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A Systems Approach to Modelling the Effects of Climate Change on Agroforestry: A Case Study in Western Tanzania

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Abstract

Climate change is anticipated to have significant effects on agricultural production in sub-Saharan Africa as the magnitude of weather events increase in severity. Smallholder farmers in western Tanzania are potentially vulnerable to climate change impact as crops rely on precipitation as the only source of water. It is prudent to evaluate different modes of agricultural adaptations, such as agroforestry, that these farmers can easily adopt to improve their resiliency to the effects of climate change. System dynamics modelling is a cost-effective tool to simulate the long-term behaviour of agroforestry systems under future climate conditions. Water, Nutrient, and Light Capture in Agroforestry Systems (WaNuLCAS) is a system dynamics model developed by the World Agroforestry Centre that was selected to investigate long-term bio-physical interactions of maize and Acacia trees. This model was calibrated to data from field research on rotational woodlots conducted in Tabora, Tanzania from 1996 to 2002 by the World Agroforestry Centre.

Four sets of experimental simulations were conducted with the WaNuLCAS model to determine the response of the agroforestry system to changes. Firstly, the model was calibrated to the “baseline” field research in Tabora. Secondly, management practices were systematically applied to the baseline to study changes in maize and wood yields and the net present value of the system. Thirdly, changing climatic conditions were applied to the model. The climate change scenarios for this study were produced by selecting a number of global climate models and emission scenarios, downscaling that data, and generating a broad set of futures by means of a stochastic weather generator. The climate variables used in this research were daily precipitation, maximum temperature and minimum temperature. The baseline period for observed days was from 1975 to 2005. Mid-term and long-term climate change scenarios were generated for 2035 to 2065 and 2065 to 2095 respectively. Finally, climate change mitigation for the agroforestry system was tested using the extreme “hot-dry” scenario from the 2035-2065 time slice; three management practices from the second set of experiments were applied to evaluate the management practices for loss prevention in maize yields and agroforestry system value.

The application of fertilizers and flexible planting dates were determined to be the most effective management practices to improve yields for the baseline scenario. The climate ensemble for each time slice shows a range of attainable maize and wood yields. The baseline scenario 6 year maize yield was 5.47 Mg ha\(^{-1}\). The 6 year maize and wood yield ranges for 2035 to 2065 are 3.98 to 8.15 Mg ha\(^{-1}\) and 37.1 to 38.0 Mg ha\(^{-1}\), respectively. The 6 year maize and wood yield ranges for 2065 to 2095 are 6.45 to 7.71 Mg ha\(^{-1}\) and 36.2 to 39.1 Mg ha\(^{-1}\), respectively. These results indicate that most climate scenarios will positively impact maize production in this region as the mean growing season temperatures will approach optimal conditions, however, crop yields will continue to be erratic inter-annual variability of rainfall. Flexibility in crop calendar planting dates was the most important management practice in climate change mitigation. Earlier planting dates reduced maize losses by 50% and increased the net present value of the system by 90% over a 10 year period. The results of this research may be informative for policy makers for food security, climate change, and agriculture in Eastern Africa.

Keywords

Climate change, system dynamics modelling, WaNuLCAS, Tanzania, vulnerability, agroforestry, Africa, development
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List of Abbreviations

ASDZB  Agroforestry for Sustainable Development in the Zambezi Basin
CFM    Change Factor Methodology
CGIAR  Consultative Group on International Agricultural Research
DAC    Development Assistance Committee
DFATD  Department of Foreign Affairs, Trade, and Development
ECBA   Economic Benefit Cost Analysis
FAO    Food and Agriculture Organization
GNI    Gross national income
GNP    Gross National Product
HDI    Human Development Index
IATI   International Aid Transparency Initiative
IDM    Inverse distance method
IDRC   International Development Research Centre
IPCC   Intergovernmental Panel on Climate Change
LAI    Leaf Area Index
LDC    Least Developed Countries
LFA    Logical Framework Approach
LIFDC  Low-Income Food-Deficit Country
LM     Logic Model
MDG    Millennium Development Goals
MfDR   Managing for Development Results
NCEP   National Center for Environmental Prediction
NOAA   National Ocean and Atmosphere Association
NPV    Net Present Value
ODA    Official Development Assistance
PMF    Performance Measurement Framework
RCM  Regional climate models
RCP  Representative Concentration Pathways
RMSE Root Mean Squared Error
UN   United Nations
USAID United States Agency for International Development
1 Introduction

It is anticipated that the number of extreme weather events such as droughts, flooding, and high temperatures will become more frequent in Africa and adversely affect vulnerable smallholder farmers (Binswanger-Mkhize & McCalla, 2010; Buontempo et al., 2015; Challinor et al., 2007; Dinar & Somé, 2008; Vermeulen et al., 2012). Africa’s dependence on rain-fed agriculture severely increases smallholder farmers’ vulnerability to climate change (Vermeulen et al., 2012).

Crops are expected to be impacted more severely by droughts (Leclerc et al., 2014) as crop growth is mainly driven by precipitation (Lobell & Burke, 2008). Sixty percent of the global population that are undernourished live in Eastern and Central Africa (Binswanger-Mkhize & McCalla, 2010). Undernourishment occurs when food intake does not produce enough energy required for daily requirements (Liu et al., 2008) and agricultural growth has direct impressions on food security (Binswanger-Mkhize & McCalla, 2010). Hence, climate change can have a direct influence on food security for smallholder farmers.

Introducing adaptive measures along various timescales has been suggested as a means to mitigate climate change impacts on food production in African countries (Challinor, et al., 2007). Several studies have shown that agroforestry methods are appropriate adaptation technologies for smallholder farmers to improve their resilience to climate change (Bishaw, 2013; Hildebrand et al., 2007; Kwesiga et al., 2003; Mbow et al., 2014; Mbwambo et al., 2003; Ramadhani et al., 2002).

Agroforestry techniques have been proven to provide benefits such as increased soil moisture and nutrient availability in soil (Atangana et al., 2014); some tree species are able to fix nitrogen from the atmosphere into the soil (Nyadzi et al., 2003). These benefit the below-ground resources and often lead to increased crop yields, which enables increased farmer income and savings (Franzel et al., 2001). Agroforestry can also contribute to reductions in deforestation, as it reduces the use of natural forests for fuel wood supply (Ramadhani et al., 2002). Fuel wood is the dominant energy source in many Eastern African countries because it is used by a large portion of the population for domestic use (Kimaro, 2009). Fuel wood is also used in Eastern Africa for commercial
purposes to cure tobacco crops (ICRAF, 2001). Adoption of agroforestry techniques are influenced by farmers’ perceptions of the direct benefits of the technology (Kalaba et al., 2010).

Rotational woodlots are an agroforestry technology that follows a scheme of intercropping maize with trees for two to three years, then allowing the field to lie fallow once the tree canopy prohibits crop growth. The trees continue to grow for the remainder of the five years before harvesting (ICRAF, 2001). The woodlots have been shown to be highly successful in reducing deforestation, approximating 1.16 hectares of woodland saved per year per farmer in western Tanzania (Ramadhani et al., 2002).

As the productivity of agriculture is highly dependent on precipitation, the vulnerability of smallholder farmers is closely associated with climate change. Vulnerability to climate change is a function of exposure to a hazard, the sensitivity to the hazard, and adaptive capacity (Antwi-Agyei et al., 2012). There are many emerging methods to estimate vulnerability; most studies incorporate an index for crop sensitivity to drought and use proxy indicators of income and education to indicate adaptive capacity (Challinor et al., 2009; Simelton et al., 2009).

1.1 Previous Studies

Climate change modelling has been studied extensively by many research centers and compiled by the Intergovernmental Panel on Climate Change (IPCC). Some previous studies have integrated climate change with crop modelling (Challinor et al., 2007; Challinor et al., 2009; Liu et al., 2008; Lobell & Burke, 2010). Dinar et al. (2008) assessed fourteen climate models to determine the best of the worst case scenarios for Africa and the results from this analysis were applied to eight agro-ecological zones of Africa, though the study does not explicitly discuss results for Tanzania. Adaptation to climate change is discussed in this study but is not modelled.

These studies have modelled relationships between changing climate and crop responses, however they do not model interactions between them and they also fail to simulate agroforestry processes (Luedeling et al., 2014). WaNuLCAS is a system dynamics model developed by the International Centre for Research in Agroforestry Research (ICRAF) as a generic tool that can be easily modified to simulate the complex interactions between wood plants and crops in different agroforestry systems (Van Noordwijk & Lusiana, 1998). WaNuLCAS has been used to model soil resource competition and identify mitigation strategies for alley cropping (Hussain et al., 2015),
to model yield differences between monoculture crops and agroforestry systems (Pinto et al., 2005), and soil conservation strategy development (Pansak et al., 2010).

More generally, the results of system dynamics simulations have been used to guide policy development in a variety of areas including international development and water resources management. For example, Gies (2013) designed a system dynamics model that evaluated the interdependencies between water availability, land degradation, food availability, and socio-economic welfare and developed drought policy recommendations for East Africa.

1.2 Knowledge Gap

To date, despite the range of areas illustrated above, it is unknown whether agroforestry systems will contribute to the resiliency of smallholder farmers under the influence of climate change (Mbow et al., 2014). Though many studies identify agroforestry as a suitable adaptation for climate change (Bishaw, 2013; Mbow et al., 2014), there are limited studies that have used modelling tools to analyse how climate change may affect agroforestry systems (Coulibaly et al., 2014) and none that evaluate climate change effects on rotational woodlot technology. This research is an important step towards assessing the long-term viability of agroforestry techniques as a means of sustainable development.

Additionally, system dynamics modelling in international development has not been explored beyond policy development. There is potential for the systems approach to be used in broader applications including project planning, evaluation, and management.

1.3 Project Background

The Consultative Group on International Agricultural Research (CGIAR) is a major multilateral partner with the Canadian International Development Agency (CIDA). The World Agroforestry Center, formerly the International Center for Research in Agroforestry (ICRAF) is one of the research centers in CGIAR and was the recipient of funding from CIDA for a large-scale project, “Agroforestry for Sustainable Development in the Zambezi Basin” (ASDZB). Phase One of the project was implemented from 1986 to 1995; Phase Two of the project was executed from 1995 to 2005 in five countries: Zambia, Zimbabwe, Malawi, Mozambique, and Tanzania (ICRAF, 2001). The main impacts were to disseminate proven agroforestry technology on a significant scale to smallholder farms, to enable national agencies to manage agroforestry extension activities and to develop and test new agroforestry technologies. The activities of the project were to identify
natural resource problems, priorities, and policies; to conduct research on germplasm and tree domestication in the Zambezi River Basin, to diversify agroforestry options for development and increase their adoption; and to develop marketing and processing strategies for new agroforestry options.

As part of this former project, research was conducted in Tabora, Tanzania on rotational woodlots that provided insights on the benefits of this mode of agroforestry for the region. The outputs from the Tabora research trials were the basis for a case study, since there was a significant amount of information available for the site. There was also the potential to inform climate change policy for CIDA, as Tanzania is a major recipient of CIDA’s funding (CIDA, 2003).

The research in this thesis is based on the previous fieldwork and analysis conducted in Tabora as part of the CIDA project.

1.4 Research Objectives

The primary research objective for this study is to examine the behaviour of rotational woodlots subject to various climate change scenarios in western Tanzania. The results will help to determine if rotational woodlots are a sustainable mode for agricultural resiliency in western Tanzania by comparing crop and wood yields, returns, and impact on vulnerability under different climate conditions. The main components of the approach are the core system dynamics modelling, WaNuLCAS, a vulnerability index, and climate change inputs. WaNuLCAS is a systems dynamics model that sub-divides interacting natural systems into different sectors; the main sectors are water use, nutrient balance, and light capture. The net present value for each harvest is calculated based on crop prices and labour inputs. The model uses Tanzanian agricultural census data and information from the outputs of the ASDZB research on rotational woodlots by ICRAF as the primary inputs for the WaNuLCAS model.

Additional research questions this study aims to answer include:

- What are the significant climate change trends anticipated for the Tabora region?
- Are rotational woodlots suitable for climate change adaptation in the Tabora region?
- Are systems dynamics simulations suitable for development planning?
• What sort of data management is required such that a systems approach can be used as a project management method?
• Can a systems approach be used in project design and planning, management and outcomes of development projects?

The outcomes of this research are as follows:
• To develop an ensemble of climate change scenarios for the Tabora region in western Tanzania for time-slices centered on the years 2050 and 2080, to represent mid and long-term climate change trends;
• To calibrate the system dynamics model with data from the ICRAF field research trials on agroforestry;
• To determine the impact of climate change on the rotational woodlot agroforestry systems;
• To incorporate a vulnerability assessment for climate change impacts including socio-economic indicators into a system dynamics model.

1.5 Statement of Originality
This research has several novel aspects:
• The development of statistically downscaled, regionally efficient climate ensembles for Eastern Africa for the 21st century.
• The simulation of rotational woodlots for a region in Tanzania.
• The use of system dynamics simulations to explore the effects of climate change on agroforestry system outputs.

1.6 Content of Thesis
The contents of this thesis are organized into five chapters. Chapter One provides an introduction to the rationale for the research. Chapter Two is the literature review that examines past research in the areas pertaining to this thesis including: the Canadian international development sector and project management tools, agriculture and agroforestry in Tanzania, modelling tools for agroforestry, socio-economic indicators for development pertaining to vulnerability to climate change, and climate change in Tanzania. Chapter Three describes the methodologies used in the model such as: the governing equations of the WaNuLCAS model, the development of the
vulnerability index and the tools used to select and generate climate change scenarios for Tanzania. Chapter Four interprets the results achieved from climate change modelling and the outputs of the WaNuLCAS model. Chapter Five discusses the implications of these results for social, economic, and environmental systems. It also provides a summary of the outcomes achieved by this research and recommends areas for improvement and further research.
2 Literature Review

The objective of this literature review is to provide relevant background information and to place the proposed research topic in context within the literature. The first section provides a review of the Canadian international development sector and a brief outline of the foreign aid budget and aid policy for Canada. It also provides a detailed description of current project management approaches for development. The second section provides information on the state of food security and agriculture in Eastern Africa, the vulnerability of smallholder farmers to climate change, and illustrates how agroforestry research and projects have contributed to farmer livelihoods.

2.1 Canadian International Development Sector

International development continues to be a significant component of the Canadian federal budget; in 2014, for instance, Canada contributed 4.9 billion USD as Official Development Assistance (ODA) (OECD, 2014). ODA is defined as “grants or loans to countries and territories on the Development Assistance Committee (DAC) List of ODA Recipients (developing countries) and to multilateral agencies [such as the World Bank] which are: (a) undertaken by the official sector; (b) with promotion of economic development and welfare as the main objective; (c) at concessional financial terms (if a loan, having a grant element of at least 25 per cent). In addition to financial flows, technical co-operation is included in aid” (OECD, 2014). In 1970, the United Nations (UN) set a target of 0.7% of gross national income (GNI) from developed countries towards ODA. The target was renewed in 2002 at the International Conference on Financing for Development in Monterrey, Mexico (UNMP, 2006); though Figure 1 shows that only five countries met or exceeded the 0.7% target in 2014. These were Sweden, Luxembourg, Norway, Denmark, and the UK. Canada’s percentage of GNI to ODA steadily decreased from a peak of 0.34% in 2010 to 0.24% in 2015 (OECD, 2014).

In 2013, the Canadian International Development Agency (CIDA) merged into the Foreign Affairs and Trade portfolio to become the Department of Foreign Affairs, Trade, and Development (DFATD). In 2015, DFATD was rebranded as Global Affairs Canada under the new federal government (Mazereeuw, 2015). However, development programs in DFATD/Global Affairs are still referred to as CIDA programs by active professionals and the same terminology will be used in this thesis.
Figure 1. Percentage of GNI to ODA for DAC countries. (OECD, 2014). The orange bar represents the Canadian GNI percentage. The green line is the mean percentage of GNI for all donors and the red line represents the target 0.7 percent of GNI.

The three current focuses of CIDA are to increase food security, secure the future of children and youth, and to stimulate economic growth (CIDA, 2003). These three areas of development align with the United Nations’ Millennium Development Goals (MDGs). The MDGs were established in 2000 to direct foreign aid into more focused areas and to establish basic indicators for development; the timeline for the realization of the MDGs was until 2015. There were eight major goals in total and each goal comprised of a subset of goals with indicators. In September 2015, the MDGs concluded and were replaced by the Global Goals for Sustainable Development (GGs). The seventeen GGs echo themes from the MDGs but have expanded emphasis and scope in three main areas: to eradicate extreme poverty, to reduce inequality and injustice, and to protect the environment (UN, 2015). Several GGs are relevant to the outcomes of this thesis and these are listed in further detail in Appendix A.
2.2 Management Practices in International Development

Multilateral agencies receive approximately 30 percent of the Canadian ODA which in 2013 was an estimated 1.3 billion dollars (OECD, 2014). As such, it is important to understand how funding is managed for projects. In 2005, many bilateral and multilateral development institutions endorsed the Paris Declaration on Aid Effectiveness. This document focused on five key principles to improve aid effectiveness: that developing countries set their own goals and strategies for development, that donor countries aligned with the developing partner objectives and frameworks, that donors coordinated and shared information and best practices to reduce overlap, and most importantly that all development institutions shifted to Managing for Development Results (MfDR) and were accountable for those development results (Killen, 2011; OECD, 2005). MfDR encompasses leadership, accountability and partnerships, monitoring and evaluation, planning and budgeting, and statistics by donor and development partner countries.

2.2.1 Results Based Management

Results Based Management (RBM) is an evidence-based decision making tool supported by the MfDR focus outlined in the Paris Declaration and the Accra Agenda for Action (OECD, 2008), though MfDR and RBM have been used interchangeably by different institutions. RBM is the current management framework used by CIDA (CIDA, 2013) and other development institutions such as the Food and Agriculture Organization (FAO) of the United Nations and the International Fund for Agricultural Development. MfDR is used to address four main questions of development project planners:

- What results are desired?
- What must be done to achieve the desired results?
- What will indicate that the desired results have been achieved?
- How can lessons be learned from the experience and applied to future performance?

RBM is a three-pronged approach and uses the Logic Model (LM), the Risk Register, and the Performance Measurement Framework (PMF). The Logical Framework Approach (LFA) is also a common term for RBM as it is known in Canada and is used interchangeably through the rest of this thesis. The Logic Model, also referred to as the logical framework matrix, is used to identify desired results, the Performance Measurement Framework is used to identify progress and success of the results being achieved throughout the project, and finally, the Risk Register helps identify
risks, and how to mitigate and manage them (CIDA, 2013). These three tools are explained in further detail in Appendix B. RBM is intended to be used by all stakeholders throughout the lifespan of a given project as a collaborative process to ensure that the ownership of the project is shared by all stakeholders.

2.2.1.1 Application of Results Based Management

When RBM is used to its fullest potential and fully incorporates stakeholder participation throughout the project lifespan, it is viewed as a very useful tool (Vahamaki, Schmidt, & Molander, 2011). The best use of RBM occurs when the institutions and partners foster an RBM culture and when the RBM systems of partner countries and donors are aligned. Generally, the consensus of the literature related to RBM is that the approach itself is not particularly flawed, rather that the implementation of RBM is what can render it less powerful overall as a planning, management, and monitoring and evaluation tool (Bakewell & Garbutt, 2005; Schroeder & Hatton, 2007; Vahamaki et al., 2011). It is widely agreed that RBM contributes to improved aid effectiveness and transparency and is contributing to the fulfillment of the Paris declaration (Killen, 2011; Vahamaki et al., 2011).

However, some literature suggests RBM is preferred by project managers and organizations; field workers are more skeptical of the usefulness of RBM as they are exposed to more complex aspects of the project (Bakewell & Garbutt, 2005; Vahamaki et al., 2011). Causality is complex and difficult to trace from the outcome level to impacts (Bakewell & Garbutt, 2005), especially when baseline data is limited or entirely unavailable in partner countries. Strengthening statistical systems in partner countries will significantly improve support for evidence-based decision making and RBM (OECD, 2009). Additionally, reliable qualitative data are limited, so monitoring impacts like capacity building and improved governance are very difficult (Vahamaki et al., 2011). Finally, the linear progression of the RBM logic model does not include feedback in the framework, rather it relies on project managers to frequently evaluate the validity of their logic models.

2.2.1.2 Contribution Analysis

In response to the challenges of including complexity within the RBM framework, contribution analysis was developed. Contribution analysis is a project management approach used in development in conjunction with RBM to attribute results directly to the activities of the project
Contribution analysis is also known as “Theory of Change” but will be referred to as contribution analysis in this thesis. It acknowledges that other factors may be influencing results outside of the program and reduces uncertainty through understanding the contribution the program is making and demonstrating or proving the performance of results achieved by the program (Vogel, 2012). However, it is challenging to monitor and evaluate assumptions made with contribution analysis if data is scarce (Bakewell & Garbutt, 2005). Contribution analysis examines several areas of the project: cause-effect relationships, outside factors that may affect the outcomes of the project, and areas where understanding of the impact of the project is weak (Mayne, 1999). Contribution analysis then seeks further evidence to support or refute links by exploring and discussing other plausible alternative explanations. During the project planning process, contribution analysis is applied by identifying, measuring, and documenting expected behavioural changes (Mayne, 1999).

2.2.2 Systems Approach

A systems approach is a general problem solving method that is goal-oriented; it determines the best actions to achieve an outcome by broadening the range of information available to the decision maker. Quantitative and qualitative data are collected on the problem and are analysed using a number of tools through which information on system complexities can be obtained: system dynamics simulation, optimization, and multi-objective analysis.

Similarly to contribution analysis, the system dynamics simulations attempts to identify and measure behavioural changes attributable to the project by demonstrating causal linkages between events and actors. System behaviour is the way elements in a system behave over time. Development project managers can use causal loop diagrams that show systemic behaviour with feedback (Hummelbrunner, 2010). Systemic behaviour in a positive loop reinforces changes between elements resulting in exponential growth (Simonovic, 2009). Negative feedback loops demonstrate goal seeking behaviour cycles that achieve a stable state. Figure 2 shows examples of positive and negative feedback loops. Mapping the project elements and actors in this manner can allow for a more flexible project management dynamic (Hummelbrunner, 2010), and paired with systems dynamics simulations, as more information about the system behaviour becomes available to project managers. Generally, project management tools in development have not progressed farther than causal loop diagrams into system complexity and modelling. Applying a systems
approach to development planning, particularly in agriculture and natural resource sectors, has the potential to fill the gap between predictive modelling and the lack of knowledge sharing, to provide new insights for policy-makers in development.

![Feedback loops](image)

**Figure 2. Feedback loops.** (a) is a positive feedback loop demonstrating exponential population growth, and (b) is a negative feedback loop demonstrating a stabilizing population decline.

System dynamics simulations can mathematically model the causal nature of development projects and provide insight into the behaviour of complex systems (Jewell, 1986; Simonovic, 2009). The design of a system dynamics model follows the engineering design process of making assumptions, goals, objectives, and criteria and emphasizes the link between system behaviour and performance to the predetermined goals. System dynamics simulations were developed as a computer tool to shift the attention of problem solvers from event-based thinking, to solving problems at a more complex level, by examining the internal structure of a system and determining the cause of behaviours. System dynamics simulations combine knowledge and understanding of analytical techniques with skills applied to real-world problems (Simonovic, 2009).

Simonovic (2009) defines a system as “a collection of various structural and non-structural elements that are connected and organized in such a way as to achieve some specific objective through the control and distribution of material resources that can be used, energy, or information”. Systems dynamics simulation identifies and connects many elements of a complex system and models behavioural trends.

The system dynamics simulations have been widely used in water resources management policy making (Ahmad & Simonovic, 2015; Davies & Simonovic, 2011; Winz, Brierley, & Trowsdale,
2009; Xi & Poh, 2013) and has percolated into some experimental applications for development. Gies (2013) used a hydrologic and system dynamics model to inform drought adaptation policies in Tanzania. Atherton (2013) developed a system dynamics model of food production with projected population growth, land use changes, and water resources for the Gambia. Li, et al. (2012) analyzed the environmental and economic effects of ecological agriculture in Gusang province, China in a system dynamics model to inform policy makers how to avoid instability in the system structure. System dynamics simulations have not been widely used for policy development in international development sectors. In particular, system dynamics simulations have not been used before to model the effects of climate change on agroforestry. (Mbow et al., 2014).

