., Baynes, T., and Reeson, A. (2010). Agent-based modeling in ecological economics. *Ann. N.Y. Acad. Sci. , 1185*, 39-53.

Henry, M., Besnard, A., Asante, W.A., Eshun, J., Adu-Bredu, S., Valentini, R., Saint-André, L. (2010). Wood density, phytomass variations within and among trees, and allometric equations in a tropical rainforest of Africa. *Forest Ecology and Management,, 260*(8), 1375-1388. doi: 10.1016/j.foreco.2010.07.040

Henry, M., Maniatis, D., Gitz, V., Huberman, D., and Valentini, R. (2011). Implementation of REDD+ in sub-Saharan Africa: state of knowledge, challenges and opportunities. *Environment and Development Economics, 16*(04), 381-404. doi: 10.1017/s1355770x11000155

Henry, M., Picard, N., Trotta, C., Manlay, R.J., Valentini, R., Bernoux, M., and Saint-André, L. (2011). Estimating Tree Biomass of Sub-Saharan African Forests: a Review of Available Allometric Equations. *Silva Fennica,, 45(3B)*, 477–569.

Hewson, J., Steininger, M.K., and Pesmajoglou, S. (2014.). REDD+ Measurement, Reporting and Verification (MRV) Manual, Version 2.0. . *USAID-supported Forest Carbon, Markets and Communities Program. Washington, DC, USA.* .

Hobley, M., and Shields, D. (2000.). *"The Reality of Trying to Transform Structures and Processes: Forestry in Rural Livelihoods,"* ODI Working Paper No. 132, . London:Overseas Development Institute, .

Houghton, R.A. (2005). Aboveground forest biomass and the global carbon balance. *Glob. Change Biol,, 11*, 945–958. doi: 10.1111/j.1365-2486.2005.00955.x

Houghton, R.A., House, J.I., Pongratz, J., van der Werf, G.R., DeFries, R.S., Hansen, M.C., Ramankutty, N. (2012). Carbon emissions from land use and land-cover change. *Biogeosciences,, 9*(12), 5125-5142. doi: 10.5194/bg-9-5125-2012

Hughes, R.F., Kauffman, J.B., and Jaramillo, V.J. (1999). Biomass, carbon, and nutrient dynamics of secondary forests in a humid tropical region of México *Ecology, 80*, 1892-1907.

Hunter, M.O., Keller, M., Victoria, D., and Morton, D.C. (2013). Tree height and tropical forest biomass estimation. *Biogeosciences,, 10*(12), 8385-8399. doi: 10.5194/bg-10-8385-2013 Hussein, K. (2002). Livelihoods approaches compared: A Multi-agency Review of Current Practices, (pp. 45). London:: Overseas Development Institute,.

INSAE. (2003). RGPH3, (Février 2002), Résultats Définitifs, Décembre 2003 *Recensement Général de la Population et de l'habitat du Bénin*.

INSAE. (2013). RGPH4, (Juin 2013), Résultats Provisoir du RGPH4 *Recensement Général de la Population et de l'habitat du Bénin*.

IPCC. (2006). *2006 IPCC Guidelines for national greehouse gase inventories: Agriculture Forestry and Other Land Use* (Vol. 4).

IPCC. (2007). Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change Cambridge University Press, Cambridge, United Kingdom and In O. R. D. [B. Metz, P.R. Bosch, R. Dave, L.A. Meyer (eds)], (Ed.), (pp. 834). New York, NY, USA.

IPCC. (2013). Climate Change 2013: The Physical Science Basis In T. F. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)] (Ed.), (pp. 1535). Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, .

Ishiwatari, R., and Uzaki, M. (1987). "Diagenetic Changes of Lignin Compounds in a More Than 0.6 Million-Year-Old Lacustrine Sediment (Lake Biwa, Japan)." *Geochimica Et Cosmochimica Acta 51, no. 2* 321-328.

Jain, A., and Dubes, R. (1998). Algorithms for clustering data. *Prentice Hall.*

Janssen, L.L.F., and Van der W.F.J.M. (1994). Accuracy assessment of satellite derived land-cover data: a review. *Photogrammetric Engineering and Remote Sensing 60*(419-426).

Jean-Louis, D. (1997). Evolution saisonnière et taux d'accroissement des surfaces terrières des ligneux dans quelques peuplements savanicoles soudaniens de l'Ouest Burkinabe. *Ecologie,, 28 (3),* , 217-232. <ird-00357108>.

Jenkins, J.C., Chojnacky, D.C., Heath, L.S., and Birdsey, R.A. (2004). Comprehensive database of diameter-based biomass regressions for North American tree species. In G. T. R. NE-319. (Ed.), (pp. 46). Newtown Square, Pennsylvania: Department of Agriculture, Forest Service, Northeastern Research Station.

Jenson, S.K., and Domingue, J.O. (1998). Extracting Topographic Structure from Digital Elevation Data for Geographic Information System Analysis. *PHOTOGRAMMETRIC ENGINEERING AND REMOTE SENSING, 54 (11),*, 1593-1600.

Jonathan, G. (2000). Sustainable livelihoods. *International Social Science Journal,, 17(4)*, 77-86.

José, de J.N. (2010). Biomass allometry for the tree species of Northern Mexico. *Tropical and Subtropical Agroecosystems,, 12*(3), 507-519.

Jose, J.J.S, Montes, R.A., and Farinas, M.R. (1998). Carbon stocks and fluxes in a temporal scaling from a savanna to a semi-deciduous forest. *Forest Ecology and Management, , 105*, 251-262.

Kaiser, H.F.. (1960). The application of electronic computers to factor analysis. . *Educational and Psychological Measurement, , 20,* , 141-151.

