Optimising risk and income under climate variability in Northern Ghana. A bio-economic modelling approach.

A thesis presented in partial fulfilment of the requirements for the degree of

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in

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David Ahiamadia

2024

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This statement declares the extent to which the COVID 19 pandemic impacted the scope of this Thesis. As of March 2020, before the lockdown in New Zealand, the original plan was to collect field data and household-level socio-economic data on smallholder farmers in northern Ghana. However, this was not carried out due to the border closures and travel restrictions. As a result, the focus of the Thesis shifted from conducting field data collection to using literature sources for the crop modelling process, and secondary data (Africa Rising Survey), literature sources, and in some instances, phone conversations from informants in the study area for the economic modelling components in Chapters 4,5, and 6. The initial plan for Chapter 3 was to use the Agricultural Production Systems Simulator (APSIM). However, given that the appropriate use of APSIM will require detailed field experimental data, collection of which was impossible under COVID-19 restrictions, AquaCrop was used as a substitute. Given AquaCrop's limited ability to simulate crop nutrient-specific crop yield responses, only nitrogen application rates and crop yield responses from literature sources were simulated by approximating the corresponding soil fertility stress in the AquaCrop modelling process.

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Soon after arriving in New Zealand from Ghana, David was trapped in his university accommodation for nearly three months due to stringent lockdown restrictions. He was even unable to meet me in person to discuss the inception of his PhD. Further, he could not establish any connections with other Ph.D. students. Though we managed to comfort him remotely, it was hard for him to bear the brunt of COVID 19 lockdown in a new country. Besides this hardship, he lost his beloved mother in Ghana. He could not even pay her last respect due to border restrictions, which affected him to a greater extent. Having heard of his mother's demise, he cried for 15 minutes over the phone without uttering a single word, and this still lingers in my memory.

David has not applied for a suspension but was granted a six-month extension.

With kind regards

Ramilan

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Abstract

Neglecting the potential threats posed by climate variability in northern Ghana during crop production may result in severe financial setbacks for farm households, hindering their ability to attain food security and reliable income goals. Northern Ghana, marked by its semi-arid climate, featuring a unimodal rainfall pattern and intense hot and dry weather conditions, faces unique crop farming challenges. Smallholder farmers in the region depend heavily on rain-fed agriculture, grappling with unpredictable temperatures and irregular precipitation. The absence of resources for implementing effective irrigation methods amplifies the vulnerability of these farmers to climate-induced crop failures.

In recent times, the adoption of climate-smart technologies (CSTs) has gained prominence as a strategy to mitigate yield losses. These include practices such as changing planting dates (PD), implementing compartmental bunding (CB), mulching (M), and transplanting (TP). Given that, this research aims to minimise the adverse effect of climate-related risks on the economic conditions of farm households, the study first employs stochastic dominance modelling to identify the most risk-efficient CSTs. The stochastic modelling process utilised the AquaCrop model to simulate yield variations by incorporating climate and soil data specific to northern Ghana.

Subsequently, from the Aquacrop derived yield variabilities, variations in income were generated using price data sourced from the Food and Agricultural Organization (FAO). The analysis revealed that changing planting date from April to May was the most risk-efficient choice for maize and sorghum under farmers' practice and recommended practice. However, transplanting was the most risk-efficient technology for rice farming. The study also highlights the importance of considering the risk-averse nature of smallholder farmers when selecting CSTs.

Further, although the stochastic dominance modelling was used to model income from different CSTs and their risk profiles, the approach does not consider the interaction between farmer resource endowments and preferences for risk management. Given that farming systems in the study area are heterogeneous, a multivariate statistical method was applied to 615 farm households using Principal Component Analysis (PCA) coupled with cluster analysis to generate farm types with similar characteristics. The farm household data was sourced from the Africa Rising Baseline Evaluation Survey for northern Ghana. The variables selected for the study were classified based on the following criteria: resource endowments, production goals, climate risk, demographics, production intensity, expenditure, and level of inputs. Eventually, farm types one, two, and three were identified as most resource-endowed, moderately resource-endowed, and less resource-endowed, respectively. This study further employs a novel weighting system to address the level of importance farmers attach to their risk and income objectives. Due to the limitations in resource endowments, all farm types attached more weight, albeit differently, to low-risk, less-income-generating activities as their climate risk management strategy.

Against this backdrop, many risk-averse smallholder households are willing to compromise by accepting lower returns in exchange for a more stable income. To achieve this, the study analyses the interactive effect of socio-economic and biophysical risk sources on the income-risk trade-off decisions of farm typologies by employing a mixed integer quadratic compromise risk programming model. The model was developed from three theories: Compromise programming, Quadratic programming, and Linear expenditure system. By generating an income-risk frontier, the model proposes a combination of crops farmers could grow to minimise risk and obtain a stable income. Further, the model analyses the implications of non-separability in consumption and production on each farm type's risk and income trade-offs and expenditure patterns. Also, farm-type wealth effects on crop choices were determined by the weight farm households attached to their risk and income objectives. As a result, the findings of this study indicate that to achieve a stable income, relatively poor households should focus on growing maize (1.07 Ha) with rice (0.68 Ha), sorghum (0.23 Ha) and groundnut (0.02 Ha), while wealthier households grow rice (2.16 Ha), plus sorghum (0.98 Ha), and groundnuts (0.36 Ha). Moderately wealthy farmers should grow maize (0.50 Ha), rice (0.36 Ha), sorghum (0.29 Ha), and groundnut (0.05 Ha). Given the heterogeneous nature of smallholder farming systems in northern Ghana, this research approach is very useful for household-level income-risk decision-making under climate risk.

Keywords: climate, crops, programming, risk, smallholder farmers, variability

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Peter, your level of intelligence is beyond my comprehension; you charted the course of my PhD. I remember very well how you suggested Compromise Programming as an ideal approach for my study. I left your office after that meeting with a clear sense of direction. I can confirm that this was a turning point in my doctoral journey. I am greatly indebted to your constructive feedback, which has improved my writing skills significantly.

Thanks to the School of Agriculture and Environment, Massey University, my office mates, flatmates, the African Students Association, and the Ghanaian community in Palmerston North for their support during my stay in New Zealand.

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DEDICATION

This thesis is dedicated to my late mother, Mrs Elizabeth Asantewaa Bright who passed away three months into my PhD. Rest well Mama!

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Chapter 1 Introduction

1.1 Introduction

As the majority of smallholder farmers in developing countries continue to depend on rainfed agricultural systems, climate variabilities such as changes in temperature and precipitation, impose significant production risk, and impacts their decision-making processes (Bhave et al., 2016). These impacts affect poverty alleviations among households in developing countries (Hallegatte et al., 2016). In West Africa, studies have revealed how developments and living conditions will be adversely affected as a result of future climatic conditions (Adiku et al., 2015). Climate change model projections have predicted worsening climatic uncertainties on the availability of water, land, and other important resources needed for crop production (Asante & Amuakwa-Mensah, 2015; Laube et al., 2012). As stated by Amikuzino and Donkoh (2012), the unpredictable pattern of rainfall in Ghana, threatens the country's food security since most Ghanaian farmers practice rain-fed agriculture.

In recent years, agriculture has been a major contributor to reducing poverty in Sub-Saharan Africa (Davis et al., 2017). About 80% of Ghana's agricultural output is produced by subsistent smallholder farmers holding approximately 1.2 hectares (3 acres) of farmland (Mahama, 2012, FAO, 2013). This makes smallholder farming a significant player in Ghana's agricultural sector. Smallholder Ghanaian farmers often lack resources such as land, labor and capital needed for production, and are mostly confronted with insufficient food, increased poverty, food insecurity, and unstable income (Asante et al., 2018).

Furthermore, farm systems among smallholder farmers in Ghana are heterogenous in nature. Farm systems are defined by Giller (2013) as a number of farm enterprises with different resource endowments, system constraints, livelihoods, and business patterns. Smallholder farming systems share certain features which makes them different from large scale commercial farms. (Kuivanen et al., 2016). The characteristics of smallholder farms in Ghana include limited land, insufficient financial and production inputs, low level of marketing of farm produce, and vulnerability to climate change among others (Kuivanen et al., 2016). The interaction between biophysical and socio-economic conditions in the context of smallholder farming systems results in smallholder farmer diversity in terms of resource endowments (Chapoto et al., 2013; Ngeleza et al., 2011; Tittonell et al., 2010). Furthermore, it is important to note that not all smallholder farmers have limited resources, hence the need to further acknowledge the concept of heterogeneity (Kuivanen et al., 2016).

Typically, studies involving stratifying farmers into typologies are useful in minimising heterogeneity, designing implementations, monitoring, and the development of agricultural projects (Alvarez et al., 2014; Byerlee et al.,1988; Emtage at al., 2007). Furthermore, farm typologies can also serve as a reliable source of information for academics researching into farming systems. Constructing smallholder farm typologies is also helpful for bio-economic modelling of farm systems for *ex ante* technology intervention analysis (Andersen et al., 2007). According to Köbrich et al. (2003), the best way to classify smallholder farming systems is to group them into subsets that are homogeneous in nature in terms of market orientation, livelihoods, enterprise size, resource endowments and constraints. The type of grouping will depend on the objective of the smallholder farmers and the kind of household data available (Kostrowicki, 1977; McKinney, 1969).

1.2 The study area

The study area covers three districts namely Tolon-Kumbungu, Savelugu Nanton, and West Mamprusi. These districts are located in the Savannah, Northern and North East regions of Ghana (Figure 1.1) which forms part of the Guinea savannah agro-ecological zone. The predominant soil type in the region is Savanah Ochrosols (Mustapha et al. 2020). The region has a land area of approximately 70,383 km2 representing about one-third of Ghana’s land mass (Mustapha et al. 2020). The Dagomba ethnic groups are the most predominant in the area, comprising about one-third of the population (Ellis-Jones et al. 2012). According to Al-Hassan and Poulton, 2009, the social structure in the area typically involves a male-headed household residing within a compound housing system. This household may consist of either the man's nuclear family or his extended family, often spanning three generations. This could include his wife or wives, sons, daughters, daughters-in-law, and grandchildren The household head has the authority to demand labour from any member to ensure constant food supply for all. This obligation persists even if the son or daughter leaves the parental compound, provided their new location is closer to the farm (Al-Hassan and Poulton, 2009). In the event of the household head's death, the responsibility for food production and managing labor needs transfers to the eldest son (Al-Hassan and Poulton, 2009).

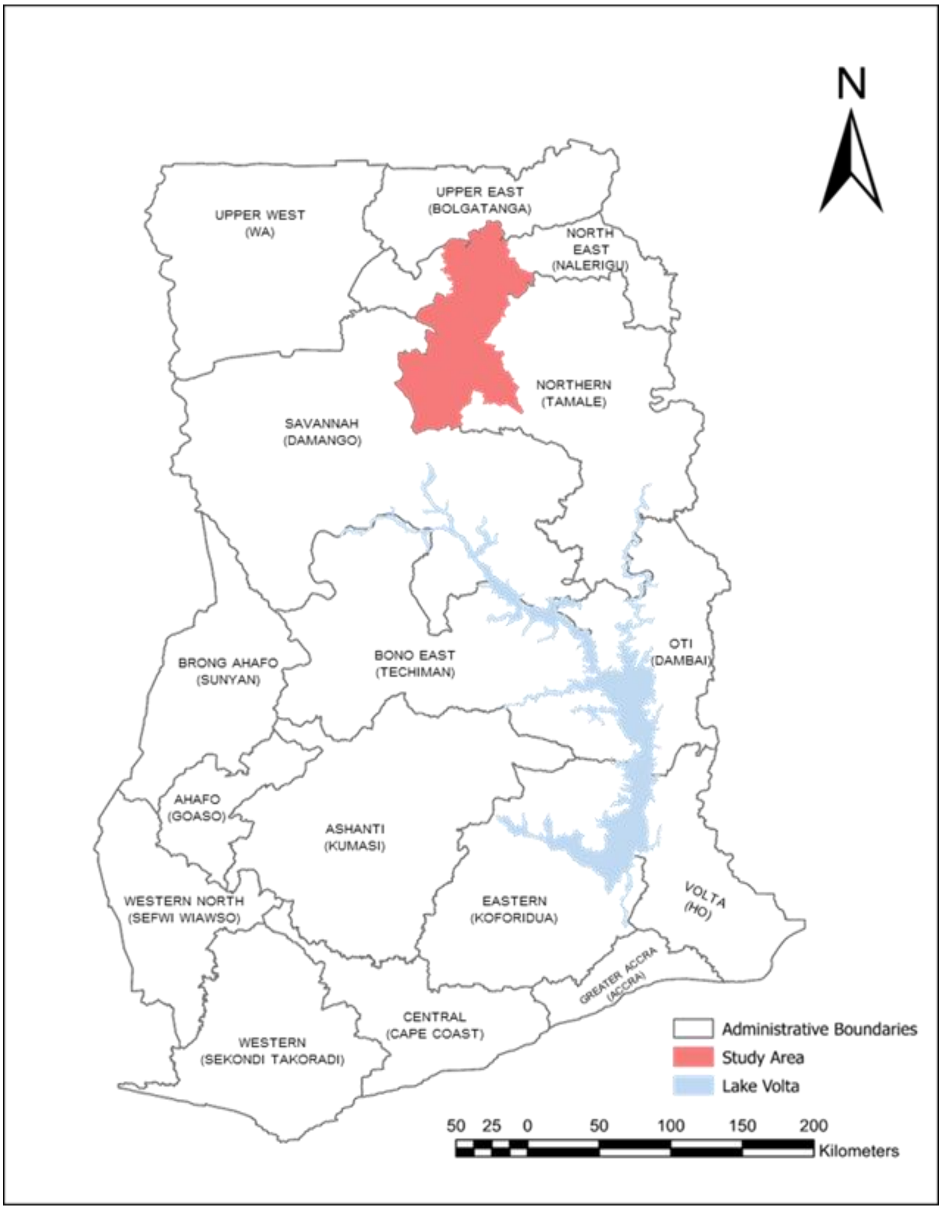

Figure 1.1. Map of Ghana showing the study area

1.3 Why northern Ghana?

This study focused on the northern region of Ghana for a number of reasons. Firstly, northern Ghana is the leading producer of most grains and cereals including maize, rice, and sorghum (Yiridoe et al. 2006). About 90.5% of the households are rain-fed crop farmers with limited capacity to mitigate the negative effects of climate variabilities due to rainfall dependency, low socio-economic development, resulting in major adverse impacts on crop yield (Antwi-Agyei et al. 2012). Apart from the commercial rice farms managed by the Ghana Irrigation Development Authority, subsistence farmers have very limited access to irrigation water (Yiridoe et al., 2006).

Secondly, it is the most climate vulnerable region in the country with limited farm-type specific climate smart research and intervention policies. The region is characterised by a long dry period of approximately seven months (Amikuzuno and Donkoh, 2012), with about 90% of the 1000mm average annual rainfall occurring between May to October each year (Owusu, 2018). The region has a unimodal rainfall distribution (see Figure 3.5), allowing only for a single growing season (Nyour et al., 2016; Yaro et al. 2015). From Yiridoe et al. (2006), scattered traces of rainfall occur from March to April, peaks in August/September and declines to almost no rain by November. The dry season is also characterised by frequent bush fires which leave the soil bare (Yirdoe et al., 2006).

Climate variability in the study area is very volatile, Figure 3.6 provides a detailed annual visualisation of the wet and dry seasons. Extremely red portions show 0 mm monthly rainfall and deep blue portions represent 300 mm or more monthly rainfall. Clearly September 2010 recorded the highest rainfall in the period at about 300mm. In addition, about 50mm of rainfall occurred in April for most years unlike 1998, 2015, 2016, and 2017 which experienced rainfall below 50mm. The heat map indicates a variation between the November to March dry season which records the lowest rainfall margins and the April to October wet season.

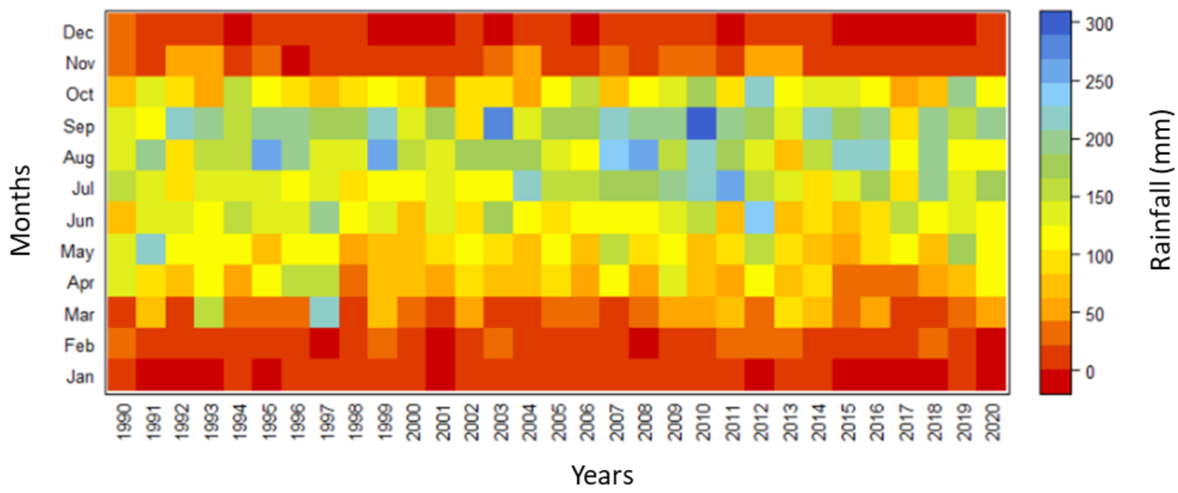

Figure 1.2. Annual visualization of wet and dry seasons

Further, of all the regions in Ghana, the northern region is the leading producer of most grains and cereals such as maize, rice, groundnut, sorghum, millet, and cowpea as well as yam and tobacco (Yiridoe et al., 2006). However, due to harsh climatic conditions and the dependence on rainfed agriculture, the region is considered as the poorest in the country with rural poverty rate reaching 52% of the rural population (Amikuzuno and Donkoh, 2012).

For the above reasons, this study focuses on analysing farm household income and risk decisions by optimising income and climate risk in the region through the development of alternative cropping patterns subject to farm household resource constraints and risk preferences. In brief the rationale of this research is to help farmers develop better cropping decisions based on optimal quantities of inputs and resources needed to maximise income and consumption whilst minimising climatic risk given the transaction costs incurred by farmers.

1.4 Research questions

Based on the above information, the following research questions have been formulated

1. What is the most ideal cropping pattern under climate risk for small holder farming households in northern Ghana?
2. Which climate-smart agriculture technologies should farmers adopt to remain resilient?
3. Do transaction costs, resource endowments, and the non-separability in production and consumption have an impact on the income-risk trade off decision making of smallholder households in northern Ghana?
4. What are the climate risk trade-off implications on household income and consumption?

1.5 Research objectives

To address these research questions, the objectives of the study were to:

1. Explore the heterogeneity among smallholder farm households in northern Ghana.
2. Identify climate-smart agricultural technologies suitable for smallholder farmers in the study area.
3. Develop a climate risk programming model for decision making on cropping patterns for smallholder farmers in northern Ghana using bio-economic and mathematical programming techniques.

4. Application of the model to analyse the effect of the climate risk on household income and consumption.
5. Application of the model to examine how transaction cost, non-separability in production and consumption, and household resource endowments affect smallholder farmers’ risk and income trade-offs.

To answer the research questions and achieve the research objectives, a compromise risk programming model will be developed. The uniqueness and relevance of the model developed in this thesis is the ability to represent the decision maker’s (smallholder farmer) preference in choosing the trade-off between risk and income for a given cropping pattern. Also, the model is capable of analysing the effect of transaction costs and non-separability between consumption and production among farm households, an area which is often neglected in studies regarding risk in farm-household decision making. The developed model potentially would measure household utility and produce a set of solutions closest to the ideal decision in a real-world sense. It also provides a platform to analyse risk in terms of variability in income arising from the variability in yield as a result of biophysical conditions related to climatic uncertainties.

The structure of the thesis begins with the introduction Chapter 1 as discussed above, followed by the literature review Chapter 2. The modelling framework is discussed in Chapter 3 and the selection of risk resilient climate smart technologies is explained in Chapter 4. Chapter 5 develops farm typologies for the bio-economic model. Chapter 6 explains the bio-economic model development process based on findings from previous chapters and analyses the income-risk trade-off decision making for smallholder farmers. Chapter 7 concludes with a general discussion of the research process, limitations and implications for future research.

Chapter 2 Literature review

2.1 Introduction

Recently, bio-economic farm models, particularly those involving the combination of biophysical and mathematical programming techniques for agricultural farm households have received significant attention (Flichman & Allen, 2015). There is increasing interest in the use of bio-economic farm models for research projects, especially those requiring multidisciplinary methods (Janssen & Van Ittersum, 2007). The dynamic effects resulting from the linkages between economic and biophysical factors such as soil and climate change indicators can be explored using bio-economic farm models (Holden, 2006). Louhichi et al. (2013) explains that the growing interest in bio-economic farm modelling in recent years among several factors could be associated to the following: (i) the surge in the demand for impact assessment tools and approaches; (ii) the search for an in-depth knowledge regarding on-farm decision making; (iii) the increase in farm specific policies and the heterogenous policy impacts at farm and regional levels; and; (vi) the fact that bio-economic farm models can be user friendly for both standard and more sophisticated computer packages (example, spreadsheets and General Algebraic Modelling System-GAMS). Also, using a mathematical programming approach, bio-economic models can be applied to household consumption risk analysis, adaptation options, and climate variability assessments (Wossen et al., 2014)

This review defines a bio-economic farm model “as a model that links a farm’s resource management decisions to current and alternative production possibilities describing input-output relationships and associated externalities” (Janssen et al., 2010 p. 863). Holden et al. (2006) justify the use of bio-economic models for policy analysis due to their ability to integrate socio-economic and bio-physical characteristics for farm level decision making. Further, Janssen and Van Ittersum (2007) revealed that the effect of policy or a change in an agricultural technology, *ex- post* or *ex-ante* can be assessed using bio-economic farm models.

According to Janssen et al. (2010), these models are mostly site-specific implying that they are often not re-used as they are mostly developed for a location or objective. Apart from the German model called Multi-Objective Decision support tool for Agro-ecosystem Management (MODAM) which has been used in different European jurisdictions including Germany, bio-economic farm models are scarcely used in different locations for different purposes (Kächele & Dabbert, 2002; Meyer-Aurich et al., 1998; Uthes et al., 2008). Another model that has been re-used for sheep arable farms is the Model of an Integrated Dryland Agricultural System (MIDAS) which was frequently used in South-West Australia (Gibson et al., 2008; Kingwell et al., 1995; Kopke et al. 2008). Similarly, MIDAS was applied to a representative farm model in Hamilton, South West Victoria, where the model was used to produce optimum long-term management strategies for different sheep pasture systems (Young et al, 2004).

On the other hand, Janssen et al. (2010) indicates that there is widespread use of crop production system models such as the Agricultural Production Systems sIMulator (APSIM) to generate inputs for bio-economic models for different locations and purposes. Also, for diverse crops and ecological conditions, the CropSyst model has been used very frequently (Confalonieri and Bocchi, 2005; Pala et al; 1996). In addition, Rosegrant et al. (2014) also revealed that output in terms of crop yield under climate change produced from the Decision Support System for Agrotechnology Transfer (DSSAT) model was used as input in the IMPACT model to assess the effect of climate change on food prices and trade on a global scale.

From the above arguments, location specificity is noted as a shortfall for most bio-economic farm models, more weaknesses will be discussed further in this chapter; however in terms of policy experimentations, intervention assessment, and land use intensification, the use of bio-economic farm modelling have become progressively popular.

2.2 Background of bio-economic farm models

Farm-level modelling is often developed using mathematical programming, econometric, simulation approach, or agent-based modelling (Louhichi, 2013). The mathematical programming approach can involve linear programming (LP), quadratic/non-linear programming (NLP), positive mathematical programming (PMP), mixed integer programming (MIP) (Louhichi, 2013). For the purposes of this study, the focus is on farm-household models based on mathematical programming models which seek to minimise or maximize a certain objective or group of objectives subject to a set of constraints. Two main categories are often associated with farm household programming models, this involves the situation where the farmer is considered as a single supplier, or group of producers who supply to the market, to make profit or those that are both producers and consumers at the same time (Louhichi & y Paloma, 2014). The latter is often applied to peasant farmers in developing countries where non-separability in consumption and production decisions including allocation of labour are often concurrent (de Janvry et al. 1991), whereas the former applies to farmers in developed countries. For each of the categories, farm-household programming models can be grouped into static or dynamic models (Flichman and Allen, 2015).

2.2.1 Static models

Janssen et al. (2010) revealed that, static farm programming models are models used to analyse bio-economic interactions without time dimension. An example of such models is the Tunisian farm model developed by linking a bio-physical model with a multi-objective programming model (Mimouni et al., 2000). Results from the bio-physical model which is the Erosion-Productivity Impact Calculator (EPIC), were produced by simulating environmental interactions such as soil tillage, erosion, weather, pollution from pesticides and nitrates, hydrology, and plant development (Mimouni et al., 2000). The results were used as input data in the form of discrete variables for a mathematical programming model, making it useful in examining the trade-offs between farm income, pollution and soil erosion levels (Flichman and Allen, 2015).

Another type of static model is the FarmDESIGN model which uses genetic algorithms, developed and implemented in an organic farm located in the Netherlands (Groot et al., 2012). It is an extension of a static model developed by Van Keulen et al. (1998) called FARM model. The FarmDESIGN model employs multi-objective optimisation which seeks to analyse the synergies between environmental and socio-economic factors by maximising profit and organic matter balance as well as minimising labour requirements and nitrogen losses in the soil (Groot et al., 2012). From the authors' perspective, the model is generic enough to be replicated in contrasting environmental regimes as it has been applied in the arid regions of Mexico (Flores-Sanchez et al., 2011), and used in research projects conducted by students in Nepal, India, and Uruguay (Flichman and Allen, 2015).

In addition, the MODAM model, is a hierarchically structured LP model which works well for multiple objectives under sustainable agricultural practices at the farm level (Kachele and Dabbert 2002; Meyer-Aurich et al., 1998; Meyer-Aurich, 2005; Uthes et al., 2008). This model helps to explain the interdependencies within agro-ecological systems and potential trade-offs (Flichman and Allen, 2015) and has been applied to several projects in north-east Germany ((Schuler & Kächele, 2003). However, although the model has not been applied in a dynamic approach, it is well suited for both dynamic and static applications and can also be used to analyse single and regional farm modelling (Zander & Kächele, 1999).

2.2.2 Dynamic models

Dynamic models are multi-stage temporal models that can analyse the consequences of decision-making over time (Propoi & Krivonozhko, 1978). A dynamic model such as the Nitrogen Dynamics in Crop rotations in Ecological Agriculture (NDICEA) model developed by Van Keulen et al. (1998) was used to estimate nitrogen leaching and soil moisture content, and to calculate the gains and losses of nitrogen in crop rotations as well as organic matter dynamics. The NDICEA model optimises crop rotation dynamics at field levels by finding the potential nitrogen (N_2) and mineral (N) fixed in the topsoil (Van Kuelen et al., 1998). Another model to be discussed in this review is the Cebalat Model which is a dynamic stochastic model used to assess the sustainability of irrigation systems in the Cebalat district located in Northern Tunisia (Belhouchette et al., 2012). The stochastic component of this model differentiates it from other models and has a moving time span of 10 years.

Further, the Nutrient use in Animal and Cropping systems (NUANCES) FARM SIMulator (NUANCES-FARMSIM) is a dynamic livestock farm model applied in the Sub-Saharan African smallholder farming context (Van Wijk, 2007). The FARM SIMulator was developed to examine the trade-offs between labour use and the allocation of resources among heterogenous farm households (Tittonel et al., 2007). Heterogeneity in smallholder farm systems form the basis of the NUANCES model, as a result of this, FARMSIM emphasises effective decision making at the smallholder farm level (Giller et al., 2006). The FARMSIM model comprises of different modules namely; the Field-scale resource Interactions, use Efficiencies and Long-term soil fertility Development module (FIELD), the LIVestock SIMulator (LIVSIM) and the HEAPSIM module for manure intake and storage and quality analysis (Tittonel et al. 2007). Simulation results from the sub-modules are combined with that of household resource constraints, objectives and resource allocation for farm level decision making (Tittonel, 2007). According to Van Wijk (2009), NUANCES-FARMSIM can be used to analyse long term farm management strategies.

Moreover, Flichman et al. (2016) also developed the Dynamic Agricultural Household Bio-Economic Simulator (DAHBSIM) model, a model suitable for developing country smallholder farm households which seeks to address challenges related to bio-physical constraints and the impact of alternative approaches to agricultural sustainability and intensification on whole farm planning. Flichman et al. (2016) explained that the model is dynamic as a result of the following: (i) values at the end of a particular simulation are employed as starting points in the next activity to be simulated (ii) the model is intertemporal, as the equations in the model (ie. the objective function and the constraints) are specified over a time period. The model dynamics are such that it can capture long-term variations in soil conditions depending on the crop management practices or decisions employed overtime (Komarek et al., 2017). In addition, the DAHBSIM model is flexible enough for updating any change in bio-physical conditions such as changes in soil moisture content, nutrients, or organic matter by taking into consideration the management decisions and type of crop grown in the previous production season (Komarek et al., 2017). Further details about the DAHBSIM model will be discussed in subsequent sections.

2.3 Approaches to bio-economic modelling

This section explains approaches used in bio-economic modelling. Studies have revealed that based on the type of farm management problem to be addressed and how sophisticated the resource management challenge is, two main types of modelling techniques are used in bio-economic modelling (Brown, 2000). These techniques are simulation modelling methods which have some form of socio-economic input and economic optimization methods which are somewhat connected to some bio-physical features (Brown, 2000). The economic optimisation method is hereafter referred to as optimisation.

2.3.1 Simulation

According to Pandey and Hardaker (1995), simulation models are models that do not usually consist of an optimising algorithm hence are useful in analysing “what if” circumstances and are also appropriate for non-linear systems that are subjected to some form of stochastic variation. For Pandey and Hardaker (1995), such models are by nature what the modeller wants to make of them depending on whether the type of data available is sustainable enough. Paul and Chanev (1998) revealed that simulation models are models used to design several agricultural systems. These models give room for the inclusion of specific features characteristic of the system being simulated such as time and behavioural dynamics (Paul and Chanev, 1998). In whole-farm modelling, approaches used for simulation models range from simple procedures to very complex ones (Panell, 1996).

Furthermore, simulation models are very applicable and useful in comparing several scenarios for policy implementation (Woodward et al., 2008). A characteristic of a simulation model is that it represents realities in a more transparent way, hence in making policy evaluations, it is reliable to compare its' output with outputs from other models (Romera, 2004). However, Woodward et al. (2008) argue that most simulation models used in farm systems only simulate on single farm basis without evaluating uncertainties. As a result of this, policy comparisons are conducted outside the simulation software (Woodward et al., 2008). This implies that users must develop their own methods in comparing risks and uncertainties when choosing amongst alternative farm management policy options (Woodward et al., 2008).

2.3.2 Optimisation

Optimisation involves finding the optimal values for decision variables given a set of constraints whose relationships must be satisfied (Loucks and van Beek, 2017). Optimisation models could be presented as linear or non-linear models (Benli and Kodal, 2003). Linear optimization models require parameters in the objective function and the constraints to be linear, however, this is not always the case in real life. On the other hand, non-linear models, like quadratic programming models, are not limited to linearity hence they are suitable for farm planning models that are not linear in nature. For non-linear real-life observations, a more reliable result can be obtained by using NLP models rather than trying to linearize non-linear functions (Benli and Kodal, 2003).

Sonmez and Altin (2004) used LP to develop a model for optimum cropping patterns under deficit and adequate water supply in the Harran plain in Turkey. Amir and Fischer (1999) also used LP to maximise net income under various water demand activities for agricultural production. Maximum net returns and cropping patterns were modelled using LP by estimating water requirements for wheat and rice as well as total water availability (Singh et al. 2001). A similar modelling approached was employed for a multi objective optimisation which used a LP algorithm to produce a lower and upper boundary of net benefits, labour, and agricultural production in India's SRI Ram Saga project (Raju and Kumar, 1999).

2.3.3 Merging static optimisation and dynamic simulation models

As indicated by Robertson et al. (2012), in order to minimise the limitations of using only static optimisation or dynamic simulation approaches, some emerging studies have employed the use both methods for whole farm modelling. The study revealed that, static optimization can be used to choose the most realistic boundaries for optimal farm decision making. Within these boundaries, bio-physical variabilities such as climate change, crop rotation, changes in input levels and variations in stocking rates can be simulated (Robertson et al., 2012).

Under conditions of resource constraints amongst smallholder farmers in Africa, combining static optimisation and dynamic simulation improves the chances of addressing matters of uncertainty (Whitbread et al., 2010). This combination approach employs the strengths of optimization and simulation by relying on the sophisticated capacity of simulation models like APSIM, coupled with results from socio-economic surveys that provide deep insight on farm household resource flows and constraints (Robertson et al., 2012). Furthermore, as bio-economic modelling is the focus of this review, the study suggests that a combination of simulation and optimisation models is crucial in developing LP and non-LP models with a bio-physical component.

2.4 Classification of bio-economic farm models

The farm household is regarded as the decision-making unit of agricultural systems, helping in the understanding of the performance of productive units and the interactions between production activities (Flichman and Allen, 2015). There are a variety of farm household bio-economic modelling approaches that can be used to assess and assist the sustainability of farms and support farm households' ability to manage and understand their production systems (Flichman and Allen, 2015). We categorise such models into mechanistic, empirical, deterministic, and stochastic models.

2.4.1 Mechanistic models

Mechanistic models are models that allow for the introduction of already existing knowledge and theory (Austin et al., 1998). These types of models also rely on knowledge from expertise in the field of study and are mostly used for large-scale economic modelling (Austin et al., 1998). Mechanistic models could be applied at different locations because they are process based (Pandey and Hardaker, 1995). However, as a result of the huge data requirements and the high cost involved in calibrating and developing such models, most researchers find it challenging to use them. (Pandey and Hardaker, 1995). Furthermore, simulations are suitably done using mechanistic models for short and long-term predictions and extrapolations (Antle and Capalbo, 2001). This is because mechanistic models can simulate exogenous behaviours not included in the observed data but consistent with scientific knowledge (Antle and Capalbo, 2001). In addition, mechanistic models can be developed by identifying the hierarchical structure of a system under study, breaking it into specific compartments and examining the behaviour of this system based on the system's key components and internal relationships (France and Kebreab, 2008). An example is a model developed by Dijkstra (1994) which uses a dynamic mechanistic approach to simulate nutrient flow, absorption, and digestion in the rumen using nutritional inputs.

Kebreab et al. (2019) revealed that a properly developed mechanistic model will at its best produce a more accurate prediction of the functions in a system to the extent that, it can extrapolate beyond the scope of data used to develop it. For instance, whilst analysing the use of mechanistic and empirical models to predict methane gas production of cattle in the United States, Keabreb et al. (2008) revealed that mechanistic models performed better than empirical models and produced a more reliable assessment of the efficacy of mitigation alternatives such as adding fat to diet to reduce methane emission or changing the sources of carbohydrate in the cattle diet at whole-farm level. France and Thornley (1984) further described mechanistic models as descriptive models that provide an understanding of a system by explaining the underlying behaviour of the processes involved at different levels. Also, mechanistic models that are well developed must have an explanatory power that can be applied generically (Clifford and Müller, 2013).

2.4.2 Empirical models

On the other hand, empirical models are developed from the data embedded in them and analyse the relationship between observed data for future purposes (Austin et al., 1998). Janssen and van Ittersum (2007) explained that future variations in events can mostly be predicted by empirical models using historical time series data. This is done by the extrapolation of such data and the description of agricultural technologies that have historical antecedents (Janssen and van Ittersum, 2007). As a result of this, dealing with new/alternative technologies, new policies or new constraints are often difficult to handle using empirical models.

More so, according to Pandey and Hardakar (1995), empirical models are site specific, they translate data inputs to model outputs. Austin et al. (1998) indicate that although empirical models are driven by observed data, they have some form of theoretical content. According to Kebreab et al. (2019), empirical models make use of experimental data to examine relationships at a specific stage of an organizational hierarchy. For instance, Niu et al. (2018) used empirical models to analyse the link between enteric methane (CH_4) emissions from cattle and milk production, feed intake on daily basis, and nutrition in diets. Kebreab et al (2019) revealed that although empirical models can describe the inherent variation in a system based on data available, they do not typically explain the underlying reasons behind the variations. This is because such models only rely on observations and results from experiments (Kebreab et al., 2019). France and Thornley (1984) also explained that empirical models can produce a better fit for a given data set compared to a mechanistic model. The reason being that empirical models have lesser constraints unlike mechanistic models which are often constrained by assumptions even when its parameters can be adjusted (France and Thornley, 1984).

2.4.3 Deterministic models

Deterministic models are models that do not include uncertain parameters; hence, researchers must be cautious in using such models because they could provide a misleading information about future uncertainties (Woodward et al., 2008). This suggests that uncertainties should be considered when analysing outputs from deterministic models. Schultz (1939) argues that farming is about managing uncertainties to a large extent rather than managing complexities. This implies that on-farm decision makers investigate and select options that are robust under uncertainties rather than just choosing the mean optimal solution (Woodward et al., 2008).

Thornley (2001) affirms that without any form of probabilities, deterministic models produce definite predictions such as livestock feed intake and plant biomass which is acceptable in some situations. This implies that deterministic models yield precise solutions from the set of equations used in the modelling process (McPhee, 2009). However, for variable observations or processes such as rainfall distribution, death, pest and disease infestations from one place to another, or the influx of predators, using deterministic models could be less satisfactory (Thornley, 2001). In addition, Pannell et al. (2000) explain that some deterministic mathematical programming models like the MIDAS developed by Kingwell and Pannell (1987) select diversified strategies for whole farm planning to reduce risk by including relevant bio-physical characteristics in the model.

2.4.4 Stochastic models

Stochastic models account for variations in probabilistic functions that may be difficult to comprehend (McPhee, 2009). They consist of at least one random element that can be predicted with a given probability distribution. The challenge with stochastic models is the difficulty with which it can be tested (Thornley, 2001). Despite the challenges involved in using stochastic models, France and Thornley (1984), argue that the more uncertain the behaviour of a system is, the better it is to develop a stochastic treatment. This is because, applying a stochastic treatment makes it easier to determine the probabilistic outcome of a random process. Also, stochasticity models can be employed as a measure of uncertainty in cause and effect relationships or population variance (Clifford and Müller, 2013).

Further studies have revealed that the application of stochastic programming and robust optimization (Mulvey et al., 1995) under uncertainty has been widespread especially in the area of production planning (Brandimarte, 2006; Escudero et al., 1993; Huang, 2005; Karabuk, 2008). According to Kazemi Zanjani et al. (2013), unlike deterministic models, stochastic models have demonstrated the relevance of including uncertain parameters into production planning. This is because, in real life situations stochastic models produce more robust results for production planning purposes than deterministic models (Kazemi Zanjani et al., 2013).