2.3 Agriculture and Agroforestry

CIDA concentrates its budget on 25 countries based on three criteria: needs, the capacity to benefit from aid, and alignment with Canadian foreign policies (Canada, 2015). In 2012, Tanzania received the highest financial aid from Canada of any of the target countries. Canada contributed 181 million Canadian dollars of ODA to Tanzania (Bhushan, 2014) and has given 576.7 million USD to Tanzania since 2009. Tanzania has been classified by the FAO as a Low-Income Food-Deficit Country (LIFDC) since the creation of the term in the 1970s (FAO, 2015b). The LIFDC list has two criteria: a per capita gross national income (GNI) below the ceiling defined by the World Bank and the food trade position based on the net trade of foodstuffs for the three previous years (FAO, 2015b). As previously mentioned, CIDA has major focuses on food security and economic growth stimulation (CIDA, 2003); the agricultural sector contributed to 24.6 percent of Tanzania’s GDP in 2007 (Maltsoglou & Khwaja, 2010) and has great potential for growth.

2.3.1 Food Security

CIDA’s current food security strategy emphasizes the importance of focusing development funding on research initiatives for climate resiliency and environmental practices, such as resource management and reduction of land degradation from agriculture. Food security is defined as the availability and seasonal stability of food from national production, imports, or food aid; regional access to food through subsistence farming, local markets, or social safety nets; and that the available food is healthy and nutritious (CIDA, 2003). Sub-Saharan Africa is estimated to have nearly 23% of its population undernourished, with 60% concentrated in Eastern and Central Africa (Binswanger-Mkhize & McCalla, 2010). Undernourishment is defined as the state when dietary
consumption is consistently below daily energy requirements to be healthy and to do light physical activity (Liu et al., 2008). Agricultural growth has a direct implication for incidence of hunger. Agricultural development can increase farm profits and lower food prices. Food price spikes are associated with several environmental factors including poor weather conditions and decreasing soil fertility. Inequitable land distribution and rapid population growth has contributed to poor soil fertility as long periods of fallow for fields can no longer be accommodated with higher demands for food (Kwesiga et al., 2003). Other factors, such as the removal of subsidies, have increased the cost for fertilizers that could improve soil fertility without the need for fallow years. Additionally, the majority of smallholder farmers rely on rain-fed agriculture so they are highly vulnerable to erratic weather conditions and future climate change.

The implications of food price increases on Least Developed Countries (LDCs) are many; for example, in 2008 high domestic food prices were linked to lower caloric intake and increased child malnutrition (Wodon & Zaman, 2010). Coping mechanisms for food pricing at the national level include decreasing import tariffs or subsidizing food prices to lessen the impact of food price spikes on their populations. However, LDCs may not be able to afford these short-term strategies or if they do use these, the Gross National Product (GNP) can be adversely affected (Binswanger-Mkhize & McCalla, 2010). Poor infrastructure and transportation costs are significant barriers to agricultural market growth in Sub-Saharan Africa. Areas where little to no progress in improving agricultural and rural development has been made are typically areas of persistent conflict, slow regional integration, and the HIV/AIDS crisis continues to have major consequences on the availability of labour for smallholder farmers (Binswanger-Mkhize & McCalla, 2010).

2.3.2 Agroforestry

Literature supports agroforestry techniques for smallholder farmers to implement as a means of sustainable development and can be used to increase the adaptive capacity of smallholder farmers by increasing income and food security (Ramadhani, 2002; Mbow et al., 2014; Kwesiga et al., 2003). The World Agroforestry Center defines agroforestry as “a dynamic, ecologically based, natural resources management system that, through the integration of trees on farms and in the agricultural landscape, diversifies and sustains production for increased social, economic, and environmental benefits for land users at all levels” (Kimaro, Timmer, Mugasha, Chamshama, & Kimaro, 2007).
Generally, farmer adoption of new technology depends highly on perceived benefits such as soil fertility improvements, water recycling, food security, ecosystem services, and farmer income (Hildebrand et al., 2007; Mbow et al., 2014). Proven benefits of these technologies are increases in crop yields, income, savings, and improved soil. However, widespread uptake of agroforestry is inhibited by land constraints, property rights, seed availability, and knowledge-intensive technology (Kalaba et al., 2010). While the first two constraints pertaining to land are difficult to overcome due to historical and cultural land ownership practices, seed availability and technical knowledge can be tackled with improvements to the agroforestry value chain and training programs (Kalaba et al., 2010; Ramadhani et al., 2002). These constraints can be categorized into technology, household, institutional, and geo-spatial areas. These broad categories contain factors that range from farmer perception of the technology, whether the trees are suitable to that climate and soil, and costs associated for inputs and outputs. Farmer specific training and incentives are recommended to promote adoption of the agroforestry technologies (Kalaba et al., 2010). Examples of agroforestry include agroforestry parklands, perennial crop based systems, farm woodlots, improved tree fallows, alley cropping systems, and rotational woodlots (Atangana et al., 2014).

**Rotational Woodlots**

The ICRAF research on rotational woodlot technology in Tanzania was studied in the Tabora Administrative District at the Tumbi Research Station and at on-farm sites. The on-farm sites were distributed across all five administrative districts in Tabora. Research on agroforestry options in Tabora Region was initiated after surveys and participatory rural appraisals were used to determine major constraints in land usage. The constraints identified were declining crop production, shortage of fuel wood for household use and tobacco curing, and declining soil fertility (ICRAF, 2001). A leading cause of deforestation of the natural Miombo woodlands in Tanzania is from farmers clearing out natural forest to create more land with nutrient rich soil when current agricultural land soil nutrition has been depleted (ICRAF, 2001). Additionally, rapid deforestation led to increasing distances to access fuel wood, creating a demand for a supply closer to villages (ICRAF, 2001; Ramadhani et al., 2002). Deforestation was accelerated through slash and burn agriculture techniques and fuel wood consumption for domestic use and tobacco curing (Waluye, 1994).
Rotational woodlot technology follows a five year scheme of growing maize with trees on the same lot for two to three years, then allowing the field to lie fallow while the trees continue to grow for the remainder of the five years before harvesting (ICRAF, 2001). Figure 3 shows an example of rotational woodlots. Economic benefits for farmers can be achieved through strategic environmental reclamation, such as rotational woodlots (Ramadhani et al., 2002). Rotational woodlots minimize the use of natural forests for fuel wood and improves soil fertility, soil structure, as well as reduce soil erosion (Kalaba et al., 2010). Furthermore, other methods like green manure can be applied in tandem to rotational woodlot technology to improve crop and tree yields (Kimaro, 2009).

Figure 3. Example of rotational woodlot intercropping. (ICRAF, 2013)

Nutrient efficient plants such as species of acacia trees can be grown successfully in low fertility soil. Nutrient efficiency is defined as the ratio of biomass to nutrient uptake. Some particularly nutrient-efficient plants may even be planted on infertile soil. A study by Kimaro (2009) examined
soil characteristics of plots of different tree species after five years and compared the soil characteristics of the rotational woodlots to the soil characteristics of the natural Miombo woodlands and found that wood productivity was three times higher in the rotational woodlots than in the natural woodlands. This was a very positive result of the study for promotion of up-taking agroforestry technologies to relieve deforestation for fuel wood. Fuel wood is the dominant energy source in many Eastern African countries because it is used by a large portion of the population for domestic use (Kimaro, 2009).

Other research on tree suitability for rotational woodlots was conducted at the Tabora locations. Australian species of Acacia were selected because they are ideal for low-fertility soils and high production of biomass. The Acacia Crassicarpa species was identified as the fastest growing tree from the Tumbi research (Kimaro, 2009). Eucalyptus trees were shown to exploit soil water resources and therefore are not suitable species for rotational woodlots because they compete with the food crops for available water (Nyadzi et al., 2003). Acacia have proven benefits, such as retrieving fixed nitrogen from soil areas lower than the crop root zone and increasing its availability to crops (Nyadzi et al., 2003). Trees were found to deplete groundwater in the dry season, but they helped to conserve water longer in the wet season. The benefits during the wet season are attributed to improved soil infiltration and soil structure from tree roots, attributed to the phenomena of tree roots intercepting the leaching of nitrogen from soil (Nyadzi et al., 2003).

The positive environmental impact on forests was measured by calculating the amount of fuel wood required to cure one hectare of tobacco for one year (Ramadhani et al., 2002). The area of the forest that would be affected by supplying the wood was considered the area of forest saved by using woodlot technology. Farmers’ interest in maintaining the technology for woodlots was high after five years, shown by several farmers expanding their woodlots from the pilot size and new farmers adopting the technology in the Tabora region. Cost inputs for trees were considered and it was determined that labour for tree lots is approximately 2.5 times more than labour for maize crops. This cost is due to the increased labour; trees require transplanting, pruning, gapping, and wood harvesting in addition to the initial investment for seedlings. However, the labour inputs for the woodlots do not compete with the labour for the food crop harvesting season so it is considered a viable option by farmers. Furthermore, the economic benefits were approximately six times greater than the traditional maize-fallow rotation (Ramadhani et al., 2002).
However, the benefits of rotational woodlots and other agroforestry technologies are uncertain under future conditions of climate change (Bishaw, 2013). Mbow et al. (2014) highlighted several unanswered questions in the current state of knowledge on the future of agroforestry:

- How will agroforestry species respond to climate change?
- What tree species work best under given site conditions?
- Are adaptation benefits greater than those of alternative land uses?

Bishaw (2013) also recommended additional areas of research:

- Better understanding of the contribution of agroforestry practices to adapt to and mitigate climate change and how climate change affects agroforestry systems;
- Development of methods and approaches scaling agroforestry technologies to attain landscape level impacts;
- Development of appropriate policies and institutional infrastructure to catalyze adoption of agroforestry.

2.4 Climate Change

2.4.1 Agricultural Impacts

It is anticipated that the number of extreme weather events such as droughts, floods, and heat waves will become more frequent in Africa and adversely affect vulnerable smallholder farmers (A. Challinor et al., 2007; Dinar & Somé, 2008; Field, Barros, Stocker, & Dahe, 2012; Vermeulen et al., 2012). Precipitation is the driving factor of crop production (Lobell & Burke, 2008); Africa’s dependence on rain-fed agriculture severely increases vulnerability to climate change. As agriculture in Tanzania is mostly rain-fed (NBS, 2012), crop growth is limited to the amount of precipitation; if precipitation increases, crop growth will also increase and vice versa. The annual total precipitation is not a good indicator of extremes or weather patterns that affect planting dates of crops (Lobell, 2013).

Studies have examined crop models and their ability to model climate change and suggest that temperature contributes the majority of the variance and uncertainty for crop models (Lobell & Burke, 2008). It is anticipated that increased temperature may reduce crop yields by approximately 20 percent (Rowhani, Lobell, Linderman, & Ramankutty, 2011). Increased temperatures and decreased rainfall will shorten the growing period across many dryland areas in sub-Saharan Africa due to the increase of evapotranspiration and reduced overland flows (Lobell, 2013).
2.4.2 Farmer Vulnerability to Climate Change

Tanzania was ranked 159th out of 187 countries on the Human Development Index (HDI) in 2014 (UNDP, 2014). The HDI is used to track development for all countries recognized by the United Nations. It is comprised of three areas, some of which are further subdivided into more specific indicators. The three areas are a “long and healthy life, access to knowledge, and standard of living” (UNDP, 2014). A healthy life is measured by life expectancy; standard of living is measured by the Gross National Income (GNI) per capita; and access to knowledge is measured by the mean years of education received by adults and the expected years of schooling for children entering school (UNDP, 2014).

Another useful indicator for development is the Gini index which measures the degree of income inequality in a country. Tanzania has a medium-low Gini Index of 37.8 (WorldBank, 2012), which indicates that the majority of the population has a moderately equal distribution of wealth; this could also mean that most of the population is relatively, equally poor. Comparatively, neighbouring Zambia has a Gini Index of 54.6 (WorldBank, 2012), which indicates a more disparate distribution of income where the rich have higher incomes and the poor have much less. Vulnerability is defined as “the degree to which an environmental or social system is susceptible to, or unable to cope with, adverse effects of climate change, including climate variability and extremes” (McCarthy, 2001). Vulnerability varies between regions for multiple reasons since it is a general term and its specificities vary greatly depending on the population, region, and climate of study.

Smallholder vulnerability to climate change has been assessed as a function of exposure, sensitivity, and adaptive capacity in several studies (A. Challinor et al., 2007; Gbetibouo, Ringler, & Hassan, 2010; Hanscom, 2015; McCarthy, 2001). Adaptive capacity is the ability of a “system to adjust to the changing climate in order to reduce potential damages and take advantage of associated opportunities” (Antwi-Agyei et al., 2012). Forms of adaptive capacity include social capital, such as farmer co-op participation; human capital measured by the literacy rate and HIV prevalence; financial capital measured by farm income and assets; and physical capital measured through an index for infrastructure which accounts for the density of road network and road quality (Gbetibouo et al., 2010).
Exposure is the extent to which climate stress affects a unit of analysis, for example, how frequent and intense droughts may occur and be and how they will affect a system such as crop production or water storage (Antwi-Agyei et al., 2012). Exposure can also be determined through different climate change scenarios taking into account past climate extremes to forecast future scenarios and changes in rainfall and temperature (Gbetibouo et al., 2010). Finally, sensitivity is the responsiveness to climate change, which can be positive or negative (Antwi-Agyei et al., 2012); sensitivity of crops to rainfall disturbances is derived from historical data for maize from available data for expected yield and actual yields.

Farmer vulnerabilities are categorized into shocks, seasonal variations, and long-term trends (Antwi-Agyei et al., 2012). Small-scale farmers currently use traditional and new coping mechanisms to maintain production during periods of high rainfall variability and short periods of drought. During long-term droughts, coping mechanisms are less sufficient and cannot provide the resilience needed to avoid seeking external help such as employment outside of agriculture or government subsidies (A. Challinor et al., 2007).

Coping mechanisms should exist at several levels to reduce vulnerability by increasing robustness and resiliency at the smallholder farmer level; these include adaptations in local governments, regional bodies such as watershed management groups, national programmes, and trans-national institutions (A. Challinor et al., 2007). National and trans-national solutions include the transition into liberal markets, increasing cash crops and exporting them. Another example of a trans-national coping is the provision of food aid for farmers affected by severe climatic events. Education can also improve the adaptive capacity of a region as knowledge contributes to human capital (Antwi-Agyei et al., 2012). Local solutions may include support from co-operatives or the development of seed banks. Common climate adaptations at the household level are changing planting dates, expanding cropland, and planting mixtures of crops that are adaptable to different climate conditions (A. Challinor et al., 2007). While the majority of the aforementioned solutions are systemic and help to achieve climate resiliency at regional and national levels, many farmers are responding to climate change at the household level by diversifying their livelihood activities outside of agriculture to generate additional cash, such as agroforestry opportunities (A. Challinor et al., 2007; Mbow et al., 2014).
2.4.3 Climate Change Modelling

General Circulation Models (GCMs) model historic and future climate scenarios from which useful climate policies can be developed. There are currently no direct models that can make confident projections from past events; however, trends and relationships between variables are valuable for future projections, as they can establish more credibility from past events (Flato et al., 2013). GCMs have coarse spatial and temporal resolutions and must be downscaled to be used for crop and local climate models that require climate data to be available at much higher resolutions. There are two main approaches to downscaling GCMs: dynamical and statistical downscaling. Dynamical downscaling uses GCM results to force higher resolution regional climate models (RCMs), whereas statistical downscaling uses empirical relationships between GCM predictor variables and observed local variables to create plausible future local conditions (Wilby & Wigley, 1997). A predictor is a process in the Global Climate Model that is chosen to determine local variables in the regional climate model. Examples of predictors are sea-level pressure or carbon dioxide concentrations and examples of local variables are precipitation and temperature (Fowler et al., 2007).

Ensemble approaches for impact studies are used to minimize the level of uncertainty from internal variabilities or structures; the median of an ensemble outperforms an individual GCM (Flato et al., 2013). Weather generators are stochastic tools to create synthetic data that match the statistical characteristics of observed data at a specified location (Srivastav & Simonovic, 2014). The use of weather generators in impact assessments is recommended by the IPCC if a long time series of data area is not available in observed records, for daily weather data where data is lacking, or if mean climate and daily variability is needed (Flato et al., 2013). Weather generators are used to generate changed climate weather records based on inputs from GCM scenarios.

Computer modelling of crops has many benefits but is subject to large amounts of uncertainty. Global climate model data is not easily applicable to crop production as the spatial scale of cropping systems are smaller than the resolution available from climate models; this requires GCM downscaling to obtain useable data (Challinor et al., 2007). Current climate models can also vary seasonally. These seasonal uncertainties can affect the magnitude and sign of crop estimates as can the choice of variable for a weather generator. A broad set of climate change scenarios is highly recommended to maintain a range of uncertainty in regional impact assessments (Challinor et al., 2007).
This can be accomplished by downscaling GCMs and emission scenarios for the region of study (Wilby & Wigley, 1997). To minimize uncertainty in this process, the IPCC recommends using several climate models to estimate a range of future possibilities (Flato et al., 2013).

2.5 Summary of Literature Review

The implementation of agroforestry systems on smallholder farms in western Tanzania may reduce farmer vulnerability to climate change but as yet, little research has been conducted. There is a large potential for the use of system dynamics simulations to inform development planning and management in agriculture and agroforestry, as there are currently few project planning tools available that capture the feedback behaviours of complex problems for development planners.

Climate change may affect the food security of smallholder farmers and adaptation to climate change may be necessary for farmers to reduce their vulnerability. Agroforestry has been determined to be a profitable and sustainable land use system (Kerr, 2002), though the impacts of climate change on agroforestry systems have not been explored. Climate change ensembles provide a range of possible futures and captures the uncertainty associated with modelling climate change.
3 Methodology

The objective of this chapter is to discuss the methods employed in the thesis and to provide a background for the case analysed. The first section describes the Zambezi Basin project on which this research is based. The second section provides relevant information on the specific case study area; the Tabora region in Tanzania is highlighted in Figure 4 below. The third section provides detailed information on the system dynamics model used for analysis, WaNuLCAS. This includes the description of the physical concepts used in the model, how inputs for the model were determined, and the added vulnerability assessment tool. The final section provides technical information on the methodology followed to produce future climate change scenario inputs for the simulations.

Figure 4. Tabora Region, Tanzania. (GoogleMaps, 2015)
3.1 Agricultural Sustainability in the Zambezi Basin

Several publications resulted from the research output on rotational woodlots in Tabora (Mbwambo et al., 2003; Nyadzi, Janssen, & Oenema, 2006; Nyadzi et al., 2003; Ramadhani et al., 2002). A range of Sustainable Agroforestry in the Zambezi Basin project documents such as the Annual Reports (ICRAF, 2001), Mid-Term Reviews (ICRAF, 2004), and Logic Models (ICRAF, 2004) were reviewed to glean data and get a thorough understanding of the outcomes and impacts the project aimed to achieve and to determine which long-term development goals may be undermined by climate change in the future. The following is a brief list of impacts and outcomes pertaining to the woodlot research in Tabora.

a) **Impact:** Contribute to poverty alleviation and better environmental management for smallholder resource-poor farmers in the Zambezi River Basin, through agroforestry technologies (ICRAF, 1996).

**Outcomes:**
- Incorporation of proven agroforestry technologies on a significant scale into smallholder farming systems in target extension areas and other critical watershed localities in the region;
- Improved sustainability of land use;
- Improvement of agricultural production;
- Development of new agroforestry technologies;
- Improved regional and in-country collaboration in research led technology development and dissemination.

b) **Impact:** By 2010, the use of agroforestry will have contributed to the well-being of two million low-income farmers within the Zambezi basin of southern Africa, through increasing food security, alleviating poverty and securing a sustainable and enhanced environment (ICRAF, 2004).

**Outcome:** Increased farmer experimentation and participation in the generation and testing of agroforestry innovations results in the development of diverse agroforestry technology options and information that are accessible to farmers and other stakeholders through the creation of the following activities:
A range of agroforestry options, developed (both on-station and on-farm) and made accessible to farmers; options include technologies suitable for women, HIV-affected and other marginalized farmers;

- Farmer research groups (especially women’s) supported to monitor performance of agroforestry options and to report on innovations. Farmer feedback disseminated;
- Technical information on environmental services of agroforestry options (e.g. carbon sequestration) generated and made available to project policy team and policymakers options.

3.2 Case Study Area: Tabora, Tanzania

This section places the Zambezi Basin rotational woodlots research into context for Tabora, Tanzania and also describes the social, economic, and physical environments of Tabora.

3.2.1 Population

The Tabora region is one of Tanzania’s thirty administrative districts. It is located in western Tanzania on the Central Plateau. The total number of agricultural households in Tabora administrative district is 294,913 households with a rural agricultural population of 1,839,844 people (NBS, 2012). This data was reported from the most recent Tanzanian National Sample Census of Agriculture, released in 2012, with data from the 2007/2008 agricultural year (NBS, 2012). The number of agricultural households increased by 18 percent from the previous census in 2003/2004. The literacy rate of the region was 63.9 percent, based on the ability to read in Swahili, English, or both (NBS, 2012).

The majority of farm households in an on-farm study of rotational woodlots in Tabora performed by Ramadhani et al., (2002), see Table 1, were led by men. However it is notable that 60 percent of households had men and women involved in managing the agroforestry plots. Seventy four percent of households had previously planted trees on their farms, though not as rotational woodlots. Forty eight percent of the households owned the land while the rest of households used land allocated by the village; this suggests land tenure issues were not a significant impediment to the implementation of rotational woodlots.
Table 1. Characteristics of farmers participating in on-farm rotational woodlots trial (n=23) (Ramadhani et al., 2002).

<table>
<thead>
<tr>
<th>Characteristics of farmers participating in the rotational woodlots trial (n = 23)</th>
<th>Minimum</th>
<th>Median</th>
<th>Maximum</th>
<th>Proportion (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age of head of household (years)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;40</td>
<td></td>
<td>9</td>
<td></td>
<td></td>
</tr>
<tr>
<td>40–60</td>
<td></td>
<td>87</td>
<td></td>
<td></td>
</tr>
<tr>
<td>&gt;60</td>
<td></td>
<td>4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ethnic group</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nyanwaizi</td>
<td></td>
<td>78</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Others*</td>
<td></td>
<td>22</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of wives</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>Household size (members)</td>
<td>1</td>
<td>14</td>
<td>23</td>
<td></td>
</tr>
<tr>
<td>Education of head of household</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No formal school</td>
<td></td>
<td>4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1–7 years (primary)</td>
<td></td>
<td>92</td>
<td></td>
<td></td>
</tr>
<tr>
<td>&gt;7 years (secondary)</td>
<td></td>
<td>4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Off-farm income (husband or wife)</td>
<td></td>
<td>39</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Decision maker</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Husband</td>
<td></td>
<td>61</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Husband and wife</td>
<td></td>
<td>39</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Farm size (ha)</td>
<td>3</td>
<td>31</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>Mode of farm acquisition</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Buying</td>
<td></td>
<td>35</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Inheritance</td>
<td></td>
<td>13</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Village allocation</td>
<td></td>
<td>52</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Farm first cultivated (year)</td>
<td>1960</td>
<td>1974</td>
<td>1988</td>
<td></td>
</tr>
<tr>
<td>Use hired labor</td>
<td></td>
<td>78</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hired laborers per season</td>
<td>2</td>
<td>4</td>
<td>10</td>
<td></td>
</tr>
<tr>
<td>Ownership of livestock</td>
<td></td>
<td>57</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cows</td>
<td>0</td>
<td>12</td>
<td>15</td>
<td></td>
</tr>
<tr>
<td>Goats</td>
<td>0</td>
<td>10</td>
<td>34</td>
<td></td>
</tr>
<tr>
<td>Sheep</td>
<td>0</td>
<td>4</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>Had planted trees before the trial</td>
<td></td>
<td></td>
<td>74</td>
<td></td>
</tr>
<tr>
<td>Species planted</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Eucalyptus spp</td>
<td></td>
<td></td>
<td>44</td>
<td></td>
</tr>
<tr>
<td>Fruit trees</td>
<td></td>
<td></td>
<td>13</td>
<td></td>
</tr>
<tr>
<td>Where planted</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>On crop field</td>
<td></td>
<td></td>
<td>44</td>
<td></td>
</tr>
<tr>
<td>Around homestead</td>
<td></td>
<td></td>
<td>30</td>
<td></td>
</tr>
<tr>
<td>On boundary</td>
<td></td>
<td></td>
<td>4</td>
<td></td>
</tr>
</tbody>
</table>

* Include Sukuma, Nyiramba, Gogo, Ha, Tusi, Manyema, Subi, Kibwa and Ziguia tribes.
3.2.2 Economy
Tabora had 600,000 hectares of land under cultivation in 2007 (NBS, 2012). The main sources of cash income for the rural agricultural households are listed in Table 2. The sale of food crops is the most common source for cash income. Maize is the staple food crop in Tabora accounting for 67 percent of the land planted with cereal crops in 2007, with an average yield of 1.3 tonnes per hectare.