Keith, H., Barrett, D., and Keenan, R. (2000). Review of allometric relationships for estimating woody biomass for New South Wales, the Australian Capital Territory, Victoria, Tasmania, and South Australia. In N. C. A. S. T. R. 5B (Ed.), (pp. 113). Canberra: Australian Greenhouse Office.

Keller, M., Palace, M., and Hurtt, G. (2001). Biomass estimation in the Tapajos National Forest, Brazil. Examination of sampling and allometric uncertainties. *Forest Ecology Management, , 154*, 371-382.

Ketterings, Q.M., Coe, R., van Noordwijk, M., Ambagu, Y., and Palm, C.A. (2001). Reducing uncertainty in use of allometric biomass equations for predicting above-ground tree biomass in mixed secondary forests. *Forest Ecology and Management,, 146*, 199-202.

Kim, J.O., and Mueller, C.W. (1978). Factor analysis: Statistical methods and practical issues. *Beverly Hills, CA: Sage.*

Kuyah, S., Dietz, J., Muthuri, C., Jamnadass, R., Mwangi, P., Coe, R, and Neufeldt, H. (2012). Allometric equations for estimating biomass in agricultural landscapes: I. Aboveground biomass. *Agriculture, Ecosystems & Environment,, 158*, 216-224. doi: 10.1016/j.agee.2012.05.011

Lambin, E.F., and Geist, H.J. (2002). "Global land-use and land-cover change: what have we learned so far?" *LUCC Report* (pp. 27-30).

Lambin, E.F., Rounsevell, M., and Geist, H. (2000). Are agricultural land-use models able to predict changes in land use intensity? *Agriculture, Ecosystems & Environment 82*(1-3), pp. 321-331. doi: 10.1016/S0167-8809(00)00235-8

Lammers, R.B., and Band, L.E. (1990). Automating object representation of drainage basins *Comput. Geosci, 16(6)* 787-810.

Landis, J.D. (1995). Imagining Land Use Futures: Applying the California Urban Futures Model. . *APA Journal 61(4)*, :438-457.

Landis, J.D., and Zhang, M. (1998). The Second Generation of the California Urban Futures Model: Part 2: Specification and Calibration Results of the Land-Use Change Submodel. In Environment and Planning B (Ed.), (Vol. 25(6):, pp. 795-824.).

Lasco, R.D., and Pulhin, F.B. (2003). Philippine forest ecosystems and climate change: carbon stocks, rate of sequestration and the Kyoto Protocol. *Annals of Tropical Research 25*, 37-51.

Le, Q.B. (2005). *Multi-agent system for simulation of land-use and land cover change: A theoretical framework and its first implementation for an upland watershed in the Central Coast of Vietnam.*

Le, Q.B., Park, S.J., and Vlek, P.L.G. (2010). Land Use Dynamic Simulator (LUDAS): A multi-agent system model for simulating spatio-temporal dynamics of coupled human–landscape system 2. Scenario-based application for impact assessment of land-use policies. *Ecological Informatics 5* 203-221. doi: 10.1016/j.ecoinf.2010.02.001

Le, Q.B., Parkb, S.J., Vlek, P.L.G., and Cremers, A.B. (2008). Land-Use Dynamic Simulator (LUDAS): A multi-agent system model for simulating spatio-temporal dynamics of coupled human–

landscape system. I. Structure and theoretical specification. *Ecological Informatics, 3*, 135.153. doi: 10.1016/j.ecoinf.2008.04.003

Lehtonen, A., Mäkipää, R., Heikkinen, J., Sievänen, R., and Liski, J. (2004). Biomass expansion factors (BEFs) for Scots pine, Norway spruce and birch according to stand age for boreal forests. *Forest Ecology and Management,, 188*(1-3), 211-224. doi: 10.1016/j.foreco.2003.07.008

Levine, J.S. (1994). Biomass burning and the production of greenhouse gases (pp. 15). Hampton, Virginia: Atmospheric Sciences Competency NASA hngley Research Center

Levy, P.E., Hale, S.E., and Nicoll, B.C. (2004). Biomass expansion factors and root : shoot ratios for coniferous tree species in Great Britain. *Forestry, , 77* (5).

Li, C.P., and Xiao, C.W. (2007). Above- and belowground biomass of Artemisia ordosica communities in three contrasting habitats of the Mu Us desert, northern China. *Journal of Arid Environments,, 70*(2), 195-207. doi: 10.1016/j.jaridenv.2006.12.017

Ligtenberg, A., Wachowicz, M., Bregt, A.K., Beulen, A., and Kittenis, D.L. (2004). A design and application of a multi-agent system for simulation of multi-actor spatial planning. *Journal of Environmental Management 72 (1, 2):* , 43 - 56.

Little, E.L.J., and Wadesworth, F.H. (1964). *Common trees of Puerto Rico and the Virgin Islands, US Department of Agriculture* (Vol. 249). Washington DC.

Litton, C.M., and Kauffman, J.B. (2008). Allometric Models for Predicting Aboveground Biomass in Two Widespread Woody Plants in Hawaii. *BIOTROPICA, 40(3):*, 313–320. doi: 10.1111/j.1744-7429.2007.00383.x

Lloyd, S. (1957). Least squares quantization in pcm. Bell Telephone Laboratories Paper. *Marray Hill.*

Lloyd, S.P. (1982). Least squares quantization in PCM. Technical Note, Bell Laboratories. *Transactions on Information Theory, 28*, 128–137.

MacQueen, J. (1967). *Some methods for classification and analysis of multivariate observations.* Paper presented at the Proc. 5th Berkeley Symposium, .