2.4.5 Handling stochasticity in programming models-A state-contingent approach

Decisions are made on the farm by farm managers or farmers however, such decisions are made at the time when the outcome is not typically known to the farmer with certainty (Rae, 1971). As a result, it is suggested to formulate most farm management problems in the form of decision theory since they consist of possible actions to be taken, probabilities, and different states of nature (Rae, 1971). Chambers and Quiggins (2000) define states of nature as “a mutually exclusive and exhaustive set of possible descriptions of the state of the world” (p.17). In terms of agricultural production, this implies that all possibilities of future weather conditions such as temperature, rain or no rain, and drought can be classified as states of nature.

Whilst explaining the outcome of risky choices, Hardaker et al. (2015) indicate that a state contingent decision is a decision made based on the expected state of nature such as the probability of rainfall, disease infestation, high or low temperatures or drought. From the studies of Chambers and Quiggin (2000), the best way to analyse and think through decision making problems in economics of uncertainty comprising of producer and consumer choices is by employing the state contingent approach. This is because agriculture production is an uncertain business hence the challenge of uncertainty is of principal concern to policy makers of all agribusiness sectors ranging from agricultural product marketing to irrigation water use efficiency (Quiggin and Chambers, 2006).

According to Hardakar et al. (2015), depending on the expected state of nature, decision trees can account for the effect of risky choices. In addition, Chambers and Quiggins (2000) explained that, the decision maker has no power over which state of nature occurs, however decisions are affected by the state of nature which eventually occurs. An example could be the case of smallholder farmers in northern Ghana who wish to cultivate maize during the growing season. However, they have a choice of two varieties, an expensive drought resistant variety and a less expensive non-drought resistant variety, both producing the same yield per acre. The farmers can do nothing about which state of nature will eventuate in the future (ie: whether it will rain in the season or not). If they choose the drought resistant variety and it rains, the farmers lose income as they could purchase a non-drought resistant variety and get the same yield. Nonetheless, if they choose a drought resistant variety and it doesn’t rain, they receive relatively higher returns. On the other hand, if they choose a non-drought resistant variety and it doesn’t rain, they lose money. However, if they choose a non-drought resistant variety and it rains, they save money. This is represented in the decision tree in Figure 2.1 below.

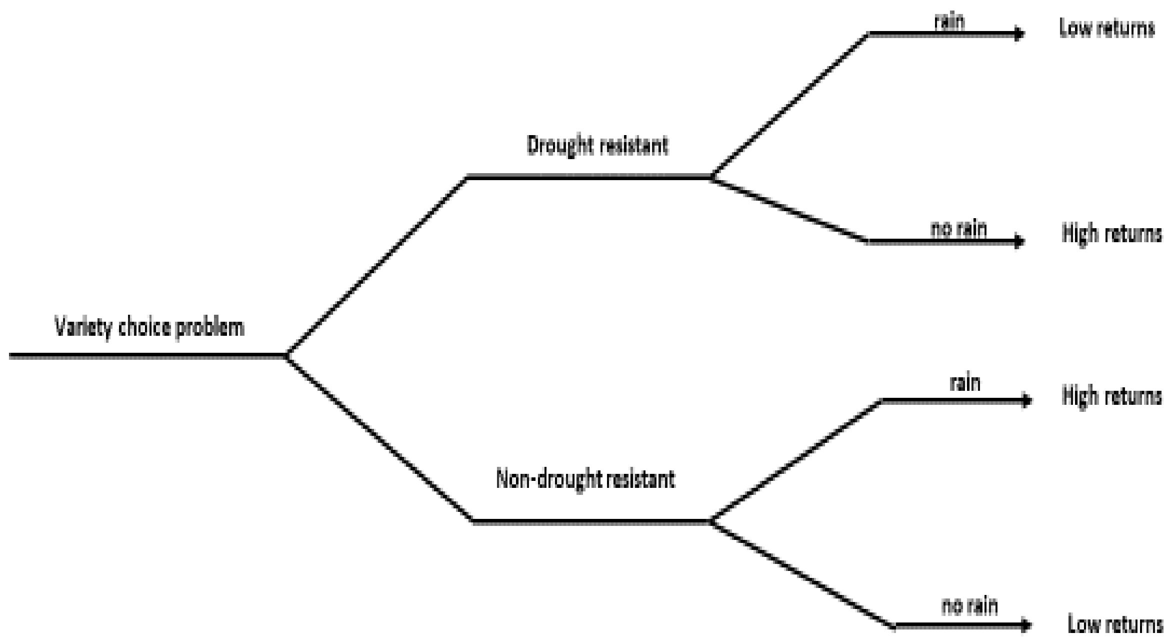

Figure 2.1. A decision tree for smallholder farmer maize variety choice
Source: Hardaker et al. (2015)

2.4.6 Discrete stochastic programming- A curse of dimensionality phenomenon

As most farm planning choice problems deal with risky events at different stages due to uncertainty, it is most appropriate to handle such problems using a discrete stochastic programming approach (Rae, 1971). This is because discrete stochastic programming is state-contingent (Trebeck and Hardaker, 1972) and can specify the probabilities of the states of nature, the consequences of the decisions made based on the state of nature which eventually occurs and its impact on the farmer's utility function to be maximized (Rae, 1971). Cocks (1968) reveals that the discrete stochastic programming procedure involves the identification of all mutually exclusive probable outcomes and the transfer of all the associated variances into an expanded linear program.

Furthermore, Hardaker et al. (2015) explained that when a discrete stochastic programming model is represented in a decision tree it can lead to a situation called 'the curse of dimensionality'. This implies that, the decision tree developed from the discrete stochastic problem has the propensity to evolve into many branches creating difficulty in solving the farmer's choice problem (Trebeck and Hardaker, 1971). As a result, to help reduce the number of possible outcomes, it is advisable to cut down the branches (Hardaker et al.

2015) by solving the corresponding problem deterministically to know whether the expected or desired results could be achieved before formulating the problem as stochastic.

2.5 Multi-criteria decision making

As stated by Zeleny (2011), all decisions made by humans are multi-criteria adding that single criterion problems are simply computations done through measurement and search. The study explains that trade-offs are crucial for human decision making between alternatives by going beyond simply measurement and search only.

From the studies of Arriaza & Gomez-Limon (2003), farm level modelling techniques which disregard multiple goals and focus on a single objective such as profit maximization can often be misleading and ineffective. Furthermore, models involving multiple goals are very useful for policy makers for building efficient and target oriented policy measures as well as improving the short falls of already existing policies (Sintori et al. 2016). However, several studies have used LP models involving single objectives to analyse farm level decision making processes (Alford et al., 2003; Biswas et al., 1984; Conway & Killen, 1987; Crosson et al., 2006; Veysset et al., 2005).

Sintori et al. (2009) reveal that for a model involving multiple goals to be developed, a detailed and more collaborative process with the representative farmer must be implemented. A widely used approach in agricultural science for multi-criteria decision making is the multi-objective and goal programming approach (Berbel & Rodriguez-Ocana., 1998; McGregor & Dent, 1993; Piech & Rehman, 1993; Siskos et al., 1994) which will be explained in the next section.

2.5.1 Goal programming

Goal programming is considered as one of the widely used decision making approaches in farm planning and could also be described as one of the oldest decision-making techniques as far as the multi-criteria concept is concerned (Romero and Rehman, 2003). Goal programming seeks to minimise deviations from targets for each objective as well as the optimisation of several goals simultaneously (Mansoori et al., 2009). Goal programming is mathematically expressed as:

$$F_i\,(\mathrm{X}) + (d_i^- - d_i^+) = g_i \tag{2.1}$$

where $F_i(X)$ is the linear function of the goal (i) to be optimized, d_i^- and d_i^+ are the associated negative and positive deviational variables for the i^{th} goal, respectively, and g_i represents the target value for the i^{th} goal . The deviational variables account for the extent to which a goal has been over-achieved or under achieved in terms of the deviation from the goal after solving the goal programming model (Mansoori et al., 2009). Romero and Rehman (2003) explained that a positive deviational variable represents an over achievement, and a negative deviational variable represents an under achievement. In developing a goal programming model, the minimisation of the deviations from the goal values could be done primarily using two main approaches namely the lexicographic method and the weighting method.

2.5.2 Lexicographic programming

Flinn et al. (1980) was the first to use lexicographic programming application for farm planning purposes. The lexicographic method assumes that decision makers are able to clearly define their goals for their farm plan, hence pre-emptive weights are attached to these goals in an order of priority (Romero and Rehman, 1984).The highest priority goal is the first to be satisfied followed by the lower priority ones, and the minimisation of the deviational variables are placed in an ordered vector formation which is referred to in literature as an achievement function (Romero and Rehman, 2003).

From equation 2.2 below lexicographic models are generally represented as:

$$Minimize\ Z = pr_i(d_i^-, d_i^+)\ , \dots \dots .. pr_m(d_m^-\ , d_m^+) \tag{2.2}$$

Subject to linear goal constraints:

$$\sum_{j=1}^{n} a_{ij}\, x_j + d_i^- - d_i^+ = g_i, i = 1{,}2\dots.. m \tag{2.3}$$

and $x_j, d_i^-, d_i^+ \geq 0$

Where pr_i represents the pre-emptive priority value of gaol (i). j is the j^{th} decision variable for any given constraint from $j = 1{,}2\dots..n$, a_{ij} is the co-efficient of the j^{th} decision variable for the i^{th} goal, x_j is the activity level of the j^{th} decision variable, i = 1,2,….m implies that the value of the goals start from i equals 1 to the m^{th} goa*l.*

2.5.3 Weighted goal programming

The weighted goal programming approach does not prioritise goals pre-emptively as is the case of lexicographic programming but rather it simultaneously involves all goals in the form of a composite objective function (Romero and Rehman, 2003). Further, this method attaches weights to the deviations from the target or aspiration levels for each goal, based on the relative level of importance the decision maker attaches to the goal under consideration (Mo'ath Alluwaici et al., 2017). Consequently, the sum of the deviations (Z) from the target levels are minimised by converting the deviations into percentages. This is done for all goals in the objective function to overcome the challenge of the different unitary measurement associated with each goal. As indicated by Charnes and Cooper (1977) weighted goal programming is mathematically expressed as:

Minimize Z = $\sum_{i=1}^{m}(W_i^- d_i^- + W_i^+ d_i^+)$ (2.4)

Subject to linear goal constraints:

$$\sum_{j=1}^{n} a_{ij}\, x_j + d_i^- - d_i^+ = g_i, i = 1,2.\dots.m \qquad (2.5)$$

and to system constraints as indicated by Mo'ath Alluwaici et al. (2017):

$$\sum_{j=1}^{n} a_{ij}\, x_j [\leq, \geq, =] g_i, j = 1,2.\dots.n \qquad (2.6)$$

Where W_i^- is the weight assigned to the negative deviational variable for the i^{th} goal, W_i^+ is the weight assigned to the positive deviational variable the i^{th} goal. All other parameters and constraints are previously defined.

2.6 Multi-objective programming

Francisco and Ali (2006) state that multi-objective programming is a form of multi-criteria decision-making framework that produces an efficient set of solutions for the decision maker to choose from. This approach allows the optimization of several objective functions subject to a given level of constraints that are often in a linearized form (Freeman & Haveman, 1970; Lara & Romero, 1994; Romero & Rehman, 1984). Francisco and Ali, (2006) added that the multi-objective approach generates a set of efficient non-dominated solutions known as a Pareto optimal solution or a non-inferior set of solutions for the decision maker. Romero and Rehman (2003) define the Pareto optimal solution as a point where it is not possible to increase the value of one objective without decreasing at least one other objective in the set of feasible solutions. Furthermore, the choice made by the decision maker from the set of non-inferior solutions which is also a measure of the boundary of the feasible region depends on the value of the trade-offs between the decision-maker's objectives (Okoruwa et al., 1996). Studies have revealed that when these efficient points are connected in a graphical format, the slope represents the trade-offs within the decision maker's objectives (Freeman & Haveman, 1970; Romero & Rehman, 1984).

Generically, Cohon & Marks (1975) postulate that a multi-objective optimization problem could be mathematically represented in a maximisation sense as:

$$\text{Maximise}(x) = Z_1(x_j), Z_2(x_j), \ldots\ldots Z_p(x_j) \tag{2.7}$$

Subject to

$$\sum_{j=1}^{n} a_{ij}\, x_j [\leq, \geq, =] f_i \tag{2.8}$$

and $x_j \geq 0$ and j = 1,2,3,4…….n

Where $\mathrm{Z}\,(x)$ represents a *p* number of objectives indicating a *p*-dimensional objective function, and x_j is a vector of *j* number of decision variables implying a *j*-dimensional vector and f_i represents the level of the i^{th} resource available. All other parameters are previously defined. Also, based on the decision makers objective, equation seven can be solved by minimising the objective function subject to the constraints. Adding to the above mathematical representation, this study reviews two main approaches used to generate the set of non-inferior solutions, namely the constrained and weighted methods.

2.6.1 Constraint method

The constraint method employs the idea of optimising a single objective out of the multiple objectives and converting the remaining objectives into constraints (Okoruwa et al., 1996). To generate the efficient non-inferior subset, the right-hand side of the remaining objectives must be parametrized within an ideal and anti-ideal space representing the lower and upper bounds within which parameter variations can occur (Romero and Rehman, 2003). This implies that for the constraint method to be efficient, the parameter constraints must be binding in an optimal sense (Romero and Rehman, 2003).

2.6.2 Weighting method

Weighted method is applied in multi-objective programming by developing a parametric variation of the weights in the objective function to be optimized (Cohon and Marks, 1975). Further, for the weighting method to generate an efficient set of solutions for the decision maker, the weights should be larger than zero (Romero and Rehman, 2003) and the weights should be strictly positive in the case of at least one objective (Cohon and Marks, 1975). Mathematically the weighting method for *p* number of objectives to be maximised can be expressed as:

$$\text{Maximise} \sum_{k=1}^{p} W_k Z_k\,(x) \tag{2.9}$$

Subject to

$$\sum_{k=1}^{n} a_{ik}\, x_k [\leq, \geq, =] f_i \tag{2.10}$$

and $W_k \geq 0$, *k*= 1,2……….*p*

Where W_k represents the weight of the kth objective to be parametrized, Z_k is the kth objective function to be optimised, x is a vector of *n* number of decision variables. All other parameters are previously defined.

2.6.3 Compromise programming

The compromise programming approach is one of the methods used in multicriteria decision making. This approach was established by Yu (1973) and Zeleny (1973). The uniqueness of this method from the approaches mentioned above is the incorporation of the measure of human preferences based on the concept of the ideal point and the family of distance functions (Romero and Rehman, 2003). Zeleny's axiom of choice clearly indicates that a rational decision maker will always prefer an alternative that is the closest to the ideal point (Zeleny, 1973). Romero and Rehman (2003) add that this distance is not in the geometric sense but as a proxy for a measure of human preference from the ideal point. As indicated by Stokes and Tozer (2002), utilising Zeleny's axiom of choice could be accomplished by indicating a distance metric and finding the most optimal set of objectives that minimise the distance from the ideal point. The distance metric when applied in a compromise programming sense produces a multi objective function that is mathematically expressed as:

$$\text{MinL}_P = [\sum_{j=1}^{N} W_J^P \quad | \frac{Z_j^* - Z_j(x)}{Z_j^* - Z_{*j}} |^p]^{1/p} \tag{2.11}$$

Subject to:

$$\sum_{j=1}^{n} a_{ij}\, x_j [\leq, \geq, =] f_i \tag{2.12}$$

where MinLp implies the search for the most minimal distance from the ideal point and actual values of the set of objectives, W_J^P is the weight associated with the *j*[th] objective for the distance metric *p* which indicates the difference between the objective and the ideal point. Z_j^* is the ideal point for the *j*[th] objective, $Z_j(x)$ is the optimised value of the *j*[th] objective generated from the compromised programming solution, Z_{*j} is the anti-ideal point for the jth objective.

2.7 Strengths and weaknesses of bio-economic farm models

Like other models, bio-economic farm models using mathematical programming techniques are characterised by strengths and weaknesses. Due to constrained optimisation approaches, modelling using bio-economic farm models seem to be close to reality for small holder farmers having limited resources and seeking to improve their livelihoods (Anderson et al., 1985). In addition, for Antle and Capalbo (2001), synergies between crops and livestock production can be analysed simultaneously with bio-economic models. They further explained that soil and climate data can be used as inputs in a bio-physical model to produce outputs in terms of crop yield and livestock production. The strength of bio-economic modelling lies in its ability to use outputs from the bio-physical model as inputs in an economic model (Wossink et al., 1992). The study also adds that when parameters change in bio-economic farm models (eg. changes in prices), sensitivity analysis can be done easily. Furthermore, bio-economic models give room for short run and long run explorations and predictions (van Ittersum et al., 1998) and allows *ex-ante* evaluation of policies and technological innovations for a series of environmental and geographical locations (Janssen and van Ittersum, 2007). According to Antle and Cobalt (2001), bio-economic models permit discrete choices to be made for technologies and land usage. A crucial feature with bio-economic models is their ability to clearly represent the linkages between production technology and biophysical or ecological process models (Antle and Cobalt, 2001). Given the strengths of bio-economic models, a lot of work has been done by researchers on economic and environmental analysis (Deybe & Flichman, 1991; Donaldson et al., 1995; Gibbons et al., 2005; Rossing et al., 1997; Torkamani, 2005)

On the other hand, bio-economic models have limitations which are defined in this review as weaknesses. Due to the reliance on representative farms, bio-economic models are often not suitable for analysing spatial variations of household socio-economic behaviour as well as connecting such behaviour to spatially explicit ecological or biophysical models (Antle and Cobalt, 2001). Another limitation of bio-economic models used in mathematical programming is the possibility that the data used for estimating technology parameters may not be representative of the population under study (Antle and Cobalt, 2001).

2.8 Bio-economic modelling: A developing country perspective.

Some bio-economic models applicable to developing countries especially Africa and South America have been recently developed (Louhichi, 2013). These models were used to analyse the impact of: public policies on poverty amongst rural households in the central plateau region of Burkina Faso (Sanfo and Gerard, 2012), alternative crop production systems for rice on subsistence farming in northern Ghana (Yirideo et al., 2006), improved access to non-farm income on the local production of food and land conservation in Ethiopian highlands (Holden et al., 2004), agricultural mechanization and increasing farm size on rural household income in the Zhejiang province of China (Van den Berg et al., 2007), the efficiency of various government policies on land degradation amongst high and low income farm households in Haiti (Dolisca et al., 2008), and new agricultural technologies on the welfare effects of smallholder subsistence farmers in northern Philippines (Laborte et al., 2009).

2.8.1 Applications of bio-economic models in Sub-Saharan Africa

2.8.2 The FISSIM bio-economic model

This review further investigates bio-economic models applicable to Sub-Saharan Africa. The FISSIM-Dev model, an extension of the generic FISSIM (Farming System Simulator) bio-economic model was purposely developed to suit a developing country context (Louhichi, 2014). In the improvement of the FISSIM MODEL into the FISSIM-Dev model, the authors considered how rural farm household behaviour in developing countries affects their livelihoods. As a result of this, the model can capture interactions within households at village level and assess the impacts of agri-food policies *ex-ante*, on small-holder farm households' livelihoods in rural economies (Louhichi, 2013).

2.8.3 The Mali Bio-economic farm household model

Another model applicable to the sub-Saharan African context is the Mali Bio-Economic Farm Household Model developed by Kuyvenhoven et al. (1998). This model is a dynamic optimisation bio-economic model which combines heterogeneous smallholder household resource endowments and bio-physical processes (Flichman and Allen, 2015). The model is an improvement of the traditional household model developed by Singh et al. (1986) and Banum and Squire (1979) which describes households whose consumption and production decisions are made non-separably (De Janvry and Sadoulet, 2006).

Kuyvenhoven et al. (1998) explained that the bio-economic model developed analyses the impact of market-led government policies in Southern Mali and also examines the effect of institutional reforms in the region within the context of population increase and reduced fallow periods due to pressure on the use of natural resources. The model uses two components, the production part identifies crop choice and suitable technology, and the household component examines the effect of price variations on the allocation of factors of production, land use, and farm-level profit making (Kuyvenhoven et al., 1998). The outcome is a dynamic linear programming (DLP) model guided by econometric specifications to optimise household farm production as described by Ruben et al. (1994).

The Mali Bio-Economic model comprises: (i) the market-led policy instrument which produces the price module and the expenditure module, (ii) the farm household stratification model which captures and includes the heterogeneity amongst farm household types into the model and expected goal weights given the household's level of resource endowments, (iii) the production activity module giving room for the inclusion of bio-physical parameters and technology choices, (iv) the farm household resources component of the model which take into account limited resources of farm households and how these resources can be allocated effectively and, (v) the savings and investment module component makes it easier to include the dynamic effect of any changes in households' initial resource endowments.

Given the structure of the model, both bio-physical and socio-economic data sources can be used to determine the net income adjustment and consumption utility objective of the model (Kuyvenhoven et al., 1998). Furthermore, for Kuyvenhoven et al. (1998), the different module combinations imply that a change in any policy instrument, for instance prices, carbon balances, or sustainable agricultural practices, will result in a corresponding adjustment in resource allocation which is referred to in this model as response multipliers.

2.8.4 The dynamic agricultural household bio-economic simulator (DAHBSIM) model

The DAHBSIM model was designed for rural agricultural households in developing countries with the main objective of analysing bio-physical constraints and its effect on whole-farm planning and management strategies in the context of agricultural sustainability and intensification (Flichman et al., 2016). A key feature of the model is the linkages it establishes between socio-economic and bio-physical scenarios to project the farm household welfare effect of changes in environmental conditions or government policies skewed towards farm input or farm output price (Flichman et al., 2016). The DAHBSIM model originated from FISSIM, the Farm Systems SIMulator model (Janssen et al., 2010) and the FISSIM-Dev models (Louhichi and Gomez y Paloma, 2014). Flichman et al. (2016) indicates that the DAHBSIM model is a dynamic model with yearly time steps. Like Komarek et al. (2017), the objective function in this model is set over a user defined time period and operated with dynamic iteration where model parameters are restructured based on the preceding year's management decisions.

The overview of the DAHBSIM model comprises 6 main modules; the bio-physical, crop, livestock, risk, farm, and household modules. The bio-physical module is the crop systems simulation component of the model that analyses the impact of climate, soil, and farm management practices on crop yield progress by simulating soil water, crop rotations and nitrogen levels (Flichman et al., 2016). Furthermore, the crop module interacts with the biophysical module by introducing a set of constraints for the specific cropping activities which includes the land constraints in terms of total cropland based on soil type, area constraints, rotation constraints, and labour constraints (Flichman et al., 2016).

The livestock component of the model plays an important role in rural livelihoods in the context of household food security, climate change, and natural resource consumption (Herrero et al., 2013). The livestock module explains the interactions between household livestock and other components of the DAHBSIM model by focussing on feed management and its effect on livestock numbers (Flichman et al., 2016). Studies have revealed that when feed management decisions are made effectively, livestock productivity also increases (Rufino et al., 2009). The livestock module also explains the integration of manure into the crop module. The reverse effect in terms of crop residue from the crop module is used as feed from the crop module into the livestock module. Further, the farm model examines linkages between crop and livestock production activities of the households, it also analyses the interaction between labour allocation on-farm as well as off-farm (Flichman et al., 2016). The model focuses on analysing the balance in land allocation for cropping, grazing, and farm output use for the purposes of own-consumption, sales for farm income, saved seeds for planting in the next season, and feed for livestock (Flichman et al., 2016).

The household component of the model explains the simultaneous relationship between production and consumption as a result of the non-separability decision making behaviour of rural farm households as described by De Janvry and Sadoulete (2006). In DAHBSIM, Flichman et al. (2016) indicate that the module describes household food consumption using a linear expenditure system approach where expenditure on food and non-food items are accounted for, like that of Louhichi and Gomez y Paloma (2014).

Furthermore, similar to Hazell and Norton (1984), the model involves the use of the mean and standard deviation where variations in historical prices and yield are captured to calculate the utility gained under each state of nature considered. Consequently, a standard deviation is calculated for the utility for all states of nature and incorporated into the objective function with a risk aversion co-efficient (Flichman et al., 2016).

2.8.5 The Burkina Faso bio-economic village model

Finally, the study includes the Burkina Faso bio-economic village model which models the response of socio-economic conditions in a village in Burkina Faso (West Africa) to market and population pressure (Brown, 2000). The model is dynamic and has a biophysical component simulating plant growth and soil conditions to predict future crop yield (Barbier, 1998). Different degrees of technological alternatives are introduced into the model (Brown, 2000). The findings from the study revealed that population pressure enhances land conservation investments and agricultural intensification but does not readily lead to improved farm incomes. However, other factors such as creating more market opportunities constitute a more rewarding contribution to productivity (Barbier, 1998).

2.9 Conclusion

This Chapter reviewed previous research in bio-economic modelling using mathematical programming approaches. The findings from the review reveal a lack of research in bio-economic modelling where the risk management behaviour of smallholder farmers is accounted for. Previous models developed have focused on analysing the interaction between environmental and socio-economic conditions of the actors involved in the modelling process without considering risk. This research attempts to fill this gap by establishing an empirical modelling framework for the study area (Chapter 3). The framework is further used as basis to develop a climate risk bio-economic model that mimics the livelihood system of farm households, risk and income trade-off decisions under climate variability, and the impact of these trade-offs on the economic conditions of the smallholder farmer.

Chapter 3 Modelling framework

3.1 Introduction

Smallholder households in Sub-Saharan Africa are characterized by the production of diverse goods or focus on the production of goods which they find themselves relatively skilful at producing (Barrett, 2008). Smallholder farm households consume some of their produce and sell the surplus to generate income to purchase other food items or other consumables they can't produce (Barret, 2008). In the context of developing countries, it is important to understand rural farm household behaviour by analysing their decisions regarding resource allocation, own-consumption, and exchange strategies (De Janvry & Sadoulet, 2006). Studies have revealed that food sources for most rural households are mainly derived from their own agricultural production (Pinstrup-Andersen, 2012). The amount of income rural households accrue from the sales of their produce is often insufficient to offset the purchase price of other foods or consumables they are unable to grow but desire to consume (De Jager et al., 2018). As a result, rural households prefer to intensify their own food production to meet their domestic consumption needs and sell the surplus in the open market (Leahy, 2018). This intensification process and selling decision requires efficient allocation of resources and exchange strategies amidst constraints like transaction costs to reduce the welfare cost of rural households. (De Janvry & Sadoulet, 2006).

Over 80% of rural households in northern Ghana generate at least 75% of their income from sales of their own food crop production (Franke & De Wolf, 2011). This implies that improving household food production and marketing is crucial for households whose consumption decisions are also embedded in their production decisions. Such households are defined as non-separable households as the decisions regarding factors such as level of production, amount of inputs, and activities are affected by their consumption preferences (De Janvry & Sadoulet, 2006).

3.2 Household food dynamics and market participation

To sustain food security and household welfare, market-led agricultural production is key (Pingali, 1997). Policy makers promote marketing of household agricultural produce with the anticipation that it will increase income for farm households as well as increase agricultural productivity as a result of an increase in the use of inputs (Ntakyo & Van den Berg, 2019). However, farm household produce marketing in rural areas especially of developing countries are confronted with weak markets characterized by market imperfections and constraints (Vermeulen et al., 2012). Access to food could be, economic access (ie. having the purchasing power to buy), the skill to produce, or the physical ability to access markets where food is sold (Ntakyo & Van den Berg, 2019). Often, household access to food occurs partly through the food market when they have sufficient funds to buy food rather than produce themselves. Nonetheless, food purchasing power does not only depend on sufficient income but also on the market price of food at the time of purchase (Staatz et al., 2009). For developing countries where agriculture is rain-fed, market-dependent households face food price volatility which mostly stems from seasonal variations and unstable foreign exchange rates making them very vulnerable to market failures. (Ntakyo & Van den Berg, 2019). The study explained that the shift from subsistent farming to market-oriented agricultural production has household specific implications which is often dependent on their resource endowments (Ntakyo & Van den Berg, 2019). According to Misselhorn et al., (2012) and Shively & Hao (2012), even when resource-poor households decide to engage in market-oriented production, they are consistently exposed to food insecurity as a result of low food supply and limited market access. De Janvry and Sadoulet (2006) corroborate this assertion by indicating that, while food market accessibility is crucial for rural farm households involved in market-oriented production, the market participation decision largely relies on the household's productive resource endowments, demand for own food consumption, and supply.

3.3 Transaction cost

As a result of the differential access to information flow and markets, transaction costs are often household specific (Bwalya et al., 2013). Transaction costs are defined as those costs incurred (ie. opportunity cost with regards to time spent or monetary cost) in scouting for a potential trading partner, negotiating, and agreeing on a contract for both parties which is eventually enforced (Jagwe et al., 2010). In the case of credit sales, farmers incur further cost to validate the reliability of buyers in order to avoid or reduce defaults in payments (Kirsten and Vink, 2005).

Over the years, transaction cost theory has been used to explain smallholder farmers' behaviour towards market participation. (Fafchamps & Hill, 2005; Goetz, 1992; Key et al., 2000). Jagwe et al. (2010) explained that farmers' market participation decisions are strongly influenced by the magnitude of the associated transaction costs. Furthermore, a basic transaction cost that farmers confront is the cost of accessing information (Shepherd, 1997). Research on the nature of the firm pioneered by Coase (1937) which was later expounded in Coase (1960) indicated that information cost has crucial implications for transaction exchanges and contracts made on the market.

Transaction costs can be categorized into fixed cost and variable costs. Fixed costs are those costs that do not vary with the amount of output traded on the market (Goetz, 1992). The scout for the best buyer or price, negotiation and bargaining activities, screening for a trustworthy buyer are all categorized as fixed cost (Kirsten and Vink, 2005). Often, the market search cost including transportation cost is lumpy such that farmers are likely to incur the same cost irrespective of the quantity of produce they have to offer (Key et al., 2000). Furthermore, since the cost of bargaining or negotiation often occurs once for each transaction, it is necessary to take note especially when market information about prices are imperfect because it has no bearing on the size of the transaction being negotiated (Key et al., 2000). On the other hand, variable costs are those market access costs that vary with the quantity of output traded (Jagwe et al., 2010). An example of a variable transaction cost is the cost of storage paid per unit of quantity stored. Similarly, payment made for loading and off-loading of produce from farm to market using human labour is charged based on quantities loaded/offloaded. In some farming communities, the cost of harvesting produce is based on the quantity of bags or acres harvested. In effect, variable and fixed transaction costs increase the actual price of the product bought and decrease the actual price received for selling the product (Jagwe et al., 2010).

Studies have revealed that most rural smallholder farmers are in remote communities with poor road networks and poor market infrastructure contributing to the high transaction cost they face in trying to access markets (Jagwe et al., 2010). Some household types even prefer not to participate in the market because in some cases the transaction costs are so extreme that markets are explicitly inaccessible (Key et al., 2000; Omamo, 1998; De Janvry & Sadoulet, 2006). In some instances, these households use part of their resources as inputs (eg. household labour), and purchase some of the inputs from the market for production purposes (Singh et al.,1986).

3.4 Non-separable farm household labour supply and demand

From the findings of Skoufias (1994), for non-separable households, there is a dependent relationship between labour supply choices and labour needs. This implies that households sometimes prefer to engage in off-farm income earning activities, however the decision to work off farm or on-farm is non-separable because labour supply off-farm cannot be treated independent of the household's labour needs. Further, based on the household's resource endowments, hired labour may not be a perfect substitute for family labour (Deolalikar and Vijverberg, 1997; Jacoby, 1991). According to Jacoby (1991) and Benjamin (1992), under such circumstances, although there is market wage for labour, it is the shadow wage that determines household labour demand and supply choices. In investigating the complex relationship between labour supply and demand for non-separable households in Sub-Saharan Africa, Skoufias (1994) revealed that variation in exogeneous variables such as input or output prices influencing farm production decisions will have a direct or indirect effect on household labour supply. Further, the study states that households spend time working on the farm until they get to a point where the marginal productivity gained from working on the farm is equal to the market wage and any extra time accrued is shared between leisure or work in the labour market.

Holding other factors constant, households whose land to labour ratio is high eventually have higher marginal productivity of labour and a higher propensity to sell their produce resulting in an increased income effect (Ntakyo & Van den Berg, 2019). As explained by Timmer (1997), where market participation is established and functioning properly, households are in a better position to generate income to ease their consumption needs against seasonality.

3.5 Theoretical model for the smallholder farm household.

Using theoretical models, this section presents a mathematical construct of agricultural household models for rural economies mostly in Sub-Saharan Africa, where consumption and production decisions are tied to each other. De Janvry and Sadoulet (2006) revealed that, household market participation in such economies can be treated as a choice variable. Based on farmers' own intelligence, they decide how much of their produce to consume and use as inputs or market. The amount marketed is positive when sales are made and negative when they consume purchases made from the market. In the absence of a transaction cost the household maximizes its utility (equation 3.1) subject to the constraints from equations 3.2 to 3.5 as indicated below:

$$u(Y - \emptyset\sigma; z_u) \tag{3.1}$$

$$\sum_{i=1}^{N} p_i^m m_i + \sum_{i=1}^{N} p_i^m (-m_i) \pm T = 0 \tag{3.2}$$

$$q_i + A_i - m_i - st_i - c_i - x_i = 0,\ i = 1, \dots,\ N \tag{3.3}$$

$$G(q, x; z_q) > 0 \tag{3.4}$$

$$c_i,\ q_i, x_i \geq 0 \tag{3.5}$$

Where u represents utility, which is a function of household's expected income Y given the household's risk perception, ∅ is the risk aversion coefficient, σ is the standard deviation in household income due to potential changes in yield and prices (Louhichi et al., 2013). z_u represents exogenous shifters in utility (eg. age, gender, marital status, ethnicity, education, religious denomination, employment, and family size).

Equation 3.2 represents the cash constraint which indicates that household expenditure on all goods (from $i = 1, \dots, N$) purchased must not exceed the revenue accrued from all sales and exogeneous transfers (T). p_i^m is the market price for good i, m_i is the quantity of good i marketed which is positive when sales are made and negative when they consume purchases made at market price p_i^m. T represents exogeneous transfers obtained from income generating activities such as selling labour, remittances, income from small business and other off-farm income sources.

Equation 3.3 is the resource balance for all goods , $i = 1, \dots, N$ produced by the households such that, the quantity produced (q_i), plus the initial endowment of each good (A_i) must be equal to the amount of each good sold (m_i), stored (st_i), consumed (c_i), and used as inputs (x_i) for selling households. In the case of a buying household, the amount of output produced, plus their initial endowment in good i (A_i), plus the amount purchased ($-m_i$), is equal to the amount consumed (c_i) and used as inputs (x_i).

In equation 3.4, G represents the production technology which is a function of the set of inputs (x), set of outputs (q), and exogenous shifters in production (z_q). Examples of exogenous shifters in production are the household's natural capital, man-made capital and institutional capital. Equation 3.5 is the non-negative condition for consumption and production of output and inputs for each given commodity (i)

Where there is a variable or a fixed plus variable transaction cost, equation 3.2 is replaced by equation 3.6 which represents the budget constraint for variable transaction costs or equation 3.7 which represents the budget constraint including variable plus fixed transaction costs. In both cases, the effective price received by the seller is reduced as a result of the transaction costs incurred in marketing the produce and the effective price paid by the buyer is increased above the market going price for similar reasons. The variable transaction costs for both seller and buyer are represented in equation 3.6 as $t_{v_i}^s$ and $t_{v_i}^b$, respectively, and are a function of exogeneous characteristics (z_t^s, z_t^b) that influence it. Examples of such exogenous characteristics are, distance from the farm to the market, ownership of a means of transportation which could be a motorbike, bicycle or a car, distance from the farm to an offloading or on-loading site, distance to a railway station etc. δ_i^s in equation 3.6 equals 1 when sales are made where m_i > 0 or 0 when there are no sales where m_i < 0. Similarly, δ_i^b equals 1 when purchases are made where $m_i < 0$ and 0 when there are no purchases where $m_i > 0$.

$$\sum_{i=1}^{N}\left[(p_i^m - t_{vi}^s(z_t^s))\delta_i^s + \left(p_i^m + t_{vi}^b(z_t^b)\right)\delta_i^b\right]m_i + T = 0 \tag{3.6}$$

For households having both variable and fixed transaction costs, the cash constraint for such households is represented by equation 3.7 below. $t_{f_i}^s$ and $t_{f_i}^b$ are the fixed transaction cost incurred by households for selling or purchasing good i, respectively.

$$\sum_{i=1}^{N}\left[(p_i^m - t_{vi}^s(z_t^s))\delta_i^s + \left(p_i^m + t_{vi}^b(z_t^b)\right)\delta_i^b\right]m_i - t_{fi}^s(z_t^s)\delta_i^s - t_{fi}^b(z_t^b)\delta_i^b + T = 0 \tag{3.7}$$

As shown in De Janvry (1991) and Key et al. (2000), the Lagrangian for the constrained optimisation problem is written as:

$$L = u(Y - \emptyset\sigma; z_u) + \sum_{i=1}^{N}\mu_i(q_i - x_i + A_i - m_i - c_i) + \phi G\left(q, x; z_q\right) + \lambda\Big[\sum_{i=1}^{N}\left[(p_i^m - t_{vi}^s(z_t^s))\delta_i^s + \left(p_i^m + t_{vi}^b(z_t^b)\right)\delta_i^b\right]m_i - t_{fi}^s(z_t^s)\delta_i^s - t_{fi}^b\left(z_t^b\right)\delta_i^b + T\Big] \tag{3.8}$$

For consumption, the first order condition is:

$$\frac{\partial L}{\partial c_i} = \frac{\partial u}{\partial c_i} - \mu_i = 0, \qquad i \in \{i \mid c_i > 0\}$$

For output, the first order condition is:

$$\frac{\partial L}{\partial q_i} = \mu_i + \phi\frac{\partial G}{\partial q_i} = 0, \qquad i \in \{i \mid q_i > 0\}$$

For inputs, the first order condition is:

$$\frac{\partial L}{\partial x_i} = -\mu_i + \phi \frac{\partial G}{\partial x_i} = 0, \qquad i \in \{i \mid x_i > 0\}$$

For produce traded on the market, first order condition is:

$$\frac{dL}{dm_i} = -\mu_i + \lambda\left[\left(p_i^m - t_{v_i}^s\right)\delta_i^s + \left(p_i^m + t_{v_i}^b\right)\delta_i^b\right] = 0, \qquad i \in \{i|m_i \neq 0\}$$

Where μ_i, ϕ, λ are the Lagrangian multipliers for resource, technology, and cash constraints, respectively.

From the Langrangian equations for traded produce, the effective market price for selling households is $p_i^m - t_{v_i}^s$ whereas that of buying households is $p_i^m - t_{v_i}^b$. We define the shadow price (p_i^a) of self-sufficient farm households as the change in the objective function (income) as a result of a unit change in marketed quantities. When this shadow price is equal to the effective market price, selling/buying households choose not to trade and remain self-sufficient adjusting production for consumption purposes only.