Table 2. Primary sources of income in Tabora (NBS, 2012).

<table>
<thead>
<tr>
<th>Cash Income Source</th>
<th>Percent of households, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food crop sales</td>
<td>60</td>
</tr>
<tr>
<td>Cash crop sales</td>
<td>11</td>
</tr>
<tr>
<td>Casual Cash Earnings</td>
<td>3</td>
</tr>
<tr>
<td>Business Income</td>
<td>6</td>
</tr>
<tr>
<td>Livestock Sales</td>
<td>4</td>
</tr>
<tr>
<td>Livestock Product Sales</td>
<td>3</td>
</tr>
<tr>
<td>Wages and Salaries</td>
<td>2</td>
</tr>
<tr>
<td>Cash Remittance</td>
<td>2</td>
</tr>
<tr>
<td>Forestry Product Sales</td>
<td>2</td>
</tr>
</tbody>
</table>

The GDP for Tabora in 2011 was estimated as 1,501,447 Tanzanian Shillings\(^1\) (Tshs) with a per capita income of 614,579 Tshs. The Tabora region contributes to 4% of the national GDP. In 2008, only 9.2% of households had access to agricultural credit (NBS, 2012).

The main cash crops grown in Tabora are cotton and tobacco. At the beginning of the ASDZB project, tobacco was the main cash crop. The prevalence of cotton as the largest regional cash crop increased by over 75% in the years between the 2003/2004 Agricultural Census and the 2007/2008 Agricultural Census. Historically, tobacco was the main cash crop and as mentioned in Chapter 2, wood for curing tobacco was harvested from the natural Miombo woodlands; reduced deforestation was a desired outcome of the ASDZB project. The total land area planted with tobacco was 31,430 hectares in the 2007/2008 growing season (NBS, 2012). Traditionally, maize is grown for two years followed by three years of tobacco. Organic fertilizers were applied to 7.7% of the total planted area and inorganic fertilizers were applied to only 11% of the total planted (NBS, 2012).

\(^1\) In 2011, 1 USD = 2158 Tsh. The per capita income was 285 USD in Tabora.
In 2016, 1 USD = 2186 Tsh.
3.3 Climate Change Projections
Regional impact assessments of climate change are computationally demanding and as such the recommendation of the IPCC to include as many GCM scenarios as possible to limit uncertainty is not efficient. A validation method (Breach et al., 2015; Srivastav & Simonovic, 2014) was implemented to reduce the number of scenarios by ranking models through quantile regression based on a skill score. The skill score was determined by the quality of each model to simulate changes within the historical distribution of variables. The reduced set of GCMs was then downscaled for this study to develop an ensemble projection of climate change in the Tabora region. Downscaling a GCM is the process by which GCM data with coarse spatial and temporal resolutions are parameterized to a higher resolution that can be used at a regional scale (Flato et al., 2013).

3.3.1 Data Collection and Preparation
The observed weather data for climate change analysis was collected from 14 stations from across eastern Africa, see Appendix C Table 29. These climate stations were selected based on proximity and the length of the dataset available from the National Ocean and Atmosphere Association (NOAA) database; the baseline period was selected from 1975 to 2005. Daily precipitation, maximum temperature, and minimum temperature were the primary variables used in this model as they were the inputs required for WaNuLCAS.

Further analysis was performed on the GCMs from the IPCC AR5 report that included climate variables that corresponded to meteorological variables for the historical scenario. Representative Concentration Pathways (RCPs) are scenario sets that consider emission, concentration, and land-use trajectories. In this study, RCP 2.6, RCP 4.5, and RCP 8.5 were included; these emission scenarios are explained in Table 3.

<table>
<thead>
<tr>
<th>Emission Scenario</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>RCP2.6</td>
<td>Peak radiative forcing around 3 W m⁻² before 2100 and decline. This scenario is considered to be a lower bound emission projection.</td>
</tr>
<tr>
<td>RCP4.5</td>
<td>Stabilization without overshoot pathway to 4.5 W m⁻² after 2100. This scenario is considered to be an intermediate emission projection.</td>
</tr>
<tr>
<td>RCP8.5</td>
<td>Rising radiative forcing pathway that reaches 8.5 W m⁻² around 2100 and continues to increase. This scenario is considered to be an upper bound emission projection.</td>
</tr>
</tbody>
</table>
These datasets were obtained from the CMIP5 through the Earth Surface Grid Federation data portal hosted by the Program for Climate Model Diagnosis and Intercomparison at the Lawrence Livermore National Laboratory. Information on each GCM’s name and resolution are listed in Table 4.

The inverse distance method (IDM) was applied to interpolate each GCM grid for comparison with historically observed meteorological station data. Two 30-year future periods were selected for analysis centered on 2050 (2035-2065) and 2080 (2065-2095). The 2050 time period has been deemed to be appropriate by other studies (Breach et al., 2015) for strategic planning, risk framing, and building resilience in agroforestry, while the 2080 time period can be used for longer term climate change impact assessments for agroforestry (EBNFLO, 2010).
### Table 4. Global climate models by region (Breach, et al., 2015).

<table>
<thead>
<tr>
<th>Region</th>
<th>Modelling Centre Name</th>
<th>Model</th>
<th>Historical Realizations</th>
<th>Resolution Lat x Lon (degrees)</th>
</tr>
</thead>
<tbody>
<tr>
<td>China</td>
<td>Beijing Climate Center, China Meteorological Administration</td>
<td>bcc-csm1-1</td>
<td>1</td>
<td>2.79 x 2.80</td>
</tr>
<tr>
<td></td>
<td>Beijing Climate Center, China Meteorological Administration</td>
<td>bcc-csm1-1-m</td>
<td>3</td>
<td>1.33 x 1.00</td>
</tr>
<tr>
<td></td>
<td>College of Global Change and Earth System Science</td>
<td>BNU-ESM</td>
<td>1</td>
<td>2.79 x 2.80</td>
</tr>
<tr>
<td></td>
<td>Institute of Atmospheric Physics, Chinese Academy of Sciences, Tsinghua University</td>
<td>FGOALS-g2</td>
<td>2</td>
<td>3.05 x 2.81</td>
</tr>
<tr>
<td>USA</td>
<td>Canadian Centre for Climate Modeling and Analysis</td>
<td>CanESM2</td>
<td>5</td>
<td>2.79 x 2.80</td>
</tr>
<tr>
<td></td>
<td>National Center of Atmospheric Research</td>
<td>CCSM4</td>
<td>3</td>
<td>0.94 x 1.25</td>
</tr>
<tr>
<td></td>
<td>Community Earth System Model Contributors</td>
<td>CESM1-CAM5</td>
<td>1</td>
<td>0.94 x 1.25</td>
</tr>
<tr>
<td></td>
<td>NOAA Geophysical Fluid Dynamics Laboratory</td>
<td>GFDL-CM3</td>
<td>1</td>
<td>2.00 x 2.50</td>
</tr>
<tr>
<td></td>
<td>NOAA Geophysical Fluid Dynamics Laboratory</td>
<td>GFDL-ESM2G</td>
<td>1</td>
<td>2.00 x 2.50</td>
</tr>
<tr>
<td></td>
<td>NOAA Geophysical Fluid Dynamics Laboratory</td>
<td>GFDL-ESM2M</td>
<td>1</td>
<td>2.00 x 2.50</td>
</tr>
<tr>
<td>France</td>
<td>National Center of Meteorological Research</td>
<td>CNRM-CM5</td>
<td>1</td>
<td>1.40 x 1.40</td>
</tr>
<tr>
<td></td>
<td>Institut Pierre Simon Laplace</td>
<td>IPSL-CM5A-LR</td>
<td>4</td>
<td>1.89 x 3.75</td>
</tr>
<tr>
<td></td>
<td>Institut Pierre Simon Laplace</td>
<td>IPSL-CM5A-MR</td>
<td>3</td>
<td>1.27 x 2.5</td>
</tr>
<tr>
<td>Australia</td>
<td>Commonwealth Scientific and Industrial Research Organization</td>
<td>CSIRO-Mk3-6-0</td>
<td>10</td>
<td>1.87 x 1.88</td>
</tr>
<tr>
<td>United Kingdom</td>
<td>Met Office Hadley Centre</td>
<td>HadGEM2-ES</td>
<td>4</td>
<td>1.25 x 1.88</td>
</tr>
<tr>
<td>South Korea</td>
<td>National Institute of Meteorological Research, Met Office Hadley Centre</td>
<td>HadGEM2-AO</td>
<td>1</td>
<td>1.25 x 1.88</td>
</tr>
<tr>
<td>Europe</td>
<td>European Earth System Model</td>
<td>EC-EARTH</td>
<td>2</td>
<td>1.12 x 1.12</td>
</tr>
<tr>
<td></td>
<td>Atmosphere and Ocean Research Institute, National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology</td>
<td>MIROC5</td>
<td>3</td>
<td>1.40 x 1.40</td>
</tr>
<tr>
<td>Japan</td>
<td>Atmosphere and Ocean Research Institute, National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology</td>
<td>MIROC-ESM</td>
<td>1</td>
<td>2.79 x 2.81</td>
</tr>
<tr>
<td></td>
<td>Atmosphere and Ocean Research Institute, National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology</td>
<td>MIROC-ESMCHEM</td>
<td>1</td>
<td>2.79 x 2.81</td>
</tr>
<tr>
<td></td>
<td>Meteorological Research Institute</td>
<td>MRI-CGCM3</td>
<td>1</td>
<td>1.12 x 1.12</td>
</tr>
<tr>
<td>Germany</td>
<td>Max Plank Institute for Meteorology</td>
<td>MPI-ESM-MR</td>
<td>1</td>
<td>1.87 x 1.88</td>
</tr>
<tr>
<td></td>
<td>Max Plank Institute for Meteorology</td>
<td>MPI-ESM-LR</td>
<td>2</td>
<td>1.87 x 1.88</td>
</tr>
<tr>
<td>Norway</td>
<td>Norwegian Climate Center</td>
<td>NorESM1-M</td>
<td>1</td>
<td>1.89 x 2.50</td>
</tr>
</tbody>
</table>
3.3.2 GCM Selection

3.3.2.1 Validation Approach

A linear quantile regression model was used to estimate the trajectory of climate variable, $Y$, for a given quantile, $\tau$. This method was adapted from (Koenker & Bassett, 1978) by Srivistav, et al. (2014) and Breach, et al. (2015). A quantile regression approach enables the temporal trend of varying quantiles of the distribution of $Y$ to be compared between the GCM data and observed data; a least squares method would limit the comparison to a trend in the mean of distribution $Y$. Equation (1) (Breach et al., 2015; Srivistav et al., 2014) demonstrates the relationship between $Y$ and time, $t$, for a given quantile, $\tau$, where $t_i$, and $\varepsilon_i$ are the time index and error index terms for time step $i$. $\beta_0^\tau$ and $\beta_1^\tau$ are regression coefficients for the quantile, $\tau$, and can be found for any value of $\tau \in [0,1]$.

$$Q_\tau(Y|t) = \beta_0^\tau + \beta_1^\tau t_i + \varepsilon_i$$  \hfill (1)

The $\beta_0^\tau$ coefficient is the climate model bias for given level $\tau$ and is accounted for in the downscaling procedure described in the proceeding section. The $\beta_1^\tau$ coefficient is a representation of the change in distribution of the climate variable $Y$ and is the basis of comparison for each GCM scenario. The regression coefficients were determined through the minimization of the error terms, using equation ((2)).

$$\beta_1^\tau = \sum_{i=1}^{N} \min |\varepsilon_i|$$  \hfill (2)

Equation ((3) (Koenker & Bassett, 1978) shows the asymmetric penalty function for values below and above the regression line that defines the quantiles.

$$\sum_{i \in [l|Y_i \geq \varepsilon_i]} \tau|\varepsilon_i| + \sum_{i \in [l|Y_i < \varepsilon_i]} (1 - \tau)|\varepsilon_i| = 0$$  \hfill (3)

Confidence intervals of 95 percent are generated for $\beta_1^\tau$ using the bootstrapping procedure described in Koenker & Hallock (2001). The confidence intervals of each simulated climate variable for the historical GCM simulation and the observations must overlap otherwise the ability of the GCM to simulate the trend of that variable is considered a failure. This process is repeated
for each GCM, emission scenario, model realization and meteorological station for the set of selected quantiles to generate a percentage of failure for a particular model and quantile (Breach et al., 2015). A high skill score is characterized by a lower percentage of failure.

Regional assessments of climatic extremes must also be evaluated to simulate the changing statistical distributions of precipitation and air temperature. These variables were chosen as they are necessary inputs to the WaNuLCAS model. Extreme quantiles are given a larger weight because the regional climate change impact assessment is directed towards the changes in the magnitude of rainfall events and the frequency of drought. These effects are accounted for by assigning a weight to the number of failures in each quantile using a quadratic function varying from 0 when \( \tau \) is 0.5, to 1 when \( \tau \) approaches 0 and 1. It is normalized so the sum of the weights are equal to 1. The overall score for each GCM is comprised of the weighted percentage of failures for a particular climate variable (Breach et al., 2015). In this study 22 evenly spaced quantiles were used to provide adequate coverage of the distribution in daily precipitation and air temperature values. Compromise programming is applied to eliminate models that under perform for the selected variables. This is achieved by a distance metric, \( L_p \) in equation ((4), from the ideal skill score which is 0 percent weighted average failure rate for the selected variables (Simonovic, 2009).

\[
L_p = \sum_{i=1}^{r} \alpha_i^p z_i^{*p}
\]  

((4)

The number of climate variables is represented by \( r \), \( \alpha \) is the relative weight for a specific variable, \( z_i^{*} \) is a vector of the weighted average failure rates for the selected climate variables. The parameter \( p \) determines the relative importance of each objective within the compromised solution, where \( 1 \leq p \leq \infty \). Therefore an optimal solution for multiple models and climate variables is achieved by minimizing \( L_p \) given a set of \( \alpha \) weights for \( r \) climate variables. Simonovic (2009) suggests the most robust solution for any multi-objective problem is to vary \( p \) and select models that achieve a high ranking throughout the set of \( p \) values, but that the solution with the shortest Euclidean distance corresponding to \( p = 2 \) to be used as the best compromise solution. The result of this process is the selection of GCMs that are efficient for the region of study.
3.3.2.2 Extremes Ensemble Approach

A scatterplot method is used to determine the GCM scenarios that represent climatic extremes. Extreme events are characterized by the combination of high temperature and low precipitation for drought and vice-versa for potential soil water logging. Four GCM scenarios were selected to represent the total range of uncertainty for future climate from annual average temperature and precipitation change combinations from the baseline period of 1975 to 2005 into the future. This procedure was adapted from the EBNFLO method (2010).

3.3.2.3 Percentile Ensemble Approach

The use of multi-model climate ensembles is recommended by the IPCC (Field et al., 2012), to quantify the spread of climate related impacts. This supports the methodology by Breach (2015) and uses the same variables. A range of scenarios within the four extremes previously selected; this range corresponds to the 5th, 25th, 50th, 75th, and 95th percentile changes for the total annual precipitation and daily average air temperature.

3.3.2.4 Statistical Downscaling

Statistical downscaling methodology was applied once the GCM scenarios were selected. Future downscaled climate variables were generated using a Change Factor Methodology (CFM) and a non-parametric weather generator. CFM is a means to solve the problem of mismatched spatial and temporal scaling between GCMs and the regions to which their data is applied (Anandhi et al., 2011). Additive and multiplicative change factors were applied to observed data to establish modeled future mean or variance. A monthly multiple change factor approach was used to scale future climate variables to account for seasonal variability. The monthly changes for a set of percentile ranges were used to perturb the historical climate conditions, giving more accurate estimates of the selected climatic variables (Breach et al., 2015). Additive change factors were applied to temperature variables and multiplicative change factors were applied to precipitation (Anandhi et al., 2011). The change factors were applied to observed station data to generate a future scaled dataset; stations are listed in Table 29 in Appendix C. The bias correction, aforementioned in relation to equation (1), is accounted for by applying the changes between GCM time slices (Ntegeka, Baguis, Roulin, & Willems, 2014).
Weather generators create synthetic data that match the statistical characteristics of observed data (Srivastav & Simonovic, 2014). The KNN-CADv4 is a multi-site, multivariate weather generator developed by King et al. (2012) and was selected for this study based on its ability to simulate precipitation and temperature with relative accuracy compared to other weather generators and preservation of spatial correlation (King et al., 2012). The model is capable of simulating multiple climate variables for any number of weather stations in a region. The WG-PCA creates a subset of potential neighbours, \( L \), from the historical record for each day in \( N \) years of record for each variable by establishing a temporal window, \( w \), centered on the selected day. In this study, \( w \), was selected to be 14 days.

\[
L = N(w + 1) - 1
\]  

The average behaviour for the climatic variables is calculated for all stations and days in the temporal window. Principal components analysis is then applied to the subset to determine which days have the most similar characteristics of the selected day by ranking the potential neighbours by a Mahalanobis distance metric from the average for the temporal window to the current day. The days with the highest rank are selected as \( K \) days, having the most similar characteristics to the selected day (King, 2012). Next, a random number \( U(0,1) \) is generated and compared to the cumulative probability distribution for the retained \( K \) days to determine the selected day’s neighbour. Perturbation of all variables is achieved by resampling a block of \( B \) days from the historical record for the selected day’s neighbour; in this study \( B \) was selected to be 10 days, following King et al. (2014). The KNNv4 weather generator was used to develop synthetic data for two future time periods: 2035 to 2065 and 2065 to 2095. These periods were selected to represent climate change in the mid to long-term time frames. Results produced by these methodologies are discussed in the following chapter.

### 3.4 System Dynamics Modelling

WaNuLCAS is a system dynamics model developed by ICRAF for the purpose of simulating complex agroforestry-crop interactions with adjustable inputs for a variety of agroforestry applications. The model consists of two parts, an Excel workbook interface that users can use to modify parameters, and the Stella model. The WaNuLCAS model emphasizes the below-ground competition for nutrients and water uptake based on effective root length densities and demand from trees and crops (Van Noordwijk et al., 2011). The user defined inputs are used throughout
the core modules of the model, see Figure 5. Core modules include rainfall interception, crop growth and management, tree growth and management, and nutrient demand. The modules consider the facilitative and competitive interactions between the trees, crops and soils in each zone and layer for light, nutrients and water. These modules produce model outputs such as crop and wood yields, water balance, nutrient balance, and profitability analysis.

The below-ground resource balance equation for water and nutrients into the agroforestry system model is defined in (6) and the parameters are further defined in Table 6.

\[
\Delta \text{Storage} = \text{Input} + \text{Recycle} - Upt_{\text{crop}} - Upt_{\text{tree,comp}} - Upt_{\text{tree,noncomp}} - \text{Loss} \tag{6}
\]

The water balance in WaNuLCAS includes rainfall, run off, infiltration, surface evaporation, leaching, and hydrostatic equilibrium (Van Noordwijk & Lusiana, 1998; Van Noordwijk et al., 2011). The nutrient balance is comprised of fertilizer inputs, losses due to leaching, recycling of crop and tree litter fall, and the uptake of nutrients from the soil. Nutrient demand for nitrogen is calculated from empirical relationships for uptake and dry matter production under non-limiting conditions where nitrogen is assumed to be 5 percent of dry matter, luxury uptake where growth is assumed to be unaffected until the nitrogen content falls below 80 percent, and atmospheric nitrogen fixation. Light capture is a determining factor for growth and is calculated from the Leaf Area Index (LAI) in each canopy layer (Van Noordwijk & Lusiana, 1998).

Figure 5. Core inputs, modules, and outputs in WaNuLCAS.
Table 5. WaNuLCAS below-ground balance components.

<table>
<thead>
<tr>
<th>Component</th>
<th>Water</th>
<th>Nitrogen</th>
<th>Light</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Input</strong></td>
<td>Rainfall, Irrigation, Runoff</td>
<td>Fertilizer</td>
<td>Sum of daily radiation</td>
</tr>
<tr>
<td><strong>Recycle</strong></td>
<td>Hydraulic lift into crop zone</td>
<td>Litterfall, crop residues</td>
<td>-</td>
</tr>
<tr>
<td><strong>Crop uptake</strong></td>
<td>Crop uptake</td>
<td>Crop uptake</td>
<td>Light captured by crop</td>
</tr>
<tr>
<td><strong>Competitive tree uptake</strong></td>
<td>Tree uptake in top layer</td>
<td>Tree uptake in top layer</td>
<td>Light captured by tree</td>
</tr>
<tr>
<td><strong>Non-competitive tree uptake</strong></td>
<td>Tree uptake in sub-layers</td>
<td>Tree uptake in sub-layers</td>
<td>Light captured by tree</td>
</tr>
<tr>
<td><strong>Losses</strong></td>
<td>Sum of percolation from lowest zones</td>
<td>Sum of leaching from lowest zone</td>
<td>Light not captured</td>
</tr>
<tr>
<td><strong>Storage</strong></td>
<td>Change in water content</td>
<td>Sum of minimum nitrogen and soil organic matter</td>
<td>-</td>
</tr>
</tbody>
</table>
3.4.1 Model Inputs

The inputs are entered into an Excel file and linked to the Stella “WaNuLCAS” model. The main inputs and their units entered, see Table 6, and categorized by climatic, management, soil, or tree/crop parameters.

<table>
<thead>
<tr>
<th>Sector</th>
<th>Parameter</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Climate</td>
<td>Rainfall (daily)</td>
<td>mm</td>
</tr>
<tr>
<td></td>
<td>Soil temperature</td>
<td>°C</td>
</tr>
<tr>
<td></td>
<td>Daily potential evapotranspiration</td>
<td>mm day⁻¹</td>
</tr>
<tr>
<td>Management</td>
<td>Tree and Crop</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Date of planting</td>
<td>Julian day</td>
</tr>
<tr>
<td></td>
<td>Tree Spacing</td>
<td>m</td>
</tr>
<tr>
<td></td>
<td>Tree planting density</td>
<td>trees ha⁻¹</td>
</tr>
<tr>
<td></td>
<td>Financial inputs*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Fertilizer application</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Date of application</td>
<td>Julian day</td>
</tr>
<tr>
<td></td>
<td>Dose of fertilizer</td>
<td>g m⁻²</td>
</tr>
<tr>
<td>Soil</td>
<td>Soil thickness</td>
<td>m</td>
</tr>
<tr>
<td></td>
<td>Texture (sand, silt, clay)</td>
<td>%</td>
</tr>
<tr>
<td></td>
<td>Organic matter</td>
<td>%</td>
</tr>
<tr>
<td></td>
<td>Phosphorous</td>
<td>mg g⁻¹</td>
</tr>
<tr>
<td></td>
<td>Nitrogen</td>
<td>mg cm⁻³</td>
</tr>
<tr>
<td></td>
<td>Bulk density</td>
<td>g cm⁻³</td>
</tr>
<tr>
<td></td>
<td>Saturated hydraulic conductivity</td>
<td>cm⁻³ cm⁻³</td>
</tr>
<tr>
<td></td>
<td>Cation exchange capacity</td>
<td>cmol kg</td>
</tr>
<tr>
<td></td>
<td>pH</td>
<td></td>
</tr>
<tr>
<td>Tree and Crop</td>
<td>Tree parameterization survey**</td>
<td></td>
</tr>
</tbody>
</table>

3.4.1.1 Climate Inputs

The climate parameters are daily inputs for precipitation, soil temperature and potential evapotranspiration. Tabora is situated at 5°1’ S latitude and 32°48’ E longitude. Climate in Tabora is warmest in September and October (ICRAF, 2001; NBS, 2012). The average temperature is 23°C, the average minimum temperature is 17°C and average maximum temperature is 28°C. The
average yearly rainfall is between 700-1000 mm and occurs during one rainy season which typically spans from November until May. The mean climate data for the baseline period from 1975 to 2005 is shown in Figure 6.