Magalhães, T.M., and Seifert, T. (2015). Tree component biomass expansion factors and root-toshoot ratio of Lebombo ironwood: measurement uncertainty. *Carbon Balance and Management, 10*(1). doi: 10.1186/s13021-015-0019-4

Mahmood, R., Pielke, R.A., Hubbard, K.G., Niyogi, D., Bonan, G., Lawrence, P., Gameda, S. (2010). Impacts of Land Use/Land Cover Change on Climate and Future Research Priorities *Bu ll . Am e r . M e t e o r o l . S o c., 91*, 37-46.

Maling, D.H. (1989). Measurements from maps. In O. Pergamon (Ed.), (pp. 112).

Martz, L.W., and Garbrecht, J. (1992). Numerical definition of drainage network and subcatchment areas from digital elevation models. *Comput. Geosci., 18(6)* 747-761.

Matthews, R.B., Gilbert, N.G., Roach, A., Polhill, J.G., and Gotts, N.M. (2007). Agent-based land-use models: a review of applications. *Landscape Ecol (22*, 1447-1459. doi: 10.1007/s10980-0079135-1

Mbaekwe, E.I., and Mackenzie, J.A. (2008). The Use of a Best-Fit Allometric Model to Estimate above Ground Biomass Accumulation and Distribution in an Age Series of Teak (Tectona grandis L.f.) Plantations at Gambari Forest Reserve, Oyo State, Nigeria. *Tropical Ecology,, 49,* , 259270.

Mbow, C., Verstraete, M.M., Sambou, B., Diaw, A.T., and Henry, N. (2013). Allometric models for aboveground biomass in dry savanna trees of the Sudan and Sudan–Guinean ecosystems of Southern Senegal. *Journal of Forest Research,, 19*(3), 340-347. doi: 10.1007/s10310-0130414-1

McAlpine, C.A., Laurance, W.F., Ryan, J.G., Seabrook, L., Syktus, J.I., and Etter, A.E. (2010). More than CO2: A broader picture for managing climate change and variability to avoid ecosystem

collapse *Curr. Opin. Environ. Sustainability, 2*, 334–336. doi: doi:10.1016/ j.cosust.2010.10.001.
McCullagh, P., and Nelder, J.A. (1989). Generalized linear models. *CRC press, 37*
McGroddy, M.E., Daufresne, T., and Hedin, L.O. (2004). Scaling of C:N:P stoichiometry in forests worldwide: implications of terrestrial Redfield-type ratios. Ecology 85: 2390–2401.
McKee, T.B., and Kleist, J.N.J.D. (1993). The relationship of drought frequency and duration to time scales. *Eighth Conference on Applied Climatology,, 1*, 17-22
Mertens, B., and Lambin, E.F. (1997). Spatial Modelling of Deforestation in Southern Cameroon. *Applied Geography, , 17(2)*, 143-162.
Montagnoli, A., Fusco, S., Terzaghi, M., Kirschbaum, A., Pflugmacher, D., and Cohen, W.B. (2015). Estimating forest aboveground biomass by low density lidar data in mixed broad-leaved forests in the Italian Pre-Alps. *Forest Ecosystems,, 2*(1). doi: 10.1186/s40663-015-0035-6
Montagu, K.D., Düttmer, K., Barton, C.V.M., and Cowie, A.L. (2005). Developing general allometric relationships for regional estimates of carbon sequestration an example using Eucalyptus pilularis from seven contrasting sites. *Forest Ecology and Management,, 204*(1), 115-129. doi: 10.1016/j.foreco.2004.09.003
Montes, N., Gauquelin, T., Badri, W., Bertaudie, V., and Zaoui, E.l.H. (2000). A non-destructive method for estimating above-ground forest biomass in threatened woodlands. *Forest Ecology and Management,, 130* 37-46.
Moore, I.D., Grayson, R.B., and Ladson, A.R. (1991). Digital terrain modelling: A review of hydrological, geomorphological, and biological applications *Hydrol. Process, 5(1)* 3-30.
Morris, D.G., and Heerdegen, R.G. (1988). Automatically drained catchment boundaries and channel networks and their hydrological applications. *Geomophology, 1* 131-141.
Moura-Costa, P., and Stuart, M. (1999). *Issues related to monitoring, verification and certification of forestry-based carbon offset projects*.
Nagelkerke, N.J.D. (1991). A note on a general definition of the coefficient of determination. *Biometrika, , 78(3), ,* 691-692. doi: 10.1093/biomet/78.3.691
Nations, U. (2005). Designing Household Survey Samples: Practical Guidelines. In D. o. E. a. S. Affairs (Ed.), (pp. 193). New York.
Návar-Chaidez, J. (2011). The spatial distribution of aboveground biomass in tropical forests of Mexico. *Tropical and Subtropical Agroecosystems, 13*, 149-158.
Nelson, B.W., Mesquita, R., Pereira, J.L.G., Aquino de Souza, S.G., Batista, G.T., and Couto, L.B. (1999). Allometric regressions for improved estimate of secondary forest biomass in the central Amazon. *Forest Ecology and Management, , 117*, 149-167.
Ngomanda, A., Obiang, N.L.E., Lebamba, J., Mavouroulou, Q.M., Gomat, H., Mankou, G.S., Picard, N. (2014). Site-specific versus pantropical allometric equations: Which option to estimate the biomass of a moist central African forest? *Forest Ecology and Management,, 312*, 1-9. doi: 10.1016/j.foreco.2013.10.029
Nogueira, E.M., Fearnside, P.M., Nelson, B.W., and França, M.B. (2007). Wood density in forests of Brazil's 'arc of deforestation': Implications for biomass and flux of carbon from land-use change in Amazonia. *Forest Ecology and Management, 248*(3), 119-135. doi: 10.1016/j.foreco.2007.04.047
O'Callaghan, J.F., and Mark, D.M. (1984). The extraction of drainage networks from digital elevation data, Comput. Vision Graphics Image. *Process, 28*, 328-344.
Odero, K.K. (2002). Extending the Sustainable Livelihoods Framework (pp. 21). University of Zimbabwe.
Oey, D.S. (1951). in Soewarsono, P.H. 1990. Specific gravity of Indonesian Woods and Its Significance for Practical Use In F. F. Department (Ed.). Bogor, Indonesia.