Furthermore, we represent household income in equation (3.9) as:

$$y = \sum_{i=1}^{N} p_i(q_i - x_i + c_i + \text{Ɣ}A_i) + T \qquad (3.9)$$

where 0 ≤ Ɣ ≤ 1, represents the percentage of endowments in good i sold for income. For households who wish to sell all their initial endowments, Ɣ = 1, whereas Ɣ = 0 if the household decides to retain its initial endowments.

In the case of a single commodity, for instance maize, for a household facing variable transaction costs, the income for selling households (y_i^s) is represented in equation 3.10. To provide a true reflection of household income, the equation includes the value of household consumption of its own production which is the product of the effective market price $p_i^m - t_{v_i}^s$ and the quantity consumed c_i.

$$y_i^s = \sum_{i=1}^{N}(p_i^m - t_{vi}^s)\ (q_i - x_i + c_i + \gamma A_i) + T \qquad (3.10)$$

From equation 3.10 above, utility for selling households (V_i^s) which is a function of the effective selling price, income and exogenous shifters in utility is written as:

$$V_i^s = (y_i^s(p_i^m - t_{vi}^s); z_u) \qquad (3.11)$$

For the self-sufficient households the amount produced must equal the amount consumed resulting in shadow price p_i^a. The value of the amount produced and consumed ($p_i^a q_i$)

serves as a component of household income. The income for this group of households (y_i^a) is defined in equation 3.12 as:

$$y_i^a = \sum_{i=1}^{N} p_i^a q_i + p_i^a \gamma A_i + T \tag{3.12}$$

The utility derived from producing at self-sufficiency (V_i^a) is a function of the shadow price, income and exogeneous shifters in utility. This is represented in equation 3.13 below as:

$$V_i^a = (p_i^a,\ y_i^a;\ z_u) \tag{3.13}$$

For buying households, income (y_i^b) is generated from exogeneous sources and transfers. The value of what they consume $(p_i^m + t_{v_i}^b)\ c_i$ and produce $(p_i^m + t_{v_i}^b\ )q_i$ is also included in the income equation 3.14 as:

$$y_i^b = \sum_{i=1}^{N} (p_i^m + t_{vi}^b)\ (q_i - x_i + c_i + \gamma A_i) + T \tag{3.14}$$

From equation 3.15, the utility for buying households (V_i^b) is a function of the household's effective buying price, income, and exogeneous shifters in utility.

$$V_i^b = (y_i^b (p_i^m + t_{vi}^b);\ z_u) \tag{3.15}$$

When both selling and buying households face fixed transaction costs t_{fi}^s and t_{fi}^b respectively, utility derived from selling or buying declines at any given price because income reduces. This is shown in equation 3.16 and 3.17 where V_o^s and V_o^b represent the reduced utility of selling and buying households, respectively.

$$V_o^s = y_i^s (p_i^m, t_{vi}^s, t_{fi}^s); z_u) \tag{3.16}$$

$$V_o^b = y_i^b (p_i^m, t_{vi}^b, t_{fi}^b);\ z_u) \tag{3.17}$$

A graphical presentation of the three utility functions V_i^s, V_i^b and V_i^a for selling, buying and self-sufficient households, respectively, is shown in Figure 3.1 below.

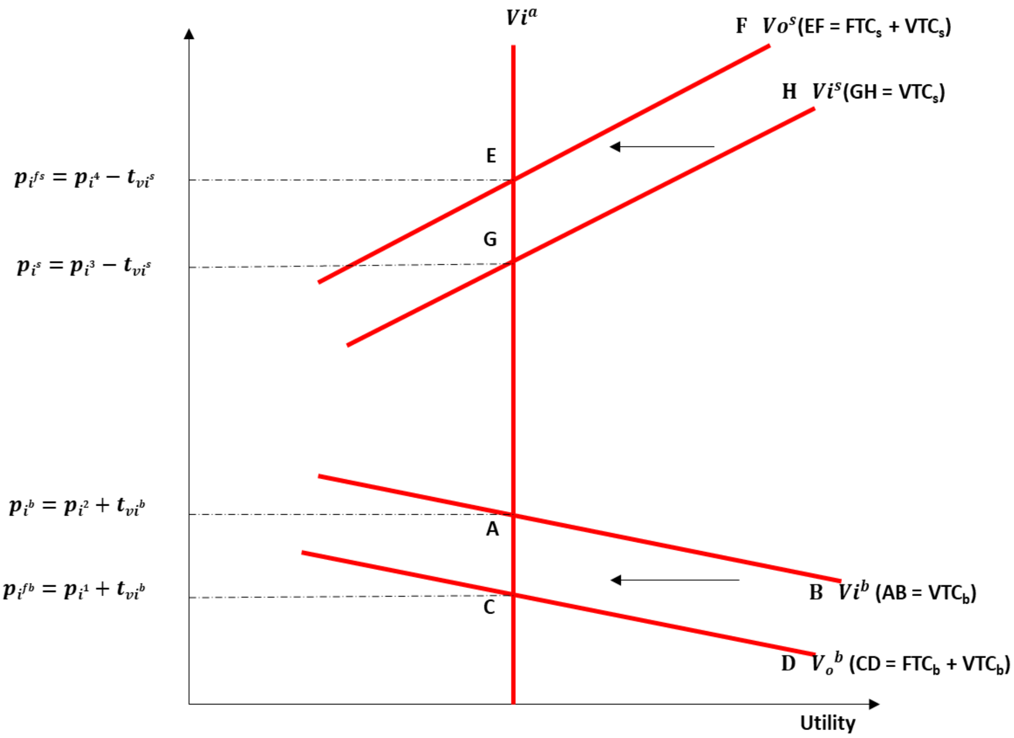

Figure 3.1. Household utility curves for both fixed and variable transaction costs

Source: Adapted from Key et. al (2000)

Figure 3.1 indicates the level of utility and market price at which households make market participation decisions. GH and EF are utility curves measuring household income derived from selling after incurring a variable transaction cost of selling (VTC_s), and variable plus fixed transaction costs of selling (FTC_s), respectively. AB and CD utility curves measure the satisfaction derived from buying at a lower effective market price under variable transaction cost of buying (VTC_b), and variable plus fixed transaction cost of buying (FTC_b), respectively. For households facing VTC_s only, at point **G**, they are indifferent between self-sufficiency and selling. At this point, the shadow price p_i^s is equal to the effective market price which is the market price less variable transaction costs incurred in selling $p_i^s = p_i^3 - t_{vi}^{\ s}$. When the effective market price begins to increase above the shadow price, households trade their produce along **GH** to increase their utility along V_i^S. On the other hand, households will choose not to trade and remain self-sufficient when there is a decline in the effective market price below the shadow price. When FTC_s is introduced, household income is reduced, hence utility shifts to the left from V_i^S to V_O^S, creating a new decision price p_i^{fs}, at which households are indifferent between selling and being self-sufficient as is the case with variable transaction costs only at point **G**. Any effective market price above p_i^{fs} will serve as an incentive for the household to sell along utility curve **EF** increasing utility along V_o^s. Below p_i^{fs} households will choose not to sell. Analogous to the selling decision, at point **A,** households facing VTC$_b$ are indifferent between buying and remaining self-sufficient. This is because at point **A**, a household's shadow price p_i^b is equal to the effective purchase price $p_i^2 + t_{vi}^b$. When the effective purchase price falls below the shadow price, households will trade as buyers and increase utility along V_i^b since they are better off buying than remaining self-sufficient. When FTC$_b$ is introduced, household utility is reduced hence the curve shifts from V_i^b to V_o^b and a new decision price p_i^{fb} at which households remain indifferent between self-sufficiency and buying is realised. When effective market price falls below p_i^{fb}, households choose to buy to increase utility V_o^b along **CD.**

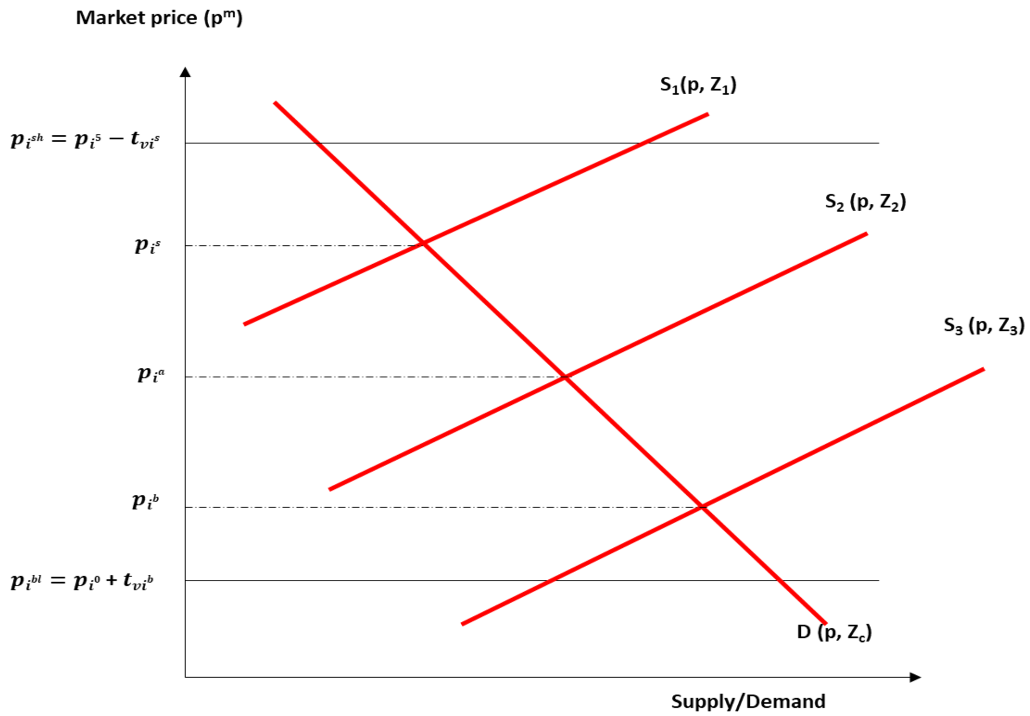

Figure 3.2. Merging supply and demand for the three categories of households
Source: Adapted from de Janvry and Sadoulete (2006)

From Figure 3.2, the study illustrates the three categories of households confronted with variable transaction costs whose food supply is a function of their respective productive resource endowments **Z_1, Z_2, Z_3** and market price **(p^m).** To analyse without complexities, the study assumes that all three categories of households have equal demand characteristics for food hence trade on the same demand curve **D** (**p, Z_c**) (De Janvry and Sadoulete, 2006). The decision to participate in the market as a net buyer or net seller as well as the decision to remain self-sufficient depends on transaction costs and their respective resource endowments (De Janvry and Sadoulete, 2006).

Above shadow price p_i^s, the quantity supplied by households **S_1 (p, Z_1)** exceeds household demand for consumption. Their highest decision price p_i^{sh}represents the maximum they can sell on the market above their shadow price p_i^s. These households are net sellers which implies that households in this category have a positive market surplus traded for income. It also indicates that trade is worthwhile only when the effective market price for selling is greater than the shadow price.

A similar situation holds for households **S_3 (p, Z_3)** who are net buyers because, although they produce to consume, they resort to trading on the market when the effective market price of buying falls below their shadow price p_i^b. This implies that a decrease in the effective market price below their shadow price will serve as an incentive to trade as buyers until they get to the lowest effective trading price $p_i^0 + t_{vi}^b$ which also gives rise to decision price p_i^{bl}.

The third category of households are the self-sufficient ones who do not trade on the market mainly because of transaction costs and market price fluctuations but produce to consume hence adjust their production and consumption decisions based on their productive resource endowments **Z_2**. This creates an internal equilibrium p_i^a which represents their shadow price. As a result of their resource endowments, this group of households fall between the shadow price band for buying and selling. This is because their shadow price is less than or equal to their effective market price for selling and greater than or equal to their effective buying price.

3.5.1 Analysing the relationship between the supply curves for the three household regimes.

The supply curve for the three household regimes is represented in Figure 3.3. The left-hand side (3A) represents the supply curve for household under variable transaction costs and the right-hand side (3B) represents variable plus fixed transaction costs. On supply curve SS, the household faces no variable or fixed transaction costs. Once variable transaction costs are introduced, the supply curve for sellers shifts upwards and for buyers, downwards. The upward or downward shift in the supply curve is because, in the presence of variable transaction costs of selling/buying, the household can only supply/buy when their effective market price is higher/lower than the shadow price for selling and buying households respectively.

Curve FG represents the supply curve for the self-sufficient households facing variable transaction costs only, whereas curve KL implies self-sufficient households facing variable plus fixed transaction costs. EF is the supply curve for buying households facing variable transaction costs only and GH is the supply curve for selling households with variable transaction costs only.

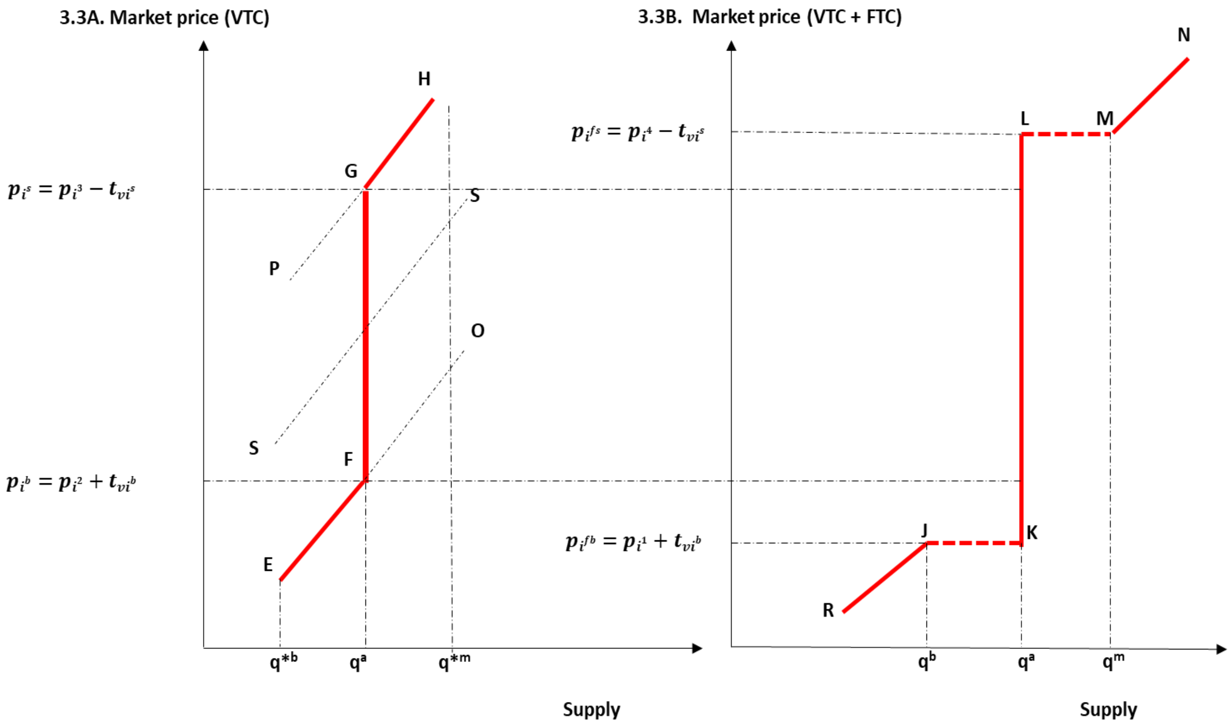

Figure 3.3. The overall supply curve for the three categories of households under variable transaction cost (3A) and variable plus fixed transaction cost (3B)

Source: Adapted from de Janvry and Sadoulete (2006) and Key et al. (2000)

The study first analyses Figure 3.3A. On supply curve EF, the effective market price incurred in buying is below the shadow price p_i^b of buying households under variable transaction costs only, hence these households trade in the market as buyers. As the effective market price decreases below the shadow price, household supply also decreases from F to E because the opportunity cost of producing is the reduced price of the product on the market (De Janvry and Sadoulete, 2006). However, when the effective market price reverses to a point where it is equal to the household's shadow price $p_i^b = p_i^2 + t_{v_i}^b$, they become indifferent between buying and remaining self-sufficient at F. Any further increase in the effective market price above the shadow price will cause the household to remain self-sufficient producing to meet their consumption needs only. This is because buying at that price will serve as a disincentive for the household as they must pay more due to an increased cost of buying.

On the other hand, selling households become indifferent between selling and remaining self-sufficient at point G where the effective market price for selling $p_i^3 - t_{v_i}^s$ is equal to their shadow price p_i^s. Once the effective market price exceeds the shadow price under variable transaction costs, the household begins to trade by selling on supply curve GH.

On Figure 3.3B, as a result of fixed transaction costs, the buying household chooses to remain self-sufficient on curve LK and not enter the market as buyers until the effective market price for buying drops to $p_i^1 + t_{v_i}^b$ creating a new decision price p_i^{fb}. At this decision price, the household is able the offset the fixed transaction costs incurred in buying to make trading profitable. Unlike the case of a variable transaction costs only, changing from the self-sufficient decision price to a selling or buying decision price requires the household to reach a production threshold q^m for sellers and q^b for buyers due to fixed transaction cost. This creates a discontinuity in the supply curve for both buyers and sellers at JK and LM respectively (Key et al., 2000). Hence the household begins to trade on the market by purchasing q^b as a buyer or marketing q^m as a seller.

As the effective market price increases above p_i^{fs} supply increases from M to N for selling households and decreases from J to R when the effective market price for buying households drops below p_i^{fb}. However, if there were no fixed transaction costs, the household will remain at point F for a buyer or G for a seller (see Figure 3.3A) and be indifferent between trading and remaining self-sufficient. The household then eventually starts trading as effective market price falls below shadow price p_i^b for buyers or rises above shadow price p_i^s for sellers.

Market participation decision prices and the quantities consumed for all categories of households are consequently incorporated into a linear expenditure system for farm households. The study argues that as utility is maximised under a given income constraint, farm household consumption decisions are made based on a demand across multiple goods as indicated in Louhichi et al. (2014). The equation for the linear expenditure system is as follows:

$$c_i p_i = \theta_i p_i + \beta_i\left(y - \Sigma\theta_j p_j\right) \tag{3.18}$$

$$\Sigma\beta_i = 1 \tag{3.19}$$

Where $c_i p_i$ is the total expenditure on good i with p_i being the price of good i and c_i the quantity of good i consumed. y represents household income which indicates the value of own consumption, net crop income plus off-farm income whereas β_i and θ_i are the parameters associated with the linear expenditure system (Komarek et al., 2017). β_i represents the marginal budget share and θ_i is the uncompressible consumption for good i below which consumption cannot decline (Louhichi et al., 2014). $\theta_j p_j$ is the total subsistence expenditure on all other commodities(j). $y - \Sigma\theta_j p_j$ is described as the supernumerary income spent on commodity (*i*) in a certain fixed proportion (β_i) (Sadoulet and De Janvry, 1995). Since the quantity of food consumed, and the level of income generated by the household for expenditure depends on the production quantities.

3.6 Aquacrop modelling

This research includes the crop modelling process needed to generate the production quantities for farm households. This first step is to begin with crop modelling using the Aquacrop model to generate crop yield variabilities in the study area. The Aquacrop model was used to simulate yield for maize, rice, sorghum, and groundnut. These crops are the top four crops cultivated in the study area (ie. Northern, Savannah, and North East regions of Ghana) based on the Africa RISING survey data. Aquacrop is a water driven yield response model used to simulate crop yield under different environmental and management conditions. (Raes et al., 2009; Steduto et al., 2009). Aquacrop has been used in different locations such as Asia (Abedinpour et al., 2012), North America (Heng et al., 2009), Southern Africa (Chibarabada et al. 2020; Bello et al. 2011), Europe (Todorovic et al., 2009), East Africa (Araya et al., 2010; Van Gaelen et al., 2015), and West Africa (Akumaga et al., 2017). Further suitability of Aquacrop has been confirmed across multiple locations (Van Galean et al., 2015).

Aquacrop comprises 2 groups of parameters which are the conservative and non-conservative parameters. The conservative parameters are default parameters that can be used for all growing conditions whereas non-conservative parameters are location specific, hence, could be altered to suit local growing conditions (Hsiao et al. 2012). Aquacrop was chosen because the model is designed to be suitable for different soil and environmental conditions, and crop cultivars. The model is also very useful in situations where experimental data is not readily available and local calibration is not possible (Hsiao et al. 2012). Aquacrop plays a major role in simulating yield variations under climate variability in a water constraint environment. Rainfed smallholder farmers in northern Ghana are challenged by harsh weather conditions caused by climatic variations (Amikuzino and Donkor, 2012). Hence, Aquacrop is suited to simulating crops grown in this region. This research simulates yield under climate variability, soil types, and farm management practices. The simulation workflow is illustrated in Figure 3.4. Climate, soil, crop parameters, and field management data are collected and used as inputs in Aquacrop. The Aquacrop model simulates crop yield based on the input data provided.

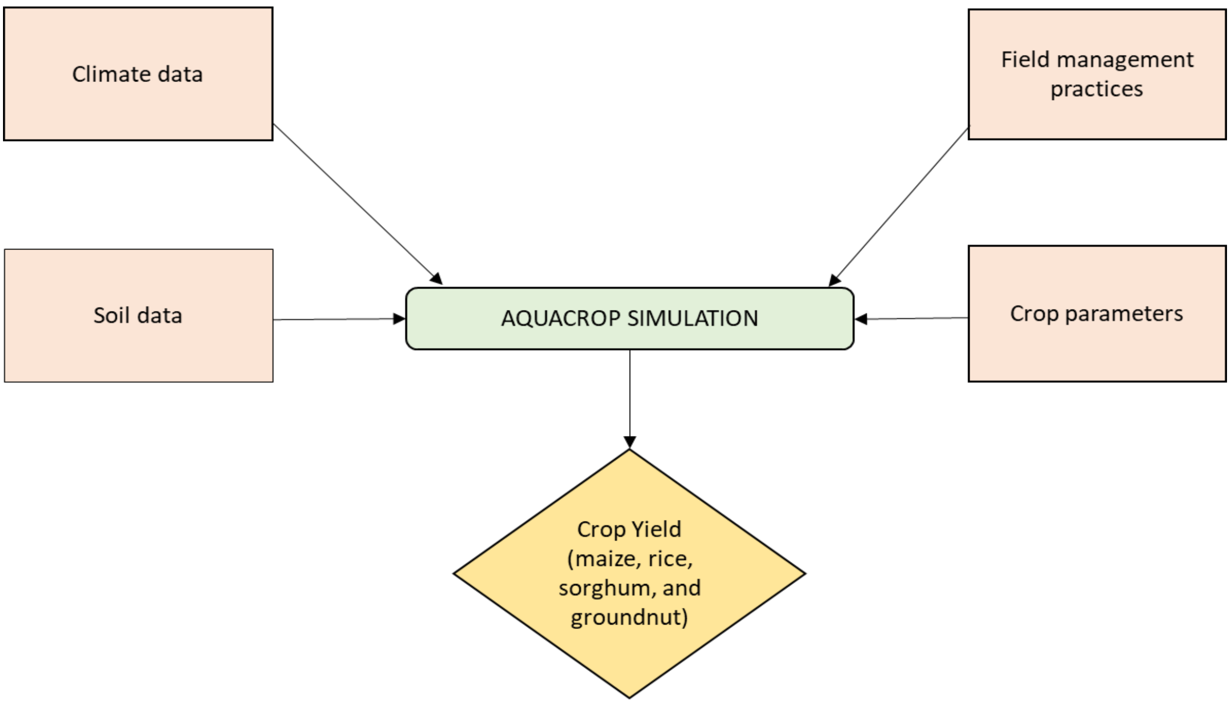

Figure 3.4. Flow chart for Aquacrop simulation process

3.7 Climate data

Aquacrop requires daily climate data on rainfall, minimum and maximum temperature, solar radiation, wind speed, and relative humidity to calculate evapotranspiration and, consequently, simulate crop yield and biomass production. Using GPS co-ordinates of the study area (i.e., Northern, Savannah, and North East regions), climate data was downloaded from the National Aeronautics and Space Administration's Prediction of Worldwide Energy Resources (NASA POWER) database. Since the daily data prior to 1990 is lacking, only daily climate data from 1st January 1990 to 31st December 2020 was used. In addition, the study utilised the AQUACROP in-built carbon dioxide (CO_2) concentration data from the Mauna Loa Observatory Laboratory in Hawaii. Given that farmers in the study area predominately practice rainfed agriculture, the study emphasised on the variability in rainfall as a primary determinant of crop yield variability including yield variabilities resulting from the application of nitrogen fertilisers. The standard deviation for daily rainfall from 1990 to 2020 was 4.2mm generating a 140% co-efficient of variation. This implies a significantly large variability in the rainfall data confirming the need to further explore how crop yield variabilities could be minimised.

3.7.1 Monthly precipitation

This section provides an overview of the monthly rainfall conditions in the study area. Research has revealed that the rainfall season in northern Ghana starts from April/May and ends in September/October each year (Amikuzinu and Donkor, 2012). This is represented in Figure 3.5, characterised by a uni-modal rainfall pattern starting from April/May to September/October and a dry period from November to March each year.

On average the mean monthly rainfall recorded from November to February for the 31-year period fell below 50mm per month with December and January experiencing almost 0mm of rainfall (see Figure 3.5). By observing Figure 3.5, although there were periods of rainfall from November to March, there is prolonged drought before the beginning of the April/May with rainfall less than 50mm per month. As a result, the cropping season for most crops in the Guinea Savannah zone for northern Ghana starts from April/May each year (FAO, 2020). Further, Figure 3.5 indicates a steady rise in rainfall pattern till it peaks in September followed by a subsequent decline from October to January.

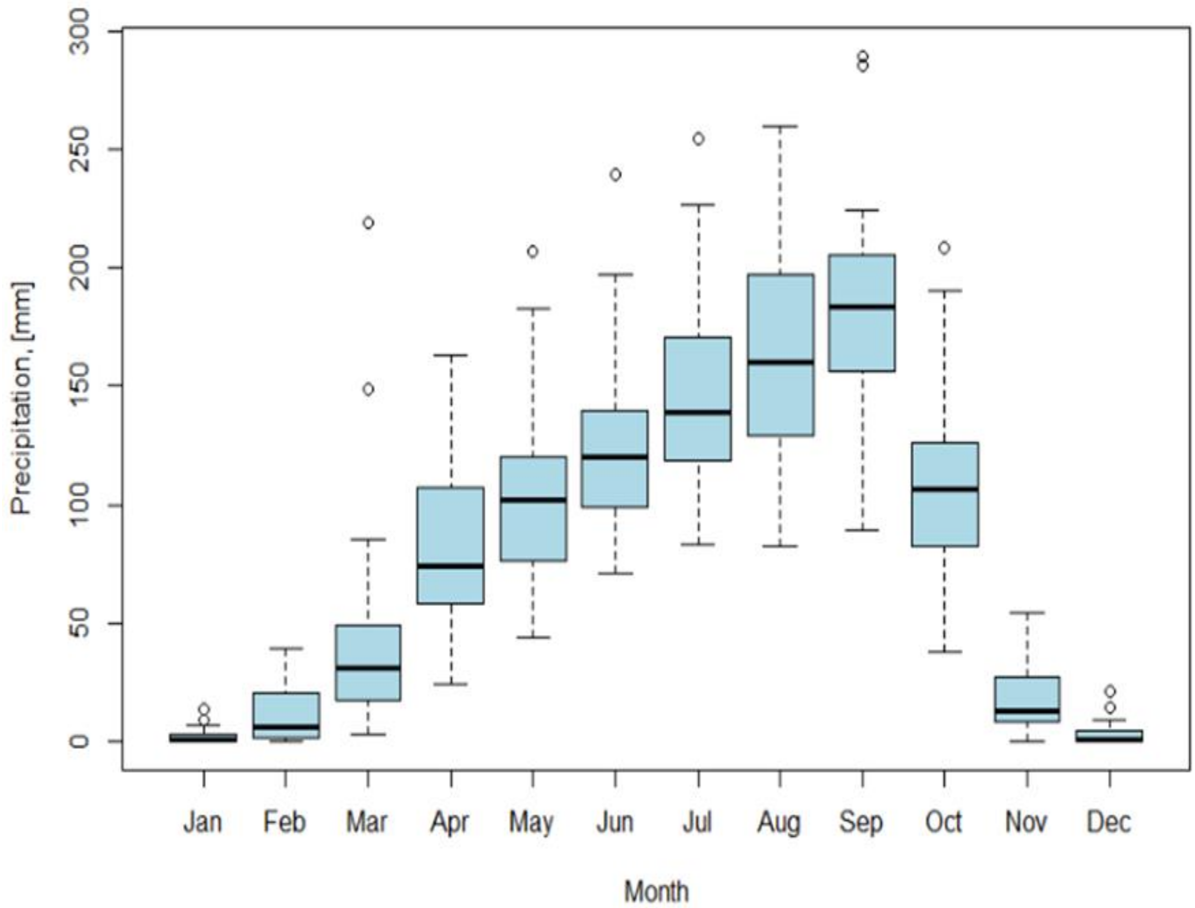

Figure 3.5. Mean monthly precipitation for the study area.

Further, , Figure 1.2 in the introductory chapter provides a detailed annual visualisation of the wet and dry seasons in the study area.

3.8 Soil profile

Data on soil profile was collected from Tetteh et al. (2016) by taking an average percentage of clay, sand, and organic matter content (OMC) for the 3 regions which were used as inputs for the USDA soil hydraulic properties calculator developed by Saxton et al. (1986).

Aquacrop requires soil related parameters on total available water (TAW), permanent wilting point (PWP), field capacity (FC), soil saturation (SAT), and saturated hydraulic conductivity (Ksat) to run simulations. Hence, the soil hydraulic properties calculator was chosen due to its ability to convert soil profile data (i.e. percentages of clay, sand, and OMC) to Aquacrop friendly parameters. The data for the soil parameters were 124g OMC, 45% sand, 51% silt, and 4% clay. After converting to Aquacrop friendly parameters, the study generated a PWP, FC, and SAT of 3.5 %Vol, 16.7 %Vol, 35 %Vol respectively. Also, a TAW of 98.3 mm/metre and Ksat of 378 (mm/day) was produced.

3.8.1 Parameters for soil fertility

Aquacrop uses a semi-quantitative approach to simulate the degree of fertility stress on biomass production as a result of nutrient deficiency (Akumaga et al. 2017). Hence, in the current study, simulating soil fertility in Aquacrop is determined by observing the ratio between the total above ground dry biomass production (*Bstress*) in kilograms per hectare for a nutrient stressed field (i.e. 0 kilogram (kg) nitrogen (N) per hectare(ha)), and the total dry above ground biomass production (*Bref*) in kg/ha of a reference field with a non-limiting soil fertility (i.e. 120 kgN/ha). This ratio is referred to as the relative biomass production (*Brel*) and is mathematically expressed as:

$$Brel = \frac{Bstress}{Bref} \times 100 \tag{3.20}$$

The study used data from Akumaga et al. (2017) as shown in Table 3.1 to calibrated soil fertility for maize at 0 kgN/Ha.

Table 3.1**.** Calibration data at 0 kgN/Ha for maize

Inputs for calibration	Value
Brel (%)	40
Maximum canopy cover (CCX) under soil fertility stress (%)	25
Canopy decline	Medium

Source: Akumaga et al. (2017)

Aquacrop estimates the relationship between relative biomass production and percentage soil fertility stress under northern Ghana environmental conditions (Figure 3.7). As a result of the 0 kgN/Ha applied, Figure 3.7 presents a relative biomass production of 22%, which results in a corresponding soil fertility stress of 70% for the study area. Furthermore, the slope of the graph implies a negative relationship between relative biomass production and percentage soil fertility stress, where an increase in soil fertility stress yields a corresponding decrease in relative biomass production.

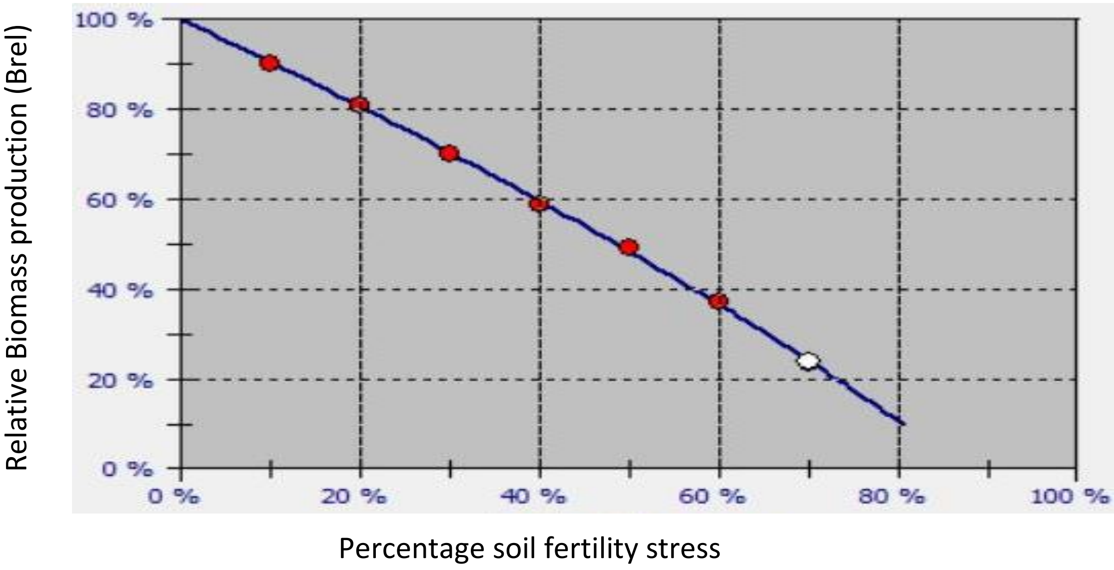

Figure 3.6. Relationship between relative biomass production and soil fertility stress

This research assumes that the relative biomass production and the corresponding level of soil fertility stress as shown in Figure 3.7 will be the same irrespective of the crop type used for soil fertility calibration. Hence, Figure 3.7 is a good generic representation of how fertile/infertile the soil is for crop growth and development under zero (0) kilogram nitrogen. As a result, Figure 3.7 is applied to all crops simulated in this study.

3.9 Simulations

Apart from groundnut, each crop was simulated from very poor to non-limiting soil nitrogen fertility conditions. The climatic data and soil profile were retained for all crops in the simulation process. All simulations produced yields from 1990 to 2020 for the three 3 districts. As there were no significant yield differences among districts, crop yields were averaged across the 3 districts each year to generate a time series yield data for the study area from 1990 to 2020.

3.9.1 Maize

Aquacrop has an in-built calibrated maize module suitable for all growing conditions. However, this study seeks to achieve simulated yield using conditions similar to northern Ghana such as soil type, climate and type of cultivar. The study utilised Aquacrop parameters and field experiments conducted by Akumaga et al. (2017) at the Institute of Agricultural Research, Ahmadu Bello University located in Zaria, northern Nigeria. The research undertook a seven-year experiment ranging from 2007 to 2013 for a hybrid maize cultivar (Oba Super 2 variety) to calibrate maize in Aquacrop under local soil and environmental conditions. The Aquacrop model simulations from the research were validated against observed yield using the root-mean-squared-error (RMSE) method.

3.9.2 Modification of non-conservative maize parameters for local conditions in northern Ghana.

The non-conservative parameters from Akumaga et al. (2017) were modified to suit growing conditions in northern Ghana. The planting date was changed from 25th May to Aquacrop generated planting date which is chosen based on the soil and climatic conditions in northern Ghana. Furthermore, to effectively account for variations in temperature and the effect of thermal time on crop growth and development, the study runs the model on a growing degree day (GDD) mode instead of calendar days by switching to the growing degree days option in Aquacrop (Karunaratne et al. 2011). In addition, calendar days has been described as not being an appropriate way of examining crop phenology since water stress which is often affected by temperature, has a crucial effect on flowering and physiological development of the crop (Azam-Ali & Squire, 2002). As a result, calendar days data from Akumaga et al. (2017) was imported into Aquacrop and converted to GDD units using climate and soil data from northern Ghana. Appendix 1 provides the full set of data in calendar days from Akumaga et al. (2017) and the corresponding data generated for northern Ghana in growing degree days (GDD).

3.9.3 Rice

Following the calibration and yield simulation for maize, Aquacrop rice was also calibrated for northern Ghana based on data from available literature. Data on soil profile, and climate were retained. The non-conservative parameters in the Aquacrop rice module were updated using Abdul-Ganiyu et al. (2018) crop parameter data already validated for Aquacrop rice in northern Ghana. However, in contrast to the objective of this study where rice yield is modelled under rainfed and different soil fertility conditions, Abdul-Ganiyu et al. (2018) calibrated Aquacrop rice under irrigation at the Savannah Agricultural Research institute located in northern Ghana. The Gbewa Jasmine 85 rice variety was used for the experimental work during the dry season in 2012/2013 and 2013/2014. This study employed all crop parameters in Appendix 2 to simulate rice yield under rainfed conditions.

3.9.4 Sorghum

Sorghum yield simulations were also modelled using the Aquacrop default sorghum file. The variety calibrated in Aquacrop is the Texas Bushland sorghum variety. Appendix 3 presents the parameters used to simulate sorghum yield in Aquacrop. The time from sowing to emergence, maximum rooting depth, canopy senescence, maturity, flowering, duration of flowering and building of harvest index were all recorded in growing degree days for reasons explained earlier in this chapter.

3.9.5 Groundnut

Given that groundnut (Arachis hypogea) is a nitrogen fixing plant, simulation was not done under different levels of nitrogen application rate. Aquacrop does not have a calibrated groundnut file like sorghum. As a result, the fruit/grain producing crop file in Aquacrop was used to create a groundnut file for calibration. This study utilized published data on crop parameters for groundnut from Chibarabada et al. (2020). The experiments used to generate this data were from field trials and environmentally controlled conditions for both rainfed and irrigation management regimes in South Africa. All parameters were recorded in growing degree days based on the climatic conditions in the study area.

Furthermore, determinacy for groundnut was not linked to flowering as the crop is an indeterminate type, hence continues to form canopy even after flowering. Trials from Chibarabada et al. (2020) not considering soil fertility stress conditions observed 0.27% initial canopy cover and 68% maximum canopy cover throughout the growth cycle of the crop (see Appendix 4). By default, Aquacrop generated the plant population, maximum effective rooting depth, and length building up harvest index under northern Ghana conditions.

3.10 Results and discussion

3.10.1 Maize

This section presents the results for maize yield. Simulated yields from varying fertility levels were compared to yields from published literature (see Table 3.2) to determine the nitrogen application rates, as Aquacrop does not explicitly state the level of nitrogen in kg per hectare terms. Based on the findings made from Fosu-Mensah et al. (2012), Essel et al. (2020), and MacCarthy et al. (2018), the study concludes that yield simulated under increasing levels of soil fertility from very poor to non-limiting conditions corresponds to 0 kg/Ha, 40 Kg/Ha, 80 kg/Ha, and 120 Kg/Ha of nitrogen.