![Figure 6. Climate normals for the Tabora region baseline period, 1975-2005.](image)

Daily precipitation data from the National Ocean and Atmosphere Association (NOAA) database for the Tabora Airport was used for precipitation inputs to the model. This station is located at 5° 4’ 58” S and 32° 49’ 58” E. Incomplete meteorological data is a significant issue in developing countries and retrieving datasets from Tanzanian weather stations was no exception. There was a significant percentage of days missing from the Tabora precipitation (42%), maximum temperature (83%), and minimum temperature (80%) records. National Center for Environmental Prediction (NCEP) data was used to fill in missing days for the Tabora dataset (Kalnay, Kanamitsu, Kistler, & Collins, 1996). NCEP data is a globally available gridded dataset and was interpolated to the coordinates of the Tabora Airport weather station. Additionally, relative humidity and wind speed were not available for the majority of stations selected for this analysis.
The Penman-Monteith equation is the method recommended by the FAO to calculate potential evapotranspiration (PET); however it requires a number of variables unavailable from the African weather stations such as wind speed and relative humidity. PET was calculated for each day using a temperature based method developed by Hamon (1963), equation (7). PET is in mm day\(^{-1}\), \(D\) is the day length in hours based on latitude, \(e_a^*\) is the saturation vapor pressure in kPa at the average daily temperature, \(T_a\). The method produces similar results to the well-known Thornwaite method and has been used in several hydrologic models (Dingman, 2008).

\[
PET = 29.8 \ D \ \frac{e_a^*}{T_a + 273.2}
\]  

\(3.4.1.2\) Management Inputs

The management inputs were based on the literature from the Tabora field trials. The tree density was 625 trees ha\(^{-1}\). The spatial properties of the agroforestry system are distributed across four horizontal zones; the trees are planted in Zone 1 and the crops are planted in Zones 2 to 4. The soil profile is represented by four horizons, site-specific physical and chemical soil properties are defined by the user, see Figure 7.

![Figure 7. WaNuLCAS spatial zoning and soil layers (Van Noordwijk et al., 2011).](image)

Calendar of Events
The planting, fertilizing, and harvesting date inputs are year and day of year, based on Mbwambo (2003), see Table 7 and Table 8. November 25 is day 330 in Julian days and November 30 is day 335. Day 150 is May 30.

Table 7. WaNuLCAS crop calendar inputs.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Plant Year</th>
<th>Day of Year</th>
<th>Harvest Year</th>
<th>Day of Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crop Planting</td>
<td>1996</td>
<td>330</td>
<td>1997</td>
<td>150</td>
</tr>
<tr>
<td></td>
<td>1997</td>
<td>330</td>
<td>1998</td>
<td>150</td>
</tr>
<tr>
<td></td>
<td>1998</td>
<td>330</td>
<td>199</td>
<td>150</td>
</tr>
<tr>
<td></td>
<td>2001</td>
<td>330</td>
<td>2002</td>
<td>150</td>
</tr>
<tr>
<td>Tree Planting</td>
<td>1996</td>
<td>335</td>
<td>2001</td>
<td>320</td>
</tr>
</tbody>
</table>

Table 8. WaNuLCAS inputs for fertilizers.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Dose g m⁻²</th>
<th>Year</th>
<th>Day of Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fertilizer N</td>
<td>5</td>
<td>1996</td>
<td>330</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>1997</td>
<td>30</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>1997</td>
<td>330</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>1998</td>
<td>330</td>
</tr>
<tr>
<td>Fertilizer P</td>
<td>1.8</td>
<td>1996</td>
<td>330</td>
</tr>
<tr>
<td></td>
<td>1.8</td>
<td>1997</td>
<td>330</td>
</tr>
</tbody>
</table>

3.4.1.3 Financial Inputs

Financial inputs for the model were based on cost and labour data from a financial analysis study on the Tabora woodlots conducted for the original study period from 1996 to 2002 (Ramadhani et al., 2002). The values in Table 31 in Appendix D show the 1996/1997 prices and are not adjusted for inflation or currency exchange. Financial analysis in the WaNuLCAS model uses Net Present Value (NPV), equation (8), to calculate the benefits of the system per hectare, where \( C_t \) is the net cash flow during the time period, \( C_0 \) is the initial cost of the investment, \( r \) is the discount rate, and \( t \) is the number of time periods.

\[
NPV = \sum_{t=1}^{\tau} \frac{C_t}{(1 + r)^t} - C_0
\]  

\( ((8) \)
3.4.1.4 Soil Inputs

The soil layer depths and zones were selected to fit the data available from the Tumbi Research Centre publications and Tabora soil profile data and are presented in Table 9 and Table 10 below (ISRIC, 1983; Mbwambo et al., 2003; Nyadzi et al., 2006; Nyadzi et al., 2003). The soil in Tabora is generally acidic sands, classified as Ferric Acrisols by FAO guidelines, and composed of 80 to 90 percent sand, with a slightly acidic pH ranging from 5.7 to 6.1 in water (Mbwambo et al., 2003; Nyadzi et al., 2006; Nyadzi et al., 2003). They are characterized by low organic carbon and nitrogen contents, and low to medium available phosphorous (ICRAF, 2001). Table 9 and Table 10 contain soil characteristic data for initial conditions of the soils at the Tumbi research station and the on-farm trials. Initial conditions across all zones were assumed to be homogeneous due to limited laboratory soil data.

Table 9. Tabora soil properties, part one.

<table>
<thead>
<tr>
<th>Depth (cm)</th>
<th>Bulk Density (g/cm³)</th>
<th>Particle Size Distribution (Sand, Silt, Clay)</th>
<th>pH</th>
<th>Total N (%)</th>
<th>Organic C (%)</th>
<th>Available P, ppm</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-10</td>
<td>1.38</td>
<td>82, 6, 12</td>
<td>6.1</td>
<td>0.06</td>
<td>0.74</td>
<td>6</td>
</tr>
<tr>
<td>10-25</td>
<td>1.38</td>
<td>84, 11, 5</td>
<td>5.4</td>
<td>0.02</td>
<td>0.19</td>
<td>11</td>
</tr>
<tr>
<td>25-75</td>
<td>1.44</td>
<td>83, 10, 7</td>
<td>5.3</td>
<td>0.013</td>
<td>0.124</td>
<td>5.6</td>
</tr>
<tr>
<td>75-150</td>
<td>1.53</td>
<td>78, 12, 9</td>
<td>5.2</td>
<td>0.01</td>
<td>0.05</td>
<td>3</td>
</tr>
</tbody>
</table>

Table 10. Tabora soil properties, part two.

<table>
<thead>
<tr>
<th>Depth (cm)</th>
<th>Exchangeable Cations (meq/100g)</th>
<th>CEC, meq/100 g</th>
<th>Total Content, ppm</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Na</td>
<td>K</td>
<td>Mg</td>
</tr>
<tr>
<td>0-10</td>
<td>0</td>
<td>0.1</td>
<td>0.9</td>
</tr>
<tr>
<td>10-25</td>
<td>0</td>
<td>0.1</td>
<td>0.7</td>
</tr>
<tr>
<td>25-75</td>
<td>0</td>
<td>0.1</td>
<td>0.6</td>
</tr>
<tr>
<td>75-150</td>
<td>0</td>
<td>0.1</td>
<td>0.2</td>
</tr>
</tbody>
</table>

The soil inputs are entered into the Excel sheet by layer and the Tomasella-Hodnett pedotransfer function (PTF) for tropical soils is used to estimate specific soil hydraulic properties (Van Noordwijk et al., 2011). The Tomasella-Hodnett PTF is continuous and estimates the average hydraulic characteristics from a wide range of parameters (Hodnett, 2002). PTFs evaluate soil hydraulic properties from commonly measured soil properties such as soil texture, organic matter,
and bulk density. Total nitrogen levels by soil layer were input from the Tabora soil profile (ISRIC, 1983), available phosphorus levels were also input from this data. Phosphorus adsorption capacity and adsorption energy were estimated from a study on similarly acidic soils in Kenya (Kisinyo et al., 2013).

3.4.1.5 Crop and Tree Inputs

The crop parameters were taken from the WaNuLCAS library for maize. An Australian species of Acacia used in the ICRAF field project at Tumbi because they are ideal for low-fertility soils and high production of biomass. The *A. Crassicarpa* species of Acacia was determined to be the most nutrient efficient tree from the studies at Tumbi (Mbwanbo et al., 2003; Nyadzi et al., 2006; Nyadzi et al., 2003); it took the least nutrients from the soil which made it an ideal species for rotational woodlots with maize or pigeon peas (Kimaro, 2009). Eucalyptus trees were shown to exploit soil water resources and therefore are not suitable species for rotational woodlots because they compete with the food crops for available water (Nyadzi et al., 2003). Acacia have proven benefits such as retrieving fixed nitrogen from soil areas lower than the crop root zone and increasing its availability to crops (Nyadzi et al., 2006). *Acacia Crassicarpa* was determined to be the fastest growing species for wood production. The species thrives in a zone with mean annual temperature ranging from 15°C to 34°C and a mean annual rainfall of approximately 500 to 3500 mm (Orwa, 2009). The Tree Parameterization Excel spreadsheet (see Table 33 and Table 34 in Appendix D) was used to determine the inputs for *Acacia Crassicarpa* for WaNuLCAS.

3.5 Vulnerability

Although financial analysis is important to understand the economic implications of climate change and the adaptive strategies, it was important to incorporate socio-economic indicators into the model for a more comprehensive understanding of agroforestry as a method of sustainable development into the future. The method was adapted from several studies (Antwi-Agyei et al., 2012; A. J. Challinor, Simelton, Fraser, Hemming, & Collins, 2010; Simelton et al., 2009) to determine the vulnerability of crop production to drought using rainfall, yield and socioeconomic data. Vulnerability is calculated for each year. The study defined vulnerability, $V$, as a function of crop exposure to drought, $E$, crop sensitivity to rainfall perturbations, $S$, and adaptive capacity, $AC$, to cope with drought, expressed in (9).
\[ V = E + S - AC \]  \hspace{1cm} (9)

The exposure index was developed by averaging the long-term growing season rainfall for the baseline period of 30 years divided by each year’s average rainfall, equation \((10)\). The baseline was selected on the basis of data availability and to provide an adequate climatological record to minimize yearly variations (Antwi-Agyei et al., 2012). A value above one indicates a high level of exposure to drought.

\[ E = \frac{\text{mean long term growing season rainfall for 1975 to 2005}}{\text{mean growing season rainfall for each year}} \]  \hspace{1cm} (10)

The sensitivity of crop harvest was determined by dividing expected yield by the actual yield of the harvest. The expected yield was calculated following the methods of previous crop vulnerability studies (Antwi-Agyei et al., 2012; Schneider & Neumaier, 2001; Simelton et al., 2009) that normalized harvest yield for each year by auto-regression in Excel 2010. This detrending was done to remove the influence of technology. The residual indicates year to year variations in yields due to weather. The expected yield is then divided by the actual yield to create the crop yield sensitivity index, equation \((11)\). A sensitivity index value above one indicates high sensitivity.

\[ \text{Crop failure sensitivity index} = \frac{\text{expected yield}}{\text{actual yield}} \]  \hspace{1cm} (11)

Adaptive capacity is the ability of farmers to adapt to the impacts of climate change and the literature suggests that adaptive capacity is dependent on livelihood assets of human, physical, financial, natural, and social capital. The literacy rate and poverty rate of the Tabora region were used as proxy indicators were used to represent livelihood assets that human capital and financial capital due to available data and based on previous research.

\[ \text{Adaptive Capacity} = \frac{\text{Literacy rate}}{100} + \frac{100 - \text{Poverty rate}}{100} \]  \hspace{1cm} (12)

The literacy rate for the Tabora region was 64% (NBS, 2012) and the poverty rate was 90% (FAOSTAT, 2014). The sum of these indicators determined the vulnerability index score for each year. A score above two indicated high vulnerability, a score between 1 and 2 indicated medium vulnerability, and a score below one indicated low vulnerability.
3.6 Experimental Simulations

The WaNuLCAS model was used to run several sets of experimental simulations. The main inputs for all experiments were shown in the previous section, when explaining WaNuLCAS inputs. The modifications of these inputs for each experiment are noted in the following section with the rationale for each modification.

3.6.1 Experiment 1: Baseline

Firstly, a baseline experiment tested the simulation outputs to calibrate the system dynamics model’s ability to replicate the field observations. The baseline represents the five year woodlot field trials at the Tumbi Research Station in Tabora (Mbwambo et al., 2003; Nyadzi et al., 2006; Nyadzi et al., 2003). The research trial began in December 1996 with the planting of 8 week old saplings with a 4 by 4 meter spacing. This spacing produces a density of 625 trees per hectare. Maize was intercropped with the trees for the first three years from 1996 to 1999, planted in ridges at 1.0 meter spacing between rows and 0.25 meter spacing within rows. Maize was not planted in 2000 and 2001 due to light competition from the overshadowing tree canopies and to allow the soil to lay fallow. Trees were harvested in early November 2001. The research trials also ran plots with continuous maize cropping as a control.

3.6.2 Experiment 2: Management Options

Several management parameters were selected for modification and applied to the baseline scenario to explore how farmers could increase crop and tree yields, see Table 11.
Table 11. Management changes to baseline agroforestry scenario and rationale.

<table>
<thead>
<tr>
<th>Type</th>
<th>Management Option</th>
<th>Description</th>
<th>Rationale</th>
</tr>
</thead>
<tbody>
<tr>
<td>WaNuLCAS</td>
<td>Potential Growth, All</td>
<td>Unlimited growth from all limiting factors</td>
<td>Maximum potential growth</td>
</tr>
<tr>
<td></td>
<td>Potential Growth, Nitrogen Only</td>
<td>Nitrogen was the only factor set as unlimited</td>
<td>Effects without nitrogen limits and benefits of fertilizers</td>
</tr>
<tr>
<td></td>
<td>Potential Growth, Phosphorous Only</td>
<td>Phosphorous was the only factor set as unlimited</td>
<td>Effects without phosphorous limits and benefits of fertilizers</td>
</tr>
<tr>
<td></td>
<td>Potential Growth, Water Only</td>
<td>Water was the only factor set to unlimited</td>
<td>Effects without water limits and potential benefits of irrigation</td>
</tr>
<tr>
<td></td>
<td>Potential Growth, Precipitation 30%</td>
<td>Rain_Multiplier switch set to 30%</td>
<td>Extreme water-limited system behaviour</td>
</tr>
<tr>
<td></td>
<td>Potential Growth, Precipitation 50%</td>
<td>Rain_Multiplier switch set to 50%</td>
<td>Water-limited system behaviour</td>
</tr>
<tr>
<td></td>
<td>Potential Growth, Precipitation 150%</td>
<td>Rain_Multiplier switch set to 150%</td>
<td>Water-plenty system behaviour</td>
</tr>
<tr>
<td>Fertilizer</td>
<td>Phosphorous only</td>
<td>1.8 g m$^{-2}$ to crops in each year of planting</td>
<td>Effects of reducing N fertilizer doses on yields and costs</td>
</tr>
<tr>
<td></td>
<td>Increase phosphorous dose</td>
<td>5.0 g m$^{-2}$ of N and P to crops in each year of planting</td>
<td>Effects of increasing P fertilizer doses</td>
</tr>
<tr>
<td></td>
<td>Increase nitrogen and phosphorus dose</td>
<td>10.0 g m$^{-2}$ of N and P to crops in each year of planting</td>
<td>Effects of increasing fertilizer doses</td>
</tr>
<tr>
<td>Calendar</td>
<td>Shift crop planting and harvesting 20 days earlier</td>
<td>Plant day 310, harvest day 130</td>
<td>Effects of advanced forecast knowledge</td>
</tr>
<tr>
<td></td>
<td>Shift crop planting 20 days later</td>
<td>Plant day 350, harvest day 170</td>
<td></td>
</tr>
<tr>
<td>Tree Species</td>
<td>Acacia Mangiferia</td>
<td>Nitrogen-fixing species from WaNuLCAS tree library</td>
<td>Effects of alternate tree species on yields and costs</td>
</tr>
<tr>
<td></td>
<td>Artocarpus Heterophyllus</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
3.6.3 Experiment 3: Climate Change

The climate change scenarios developed from Section 3.3 were selected to provide a range of yields obtainable for the wood and maize under a range of future climate change scenarios for the time slices from 2035-2065 and 2065-2095. The selected scenarios are listed in Table 15, page 57.

3.6.4 Experiment 4: Climate Change Mitigation

The extreme “dry-hot” climate change scenario from 2035-2065, CSIRO-Mk3-6-0- Run 2 -rcp2.6, was selected to test if management practices from Experiment 2 could mitigate some effects of climate change. The management practices applied to this scenario were the application of fertilizer at with doses of 5 g m\(^2\) of nitrogen and phosphorus fertilizers in each year of planting, by shifting the crop calendar earlier by 20 days and by shifting the crop calendar later by 20 days.

In summary, the WaNuLCAS model was calibrated to the Tabora field trials conducted by ICRAF. Several management practices were modified to test hypotheses on crop and wood yields. The ensembles of climate scenarios that were selected and downscaled for the Tabora region for the time periods for 2035-2065 and 2065-2095 were input into the calibrated WaNuLCAS model to determine how the agroforestry system will be affected under varying climate conditions. Finally, management techniques were applied to the agroforestry system with inputs from an extreme climate change scenario to determine the efficiency of management practices in mitigating the effects of climate change. This research combines a vulnerability assessment and climate change modelling with the existing WaNuLCAS model to evaluate the performance of agroforestry systems under a range of future conditions. The results of this research are presented in the following chapter.
4 Results

The results obtained from the methodologies described in Chapter Three are presented in the following chapter. Firstly, the results of developing climate change ensembles for Eastern Africa are presented. The GCM selection method reduced the number of climate models for further investigation and the results of this process are shown in Section 3.3. Specific climate scenarios were selected for further analysis by following the extreme and percentile methods (EBNFLO, 2010). Climate trends of these scenarios were analyzed by comparing climate statistics from the baseline 1975 to 2005 climate period to the predicted climate scenarios for the periods for 2035 to 2065 and 2065 to 2095. The climate statistics that were compared are monthly and annual means of daily maximum and minimum temperatures, monthly and annual precipitation totals, the number of wet days and the number of days over 30 °C.

Secondly, the results from the system dynamics experiments are presented. The first experiment compared the performance of the WaNuLCAS model to the case study results observed at Tabora in the ICRAF research trials (Mbwanbo et al., 2003; Nyadzi et al., 2006; Nyadzi et al., 2003). Next, management options were applied to the baseline to gain insight on the behaviour of the system. Third, the results from the climate change analysis for the time periods 2035 to 2065 and 2065 to 2095 were input to the WaNuLCAS model and analysed to assess the effects on crop yields, tree biomass yields, farmer income and farmer vulnerability. Finally, some of the management practices studied in the second experiment were applied to future climate scenarios to see if climate change effects could be mitigated.

4.1 Climate Change

4.1.1 GCM Selection

Selecting efficient GCMs reduces the number of scenarios that are considered for analysis which decreases computational time and time spent on analysis. It is recommended that this method is used to select regionally appropriate GCMs for developing countries as this will reduce costs for climate impact studies. The selection of regionally efficient GCMs followed the validation approach, which uses linear quantile regression to estimate the performance of the trajectory of each climate variable in the future time slices to observed data. The climate variables evaluated for the performance of each GCM were daily precipitation, daily maximum air temperature, and
daily minimum temperature. The confidence intervals of each simulated climate variable for the historical GCM simulation and the observations must overlap otherwise the ability of the GCM to simulate the trend of that variable is considered a failure. This process was repeated for each GCM, emission scenario, model realization, and meteorological station for the set of selected quantiles to generate a percentage of failure for each model and quantile (Breach et al., 2015).

Each GCM received a skill score for each variable, represented in Figures 8-10. The skill scores represent the weighted mean percentage of failures across model realizations and climate stations; a model that scores a higher level of skill is assumed to perform better for the region of interest. Figure 8 shows that for precipitation, the lowest quantile is simulated by all GCMs with few, to no failures, but this trend quickly diverges for higher quantiles.

![Figure 8](image.png)

**Figure 8.** Percentage of failures for precipitation by model for each quantile sorted top to bottom by weighted mean.

The highest skill score for predicting the change in distribution of the precipitation totals over the observation period was achieved by MPI-ESM-MR with a mean weighted failure of 17 percent.
The ninth to twenty-second models have identical failure rates in all quartiles with a mean weighted failure of 74 percent. The failure rates are 100 percent above the 48th percentile for these models, which indicates the structure of these models may not be as applicable as the eight highest ranking models for simulating changes in precipitation for Tanzania.

Regarding the daily mean air temperature, the skill scores for daily maximum air temperature had a wider variety of failure rates among the quartiles between models. All of the models achieved a mean weighted failure rate between 63 percent and 90 percent. Although 100 percent failure rates were less common throughout the models than for precipitation, the mean weighted failure rates of the top skill scoring models were significantly higher. The highest ranking model for maximum temperature is MIROC5 with a mean weighted failure rate of 63 percent. In contrast to precipitation and maximum temperature, the skill level of minimum temperature is very poor across all models and quartiles. The mean weighted failure rates range from 72 percent for the EC-Earth model (the best), to 100 percent by six of the worst performing models.

![Figure 9. Percentage of failures for maximum air temperature by model for each quantile sorted top to bottom by weighted mean.](image-url)
GCMs were selected for further analysis by determining a subset of models that are more robust at simulating both precipitation and temperature. This was achieved by a compromise multi-objective programming method where rankings were determined by a distance metric from the ideal point for p values of 1, 2, and 100 and the α term was equal for precipitation, maximum temperature, and minimum temperature. This subset of models is selected by the consistently top performing N models, Figure 11 illustrates the relationship between N and the number of models. As N decreases, fewer models meet the stricter criterion to be included in the robust model set. For the Tabora set, there is a break-line at N=11, at which point a reduction in N does not further eliminate GCMs from analysis until N=7. A similar break-line occurs in the analysis by Breach (Breach et al., 2015; 2006; 2003). GCMs below the break-line are deemed as robust in simulating precipitation and temperature over the historically observed period and are kept for further analysis.

Figure 10. Percentage of failures for minimum air temperature by model for each quantile sorted top to bottom by weighted mean.
Figure 11. Relationship between the number of selected models that consistently appear in the top $N$ models. The dotted breakline represents the point at which a stricter selection criterion does not eliminate any further models for $7 \leq N \leq 11$.

The total number of GCM-scenarios prior to model elimination with the validation method was 178. After model elimination with the validation method, compromise programming was used to select a robust subset of 11 models after which 97 GCM scenarios remained that provided plausible projections for future climate change in Tabora. The distance metric results from the quantile regression for each climate variable were used to rank the GCMs on performance. A sensitivity analysis for three cases was performed by varying the weights for each climate variable, Table 12. Within each case, the parameter $p$ determines the relative importance of each objective within the compromised solution. The solution with the shortest Euclidean distance corresponding to $p = 2$ was used as the best compromise solution for each case and GCMs that achieved high ranking with under varying $p$-values were considered more robust (Simonovic, 2009).

Case A represents an equal weighting of precipitation, maximum temperature, and minimum temperature; this weighting was selected as a standard to compare the effects of weighting variables in the compromise programming analysis. Case B represents a ratio of 3:2:1 for precipitation, maximum temperature, and minimum temperature; this weighting was selected based on the lower performance of the mean weighted failure rate where models consistently
scored low for maximum temperature and even lower for minimum temperature. Case C represents a variable ratio of 2:1:1 for precipitation, maximum temperature, and minimum temperature which gives maximum and minimum temperature variables equal weighting; this scenario assumes overall precipitation and temperature are equally important for the model into which the data is being input. The highest ranking models of Case C were selected for further analysis.

Table 12. Compromise programming results and p-value sensitivity

<table>
<thead>
<tr>
<th>Model</th>
<th>Case A</th>
<th>Case B</th>
<th>Case C</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>p 1</td>
<td>2</td>
<td>100</td>
</tr>
<tr>
<td>BNU-ESM</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>CanESM2</td>
<td>5</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>CESM1-CAM5</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>CCSM4</td>
<td>13</td>
<td>7</td>
<td>5</td>
</tr>
<tr>
<td>CSIRO-Mk3-6-0</td>
<td>3</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>EC-EARTH</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>FGOALS-g2</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>GFDL-CM3</td>
<td>2</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>GFDL-ESM2M</td>
<td>7</td>
<td>8</td>
<td>13</td>
</tr>
<tr>
<td>HadGEM2-AO</td>
<td>11</td>
<td>10</td>
<td>12</td>
</tr>
<tr>
<td>HadGEM2-ES</td>
<td>4</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>IPSL-CM5A-LR</td>
<td>8</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>IPSL-CM5A-MR</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>MIROC5</td>
<td>6</td>
<td>9</td>
<td>14</td>
</tr>
<tr>
<td>MRI-CGCM3</td>
<td>14</td>
<td>11</td>
<td>8</td>
</tr>
<tr>
<td>NorESM1-M</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

There are currently no GCMs developed specifically for performance in African regions; the results of the validation approach are useful to demonstrate how GCMs developed for other regions (see Table 4, page 30) compare and perform for the East African region. The same models consistently ranked in the top five for each case. The top ranking GCMs for Case C were the American GFDL-CM3 model from the NOAA Geophysical Laboratory, the Australian CSIRO-Mk3-6-0 model, the United Kingdom’s HadGEM2-ES model, the French IPSL-CM5A-MR, and the Canadian CanESM2 model.
4.1.2 Climate Ensemble Development

The methods of extremes and percentile ensembles were used to further reduce computational time and analysis of the GCMs; model ensembles preserve the range of uncertainty for future climate change impacts for the Tabora region. The subsets for the time slices and ensemble methods are exhibited in Table 15. After selecting the models for extreme and percentile ensemble methods, the GCM data was downsampled using the KNNv4 weather generator. The weather generator created synthetic data that matches the statistical characteristics of the observed data for the two future time periods for this study: 2035 to 2065 and 2065 to 2095.