Orekan, V.O.A. (2007). *Implementation of the local land-use and land-cover change model CLUE-s for Central Benin by using socio-economic and remote sensing data.* (PhD), University of Bonn, Bonn, im April 2007. Retrieved from http://hss.ulb.uni-bonn.de/diss_online

Parker, D.C., Manson, S.M., Janssen, M.A., Hoffmann, M.J., and Deadma, P (Eds.). (2002). *MultiAgent Systems for the Simulation of Land-Use and Land-Cover Change: A Review*.

Pelletier, J., Ramankutty, N., and Potvin, C. (2011). Diagnosing the uncertainty and detectability of emission reductions for REDD+ under current capabilities: An example for Panama. *Environ. Res. Lett,, 6*.

Pielke, R.A., Andy, P., Dev, N., Rezaul, M., Clive, M., and Faisal, H. (2011). Land use/land cover changes and climate: modeling analysis and observational evidence. *Advanced Review, 2*, 828-850. doi: 10.1002/wcc.144

Pielke, R.A., Eastman, Sr.J., Chase, T.N., Knaff, J., and Kittel, T.G.F. (1998). The 1973-1996 trends in depth-averaged tropospheric temperature. *J. Geophys. Res, 103 (16)*, 927- 933. Pielke, R.S. (2005). Land use and Climate Change. *Science*.

Protocol, K. (1997). *Kyoto Protocol to the United Nations Framework Convention on Climate Change*. Bonn: United Nations Climate Change Secretariat.

Puyravaud, J-P. (2003). Standardizing the calculation of the annual rate of deforestation. *Forest Ecology and Management,, 177*(1-3), 593-596. doi: 10.1016/s0378-1127(02)00335-3

Quinn, P., Beven, K., and Lamb, R. (1995). The ln(a/tanß) index: how to calculate it and how to use it within the TOPMODEL framework. *Hydrol. Process. , 9*, 161-182.

Railsback, S.F., Lytinen, S.L., and Jackson, S.K. (2006). Agent-based Simulation Platforms: Review and Development Recommendations. *SIMULATION 82*, 609-623. doi: 10.1177/0037549706073695

Rasmussen, M.O., Göttsche, F-M., Diop, D., Mbow, C., Olesen, F-S., Fensholt, R., and Sandhol, I. (2011). Tree survey and allometric models for tiger bush in northern Senegal and comparison with tree parameters derived from high resolution satellite data. *International Journal of Applied Earth Observation and Geoinformation, 13*(4), 517-527. doi: 10.1016/j.jag.2011.01.007

Rosa, E.A., and Dietz, T. (1998). Climate change and society: speculation, construction and scientific investigation. *International Sociology, , 13 (4),* , 421/455.

Sallenave, P. (1955). Propriétés Physiques et Mécaniques des Bois. *CTFT, Nogent sur Marne, France*.

Sallenave, P. (1964). *Propriétés Physiques et Mécaniques des Bois*. CTFT, Nogent sur Marne, France.

Sawadogo, L., Savadogo, P., Tiveau, D., Sidzabda, D.D., Zida, D., Nouvellet, Y., Guinko, S. (2010). Allometric prediction of above-ground biomass of eleven woody tree species in the Sudanian savanna-woodland of West Africa. *Journal of Forestry Research,, 21*(4), 475-481. doi: 10.1007/s11676-010-0101-4

Schneider, L.C., and Pontius, JrR.G. (2001). Modeling land-use change in the Ipswich watershed, Massachusetts USA. *Agric. Ecosyst. Environ, 85*, 83–94.

Schoroth, G., D'Angelo, S.A., Teixeira, W.G., Haag, D., and Leiberei, R. (2002). Conversion of secondary forest into agroforestry and monoculture plantations in Amazonia: consequences for biomass, litter and soil carbon stocks after 7 years. *Forest Ecology and Management,, 163*, 131-150.

Segura, M. (2005). Allometric Models for Tree Volume and Total Aboveground Biomass in a Tropical Humid Forest in Costa Rica. *BIOTROPICA 37(1)*, 2-8

Senay, G.B. (2008). Modeling Landscape Evapotranspiration by Integrating Land Surface Phenology and a Water Balance Algorithm. *algorithms, 1*(2), 52-68. doi: 10.3390/a1020052

Shirima, D.D., Munishi, P.K.T., Lewis, S.L., Burgess, N.D., Marshall, A.R., Balmford, A., Zahabu, E.M. (2011). Carbon storage, structure and composition of Miombo woodlands in Tanzania's Eastern Arc Mountains. *Afr J Ecol,, 49*, 332-342.

Smith, P., Bustamante, M., Ahammad, H., Clark, H., Dong, H., Elsiddig, E.A., Tubiello, F. (2014). *Introductory Chapter. In: Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Edenhofer, O., R. Pichs-Madruga, Y. Sokona, E. Farahani, S. Kadner, K. Seyboth, A. Adler, I. Baum, S. Brunner, P. Eickemeier, B. Kriemann, J. Savolainen, S. Schlömer, C. von*

Smits, P.C., Dellepiane, S.G., and Schowengerdt, R.A. (1999). Quality assessment of image classification algorithms for land-cover mapping: a review and proposal for a cost-based approach. *International Journal of Remote Sensing,, 20*, 1461-1486.