As shown in Table 3.2, MaCarthy et al. (2018) simulated maize yield under non-limiting rain-fed conditions in Yendi (northern Ghana) using 120 kg/ha of nitrogen fertilizer. The findings indicate that using the Obatampa maize variety yielded a mean value of 3.98 tons/ha from 1980 to 2009. This corresponds to the Aquacrop yield mean value of 3.62 tons/Ha (Table 3.2) from 1990 to 2020. Other research works by Fosu-Mensah et al. (2012) also recorded close figures to the Aquacrop results in this study (Table 3.2).

Table 3.2**.** Comparing Aquacrop simulated yield with literature yield for maize.

Nitrogen application rate	Aquacrop mean yield (tons/Ha)	Yield from literature sources (tons/Ha)	Literature source
0 Kg/Ha	0.91	0.918	Fosu-Mensah et al. (2012)
40 Kg/Ha	2.25	2.39	Fosu-Mensah et al. (2012)
80 Kg/Ha	3.22	3.269	Fosu-Mensah et al. (2012)
120kg/Ha	3.62	3.982	MacCarthy et al. (2018)

3.10.2 Rice

Similar to maize, rice yield simulations were performed under varying soil fertility in Aquacrop as a proxy for varying nitrogen application levels. Yield response to nitrogen levels were found from literature sources and compared with the results from this study. As shown in Table 3.3, increasing levels of nitrogen corresponds with an increasing effect on rice yield at a decreasing rate.

Table 3.3**.** Comparing Aquacrop simulated yield with literature yield for rice

Levels of nitrogen application	Aquacrop mean yield (tons/Ha)	Yield from literature in tons/Ha	Literature source
0 Kg/Ha	1.49	1.70	Moro et al. (2015)
30 Kg/Ha	3.28	3.20	Moro et al. (2015)
60 Kg/Ha	4.64	4.92	Tsujimoto et al. (2017)
100kg/Ha	4.96	5.0	Martínez and Furtz (2021)

The rice yield simulated in this research under non-limited soil fertility conditions were lower compared to the yield reported by Abdul Ganiyu et al. (2018). Under non-limiting soil fertility conditions, the current study simulated a mean yield of 4.96 tons/Ha under rainfed conditions whereas a 6.43 tons/Ha was simulated under irrigated conditions in northern Ghana (Abdul-Ganiyu et al., 2018), representing a yield gap of about 30.4%. The differences in yield could be attributed to water limitations at crucial stages of the plant's growth and development under rainfed conditions. At the national level, Anang et al (2016), alluded to a rice yield gap of 38.5% under rainfed conditions, implying a potential increase in yield when irrigation methods are employed.

3.10.3 Sorghum

Sorghum simulation results were produced in Aquacrop for varying levels of soil fertility. Table 3.4 shows Aquacrop yields corresponding to those with similar nitrogen application rates from literature.

Table 3.4. Comparing Aquacrop simulated yield with literature yield for sorghum

Levels of nitrogen application	Aquacrop mean yield (tons/Ha)	Yield from literature in tons/Ha	Literature source
0 Kg/Ha	0.78	0.71	Kpongor et al. (2006)
40 kg/Ha	2.65	2.53	Melaku et al. (2018)
80 Kg/Ha	3.07	2.86	Kpongor et al. (2006)
100 Kg/Ha	3.27	3.67	Martínez and Furst (2021)

3.10.4 Groundnut

Yield simulations range on average from 1990 to 2020 for the study area was 2.26 tons/ha. Chibarabada et al. (2020) reported 2.0 tons/hectare under rainfed conditions indicating a close relationship with the study results. The average yield for groundnut in northern Ghana based on data collected from Ghana's Ministry of Food and Agriculture from 2000 to 2020 is 1.79 tons/ha. This represents a 20.7% decline in yield from the simulated yield in this study. Since Aquacrop is a point-based simulation process, the yield reduction could be attributed to the spatial differences in soil fertility and farmer specific farm management practices at regional scale.

3.11 Soil fertility effect on yield and variability

Under increasing soil fertility conditions, yield for maize increased from 0.91 tons/ha for 0kg/ha of nitrogen to 3.62 tons/ha at 120kg/ha of nitrogen. As soil fertility increases, yield increases at a decreasing rate (see Figure 3.8), and the standard deviation also increases for all crops (Appendix 5). This implies that there is a diminishing return to yield and a potential increase in variability when fertiliser application rates increase. One of the key ways to minimise variability in yield is to employ climate smart technologies that save water for plants to effectively utilise the effect of an increase in fertility levels.

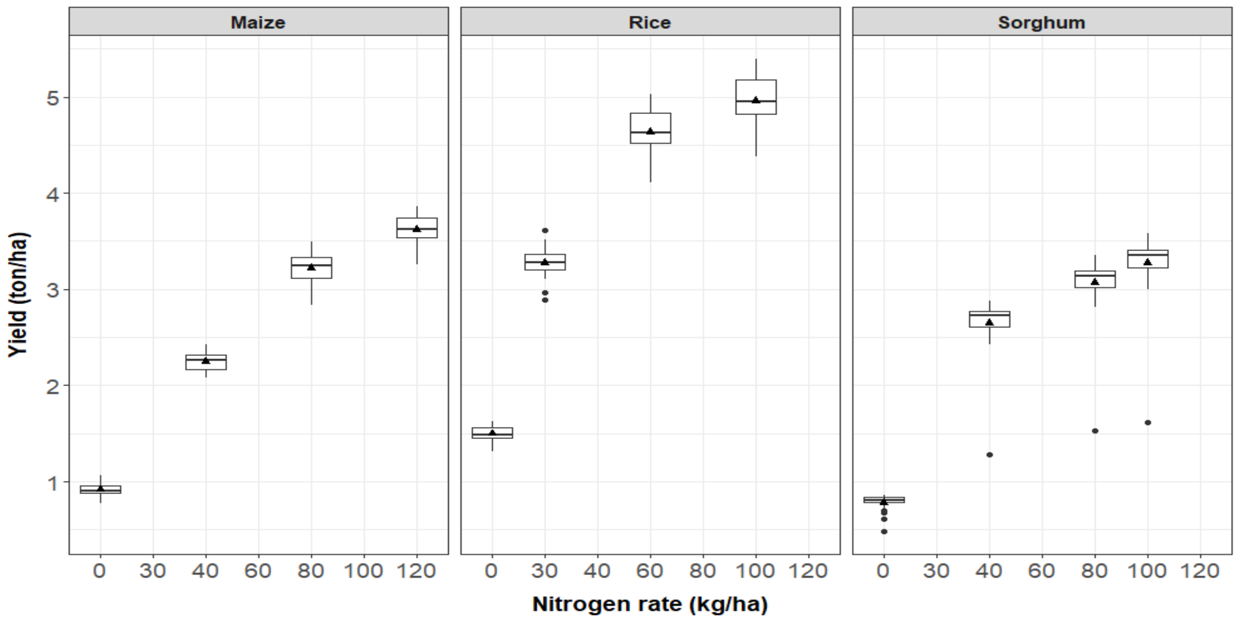

Figure 3.7. Crop yield per nitrogen application rate for maize, rice, and sorghum

NB: Triangular points and black line within the box plots represent the mean and median respectively.

3.12 Conclusion

As part of the bio-economic modelling process, this Chapter first described the theoretical framework of the study. A mathematical construct from previous research was used to explain the utility of farm households when income is gained or lost in the context of risk aversion, potential changes in income, exogeneous shifters in utility (i.e age, gender, education etc), fixed and variable transaction cost, market participation, and expenditure. Further, the study provides a detailed theoretical analysis of how changes in the effective market price could influence production quantities of both buying and selling households. By including the Aquacrop simulations, the study draws more insight on how bio-physical factors over a period could be analysed in conjunction with the economic conditions of farm households to generate meaningful outcomes for policy. Given the key crops cultivated in the study area; maize, rice, sorghum, and groundnut yields were simulated with emphasis on soil type, crop parameters, and climatic conditions. Empirical data for crop modelling in Ghana was a major challenge in developing crop parameters in this Chapter. However, data from literature and other relevant sources were largely employed to simulate yield under different climatic and soil nutrition conditions. Also, the variability in crop yield revealed in this Chapter gives room for further analysis into how climate smart technologies (CSTs) such as changing planting date, compartmental bunding, mulching, and transplanting could contribute to improving the resilience of smallholder farmers. As a result, Chapter 4 investigates how to select the most ideal *CST* that could minimise yield variabilities among smallholder farmers.

3.13 Appendix

Appendix 1: Non conservative crop parameters for Zaria (northern Nigeria) in calendar days and northern Ghana in growing degree days

Location	**Northern Nigeria**		**Northern Ghana**	
Crop Parameters	Value	Units	Value	Units
Time from sowing to emergence	7	Days	132	GDD
Time to maximum canopy cover	74	Days	1352	GDD
Time from sowing to maximum rooting depth	65	Days	1195	GDD
Time from sowing to start of canopy senescence	91	Days	1653	GDD
Time from sowing to maturity	120	Days	2175	GDD
Time from sowing to flowering	67	Days	1230	GDD
Duration of flowering	30	Days	532	GDD
Maximum effective rooting depth	1.0	metre	1.0	metre
Minimum effective rooting depth	0.30	metre	0.30	metre
Reference harvest index (HI)	40	%	40	%
Building up of Harvest Index	53	Days	872	GDD
Cultivar (Oba super 2)	-	Oba super 2	-	Oba super 2
Plant population	53,333	Plants/Ha	53,333	Plants/Ha
Sowing date	25th May	Date	Varies from year to year	Date
Nitrogen application rates in kilograms/hectare (kg/ha)	0,30,60,90	kg/ha	0,40,80,100	kg/ha

Note: GDD represents growing degree days

Appendix 2: Crop parameters for rice in northern Ghana

Crop Parameters	Value	Units
Base temperature	8.0	°C
Upper temperature	30.0	°C
Canopy size for transplanted seedling	5.5	cm^2/plant
Time from transplanting to recovery (growing degree days-GDD)	92	GDD
Maximum canopy cover (almost entirely covered)	95	%
Time from transplanting to maximum rooting depth (Aquacrop default)	302	GDD
Time from transplanting to start of canopy senescence	1376	GDD
Time from transplanting to maturity	1992	GDD
Time from transplanting to flowering	1292	GDD
Duration of flowering	227	GDD
Maximum effective rooting depth	0.60	metre
Minimum effective rooting depth	0.30	metre
Reference harvest index (HI)	55	%
Building up of Harvest Index	654	GDD
Normalized water productivity	19	Gram/m^2
Minimum air temperature below which pollination starts to fail	8	°C
Maximum air temperature above which pollination starts to fail	35	°C
Minimum growing degrees required for full biomass production	10	°C
Shape factor for water stress co-efficient for stomatal control	3	-
Shape factor for water stress co-efficient for canopy senescence-upper threshold	3	-
Plant population	250000	Plants/Ha
Sowing date	Varies from year to year	Date
Soil fertility stress	70	%

Source: Adbul-Ganiyu et al. (2018)

Appendix 3: Crop parameters for sorghum

Crop Parameters	Value	Units
Base temperature	8.0	°C
Upper temperature	30.0	°C
Canopy size for transplanted seedling	3	cm^2/plant
Time from sowing to emergence (growing degree days-GDD)	248	GDD
Maximum canopy cover (fairly covered)	70	%
Time from sowing to maximum rooting depth	1797	GDD
Time from sowing to start of canopy senescence	1709	GDD
Time from sowing to maturity	1904	GDD
Time from sowing to flowering	1230	GDD
Duration of flowering	369	GDD
Maximum effective rooting depth	1.80	metre
Reference harvest index (HI)	45	%
Length building up of Harvest Index	674	GDD
Normalized water productivity	33.7	Gram/m^2
Minimum air temperature range	+5 to +10	°C
Maximum air temperature range	+40 to +45	°C
Shape factor for water stress co-efficient for stomatal control	3	-
Plant population	74000	Plants/Ha
Sowing date	Varies from year to year	Date
Soil fertility stress	70	%

Appendix 4: Crop parameters for groundnut

Crop Parameters	Value	Units
Base temperature	8.0	°C
Upper temperature	30.0	°C
Initial canopy cover	0.27	%
Canopy size for seedlings	5	cm^2/plant
Time from sowing to emergence (growing degree days-GDD)	127	GDD
Maximum canopy cover (fairly covered)	68	%
Time from sowing to maximum rooting depth	1797	GDD
Time from sowing to start of canopy senescence	1592	GDD
Time from sowing to maturity	2320	GDD
Time from sowing to flowering	595	GDD
Duration of flowering	798	GDD
Minimum effective rooting depth	0.3	m
Maximum effective rooting depth (Aquacrop default)	1	metre
Reference harvest index (HI)	24	%
Length building up harvest index (Aquacrop default)	950	GDD
Normalized water productivity	15	Gram/m^2
Minimum air temperature affecting pollination		°C
Maximum air temperature affecting pollination	34	°C
Canopy expansion response to water stress	Moderately tolerant	-
Stomatal closure response to water stress	Moderately sensitive	-
Early canopy senescence response to water stress	Moderately tolerant	-
Aeration stress to waterlogging	Moderately tolerant	
Determinacy linked with flowering	No (indeterminate crop	-
Plant population (Aquacrop default)	54000	Plants/Ha
Sowing date	Varies from year to year	Date
Soil fertility stress	None	-

Appendix 5: Summary statistics per crop per level of soil fertility

Nitrogen application rate	Maize yield			
	Min	Max	Mean	Std
0 kg/ha	0.79	1.07	0.91	0.07
40 kg/ha	2.08	2.43	2.25	0.10
80 kg/ha	2.83	3.49	3.22	0.14
120 kg/ha	3.26	3.86	3.62	0.15
	Rice yield			
0 kg/ha	1.32	1.63	1.49	0.08
30 kg/ha	2.89	3.61	3.28	0.15
60 kg/ha	4.29	5.03	4.64	0.21
100 kg/ha	4.38	5.3	4.96	0.23
	Sorghum yield			
0 kg/ha	0.49	0.86	0.78	0.80
40 kg/ha	1.28	2.88	2.65	0.28
80 kg/ha	1.53	3.35	3.07	0.31
100 kg/ha	1.62	3.58	3.27	0.34
	Groundnut yield			
0 kg/ha	2.08	2.46	2.26	0.10

Chapter 4 Enhancing climate resilience in Northern Ghana: A stochastic dominance analysis of risk-efficient climate smart technologies

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4.1 Introduction

As a result of the rainfed dependent agricultural systems in northern Ghana, climate variabilities such as temperature and precipitation changes pose significantly impact on farmers' decision-making processes (Bhave et al., 2016). Wossen et al. (2014) indicate that such changes in temperature and precipitation could have dire implications on the food security and economic wellbeing of smallholder farm households. According to Issahaku and Awudu (2019), the high level of climate variability in the last 40 years has created uncertainty in the agricultural production system, exposing poor farmers to higher crop production risk. Climate vulnerability in developing countries has been attributed to the high level of poverty, resource constraints, low adaptive capabilities as a result of the lack of adequate infrastructure and technology, and weaknesses in institutional frameworks (Serdeczny et al., 2017).

To enhance climate risk resilience, climate-smart technologies (*CSTs*) such as changing planting dates, drought-resistant crop varieties, irrigation, and soil water conservation technologies have been employed in developing countries to improve crop yield (Di Falco and Veronesi 2013, Adamson et al. 2017). According to the Food and Agricultural Organisation (FAO), a climate smart technology (*CST*) is described as an activity that enhances the productivity and profitability of farms, increases resilience to climate change, and reduces environmental impact (Issahaku and Abdulai, 2019).

Various studies such as Abegunde et al. (2019), Antwi-Agyei et al. (2021), Chinseu et al. (2018), Dougill et al. (2021) and Makate (2019), have highlighted the importance of *CSTs* in improving food security in developing countries. However, there are some notable trade-offs associated with using some of them. For example, mixed cropping is a *CST* that is capable of improving the adaptability of smallholder farmers by increasing their income and reducing production risk relative to growing a single crop; however, it may result in over-crowding on the farm, reduction in soil nutrients, and may eventually cause land degradation (Antwi-Adjei et al. 2023). Also, irrigation methods are helpful in reducing yield losses, but such technologies are likely to be expensive for smallholder farmer.

Several research institutions in Ghana, such as the Centre for Scientific and Industrial Research, Universities, and the Ministry of Food and Agriculture, have developed *CSTs* to support farmer adaptation to climate change.

According to Nakuja et al. (2012), *CSTs* in northern Ghana include, but are not limited to, tree planting, irrigation, early maturing and drought tolerant varieties, conservation agriculture, row planting, inorganic fertilizers, and high-yielding varieties. Promoting *CSTs* in Ghana under the National Climate Smart Agriculture Program and the Food Security Action Plan has created a roadmap to scale up the adoption of climate smart intervention activities in all agroecological regions countrywide (Essegbey et al., 2015). Despite these initiatives, the level of *CST* adoption is low (Barasa et al., 2021, Djido et al., 2021). This increases the exposure of smallholder farmers to production risk under increasing climate variability.

4.2 Research gap

Issahaku and Abdulai (2020) revealed that employing *CSTs* such as drought-resistant and early maturing varieties plus soil and water conservation resulted in increased income and reduced exposure to production risk, especially when these *CSTs* are jointly adopted. Since using *CSTs* are necessary for risk management in agriculture, it is crucial to analyse this from the perspective of the smallholder farmer's risk preference. However, there is a lack of research in northern Ghana on the connection between using *CSTs* and smallholder farmers' risk preferences. This study seeks to contribute to closing the gap by analysing how risk-efficient *CSTs,* namely changing planting date *(PD),* transplanting *(TP)*, mulching *(M),* and compartmental bunding *(CB),* are, from the perspective of risk aversion among smallholder farmers, using a stochastic dominance approach.

4.3 Stochastic dominance modelling

Several studies have been conducted on risk ordering using stochastic dominance (Anderson, 1974, Hardaker et al., 2015). These studies explained the preference assumption and ordering rules for first and second-order stochastic dominance. They revealed that for first-order stochastic dominance *(FSD)*, the decision maker prefers more to less of the random variable, such as gross margin *(GM).* In the current study, this implies that smallholder farmers want to maximise their satisfaction when using *CSTs*. So in selecting the most risk-efficient *CST*, they will eliminate alternatives with high probabilities of low *GM* outcomes. For two technologies *X* and *Y*, each with a distribution of *GM* outcomes defined by *CDFs,* $F_X(GM)$ and $F_Y(GM)$, respectively, technology X dominates Y in the first-degree sense if and only if: $F_X(GM) \leq F_Y(GM)$ and $F_X(GM) < F_Y(GM)$ for at least one *GM* outcome (Anderson, 1974). For the *FSD* condition, $F_X(GM)$ graphically falls below $F_Y(GM)$ (Figure 4.1).

Also, FSD is transitive, in the sense that when another alternative *(Z)* is included, one can conclude that if $F_X(GM) \leq F_Y(GM)$, and $F_Y(GM) \leq F_z(GM)$, then $F_x(GM) \leq F_z(GM)$ (Bezuneh, 1991).

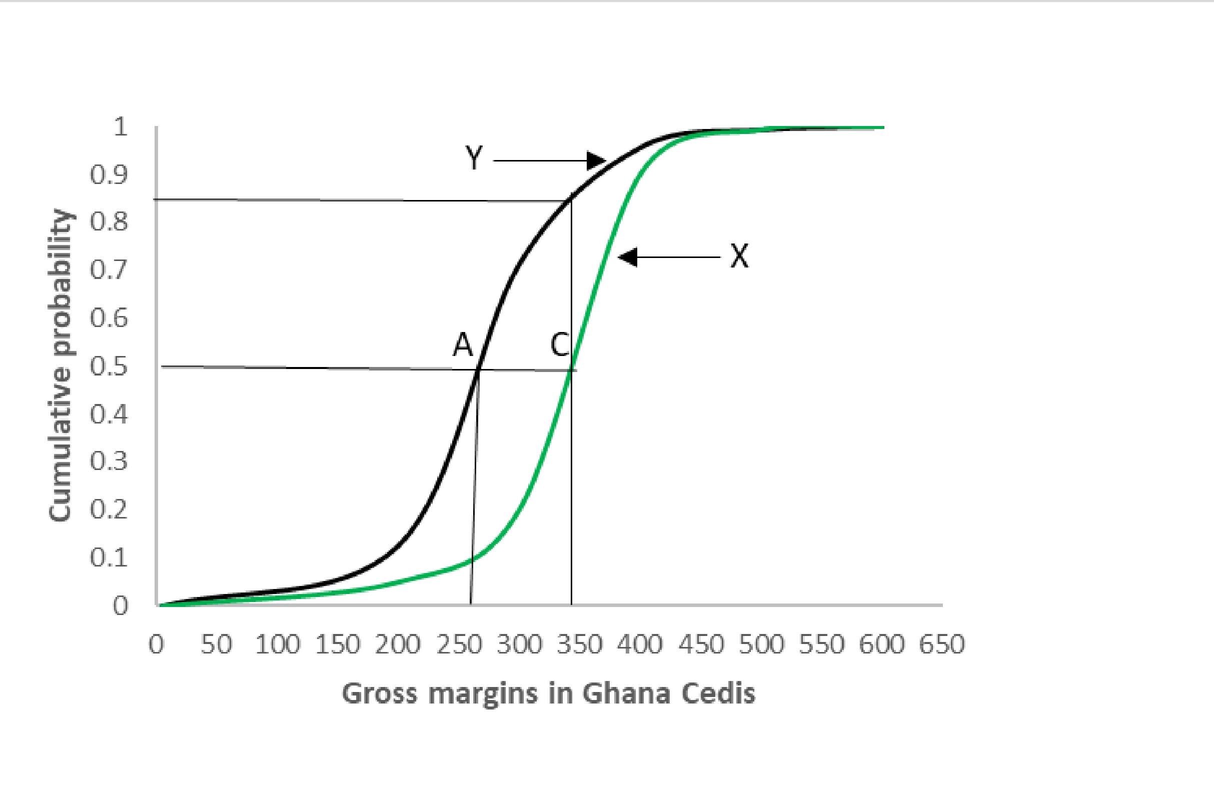


Figure 4.1. Cumulative distribution functions (CDFs) for technologies X and Y showing first-order stochastic dominance.

The *CDFs* in Figure 4.1 show the probability of an event occurring at a point or at an interval. The 0.5 and 0.85 cumulative probabilities imply that the probability of receiving between 0 to 350 Ghana cedis (GH₵) at point C is 50% for technology *X* and 85% for technology *Y* respectively (Figure 4.1). This means, relative to technology *X*, there is a higher probability of achieving a low *GM* outcome when technology *Y* is used as both cumulative probabilities (i.e. 0.5 for *X* and 0.85 for *Y*) occur at an interval of GH₵ 0 to GH₵ 350. Alternatively, at a cumulative probability of 50% (0.5) for both technologies, farmers receive between GH₵ 0 to GH₵ 350 (point C) for using technology *X*, but only GH₵ 0 to GH₵ 250 (point A) using technology *Y*. A rational smallholder farmer who prefers more to less will always choose technology *X* over *Y*.

To tie in the concept of risk aversion, second-degree stochastic dominance (*SSD*) is employed when the cumulative distributions of the technologies cross (Figure 4.2). In Figure 4.2, technology *X* dominates *Y* at lower regions of *GM* (i.e. between *D* and *E*). In contrast, at higher regions between *E* and *F*, technology *Y* dominates *X*, violating *FSD*. *SSD* approaches this by searching for the undominated option from these alternatives using the area under the curve of the *CDF* for all levels of *GM* outcomes for those technologies (Hardaker et al., 2015). The technology with the smallest area under the curve represents the most preferred option for a risk-averse farmer, given that the farmer's utility is monotonically increasing at a decreasing rate. This is mathematically expressed as:

$$\int_{-\infty}^{GM} F_X(GM)dGM \leq \int_{-\infty}^{GM} F_Y(GM)dGM \qquad (4.1)$$

Where $-\infty$ to *GM* represents the *GM* range from negative infinity *(*$-\infty$), which is the lowest *GM* to the highest for technology *X* and *Y,* respectively. From equation 4.1, $F_X(GM)$ second-order stochastically dominates $F_Y(GM)$.

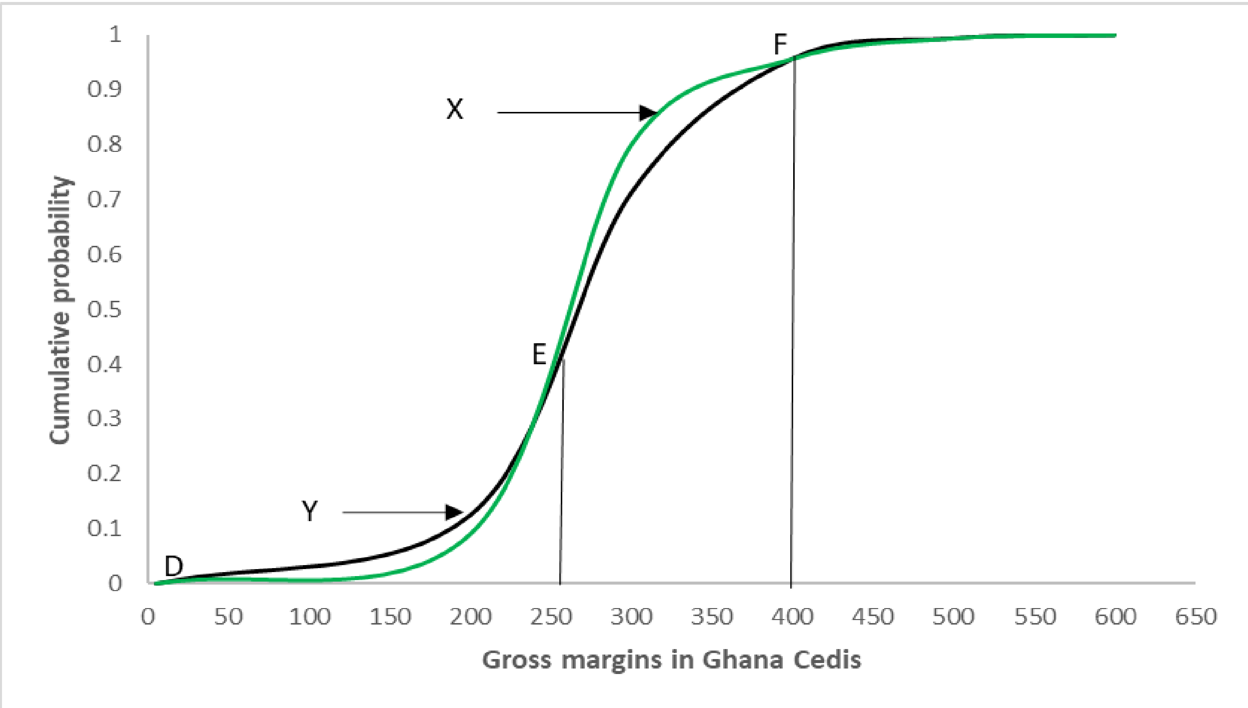


Figure 4.2. Cumulative distribution functions (CDFs) for technologies X and Y showing second-order stochastic dominance (SSD)

Research institutions in Ghana have recommended many *CSTs*, but there is a lack of research-led evidence on which *CSTs* are the most risk-efficient ones within the framework of the smallholder farmer's expected utility. As a result, the objectives of this research are to:

1. Determine whether *CSTs* in northern Ghana produce higher yields as farmers will rationally prefer *CSTs* that have a higher chance of increasing their yield.

2. Determine the risk efficiency of *CST*, based on the assumption that smallholder farmers are risk averse.

3. Identify which *CSTs* can be employed at a lower cost whilst enhancing the climate resilience of the smallholder farmer.

4.4 Study area

The study area is made up of 3 regions namely; the Savannah, Northern and North East regions of Ghana (Figure 4.3) and is situated in the Guinea savannah agro-ecological zone. Soil types in the region are predominantly Savanah Ochrosols (Mustapha et al. 2020) with a land area of approximately 70,383 km^2 representing about one-third of Ghana's land area (Mustapha et al. 2020). Northern Ghana is the leading producer of most grains and cereals including maize, rice, and sorghum (Yiridoe et al. 2006). About 90.5% of the households are rain-fed crop farmers with limited capacity to mitigate the negative effects of climate variabilities due to low socio-economic development, resulting in major adverse impacts on crop yield (Antwi-Agyei et al. 2012).

The rainfall season in northern Ghana begins in April/May and ends in September/October each year. Northern Ghana is the most climate-vulnerable region in the country (Amikuzinu and Donkor, 2012) and is characterised by a uni-modal rainfall pattern. The rainfall pattern in the region usually peaks in September, followed by a subsequent decline from October to January (Appendix 1). The mean monthly rainfall recorded from November to March usually falls below 50mm per month, with December and January experiencing almost 0mm of rain (Appendix 1). Although there are episodes of rainfall from November to March, there is a prolonged drought before the beginning of the April/May rainy season, which records more than 50mm of rain per month. Hence, the cropping season for most crops in the Guinea Savannah zone for northern Ghana starts in April/May each year (FAO, 2020).

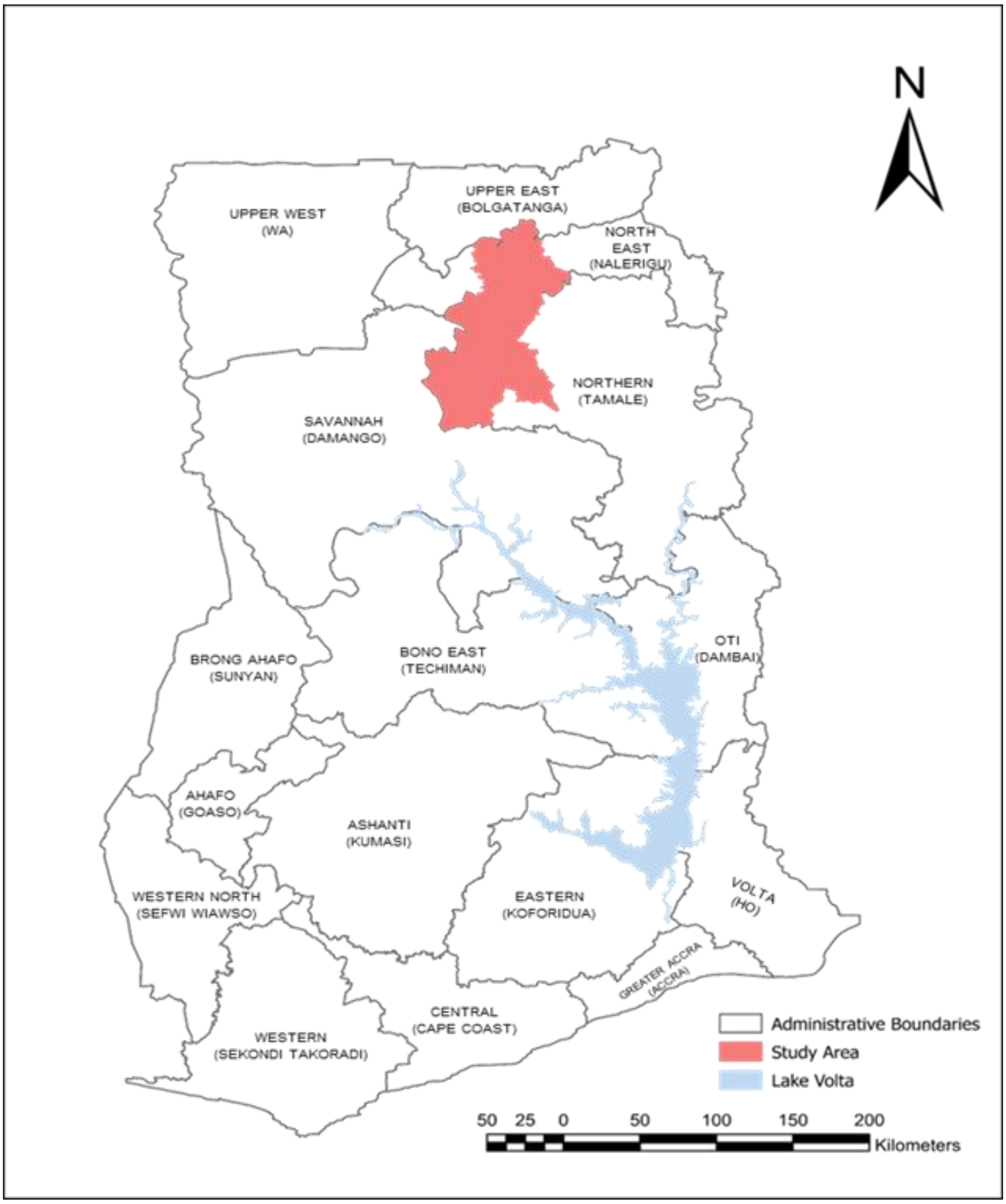


Figure 4.3. Map of Ghana showing regional capitals.

4.5 Method of analysis

4.5.1 Aquacrop simulation

To estimate the appropriate *GM* distributions for stochastic dominance modelling, this research uses Aquacrop models to simulate yields for three main crops cultivated in the study area (i.e. maize, rice, and sorghum but not groundnut[1]) given the soil type, *CSTs*,

[1]Since this Chapter is based on recommended practice and farmer practice having different nitrogen application rates, groundnut was excluded from the simulations.

farmers' practice (*FP*) and recommended practice (*RP*). In the current study, *FP* refers to nitrogen application rates generally practiced by farmers in the study area, whereas *RP* refers to recommended nitrogen application rates per crop from literature sources such as MacCarthy et al. (2017), MacCarthy et al. (2010), and Ragassa et al. (2013). The structure and flow of this modelling process is illustrated in Figure 4.4. The following subsections describe the process in detail.

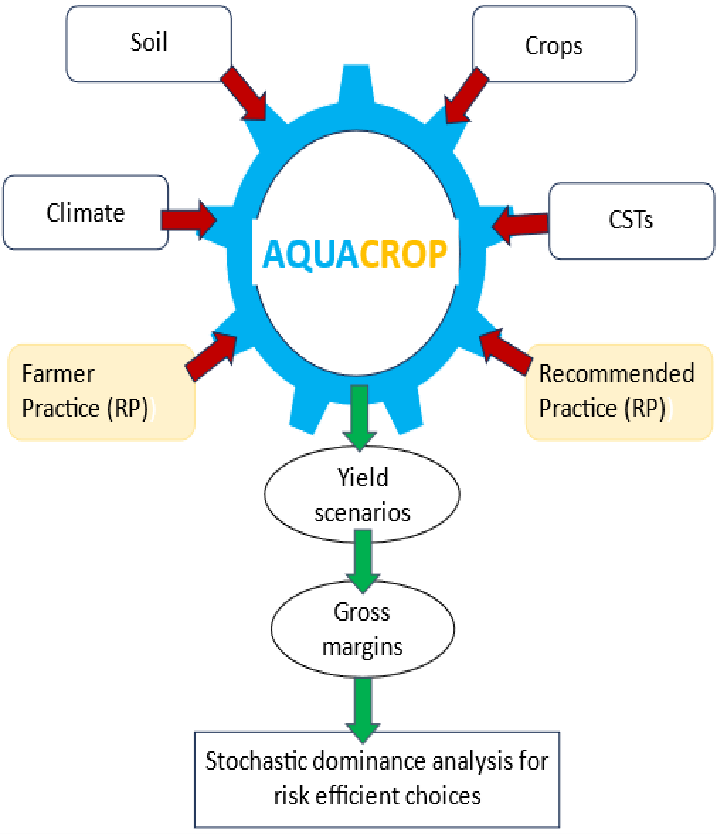


Figure 4.4. Modelling framework for stochastic dominance analysis.

4.5.2 Soil

The soil type in the study area is characterised by moderately coarse fragments (Tetteh et al. 2016). Data on soil profile was collected from Tetteh et al. (2016) by taking the percentage of sand, silt, clay, and organic matter (*OM*) in g/kg of soil in the study area. The United States Department of Agriculture (*USDA*) soil hydraulic properties calculator converts the soil profile data comprising 124g (*OM*)/kg of soil, and soil with 45% sand, 51% silt, and 4% clay to Aquacrop-usable parameters. The results indicate that the soil properties formed a silty loam textural class at a permanent wilting point (*PWP*) of 3.5 %Vol (i.e. 3.5% of water per metre cube of soil), field capacity (*FC*) of 16.7 %Vol, saturation point (*SAT*) of 35 %Vol, total available water (*TAW*) of 98.3 mm/m of soil and a saturated hydraulic conductivity (Ksat) of 378 mm/day. These soil profile parameters were used to run all crop simulations in Aquacrop.

4.5.3 Climate

Aquacrop requires daily climate data on rainfall, minimum and maximum temperature, solar radiation, wind speed, and relative humidity to calculate evapotranspiration and consequently simulate crop yield and biomass production. Climate data from 1st January 1990 to 31st December 2020 was downloaded from the National Aeronautics and Space Administration's POWER (Prediction of Worldwide Energy Resources) database (NASA, 2023) using the GPS coordinates of the study area. In addition, the research utilised the Aquacrop in-built carbon dioxide (CO_2) concentration data from the Mauna Loa Observatory Laboratory in Hawaii.

4.6 Crops

4.6.1 Maize

Aquacrop has an in-built maize-calibrated module suitable for all growing conditions. However, the current study seeks to achieve simulated yields using conditions similar to northern Ghana: soil type, climatic conditions, and cultivar. As there is no Aquacrop appropriate experimental data for maize in northern Ghana, the study utilised Aquacrop parameters and field experiments conducted by Akumaga et al. (2017) at the Institute of Agricultural Research, Ahmadu Bello University, located in Zaria, northern Nigeria. This was a seven-year experiment from 2007 to 2013 for a hybrid maize cultivar (Oba Super 2 variety) used to calibrate maize in Aquacrop under local soil and environmental conditions. The Aquacrop model simulations from the research were validated against observed yield using the root mean squared error (*RMSE*) method.

The parameters from Akumaga et al. (2017) were modified to suit growing conditions in northern Ghana. The current study employed Aquacrop generated planting dates, which are chosen based on the soil and climatic conditions each year in northern Ghana. To effectively account for variations in temperature and the effect of thermal time on crop growth and development, the study runs the model on a growing degree day (*GDD*) mode instead of calendar days by switching to the growing degree days option in Aquacrop (Karunaratne et al. 2011). In addition, calendar days have been described as an inappropriate way of examining crop phenology since water stress which is often affected by temperature, has a crucial effect on flowering and physiological development of the crop (Azam-Ali & Squire, 2002). As a result, calendar-days data from Akumaga et al. (2017) was imported into Aquacrop and converted to *GDD* units using climate and soil data from northern Ghana. The data generated for northern Ghana in growing degree days (*GDD*) is represented in Appendix 2.