In Figure 12 the changes in annual average air temperature and annual total precipitation are shown for each scenario from the models remaining after the validation approach for the 2035-2065 time period. The selected models after the extreme and percentile ensemble approaches are represented by filled markers. The distributions for precipitation and temperature are concentrated at 0.9 percent and 2.3 °C with standard deviations of 40 percent and 0.7 °C respectively. The extreme ensemble combinations of precipitation and temperature changes range from -57.16 to 96.27 percent and 1.47 to 3.43 °C, see Table 13.

Table 13. Extreme ensemble scenarios for 2035 to 2065

<table>
<thead>
<tr>
<th>Model</th>
<th>RCP</th>
<th>Run</th>
<th>Percent Change in Precipitation</th>
<th>Absolute Change in Temperature</th>
<th>Case</th>
</tr>
</thead>
<tbody>
<tr>
<td>CESM1-CAM5</td>
<td>RCP85</td>
<td>r1i1p1</td>
<td>96.27</td>
<td>3.43</td>
<td>wet-hot</td>
</tr>
<tr>
<td>CSIRO-Mk3-6-0</td>
<td>RCP45</td>
<td>r8i1p1</td>
<td>-53.12</td>
<td>1.47</td>
<td>dry-cool</td>
</tr>
<tr>
<td>CSIRO-Mk3-6-0</td>
<td>RCP85</td>
<td>r8i1p1</td>
<td>-57.16</td>
<td>2.28</td>
<td>dry-hot</td>
</tr>
<tr>
<td>MIROC5</td>
<td>RCP26</td>
<td>r5i1p1</td>
<td>64.19</td>
<td>1.79</td>
<td>wet-cool</td>
</tr>
</tbody>
</table>

In Figure 13 the changes in annual average air temperature and annual total precipitation are shown for each scenario from the models remaining after the validation approach for the 2065-2095 time period. The selected models after the extreme and percentile ensemble approaches are represented by filled markers. The distributions for precipitation and temperature are concentrated at -3.0 percent and 3.2 °C with standard deviations of 43 percent and 1.5 °C, respectively. The extreme ensemble combinations of precipitation and temperature changes range from -63.56 to 141.94 percent and 0.98 to 5.85 °C, see Table 14. The selected GCM-scenarios for the extreme and percentile ensemble methods for each time slice are presented in Table 15.
Table 14. Extreme ensemble scenarios for 2065 to 2095.

<table>
<thead>
<tr>
<th>Model</th>
<th>RCP</th>
<th>Run</th>
<th>Percent Change in Precipitation</th>
<th>Absolute Change in Temperature</th>
<th>Case</th>
</tr>
</thead>
<tbody>
<tr>
<td>BNU-ESM</td>
<td>rcp26</td>
<td>r1ilp1</td>
<td>76.40</td>
<td>2.79</td>
<td>wet-cool</td>
</tr>
<tr>
<td>BNU-ESM</td>
<td>rcp85</td>
<td>r1ilp1</td>
<td>141.94</td>
<td>5.85</td>
<td>wet-hot</td>
</tr>
<tr>
<td>CSIRO-Mk3-6-0</td>
<td>rcp85</td>
<td>r8ilp1</td>
<td>-63.56</td>
<td>4.20</td>
<td>dry-hot</td>
</tr>
<tr>
<td>EC-EARTH</td>
<td>rcp26</td>
<td>r12ilp1</td>
<td>-55.14</td>
<td>0.98</td>
<td>dry-cool</td>
</tr>
</tbody>
</table>
Figure 12. Changes in annual temperature change and annual total precipitation for the period from 2035 to 2065. The black markers represent the scenarios selected by the percentile and extreme methods.
Figure 13. Changes in annual temperature change and annual total precipitation for the period from 2065 to 2095. The black markers represent the scenarios selected by the percentile and extreme methods.
4.1.3 Climate Statistics

Climate trends of these scenarios were analyzed by comparing climate statistics from the baseline 1975 to 2005 climate period to the predicted climate scenarios for the periods for 2035 to 2065 and 2065 to 2095. The climate statistics that were compared are monthly and annual mean of daily maximum and minimum air temperatures, monthly and annual precipitation totals, the number of wet days, and the number of days over 30 °C.

Table 15. Selected GCMs from extremes and percentile ensemble methods.

<table>
<thead>
<tr>
<th>Time Slice</th>
<th>Method</th>
<th>GCM Scenario</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model</td>
<td>Scenario</td>
</tr>
<tr>
<td>2035-2065</td>
<td>Extremes</td>
<td>CESM1-CAM5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>CSIRO-Mk3-6-0</td>
</tr>
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<td></td>
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<tr>
<td></td>
<td></td>
<td>MIROC5</td>
</tr>
<tr>
<td></td>
<td>Percentile Ensemble</td>
<td>CanESM2</td>
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<tr>
<td></td>
<td></td>
<td>CanESM2</td>
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<tr>
<td></td>
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<td></td>
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<td>CSIRO-Mk3-6-0</td>
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<td></td>
<td>EC-EARTH</td>
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<tr>
<td></td>
<td></td>
<td>HadGEM2-ES</td>
</tr>
<tr>
<td></td>
<td></td>
<td>MIROC5</td>
</tr>
<tr>
<td>2065-2095</td>
<td>Extremes</td>
<td>BNU-ESM</td>
</tr>
<tr>
<td></td>
<td></td>
<td>BNU-ESM</td>
</tr>
<tr>
<td></td>
<td></td>
<td>CSIRO-Mk3-6-0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>EC-EARTH</td>
</tr>
<tr>
<td></td>
<td>Percentile Ensemble</td>
<td>CanESM2</td>
</tr>
<tr>
<td></td>
<td></td>
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<tr>
<td></td>
<td></td>
<td>CESM1-CAM5</td>
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<tr>
<td></td>
<td></td>
<td>CSIRO-Mk3-6-0</td>
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<td>CSIRO-Mk3-6-0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>HadGEM2-ES</td>
</tr>
<tr>
<td></td>
<td></td>
<td>MIROC5</td>
</tr>
</tbody>
</table>
4.1.3.1 2035-2065

In Figure 14, the changes in monthly mean maximum and minimum temperatures and number of days greater than 30°C are plotted for the 2035-2065 period. The monthly changes in mean maximum temperature demonstrated a median increase ranging from 1.8 to 2.8°C. The CanESM2-RCP8.5-r4 scenario exhibited the highest increase in monthly mean maximum temperature for August with an absolute change of 5.0°C, raising the monthly mean maximum temperature to 34.6°C compared to the Tabora baseline mean maximum temperature 29.6°C. The monthly changes in mean minimum temperature demonstrated a median increase ranging from 2.0 to 3.2°C for the dry season months from May to September. The wet season shows median minimum temperature increases ranging from 1.8 to 2.6°C. The CanESM2-RCP8.5-r5 scenario exhibited the highest increase in monthly mean minimum temperature for August with an absolute change of 5.7°C raising the monthly mean minimum temperature to 20.9°C compared to the Tabora baseline mean minimum temperature of 15.2°C. All scenarios anticipate the number of days above 30°C, or 30 degree days to increase in all months. The months with the greatest increase in hot days are June, July and August with median increases of 13, 20 and 17 days warmer than 30°C. The increase in 30 degree days in the dry season may impact soil water as a higher rate of evaporation would be expected with higher temperatures.

The mean monthly total precipitation for the 2035-2065 time slice, see Figure 15, does not show very significant changes from the baseline period. Precipitation and temperature are plotted for each scenario with the results from WaNuLCAS in Appendix F and visualize the variability between generated scenarios.

Figure 16 shows the annual mean temperatures and total precipitation over the 2035-2065 period to demonstrate the variability of each model within the 30 year period, compared to the Tabora baseline period from 1975 to 2005. The annual total precipitation demonstrates the variability of precipitation between models better than monthly mean total precipitation over the 30 year period as the variations are not lost by taking the average for the 30 year normal.

4.1.3.2 2065-2095

In Figure 17 the changes in monthly mean maximum and minimum temperatures and the number of days greater than 30°C are plotted for the 2065-2095 period. The monthly changes in mean
maximum temperature demonstrated a median increase ranging from 3.1 to 4.4°C for the dry season months from May to September. The wet season shows median maximum temperature increases ranging from 2.8 to 3.2°C. The EC-EARTH-r12 -RCP2.6 scenario exhibited the highest increase in monthly mean maximum temperature for August with an absolute change of 7.6°C raising the monthly mean maximum temperature to 37.9°C compared to the Tabora baseline mean maximum temperature 29.6°C. The monthly changes in mean minimum temperature demonstrated a median increase ranging from 3.4 to 3.9°C for the dry season months from May to September. The wet season shows median minimum temperature increases ranging from 3.9 to 5.2°C in the dry season and 3.3 to 4.3°C in the wet season. The EC-EARTH-r12 -RCP2.6 scenario exhibited the highest increase in monthly mean minimum temperature for August with an absolute change of 8.6°C raising the monthly mean minimum temperature to 23.7°C compared to the Tabora baseline mean minimum temperature of 15.2°C.

All scenarios anticipate the number of 30 degree days to increase in all months. The months with the greatest increase in hot days are May, June, July, and August with median increases of 14, 22, 26, and 19 days warmer than 30°C. These results for May and June are particularly significant compared the Tabora baseline. May and June have 0 and 1 day above 30°C respectively whereas the predicted changes would increase the days to 15 and 22 days above 30°C.

The BNU-ESM scenarios model a significant change in precipitation for August, where the number of wet days over the 30 period average at 28 days compared to the Tabora baseline period of 1.4 wet days. The BNU-ESM model ranked low in performance in the compromise programming validation method, which may suggest the BNU-ESM model structure is not appropriate for the Tabora region. The mean monthly total precipitation for the 2065-2095 time slice, see Figure 18, does not show very significant changes from the baseline period. The precipitation graphs for all models are in Appendix F and visualize the variability between generated scenarios.

Figure 19 shows the annual mean temperatures and total precipitation over the 2065-2095 period to demonstrate the variability of each model within the 30 year period, compared to the Tabora baseline period from 1975 to 2005. The trend for the annual maximum temperature increases over the 30 year period and the annual total precipitation decreases over the 30 year period. The
variability of precipitation is better represented by the annual total precipitation as the range is not smoothed by averaging.

The largest changes in temperatures for both time periods are anticipated to occur in the dry season month from May to August, it is possible that these changes may not significantly impact maize crop growth as the growing season takes place from December to April. The individual plot of maximum and minimum temperature and precipitation for each model and time slice is in Appendix F with results from the WaNuLCAS simulations.
Figure 14. Monthly climate statistics for temperature from 2035 to 2065 compared to the Tabora baseline data.
Figure 15. Monthly climate statistics for precipitation from 2035 to 2065 compared to the Tabora baseline data.
Figure 16. Annual climate statistics for temperature precipitation from 2035 to 2065 compared to the Tabora baseline data.
Figure 17. Monthly climate statistics for temperature from 2065 to 2095 compared to the Tabora baseline data.
Figure 18. Monthly climate statistics for precipitation from 2065 to 2095 compared to the Tabora baseline data.
Figure 19. Annual climate statistics for temperature and precipitation from 2065 to 2095 compared to the Tabora baseline data.
4.2 System Dynamics Simulations
The experimental results of the WaNuLCAS simulations are discussed as they were presented in Section 3.6, page 44. The first experiment compares the baseline simulation to the observed results from Tabora. The second set of experiments shows the impact of management changes to the baseline simulation. The third set of experiments demonstrate the effects of climate change on the agroforestry system. The fourth set of experiments applies some of the management changes in combination with the climate change inputs to explore mitigation of climate change for the agroforestry systems.

4.2.1 Experiment 1: Baseline
Site-specific data was gleaned from previous research papers and studies conducted in the area, as described in Section 0, page 37. Observed yields at Tumbi research station from 1996 to 2002 were compared to simulated yields for two cases:


The on-farm results wood yields were taken from nine trees from an area of 25 meters by 25 meters on each farm, however only four farms were sampled. The precise topography and soil conditions of the farms are unknown and some assumptions were made for the initial condition parameters and settings of the WaNuLCAS model such as a ground slope of 0.1%. Soil conditions were taken from data from the Tabora field research.
Figure 20 shows the climate inputs used for the baseline simulation. The mean temperature for the baseline growing seasons, December to May, was 20.7 ºC. The total precipitation, mean temperature and number of 30 degree days are listed in Table 16. The precipitation was considered erratic for the field trial period (Mbwambo et al., 2003) and the large amount of precipitation that occurred in the growing season of 1998 may be the main factor in the large crop yields obtained in that year.

Table 16. Baseline growing season climate.

<table>
<thead>
<tr>
<th>Growing season</th>
<th>Total Precipitation (mm)</th>
<th>Mean Temperature (ºC)</th>
<th>30 Degree Days</th>
</tr>
</thead>
<tbody>
<tr>
<td>1997</td>
<td>940.0</td>
<td>20.6</td>
<td>2</td>
</tr>
<tr>
<td>1998</td>
<td>631.1</td>
<td>20.6</td>
<td>10</td>
</tr>
<tr>
<td>1999</td>
<td>489.9</td>
<td>20.9</td>
<td>13</td>
</tr>
<tr>
<td>2000</td>
<td>711.1</td>
<td>20.3</td>
<td>5</td>
</tr>
<tr>
<td>2001</td>
<td>653.9</td>
<td>21.1</td>
<td>18</td>
</tr>
<tr>
<td>2002</td>
<td>714.6</td>
<td>20.8</td>
<td>14</td>
</tr>
</tbody>
</table>
Figure 21. Observed and simulated results for maize and wood yields for the baseline period. The blue and green bars represent the observed results from Tabora research (Mbwambo et al. 2003), the orange and red bars represent simulated WaNuLCAS results. The thick bars for 2001 represent wood yields. The error bars represent the observed standard deviation from the Tabora research results.

The simulated results show the agroforestry system yields are similar to the observed results. Figure 21 shows the agroforestry system maize yields for the simulated results are 1.13, 2.88, 0.53 and 0.93 Mg ha\(^{-1}\) for the years 1997, 1998, 1999, and 2002, respectively. Monocrop system maize yields for the simulated results were 1.13, 3.53, 0.53 and 1.0 Mg ha\(^{-1}\) for the years 1997, 1998, 1999, and 2002, respectively. The difference in simulated yields between systems for 1998 is due to reduced growth in zones under the simulated tree canopy. The observed yields for 1999 indicate that canopy cover under the agroforestry system limited growth but this difference was not modelled well between the simulations for the agroforestry and monocrop systems. The simulation results for the monocrop system overestimated the maize yields achieved in 1998 by 60% and in 2002 by 66%. Maize yields were underestimated in 1999 by 52%, when compared to the observed mean. While these differences are significant it was noted that the standard deviation of observed values were 30% to 80% of the observed mean, generally simulated maize yields were within the range of observed results.
Wood yields achieved by the simulations were 33.5 Mg ha\(^{-1}\) which were very similar to the observed mean of 35.0 Mg ha\(^{-1}\). Table 17 shows the agroforestry system achieves a NPV of 165,002 Tsh after 6 years compared to 147,461 Tsh attained by the monocrop system (including 2002 maize benefits). It is notable that the agroforestry system costs of planting trees is quite significant for farmers and has a longer payback period. The NPV of the simulated monocrop overestimate benefits as the crop yields were higher than the observed results. The simulated NPV for the baseline agroforestry system will be used for comparison in Experiments 2 to 4.

**Table 17. Net present value of baseline simulations.**

<table>
<thead>
<tr>
<th>Net Present Value (Tsh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agroforestry</td>
</tr>
<tr>
<td>Monoculture</td>
</tr>
</tbody>
</table>

The vulnerability index, see Figure 22, is a function of exposure, sensitivity and adaptive capacity, defined in section 3.5, and primarily indicates food security. A vulnerability index value below 1 indicates low vulnerability, an index value between 1 and 2 indicates moderate vulnerability, and a vulnerability index greater than 2 indicates high vulnerability for food insecurity. The simulation results for the vulnerability index of the baseline period shows the high maize yields achieved in 1998 results in a low vulnerability and the low maize yields contribute significantly to high vulnerability in 1999 and 2002. The vulnerability indices for the agroforestry and monoculture systems are almost identical as they are subject to the same exposure and adaptive capacity, and the maize yields attained by the systems were similar.

Vulnerability was only calculated for years with a crop harvest. Exposure was calculated from the long-term mean growing season rainfall and the growing season rainfall for each year. The sensitivity was calculated from the mean long-term expected maize yield (FAOSTAT, 2014) and the simulated maize yield in each year. The adaptive capacity is a function of the literacy rate and poverty rate which were estimated at 64 and 90 percent, respectively from the 2014 FAO Statistics report (FAOSTAT, 2014). Adaptive capacity was kept as a constant because there are many factors that influence the poverty rate and it was determined to be beyond the scope of this research to include the income from the wood yields. The wider discussion on the use of the vulnerability index as an appropriate indicator is expanded upon further in Chapter 5.
The results were analyzed for goodness of fit using equations (13) and (14) where $O$ is the observed value and $P$ is the predicted value. The modelling efficiency, 0.995, is close to the optimal value of 1, suggesting that the model performs well for the number of data points available. The Root Mean Squared Error (RMSE) of 0.586 could be improved by a larger observed data set. These results are summarized in Figure 23. The observed data were from the summarized (average) results in Mbwambo (2003) and were limited to 9 data points.

$$EF = \frac{\sum_{i=1}^{n}(O_i - O_{mean})^2 - \sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}(O_i - O_{mean})^2}$$  \hspace{1cm} (13)

$$RMSE = \left( \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n} \right)^{0.5}$$  \hspace{1cm} (14)

<table>
<thead>
<tr>
<th>Goodness of Fit</th>
<th>Model</th>
<th>Optimum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Modelling Efficiency</td>
<td>0.995</td>
<td>1</td>
</tr>
<tr>
<td>Root Mean Squared Error</td>
<td>0.586</td>
<td>0</td>
</tr>
</tbody>
</table>
4.2.2 Experiment 2: Management

This experiment was conducted to determine the effect of farmer management choices on simulated yields, NPV, and vulnerability. The baseline climate inputs were maintained to isolate the result of the management practices on the system. These management practices are described for each simulation in Table 11, page 45. The results of each simulation are plotted in Appendix E.

4.2.2.1 WaNuLCAS Potential Growth Switches

The use of potential growth switches in WaNuLCAS are helpful to inform management practices and policy changes to the system. Unlimited pools of water, nitrogen, and phosphorus can be switched on or off to see how production is affected without constraints on these basic resources. WaNuLCAS also has a “Rain Multiplier” switch and it was used to simulate extreme precipitation conditions of 30%, 50% and 150% of baseline precipitation. While the potential growth conditions are largely unachievable in reality, the switches are used to optimize management practices.

4.2.2.1.1 WaNuLCAS Potential Growth: Nitrogen, Phosphorus, and Water

The potential growth without any limitations (N, P, and water) show that maize yields and wood yields could attain up to 9.4 Mg ha\(^{-1}\) and 462 Mg ha\(^{-1}\) annually, respectively. The percent difference of maize yields from the baseline maize yields ranges from 227% to 1670%. The NPV for this
scenario is 1,502,800 Tsh and the payback period is one growing season. The vulnerability was reduced below 1 for all years except 1999 because the level of exposure was fixed to the baseline level; precipitation did not change and the growing season precipitation was 490 mm, a 43% reduction from the mean long-term growing season of 857 mm.

4.2.2.1.2 WaNuLCAS Potential Growth: Nitrogen

The simulated potential growth without nitrogen limitations increased maize yields by 6%, 16% and 7% for 1997 to 1999 compared to the baseline, suggesting a small deficit of nitrogen for the baseline. Increased yields may be achieved by increasing the dose of nitrogen fertilizers. The maize yield in 2002 under unlimited nitrogen was reduced from the baseline by 11% to 0.82 Mg ha\(^{-1}\) which may be attributable to reduced availability of nutrients spent by previous harvests. The wood yields were 33.2 Mg ha\(^{-1}\). The NPV for this scenario is 156,519 Tsh and the payback period is two growing seasons. The NPV is 5% lower than the baseline due to the reduced yields in 2002 for maize and the slightly reduced yields of wood yield. The vulnerability index for this scenario ranged from 0.2 to 1.0, indicating a low risk of food insecurity.

4.2.2.1.3 WaNuLCAS Potential Growth: Phosphorus

The simulated potential growth without phosphorus limitations indicate crop yields could attain 8.5, 6.6, 4.9 and 3.5 Mg ha\(^{-1}\) in harvest years from 1997 to 2002. Wood yields could attain 292.4 Mg ha\(^{-1}\), an increase of 774% from the baseline wood yield of 33.5 Mg ha\(^{-1}\). These conditions are not achievable in reality due to the limitations on phosphorus adsorption and transportation in soils. WaNuLCAS indicates phosphorus is the largest limiting factor for wood and crop yields. The results of this run may indicate that the site characterization for WaNuLCAS may not represent phosphorus adsorption and transportation or that the tree parameterization should be modified to better characterize tree sensitivity to phosphorus. Such data was not available for this study but its availability would improve future studies with WaNuLCAS. The NPV for this run was 973,327 Tsh, an increase of 490% from the baseline NPV of 165,002 Tsh. The vulnerability index for this scenario ranged from 0.2 to 1.3, indicating a low risk of food insecurity.

4.2.2.1.4 WaNuLCAS Potential Growth: Water

The simulated potential growth without water limitations indicate crop yields could attain 1.1, 3.2, 0.55 and 0.88 Mg ha\(^{-1}\) in harvest years from 1997 to 2002. The maize yield in 1997 was simulated
to be the same as the baseline, indicating water was not a limiting factor for growth that year. The maize yields were reduced by 4% in 2002 which may be attributable to reduced availability of nutrients spent by previous harvests. Wood yields could attain 34.7 Mg ha$^{-1}$, an increase of 3.7% from the baseline wood yield of 33.5 Mg ha$^{-1}$. The NPV for this run was 149,717 Tsh, a reduction of 9% from the baseline NPV of 165,002 Tsh. The vulnerability index for this scenario ranged from 1.0 to 3.6, indicating varying levels of food insecurity from medium to high risk.

4.2.2.1.5 WaNuLCAS Potential Growth: 30% Precipitation

Simulated growth under 30% of the baseline precipitation indicate crop yields could be reduced by 35%, 82%, 65% and 79% to 0.74, 0.51, 0.18 and 0.2 Mg ha$^{-1}$, respectively, in harvest years from 1997 to 2002. Wood yields were reduced by 60% to 13.7 Mg ha$^{-1}$. The NPV for this simulation was 7,240 Tsh, a reduction of 95% from the baseline NPV of 165,002 Tsh. The vulnerability index for this scenario ranged from 2 to 8.7, indicating a high risk of food insecurity under drought-like conditions.

4.2.2.1.6 WaNuLCAS Potential Growth: 50% Precipitation

Simulated growth under 50% of the baseline precipitation indicate crop yields could be reduced by 3.6% and 57% to 1.08 and 1.24 Mg ha$^{-1}$, respectively, in harvest years 1997 and 1998 and indicate crop yields could be increased by 21% and 9% to 0.64 and 1.0 Mg ha$^{-1}$, respectively, in harvest years 1999 and 2002. Changes in wood yields were negligible, approximately 0.3%, yielding 33.6 Mg ha$^{-1}$. The NPV for this simulation was 94,870 Tsh, a reduction of 42% from the baseline NPV of 165,002 Tsh. The reduction in NPV is due to reduced maize yields in the first two harvest years. The vulnerability index for this scenario ranged from 1.5 to 3.2, indicating a medium to high risk of food insecurity under drought–like conditions.

4.2.2.1.7 WaNuLCAS Potential Growth: 150% Precipitation

Simulated growth under 150% of the baseline precipitation indicate maize yields could be increased by 340%, 156% and 31% to 5.0, 1.36 and 1.22 Mg ha$^{-1}$, respectively, in harvest years 1997, 1999 and 2002. The maize yields were reduced by 27% in 1998 to 2.0 Mg ha$^{-1}$, this may be due to nutrient depletion from the previous high yield harvest. Wood yields were increased by 9.6% to 36.7 Mg ha$^{-1}$. The NPV for this run was 297,630 Tsh, an increase of 80% from the baseline
NPV of 165,002 Tsh. The vulnerability index for this scenario ranged from 0.5 to 2.0, indicating a low to medium risk of food insecurity.