Sørensen, R., Zinko, U., and Seibert, J. (2006). On the calculation of the topographic wetness index: evaluation of different methods based on field observations. *Hydrology and Earth System Sciences, , 10,* , 101-112, .

Sow, P., Adaawen, S., and Scheffran, J. (2014). Migration, Social Demands and Environmental Change amongst the Frafra of Northern Ghana and the Biali in Northern Benin. *Sustainability, 6*(1), 375-398. doi: 10.3390/su6010375

Stéphenne, N., and Lambin, E.F. (2001). A dynamic simulation model of land-use changes in Sudanosahelian countries of Africa (SALU). *Agriculture, Ecosystems and Environment 85* 145-161.

Stevens, J. (1986). Applied multivariate statistics for the social sciences. *Hillsdale, NJ: Lawrence Erlbaum Associates*.

Sugiura, N. (1978). Further analysis of the data by Akaike's information criterion and the finite corrections *Communications in Statistics: Theory and Methods A7,* , 13-26.

Swallow, S.K., Talukdar, P., and Wear, D.N. (1997). Spatial and Temporal Specialization in Forest Ecosystem Management under Sole Ownership. *American Journal of Agricultural Economics 79*, 311-326.

Tackenberg, O. (2007). A new method for non-destructive measurement of biomass, growth rates, vertical biomass distribution and dry matter content based on digital image analysis. [Validation Studies]. *Ann Bot, 99*(4), 777-783. doi: 10.1093/aob/mcm009

Tarboton, D.G. (1997). A new method for the determination of flow directions and upslope areas in grid digital elevation models. *Water resources research, 33(2)*, 309-319.

Tarboton, D.G., Bras, R.L., and Rodriguez-Iturbe, I. (1992). A physical basis for drainage density *Geomorphology, 5(1/2)*, 59-76.

Ter-Mikaelian, M.T., and Korzukhin, M.D. (1997). Biomass equations for sixty-five North American tree species. *Forest Ecology and Management, , 97*, 1-24.

Turton, C. (2000.). *"The Sustainable Livelihoods Approach and Program Development in Cambodia,"* ODI Working Paper No. 130. London: ODI.

UNFCCC. (2013). SAFEGUARDS in REDD plus under the Cancun Agreement (pp. 11). Cancum.

United Nations. (2005). *Designing Household Survey Samples: Practical Guidelines*. New York, 2005.

Van der Veen, A., and Otter, H.S. (2001). Land use changes in regional economic theory. *Environmental Modeling and Assessment 6:* , 145-150.

Vanclay, J.K. (1994). *Modelling forest growth and yield: applications to mixed tropical forests*. CAB International, . Wallingford, UK.

Veldkamp, A., and Fresco, L.O. (1996a.). CLUE: A Conceptual Model to Study the Conversion of Land Use and Its Effects. *Ecological Modelling 85*, 253-270.

Veldkamp, A., and Fresco, L.O. (1996b). CLUE-CR: An Integrated Multi-Scale Model to Simulate Land Use Change Scenarios in Costa Rica. *Ecological Modelling 91*, 231-248.

Verburg, P.H., de Nijs, T.C.M, and van Eck, J. (2004). A method to analyse neighbourhood characteristics of land use pattern. *Computers, Environment and Urban Systems 28(6)*, 667690.

Villamor, G.B. (2012). *Flexibility of multi-agent system models for rubber agroforest landscapes and social response to emerging reward mechanisms for ecosystem services in Sumatra, Indonesia.* Ecology and Development Series No. 88, 2012.

Vitousek, P.M., Mooney HA, Lubchenco J, & Melillo JM. (1997). Human Domination of Earth's Ecosystems *Science 277(15)*, 494-499.

Voinov, A., Costanza, R., Wainger, L., Boumans, R., Villa, F., Maxwell, T., and Voinov, H. (1999). Patuxent Landscape Model: Integrated Ecological Economic Modeling of a Watershed. *Environmental Modelling and Software 14*, 473-491.

Von, M.H.J. (1983). *Arbres et Arbustes du Sahel: Leurs caracteristiques et leurs utilisations*. Germany.

Wallace, R. (1989). *Finding natural clusters through entropy minimization.* Carnegie-Mellon Uiversity.

Wear, D.N., and Bolstad, P. (1998). Land-Use Changes in Southern Appalachian Landscapes: Spatial Analysis and Forecast Evaluation. *Ecosystems 1(6)*, 575-594.

Wilson, J.P., and Gallant, J.C. (2000). *Terrain analysis: principles and applications*: Wiley.

Wood, E.C., Lewis, J.E., Tappan, G.G., and Lietzow, R.W. (1997). The Development of a Land Cover Change Model for Southern Senegal. Presented at Land Use Modeling Workshop. In S. F. EROS Data Center, S.Dak., June 5-6. (Ed.).

Zheng, D., John, R., Jiquan, C., Thomas, C., Mary, B., James, L.M., and Soung-Ryoul, R. (2004). Estimating aboveground biomass using Landsat 7 ETM+ data across a managed landscape in northern Wisconsin. *Remote Sensing of Environment, 7*, 30.