4.6.2 Sorghum

To the best of our knowledge, no Aquacrop-appropriate experimental data was available for sorghum for Sub-Saharan Africa. As a result, sorghum yield simulations were modelled using the Aquacrop default sorghum file under the study area's climatic and soil conditions used to simulate maize. The variety calibrated in Aquacrop is the Texas Bushland sorghum variety. Appendix 3 represents the parameters used to simulate sorghum yield in Aquacrop. The time from sowing to emergence, maximum rooting depth, canopy senescence, maturity, flowering duration, and building of harvest index were recorded in growing degree days for reasons explained earlier.

4.6.3 Rice

The Aquacrop rice model was also calibrated for northern Ghana based on data from available literature. Data on soil profile and climate were retained in the Aquacrop model. The parameters in the Aquacrop default rice file were updated using the Abdul-Ganiyu et al. (2018) crop parameter data already validated for the Aquacrop rice model for northern Ghana (Appendix 4). However, unlike the current study, where rice yield is modelled under rainfed conditions, Abdul-Ganiyu et al. (2018) calibrated Aquacrop rice under irrigation at the Savannah Agricultural Research Institute in northern Ghana. The Gbewa Jasmine 85 rice variety was used for the simulation. This variety was experimented in the study area during the 2012/2013 and 2013/2014 dry seasons.

4.7 Generating Gross Margins (*GMs)*

Aquacrop yields over the 31 years were used to generate gross margins (*GMs*) for cropping activities using equations 4.2 to 4.4. In the current study, all economic variables were measured in GH₵ at the current exchange rate of GH₵ 1 to $NZD 0.13 and $USD 0.08 (FORBES, 2024). Prices were obtained from the FAO annual crop prices database. Further, the FAO producer price index was used for inflation adjustment. Crop production budgets were derived from Wongaa et al. (2019), Akuriba and Brempong (2012), and Akolgo (2021) for maize, sorghum, and rice, respectively. The opportunity cost of family labour was included using labour cost in the working area as a proxy. All prices, including that of crop budgets were converted to 2020 real prices using equation 4.2.

$$RP_{it} = \frac{PPI_{ic}}{PPI_{it}} \times NP_{it} \tag{4.2}$$

Where:

RP_{it} = Real price/tonne (GH₵) for the i^{th} crop in year *t*

PPI_{ic} = Producer price (GH₵) index for the i^{th} crop in the base year (2020)

PPI_{it} = Producer price (GH₵) index for the i^{th} crop in year *t*

NP_{it} = Nominal price/tonne (GH₵) for the i^{th} crop in year *t*

The GMs derived are expressed in equation 4.3 as:

$$GM_{it} = R_{it} - C_i \tag{4.3}$$

Where:

$$R_{it} = RP_{it} * Q_{it} \tag{4.4}$$

$R_{it} =$ Revenue (GH₵/Ha) for the i^{th} crop in year *t*

$Q_{it} =$ Yield (tonnes/Ha) for the i^{th} crop produced in year *t*

C_i = The cost of production (GH₵/Ha) incurred for the i^{th} crop

GM_{it} = Gross margin (GH₵/Ha) for the i^{th} crop in year *t*

4.8 Scenarios modelled

Having calibrated the model, the study addressed the research questions by simulating crop yields for maize, sorghum, and rice from 1990 to 2020. The Africa RISING survey revealed that farmers used on average, 27 kg/Ha and 28 kg/Ha of nitrogen for maize and rice, respectively. MacCarthy et al. (2017) confirmed that most farmers, on average, apply less than 30kg/Ha of nitrogen for maize farming in northern Ghana. However, farmers in the region do not often use fertilizers for cultivating sorghum (MacCarthy et al., 2010). The recommended nitrogen (N) application rates for maize, sorghum, and rice are 60 kgN/Ha (MacCarthy et al., 2017), 80 kgN/Ha (MacCarthy et al., 2010), and 60-80 kgN/Ha (Ragasa et al., 2013) respectively. In the current study, the application rates for *FP* were 30 kgN/Ha, 0 kgN/Ha, and 28 kgN/Ha for maize, sorghum, and rice, respectively, whereas *RP* was 60 kgN/Ha for both maize and rice and 80 kgN/Ha for sorghum. For each *FP* and *RP*, four scenarios were modelled for maize and sorghum, starting from planting in April with no climate smart technology (*Base*), *PD* from April to May, *M*, and *CB* (Table 4.1). However, as rice is cultivated in June, which is almost close to the peak of the rainy season, only direct planting (*DP*), *TP*, and *PD* from June to July were modelled for both *FP* and *RP*.

Table 4.1**.** Scenarios simulated.

Crop	**Farmers' practice (N kg/ha)**	**Recommended practice (N kg/ha)**	**Scenarios**
Maize	30	60	Planting in April with no CST (*Base*), Changing planting date from April to May (*PD*), Mulching (*M*), Compartmental bunding (*CB*)
Sorghum	0	80	
Rice	28	60	Direct planting (*DP*), Changing planting date from June to July (*PD*), Transplanting (*TP*)

Further, for each scenario, the time series yield data from the simulations per crop were converted to *GMs* through the previously discussed procedure for generating *GMs*. The *GM* outcomes are then used to generated cumulative probabilities. The cumulative probabilities are plotted against the *GM* outcomes from the lowest to the highest *GM* for all scenarios per crop to produce *CDFs*. The area under the *CDFs* for each crop will be calculated and the smallest selected as the most preferred scenario for smallholder farmers. All biophysical and statistical computations were completed in Aquacrop version 6.1 (Raes et al., 2017) and R version 4.2.3 (R Core Team, 2023) respectively.

4.9 Results

4.9.1 Yield

4.9.2 Maize

Average maize yield results under *FP* were 1.88 tonnes/ha, 1.91 tonnes/ha, 1.89 tonnes/ha, and 1.96 tonnes/ha for *Base, M, CB,* and *PD,* respectively (Appendix 5). These results are similar to the average yield of Wongnaa et al. (2019) at 1.8 tonnes/Ha for a 2015 field survey on smallholder farming communities in northern and southern Ghana. However, under *RP*, the average yields for *M*, *CB,* and *PD* were 3.47 tonnes/Ha, 3.50 tonnes/Ha, and 3.57 tonnes/Ha, respectively, whereas that of *Base* was 2.81 tonnes/Ha, which corresponds with the 2.72 tonnes/Ha average yield reported by Essel et al. (2020) for maize in Ghana when 60 kg/Ha of nitrogen was applied. In the current study, the coefficient of variation is used as a measure of variability. This implies that the coefficient of variation for yield reduced from *Base* to *PD* for both *FP* (i.e. from 7% to 2%) and *RP* (i.e. from 12% to 3%) (Appendix 5), representing a 71.4% and 75% reduction in variability for both *FP* and *RP,* respectively. The coefficient of variation under *RP* for *Base* shows a 45.5% reduction in variability when compared to the 22% coefficient of variation reported by MaCarthy et al. (2018) at an application rate of 120 kgN/Ha under rainfed conditions in Yendi.

4.9.3 Sorghum

For Sorghum under *FP*, since no fertiliser was applied, as is the usual practice of smallholder farmers in the region, the yield was low on average, and there was little difference in average yield for *Base* and *CSTs*. On average, yield for *FP* across all scenarios was 0.82 tonnes/Ha, which is in line with the 0.71 tonnes/Ha and 0.61 tonnes/Ha reported by Kpongor et al. (2006) and Akuriba and Brempong (2012) respectively. Specifically, *Base, M, CB*, and *PD* yielded 0.81 tonnes/Ha, 0.82 tonnes/Ha, 0.82 tonnes/Ha, and 0.83 tonnes/Ha under *FP* (Appendix 5). The coefficient of variation reduced from 5% for *Base* to 4% for *CSTs (i.e. M, CB,PD),* representing a 20% reduction in variability.

Under *RP*, the coefficient of variation fell from 23% for Base to 11% for *PD,* representing a 52.2% reduction in variability. The average yield for sorghum under *Base* was 2.61 tonnes/Ha, whereas that of *M, CB,* and *PD* were 2.76 tonnes/Ha, 2.61 tonnes/Ha, and 2.84 tonnes/Ha, respectively (Appendix 5). Similarly, studies conducted by Kpongor et al. (2006) revealed sorghum yield for northern Ghana was 2.86 tonnes/Ha when 80 kg N was applied.

From the results of this study, *PD* had the highest yield and lowest coefficient of variation for both *FP* and *RP*, as is the case for maize.

4.9.4 Rice

As rice production occurs close to the peak of the rainy season, climate variability did not reflect across the *CST* scenarios for both *FP* and *RP*. Under *FP*, average rice yields for *DP* and *PD* were 3.03 and 3.07 tonnes/Ha, respectively, but increased to 3.21 tonnes/Ha when transplanted. On the other hand, yield for *RP* increased on average from 4.79 tonnes/ha for *DP* to 4.83 tonnes/ha for *PD* from June to July and further increased to 5.06 tonnes/ha for *TP* (Appendix 5). This implies that growing transplanted seedlings benefits farmers under both practices, albeit marginal.

4.10 Gross Margins (GMs)

4.10.1 Maize

Average maize *GM* under *FP* was 819 GH₵/Ha for *Base*, which is between the 948 GH₵/Ha and 510 GH₵/Ha reported by Bidzakin et al. (2014) and Wongnaa et al. (2019), respectively. Since there was no significant change in mean yield for maize under *FP*, the average *GM* also reflected no substantial change relative to *Base* except *M,* which showed a decline in *GM* of 70 GH₵/Ha as a result of the high cost of mulching at 588 GH₵/Ha (Anane et al., 2020). The findings of Anane et al. (2020) reveal that farmers were better off growing maize without maize straw mulch when a cost-benefit analysis for maize cultivation under organic mulching and intercropping was conducted. On the other hand, cultivating using *RP* produced an increase in *GM* from *Base* to *M, CB*, and *PD* with these being 1,661 GH₵/Ha, 1,788 GH₵/Ha, 2,348 GH₵/Ha, and 2,478 GH₵/Ha, respectively (Appendix 5). Also, the *GM* coefficient of variation under *RP* reduced from 34% for *Base* to 24% for *PD,* representing a 29.4% reduction in variability due to implementing a *CST* (Appendix 5).

4.10.2 Sorghum

Under *FP*, average *GM* for sorghum was 640 GH₵/Ha, 68 GH₵/Ha, 598 GH₵/Ha and 678 GH₵/Ha for *Base, M, CB,* and *PD,* respectively (Appendix 5). The average sorghum *GM* for *RP* was 605 GH₵/Ha, 307 GH₵/Ha, 558 GH₵/Ha, and 1,048 GH₵/Ha for *Base, M, CB,* and *PD*, respectively. The low *GM* for *M* for both practices is due to previously discussed reasons regarding cost of mulch. Also, the sorghum *GM* coefficient of variation reduced from *Base* to

PD under *RP* but showed no change under *FP*. The reduction in *RP* coefficient of variation was 57.5% (i.e. from 2.14 to 0.91).

4.10.3 Rice

The average *GM* for rice under *FP* was 3,586 GH₵/Ha using the *DP* method whereas PD and TP were 3,666 GH₵/Ha and 3,747 GH₵/Ha, respectively. On the other hand, the *GM* for rice on average for *RP* increased beyond *FP* to 6,152 GH₵/Ha, 6,213 GH₵/Ha, and 6,523 GH₵/Ha for *DP, PD*, and *TP,* respectively (Appendix 5). This implies that for both practices, *TP* remained profitable with very few differences in *GMs* for *DP* and *PD*. Also, variability did not reflect enough across both practices, as the coefficient of variation only varied from 18% for *RP* to 21% for *FP* (Appendix 5).

4.11 Cumulative distribution functions (*CDFs*) and stochastic dominance

Based on the *GM* outcomes, *CDFs* for *Base* and each *CST* were plotted to determine FSD and SSD. The findings for the total area under the *CDFs* are presented in Table 4.2, being a product of the change in *GM*, and the corresponding cumulative distribution accumulated from the lowest *GM* to the highest *GM* for *Base* and all *CSTs*. The scenario with the smallest area under the *CDFs* per practice for each crop is selected as the less risky one and most dominant by SSD.

Table 4.2. Area under the cumulative distribution functions (*CDFs)* under farmers' practice (FP) and recommended practice (RP) for maize, rice, and sorghum in Ghana cedis (GH₵)

Scenarios[2]	**Farmers' Practice**			**Recommended Practice**		
	Maize	**Sorghum**	**Rice**	**Maize**	**Sorghum**	**Rice**
Base	973	305	-	2,495	1,607	-
M	1,749	884	-	2,358	1,926	-
CB	968	347	-	1,861	1,662	-
PD	876	265	1,203	1,672	1,172	1,789
DP	-	-	1,281	-	-	1,842
TP	-	-	1,119	-	-	1,489

[2]*Base = No use of climate smart technology, M = Mulching, CB = Compartmental bunding, PD = Changing planting date, DP = Direct planting, TP = Transplanting*

4.11.1 CDFs for maize GMs

Under *FP*, *Base, CB*, and *PD* were first-order stochastically dominant over *M* as their curves are completely to the right of *M* making all *GM* probability outcomes from the lowest to the highest *GM* for *Base, CB,* and *PD* better than *M* (Figure 4.5). In Table 4.2, for *FP*, *PD* < *CB* < *Base* implying that the area under the curve for *PD* is the least so *PD* dominates *CB* and *Base*, by *SSD*. Furthermore, under *RP, PD* < *CB* < *M* < *Base,* hence *PD* dominates all *CSTs* including *Base* by *SSD*.

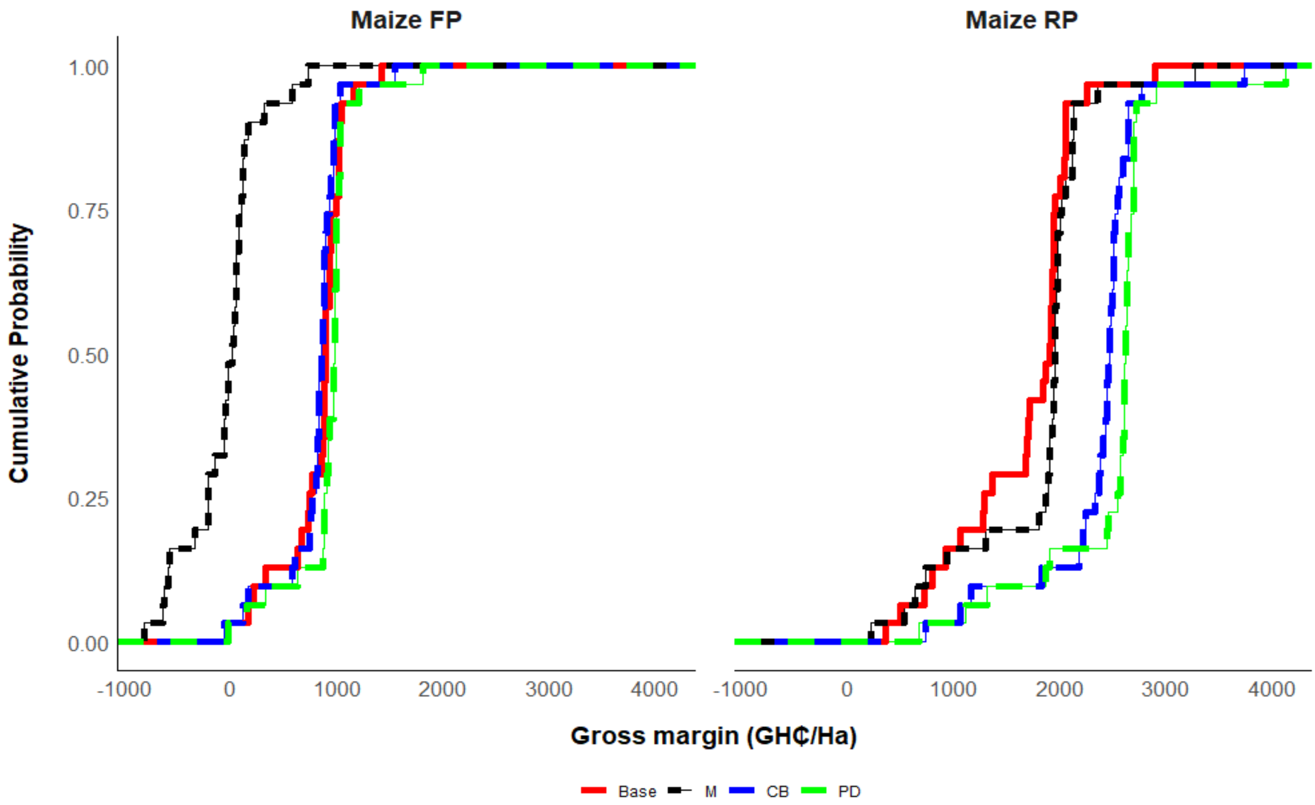


Figure 4.5. Cumulative distribution functions (CDFs) for maize under farmers' practice (Maize FP) and recommended practice (Maize RP).

4.11.2 CDFs for sorghum GMs

The *CDFs* for sorghum followed a similar trend to maize for *FP.* From Figure 4.6, under *FP, Base, CB,* and *PD* were first-order stochastically dominant over *M* for reasons previously explained, and from Table 4.2, *PD* dominates *CB* and *Base* by *SSD* as *PD* < *Base* < *CB*. On the other hand, under *RP, Base* < *CB* < *M* by *SSD* (Table 4.2), however *PD* was first-order stochastically dominant over all *CSTs* including *Base*, which implies that relatively, the *GM* outcomes for PD are strictly better for at least one outcome, hence the most preferred.

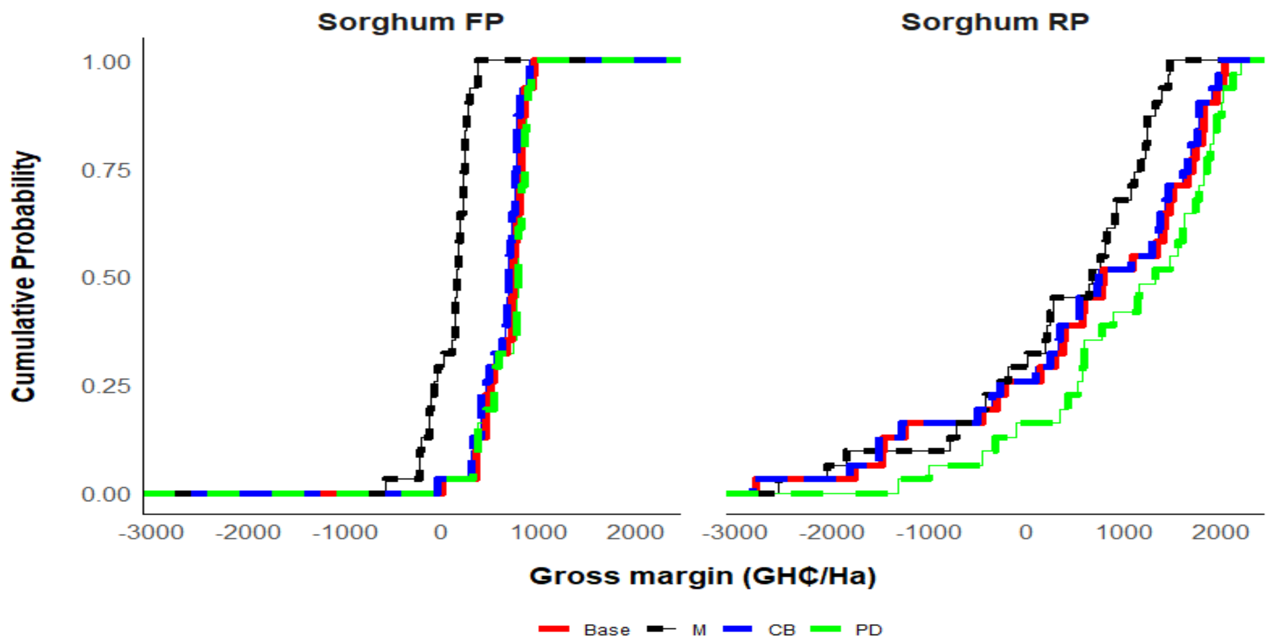


Figure 4.6. Cumulative distribution functions (CDFs) for sorghum under farmers' practice (FP) and recommended practice (RP).

4.11.3 CDFs for rice GMs

From Figure 4.7, the area under the *CDFs* for both practices for rice revealed that *TP* is *SSD* over *DP* and *PD* as the area under the *CDF* for *TP* is the least for both *FP* and *RP* at 1119 GH₵ and 1489 GH₵, respectively (Table 4.2). When ranking in order of *SSD*, *TP* < *PD* < *DP*.

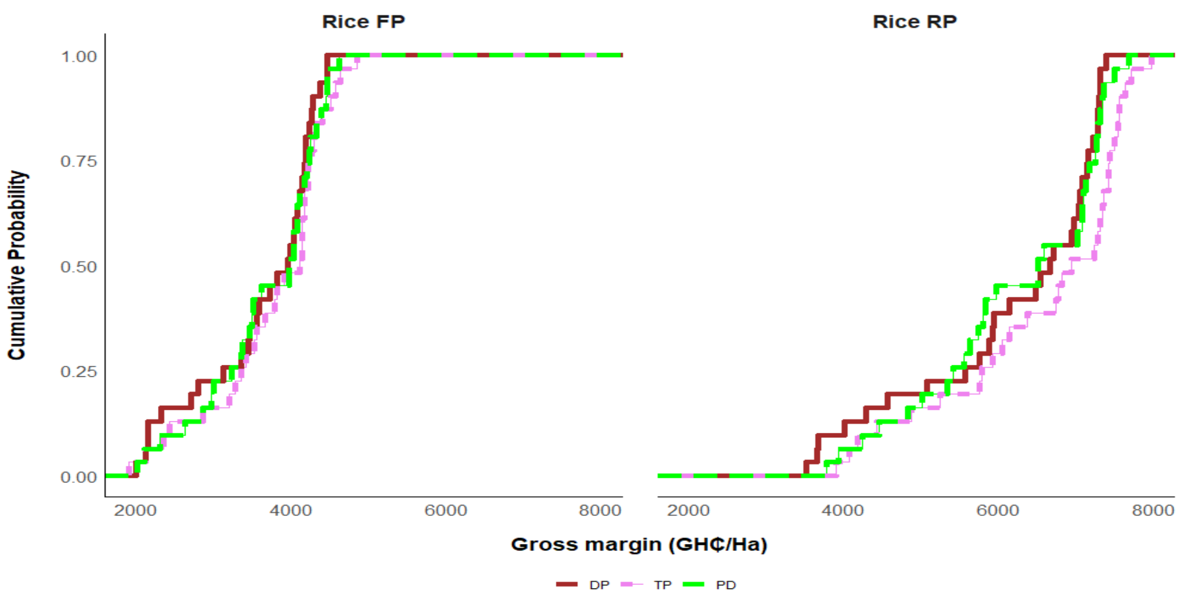


Figure 4.7. Cumulative distribution functions (CDFs) for rice under farmers' practice (FP) and recommended practice (RP)

4.12 Discussion

The results of this study demonstrate a general increase in crop yield and variability from *FP* to *RP*. However, under *RP*, the increase in variability (i.e. yield and *GM*) is minimised when *CSTs* are applied mainly for *PD,* making *PD* stochastically dominant over *Base* and other *CST* scenarios for maize and sorghum. This supports the concept that CSTs can enhance climate risk resilience and minimise the adverse effect of climatic variability.

As *FP* and *RP* were modelled under different fertiliser application rates, the coefficient of variation which is a unitless measure of variability was employed instead of variance or standard deviation to compare variability across practices on an equal scale. The reduction in maize yield variability as measured by the coefficient of variation from *Base* to *PD* was 71.4% and 75% under *FP* and *RP,* respectively, whereas that of sorghum yield variability was 20% and 52.2% under *FP* and *RP*, respectively. Reasons contributing to the lower percentage reduction in sorghum yield variability relative to maize when *CSTs* are applied could be attributed to the drought-tolerant nature of the crop (Yahaya et al., 2023). In addition, sorghum has been identified to often thrive under changing climatic conditions and can tolerate heat (Chadalavada et al., 2021). This suggests that the crop is less sensitive to water stress, making *CSTs* have little impact on yield variability reduction. Further, water is not a limiting factor for rice as it is grown close to the peak of the rainy season. Therefore, the impact of *CSTs* on reducing yield variability is marginal.

The results of this study also reveal how the cost of *CSTs* affect the decision-making for risk-efficient *CSTs* among risk-averse farmers. Across all *CSTs,* mulching was the least preferred in terms of *FSD* and *SSD*. This is mainly due to the high cost of mulching, which eventually reduces *GMs*. As most risk-averse farmers in the study area are relatively poor smallholder farmers, the ideal *CST* should be low-cost to attract adoption (Zakaria et al. 2020).

Further, the results indicate that changing the planting date for maize and sorghum from April to May is risk efficient as against other climate smart scenarios primarily due to the relatively higher *GM*, yield, and the reduction in *GM* variability. In addition, transplanting rice appeared to be the most preferred option for the risk-averse smallholder farmers as yield and *GM* for *TP* increased under *FP* and *RP,* whereas *PD* from June to July was less preferred. The lack of preference for rice planting in July for smallholder farmers could be explained by the fact that, the rainfall in the study area significantly drops after the

September peak (Appendix 1). Also, under *FP* and *RP* except for mulching, it is less risky for maize farmers to employ *CB* and *PD* as a climate risk resilient strategy compared to *Base*. These results imply that *CST* recommendations should be driven primarily by cost, yield, and the *GM* variabilities associated with using them.

Studies by Boansi et al. (2023) have revealed yield gaps for maize in northern Ghana ranging from 52.5% to 84.2% and 37.5% to 80.5% in the Ginnea Savannah and Sudan Savannah zones respectively. Further, the average yield of a sorghum farmer in northern Ghana spans from 0.5 to 1.2 tons/Ha which is less than the attainable yield of 2 tons/Ha (Abdul-Rahaman, 2023), representing a yield gap range from 66.7% to 300%. Findings from Dossou-Yovo (2020) also specified the yield gap for rice in the study area to be approximately 2.5 tons/Ha. The current research affirms that, attainable yields indicated by research institutions and the Ministry of Food and Agriculture in Ghana are often not achieveable under FP due to poor soil fertility, the lack of resources needed to obtain farming inputs, and the limited adoption of risk resilient climate smart technologies. This calls for the need to implement policies that adopt yield enhancing climate smart technologies to minimise smallholder farmers' exposure to the vulnerabilities of harsh weather conditions.

4.13 Implications of the study

The findings of this study have several significant implications for agricultural practices, particularly in the context of enhancing climate resilience. Clearly, time of planting is a critical factor and government policies should focus on seasonal climate forecasting similar to An-Vo et al. (2021) to identify optimal planting windows. Further, the implications of the study imply that climate smart approaches should emphasise on selecting suitable *CSTs* based on crop characteristics and local climatic conditions, thereby supporting sustainable agricultural productivity and improving the livelihoods of risk-averse smallholder farmers. The findings indicate a need for policymakers and agricultural extension services to promote *CSTs* that are economically feasible and provide crucial benefits in terms of yield stability and profitability. By focusing on the most cost-effective and efficient *CSTs*, such as optimized planting dates and crop-specific strategies, agricultural policies can better support smallholder farmers in building resilience against climatic variability. Further, despite its potential benefits, mulching was the least preferred *CST* due to its high costs, which negatively affect gross margins (GM). This underscores the need for low-cost *CST* options that can still effectively enhance yield and GM stability. Policy interventions aimed at subsidising the costs of *CSTs* or providing financial support for smallholder farmers could facilitate the broader adoption of these technologies.

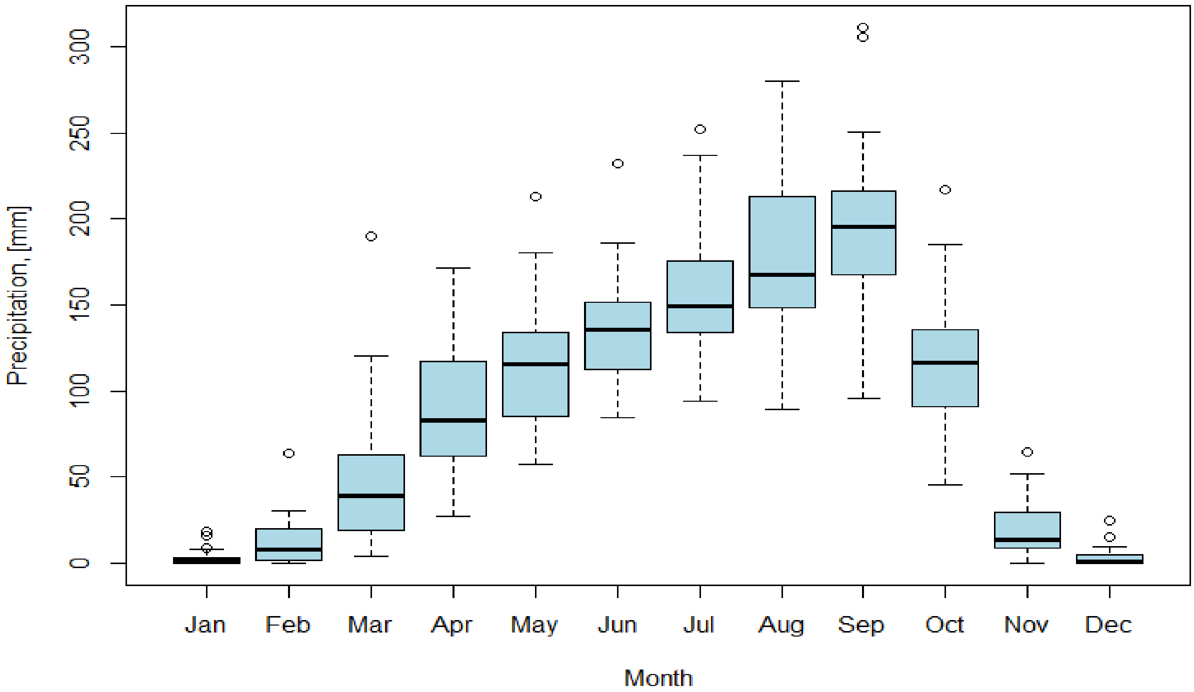
4.14 Conclusion

In this research, maize, rice, and sorghum crop yields for northern Ghana were simulated using soil type, crop parameters, and climatic conditions to generate yield and *GM* outcomes for stochastic dominance analysis. As evident in literature, selecting risk-efficient *CSTs* in northern Ghana from the perspective of smallholder farmers' risk aversion is a significant gap. The findings of this study have revealed the usefulness of low-cost and risk-efficient technologies such as changing planting dates and transplanting as a crop-specific risk management guide for *CST* adoption policies under the assumption that smallholder farmers in the study area are risk averse. The information on *CST* alternatives revealed in this study could be used to provide assistance to climate smart intervention practitioners as to which technology is suitable for the smallholder farmer in the context of cost, when to plant, how to plant and the expected returns.

Despite the usefulness of this research, a key challenge in the study was the lack availability of empirical data for crop modelling. Also, the stochastic dominance approach provides no room to analyse the interaction effect between the *CSTs*, the heterogeneity of farm households, and other socio-economic conditions that may affect farmers decision making under risk. The study recommend that more crop experiments should be conducted in the study area and future research should focus on a rather sophisticated model that captures the resource constraints of smallholder farmers, by considering farm typologies that minimise heterogeneity, and other relevant economic indicators.

4.15 Appendix

Appendix 1: Mean monthly precipitation for northern Ghana



Appendix 2: Maize crop parameters for northern Ghana

Crop Parameters	Value
Time from sowing to emergence (GDD-Growing Degree Days)	132
Time to maximum canopy cover (GDD)	1352
Time from sowing to maximum rooting depth (GDD)	1195
Time from sowing to start of canopy senescence (GDD)	1653
Time from sowing to maturity (GDD)	2175
Time from sowing to flowering (GDD)	1230
Duration of flowering (GDD)	532
Maximum effective rooting depth (metre)	1.0
Minimum effective rooting depth (metre)	0.30
Reference harvest index (%-Percentage)	40
Building up of Harvest Index (GDD)	872
Cultivar (Oba super 2)	-
Plant population (Plants/Ha-Plants per hectare)	53,333
Sowing date (Date)	Varies from year to year
Nitrogen fertilizer application rate (kgN/ha-Kilograms of nitrogen per hectare)	30 and 60
Soil fertility stress (%)	70

Appendix 3: Crop parameters for sorghum

Crop Parameters	Value
Time from sowing to emergence (GDD-Growing Degree Days)	248
Maximum canopy cover (%-Percentage)	70
Time from sowing to maximum rooting depth (GDD)	1797
Time from sowing to start of canopy senescence (GDD)	1709
Time from sowing to maturity (GDD)	1904
Time from sowing to flowering (GDD)	1230
Duration of flowering (GDD)	369
Maximum effective rooting depth (metre)	1.80
Reference harvest index (%)	45
Length building up of Harvest Index (GDD)	674
Normalized water productivity (gram/m^2 -grams per square metre)	33.7
Minimum air temperature range (^{o}C-Degrees Celsius)	+5 to +10
Maximum air temperature range (^{o}C)	+40 to +45
Shape factor for water stress coefficient for stomatal control	3
Plant population (Plants/Ha-Plants per hectare)	74000
Sowing date (date)	Varies from year to year
Nitrogen fertilizer application rate (kgN/ha-Kilograms of nitrogen per hectare)	0 and 80
Soil fertility stress (%)	70

Appendix 4: Crop parameters for rice in northern Ghana

Crop Parameters	Value
Base temperature (^{o}C-Degrees Celsius)	8.0
Upper temperature (^{o}C)	30.0
Canopy size for transplanted seedling (cm^2/plant-Centimetre squared per plant)	5.5
Time from TP to recovery (GDD-Growing Degree Days)	92
Maximum canopy cover (almost entirely covered) (%-Percentage)	95
Time from TP to maximum rooting depth (GDD)	302
Time from TP to start of canopy senescence (GDD)	1376
Time from TP to maturity (GDD)	1992
Time from TP to flowering (GDD)	1292
Duration of flowering (GDD)	227
Maximum effective rooting depth (metre)	0.60
Minimum effective rooting depth (metre)	0.30
Reference harvest index (%)	55
Building up of Harvest Index (GDD)	654
Normalized water productivity (gram/m^2 -grams per square metre)	19
Minimum air temperature below which pollination starts to fail (^{o}C)	8
Maximum air temperature above which pollination starts to fail (^{o}C)	35
Minimum growing degrees required for full biomass production (^{o}C)	10
Shape factor for water stress co-efficient for stomatal control	3
Shape factor for water stress co-efficient for canopy senescence-upper threshold	3
Plant population for DP and TP (Plants/Ha- Plants per hectare)	250000
Sowing date (Date)	Varies from year to year
Soil fertility stress (%)	70

Source: Adbul-Ganiyu et al. (2018)

Appendix 5: Average yield, gross margin, and coefficient of variation under farmers' practice and recommended practice for maize, rice, and sorghum.

Scenarios[4]	Farmers' Practice			Recommended Practice		
	Mean yield (tonnes per ha)					
	Maize	Sorghum	Rice	Maize	Sorghum	Rice
Base	1.88	0.81	-	2.81	2.61	-
M	1.91	0.82	-	3.47	2.76	-
CB	1.89	0.82	-	3.50	2.61	-
PD	1.96	0.83	3.07	3.57	2.83	4.83
DP	-	-	3.03	-	-	4.79
TP	-	-	3.21	-	-	5.06
	Yield -Coefficient of variation					
	Maize	Sorghum	Rice	Maize	Sorghum	Rice
Base	0.07	0.05	-	0.12	0.23	-
M	0.04	0.04	-	0.08	0.16	-
CB	0.04	0.04	-	0.03	0.23	-
PD	0.02	0.04	0.05	0.03	0.11	0.06
DP			0.05	-	-	0.05
TP			0.04	-	-	0.03
	Mean Gross Margin (GH₵/Ha /ha)					
	Maize	Sorghum	Rice	Maize	Sorghum	Rice
Base	819	640	-	1,661	605	-
M	-70	68	-	1,788	307	-
CB	797	598	-	2,348	558	-
PD	908	678	3,666	2,478	1,048	6,213
DP	-	-	3,586	-	-	6,152
TP	-	-	3,748	-	-	6,523
	Gross margin coefficient of variation					
	Maize	Sorghum	Rice	Maize	Sorghum	Rice
Base	0.36	0.33	-	0.34	2.14	-
M	-4.83	3.13	-	0.34	3.46	-
CB	0.36	0.36	-	0.23	2.31	-
PD	0.34	0.33	0.19	0.24	0.91	0.18
DP	-	-	0.21	-	-	0.20
TP	-	-	0.20	-	-	0.18

[4]Base = No use of climate smart technology, M = Mulching, CB = Compartmental bunding, PD = Changing planting date, DP = Direct planting, TP = Transplanting

Chapter 5 Heterogeneity in resource endowments and climate risk perceptions for tailored climate risk interventions

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UNIVERSITY OF NEW ZEALAND

GRADUATE RESEARCH SCHOOL

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DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS

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Doctoral Research Committee
May 2023

5.1 Introduction

Farm typologies have been used to address heterogeneity among farming systems. Farm typologies are defined as the grouping of farms into subsets of farms with similar characteristics (Köbrich et al., 2003). Daloğlu et al. (2014) described farm typology as an approach to explaining farm household diversity, especially for policy recommendations. The complexity of farming systems among farm households, makes it difficult to recommend policies for individual farmers (Sarker et al., 2021). Many technological interventions aimed at boosting smallholder farms in developing countries have been met with resistance due to their incompatibility with the specific characteristics of farms in the target regions (Kaur et al., 2021).Therefore, classifying farm households into similar groups allows for context specific technological interventions. Farm typologies have increasingly been used as a guide for introducing innovative agricultural technologies relevant to climate change-related implications (Pacini et al., 2014).

A typology should exhibit a characteristic of the category it represents. An ideal typology must have the maximum heterogeneity among farm types (*FTs*) and the maximum homogeneity within the category it represents (Köbrich et al., 2003). Most of the categorisation methods employed in conducting farm typology research often depend on production factors in the form of structural variables such as land, labour, and capital as well as output indicators such as household income, crop yield per hectare, and asset gains (Tittonell et al., 2020). Also, the structural traits of *FTs* are connected to the level of inputs, farm size, and variable reliability (Kumar et al., 2019). Often, the diversity in asset ownership and capital endowment forms the basis for variability in structural variables when developing farm typologies (Shukla et al., 2019). Structural typologies are used to investigate how these variables are managed by the farm type (*FT*) (Tittonell et al., 2005).

In contrast, functional typologies capture farmers' behaviour and decisions made by farmers based on the constraints encountered in their livelihood pursuits (Tittonell, 2014), which could be climatic or socio-economic in nature (Mettrick, 1993). Functional typologies support the realisation of the household response approach to shocks such as the impact of new policy implementation, price spikes, persistent droughts, soil degradation, and natural disaster occurrence (Bathfield et al., 2016). Functional typology data differs from structural types as it involves narratives that can be applied quantitatively or qualitatively using custom scores, binary, ordinal, or nominal values, and ranks (Tittonell et al., 2020).