4.2.2.2 Fertilizer Applications

4.2.2.2.1 Fertilizer: No Nitrogen

Simulated growth without nitrogen fertilizers (phosphorus was maintained at the baseline dose of 1.8 g m$^{-2}$) indicated increased maize yields of 1% to 1.14 Mg ha$^{-1}$ in 1997 and 6% to 3.05 and 0.56 Mg ha$^{-1}$ in 1998 and 1999, respectively. Maize yields were reduced by 5.6% to 0.88 Mg ha$^{-1}$ in 2002. Wood yields changes were negligible (<1%) from the baseline simulation. The NPV for this run was 150,691 Tsh, a reduction of 8.7% from the baseline NPV of 165,002 Tsh. The vulnerability index for this scenario ranged from 1.1 to 3.6, indicating a medium to high risk of food insecurity.

4.2.2.2.2 Fertilizer: Nitrogen and Phosphorus, 5 g

Simulated growth with nitrogen and phosphorus doses of 5 g m$^{-2}$ fertilizers indicated increased maize yields of 1% to 1.14 Mg ha$^{-1}$ in 1997, 12% to 3.22 Mg ha$^{-1}$ in 1998 and 5.7% to 0.56 Mg ha$^{-1}$ in 1999. Maize yields were reduced by 6.5% to 0.87 Mg ha$^{-1}$ in 2002. Wood yields were reduced by 10% to 33.4 Mg ha$^{-1}$. The NPV for this simulation was 148,120 Tsh, a reduction of 10% from the baseline NPV of 165,002 Tsh. The vulnerability index for this scenario ranged from 1.0 to 3.6, indicating a medium to high risk of food insecurity.

4.2.2.2.3 Fertilizer: Nitrogen and Phosphorus, 10 g

Simulated growth with nitrogen and phosphorus doses of 10 g m$^{-2}$ fertilizers indicated increased maize yields of 1% to 1.14 Mg ha$^{-1}$ in 1997, 13% to 3.25 Mg ha$^{-1}$ in 1998 and 1.5% to 0.54 Mg ha$^{-1}$ in 1999. Maize yields were reduced by 7% to 0.87 Mg ha$^{-1}$ in 2002. Wood yields were increased by 9.6% to 36.7 Mg ha$^{-1}$. The NPV for this simulation was 140,819 Tsh, a reduction of 15% from the baseline NPV of 165,002 Tsh due to increased costs to farmers. The vulnerability index for this scenario ranged from 1.0 to 3.7, indicating a medium to high risk of food insecurity.

4.2.2.3 Planting and Harvesting Date Shifts

These simulations were selected to demonstrate the importance of seasonal forecasting information for farmers. A uniform shift of the calendar was applied to the calendar (all years have the same planting and harvesting date), however, in reality crop calendars are flexible and would only be
limited by labour availability and seasonal forecast information. These points are discussed further in Chapter 5.

4.2.2.3.1 Crop Calendar 20 Days Earlier

Simulated growth indicate crop yields were reduced by 42%, 51% and 3% to 0.65, 1.39 and 0.51 Mg ha\(^{-1}\), respectively, in harvest years 1997, 1999 and 2002. The maize yields were increased by 77% in 2002 to 1.64 Mg ha\(^{-1}\), this may be due to nutrient depletion from the previous high yield harvest. Wood yields were increased by 11% to 37 Mg ha\(^{-1}\). The NPV for this run was 84,039 Tsh, a reduction of 49% from the baseline NPV of 165,002 Tsh. The vulnerability index for this scenario ranged from 1.2 to 3.7, indicating a medium to high risk of food insecurity. Table 19 shows the early planting season precipitation, mean temperature and number of 30 degree days.

**Table 19. Early planting climate growing season precipitation, mean temperature, and 30 degree days.**

<table>
<thead>
<tr>
<th>Growing season</th>
<th>Total Precipitation (mm)</th>
<th>Mean Temperature (°C)</th>
<th>30 Degree Days</th>
</tr>
</thead>
<tbody>
<tr>
<td>1997</td>
<td>1084.2</td>
<td>20.6</td>
<td>5</td>
</tr>
<tr>
<td>1998</td>
<td>667.2</td>
<td>21.0</td>
<td>26</td>
</tr>
<tr>
<td>1999</td>
<td>577.4</td>
<td>21.1</td>
<td>20</td>
</tr>
<tr>
<td>2000</td>
<td>801.4</td>
<td>20.4</td>
<td>14</td>
</tr>
<tr>
<td>2001</td>
<td>658.0</td>
<td>21.4</td>
<td>32</td>
</tr>
<tr>
<td>2002</td>
<td>826.6</td>
<td>20.8</td>
<td>14</td>
</tr>
</tbody>
</table>

4.2.2.3.2 Crop Calendar 20 Days Later

Simulated growth under this management regime indicate crop yields could be increased by 234%, 32% and 33% to 3.78, 3.82 and 0.70 Mg ha\(^{-1}\), respectively, in harvest years 1997, 1998 and 1999. The maize yields were reduced by 49% in 2002 to 0.47 Mg ha\(^{-1}\), this may be due to nutrient depletion from the previous high yield harvest. Wood yields increased marginally by 1.8% to 32.9 Mg ha\(^{-1}\). The NPV for this simulation was 255,965 Tsh, an increase of 55% from the baseline NPV of 165,002 Tsh. The vulnerability index for this scenario ranged from 0.4 to 3.3, indicating a low risk of food insecurity in some years and high risk in others, but generally higher vulnerability than
the baseline except in 2002. Table 20 shows the early planting season precipitation, mean temperature and number of 30 degree days.

Table 20. Late growing season precipitation, mean temperature, and 30 degree days.

<table>
<thead>
<tr>
<th>Growing season</th>
<th>Total Precipitation (mm)</th>
<th>Mean Temperature (°C)</th>
<th>30 Degree Days</th>
</tr>
</thead>
<tbody>
<tr>
<td>1997</td>
<td>775.5</td>
<td>20.5</td>
<td>2</td>
</tr>
<tr>
<td>1998</td>
<td>583.0</td>
<td>20.3</td>
<td>4</td>
</tr>
<tr>
<td>1999</td>
<td>443.9</td>
<td>20.7</td>
<td>4</td>
</tr>
<tr>
<td>2000</td>
<td>545.9</td>
<td>20.5</td>
<td>5</td>
</tr>
<tr>
<td>2001</td>
<td>596.3</td>
<td>20.9</td>
<td>11</td>
</tr>
<tr>
<td>2002</td>
<td>649.3</td>
<td>20.6</td>
<td>6</td>
</tr>
</tbody>
</table>

4.2.2.4 Tree species

Other nitrogen-fixing trees were selected from the WaNuLCAS tree library to explore the effects other species might have on the maize yields and NPV of the system.

4.2.2.4.1 Acacia Mangifera

Simulated growth with the species *Acacia Mangifera* indicate crop yields were reduced by 11.5%, 23.5% to 1.0, and 2.2 Mg ha$^{-1}$, respectively, in harvest years 1997, 1998 and 1999. The maize yields were increased by 13% in 2002 to 1.05 Mg ha$^{-1}$, this may be due to higher nutrient availability from the previous low yield harvests. Wood yields were merely 6.4 Mg ha$^{-1}$, which is 80% of the wood yields achieved by *Acacia Crassicarpa*. The NPV for this run was 32,666 Tsh, a 80% from the baseline NPV of 165,002 Tsh. The vulnerability index for this scenario ranged from 1.0 to 3.6, indicating a high risk for food insecurity. The low maize and wood yields attained indicate that this species is not a suitable to improve soil fertility for crops or as a viable source of wood production for economic activities such as fuel wood or timber.

4.2.2.4.2 Artocarpus Heterophyllus

Simulated growth with the species *Artocarpus Heterophyllus* indicate maize yields were increased by 12% and 2.6% to 3.22, and 0.54 Mg ha$^{-1}$, respectively, in harvest years 1998 and 1999. Maize yields were reduced by 1.5% and 3.4% to 1.1, and 0.9 Mg ha$^{-1}$, respectively, in harvest years 1997 and 2002. Wood yields were 17.4 Mg ha$^{-1}$, which is 47% of the wood yields achieved by *Acacia*
Crassicarpa. The NPV for this run was 123,217 Tsh, a 25% decrease from the baseline NPV of 165,002 Tsh. The vulnerability index for this scenario ranged from 0.9 to 3.6, indicating a high risk for food insecurity. The maize yields achieved with this species were similar to yields achieved with Acacia Crassicarpa, though the wood yield was significantly lower than Acacia Crassicarpa and therefore less suitable for wood production.

4.2.2.5 Summary of Management Experimental Simulations

The results of these varying management techniques and model exploration demonstrate the complexity of the agroforestry system yields; an increase in a nutrient or water source does not equate to a certain increase in maize yields. The simulations indicate the Acacia Crassicarpa species to be resistant to water shortages and that the other simulated tree species may not be suitable alternatives for this region. The effects of fertilizers on maize yields were minimal for the baseline period. This may indicate that nutrients were not the major limiting factors for growth or that the site characterization of Tabora for WaNuLCAS inputs is not representative for phosphorus adsorption and transport. Increasing doses of fertilizers increase costs for farmers if they are not producing their own fertilizers from pastoral activities. The NPV is heavily influenced by the success of maize yields early in the five year period as those yields are discounted less. The use of the vulnerability index may not be particularly useful for farmers but is useful when comparing management scenario efficiency in reducing food insecurity and may also be useful when comparing different regions as previous studies have used the tool (Antwi-Agyei et al., 2012; Simelton et al., 2009).

4.2.3 Experiment 3: Climate Change

This experiment used the downscaled climate scenarios developed in Section 4.1 for the time slices 2035-2065 and 2065-2095 as climate inputs for the WaNuLCAS model and was conducted to determine the effect of climate change on simulated yields, NPV, and vulnerability. A 6 year period from the beginning of each time slice was compared to the baseline scenario and the 30 year trends for maize and wood yields in rotational woodlots were also analyzed to gain insight to long-term system behaviour.
Firstly, the maize and wood yields and NPV attained for each scenario for a 6 year period (2035-2041), see Table 21 (below), were compared to the baseline scenario. The only climate scenario to simulate reduced maize yields from the baseline scenario was CSIRO-Mk3-6-0 Run 2 RCP 2.6, which is the extreme “hot-dry” scenario with a mean annual increase in temperature of 2.3°C and decrease of 57% in total annual precipitation. The maize yields were reduced by 27% to 3.98 Mg ha\(^{-1}\), the wood yields increased by 14.5% to 38.4 Mg ha\(^{-1}\) from the baseline for the 6 year period. The NPV for this scenario was reduced by 42% to 95,550 Tsh. This model was selected for Experiment 4 to see if the climate change effects can be mitigated through management practices.

All models simulated increased wood yields ranging from 10% to 16% from the baseline 33.5 Mg ha\(^{-1}\). The range of NPV is due to discounting income from later harvests; high maize yields earlier in the 6 year period lead to a higher NPV.

### Table 21. Comparison of WaNuLCAS results from 2035-2065 climate change scenario inputs for 6 year period (2065-2071).

<table>
<thead>
<tr>
<th>2035-2065 Scenario</th>
<th>Total Maize Yield (Mg ha(^{-1}))</th>
<th>Average Maize Yield (Mg ha(^{-1}))</th>
<th>Wood yield (Mg ha(^{-1}))</th>
<th>NPV6 (Tsh ha(^{-1}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>CSIRO-Mk3-6-0 Run 2 RCP 2.6</td>
<td>3.98</td>
<td>0.99</td>
<td>38.36</td>
<td>95,550.00</td>
</tr>
<tr>
<td>CanESM2 Run 5 RCP 8.5</td>
<td>5.77</td>
<td>1.44</td>
<td>37.63</td>
<td>142,931.00</td>
</tr>
<tr>
<td>CESM1-CAM5 Run 1 RCP 8.5</td>
<td>6.04</td>
<td>1.51</td>
<td>39.06</td>
<td>147,593.00</td>
</tr>
<tr>
<td>MIROC5 Run 5 RCP 2.6</td>
<td>5.85</td>
<td>1.46</td>
<td>37.55</td>
<td>148,186.00</td>
</tr>
<tr>
<td>CanESM2 Run 4 RCP 4.5</td>
<td>6.75</td>
<td>1.69</td>
<td>37.69</td>
<td>150,267.00</td>
</tr>
<tr>
<td>CSIRO-Mk3-6-0 Run 8 RCP 8.5</td>
<td>6.75</td>
<td>1.69</td>
<td>37.69</td>
<td>150,267.00</td>
</tr>
<tr>
<td>HadGEM2-ES Run 2 RCP 4.5</td>
<td>6.75</td>
<td>1.69</td>
<td>37.69</td>
<td>150,267.00</td>
</tr>
<tr>
<td>Baseline</td>
<td>5.47</td>
<td>1.37</td>
<td>33.50</td>
<td>165,002.00</td>
</tr>
<tr>
<td>CSIRO-Mk3-6-0 Run 9 RCP 8.5</td>
<td>6.96</td>
<td>1.74</td>
<td>37.89</td>
<td>170,674.00</td>
</tr>
<tr>
<td>CanESM2 Run 5 RCP 4.5</td>
<td>6.45</td>
<td>1.61</td>
<td>38.20</td>
<td>172,688.00</td>
</tr>
<tr>
<td>EC-EARTH Run 12 RCP 2.6</td>
<td>7.06</td>
<td>1.77</td>
<td>37.42</td>
<td>180,665.00</td>
</tr>
<tr>
<td>CSIRO-Mk3-6-0 Run 8 RCP 4.5</td>
<td>6.69</td>
<td>1.67</td>
<td>37.10</td>
<td>188,442.00</td>
</tr>
<tr>
<td>CSIRO-Mk3-6-0 Run 5 RCP 4.5</td>
<td>7.15</td>
<td>1.79</td>
<td>39.02</td>
<td>198,538.00</td>
</tr>
<tr>
<td>MIROC5 Run 2 RCP 8.5</td>
<td>7.67</td>
<td>1.92</td>
<td>38.71</td>
<td>198,817.00</td>
</tr>
<tr>
<td>CSIRO-Mk3-6-0 Run 5 RCP 8.5</td>
<td>8.15</td>
<td>2.04</td>
<td>38.08</td>
<td>215,950.00</td>
</tr>
</tbody>
</table>

Though the 6 year baseline period comparison shows increased maize yields, the average yields over the 30 year periods decrease from the baseline mean national yield of 1.47 and range from 0.9 to 1.7, see
Table 22 for long-term maize yields by scenario. The CAN-ESM2 Run 5 RCP 8.5 demonstrates the highest long-term yield, this scenario was selected as the 95th percentile of models from the percentile ensemble method for mean temperature. This supports the hypothesis that higher temperature may increase maize yields for the Tabora region. The maize yields are erratic due to the high inter-annual variability of rainfall. The wood yields for all models show a decreasing, cyclical pattern due to nutrient depletion however, as aforementioned, tree parameterization may be greatly improved and scientific studies would make the model more robust. The long-term results of each model are plotted in Appendix F.

Table 22. Long-term average maize yield for each 2035-2065 climate scenario.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Average Maize Yield (Mg ha⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CanESM2 r4i1p1 rcp45</td>
<td>1.0</td>
</tr>
<tr>
<td>CanESM2 r5i1p1 rcp45</td>
<td>1.1</td>
</tr>
<tr>
<td>CanESM2 r5i1p1 rcp85</td>
<td>1.7</td>
</tr>
<tr>
<td>CESM1-CAM5 r1i1p1 rcp85</td>
<td>0.9</td>
</tr>
<tr>
<td>CSIRO-Mk3-6-0 r2i1p1 rcp26</td>
<td>0.9</td>
</tr>
<tr>
<td>CSIRO-Mk3-6-0 r5i1p1 rcp45</td>
<td>1.1</td>
</tr>
<tr>
<td>CSIRO-Mk3-6-0 r5i1p1 rcp85</td>
<td>1.1</td>
</tr>
<tr>
<td>CSIRO-Mk3-6-0 r8i1p1 rcp45</td>
<td>1.1</td>
</tr>
<tr>
<td>CSIRO-Mk3-6-0 r8i1p1 rcp85</td>
<td>1.0</td>
</tr>
<tr>
<td>EC-EARTH r12i1p1 rcp26</td>
<td>1.1</td>
</tr>
<tr>
<td>HadGEM2-ES r2i1p1 rcp45</td>
<td>1.0</td>
</tr>
<tr>
<td>MIROC5 r2i1p1 rcp85</td>
<td>1.0</td>
</tr>
<tr>
<td>MIROC5 r5i1p1 rcp26</td>
<td>1.0</td>
</tr>
</tbody>
</table>

2065-2095

The maize and wood yields and NPV attained for each scenario for a 6 year period (2065-2071), see Table 23 (below), are compared to the baseline scenario. The only climate scenarios to have reduced maize yields from the baseline scenario were the BNU-ESM scenarios. The BNU-ESM model was found to be poor for modelling precipitation for the month of August in the Tabora region and the reduction in maize yields could be attributed to the distribution of precipitation.

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Note there are 12 climate scenarios analyzed in this section as the WaNuLCAS model failed with the following models: CanESM2 Run5 RCP 4.5 and 8.5.
away from the traditional wet season. The maize yields were reduced by 10% to 4.9 Mg ha\(^{-1}\), the wood yields increased by 14.5% to 38.4 Mg ha\(^{-1}\) from the baseline for the 6 year period. The NPV for this scenario was increased by 20% to 199,386 Tsh. All other climate scenarios simulated increased maize yields ranging from 0% to 41% from the baseline 5.47 Mg ha\(^{-1}\). All models simulated increased wood yields ranging from 8% to 16% from the baseline 33.5 Mg ha\(^{-1}\). All scenarios attained a NPV greater than the baseline and the range of NPV is due to discounting income from later harvests; high maize yields earlier in the 6 year period lead to a higher NPV.

**Table 23. Summary of WaNuLCAS results from 2065-2095 climate change scenario inputs for 6 year period (2065-2071).**

<table>
<thead>
<tr>
<th>2065-2095 Scenario</th>
<th>Total Maize Yield (Mg ha(^{-1}))</th>
<th>Average Maize Yield (Mg ha(^{-1}))</th>
<th>Wood yield (Mg ha(^{-1}))</th>
<th>NPV6 (Tsh ha(^{-1}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>5.47</td>
<td>1.37</td>
<td>33.50</td>
<td>165,002.00</td>
</tr>
<tr>
<td>CSIRO-Mk3-6-0 Run 2 RCP 2.6</td>
<td>6.45</td>
<td>1.61</td>
<td>38.09</td>
<td>188,630.00</td>
</tr>
<tr>
<td>CanESM2 Run 3 RCP 8.5</td>
<td>6.41</td>
<td>1.60</td>
<td>37.02</td>
<td>189,183.00</td>
</tr>
<tr>
<td>CSIRO-Mk3-6-0 Run 8 RCP 8.5</td>
<td>6.10</td>
<td>1.53</td>
<td>36.24</td>
<td>195,619.00</td>
</tr>
<tr>
<td>BNU-ESM Run 1 RCP 8.5</td>
<td>4.90</td>
<td>1.23</td>
<td>38.39</td>
<td>199,386.00</td>
</tr>
<tr>
<td>HadGEM2-ES Run 3 RCP 2.6</td>
<td>5.47</td>
<td>1.37</td>
<td>38.54</td>
<td>199,532.00</td>
</tr>
<tr>
<td>CSIRO-Mk3-6-0 Run 5 RCP 8.5</td>
<td>5.84</td>
<td>1.46</td>
<td>38.84</td>
<td>204,216.00</td>
</tr>
<tr>
<td>CSIRO-Mk3-6-0 Run 4 RCP 8.5</td>
<td>7.17</td>
<td>1.79</td>
<td>37.47</td>
<td>205,199.00</td>
</tr>
<tr>
<td>CSIRO-Mk3-6-0 Run 3 RCP 2.6</td>
<td>7.71</td>
<td>1.93</td>
<td>37.72</td>
<td>210,158.00</td>
</tr>
<tr>
<td>EC-EARTH Run 12 RCP 2.6</td>
<td>6.87</td>
<td>1.72</td>
<td>37.63</td>
<td>213,523.00</td>
</tr>
<tr>
<td>MIROC5 Run 3 RCP 4.5</td>
<td>6.49</td>
<td>1.62</td>
<td>38.23</td>
<td>232,644.00</td>
</tr>
<tr>
<td>BNU-ESM Run 1 RCP 2.6</td>
<td>5.25</td>
<td>1.31</td>
<td>39.12</td>
<td>235,270.00</td>
</tr>
<tr>
<td>CSIRO-Mk3-6-0 Run 4 RCP 4.5</td>
<td>5.68</td>
<td>1.42</td>
<td>38.00</td>
<td>265,457.00</td>
</tr>
</tbody>
</table>

Similarly to the 2035-2065 time slice, the average maize yields over the 30 year periods decrease from the baseline mean national yield of 1.47 and range from 0.9 to 1.1, see Table 24 for long-term maize yields by scenario. The maize yields are erratic due to the high inter-annual variability of rainfall. The wood yields show a decreasing, cyclical pattern in yields due to nutrient depletion however, as aforementioned, tree parameterization may be greatly improved and scientific studies would make the model more robust. The long-term results of each model are plotted in Appendix F.
Table 24. Long-term average maize yield for each 2065-2095 climate scenario.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Average Maize Yield (Mg ha(^{-1}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>BNU-ESM r1i1p1 rcp26</td>
<td>0.9</td>
</tr>
<tr>
<td>BNU-ESM r1i1p1 rcp85</td>
<td>0.9</td>
</tr>
<tr>
<td>CSIRO-Mk3-6-0 r2i1p1 rcp26</td>
<td>1.0</td>
</tr>
<tr>
<td>CSIRO-Mk3-6-0 r3i1p1 rcp26</td>
<td>1.1</td>
</tr>
<tr>
<td>CSIRO-Mk3-6-0 r4i1p1 rcp45</td>
<td>1.0</td>
</tr>
<tr>
<td>CSIRO-Mk3-6-0 r4i1p1 rcp85</td>
<td>1.0</td>
</tr>
<tr>
<td>CSIRO-Mk3-6-0 r5i1p1 rcp85</td>
<td>1.0</td>
</tr>
<tr>
<td>CSIRO-Mk3-6-0 r8i1p1 rcp85</td>
<td>1.0</td>
</tr>
<tr>
<td>CanESM2 r3i1p1 rcp85</td>
<td>0.9</td>
</tr>
<tr>
<td>EC-EARTH r12i1p1 rcp26</td>
<td>1.0</td>
</tr>
<tr>
<td>HadGEM2-ES r3i1p1 rcp26</td>
<td>1.0</td>
</tr>
<tr>
<td>MIROC5 r3i1p1 rcp45</td>
<td>1.0</td>
</tr>
</tbody>
</table>

Long-term growth patterns of the woodlots are unknown, though a study on the uptake of the technology in Uganda implies that the benefits continue after the first rotation (Buyinza, Ntakimanye, Nabanoga, & Banana, 2008). Furthermore, the cost of tree saplings or seeds could be reduced if farmers collected seeds and planted their own after the first rotation (Nyoka et al., 2011); data was not available for seed collection to evaluate the cost reductions. The mitigation of climate change using management practices is further explored in the next section.

4.2.4 Experiment 4: Climate Change Mitigation

Three different management practices from Experiment 2 were applied to the CSIRO-Mk3-6-0 Run 2 RCP 2.6. This was the only climate scenario to have reduced maize yields from the baseline scenario and was the extreme “hot-dry” scenario for the 2035-2065 time slice. The scenario shows a mean annual increase in temperature of 2.3°C and 57% decrease in total annual precipitation. The maize yields were reduced by 27% to 3.98 Mg ha\(^{-1}\), and the wood yields increased by 14.5% to 38.4 Mg ha\(^{-1}\) from the baseline for the 6 year period. The NPV for this scenario was reduced by 42% to 95,550 Tsh from the baseline 165,002 Tsh. The simulations for this experiment were run for 10 years and compared to a 10 year period (2035-2045) for the CSIRO-Mk3-6-0 Run 2 RCP 2.6 scenario in Experiment 2.

Adaptation of the crop calendar to an earlier planting day (Julian day 310, originally 330) was found to be the most successful management practice in mitigating climate-induced losses. Maize...
yields were by increased by 50% over the 10 year period with a mean yield of 1.69 Mg ha\(^{-1}\), see Table 25 below. The application of 5 g m\(^{-2}\) of nitrogen and phosphorus fertilizers reduced losses by 16% over the 10 year period. Later planting dates for this climate scenario are not recommended as maize yields were reduced every year, by an average of 45% over the 10 year period.