Zianis, D., and Mencuccini, M. (2005). On simplifying allometric analyses of forest biomass. *Forest Ecology and Management,, 187*(2-3), 311-332. doi: 10.1016/j.foreco.2003.07.007

9 APPENDICES

9.1 Appendix 1. Land use cover change matrix between 2001 and 2013

Table 9. 1 Land use transition matrix between 2001 and 2013

Land use /cover in 2013		Land use / cover in 2001											
		Riparian forest and woodland	Savanna woodland	Shrub savanna	Grassland savanna	Crop and fallow	Bareland	Setlement	Agroforestry system	Plantation	Rivers and water body	Roads	Total (ha) in 2001
	Riparian forest and woodland	162.27	1150.47	116.91	31.59	70.11	0.00	0.00	0.00	0.00	0.00	0.00	1531.35
	Savanna woodland	81.63	1944.99	618.12	44.73	544.23	0.54	2.70	0.00	0.27	0.00	0.81	3238.02
	Shrub savanna	62.73	1900.26	2225.34	17.73	2803.23	12.96	147.87	2.34	5.13	0.00	12.96	7190.55
	Grassland savanna	0.09	2.52	43.92	0.09	7.20	0.00	3.51	0.00	0.00	0.00	0.00	57.33
	Crop and fallow	15.93	429.03	1244.16	0.81	4572.63	4.50	290.70	16.65	5.40	0.00	16.02	6595.83
	Bareland	0.63	7.02	11.07	0.00	3.78	89.55	10.08	0.09	0.00	0.00	0.18	122.40
	Setlement	0.00	0.36	1.98	0.00	2.52	0.09	28.80	0.00	0.00	0.00	0.00	33.75
	Agroforestry system	0.00	0.09	0.00	0.00	0.36	0.00	0.09	1.53	0.00	0.00	0.00	2.07
	Plantation	0.18	0.09	0.27	0.00	2.16	0.09	0.27	0.00	5.94	0.00	0.00	9.00
	Rivers and water body	17.73	38.52	14.85	1.62	26.46	0.00	0.45	0.00	0.09	244.89	0.00	344.61
	Roads	0.00	3.15	5.94	0.00	11.79	0.18	3.87	0.09	0.00	0.63	106.83	132.48
	Total (ha) in 2013	341.19	5476.50	4282.56	96.57	8044.47	107.91	488.34	20.70	16.83	245.52	136.80	**19257.39**

Legend: The yellow cell represents the unchanged pixels between 2001 and 2013. The cells up and bellow yellow cells explain the value of pixels that were changed from one LUC to another between 2001 and 2013. The red cell is the total area in hectares.

Table 9.2 Gini values of each scenario during 12 years simulation

Years	Scenarios			
	LUS1	LUS2	LUS3	LUS4
1	0.33	0.33	0.33	0.33
2	0.36	0.36	0.35	0.36
3	0.38	0.37	0.38	0.38
4	0.40	0.40	0.40	0.39
5	0.43	0.42	0.43	0.42
6	0.45	0.44	0.44	0.44
7	0.49	0.46	0.46	0.46
8	0.51	0.48	0.48	0.48
9	0.52	0.50	0.50	0.50
10	0.55	0.52	0.52	0.51
11	0.58	0.54	0.53	0.53
12	0.59	0.57	0.55	0.54

9.2 Appendix 2. Simulated major land-use/cover changes

The following figures expressed the simulated land-use/cover changes from 2013 to 2025 for the four scenarios.

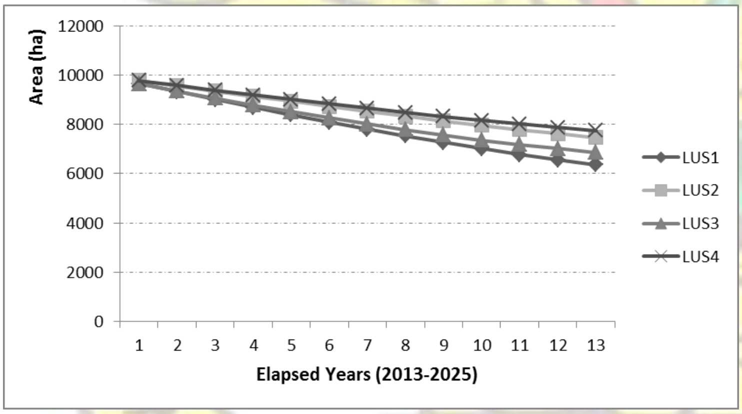


Figure 9. 1. Comparison of simulated changes in forest land (ha) under four scenarios

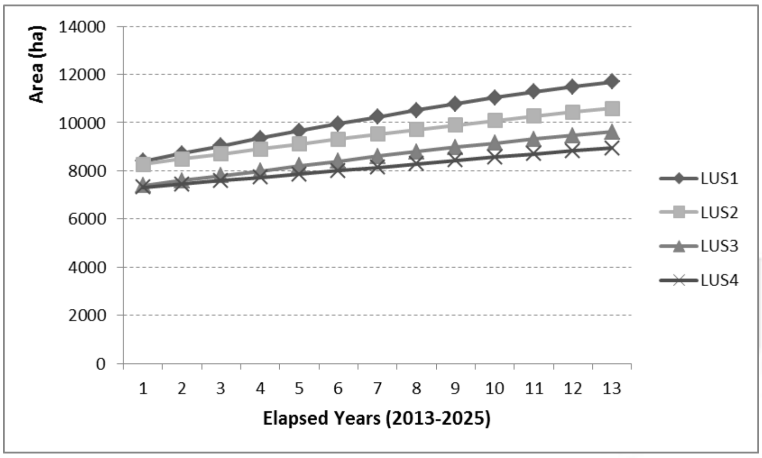


Figure 9. 2. Comparison of simulated changes in cropland (ha) under four scenarios