The method used in identifying farm typologies can be either a statistical or participatory approach or a combination of both (Tittonell et al., 2020). Several statistical methods have been used to categorise *FTs* in recent decades. Some of these are multivariate statistical analyses such as the principal component analysis (*PCA*), or factor analysis coupled with cluster analysis (Bhattarai et al., 2017; Chavez et al., 2010), the Bayesian system (Paas & Groot, 2017; Tiffin, 2006), and the multi-dimensional scaling approach (Pacini et al., 2014). The synthetic variables are often formed using a dimension reduction technique such as the PCA scores (Tittonell et al., 2010). The above methods assemble farm households over a central concept such that observations around this central concept are further grouped into clusters (Tittonell et al., 2020). The larger the observations in the datasets, the better and more powerful it is to create distinctive clusters.

This study uses multivariate statistics to develop farm typologies. These typologies will clarify the key factors affecting climate vulnerability and resilience in farm households, and account for the diverse and complex nature of farming systems. Major factors contributing to climate vulnerability among smallholder farmers in northern Ghana are natural disasters such as floods, drought, and inadequate infrastructure, leading to regional food insecurity (Atanga and Tankpa, 2021). The region is also affected by increasing pest and disease infestations, a growing population, and the intensification of land use (Asravor, 2019). Choudhary et al. (2016) add that pests and diseases are the most relevant production risk after the drought.

With its low-income levels, the northern region ranks lowest in Ghana's ability to adapt to risks, making it the most vulnerable region to climate change and other stressors (Asravor, 2019). Interestingly, research by Ndamani and Watanabe (2017) found that resource-poor farmers in northern Ghana perceive climate risk more acutely than their better-resourced counterparts. The study reveals that farmers with greater resources tend to be less concerned about the impact of climate risks on agriculture. This is likely because they have the ability to generate alternative income sources, buffering the financial strain of severe climate-related agricultural disruptions (Ndamani and Watanabi, 2016). According to Huet et al. (2020), the amount of resource endowment available for the farmer is an indicator of the production orientation of the farm, the perception of whether a particular type of hazard is relevant or not, the effect of the hazard, and the kind of appropriate management approach to employ. Due to low resource endowments, poor farmers are likely to be more risk-averse than wealthy farmers (Kisaka-Lwayo and Obi, 2012). Hence, management options employed by farmers in their quest to minimise the adverse effects of climate risk is crucial.

Sub-Saharan African farmers manage risk in several ways, such as (i) engaging in activities that generate off-farm income (Douxchamps et al., 2016)(ii) altering planting dates (Milgroom & Giller, 2013; Traore et al., 2013), (iii) employing crop diversity approaches (Frison et al., 2011), (iv) livestock rearing (Valbuena at al., 2015), (v) minimizing the consumption of food (Wichern, 2019) or sharing farm produce with other members of the household (Guirkinger and Platteau, 2014). Most studies on agricultural risk and farm typologies in northern Ghana, such as Kyire et al. (2023), Asravor (2019), Asravor (2018), Asravor and Sarpong (2022), and Kuivanen et al. (2016) either focused on agricultural risk perception, risk preference and risk management, or farm typologies, in isolation. None of these studies analysed farm typology with reference to climate risk perception and response strategies. This study investigates this gap to provide institutions implementing climate-smart policies with research-based insights into farmers' risk perception and responses, focusing on farm type specific differences.

Based on the above discussion, this study investigates three objectives:

(i) recognising the heterogeneity among farm households by classifying them into farm typologies. (ii) examining the typology specific degree of climate risk perception and management strategies, and (iii) determining whether farmers prioritise higher-income generating activities despite greater climate risk, or lower-income generating activities with less risk.

These objectives are achieved through empirical analysis focusing on variables that capture the socio-economic conditions, climate risk perception and management among smallholder farmers. Farm typologies are constructed from these variables using *PCA* followed by cluster analysis. Given the study area's dependence on rain-fed agriculture, where both insufficient and excessive rainfall significantly impact crop yield, the study used drought and/or flood as a proxy for climate risk. Also, the study developed a novel weighting technique to evaluate the relative importance that farmers assign to their climate risk management goals. This research measures climate risk perception using a robust index based on households' perceived susceptibility to drought or flood. Farm types (*FTs*) with higher scores on the perception index perceive drought or flood as their most severe risk, while others prioritize it less. In conclusion, the study acknowledged the research limitations and explored how the findings can inform farm-type-specific policy interventions at the district level.

5.2 The study area description and data

5.2.1 Study area

The study area for this research is the Northern, Savannah, and North East regions of Ghana (Figure 5.1). The agroecology in the regions is mostly grassland with shrubs and trees (Yiridoe et al. 2006) with a land area of about 70,383 km^2. Despite the geographical size, the 3 regions are economically poor, with very minimal industrialisation (Kuivanen, 2016). The regions are characterised by sandy soils, with 80% of the soils having less than 6% clay content (Tetteh et al., 2016). In addition, there is a high concentration of rugged and compact gravel in the sub-soils (Ellis-Jones et al., 2012), leaving the topsoil more susceptible to drought.

The Dagomba ethnic groups are the most predominant in the area, comprising about one-third of the population (Ellis-Jones et al. 2012). The social organisation is such that a typical household will consist of a male-headed farm household living together in a compound housing system with either his nuclear or extended family made up of approximately three generations (i.e., wife/wives, sons, daughters, daughters-in-law, and grandchildren) (Al-Hassan and Poulton, 2009). The head can demand labour from any household member to ensure a constant food supply for all, even if the son or daughter leaves the parental compound, provided their new location is closer to the farm (Al-Hassan and Poulton, 2009). If the household head dies, the responsibilities of food production and labour demand shift to the eldest son (Al-Hassan and Poulton, 2009).

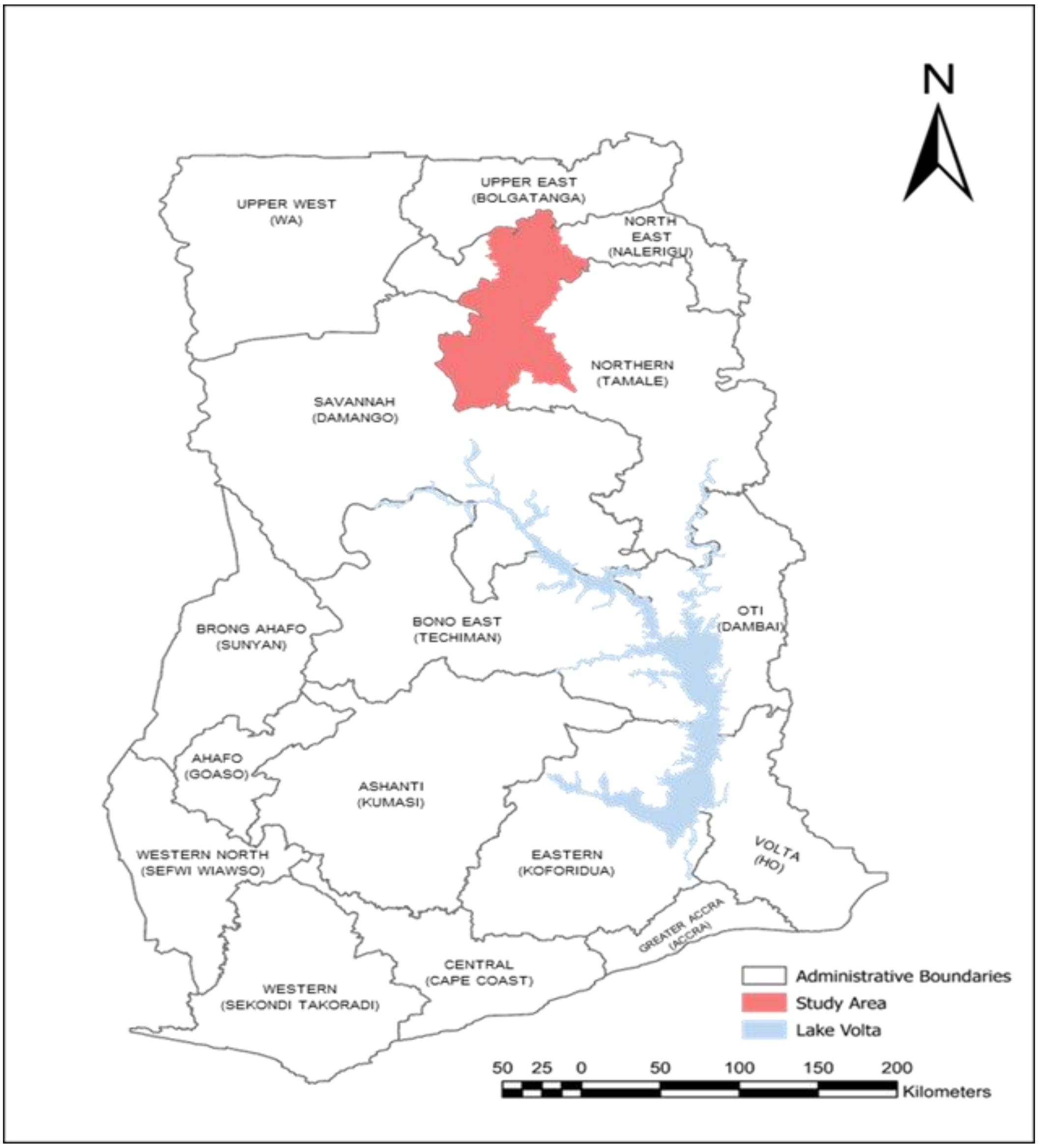

Figure 5.1. Map of Ghana

5.2.2 Data description

Administered in 2014, the baseline evaluation survey of the Ghana Africa RISING Program and the International Food Policy Research (IFPRI) was collected from 1,284 households in Ghana's Northern[2], Upper East, and Upper West regions. The survey interviewed farm households with predominantly low educational levels and poor housing conditions. The current study focused on Northern, Savannah and North East regions comprises 615

[2] As of 2018, Ghana approved a referendum to create six new regions. Northern Ghana was affected and divided into Northern, Savannah, and North East regions by 2019.

households, 45 modules with 483 variables. Key modules in the dataset relevant to this study include but not limited to food consumption, asset ownership, crop production, other income sources, and livestock ownership. Variables comprise, among others, crop yield for maize, rice, groundnuts, and sorghum; input/output quantities and prices; land size, off/on-farm income; labour availability; resource endowments; crop quantity harvested, sold, or consumed; number of livestock; climate risk; and farm household demographics.

5.3 Method of Analysis

The analytical method is illustrated in Figure 5.2. Classification of variables, multivariate statistical analysis, characterisation of farm typologies, the determination of climate risk perception index for each *FT*, and the development of weights farmers attach to their risk management objectives were conducted sequentially.

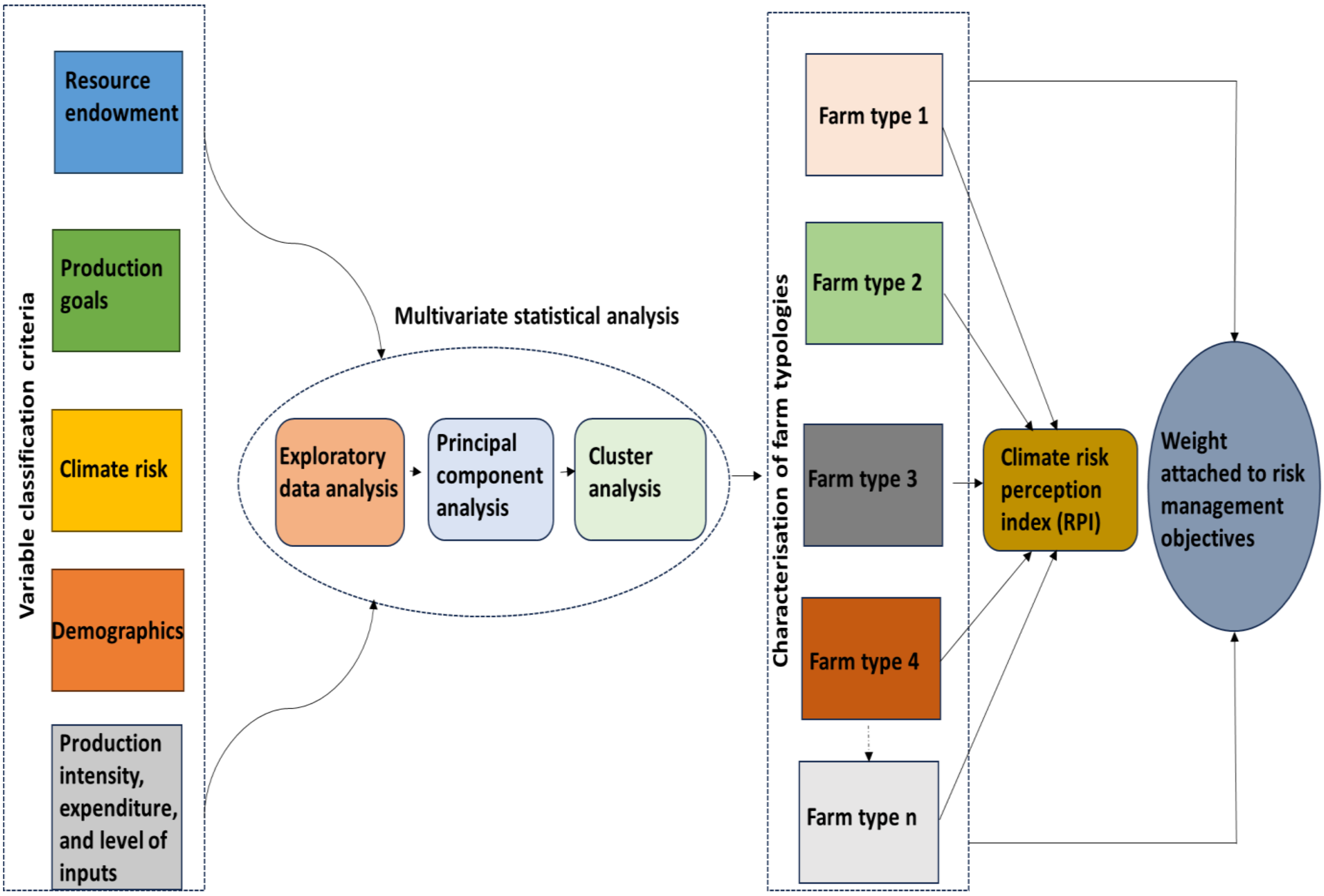

Figure 5.2. Analytical framework

5.3.1 Variable classification criteria

The variables for the construction of farm typologies were classified into five sections. Appendix 1 indicates the criteria used for the classification. Under the resource endowment criteria, variables on household income, land area (i.e. farm household land holding), asset value, and quantity of crops stored are selected. The production goals criteria capture own consumption and crops harvested variables. Further, drought or flood severity rank, and drought or flood management were included as variables under the climate risk criteria. The climate risk management variables were represented in the study using household frequency of response in the survey to 12 drought or flood management strategies (i.e., sold durable assets, sold agricultural assets, sold crop stock, sold livestock, looked for jobs, relied on own saving, engaged in prayers, received unconditional help from friends and family, changed eating habits, migrated, did nothing, other activities). Household climate risk perception was scored on a 3-point scale from most severe (3), second most severe (2) to third most severe (1). Under the demographics criteria, variables such as family size, maximum level of education, and average age were used. Finally, crop yield, storage losses, labour requirements, expenditure, and input variables were employed under the production intensity, expenditure, and level of inputs criteria. In the current study, all economic variables are measured in Ghana cedis (GH₵) at the current exchange rate of 1 GH₵ to 0.15 NZD (New Zealand Dollars) and 0.087 USD (United States Dollars), and all statistical computations are completed in R version 4.2.3 (R Core Team, 2023).

5.3.2 Multivariate statistical analysis.

Firstly, an exploratory data analysis using histograms and boxplots were applied to clean the data by removing unavailable observation and outliers due to the sensitivity of Principal Component Analysis (PCA) to outliers (Alvarez et al., 2014). This process resulted in 406 households and 57 variables. Two multivariate statistical methods used in many publications for constructing farm typologies (i.e., the PCA and cluster analysis) were applied in this research (Kuivanen et al., 2016; Bidogeza et al., 2009; Chavez et al., 2010; Cortez-Arriola et al., 2015; Kobrich et al., 2003; Tittonell et al. 2010) to create a cluster of farm typologies.

5.3.3 Principal component analysis

To generate the principal components, a KEISER Meyer-Oklin test was applied to the data to check for sampling adequacy which generated a value of 0.79 greater than the critical value at 0.6. The fitted model for the principal component analysis is indicated in equation 5.1 as:

$$\mathrm{PCA} = \sum_{n=1}^{N} a_n * V_n \tag{5.1}$$

Where *n= 1* to the n^{th} variable, and coefficient a_n represents the weights (eigen vectors) assigned to the value of each n^{th} original variable (V_n). The PCA calculated determines how much each variable contributes to the overall variation in the data.

Further, the principal components (*PCs*) were selected based on the cumulative variance percentage and the Kaiser criterion. From Appendix 4, 13 PCs explained 62% of the variations in the data. In addition, the Kaiser criterion also indicates that *PCs* with eigenvalues greater than 1.0 could be retained due to the assumption that eigen values less than one explain less variability (Kaufman and Dunlap, 2000). Hence, based on the cumulative variance and the Kaiser criterion, only *PCs* with an eigenvalue more than 1.2 in Figure 5.3 were selected, resulting in the retention of 13 *PCs*.

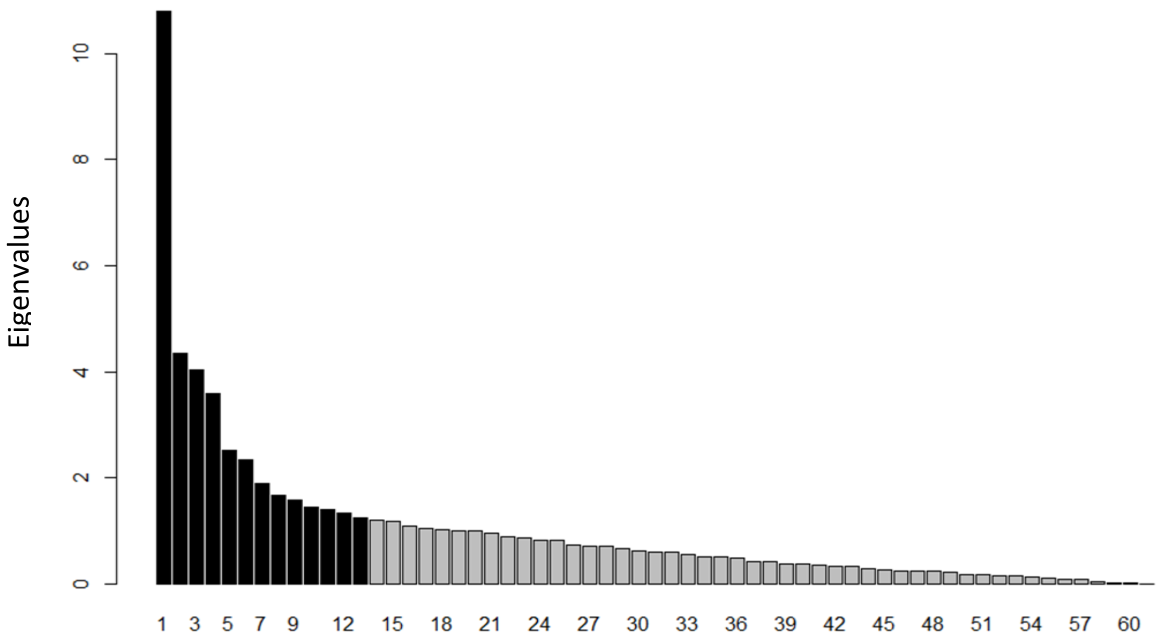

Figure 5.3. Scree plot showing principal components and their corresponding eigenvalues.

5.3.4 Contribution of variables to PCs

The contribution of each variable to the *PCs* selected is considered significant if it has an absolute value of more than 0.18 (Field et al., 2012). All variables contributed significantly to at least one of the 13 *PCs* selected. *PC* 1 had the most significant number of variables. All variables in *PC* 1 had negative loadings and revolved around family size, land area, the value of inputs used, labour requirements, own consumption, and expenditure on non-food and maize storage (Appendix 2). However, variables in *PC* 2 were specifically rice related, consisting of yield, sales, and storage.

Similarly, *PC* 3 variables also revolved around one crop (i.e. groundnut). The variables were yield, sales from harvested quantities, and storage. Sorghum-related variables such as yield, quantity sold, and stored were concentrated in *PC* 4. PC 5 was made up of asset value and expenditure. PC 6 featured land preparation and planting variables in female person days, and *PC* 7 and *PC* 8 were characterised by livestock assets and climate risk variables, respectively. For *PC* 9, only the maximum level of education contributed significantly, whereas *PC* 10 comprised average age and monthly income, post-harvest losses for groundnut, and household rank for drought and flood. Finally, *PC* 11, *PC* 12, and *PC* 13 were made up of additional labour expenses, weeding in female person days, and post-harvest losses for maize and rice variables, respectively.

5.3.5 Cluster analysis

Results from the *PCA* were employed as inputs for hierarchical clustering using Ward's method (Ward, 1963). This method employed an agglomerative hierarchical approach by measuring the Euclidian distance between households in the data depending on the *PCs* they belong (Barba-Escoto et al., 2019), forming a cluster dendrogram. Further, similar to Lopez -Ridaura et al. (2018), the study used the silhouette test which selects the maximum average width of different clusters by comparing intraclass similarities (Rousseeuw, 1987) to enforce the optimal number of clusters for this study, resulting in the selection of 3 clusters (Figure 5.4).

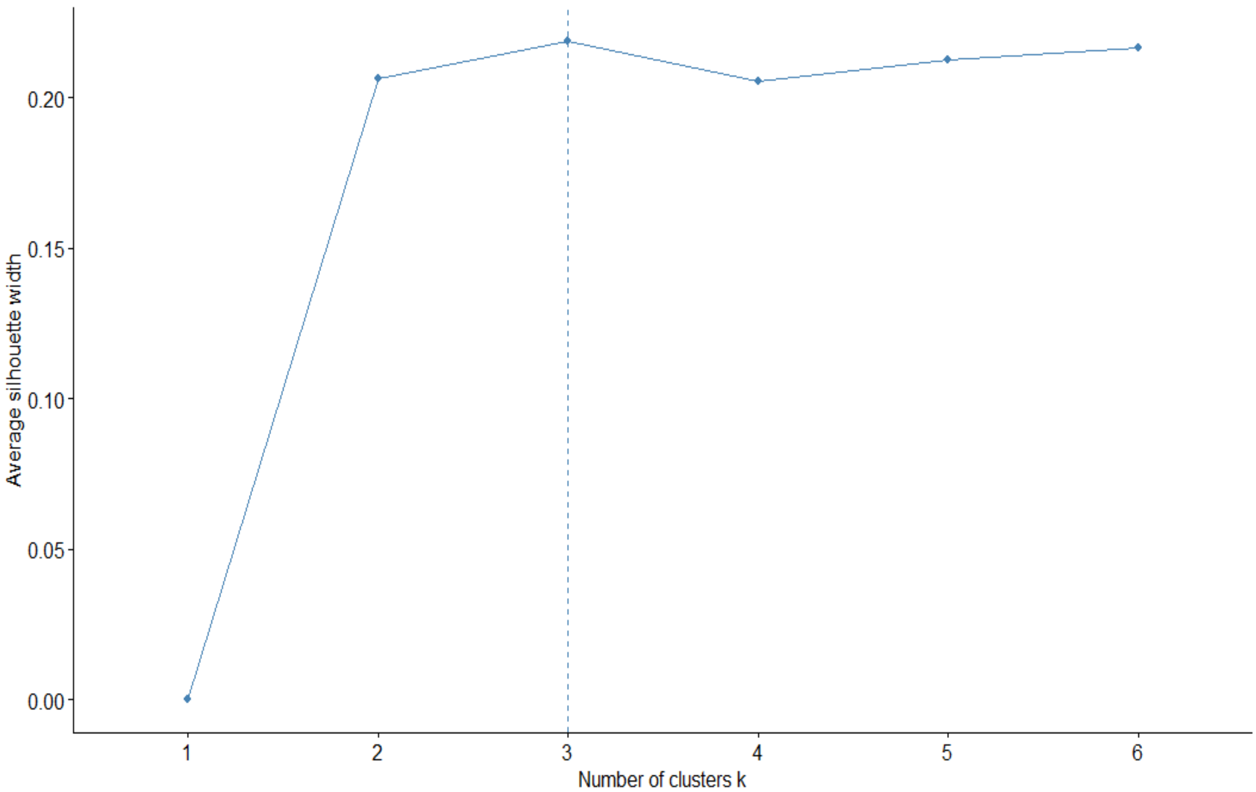

Figure 5.4. Optimal number of clusters.

Consequently, a 3-cluster dendrogram was created. By observing the dendrogram in Figure 5.5, each cluster was assigned to a *FT*, and *FT* 2 appears to have the largest group, followed by *FTs* 1 and 3. The processes used to identify the different characteristics between *FTs* regarding climate risk perception and management are further discussed in the next section.

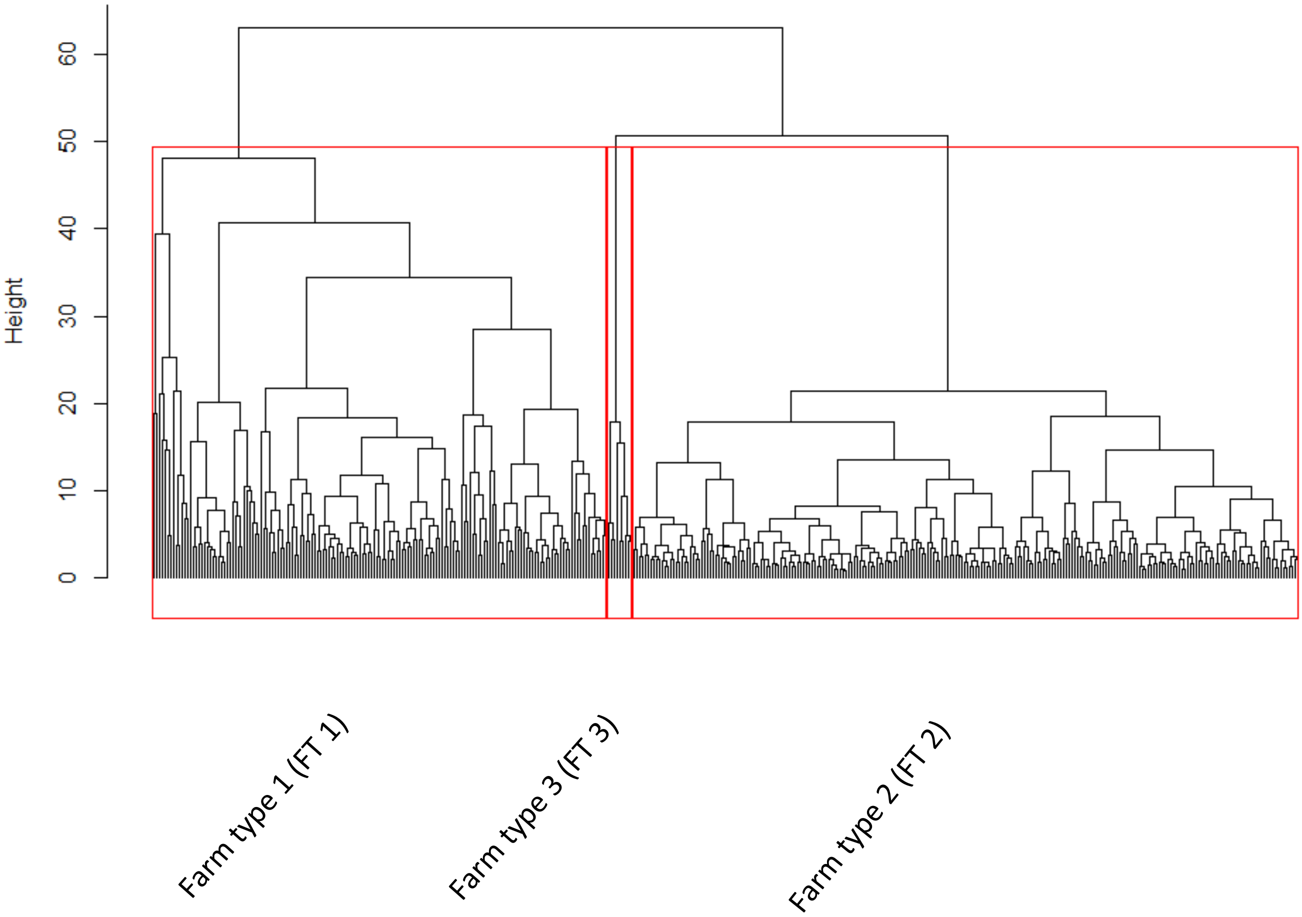

Figure 5.5. Cluster Dendrogram

5.3.6 Climate risk perception index

The study analysed how farmers perceive climate risk and subsequently explored the weight they attach to their climate risk management objectives. The perception statement asked from the survey was whether farmers felt drought or flood was their most severe, second most severe, or third most severe risk. The perception index employed by Kyire et al. (2023), Avane et al. (2022), Amrago and Mensah (2022), and Amfo et al. (2020) was used to gauge the climate risk perception for each *FT*. This is represented in equation 5.2 as:

$$Perception\ index = \frac{\sum_{r=1}^{3}(Frequency_r * rank_r)/n}{N} \qquad (5.2)$$

where r = *1 to 3* (i.e. from third most severe ($rank_1$), second most severe ($rank_2$), to most severe ($rank_3$)), $Frequency_r$ = Frequency of respondents for the r^{th} perception rank , n = number of respondents, and N = number of perception statements asked during the survey. The value for the perception index ranges from 3 to 1, implying that *FTs* with the largest, medium, or lowest perception index feel climate risk is their most severe, second most severe, or third most severe risk, respectively.

5.3.7 Weight attached to climate risk management objectives.

Per the Africa RISING survey data, farm households' drought or flood management involved activities listed in Table 5.1. The current study categorises these activities into high-risk, more-income, and low-risk, less-income generating activities (Table 5.1).

Table 5.1. Categorisation of drought or flood management activities

High-risk, more-income generating activities	**Low-risk, less-income generating activities**
Sold durable assets	Engaged in prayers, sacrifices, and divine consultations
Sold agricultural assets	Did nothing
Sold crop stock	Received unconditional help from friends and relatives
Sold livestock	Changed eating habits
Relied on own savings	Household members migrated
Adult household had to find work	Others

The assumption was that, in the event of drought or flood, relatively well-endowed farmers would engage in high-risk activities that translate into income to attempt to offset any losses. On the other hand, the less endowed farmers who do not have the resources to generate income will focus on less-income-generating activities with little risk. To identify the level of importance attached to these activities, the study assigned weights based on the percentage (%) frequency of respondents for each of the two risk management categories (i.e. *w% freq of respondents per category*) listed in Table 5.1. The percentage frequency value for each category per *FT* represents the weight the *FT* attaches to that category. Farm typologies are classified as risk-averse or risk-loving depending on the percentage frequency per category. The percentage frequency is mathematically expressed as:

$$w\%\ Freq\ of\ respondents\ per\ category = \frac{Frequency\ of\ respondents\ per\ category}{Total\ number\ of\ respondents} * 100 \quad (5.3)$$

5.4 Results

Table 5.2 indicates the size of each *FT* and the specific characteristics that differentiate them. *FT* 1 consists of 39.7% of all households sampled and has 161 members, followed by *FT* 2, with 236 members for 58.1% of total households sampled. *FT 3* has 9 members, representing 2.2% of the households sampled. All *FTs* had varying degrees of positive climate risk perception index. *FT 1* exhibits the characteristics of a well-resourced, less risk-averse *FT* with the lowest climate risk perception index. In contrast, *FT 2* typically has a moderate resource-endowed, risk-averse, and climate risk perception index. Furthermore, *FT 3* is the poorest regarding resource endowment with the highest risk aversion and climate risk perception index. The following section explains the characteristics of each *FT* in detail.

Table 5.2**.** Characteristics of *FTs*

Farm type	**Size (Number of households)**	**Percentage share**	**Main characteristic**
1	161	39.7%	Well-resource-endowed farmers, less risk-averse, lowest climate risk perception index
2	236	58.1%	Moderately resource-endowed farmers, moderately risk-averse, medium climate risk perception index
3	9	2.2%	Poorly resource-endowed farmers, more risk-averse, highest climate risk perception index
TOTAL	**406**	**100%**	

5.4.1 Detailed characteristics of FTs

5.4.2 Farm type 1 (FT 1)

Of the 406 households selected in the current study, the 161 clustered in *FT* 1 could be described as relatively more resource-endowed due to the size of their average land holding (6.4 Ha) and average value of assets (GH₵ 2,356), including that of livestock owned (GH₵ 4,905) (Appendix 3). They have the highest average annual food and non-food expenditures of about GH₵ 2,686 and GH₵ 3,175, respectively. With an average family size of 12, households store, consume, and sell the largest quantities of maize, rice, and groundnut harvested except sorghum, which they do not cultivate. Relative to other *FTs*, the average yield for maize, rice, and groundnut were the highest at 1,276 kg/Ha, 928 kg/Ha, and 401 kg/Ha, respectively. *FT* 1 represents the group with the largest average value of fertiliser used (GH₵ 599) and labour requirements in person days for all activities (Appendix 3). They have the largest storage quantities for maize (1096.4 kg), rice (645 kg), and groundnut (271 kg) after harvest, making them more food-sufficient than other *FTs*.

5.4.3 Farm type 2 (FT 2)

On average, households in *FT* 2 have the smallest groundnut productivity (i.e. groundnut yield) at 155.5 kg/Ha. However, they are the second most productive *FT* for maize (733.7 kg/Ha) and rice (305 kg/Ha) and again do not cultivate sorghum. On average, households in this *FT* have the lowest total male and female labour requirements for land preparation and weeding (Appendix 2). Given an average family size of 9, they are the second largest own consumers of maize (504 kg), rice (55 kg), and groundnut (29 kg). This group of farmers are characterised by a relatively small quantity of groundnut harvested (138 kg) and sold (56 kg). Additionally, they are the second in terms of average land holding (3.2 Ha), value of livestock (GH₵ 1,042) and assets (GH₵ 669) owned, value of fertiliser (GH₵ 213) and pesticides (GH₵ 49.5) purchased, annual food (GH₵ 1860) and non-food expenditures (GH₵ 2,096), and storage quantities of maize (455.3 kg) and rice (127 kg). Based on these characteristics, households in *FT* 2 are categorised as moderately resource-endowed households.

5.4.4 Farm type 3 (FT 3)

Households in *FT* 3 are the only group that cultivate sorghum (Appendix 2). Given their relatively low average household size (8) and land holding (3 Ha), they produce the lowest average yield of maize (566 kg/Ha) and rice (90 kg/Ha) compared to other *FTs* but are the second most productive group in groundnut (209 kg/Ha) cultivation. Sorghum yield on average for this *FT* is 470 kg/Ha. They have the lowest value of fertilisers used and pesticides purchased at GH₵ 41 and GH₵ 25, respectively. In terms of average labour requirements, this *FT* requires the smallest number of male person days for fertilising (0.7) and other activities (1.6), and the least female person-days required for planting (14.2), fertilising (0.7), and harvesting (18.9) (Appendix 2). Households in this *FT* distinguish themselves from all *FTs* by not consuming any of the rice they produce, which could be attributed to the relatively low quantity of rice harvested (61.1 kg). Their lack of productivity is reflected in their relatively low average storage quantities for maize (275 kg) and rice (50 kg), with no amount for sorghum, indicating that all sorghum is consumed or sold. On average, they consume 193 kg of the sorghum produced and sell 11.1 kg to make some income (Appendix 2). Based on the characteristics described and given that this farm type has the lowest average value of livestock owned (GH₵ 620.6), assets (GH₵ 207), and amount spent annually on purchasing food (GH₵ 1,399) and non-food (GH₵ 1,386), they are considered as the lowest resource endowed cluster. Regarding education, the maximum level for all *FT*s in this study is junior high school. Further details about each *FT* are available in Appendix 2.

5.5 Risk characteristics of *FTs*: climate risk perception and management strategies.

5.5.1 Climate risk perception index

Employing the perception index formula in equation 5.2, Table 5.3 generates the climate risk perception index for each *FT* based on how they rank their perception of drought or flood. All *FTs* had a climate risk perception index greater than 2.0 (i.e. second most severe rank), implying that most households in each *FT* perceived drought or flood as their most severe risk. The poorest of the *FTs* (i.e. *FT* 3), had the highest perception index at 2.55, followed by *FT* 2 (2.33) and *FT* 1 (2.31).

Table 5.3. Climate risk perception index

FTs[a]	Risk perception rank for drought or flood	Frequency of respondents ($frequency_r$)	Perception rank ($rank_r$)	Total number of respondents (n)	Number of perception statements (N)	Climate risk perception index
FT 1	Most severe	72	3	161	1	2.31
	Second most severe	67	2			
	Third most severe	22	1			
FT 2	Most severe	115	3	236	1	2.33
	Second most severe	86	2			
	Third most severe	35	1			
FT 3	Most severe	7	3	9	1	2.55
	Second most severe	0	2			
	Third most severe	2	1			

[a]*FTs = Farm types, FT1 = Farm type 1, FT2 = Farm type 2, FT3 = Farm type 3*

5.5.2 Climate risk management strategies

Using equation 5.3, Table 5.4 produces the weights households attached to their drought or flood management objectives. Most households across *FTs* tend to engage in low-risk, less-income generating activities as their drought or flood management strategy. For *FT* 1, about 61.5% engaged in prayers and divine consultation, did nothing, received unconditional help from relatives, changed eating habits, migrated, had to find work, or engaged in other activities. On the other hand, 38.5% of the households either sold their assets, crop stock, livestock, or relied on their savings. A similar trend occurs for *FT* 2 and 3 where a higher percentage (i.e. 69.1% for *FT* 2 and 88.9% for *FT* 3) of households were identified to be engaging in low-risk less-income generating activities relative to high risk more income-generating activities (i.e. 30.9% for *FT* 2 and 11.1% for *FT* 3). As a result, we categorise *FT* 1 as less risk-averse, *FT* 2 as moderately risk-averse, and *FT* 3 as more risk-averse.

Table 5.4. Household size and the weight attached to risk management objectives.