**Table 25. Maize yields for climate change mitigation simulations.**

<table>
<thead>
<tr>
<th>Simulation</th>
<th>Maize Yield (Mg ha(^{-1}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>2036</td>
<td>0.54 1.30 1.60 1.58 1.93 0.85 1.30</td>
</tr>
<tr>
<td>2037</td>
<td></td>
</tr>
<tr>
<td>2038</td>
<td></td>
</tr>
<tr>
<td>2041</td>
<td></td>
</tr>
<tr>
<td>2042</td>
<td></td>
</tr>
<tr>
<td>2043</td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td></td>
</tr>
</tbody>
</table>

The wood yields in 2040 varied from 38.8 to 42.5 Mg ha\(^{-1}\) and from 12.5 to 15.8 Mg ha\(^{-1}\). The later planting date of maize resulted in the highest wood yields which may be due to reduced competition between maize and trees for water and nutrients during the tree’s vegetative period.

**Table 26. Wood yields for climate change mitigation simulations.**

<table>
<thead>
<tr>
<th>Simulation</th>
<th>Wood Yield (Mg ha(^{-1}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>2040</td>
<td>38.4 14.2</td>
</tr>
<tr>
<td>2045</td>
<td></td>
</tr>
</tbody>
</table>

The 10 year NPV was calculated for the three practices to compare to the climate change scenario simulation from Experiment 3, see Table 28. The net present value of the system was increased by 90% to 124,126 Tsh from 95,550 Tsh. Fertilizer application increased the NPV by 27% to 157,542 Tsh.

**Table 27. 10 year NPV of climate change mitigation simulations.**

<table>
<thead>
<tr>
<th>Simulation</th>
<th>10 year NPV (Tsh ha(^{-1}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>CSIRO-Mk3-6-0 Run 2 RCP 2.6</td>
<td>124,126</td>
</tr>
</tbody>
</table>
The growing seasons for the simulations are summarized in Table 28. The growing season for the early planting date increased growing season precipitation by 18% and the days above 30°C increased by 8% over the 10 year period. The growing season for the late planting date reduced growing season precipitation by 12% over the 10 year period.

Table 28. Growing season characteristics of Experiment 4 simulations.

<table>
<thead>
<tr>
<th>Calendar DoY 310</th>
<th>Fertilizer (N &amp; P, 5 g) DoY 330</th>
<th>Calendar DoY 350</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pr. T&lt;sub&gt;mean&lt;/sub&gt; Days</td>
<td>Pr. T&lt;sub&gt;mean&lt;/sub&gt; Days</td>
<td>Pr. T&lt;sub&gt;mean&lt;/sub&gt; Days</td>
</tr>
<tr>
<td>2036 1118.3 21.6 20</td>
<td>1000.4 21.5 14</td>
<td>898.3 21.5 10</td>
</tr>
<tr>
<td>2037 900.1 21.7 16</td>
<td>861.7 21.4 4</td>
<td>793.7 21.3 1</td>
</tr>
<tr>
<td>2038 1059.1 21.3 15</td>
<td>974.9 21.0 8</td>
<td>773.4 21.2 10</td>
</tr>
<tr>
<td>2041 912.2 21.9 18</td>
<td>813.2 21.7 11</td>
<td>764.5 21.5 5</td>
</tr>
<tr>
<td>2042 1100.7 21.5 19</td>
<td>1075.4 21.2 3</td>
<td>971.3 21.2 1</td>
</tr>
<tr>
<td>2043 786.1 21.6 28</td>
<td>716.7 21.4 17</td>
<td>560.9 21.5 22</td>
</tr>
</tbody>
</table>
5 Conclusion

5.1 Overview
Climate change is anticipated to have significant effects on agricultural production in sub-Saharan Africa as the mean temperature could increase by 2 °C to 4°C by the end of the century. Smallholder farmers in western Tanzania are vulnerable to climate change impact as agricultural production is dependent on precipitation for irrigation. It is prudent to evaluate different modes of agricultural adaptations, such as agroforestry, that these farmers can easily adopt to improve their resiliency to the effects of climate change. System dynamics modelling is a cost-effective tool to simulate the long-term behaviour of agroforestry systems for a range of future climate conditions. Water, Nutrient, and Light Capture in Agroforestry Systems (WaNuLCAS) is a system dynamics model developed by the World Agroforestry Centre that was selected to investigate long-term biophysical interactions of maize and Acacia trees. This model was calibrated to data from field research on rotational woodlots conducted in Tabora, Tanzania from 1996 to 2002 by the World Agroforestry Centre. Several experimental simulations were selected to demonstrate the potential of the system dynamics simulations for development project planning and management.

5.2 Summary of Results
Firstly, the WaNuLCAS model was calibrated to data collected and reported from the Tabora field trials conducted by ICRAF for a rotational woodlot arrangement and a monocrop arrangement. The agroforestry system simulations achieved values closer to the observed mean values when compared to the monocrop system. The models’ goodness of fit were calculated using modelling efficiency and RMSE. The modelling efficiency was 0.995 and the root mean squared error (RMSE) was 0.586. The modelling efficiency was close to the optimal value of 1 due to the small range and number of data points available for comparison. The RMSE could be improved with a larger data set of observed values.

Secondly, several management practices were selected to assess the possibilities of improving the simulated crop and wood yields occurring for the baseline conditions. Unlimited growth tools in WaNuLCAS were used to determine limiting factors for the agroforestry system and management practices were developed from the initial management simulations. Phosphorus was determined to be a major limiting factor for the growth of maize and wood; increasing phosphorus fertilizer doses was simulated as a result of this finding. The results from the varied management practices and
model exploration demonstrated the complexity of the agroforestry system yields. The simulations indicated the Acacia Crassicarpa species to be resistant to water shortages and that the other simulated tree species were not suitable alternatives for this region. Modifications to the crop planting and harvesting dates indicated flexible crop calendars can greatly impact yields and highlight the importance of seasonal forecasting and the widespread availability of that information for farmers.

Climate change scenarios were selected with the validation method and the percentile and extremes ensemble approaches to create regionally efficient ensembles downscaled for the Tabora region for the time periods 2035-2065 and 2065-2095. These climate scenarios were then statistically downscaled using the KNNv4 weather generator. These downscaled scenarios were then used as inputs into the WaNuLCAS model to determine the effects of climate change on the agroforestry system. The long term average maize yields were found to range from 0.9 to 1.7 Mg ha\(^{-1}\) for 2035-2065 and 0.9 to 1.1 Mg ha\(^{-1}\). Maize yields increased under 13 of 14 scenarios for the 2035-2065 time slice when compared to the baseline. The mean increase in maize yield was 0.66 Mg ha\(^{-1}\) from the 5.47 Mg ha\(^{-1}\) 6 year total baseline scenario. Comparatively, the mean increase in total maize for the 2065-2095 time period was 0.73 Mg ha\(^{-1}\) from the 5.47 Mg ha\(^{-1}\) baseline scenario. This may be because the optimal temperature for maize is 20°C for the varieties of maize grown in East Africa; maize can grow sufficiently under high temperatures (up to 45 °C) provided there is adequate water (FAO, 2015a).

Finally, the “dry-hot” extreme climate change scenario for the time slice 2035 to 2065 was selected to determine the efficiency of fertilizer application and crop calendar shifting management practices in mitigating the effects of climate change. Earlier planting dates reduced maize losses by 50% and increased the net present value of the system by 90% over a 10 year period.

5.3 Research Questions

What are the significant climate change trends anticipated for the Tabora region?

The regionally efficient climate ensembles developed for this study show that mean temperature will increase by 2.2 °C for 2035-2065 and 3.0 °C for 2065-2095. The range for precipitation varies from a 45% decrease to 60% increase for 2035-2065 and a 56% decrease to a 53% increase for 2065-2095. The large variation in precipitation results for the models is a result of the large natural variability and the imperfect structure of climate models (Ansuategi, 2000).
Are rotational woodlots suitable for climate change adaptation in the Tabora region?

The simulations showed that the woodlots provide additional income and benefits such as a sustainable source for fuel wood. Maize production will remain viable under increasing temperatures but irrigation may be necessary under more extreme precipitation scenarios. Simple irrigation methods, such as a drip-irrigation system, could improve yields under drier climate scenarios (Friedlander, Tal, & Lazarovitch, 2013). This was supported by the investigation with unlimited water resources in WaNuLCAS (Experiment 2).

Are systems dynamics simulations suitable for development planning?

System dynamics simulations have potential as useful tools for project planners as they can provide insight to complex systems that may costly to investigate in other ways. System dynamics simulations may reduce the cost of evaluating development project options. This saves time and money for development organizations while providing useful data for planning and management of systems.

What sort of data management is required such that systems approach can be used as a project management method? Can a systems approach be used in project design and planning, monitoring and evaluation of development projects?

Agricultural systems are complex physical systems that require site-specific knowledge to accurately represent conditions for the system. CIDA projects records are published as per the International Aid Transparency Initiative (IATI) standard (CIDA, 2016), which makes aid spending easier to find, use, and compare. However, only high-level results achieved by the project and spending data are available. The physical and socio-economic data required for the WaNuLCAS model are not supported by this system. The International Development Research Centre (IDRC) supports and disseminates research findings from IDRC-funded research in development (IDRC, 2016). Outputs, final reports, articles, policy briefs, and conference papers are aggregated through their digital library. The data made available by the IDRC is a step in the right direction for Canada to facilitate development planning decisions based on evidence-based approaches. In 2016, the United States Agency for International Development (USAID) launched AidData.org (USAID, 2016), a development research and innovation lab that analyzes development data and provides a portal for planners to access data from past development projects.
The IDRC and AidData are liberating development data to improve planning and management of future aid projects. It may be possible through these new databases that the full potential of the systems approach and system dynamics simulations may be achieved.

5.4 Practical Applications of Research

The practical implications of this research for development officers in Tanzania and other areas of East Africa are numerous. Development planners and government officials and scientists can use the downscaled daily climate data from this study for further analysis of agroforestry and other agricultural systems, as well as a range of other applications.

Over the next few decades, the daily temperature is estimated to rise by two degrees or more, and the annual rainfall will decrease, as a result of global climate change. Although the annual total rain will decrease, it will arrive with more severity, thus increasing the risk of erosion. Farmers should try to mitigate the damage due to climate change to crops by:

- use agroforestry rather than monocrops, for example, Acacia trees with maize;
- plant the most suitable tree species which was found to be Acacia Crassicarpa for fast growth;
- plant the maize two weeks earlier than usual;
- plant the trees at a 4m by 4m spacing;
- plant three crops of maize and then allowing the land to lie fallow for another two years;
- harvest the Acacia trees five years after planting, and then start the process over again;
- increase the amount of phosphorus fertilizers to 5 grams per square meter and maintain the nitrogen fertilizer dosage at 5 grams per square meter;
- use an improved irrigation system (e.g. drip irrigation) to make better use of accumulated rainwater;
- using seasonal forecasting to maximize crop yields in a given season.

For development project managers, system dynamic simulations could also be used as a monitoring and evaluation tool throughout the lifespan of the project. Firstly, provided with sufficient data, a system dynamics model could be developed and calibrated using baseline data at the beginning of a project to simulate possible outcome of project activities. At the mid-term of the project, the results of the simulations could be compared to the mid-term results achieved and another round of simulations could be conducted using the new information gleaned from the
ongoing project to simulate possible outcomes to the end of the project life and beyond thereby suggesting modifications to the project. This process would be repeated at the end of the project life to compare the simulations and model structure from the different planning stages to gain insight and better capture project outcomes and impacts and also increase the efficiency of future project planning. System dynamics simulations may also suggest the most appropriate data and form to capture, as well as archiving for optimal future usage.

5.5 Future Areas of Study
Several areas were identified for improving the robustness of the WaNuLCAS model for rotational woodlots in Tabora:

- Tree parameterization: the long-term tree growth for sequences of rotations have not been studied and some growth behaviour of the trees at Tabora were estimated using the WaNuLCAS survey. It is uncertain how rotational woodlots perform in the long-term as there is gap in the literature on rotational woodlots for periods greater than 6 to 8 years (Kimaro et al., 2007; Mbwambo et al., 2003). This could be improved by continued research on agroforestry and the determination of allometric growth equations for this species and other species used in agroforestry systems.

- Adaptive capacity: adaptive capacity is a function of the literacy rate and poverty rate which were estimated at 64 and 90 percent, respectively from the 2014 FAO Statistics report (FAOSTAT, 2014). Adaptive capacity was kept as a constant because there are many factors that influence the poverty rate and it was determined to be beyond the scope of this research to include the income from the wood yields into the adaptive capacity term. The effects of this could be explored in the future.

- Some common farmer management practices, such as pruning, were not modelled in WaNuLCAS for this study due to a lack of data on these practices. This could be improved by providing more reliable data on crop management and tree management preferences of farmers could produce a more realistic investigation of the implementation of agroforestry techniques and their outcomes on crop yield, wood yield, and farmer vulnerability to climate change. The simulation results were compared to research station data. It can be difficult to capture the variable nature of crop management and the application of farmer knowledge within a given year without adequate data.
Unfortunately, raw data was no longer available from this study as the data was not stored in a computer accessible by ICRAF at the time of this research. The wider public availability of agricultural data could greatly improve modelling efficiency of agroforestry and agricultural, enabling the improved management of development projects in agriculture and increased benefits for the rural poor of the developing world, as aforementioned.

The following are aspects that could be considered for future work to improve model performance.

**Fertilizers**

 Recommending increased fertilizer application as a management practice should be carefully considered as the costs to the farmer are also increased; however, thoughtful planning for appropriate sourcing can reduce fertilizer costs. For example, the incorporation of agro-pastoral management practices can effectively produce animal manure as a source of nitrogen fertilizer (Kerr, 2002). Large scale application of fertilizers in developing and developed countries can contribute to local water pollution. However, low and infrequent application rates of fertilizers and reduced erosion using agroforestry systems would not likely contribute to significant environmental degradation from fertilizers.

**Forecasting**

 The importance of forecasting to maximize the seasonal precipitation for maize production was highlighted by the modification of the crop calendar in Experiment 2. It is evident that management practices can prevent losses to climate change if forecasting knowledge is available (Hansen, Mason, Sun, & Tall, 2011; Sheffield et al., 2014).

**Labour, Markets, and NPV**

 The economic sensitivity of the agroforestry system could be explored in future work by modifying the discount rate, costs of labour, and costs of inputs such as fertilizers and seeds. The availability and costs of labour may vary by season (Crush, Frayne, & Southern African Migration, 2010; Tienda, 2006) or increase in the future due to mass migration to urban areas (Saunders, 2010). The costs of seedlings for trees could be reduced or eliminated if farmers collect seed pods from their
own trees (Nyoka et al., 2011). This was not incorporated into the WaNuLCAS model as data was not available for the required labour inputs.

The analysis used the 6 year baseline period for NPV comparisons. NPV was a useful tool for analysis in this study to help distinguish the value added of management practices. The NPV is useful for short-term analyses and comparisons but is not effective for the long-term viability of the system. After approximately 10 years, the effects of costs and benefits on the NPV are indistinguishable as they are discounted so heavily. Furthermore, other economic analyses such as an Economic Benefit Cost Analysis (ECBA) framework (Ribeiro, 2011) may be more appropriate to capture social benefits, such as reduced deforestation and decreased time and labour spent gathering fuel wood.

**Vulnerability**

Vulnerability to climate change is a function of exposure to a hazard, the sensitivity to the hazard, and adaptive capacity (Antwi-Agyei et al., 2012; Simelton et al., 2009). This study used the precipitation in the growing season to indicate exposure, yields to indicate crop sensitivity to drought and use proxy indicators of income and education to indicate adaptive capacity (A. J. Challinor et al., 2009; Simelton et al., 2009). This index was useful when comparing climate model maize yields and identifying years with high vulnerability. This tool was useful in identifying years with low yields, and could help identify years that would benefit from added management practices.

5.6 **Final Comments**

Agroforestry is a climate change adaptation technology that is a combined land-use system with crops and trees. Adaptation is a key area of interest for East African food security policymakers as the climate changes and food sources for smallholder farmers increase in vulnerability. System dynamics modelling can help policymakers such as governments and multilateral organizations to explore the effects of climate change on agricultural systems and adaptation possibilities using computer simulations to tailor simulations to specific regions, improving the efficiency of development fund spending. There is a great opportunity to use system dynamics simulations to inform development planning and management in agriculture and agroforestry, as there are currently few project planning tools available that capture the feedback behaviours of complex
problems for development planners. The efficiency of other agroforestry schemes may be evaluated using this study’s downscaled climate data for the Eastern African region.
6 Bibliography


Bishaw, B. (2013). Farmers' strategies for adapting to and mitigating climate variability and change through agroforestry in ethiopia and kenya: Oregon State University.


CIDA. (2013). Results-Based Management Tools at CIDA: A how-to guide: Canadian International Development Agency.


Appendix A: Global Goals

The following global goals and their respective targets pertain the role of agroforestry in development and to the outcomes of the current research:

- **Goal 1: End poverty in all its forms everywhere,**
  - By 2030, build the resilience of the poor and those in vulnerable situations and reduce their exposure and vulnerability to climate-related extreme events and other economic, social and environmental shocks and disasters.

- **Goal 2: End hunger, achieve food security and improved nutrition and promote sustainable agriculture.**
  - By 2030, end hunger and ensure access by all people, in particular the poor and people in vulnerable situations, including infants, to safe, nutritious and sufficient food all year round;
  - By 2030, ensure sustainable food production systems and implement resilient agricultural practices that increase productivity and production, that help maintain ecosystems, that strengthen capacity for adaptation to climate change, extreme weather, drought, flooding and other disasters and that progressively improve land and soil quality.

- **Goal 12: Ensure sustainable consumption and production patterns.**
  - Support developing countries to strengthen their scientific and technological capacity to move towards more sustainable patterns of consumption and production.

- **Goal 13: Take urgent action to combat climate change and its impacts.**
  - Strengthen resilience and adaptive capacity to climate-related hazards and natural disasters in all countries.

- **Goal 15: Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss.**
  - By 2020, promote the implementation of sustainable management of all types of forests, halt deforestation, restore degraded forests and substantially increase afforestation and reforestation globally;
By 2020, ensure the conservation, restoration and sustainable use of terrestrial and inland freshwater ecosystems and their services, in particular forests, wetlands, mountains and drylands, in line with obligations under international agreements” (UN, 2015).
Appendix B: Results Based Management Tools

The Logic Model is the framework for the planning stages of a project. The LM is comprised of different levels: inputs, activities, outputs, and results (CIDA, 2013). Inputs are defined as resources required to produce outputs from activities. Activities can be work or actions taken to produce outputs. Results are outcomes that can be further reduced to immediate, intermediate and ultimate outcomes. Immediate outcomes are short term results that are closely related to project outputs such as a change in knowledge, access, or skills. Intermediate outcomes are changes in behaviours and practices following immediate outcomes. The ultimate outcome is a sustained change over time attributed to the project. All results are expected to be specific and easily quantifiable. Logic Models have some disadvantages, such as the inability to quantify time or numbers within the tool, so the Logic Model is typically paired with the PMF to report results with metrics and changes over time (CIDA, 2013).

![Diagram of the Logic Model](image)

**Figure 24. Results chain in RBM.**

The Risk Register is compiled in the planning stage and is expected to be updated throughout the project as risks may change in severity or probability. Risks are identified and defined then linked to either a specific outcome from the LM or can apply to the entire project. Each identified risk should have a response strategy to mitigate or minimize the risk to the project. The risk level is then determined after the response strategy would be applied. The Performance Measurement Framework (PMF) is the tool used to compile baseline data, targets, and to identify which stakeholders are responsible for data collection for elements of the project (CIDA, 2013). The PMF is used in monitoring and evaluation throughout the lifespan of the project and analysis of the PMF can identify early successes and failures of project elements, so that project managers can apply lessons learned for increased success in the project’s future. Extremely specific outcomes should
be selected in the LM and PMF for tracking program performance (Mayne, 1999). These other tools are important for RBM, but are less relevant in relation to this research as they pertain more to monitoring and evaluation rather than development planning.

Mis-use of RBM has been critiqued for the way it has been used rather than the approach itself (Schroeder & Hatton, 2007). There are three typical scenarios where RBM fails.

i) RBM can fail when is used retroactively, after the planning process of a project and its goals and activities are input into the logic model, rather than using RBM as a tool to plan activities to meet outcome objectives (Hummelbrunner, 2010). This happens frequently with NGOs that do not use RBM as management strategy within their own structure and only uses RBM frameworks strictly to meet the donor requirements to obtain funding (Bakewell & Garbutt, 2005). Furthermore, if stakeholders are not involved in the process of composing the Logic Model and PMF, it can become an imposing development strategy instead of being participatory (Hummelbrunner, 2010; Schroeder & Hatton, 2007).

ii) RBM can also fail when it is oversimplified and lacks clarity, which renders it useless to project stakeholders (Hummelbrunner, 2010). This occurs when the administrative capacity of the implementing organization is limited by human and financial constraints and cannot allocate enough resources to fully implement RBM (Vahamaki et al., 2011).

iii) Finally RBM can fail when its tools are used rigidly and not updated or adapted at least once during the lifespan of the project (Dale, 2003; Hummelbrunner, 2010). Dynamic learning occurs when the LM is reviewed and updated at regular intervals to investigate activities and their achievements and to determine if project management approaches should be modified.
Appendix C: Meteorological Stations Data

This appendix contains data on the weather stations used to create the climate change scenarios. Table 29 is a list of the stations used with their latitude and longitude. Table 30 is a list of the data missing for each variable from each weather station, these missing values were replaced using interpolated NCEP re-analysis data.

Table 29. Meteorological stations used in climate change analysis.

<table>
<thead>
<tr>
<th>Station name</th>
<th>Country</th>
<th>Latitude</th>
<th>Longitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tabora Airport</td>
<td>Tanzania</td>
<td>-5.083</td>
<td>32.833</td>
</tr>
<tr>
<td>Mwanza</td>
<td>Tanzania</td>
<td>-2.467</td>
<td>32.917</td>
</tr>
<tr>
<td>Dodoma</td>
<td>Tanzania</td>
<td>-6.167</td>
<td>35.767</td>
</tr>
<tr>
<td>Kigali Intl</td>
<td>Rwanda</td>
<td>-1.969</td>
<td>30.139</td>
</tr>
<tr>
<td>Kasama</td>
<td>Zambia</td>
<td>-10.217</td>
<td>31.133</td>
</tr>
<tr>
<td>Jomo Kenyatta International Airport</td>
<td>Kenya</td>
<td>-1.317</td>
<td>36.917</td>
</tr>
<tr>
<td>Eldoret International Airport</td>
<td>Kenya</td>
<td>0.404</td>
<td>35.239</td>
</tr>
<tr>
<td>Songea</td>
<td>Tanzania</td>
<td>-10.667</td>
<td>35.583</td>
</tr>
<tr>
<td>Zanzibar</td>
<td>Tanzania</td>
<td>-6.222</td>
<td>39.225</td>
</tr>
<tr>
<td>Kitale</td>
<td>Kenya</td>
<td>1.016</td>
<td>35.00</td>
</tr>
<tr>
<td>Dar Es Salaam International Airport</td>
<td>Tanzania</td>
<td>-6.867</td>
<td>39.2</td>
</tr>
<tr>
<td>Mombasa</td>
<td>Kenya</td>
<td>-4.033</td>
<td>39.617</td>
</tr>
<tr>
<td>Malindi</td>
<td>Kenya</td>
<td>-3.229</td>
<td>40.102</td>
</tr>
<tr>
<td>Garissa</td>
<td>Kenya</td>
<td>-0.467</td>
<td>39.633</td>
</tr>
</tbody>
</table>
Table 30. Percent of daily climate variable data at each weather station (Menne et al., 2012).