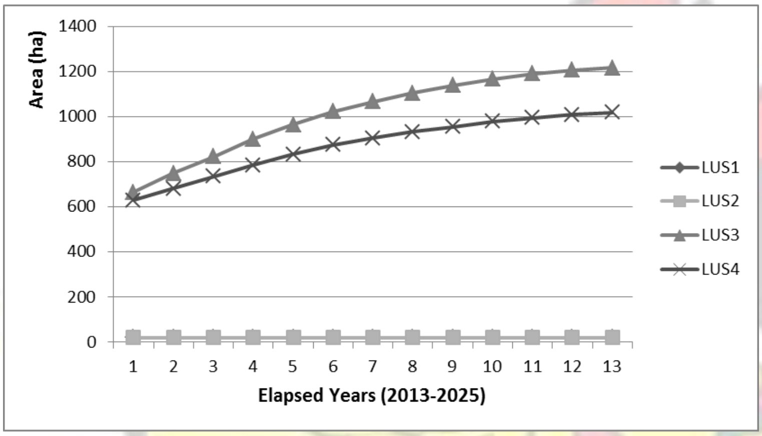


Figure 9. 3. Comparison of simulated changes in agroforestry system (ha) under four scenarios

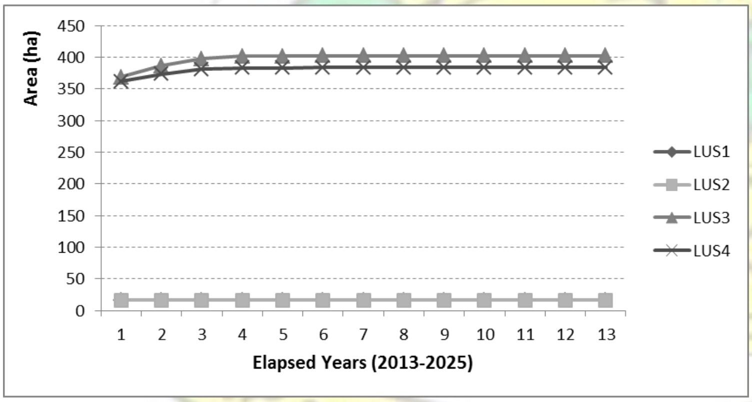


Figure 9. 4. Comparison of simulated changes in plantation (ha) under four scenarios

9.3 Appendix 3. Simulated carbon and nitrogen stocks

The following figures showed the simulated carbon stocks under the four scenarios.

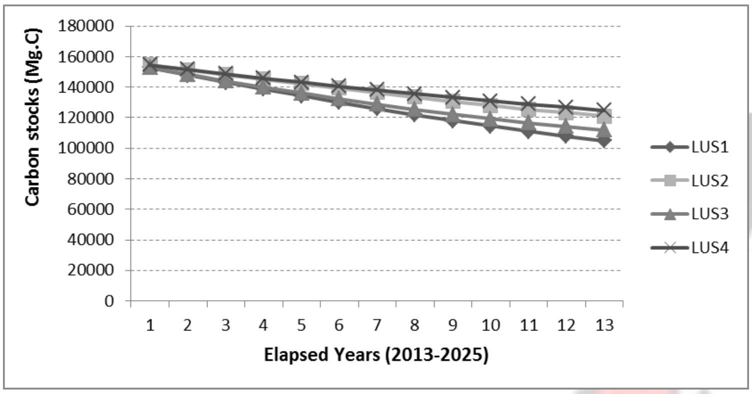


Figure 9. 5. Comparison of simulated carbon stocks in forest land (ha) under four scenarios

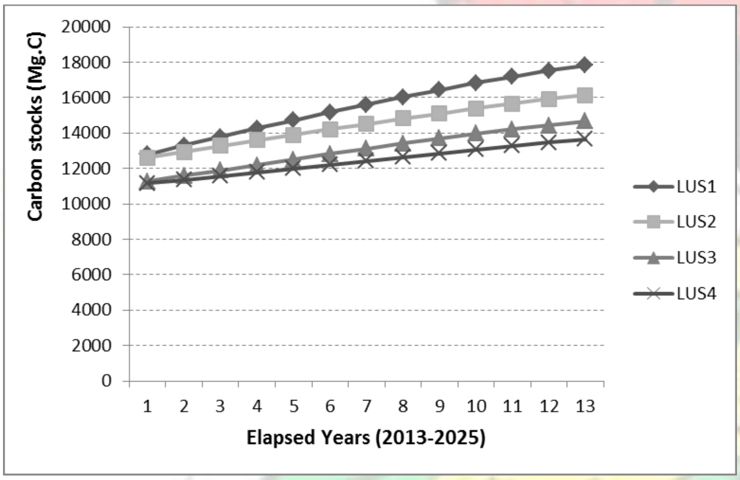


Figure 9. 6. Comparison of simulated carbon stocks in cropland land (ha) under four scenarios

Figure 9. 7. Comparison of simulated carbon stocks in agroforestry system (ha) under four scenarios