High-risk, more income-sourcing activities	**FT 1**		**FT 2**		**FT 3**	
	h^c	**w(%)**	**h**	**w(%)**	**h**	**w(%)**
Sold durable assets	0		1		0	
Sold agricultural assets	2		1		0	
Sold crop stock	2		7		0	
Sold livestock	4		2		0	
Relied on own savings	54		62		1	
Frequency of respondents for high-risk, more-income generating activities	**62**	**(38.5%)**	**73**	**(30.9%)**	**1**	**(11.1%)**
Low-risk less-income activities						
Engaged in prayers, sacrifices, and divine consultations	39		41		3	
Did nothing	45		69		3	
Received unconditional help from friends/relatives	4		14		2	
Changed eating habits (skipped eating for days, reduced food proportions or number of meals per day)	2		16		0	
Household members migrated	0		1		0	
Adult households had to find work	1		0		0	
Others	8		22		0	
Frequency of respondents for low-risk, less-income generating activities	**99**	**(61.5%)**	**163**	**(69.1%)**	**8**	**(88.9%)**
Total household size/weight attached	**161**	**100%**	**236**		**9**	**100%**

h^c= number of households, w% = weight attached in percentages per risk management objective (i.e. high-risk more income and low-risk less-income generating activities), FT1 = Farm type 1, FT2 = Farm type 2, FT3 = Farm type 3.

5.6 Discussion

The findings from this study reveal strong linkages between farm types (*FTs*) in terms of resource endowment, climate risk perception and management, in the study area. Well-resource-endowed farmers in *FT1* had on average, higher asset endowments than those in other *FTs*. From the findings, we concur that there were significant differences in the production capacity of relatively impoverished and affluent *FTs*. Crop yields from well-endowed and less risk-averse *FTs* were higher than the less-endowed ones. Also, poor farmers do not store more of their yield, which could be due to a lack of storage and immediate cash needs; hence, they prefer to sell or consume their produce immediately after harvest to avoid post-harvest losses and resort to finding options to purchase food for the rest of the year. (Tittonell, 2014). This puts them in an entrenched poverty trap, giving no room for welfare improvement. Furthermore, relatively poor *FTs* are forced to accept low prices as they cannot take advantage of the potential future price increase during off-seasons when market supply is low. Any intervention that seeks to develop yield productivity and reliable storage facilities for these *FTs* will serve as an essential economic relief and improve resilience to climate risk.

The current study reveals a key relationship between household wealth, climate risk perception, and risk aversion in the sense that the wealthier the farm type, the lesser their climate risk perception index, and the less risk-averse thereof. There is also a clear indication that smallholder farmers are highly susceptible to drought or flood. This is evident in the weights (i.e. % weight) they attached to low-risk less-income generating activities as their management strategy in the event of a drought or flood. It points to the fact that, by the assumption in this study, all *FTs* fall within the risk aversion category. A striking observation from the findings of this study is that, except for *FT* 2, more than half of the households in each *FT* chose to do nothing or engage in prayers, sacrifices or spiritual consultations as their climate risk management strategy. In *FT* 1, 2, and 3, up to 84, 110, and 6 households either engaged in prayers, sacrifices, spiritual consultations or did nothing to address the effect of drought or flood (Table 5.4). This represents 52%, 47%, and 67% of the households in *FTs* 1,2 and 3, respectively, implying a high level of vulnerability and lack of resilience toward climate risk.

From these findings, the study concludes that most households tend to participate in perceived less risky activities as a climate risk management strategy, primarily due to the general lack of resource endowments to take on high-risk, more income generating activities. The study findings are in line with Barr and Genicot (2008), Binswanger (1980), Binswanger (1981), Bezuneh (1991), Kisaka-Lwayo and Obi (2012) and Wik et al. 2004 where smallholder farmers in developing countries like Zimbabwe, Zambia, India, and South Africa are deemed to be risk-averse due to inadequate levels of resource endowments and capacity to mitigate risk.

5.7 Implications of the study

The results of this study have several important implications for agricultural policy, climate risk management, and poverty alleviation, especially regarding smallholder farmers in developing countries. The findings suggest that policies should focus on enhancing the capacity of less-endowed farmers to manage climate risks effectively. This could include improving access to agricultural extension services, providing training on climate-resilient agricultural practices, and facilitating access to credits tailored to the needs of smallholder farmers. Additionally, creating community-based support systems that encourage the adoption of risk management practices could help reduce the reliance on passive action and non-technical methods. The preference for prayers, sacrifices, and spiritual consultations as climate risk management strategies among many farmers indicates the influence of socio-cultural beliefs on agricultural practices especially when farmers are economically disadvantaged. Government policies should focus subsidising input cost to help increase income levels as risk management strategies of most smallholder farmers are linked to their economic conditions and socio-cultural beliefs. In brief, this study highlights the need for a multi-faceted approach to improving the resilience and productivity of smallholder farmers. Enhancing resource endowment, providing reliable storage facilities, offering targeted financial and technical support, and considering socio-cultural factors in program design are crucial for enabling smallholder farmers to overcome poverty traps and build resilience to climate risks.

5.8 Conclusion

The study explored 406 households from three regions (ie., Northern, Savannah, and North East regions), with diversified farming portfolios narrowed into a more homogeneous group of farmers using *PCA* and cluster analysis. A reasonably consistent pattern in resource endowment, climate risk perception and climate risk management amongst all *FTs* was revealed. The above discussion postulates important lessons on the relevance of creating more homogeneous farm household characteristics and the intra-farm type relationships under three main perspectives: household wealth, climate risk perception, and the weight farmers attach to their climate risk management objectives. The findings of this study could be used to guide policy implementors to avoid blanket implementation of agriculture support activities but rather emphasise tailor-made case-specific intervention programs. The support for farmers could focus on a broader spectrum by providing good agricultural practices to improve crop productivity and reduce risk exposure, creating market linkages for households to make more income, and providing less expensive farm inputs and welfare support systems to smallholder farmers. To conclude, the study indicates that although the findings of this study are very useful in understanding farm type socio-economic differences, it does not include the interactive effect of the limitations in household resource endowments, the weight farmers attach to climate risk, and other socio-economic conditions. As a result, it is important to undertake further analysis into how these interactions affect the economic well-being and on-farm decision making under climate risk.

5.9 Appendix

Appendix 1: Criteria and variables for typology construction

Criteria	**Variables**
Resource endowments	Value of assets (Ghana cedis-GH₵) Value of livestock owned (GH₵) Average exogeneous monthly income (GH₵) Land holding (ownership) (Hectares-Ha) Maize stored (Kilograms-kg) Rice stored (kg) Sorghum stored (kg) Groundnut stored (kg)
Production goals	Own consumption of maize (kg) Own consumption of rice (kg) Own consumption of sorghum (kg) Own consumption of groundnut (kg) Number of own livestock consumed (number) Maize harvested (kg) Rice harvested (kg) Sorghum harvested (kg) Groundnut harvested (kg) Maize sold (kg) Rice sold (kg) Sorghum sold (kg) Groundnut sold (kg)
Climate risk	Household management of drought or flood (frequency) Household rank for the severity of drought or flood (rank)
Demographics	Family size (Number) Maximum level of education (custom score) Age (Average per household)

Appendix 1 cont'd: Criteria and variables for typology construction

Criteria	Variables
Production intensity, expenditure, and level of inputs	Maize yield (kg/ Ha) Rice yield (kg/ Ha) Sorghum yield (kg/Ha) Groundnut yield (kg/Ha) Fertiliser used (kg/Ha) Purchased pesticides (GH₵) Additional labour expenses (GH₵) Expenditure on livestock (GH₵) Crop area for maize (Ha) Crop area for rice (Ha) Crop area for sorghum (Ha) Crop area for groundnut (Ha) Value of fertilizer used (GH₵) Total male person days land preparation (Person days) Female person days for land preparation (Person days) Male person days for planting (Person days) Female person days for planting (Person days) Male person days for fertilizing (Person days) Female person days for fertilizing (Person days) Male person days for weeding (Person days) Female person days for weeding (Person days) Male person days for harvesting (Person days) Female person days for harvesting (Person days) Male person days for other labour required activities (Person days) Female person days for other labour required activities (Person days) Maize post-harvest losses (Percentage-%) Rice post-harvest losses (%) Sorghum post-harvest losses (%) Groundnut post-harvest losses (%) Annual food expenditure (GH₵) Annual non-food expenditure (GH₵)

Appendix 2: The most relevant variable loadings to principal components

Variables	Contribution to principal components
	PC1
Family size (number)	-0.45
Land area (Hectares (Ha))	-0.77
Value of fertiliser used (Ghana cedis (GH₵))	-0.64
Value of pesticides purchased (GH₵)	-0.67
Planting (male person days)	-0.53
Fertilising (male person days)	-0.62
Fertilising (female person days)	-0.33
Weeding (male person days)	-0.53
Harvesting (female person days)	-0.65
Labour for other activities (male person days)	-0.54
Maize harvest sold (kg)	-0.43
Own maize consumption (kg)	-0.55
Maize harvest without stover (kg)	-0.62
Own rice consumption (kg)	-0.45
Own groundnut consumption (kg)	-0.34
Groundnut harvest without stover (kg)	-0.63
Maize stored (kg)	-0.48
Annual expenditure on non-food (GH₵)	-0.45
	PC2
Rice Yield(Kg)	0.56
Rice harvest sold (kg)	0.60
Rice stored (kg)	0.60
	PC3
Groundnut Yield (kg/Ha)	-0.62
Groundnut harvest sold (kg)	-0.61
Groundnut stored (kg)	-0.58
	PC4
Sorghum yield (Kg/Ha)	-0.78
Sorghum harvest sold (kg)	-0.23
Own sorghum consumption (kg)	-0.86
	PC5
Asset value (GH₵)	0.32
Annual expenditure on food (GH₵)	0.64
Maize yield (kg/Ha)	-0.54

Appendix 2 cont'd

Variables	Contribution to principal components
	PC6
Land preparation (male person days)	-0.41
Land preparation (female person days)	-0.29
Planting (female person days)	-0.47
	PC7
Value of livestock owned (GH₵)	-0.47
Owned livestock consumed (number)	-0.51
Livestock sold (number)	-0.45
Livestock income earned (GH₵)	-0.38
Livestock expenditure (GH₵)	-0.47
	PC8
Household response to drought or flood (custom score)	0.41
	PC9
Maximum level of education	0.43
	PC10
Mean Age	-0.35
Post-harvest losses for groundnut (%)	0.25
Average exogeneous monthly income (GH₵)	-0.33
Household rank for drought or flood	-0.30
	PC11
Additional labour expenses (GH₵)	0.44
	PC12
Weeding (female person days)	-0.44
	PC13
Maize post-harvest losses (%)	0.29
Rice post-harvest losses (%)	0.34

Appendix 3: Values of each variable per farm type

Criteria/Variables	Farm types (FTs)		
Production intensity, expenditure, and level of inputs	**1**	**2**	**3**
Maize yield (Kilograms (kg)/Hectare (Ha))	1276.4	733.7	566.4
Rice yield (kg/Ha)	928	305.2	90.3
Sorghum yield (kg/Ha)	0	0	470.4
Groundnut yield (kg/Ha)	401	155.5	209
Crop area for maize (Ha)	2.4	1.4	1.2
Crop area for rice (Ha)	1.4	0.4	0.2
Crop area for sorghum (Ha)	0	0	0.6
Crop area for groundnut (Ha)	1	0.4	0.6
Expenditure on livestock (GH₵ (Ghana cedis))	52	14	7.1
Value of fertiliser used (GH₵)	598.7	213.2	41.1
Value of purchased pesticides, herbicides (GH₵)	147.8	49.5	24.7
Additional labour expenses (GH₵)	103.4	95.9	155
Male person days land preparation (Person days)	25	14	21
Female person days for land preparation (Person days)	1.4	0.6	1.5
Male person days for planting (Person days)	26	12	17
Female person days for planting (Person days)	31	15	14
Male person days for fertilising (Person days)	10.7	4	0.7
Female person days for fertilising (Person days)	5.6	2	0.7
Male person days for weeding (Person days)	69.1	41	45.9
Female person days for weeding (Person days)	7.9	3	7.3
Male person days for harvesting (Person days)	54	23.2	22.8
Female person days for harvesting (Person days)	53.4	22.9	18.9
Male person days for other activities (Person days)	8.4	3.4	1.6
Female person days for other activities (Person days)	0.7	0.2	0.2
Annual food expenditure	2,686	1860	1,399
Annual non-food expenditure	3,175	2,096	1,386
Maize post-harvest losses (percentages (%))	22.3	25.4	44.4
Rice post-harvest losses (%)	5.6	0.8	0
Sorghum post-harvest losses (%)	0	0	0
Groundnut post-harvest losses (%)	6.8	0.8	0
Production goals	**1**	**2**	**3**
Own consumption of maize (kg)	955.9	504.3	445.7
Own consumption of rice (kg)	204.2	55	0
Own consumption of sorghum (kg)	0	0	193.2
Own consumption of groundnut (kg)	64.5	28.8	0
Number of own livestock consumed (number)	7	4	7
Maize harvested (kg)	2,259.2	765	572
Rice harvested (kg)	1248.8	239.4	61.1
Sorghum harvested (kg)	0	0	220
Groundnut harvested (kg)	584.7	137.7	313.3
Maize harvest sold (kg)	434.3	82.1	77.8
Rice harvest sold (kg)	491.1	115.3	38.9
Sorghum harvest sold (kg)	0	0	11.1
Groundnut harvest sold (kg)	275.4	56.2	186.7

Appendix 3 continued

Criteria/Variables	**Farm types (FTs)**		
Resource endowment	**1**	**2**	**3**
Value of assets (GH₵)	2,355.8	668.7	207
Value of livestock owned (GH₵)	4,905.2	1042.4	620.7
Average exogeneous monthly income (GH₵)	133	111	130
Landholding (Land ownership) (Ha)	6.4	3.2	3.0
Maize stored (kg)	1096.4	455.3	275.2
Rice stored (kg)	645	127	50
Sorghum stored (kg)	0	0	0
Groundnut stored (kg)	271.8	54.9	40
Demographics			
Family size (Number)	12	9	8
Mean Age (Number)	22	24	25
Maximum level of education (custom score)	1	1	1

Appendix 4

Principal Components	**Eigen value**	**Percentage variance**	**Percentage cumulative variance**
PC1	10.7	17.4	17.4
PC2	4.4	7.0	24.4
PC3	4.0	6.5	30.0
PC4	3.6	5.8	36.7
PC5	2.5	4.1	40.8
PC6	2.3	3.8	44.6
PC7	1.9	3.1	47.7
PC8	1.7	2.7	50.3
PC9	1.6	2.5	52.9
PC10	1.5	2.3	55.2
PC11	1.4	2.2	57.5
PC12	1.3	2.1	59.6
PC13	1.3	2.0	61.6

Chapter 6 A mixed-integer quadratic compromise risk-programming model for income-risk trade-off decision-making under climate variability.

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1

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6.1 Introduction

Understanding the trade-off between risk and income is increasingly important in today's global agriculture, especially in tropical Sub-Saharan African farming systems. Agricultural risk resulting from climate variability has long been identified as a threat to the smallholder farmer's ability to remain resilient (Wood et al., 2014). From research findings, increasing temperatures have adverse effect on crop yield (Funk & Brown, 2009; Gourdji et al., 2013; Lobell et al., 2011; Lobell & Field, 2007), and these effects are more profound, especially in tropical climates (Mendelsohn et al., 1994; Schlenker and Lobell, 2010). Coincidentally, most developing countries, including Ghana, are located in warmer regions, making the area more prone to drought, which further exacerbates the plight of smallholder farmers (Ericksen et al., 2011; Füssel, 2010; Jarvis et al., 2011; Mehndelson et al., 2006). Studies have revealed that drought is deemed as a climatic condition that results in significant losses for most farmers, especially in the semi-arid regions of the world (Keshavarz & Karami, 2014) and the most complex to handle among all natural disasters(Wilhite et al., 2007)

To mitigate the effect of climate variability, it is crucial to implement climate-driven adaptation techniques that focus on altering farm and land management practices (Jarvis et al., 2011). An adaptation technique could involve reducing land allocations to crop enterprises, especially for crops generating lower returns with highly variable income over time relative to other crops. In northern Ghana, farmers use informal risk management strategies such as crop and income diversification, utilising savings, or asset selling (Kyire et al., 2023). As a result, the current study acknowledges that due to climate variability and smallholder farmers' willingness to manage risk, they are constantly confronted with making difficult decisions that require them to minimise risk whilst expecting to make some reasonable income within the feasibility of their resource constraints. Satisfying these conflicting objectives can be daunting as smallholder farmers have limited capacities to offset adverse effects of climate risk. Consequently, farmers tend to compromise by accepting relatively low returns in exchange for a more stable income to keep them resilient. This study contributes to achieving this by developing a mixed integer quadratic compromise risk programming model that uses a multi-objective non-linear mathematical programming algorithm to identify optimal crop production portfolios under climate variability. By adapting their risk management in line with the recommendations from this research, farmers can avoid making unrealistic income targets that increase their climate risk vulnerabilities.

Research in agricultural risk decision-making, especially regarding climate-risk model development in northern Ghana, is extremely limited. Karlan et al., 2014 conducted survey experiments through focus group discussions among smallholder farmers in northern Ghana to investigate farmers' investment decisions when credit and risk constraints are relaxed. From the survey, although farmers complained about their lack of capital and the difficulty in accessing agricultural credit, they acknowledged the effect of rainfall risk and were willing to reduce their cash investment in farming to trade-off less risk for a more stable income. Moreover, studies by Asravor (2019), Antwi-Adjei et al. (2018), Kyire et al. (2023), Nkegbe and Kuunibe (2014), and Wossen et al. (2014) have either focused on consumption risk, climate variability, risk preferences, risk adoption, risk management, or risk perceptions without analysing the trade-off between income and risk given the limited resources of the smallholder farmer. To attempt to fill this gap, the model developed in this study minimises farm household risk at expected levels of income under different resource constraints with an objective of determining climate-risk resilient crop combinations for different farm types. The model analyses income risk trade-offs based on household wealth, consumption, production, and expenditure.

6.2 Study area

The study area is located in the Northern, Savannah, and North East regions of Ghana (Figure 6.1), comprising five districts. The inhabitants of the study area are predominantly from the Dagomba ethnic group, made up of approximately one-third of the region's population (Ellis-Jones et al. 2012). A household is typically male headed, living in a compound house with both nuclear and extended family members comprising about three generations (i.e. household head and wife/wives, children and their spouses, and grandchildren) (Alhassan and Poulton, 2009). The household head has the power to demand labour from any member of the household to ensure food supply; however, at his demise, the eldest son takes full leadership responsibility for the household (Alhassan and Poulton, 2009).

Soil types are characterised by Savanah Orchrosols, with an approximate land area of 70,383 km^2 (Mustapha et al. 2020). Due to the annual unimodal rainfall pattern, crop cultivation usually occurs in one season starting from April/May each year (FAO, 2020). Rainfall often begins in April/May, peaks in August, and ends in September/October. Despite this, the region produces most of Ghana's maize, sorghum, and rice (Yiridoe et al. 2006).

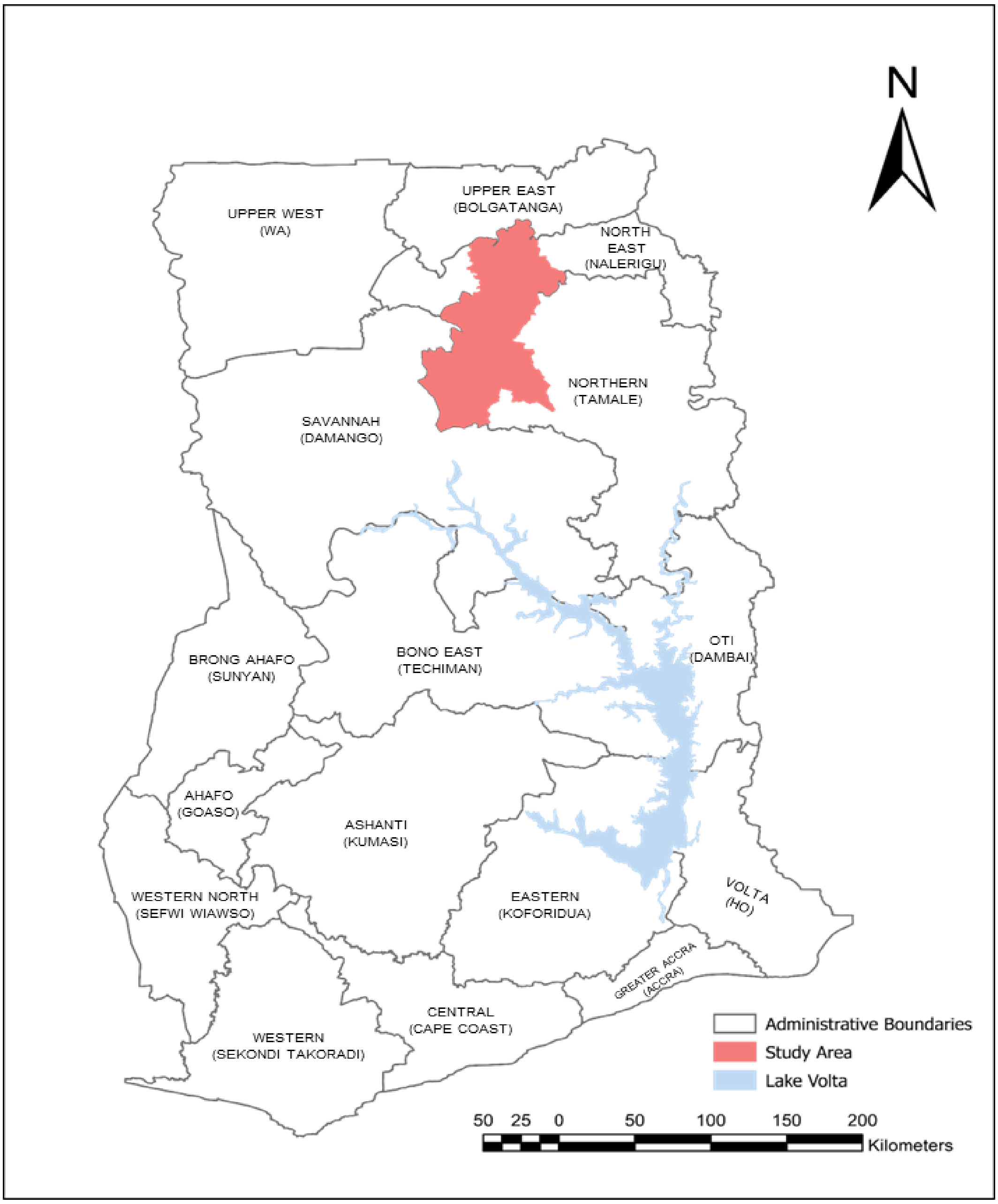


Figure 6.1. Map of Ghana showing study area, regions, and regional capitals in brackets.

6.3 The model

The model consists of three components (i.e. quadratic programming, compromise risk programming, and linear expenditure system). Each component is explained below.

6.3.1 Quadratic programming

This research employs a quadratic programming approach first introduced by Hazell and Norton (1986) and further discussed in Hardaker et al. (2015) to minimise risk on smallholder farms. In this study, risk is measured as variance (σ^2) of net income in Ghana cedis (GH₵). The model builds on the quadratic programming model of Hazell and Norton (1986) by incorporating multi-objective decision-making on risk and income (hereafter referred to as expected net income) as part of the livelihood system of smallholder farmers. The study considers smallholder farmers in northern Ghana cultivating *i* crops (i.e. maize, rice, sorghum, and groundnut) with varying nitrogen application rates except groundnut due to its nitrogen-fixing properties. Farmers wish to remain climate resilient and avoid over or under-purchasing of fertilisers. In addition, farmers are willing to compromise by trading off some level of risk to generate a more stable expected net income to possibly cater for household expenditures. Ideally, the amount of risk traded in return for a stable expected net income depends on the wealth of the farmers due to the differences in the importance attached to risk and expected net income amongst relatively wealthy and poor farmers. The primary objective of farmers is to minimise risk at expected levels of net income by choosing appropriate cropping portfolios from an array of cereal cropping choices such that only the optimal fertiliser application rate per crop is used. Also, irrespective of market prices, farmers want to consume a portion of what they produced and still be able to pay for the fixed and variable transaction costs associated with selling the produce remaining after satisfying consumption requirements. To achieve this, the model minimises equation 6.1 subject to equations 6.1a to 6.10 while parameterising equation 6.11 from the least to the highest possible expected net income to generate an efficient set using parametric fixed interval programming, as discussed in Hazell and Norton (1986). Finally, a compromise risk programming model is employed for expected net income and risk trade-off analysis.

$$Minimise(\sigma^2) = \sum_{i=1}^{I} \sum_{j=1}^{J} X_i \, X_j \left(\sigma_{ij}\right) \text{ (Objective function)} \tag{6.1}$$

$$X_i \leq \sum_{p=1}^{P} A_p \, X_{ip} \; \forall \; i \textit{ (Crop fertiliser application rate selection constraint)} \tag{6.1a}$$

$$\sum_{p=1}^{P} A_p \leq 1 \textit{ (Binary fertiliser constraint)} \tag{6.1b}$$

$\sum_{i=1}^{I} X_i \leq L$ (Land constraint) (6.2)

$\sum_{i=1}^{I} \Psi_i(X_i) \leq \Psi$ *(labour constraint*) (6.3)

$Q_i * X_i - W_i - \sum_{m=1}^{12} M_{im} - CN_i \geq 0 \ \forall \ i$ (production balance constraint) (6.4)

$SR_i(X_i) - B_i - W_i = 0 \ \forall \ i$ *(seed balance constraint)* (6.5)

$\sum_{i=1}^{I} \Phi_i CN_i \geq \alpha_F$ *(human calorific consumption constraint)* (6.6)

$\sum_{i=1}^{I} prot_i CN_i \geq Sub_{PROT}$ *(human protein consumption constraint)* (6.7)

$X_i(a_{ei}) - \sum_{f=1}^{2} QFERT_{fi} * K_{ef} \leq 0 \ \forall \, i, e$ (nutrient balance constraint) (6.8)

$\text{TR} = \sum_{i=1}^{I} \sum_{m=1}^{12} (M_{im} * S_{im})(RP_{im}) + \text{y}$ *(total revenue constraint)* (6.9)

$\text{OC} = \sum_{i=1}^{I} \sum_{m=1}^{12} \{M_{im}(VTC_i) + TOTC_i X_i + \sum_{f=1}^{2} (QFERT_{fi}(P_f)) + B_i(P_{Bi})\} +$

FTC (operating cost constraint) (6.10)

$Y = TR - OC$ *(expected net income constraint)* (6.11)

6.3.2 Objective function

Equation 6.1 represents the objective function where σ^2 is the total variance of net income for all crop activities, *i,j* represents 1…4 crop activities (i.e. maize, rice, sorghum, and groundnut), each comprising sets *h, r, s,* and *g*. For each set, *h* is the set of maize fertiliser application rate (i.e. 0 kgN/ha, 40 kgN/ha, 80 kgN/ha, and 120 kgN/ha), *r* is the set of rice fertiliser application rate (i.e. 0 kgN/ha, 30 kgN/ha, 60 kgN/ha, and 100 kgN/ha), *s* is the set of sorghum fertiliser application rate (i.e. 0 kgN/ha, 40 kgN/ha, 80 kgN/ha, and 100 kgN/ha), and *g* is the set of groundnut fertiliser application rate (i.e. 0 kgN/ha). X_i and X_j are the activity levels of the i^{th} and j^{th} crops (ha), respectively, σ_{ij} is the covariance of income between *i and j*, and σ_i^2 is the variance when *i = j (Appendix 1).* The crop specific fertiliser application rates were generated using the Aquacrop model in Chapter 3

6.3.3 Fertiliser application rate selection and binary constraint

Equation 6.1a selects optimal fertiliser application rate per crop when $i = h, r, s,$ and g. *Also,* $p=1\ldots P$, represents the levels of fertiliser application rates per crop from the lowest to the highest and $A_p = \begin{cases} 1 \; if\ the\ p^{th}\ fertiliser\ application\ rate\ is\ selected \\ 0 \; otherwise. \end{cases}$ For each crop, the activity level (X_i) must not exceed the sum product of A_p and the activity levels of the p^{th} fertiliser application rate (X_{ip}). In addition, the sum of the binary coefficients (A_p) across all levels of fertiliser application rates per subset (i.e. *h, r, s*, and *g*) should be less than or equal to 1 (equation 6.1b). Satisfying the constraints in equations 6.1a and 6.1b imposes the selection of only one fertiliser application rate per crop. This is to avoid managerial complications arising from managing multiple fertiliser regimes.

6.3.4 Land constraint

Land is included in the model as a fixed asset. Land is acquired in northern Ghana through a customary land tenure system (Yiridoe et al., 2006). Based on the model constraint in equation 6.2, the total amount of land cultivated in hectares for X_i must not exceed the land available for the household (L).

6.3.5 Labour constraint

From equation 6.3, the total labour required for all *i* crop activities (Ψ_i) must be less than or equal to the labour available (Ψ) for the farm household.

6.3.6 Production balance constraint

Equation 6.4 is the production balance constraint. It links the bio-economic indicators such as crop yield, consumption, produce sales, and seed requirements across key model components. Also, since crop yield has alternative uses, this constraint accounts for how much of the quantity produced is used for seeds, sales, and consumption. Based on the structure of the model, the quantity of grain produced is a product of average yield (Q_i) and activity level (X_i) of the i^{th} crop as previously defined. Like Hildebrand & Cabrera (2003), the crop production activity generates a production quantity ($Q_i * X_i$) into the production balance constraint (a positive coefficient). After that, the total household consumption requirement (CN_i) is first satisfied by taking out the calorific(Φ_i) and protein ($prot_i$) equivalence per kilogram of subsistence consumption quantities from the production balance constraint into the energy balance and protein balance constraints in equations 6.6

and 6.7 respectively through a transfer activity. Similarly, the quantity for own seed used (W_i) is also transferred into the seed balance constraint in equation 6.5. The remaining quantities (M_{im}) are stored for sale in the m^{th} month after harvest. In brief, for each crop, quantity produced must be greater than or equal to the quantities used as seeds, consumed, and stored for sale.

6.3.7 Seed balance constraint

The seed balance constraint in equation 6.5 was developed in the model to account for consistency in allocating seed supply and usage on a per-hectare basis. Also, own seed use was included to mimic farmers' behaviour of either using their own seeds from harvest or purchasing a hybrid or any preferred seed type depending on how relatively expensive seeds are on the market. The structure of the model is such that, for each of the four crops cultivated, the quantity of seeds required *(SR_i)* in kg/Ha must be equal to the quantity of own seeds used for planting and or purchased (B_i) in kilograms. As own seed use is a transfer activity from equation 6.4, the optimal solution is determined by the opportunity cost of using own seeds for the next season rather than selling or consuming. If the opportunity cost is high, the model selects a seed buying option as the optimal solution in compliance with the quantities required per hectare.

6.3.8 Human calorific consumption constraint

From equation 6.6, the quantity of grain sold is only determined after households have met their subsistence energy consumption needs (α_F). The model's consumption component reduces the household's income level because they consume as much of their harvest as needed. Equation 6.6 indicates that the total amount of calories consumed from the crops produced ($\Phi_i\, CN_i$) must be equal to or greater than the subsistent calories demanded by the household from their own harvest (i.e. subsistence own calorific consumption).

6.3.9 Human protein consumption constraint

The protein consumption constraint in equation 6.7 is to account for households' tendency to consume more protein when their expected net income increases. To achieve this, the total protein consumed in g/kg from all crops *($prot_i\, CN_i$)* should be equal to or greater than the subsistence own protein consumption *(Sub_{PROT})* of the farm household.

6.3.10 Nutrient balance constraint

In equation 6.8, a_{ei} is the amount of the e^{th} soil nutrient elements (i.e. Nitrogen (N), Phosphorous (P), Potassium (K)) required to produce a hectare of the i^{th} crop activity. As a result, equation 6.8 shows that the total amount in kilograms of the e^{th} nutrient element needed for the i^{th} level of crop activity (a_{ie} * X_i) must not exceed the amount of elements supplied by all fertilisers in kilograms ($QFERT_{fi}$ *K_{ef}). Where $QFERT_{fi}$ is the optimal quantity of the f^{th} fertiliser used by the i^{th} crop (kg), and K_{ef} is the crop nutrient content (percentage) for the e^{th} nutrient element per kg of the f^{th} fertiliser used. In this study, the crop nutrient elements are derived from two fertiliser types, hence *f* represents urea or compound fertiliser (i.e., NPK 15:15:15). The Africa RISING survey results indicate that these two fertiliser types are predominantly used in the study area. The percentage of N supplied by urea is 46%. It is assumed that the optimal quantity of the f^{th} fertiliser calculated in equation 6.8 will be used up during the plant growth and development process for the i^{th} crop activity.

6.3.11 Total revenue, operating cost, and expected net income constraints

From equation 6.9, *TR* is the total revenue (GH₵) accrued by the household; S_{im} is the storage loss coefficient for the i^{th} crop in the m^{th} month ranging from $0 \leq S_{im} \leq 1$ (Appendix 2). RP_{im} is the selling price (GH₵) for the i^{th} crop in the m^{th} month, and *y* represents the household's monthly off-farm income (GH₵). This constraint implies that the revenue from selling all crops in all months after storage losses plus the off-farm income received by the household at the point of sale should be equal to the total revenue. Also, equation 6.10 represents the operating cost (OC) for farm households where VTC_i = the variable transaction cost for the i^{th} crop (GH₵), $TOTC_i$ = the total cost of producing the i^{th} crop (GH₵) excluding the cost of seeds and fertilisers, P_f = the price of the f^{th} fertiliser used (GH₵), P_{Bi} = the price of seeds purchased for the i^{th} crop (GH₵), and *FTC* = fixed transaction cost paid by the household (GH₵). The expected net income constraint in equation 6.11 implies that the difference between total revenue (TR) and operating cost (*OC*) is equal to expected net income (*Y*).

6.4 Compromise risk programming

The expected net income and variance (i.e. EV) frontier generated from solving equations 6.1 to 6.11 gives the farmer no information about the ideal net income-risk trade-off on the frontier. As a result, a pay-off matrix can be generated by solving for the ideal and anti-ideal solution for each objective (i.e. lowest risk and highest expected net income) (Romero and Rehman, 2003). In the current study, parametric programming of the expected net income's lower and upper limits generated the corresponding lower and upper limit for variance of net income. These limits represent the ideal (i.e. upper limit) and anti-deal (i.e. lower limit) values for expected net income and vice versa for risk. As indicated by Yu (1973) and Zeleny (1973) this study estimates the ideal points for both objectives as the reference point for measuring the closest distance from the EV frontier to the ideal point. There are variants of multi-criteria decision making (MCDM) approaches. The compromise programming method by Zeleny (1973) is preferred in this study to the Vise Kriterijumska Optimizacija Kompromisno Resenje (VIKOR) method due to the more objective technique used in attaching weights as explained in Chapter 5 rather than the subjective ranking of alternatives in the VIKOR approach proposed by Opricovic (1998). In this study, the compromise programming approach is premised on the assumption that smallholder farmers are risk averse and will prefer solutions that are closest to the ideal points of both objectives. The weights farmers attach to their expected net income and risk minimisation objectives are included to model farmer’s risk management behaviour. Given these weights, the distance measurement approach is used to determine the compromised region on the frontier. To ease geometric interpretation and computational complexities that arise when measuring distances in an n-dimensional space (where n > 2), only the longest distance (L_1) and shortest distance (L_∞) metrics were employed (Romero and Rehman, 2003). When both distances from the EV frontier to the ideal point are minimised, a compromise solution boundary on the frontier is achieved as follows:

$$Minimise L_1 = \left(\sum_{G=1}^{2} \mathrm{W}_G^h \left|\frac{G^*-G}{G^*-\check{G}}\right|^h\right)^{1/h} \text{(Objective function- } L_1 \text{ metric)} \qquad (6.12)$$

Subject to:

Equations 6.1a to 6.10

$Vsupnumic_{Lk} = Y - \sum_{NF=1}^{Ð}(EXP_{NF})$ (supernumerary income constraint) (6.13)

$\sum_{F=1}^{đ} EXP_F + \beta_F * \beta_s * Vsupnumic_k = TEXP_{Fk} \ \forall \ Vsupnumic_k \geq 0$ (food expenditure constraint) (6.14)

$\sum_{F=1}^{đ}(EXP_F) \leq TEXP_{Fk}$ (6.15)

$\sum_{NF=1}^{Ð}(EXP_{NF}) + \beta_{NF} * \beta_s * Vsupnumic_k = TEXP_{NFK}) \ \forall \ Vsupnumic_k \geq 0$ (non-food expenditure constraint) (6.16)

$\sum_{NF=1}^{Ð}(EXP_{NF}) \leq TEXP_{NFK}$ (6.17)

$\beta_F + \beta_{NF} = 1$ *(budget share constraint)* (6.18)

The constraints in equations 6.13 to 6.18 were incorporated into the model to analyse the effect of risk and expected net income on household expenditure using the linear expenditure system (*LES*) propounded by Stone (1954).

6.4.1 Objective function- L_1 metric

To achieve the longest distance metric, the objective function in equation 6.12 is minimised subject to equations 6.1a to 6.10, and 6.13 to 6.18, where *G = Y* (expected net income objective) or σ^2 (risk objective). G^*= ideal value for *G*, $\breve{G}$ = anti-ideal value for G, W_G^h represents weights the households attach to the expected net income and risk objectives, where *h* is the distance metric equal to 1 for the longest distance metric.

6.4.2 Supernumerary income constraint

The study models the *LES* using compromise risk programming by determining the residual income left after subsistence spending on non-food items when the longest or the shortest distance metric is applied. This is indicated in equation 6.13 as the supernumerary income *($Vsupnumic_k$)*, where *k=1* for the longest distance metric or ∞ for the shortest distance metric. It is determined by finding the difference between the compromise risk *Y* and the total subsistence expenditure incurred by the household on non-food commodities *(EXP_{NF})* ranging from *NF = 1…….Đ*. Subsistence food expenditure *(EXP_F)* was not included in generating the supernumerary income due to the fact that the non-separability in production and consumption captured in equation 6.4 reduces expected net income. Hence, the study argues that contrary to the literature on LES, there is no need to deduct subsistence food expenditure from the expected net income when computing the supernumerary income for the current study.

6.4.3 Food and non-food expenditure plus marginal budget share constraints

From equation 6.14, subsistence expenditure on food ranging from *F= 1…..,d* plus a fraction of the supernumerary income, is equal to the total food expenditure *($TEXP_{Fk}$)*. Equation 6.16 follows the same procedure for non-food expenditure. In this study, the percentage share of total household expenditure on food and non-food from the Africa RISING survey data will respectively be used to represent β_F (i.e. budget share for food) and β_{NF} (i.e. budget share for non-food). β_s represents the spending margin of the household, which is 90% of $Vsupnumic_k$, given the assumption that farmers will save at least 10% of their supernumerary income. In the event where $Vsupnumic_k$ = 0, subsistence expenditure on non-food is equal to total expenditure on non-food. Also, the budget share for food and non-food items in equation 6.18 should sum to 1 (Louhichi et al. 2014), due to the assumption that, other than the 10% of the $Vsupnumic_k$ saved, all supernumerary income is spent on food and non-food items.