<table>
<thead>
<tr>
<th>Station Name</th>
<th>Country</th>
<th>Percent Missing</th>
<th>PPT</th>
<th>TMAX</th>
<th>TMIN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tabora Airport</td>
<td>Tanzania</td>
<td></td>
<td>42.81</td>
<td>82.68</td>
<td>79.57</td>
</tr>
<tr>
<td>Mwanza</td>
<td>Tanzania</td>
<td></td>
<td>39.86</td>
<td>78.77</td>
<td>72.99</td>
</tr>
<tr>
<td>Dodoma</td>
<td>Tanzania</td>
<td></td>
<td>81.34</td>
<td>77.13</td>
<td>71.29</td>
</tr>
<tr>
<td>Kigali International Airport</td>
<td>Rwanda</td>
<td></td>
<td>77.27</td>
<td>77.82</td>
<td>75.11</td>
</tr>
<tr>
<td>Kasama</td>
<td>Zambia</td>
<td></td>
<td>47.12</td>
<td>90.53</td>
<td>79.18</td>
</tr>
<tr>
<td>Jomo Kenyatta International Airport</td>
<td>Kenya</td>
<td></td>
<td>14.04</td>
<td>24.90</td>
<td>28.42</td>
</tr>
<tr>
<td>Eldoret International</td>
<td>Kenya</td>
<td></td>
<td>61.22</td>
<td>62.03</td>
<td>54.79</td>
</tr>
<tr>
<td>Songea</td>
<td>Tanzania</td>
<td></td>
<td>94.50</td>
<td>99.08</td>
<td>87.92</td>
</tr>
<tr>
<td>Zanzibar</td>
<td>Tanzania</td>
<td></td>
<td>80.22</td>
<td>83.48</td>
<td>78.78</td>
</tr>
<tr>
<td>Kitale</td>
<td>Kenya</td>
<td></td>
<td>33.28</td>
<td>27.54</td>
<td>23.66</td>
</tr>
<tr>
<td>Dar Es Salaam International Airport</td>
<td>Tanzania</td>
<td></td>
<td>36.34</td>
<td>20.42</td>
<td>20.42</td>
</tr>
<tr>
<td>Mombasa</td>
<td>Kenya</td>
<td></td>
<td>12.82</td>
<td>31.26</td>
<td>26.87</td>
</tr>
<tr>
<td>Malindi</td>
<td>Kenya</td>
<td></td>
<td>49.94</td>
<td>100.00</td>
<td>100.00</td>
</tr>
<tr>
<td>Garissa</td>
<td>Kenya</td>
<td></td>
<td>16.25</td>
<td>28.81</td>
<td>24.16</td>
</tr>
</tbody>
</table>
Appendix D: WaNuLCAS Inputs

This Appendix contains tables of inputs used for the WaNuLCAS model.

**Table 31. Financial inputs for WaNuLCAS (Ramadhani et al., 2002)**

<table>
<thead>
<tr>
<th>Inputs and Outputs</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Maize</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Maize Seed Price</td>
<td>110</td>
<td>tshs/ha</td>
</tr>
<tr>
<td>Maize Seed Rate Year 1</td>
<td>25</td>
<td>kg/ha</td>
</tr>
<tr>
<td>Maize Seed Rate Year 2</td>
<td>20</td>
<td>kg/ha</td>
</tr>
<tr>
<td>Fertilizer Rate</td>
<td>4</td>
<td>bags urea/ha</td>
</tr>
<tr>
<td>Fertilizer Cost</td>
<td>12000</td>
<td>tshs per bag</td>
</tr>
<tr>
<td>Threshing</td>
<td>2205</td>
<td>tshs/100kg</td>
</tr>
<tr>
<td>Maize Yield, Pure Stand</td>
<td>1943</td>
<td>kg/ha</td>
</tr>
<tr>
<td>Maize Yield With Trees Year 1</td>
<td>1749</td>
<td>kg/ha</td>
</tr>
<tr>
<td>Maize Yield With Trees Year 2</td>
<td>1090</td>
<td>kg/ha</td>
</tr>
<tr>
<td>Maize Price</td>
<td>48.5</td>
<td>tshs/kg</td>
</tr>
<tr>
<td><strong>Tree</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Transplanting, Watering, Digging Micro-catchments</td>
<td>88</td>
<td>tree/day</td>
</tr>
<tr>
<td>Transplanting Cost</td>
<td>1486</td>
<td>tshs/ha</td>
</tr>
<tr>
<td>Mortality Rate</td>
<td>34</td>
<td>%</td>
</tr>
<tr>
<td>Gapping Rate</td>
<td>34</td>
<td>%</td>
</tr>
<tr>
<td>Tree Population</td>
<td>625</td>
<td>trees/ha</td>
</tr>
<tr>
<td>Wood Price</td>
<td>3143</td>
<td>tshs/ Mg</td>
</tr>
<tr>
<td>Wood Yield</td>
<td>117.462</td>
<td>t/ha</td>
</tr>
<tr>
<td>Wood Harvesting</td>
<td>55417</td>
<td>tshs/ha</td>
</tr>
<tr>
<td>Tree Seedling Price</td>
<td>40</td>
<td>tshs/seedling</td>
</tr>
<tr>
<td>Tree Costs</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Other</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wage Rate</td>
<td>350</td>
<td>tshs/ha</td>
</tr>
<tr>
<td>Discount Rate</td>
<td>20</td>
<td>%</td>
</tr>
<tr>
<td><strong>Labour Requirements</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Land Prep</td>
<td>14.6</td>
<td>workdays/ha</td>
</tr>
<tr>
<td>Maize Sowing</td>
<td>4.3</td>
<td>workdays/ha</td>
</tr>
<tr>
<td>Activity</td>
<td>Workdays/ha</td>
<td></td>
</tr>
<tr>
<td>--------------------------</td>
<td>-------------</td>
<td></td>
</tr>
<tr>
<td>Weeding</td>
<td>16</td>
<td></td>
</tr>
<tr>
<td>Fertilizer Application</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>Maize Harvesting</td>
<td>12.1</td>
<td></td>
</tr>
<tr>
<td>Maize Threshing</td>
<td>6.3</td>
<td></td>
</tr>
<tr>
<td>Trees Seedling Transplanting</td>
<td>7.1</td>
<td></td>
</tr>
<tr>
<td>Tree Seedling Gapping</td>
<td>2.4</td>
<td></td>
</tr>
<tr>
<td>Tree Pruning</td>
<td>8.8</td>
<td></td>
</tr>
<tr>
<td>Wood Cutting</td>
<td>36.5</td>
<td></td>
</tr>
<tr>
<td>Wood Chopping</td>
<td>121.9</td>
<td></td>
</tr>
</tbody>
</table>
Table 32. Crop parameters from WaNuLCAS library (Van Noordwijk et al., 2011).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Units</th>
<th>Maize</th>
</tr>
</thead>
<tbody>
<tr>
<td>Length of generative stage</td>
<td>days</td>
<td>80</td>
</tr>
<tr>
<td>Length of vegetative stage</td>
<td>days</td>
<td>100</td>
</tr>
<tr>
<td>Is it annual crop? 1=yes, 0 = no</td>
<td>[]</td>
<td>1</td>
</tr>
<tr>
<td>Production of dry matter per day</td>
<td>kg/(m2.day)</td>
<td>0.014</td>
</tr>
<tr>
<td>Seed weight</td>
<td>kg/m2</td>
<td>0.004</td>
</tr>
<tr>
<td>Water requirement for dry matter production</td>
<td>l/kg</td>
<td>500</td>
</tr>
<tr>
<td>Ratio of height increment to biomass incr.</td>
<td>m/kg2</td>
<td>7</td>
</tr>
<tr>
<td>Maximum proportion of crop biomass remobilized as storage</td>
<td>1/day</td>
<td>0.05</td>
</tr>
<tr>
<td>component</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Extinction light coefficient</td>
<td>[]</td>
<td>0.65</td>
</tr>
<tr>
<td>Relative light intensity at which shading starts to affect crop</td>
<td>[]</td>
<td>0.9</td>
</tr>
<tr>
<td>growth</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Maximum Leaf Area Index</td>
<td></td>
<td>7</td>
</tr>
<tr>
<td>Rainfall water stored at leaf surface</td>
<td>mm</td>
<td>1</td>
</tr>
<tr>
<td>Hydraulic conductivity of roots</td>
<td>cm/day</td>
<td>0.00001</td>
</tr>
<tr>
<td>Maximum plant potential</td>
<td>cm</td>
<td>-5000</td>
</tr>
<tr>
<td>Minimum plant potential</td>
<td>cm</td>
<td>-15000</td>
</tr>
<tr>
<td>Canopy biomass for closed canopy</td>
<td>kg/m2</td>
<td>0.2</td>
</tr>
<tr>
<td>N concentration in crop tissue</td>
<td>[]</td>
<td>0.01</td>
</tr>
<tr>
<td>P concentration in crop tissue</td>
<td>[]</td>
<td>0.0025</td>
</tr>
<tr>
<td>N concentration in young crop biomass</td>
<td>[]</td>
<td>0.015</td>
</tr>
<tr>
<td>P concentration in young crop biomass</td>
<td>[]</td>
<td>0.007</td>
</tr>
<tr>
<td>N concentration in roots</td>
<td>[]</td>
<td>0.01</td>
</tr>
<tr>
<td>Type of N2 fixation</td>
<td>[]</td>
<td>0</td>
</tr>
<tr>
<td>Proportion of N from atmosphere</td>
<td>[]</td>
<td>0</td>
</tr>
<tr>
<td>Responsiveness of N2 fix. to N stress</td>
<td>[]</td>
<td>1</td>
</tr>
<tr>
<td>Fraction of reserve pool for N2 fix.</td>
<td>1/day</td>
<td>0.1</td>
</tr>
<tr>
<td>Dry weight cost for N2 fixation</td>
<td>kg(DW)/g(N)</td>
<td>0.01</td>
</tr>
<tr>
<td>Root tip diameter</td>
<td>cm</td>
<td>0.02</td>
</tr>
<tr>
<td>Max. root length density in layer1</td>
<td>cm/cm3</td>
<td>5</td>
</tr>
<tr>
<td>Max. root length density in layer Run 2</td>
<td>cm/cm3</td>
<td>3</td>
</tr>
<tr>
<td>Max. root length density in layer3</td>
<td>cm/cm3</td>
<td>0.3</td>
</tr>
<tr>
<td>Max. root length density in layer4</td>
<td>cm/cm3</td>
<td>0</td>
</tr>
<tr>
<td>Total root length per unit area</td>
<td>cm/cm2</td>
<td>100</td>
</tr>
<tr>
<td>Decrease of root with depth</td>
<td>l/m</td>
<td>7</td>
</tr>
<tr>
<td>Length per unit root dry weight</td>
<td>m/g</td>
<td>200</td>
</tr>
<tr>
<td>Root half life</td>
<td>days</td>
<td>50</td>
</tr>
<tr>
<td>Root affected by water or nutrient stress</td>
<td>[]</td>
<td>2</td>
</tr>
<tr>
<td>Parameter</td>
<td>Value</td>
<td></td>
</tr>
<tr>
<td>------------------------------------------------------------</td>
<td>---------</td>
<td></td>
</tr>
<tr>
<td>Root distribution by depth in good uptake</td>
<td>[] 1</td>
<td></td>
</tr>
<tr>
<td>Fraction of roots infected by mychorriza</td>
<td>[] 0.25</td>
<td></td>
</tr>
<tr>
<td>Reduction of constant P by root activity</td>
<td>mg/cm 0</td>
<td></td>
</tr>
<tr>
<td>Relative transfer rate for N pool</td>
<td>cm²/day 0</td>
<td></td>
</tr>
<tr>
<td>Relative transfer rate for P pool</td>
<td>cm²/day 0</td>
<td></td>
</tr>
<tr>
<td>Lignin fraction of crop residue</td>
<td>[] 0.2</td>
<td></td>
</tr>
<tr>
<td>Lignin fraction of crop root residue</td>
<td>[] 0.2</td>
<td></td>
</tr>
<tr>
<td>Polyphenol fraction of crop residue</td>
<td>[] 0</td>
<td></td>
</tr>
<tr>
<td>Polyphenol fraction of crop root residue</td>
<td>[] 0</td>
<td></td>
</tr>
<tr>
<td>Crop cover efficiency factor</td>
<td>[] 0.3</td>
<td></td>
</tr>
<tr>
<td>Fraction of crop eaten by pigs</td>
<td>[] 0</td>
<td></td>
</tr>
<tr>
<td>Fraction of crop eaten by monkeys</td>
<td>[] 0</td>
<td></td>
</tr>
<tr>
<td>Fraction of crop eaten by locust</td>
<td>[] 0</td>
<td></td>
</tr>
<tr>
<td>Fraction of crop eaten by nematode</td>
<td>[] 0</td>
<td></td>
</tr>
<tr>
<td>Fraction of crop eaten by goat</td>
<td>[] 0</td>
<td></td>
</tr>
<tr>
<td>Fraction of crop eaten by buffalo</td>
<td>[] 0</td>
<td></td>
</tr>
<tr>
<td>Fraction of crop eaten by birds</td>
<td>[] 0</td>
<td></td>
</tr>
<tr>
<td>Standard moisture content</td>
<td>[] 0.15</td>
<td></td>
</tr>
</tbody>
</table>
Table 33. Tree parameterization survey (Van Noordwijk et al., 2011).

<table>
<thead>
<tr>
<th>Growth Stage</th>
<th>Answer</th>
<th>Possible range</th>
</tr>
</thead>
<tbody>
<tr>
<td>At what age in years will tree start to flower?</td>
<td>1.5</td>
<td></td>
</tr>
<tr>
<td>How many days between flowering and fruit ripening?</td>
<td>182.5</td>
<td></td>
</tr>
<tr>
<td>What is the first month of year that it can flower?</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td>What is the last month of year for flowering?</td>
<td>8</td>
<td></td>
</tr>
<tr>
<td>What is the 'physiological age' at planting time (years)?</td>
<td>0.167</td>
<td></td>
</tr>
<tr>
<td>What is the minimum time between pruning and flowering (years)?</td>
<td>0.2</td>
<td></td>
</tr>
</tbody>
</table>

**Growth**

| How do you rank growth rate under local circumstances? | 4 | 1= slow, 2= medium, 3= fast, 4= very fast |
| Does the tree store a lot of reserves in trunks & roots? | 2 | 1= a lot, 2= average, 3= little |
| Are leaves large & heavy relative to the twigs? | 2 | 1= small & few, 2= normal, 3= heavy |
| Are leaves thick (or heavy per unit surface area)? | 2 | 1= thick, 2= normal, 3= thin |
| Is tree dry matter production proportional to its water use? | 2 | 1= efficient, 2= normal, 3= less than proportional |

**Fruit**

| Fruit growth follows Oil Palm rules? | 0 | 1= yes, 0= no |

**Canopy**

| What is the ratio of radius & height of the canopy? | 1 | |
| How high can the green part of the tree canopy be? [m] | 4 | |
| What is the maximum radius of the tree canopy? [m] | 4 | ok! |
| How dense is the canopy of a full grown tree? | 2 | 1= very open, 2= open, 3= dense, 4= very dense |
| Does the tree canopy grow at maximum density? [0-1] | 1 | 0.5= starts relatively open, 1= no change |

**Light Capture**

<p>| What is the colour of the leaves? | 1 | 1= light green, 2= normal, 3= dark green |
| Does the tree slow down in growth in partial shade? | 0.5 | 0.5= no impact till 50% shade |</p>
<table>
<thead>
<tr>
<th>Rain Interception</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td>What type of surface do the leaves have?</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1= waxy, 2= normal, 3= hairy</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Tree Water</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Does the tree show early signs of water stress?</td>
<td>1= sensitive, 2= normal, 3= tolerant</td>
</tr>
<tr>
<td>Does the tree stop growing at moderate water stress?</td>
<td>1= sensitive, 2= normal, 3= tolerant</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Litterfall</th>
<th>2</th>
</tr>
</thead>
<tbody>
<tr>
<td>How does the tree drop its leaves under water stress ?</td>
<td>1= few, 2= normal, 3= all-at-once</td>
</tr>
<tr>
<td>Does the tree drop its leaves under mild stress?</td>
<td>1= early, 2= normal, 3= late</td>
</tr>
<tr>
<td>Does the tree withdraw a lot of nutrients before litter-fall?</td>
<td>1= little, 2= normal, 3= much</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>N Fixation</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Is the tree known to be a good N2 fixer?</td>
<td>0= none, 1= low, 2= normal, 3= high</td>
</tr>
<tr>
<td>Do you want the N fixation rate to respond to N stress in the tree?</td>
<td>0= no, 1= yes</td>
</tr>
<tr>
<td>Does N fixation respond strongly to N stress?</td>
<td>0= not, 4= very strong</td>
</tr>
<tr>
<td>What are the C costs for N fixation in this tree?</td>
<td>1= low, 2= normal, 3= high</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>N&amp;P Concentration</th>
<th>2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Are woody parts known to be rich in N ?</td>
<td>1= low, 2= normal, 3= high</td>
</tr>
<tr>
<td>Are fruits known to be rich in protein?</td>
<td>1= low, 2= normal, 3= high</td>
</tr>
<tr>
<td>Is the N/P ratio of all tree tissues low, normal or high?</td>
<td>1= low, 2= normal, 3= high</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Litter Quality</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Lignin fraction of litterfall</td>
<td>0.11</td>
</tr>
<tr>
<td>Lignin fraction of pruned biomass</td>
<td>0.15</td>
</tr>
<tr>
<td>Lignin fraction of root</td>
<td>0.1</td>
</tr>
<tr>
<td>Polyphenol fraction of litterfall</td>
<td>0.04</td>
</tr>
<tr>
<td>Polyphenol fraction of pruned biomass</td>
<td>0</td>
</tr>
<tr>
<td>Polyphenol fraction of root</td>
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<tr>
<td>Parameters</td>
<td>Units</td>
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<tr>
<td>------------------------------------------------</td>
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</tr>
<tr>
<td><strong>Growth Stage</strong></td>
<td></td>
</tr>
<tr>
<td>Length of vegetative cycle</td>
<td>days</td>
</tr>
<tr>
<td>Length of generative cycle</td>
<td>days</td>
</tr>
<tr>
<td>Earliest day to flower in a year</td>
<td>Julian day</td>
</tr>
<tr>
<td>Latest day to flower in a year</td>
<td>Julian day</td>
</tr>
<tr>
<td>Initial stage</td>
<td>[]</td>
</tr>
<tr>
<td>Stage after pruning</td>
<td>[]</td>
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<tr>
<td><strong>Growth</strong></td>
<td></td>
</tr>
<tr>
<td>Max. growth rate</td>
<td>kg m⁻²</td>
</tr>
<tr>
<td>Fraction of growth reserve</td>
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<tr>
<td>Leaf weight ratio</td>
<td>[]</td>
</tr>
<tr>
<td>Specific leaf area</td>
<td>m²/kg</td>
</tr>
<tr>
<td>Water for dry matter production</td>
<td>1 kg⁻¹</td>
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<tr>
<td><strong>Fruit</strong></td>
<td></td>
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<td>Fruit growth follows Oil Palm rules?</td>
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<tr>
<td><strong>Canopy</strong></td>
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</tr>
<tr>
<td>Max. canopy height above bare stem</td>
<td>m</td>
</tr>
<tr>
<td>Ratio between canopy width and height</td>
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</tr>
<tr>
<td>Max. canopy radius</td>
<td>m</td>
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<tr>
<td>Maximum leaf area index</td>
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</tr>
<tr>
<td>Ratio leaf area index min. and max.</td>
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<tr>
<td><strong>Light capture</strong></td>
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<td>Light intensity affecting tree growth</td>
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<tr>
<td>Extinction light coefficient</td>
<td>[]</td>
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<tr>
<td><strong>Rain interception</strong></td>
<td></td>
</tr>
<tr>
<td>Rainfall water stored at leaf surface</td>
<td>mm</td>
</tr>
<tr>
<td><strong>Tree Water</strong></td>
<td></td>
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<tr>
<td>Plant potential for max. transpiration</td>
<td>cm</td>
</tr>
<tr>
<td>Plant potential for min. transpiration</td>
<td>cm</td>
</tr>
<tr>
<td><strong>N Fixation</strong></td>
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</tr>
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<td><strong>N Fixation Constant</strong></td>
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<tr>
<td>Type of N² fixation</td>
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<tr>
<td>Proportion of N from atmosphere</td>
<td>[]</td>
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<tr>
<td>Fraction of reserve pool for N² fix.</td>
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<tr>
<td>Dry weight cost for N² fixation</td>
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<td>Responsiveness of N² fix. to N stress</td>
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<tr>
<td><strong>N Concentration</strong></td>
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<tr>
<td>N concentration in carbohydrate reserves</td>
<td>g/g</td>
</tr>
<tr>
<td>N concentration in leaf component</td>
<td>g/g</td>
</tr>
<tr>
<td>N concentration in twig component</td>
<td>g/g</td>
</tr>
<tr>
<td>N concentration in wood component</td>
<td>g/g</td>
</tr>
<tr>
<td>N concentration in fruit component</td>
<td>g/g</td>
</tr>
<tr>
<td>N concentration in root component</td>
<td>g/g</td>
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</table>

Table 34. Tree parameterization generated parameters (Van Noordwijk et al., 2011)
<table>
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<tr>
<th>P Concentration</th>
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<th>g/g</th>
<th>0.022</th>
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<tbody>
<tr>
<td>P concentration in carbohydrate reserves</td>
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<tr>
<td>P concentration in leaf component</td>
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<td>g/g</td>
<td>0.00375</td>
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<tr>
<td>P concentration in twig component</td>
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<td></td>
<td>0.0015</td>
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<tr>
<td>P concentration in wood component</td>
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<td>g/g</td>
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<tr>
<td>P concentration in fruit component</td>
<td></td>
<td></td>
<td>0.0015</td>
</tr>
<tr>
<td>P concentration in root component</td>
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<td>g/g</td>
<td>0.00158</td>
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<table>
<thead>
<tr>
<th>Litterfall</th>
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<tbody>
<tr>
<td>Litterfall caused by drought</td>
<td>day-1</td>
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<td>Threshold value for litterfall due to drought</td>
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<td>Reducing factor for N of litterfall</td>
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Appendix E: Experiment 2 Supplementary Results

Figure 25. WaNuLCAS potential growth for nutrients and water
Figure 26. WaNuLCAS potential growth for unlimited nitrogen.
Figure 27. WaNuLCAS potential growth for unlimited phosphorus.
Figure 28. WaNuLCAS potential growth for unlimited water.
Figure 30. 50% precipitation.
Figure 31. 150% precipitation.
Figure 32. No nitrogen fertilizers applied.
Figure 33. 5 g m⁻² dose of nitrogen and phosphorus fertilizers.
Figure 34. 10 g m$^{-2}$ dose of nitrogen and phosphorus fertilizers.
Figure 35. Crop calendar DOY 310.
Figure 36. Crop calendar DOY 350.
Figure 37. Acacia Mangifera.
Figure 38. Autocarpus Hetrophyllus.
Appendix F: Experiment 3 Supplementary Results

Figure 39. 2035-2065 CanESM2 Run 4 rcp4.5
Figure 40. 2035-2065 CanESM2 Run 5 rcp4.5
Figure 41. 2035-2065 CanESM2 Run 5 rcp8.5
Figure 42. 2035-2065 CESM1-CAM5 Run 1 rcp8.5
Figure 43. 2035-2065 CSIRO-Mk3-6-0 Run 2 rcp2.6
Figure 44. 2035-2065 CSIRO-Mk3-6-0 Run 5 rcp4.5
Figure 45. 2035-2065 CSIRO-Mk3-6-0 Run 5 rcp8.5
Figure 46. 2035-2065 CSIRO-Mk3-6-0 Run 8 rcp4.5
Figure 47. 2035-2065 CSIRO-Mk3-6-0 Run 9 rcp8.5
Figure 48. 2035-2065 EC-EARTH Run 12 rcp2.6.
Figure 49. 2035-2065 HadGEM2-ES Run 2 rcp4.5.
Figure 50. 2035-2065 MIROC5 Run 2 rcp8.5.
Figure 51. 2035-2065 MIROC5 Run 5 rcp2.6.
Figure 52. 2065-2095 BNU-ESM Run 1 rcp2.6.
Figure 53. 2065-2095 BNU-ESM Run 1 rcp8.5.
Figure 54. 2065-2095 CanESM2 Run 3 RCP 8.5.
Figure 55. 2065-2095 CSIRO-Mk3-6-0 Run 2 RCP 2.6.
Figure 56. 2065-2095 CSIRO-Mk3-6-0 Run 3 RCP 2.6.
Figure 57. 2065-2095 CSIRO-Mk3-6-0 Run 4 RCP 4.5.
Figure 58. 2065-2095 CSIRO-Mk3-6-0 Run 4 RCP 8.5.
Figure 59. 2065-2095 CSIRO-Mk3-6-0 Run 5 rcp8.5.
Figure 60. 2065-2095 CSIRO-Mk3-6-0 Run 8 RCP 8.5.
Figure 61. 2065-2095 EC-EARTH Run 12 RCP 2.6.
Figure 62. 2065-2095 HadGEM2-ES Run 3 RCP 2.6
Figure 63. 2065-2095 MIROC5 Run 3 RCP 4.5.
Appendix G: Experiment 4 Supplementary Results

Figure 64. Experiment 4: Fertilizer application
Figure 65. Experiment 4: DOY 310
Figure 66. Experiment 4: crop calendar DOY 350
Curriculum Vitae

Name: Elaine Samuel

Post-secondary Education and Degrees:
The University of Western Ontario
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2013

Related Work Experience:
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The University of Western Ontario
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