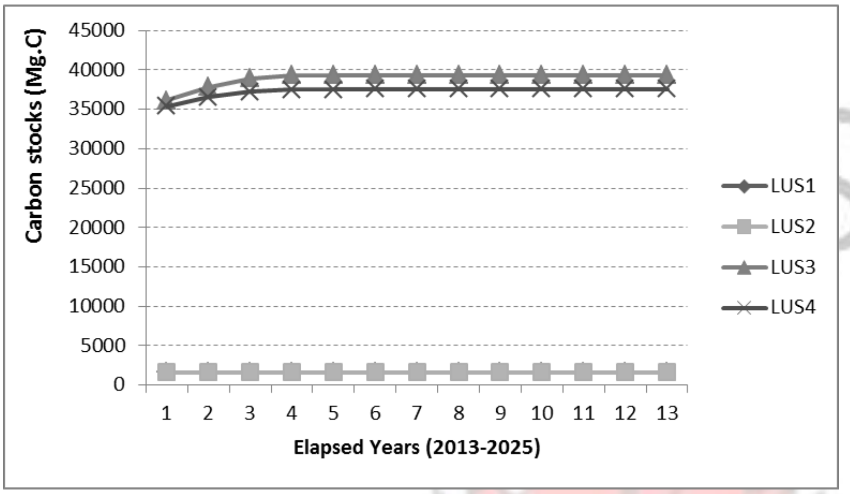


Figure 9. 8. Comparison of simulated carbon stocks in plantation (ha) under four scenarios

9.4 Appendix 4. Simulated socio-economic status of the site

The socio-economic status of households on the horizon 2025 were illustrated through the annual gross income based cultivated (annual and perennial crops, agroforestry and plantation) and annual gross income based carbon credits if a carbon fund project is implemented.

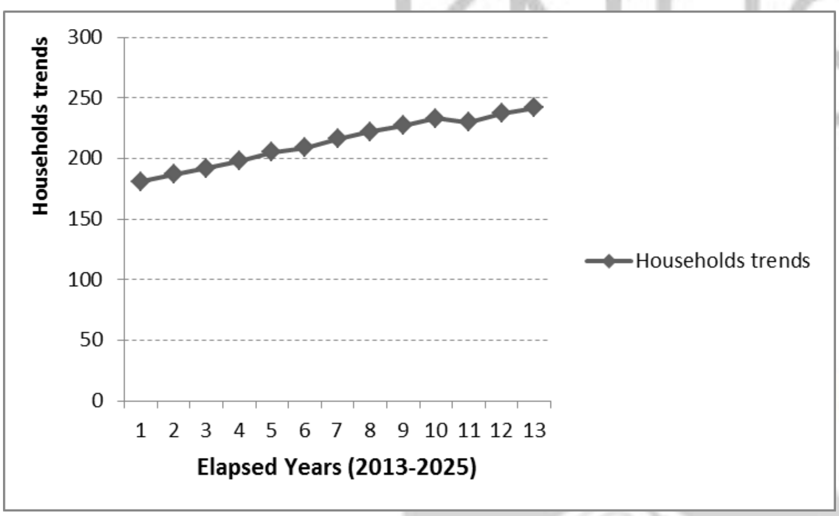


Figure 9. 9. Simulated households dynamics under the four scenarios Note:

The household's trend does not change for the four scenarios

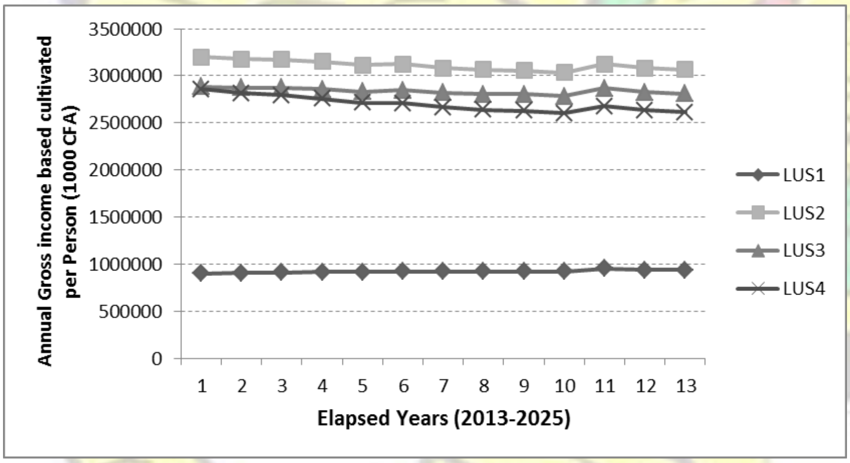


Figure 9. 10. Simulated annual gross income based cultivated under four scenarios

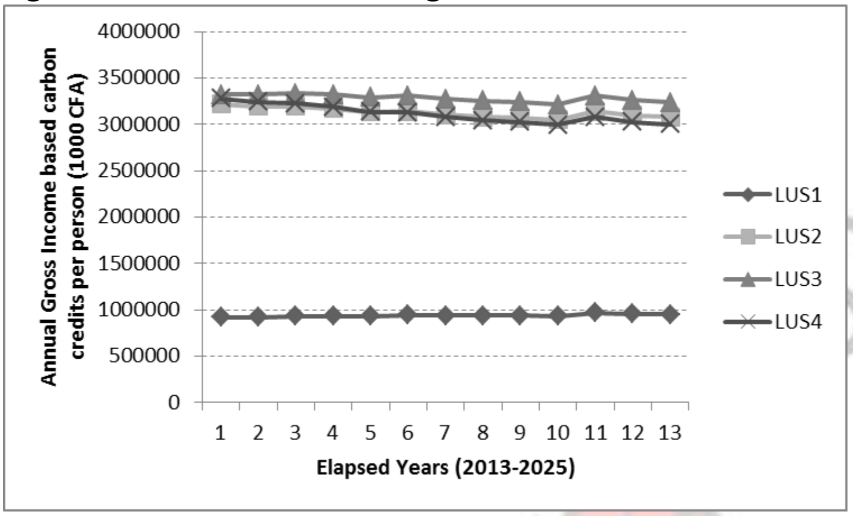


Figure 9. 11. Simulated annual gross income based cultivated and carbon credits under four scenarios