6.4.4 Objective function - L_∞ metric

Under this objective function, the shortest distance is generated to get the compromise risk solution set boundary at L_∞ . The largest deviation from among the individual members of the efficient set is minimised to determine the shortest distance from the ideal point to the frontier (Ballestero and Romero, 1998). To achieve this, the largest deviation ($\bar{\iota}_G$) is set up in the model as a placeholder and minimised subject to household level constraints and expressed mathematically as:

$$Minimising L_\infty = \bar{\iota}_G \text{ (Objective function- } L_\infty \text{ metric)} \quad (6.19)$$

Subject to the following:

Equations 6.1a to 6.10

Equations 6.13 to 6.18 where $k = \infty$

$$\text{W}_G \left|\frac{G^{*}-G}{G^{*}-\breve{G}}\right| \leq \bar{\iota}_G \;\; \forall\, G = Y\,, \sigma^2 \text{(Weighted risk and expected net income constraint)} \qquad (6.20)$$

6.4.5 Weighted risk and expected net income constraint

Equation 6.20 implies that the weighted degree of closeness for the expected net income and risk objectives should be less than or equal to the largest deviation ($\bar{\iota}_G$). Solving for the longest and the shortest distance metrics subject to their respective constraints produces the compromise solution boundaries on the EV frontier. All mathematical and statistical algorithms were completed in General Algebraic Modelling System (GAMS) version 41.5.0 (GAMS, 2023), and R version 4.2.3 (R Core Team, 2023).

6.5 Data

6.5.1 Annual yield ($\bar{Q}$) and net income ($\hat{Y}$)

The model is applied to the 3 farm typologies in the study area referred to as FT1 (well-resource-endowed farm type 1), FT2 (moderately-resource-endowed farm type 2), and FT3 (poorly-resource-endowed farm type 3) developed in Chapter 5. The annual yield data is generated from Aquacrop yield modelling from 1990 to 2020 using soil profile data in the study area from Tetteh et al. (2016) and climatic data for the study area from the NASA POWER database. Crop parameters from Akumaga et al. (2017), Abdul Ganiwu et al. (2018), Chibarabada et al. (2020) and Aquacrop default sorghum file were used to model maize, rice, groundnut, and sorghum crop yield, respectively, in Aquacrop for different nitrogen fertiliser application rates except groundnut. The modelling process produced the crop yield results indicated in Appendix 3, and the fertiliser application rates were selected based on the crop modelling literature in the study area such as MacCarthy et al. (2018), Jiménez Furtz (2021), and Kpongor et al. (2006)).

A combination of crop price per year from the FAO database (Appendix 4), and yield variability plus cost of production per nitrogen fertilisation level was used to generate variability in net income for the period. In the current study, all economic variables are measured in GH₵ at the current exchange rate of GH₵ 1 to $NZD 0.13 and $USD 0.08 (FORBES, 2024). Also, all nominal prices from 1990 to 2020, including the cost of production were converted to 2020 real prices (RP_{it}) with 2020 as the base year. The net income is estimated as:

$\hat{Y}_{it} = R_{it} - C_i$ *for all i* (6.21)

Where: R_{it} = RP_{it}* $\bar{Q}_{it}$ *for all i and all t* (6.22)

$\hat{Y}_{it}$ = Net income (GH₵/ha) for the i^{th} crop in year t

R_{it} = Revenue (GH₵/ha) for the i^{th} crop in year t

$\bar{Q}_{it}$ = Quantity (kg) for the i^{th} crop produced in year t.

C_i = The cost of production (GH₵/ha) incurred for the i^{th} crop from Wongnaa et al (2019), Akolgo et al. (2021), Akuriba and Brempong (2012), and Kotu et al., 2022) for maize, rice, sorghum, and groundnut, respectively, where the opportunity cost of family labour was accounted for using labour cost in the study area as a proxy.

6.5.2 Resource endowments and technical coefficients

Data on household resource endowments from the Africa RISING Survey is presented in Table 6.1 for each farm type. Total land, labour, and monthly exogenous income available for all farm types are presented in Table 6.1. Since this research focuses on the key crops cultivated in the study area, for each farm type, the sum of the median values of land area available for maize, rice, sorghum, and groundnut was used. Further, subsistence expenditures on food and non-food were determined using the cut-off point for food and non-food expenditure variables in the first quartile of each farm type. Own food consumed before sales is used to represent subsistence nutrients consumed (i.e. calories and protein) from own crops per farm type (see Appendix 6 & 7 for calories and proteins consumed respectively). In the current study, sales are made monthly at the market selling price per crop (Appendix 5), and storage losses for each month are also captured by assuming a 3% monthly loss exponentially (i.e. from the first month after harvest to the 12th month) to crop quantities before sales. Furthermore, the study acknowledges that market selling decisions may be affected by market price, space rent for selling produce usually determined by market queens, and market transaction cost (i.e. per unit cost of transportation, plus any unit cost incurred for selling). In this study, market transaction costs per unit of each crop and selling space cost per year, irrespective of the quantities sold, are referred to as variable (VTC) and fixed transaction cost (FTC), respectively. This study attributes 33% of the selling price to VTC (Kotu et al., 2022) and GH₵ 100 per year to FTC based on information received on selling space charged by market queens from a key informant in the study area. Also, as shown in Table 6.1, based on the farm typology results, all farm types attached more weight to risk than expected net income mostly due to the risk-averse behaviour of farmers.

Table 6.1. Data on resource endowments and technical coefficients per farm type

Resource endowments	FT1	FT2	FT3
Land (Ha)	3.5	1.2	2.0
Labour (person-days)	228	109	119
Monthly exogenous income (GH₵)	133	111	130
Subsistence expenditure on food (GH₵)	1,320	1011	1102
Subsistence expenditure on non-food (GH₵)	1,657	961	661
Own calories consumed (calories)	4,480,607	2,158,323	2,262,739
Own protein consumed (grams)	78,976	37,520	43,611
Monthly storage losses (%)	3%	3%	3%
Fixed transaction cost (GH₵)	100	100	100
Variable transaction cost (% of selling price)	33%	33%	33%
Weight attached to risk (%)	61.5%	69.1%	88.9
Weight attached to expected net income (%)	38.5%	30.9%	11.1
Budget share for food (%)	45%	47%	50.2
Budget share for non-food	55%	53%	49.8

Further, technical coefficients for each nitrogen application rate (Table 6.2) were determined per crop for seed requirements/hectare(Ha), energy in calories/kg, protein in g/kg, average yield/Ha, total cost of production/Ha without seed and fertiliser cost, and labour requirements/Ha. Seed and fertiliser cost is calculated in the model based on the optimal quantities to be purchased per farm type. To achieve this, seed price and fertiliser price per kilogram from discussions with key informant in the study area in June 2020 were used. A kilogram of seeds costs GH₵ 4.75, GH₵ 6.75, GH₵10, and GH₵ 2.57 for maize, rice, sorghum, and groundnut, respectively. Whereas fertiliser price per kilogram was GH₵ 5 and GH₵ 6.5 for urea (i.e. NPK-46:0:0) and compound fertilisers (i.e. NPK-15:15:15), respectively.

Data on seed requirements per hectare was obtained from Pauw (2022) for maize and rice, whereas data from Ajeigbe et al., (2020) and Demeter (2023) were used for sorghum and groundnut, respectively. Also, the energy content in calories per kilogram and protein content in g/kg for each crop were derived from Hoddinott (1999) and USDA (2023), respectively. The average yield per hectare represents the average value from Aquacrop yield simulations for each crop per fertiliser application rate. Further, due to the lack of data availability, the total cost/Ha (without seed and fertiliser cost) and labour requirements/Ha for each fertiliser application rate for maize, rice and sorghum were determined by extrapolating average figures from literature sources on pro-rata basis (see Appendix 8 for details). In addition, the total cost/Ha for groundnut was derived from Kotu et al. (2022). Also, due to the similarities in the growing requirements for groundnut and sorghum, the extrapolated value for labour requirements for sorghum was retained for groundnut (Table 6.2). Also, labour requirements for groundnut was 103 person days/Ha (Table 6.2), obtained from Govindaraj and Mishra (2011) by converting human labour hours/Ha to person days/Ha at a conversion rate of 8 hours for 1 person-day.

Table 6.2. Data on technical coefficients per fertiliser application rate

Maize-Technical coefficients per fertiliser application rate						
Fertiliser application rate	**Seed Requirements /Ha**	**Energy (Calories/ Kg)**	**Protein (g/kg)**	**Average yield/Ha**	**Total Cost/Ha**	**Labour requirement/Ha**
0 kgN	10kg	3590	62	914 kg	589 (GH₵)	32.5 person-days
40 kgN				2251 kg	968 (GH₵)	80.5 person-days
80 kgN				3,221 kg	1,244 (GH₵)	114.5 person days
120 kgN				3,622 kg	1,358 (GH₵)	128.8 person-days
Rice-Technical coefficients per fertiliser application rate						
0 kgN	25kg	3,330	70.4	1,498 kg	1,132 (GH₵)	47.4 person-days
30 kgN				3,276 kg	1,944 (GH₵)	103 person-days
60 kgN				4,637 kg	2,580 (GH₵)	146 person-days
100 kgN				4,961 kg	2,731 (GH₵)	156.9 person-days
Sorghum-Technical coefficients per fertiliser application rate						
0 kgN	8 kg	3,430	82.7	783 kg	737 (GH₵)	30.9 person-days
40 kgN				2,652 kg	1,505 (GH₵)	104.8 person-days
80 kgN				3,069 kg	1,742 (GH₵)	121.3 person-days
100 kgN				3,274 kg	1,858 (GH₵)	129.4 person-days
Groundnut-Technical coefficients per fertiliser application rate						
0 kgN	35 kg	5720	232	2,225 kg	1,408 (GH₵)	103 person-days

6.6 Results

6.6.1 Farm type 1 (Most resource endowed)

The ideal point for the smallholder farmer is GH₵113,976 and GH₵10,590 for variance and expected net income respectively (Table 6.3). However, this is unattainable in real-life due to resource constraints, as a result, to achieve a more realistic measure of variance and expected net income, the longest distance metric (L_1) generates an optimal crop combination of 1.10 (Ha) for maize (0kgN), 1.91 (Ha) for rice (0kgN), and 0.49 Ha for groundnut (Table 6.3). The corresponding measure of variance and expected net income for the smallholder farmer is GH₵ 1,517,297 and GH₵ 3,763 respectively. On the other hand, the shortest distance metric (L_∞) revealed 2.16 Ha for rice (0kgN),0.98 Ha for sorghum (40 kgN), and 0.36 Ha for groundnut with a variance of GH₵ 3,108,187 and an expected net income of GH₵ 6,151.

Table 6.3. Optimal crop combination and compromised region per farm type

FTs*	Distance metric	Optimal level of crop activity (Ha)				Compromised region		Ideal point	
		Maize (Ha)	Rice (Ha)	Sorghum (Ha)	Groundnut (Ha)	Variance (GH₵)	Exp. Inc# (GH₵)	Variance (GH₵)	Exp. Inc (GH₵)
FT1	Longest distance Metric (L_1)	1.10 (0 kgN)	1.91 (0 kgN)	None	0.49 Ha	1,517,297	3,763	113,976	10,590
	Shortest distance Metric (L_∞)	None	2.16 (0kgN)	0.98 (40kgN)	0.36 Ha	3,108,187	6,151		
FT2	Longest distance Metric (L_1)	0.54 (0kgN)	0.44 (0 kgN)	0.19 (40 kgN)	0.04 Ha	138,039	961	25,652	3,750
	Shortest distance Metric (L_∞)	0.50 (0 kgN)	0.36 (30 kgN)	0.29 (40 kgN)	0.05 Ha	331,724	1,812		
FT3	Longest distance Metric (L_1)	0.91 (0kgN)	0.35 (0kgN)	0.10 (40 kgN)	0.02 Ha	90,231	661	27,121	5,290
	Shortest distance Metric (L_∞)	1.07 (0kgN)	0.68 (0 kgN)	0.23 (40 kgN)	0.02 Ha	275,338	1,722		

* *FTs = Farm types, FT1=Farm type 1, FT2=Farm type 2, FT3=Farm type 3*

#*Exp.Inc = Expected net income*

Figure 6.2 illustrates the findings of this study for Farm type 1. The closest compromised region from the frontier to the ideal point in Figure 6.2 ranges from points A to B. Also, with each point on the EV space having coordinates of variance and expected net income. The longest distance measures (L_1) from point C (GH₵113,976, GH₵10,590) to point A (GH₵ 1,517,297, GH₵ 3,763), and the shortest (L_∞) to point B (GH₵ 3,108,187, GH₵ 6,151) (Figure 6.2).

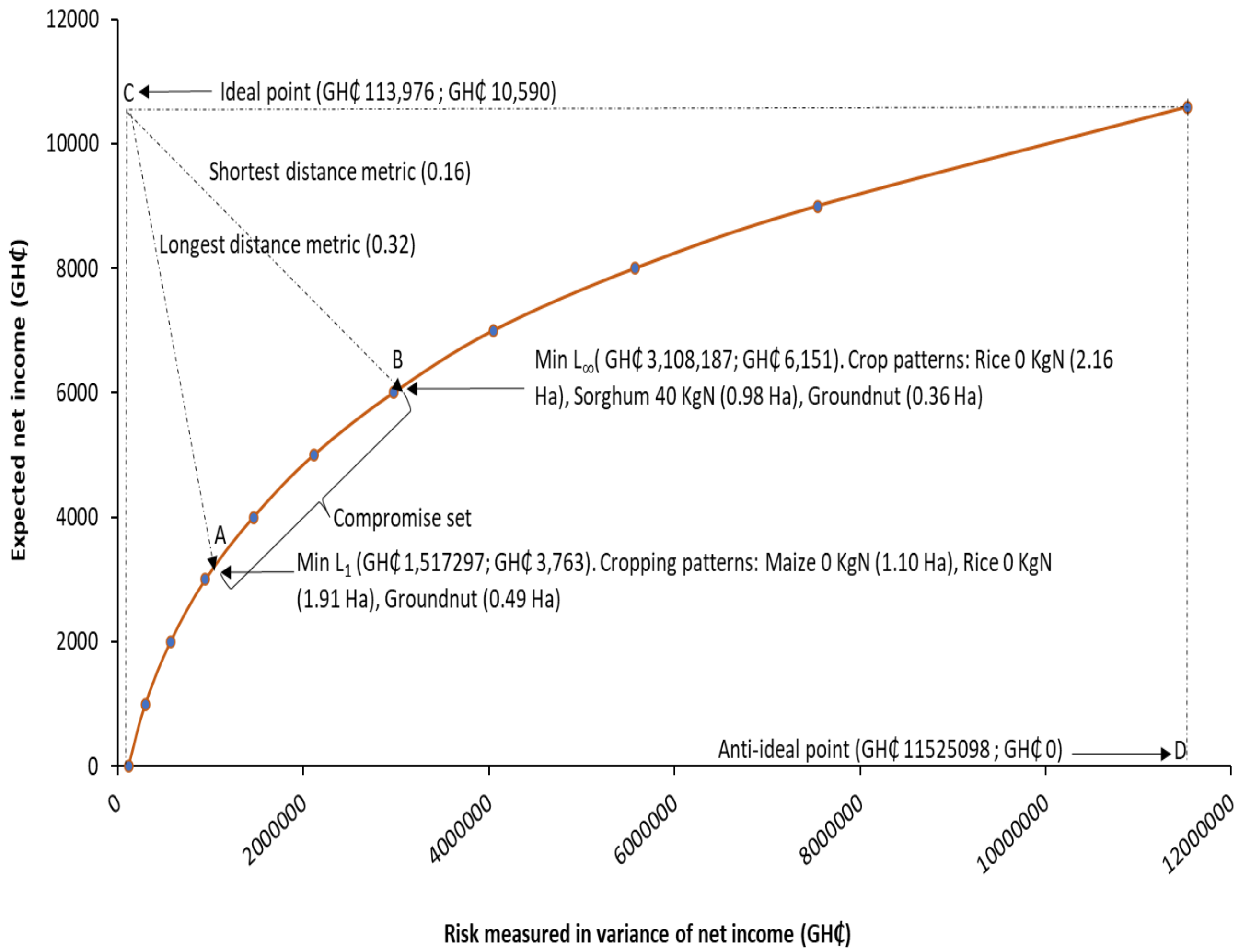


Figure 6.2. Compromise risk solution for farm type 1

6.6.2 Farm type 2 (Moderately resource endowed)

For farm type 2, the ideal point for the smallholder farmer is GH₵ 25,652 for variance and GH₵ 3,750 for expected net income respectively (Table 6.3). For the L_1 metric, the optimal crop combinations are 0.54 Ha at 0 kgN for maize, 0.44 Ha at 0 kgN for rice, 0.19 Ha at 40 kgN for sorghum, 0.04 Ha for groundnut with a corresponding variance and expected net income of GH₵ 138,039 and GH₵ 961 respectively. For the L_∞ metric, the study generated an expected net income of GH₵ 1,812, a variance of GH₵ 331,724, and an optimal crop area of 0.50 Ha for maize (0 kgN), 0.36 Ha for rice (30 kgN), 0.29 Ha for Sorghum (40 kgN), and 0.05 Ha for groundnut (Table 6.3). From Figure 6.2, the compromised region, closest to the ideal point(F) is from point E (GH₵ 138,039, GH₵ 961) to point F (GH₵ 331,724, GH₵ 1,812) for the L_1 and L_∞ ,metrics respectively.

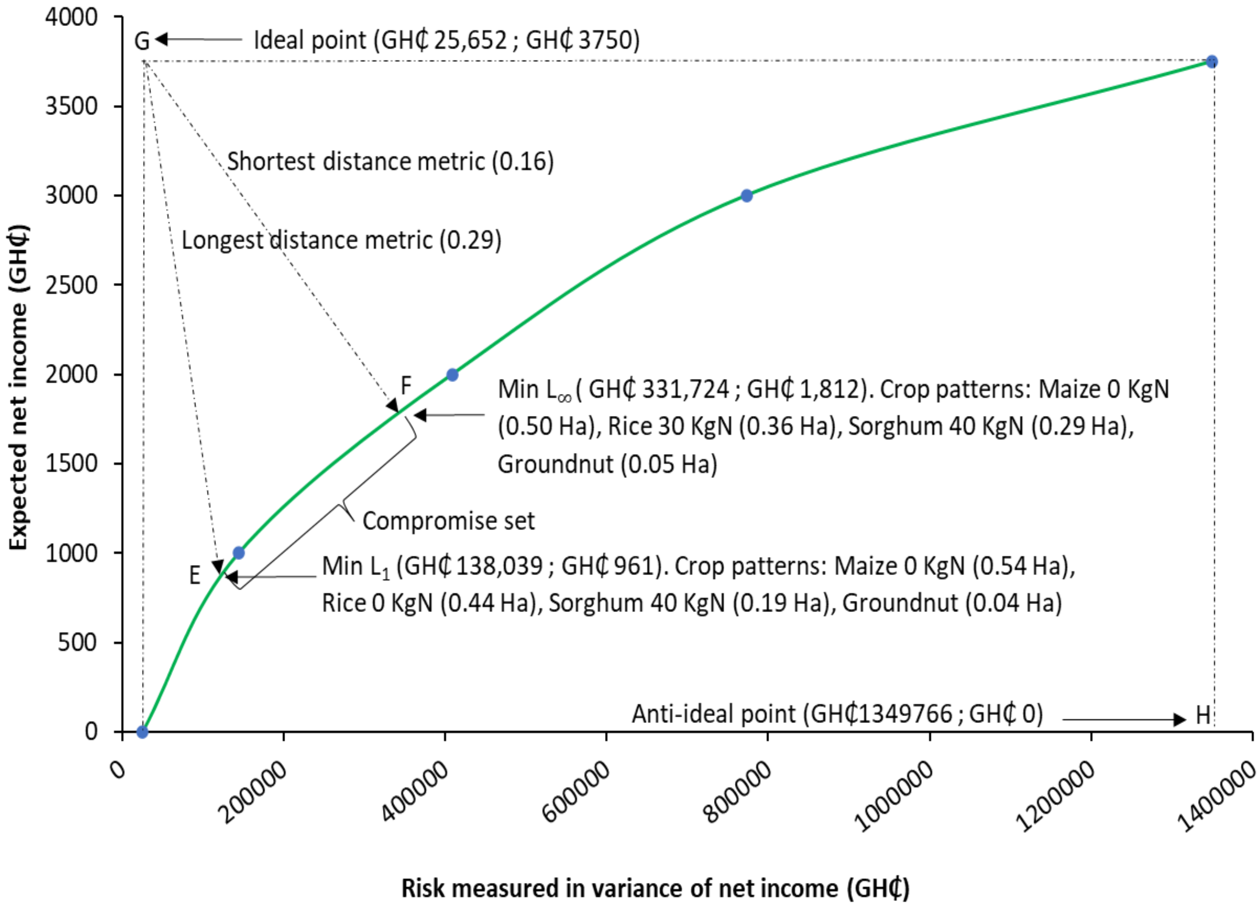


Figure 6.3. Compromise risk solution for farm type 2

6.6.3 Farm type 3 (Least resource endowed)

For FT3, similar to the proposition of Audsley et al. (2006), the study reveals that given the low level of expected net income at the L_1 metric some of the land area available for the farm type is abandoned to minimise risk. The optimal crop areas revealed for the L_1 metric as shown in Table 6.3 are 0.91 Ha (Maize 0 KgN), 0.35 Ha (Rice 0 KgN), 0.10 Ha (Sorghum 40 KgN), and 0.02 Ha (Groundnut). The expected net income is valued at GH₵ 661 at a variance of GH₵ 90,231. For the L_∞ metric, the shortest distance produces 1.07 Ha of Maize (0 KgN), 0.68 Ha of Rice (0 KgN), 0.23 Ha of Sorghum (40 KgN), and 0.02 Ha of groundnut at a variance and expected net income of GH₵ 275,338 and GH₵ 1,722, respectively. The compromised region is effectively represented in Figure 6.4 from point J(GH₵ 90,231, GH₵ 661) to point K(GH₵ 275,338, GH₵ 1,722) for the L_1 and L_∞ metrics respectively.

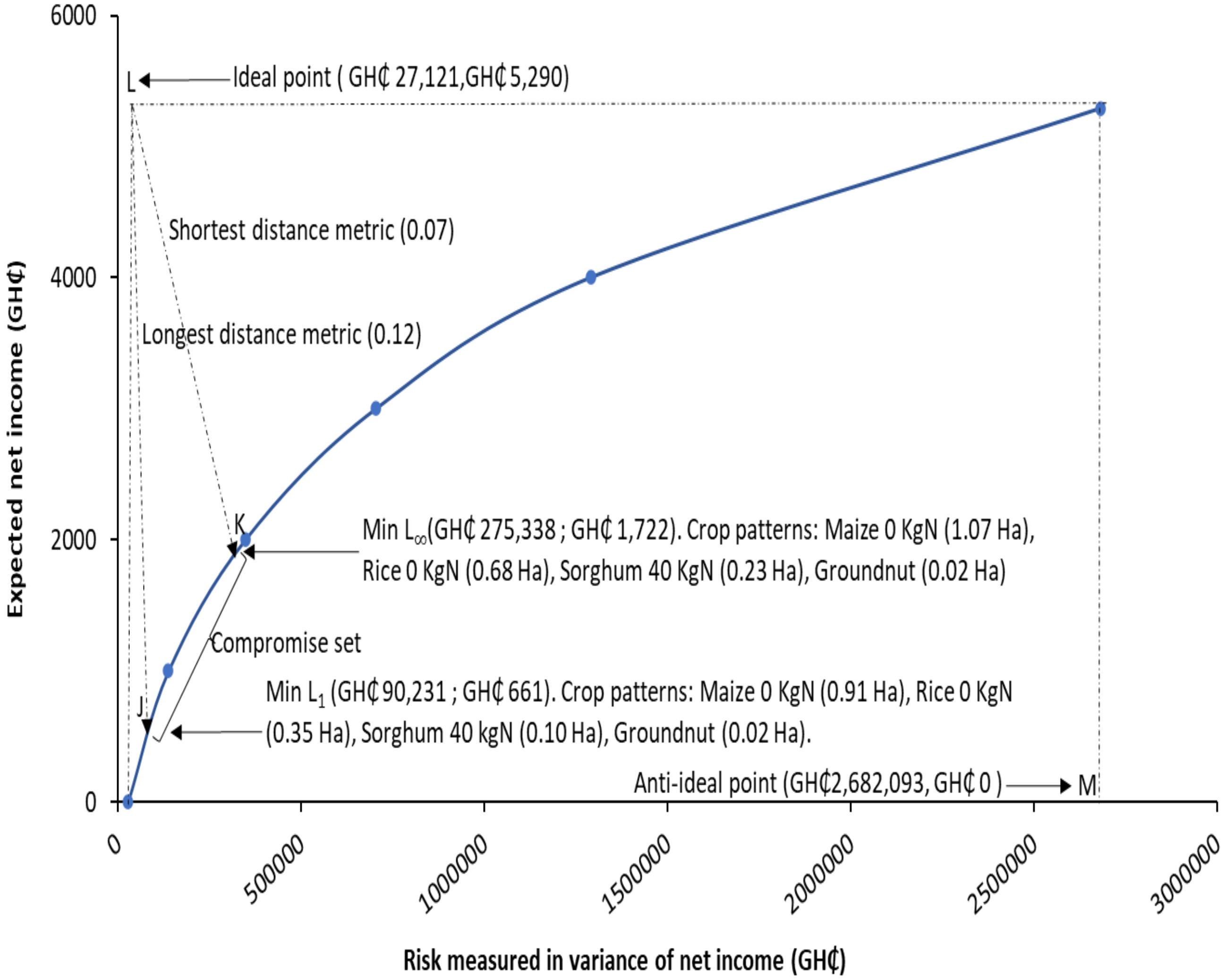


Figure 6.4. Compromise risk solution for farm type 3

6.7 Discussion

As indicated in the introduction, this research aimed to investigate the expected net income-risk decision-making trade-offs under climate variability in the context of the smallholder farmers' livelihood systems characterised by resource limitations. This study developed a model that captures the complexities between risk and expected net income, and the non-separability in consumption and production of the smallholder farmer. By minimising risk at parametrically determined expected net-income levels whilst applying weights to each objective, the study results generated solutions as close as possible to the ideal point located in the north-western quadrant of the EV space for Figures 6.2, 6.3, and 6.4.

Given that the curvature of each EV frontier has Pareto efficient coordinates, determining the most suitable point on the frontier will depend on the expected net income-risk decision-making behaviour of the FTs. From the study results, except for FT 1, more maize is produced at the lower bound of the compromise solution (L_1 metric) where expected income is relatively low (Figures 6.2 to 6.4). This implies that the risk of losing income reduces when more maize is cultivated if the farmer expects a lower net income target. On the other hand, as expected net income target increases, land allocations gradually shift to relatively expensive but high-return crops, especially rice. For the wealthiest FT in Figure 6.2, rice featured prominently in the L_1 and L_∞ metric of the compromise risk solution bounds while maintaining a relatively lower land area for maize. The study reveals that rice, sorghum, and groundnut crop areas are increasingly cultivated when farmers become wealthier due to increased returns, higher operation cost requirements, and a relatively higher opportunity cost of consumption. Farmers appear not to worry about producing more maize as they become wealthier because the income generated from high value crops like rice and groundnuts could partly be used to purchase maize at a relatively cheaper cost for consumption purposes. The results also indicate that all FTs increase their expenditure beyond subsistence when expected net income increases to the L_∞ metric (Appendix 9).

The study findings show a risk trade-off associated with the expected net income for each FT. For FT1, the L_1 metric indicates that farmers can trade off risk as much as GH₵ 1,517,297 in variance of net income (i.e. a standard deviation of GH₵ 1,232) for an expected net income of GH₵ 3,763 with the most preferred crop combinations indicated in Figure 6.2. This represents a potential loss of approximately 32.7% of expected net income. On the other hand, the income-risk trade-off at the L_∞ metric is an expected net income of GH₵ 6,151 and a trade-off risk valued at GH₵ 3,108,187 (i.e. a standard deviation of GH₵ 1,763), representing about 28.7% potential loss in expected net income. Similarly, given the expected net income-risk trade-offs at the compromise risk solution bounds for FT2 and FT3 in Figures 6.3 and 6.4, there is approximately 38.7% and 31.9% potential loss in expected net income at the L_1 and L_∞ metrics metric, respectively, for FT2, whereas that of FT3 showed a 44.5% and 30.5% possible loss in expected net income for the L_1 and L_∞ metrics respectively. From these percentages, it can be argued that the lack of return on risk due to own subsistence consumption is the reason for the non-zero starting points for risk on the EV frontiers in Figures 6.2, 6.3, and 6.4. Farmers on the lower bound of the compromise risk region are not able to produce enough to offset the effect of risk associated with the non-separability in own consumption and production. This contributes to the high potential losses in expected net income, especially for the poorest FT3.

Also, it is useful to analyse the impact of a unit change in the available resources on the expected net income and variance of farm households, however, no shadow price decomposition methods have been propounded for compromise programming (Stokes and Tozer, 2002), unlike other multi-objective programmes in McCarl et al. (1996) and Caldeira et al. (2018).

6.7.1 Model validation

The outcome of this research is consistent with the cropping pattern, consumption, and expenditure behaviour of farm households in the study area. From the findings, all FT's use their own seeds (Appendix 9) rather than purchase, which is a usual practice among smallholder farmers in northern Ghana (Madin et al., 2022) mostly due to the high cost of purchased seeds. Furthermore, since maize is an integral part of households' diet, farmers produce maize at low fertiliser application rates (Figures 6.2 to 6.4) to meet their subsistent needs before sales if there are surpluses. Anang et al. (2022) attribute poor farm households' persistent cultivation of low-yield maize to the lack of resource endowment and the cropping environment farmers find themselves. The results indicate that, similar to de Jager et al. (2018), as farmers become wealthier, they shift from own consumption of maize to crops with high protein. In Appendix 9, all FTs consumed more maize than groundnut for the L_1 metric, however, as farmers' expected net income increases to the L_∞ metric, groundnut consumption begins to increase till it peaks at FT 1 with the exception of the poorest FT (i.e. FT 3). Consequently, the study further reveals that, after subsistence own consumption, optimum sales are made from September to December, with particular emphasis on rice sold in December for all FTs (Appendix 9). This could be attributed to the increased demand for food, especially rice, heading up to and during the Christmas season.

Also, due to the lack of storage facilities, farmers are forced to sell earlier after the August/September harvest (Darfour & Rosentrater, 2016); otherwise, they risk losing their storage quantities, which may result in a reduction in their expected net income.

6.8 The implications of the study

The findings of this study have practical implications for smallholder farmers, particularly in managing income variability as a measure of risk and maximizing expected net income under climate variability. Understanding the trade-offs between risk and expected net income is crucial for effective farm management especially in dryland agriculture. By using the findings of this study, smallholder farmers can make informed decisions about how to allocate their limited resources to have preferred risk and income outcomes. Policy makers can use this model, to choose crop combinations that align with farmers' risk tolerance levels while optimising expected returns. This approach helps farmers avoid significant income losses, particularly during adverse climatic conditions. Further, the study results imply that agricultural extension services should focus on educating farmers about the benefits of crop diversification, optimal sales timing, and the use of storage facilities. Training programs that enhance farmers' understanding of income-risk trade-offs and provide them with tools to make informed decisions can significantly improve their resilience to climate variability. The study provides valuable insights into how smallholder farmers can manage the complexities between risk and expected net income by diversifying crops, investing in storage, optimising sales timing, and aligning production with market demand. Thus, farmers can enhance their income stability, improve food security, and build resilience against climate-related risks.

6.9 Conclusion

The study identified the lack of research on risk and income trade-offs associated with smallholder farming systems in northern Ghana. Subsequently, this research analysed income-risk trade-offs while maintaining the level of importance farmers attribute to their risk minimisation and expected net income levels. The model developed is suitable for farming systems among smallholder farmers in northern Ghana and could be applied in other developing countries. This research posits that although generating farm typologies minimises heterogeneity among FTs, there is still some level of intra-farm type wealth variations making the compromise solution sets proposed in this study a flexible approach for risk minimisation recommendations for smallholder farmers in northern Ghana.

Also, insurance underwriters could use this model to gauge farmers' loan default risk by determining whether farmers fall within the compromise risk region when recommending loan approvals to banks. This helps to avoid unrealistic income expectations that may result in high loan default rates by farmers. In addition, agribusiness organisations could use the model to advise climate-resilient cropping combinations for smallholder farmers. Also, from a theoretical perspective, addressing the utility measurement problem is not needed in this model; hence, researchers are not required to make rigid assumptions about the utility of the smallholder farmer because the compromise region could serve as the landing point for the utility curve of the smallholder farmer. This research acknowledges the usefulness of this model for on-farm-level decision-making under climate risk; however, since off-farm risk sharing such as purchasing of crop insurance was not included, it is recommended that future research could attempt to investigate and analyse the applicability of the model in that regard to understand its implications for agricultural risk decision making.

Finally, the study recommends that government and non-governmental organisations should focus on supporting farmers with resources to improve productivity while minimising risk to enhance the livelihood conditions of smallholder farmers. Also, supporting farmers to increase resource endowments and productivity will contribute to reducing the reliance on own consumption and the resulting potential loss in expected net income, most importantly for farmers preferring an expected net income at the lower bound of the compromise risk region.

6.10 Appendix

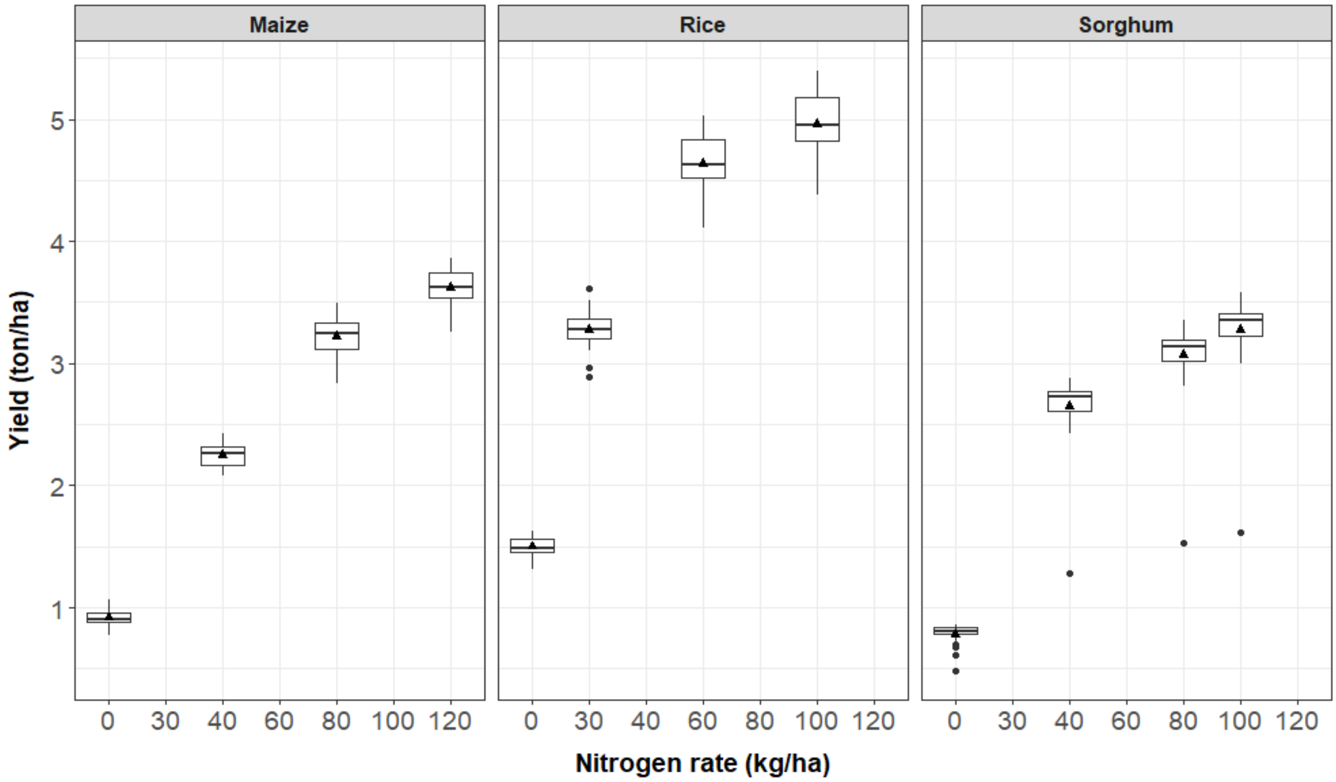
Appendix 1: Variance-Covariance matrix in GH₵ for maize, rice, sorghum, and groundnut fertiliser application rates

Crops	**Maize (120kgN)**	**Maize (80kgN)**	**Maize (40kgN)**	**Maize (0kgN)**	**Rice (100kgN)**	**Rice (60kgN)**	**Rice (30kgN)**	**Rice (0kgN)**	**Sorghum (100kgN)**	**Sorghum (80kgN)**	**Sorghum (40kgN)**	**Sorghum (0kgN)**	**Groundnut**
Maize (120kgN)	355,854	319,488	214,094	73,866	387,764	378,558	274,613	113,799	298,914	279,724	245,464	84,753	467,133
Maize (80kgN)	319,488	288,825	193,547	67,282	373,251	362,175	262,533	109,566	285,752	267,332	234,101	79,647	430,054
Maize (40kgN)	214,094	193,547	130,647	45,404	259,725	251,345	181,769	76,209	197,266	184,649	161,345	54,668	294,068
Maize (0kgN)	73,866	67,282	45,404	19,613	90,649	87,642	64,258	27,816	74,402	69,705	59,881	19,975	102,997
Rice (100kgN)	387,764	373,251	259,725	90,649	1,731,335	1,595,185	1,117,165	504,308	737,492	691,818	590,090	184,521	796,808
Rice (60kgN)	378,558	362,175	251,345	87,642	1,595,185	1,474,552	1,033,097	466,060	698,239	654,951	559,255	174,836	760,391
Rice (30kgN)	274,613	262,533	181,769	64,258	1,117,165	1,033,097	741,241	332,333	479,497	449,528	381,951	119,815	553,256
Rice (0kgN)	113,799	109,566	76,209	27,816	504,308	466,060	332,333	154,157	216,622	203,006	173,502	54,387	248,166
Sorghum (100kgN)	298,914	285,752	197,266	74,402	737,492	698,239	479,497	216,622	1,157,366	1,082,514	947,238	261,871	701,712
Sorghum (80kgN)	279,724	267,332	184,649	69,705	691,818	654,951	449,528	203,006	1,082,514	1,012,663	886,236	245,371	656,086
Sorghum (40kgN)	245,464	234,101	161,345	59,881	590,090	559,255	381,951	173,502	947,238	886,236	778,040	216,498	568,508
Sorghum (0kgN)	84,753	79,647	54,668	19,975	184,521	174,836	119,815	54,387	261,871	245,371	216,498	64,983	181,070
Groundnut	467,133	430,054	294,068	102,997	796,808	760,391	553,256	248,166	701,712	656,086	568,508	181,070	968,334

Appendix 2: Co-efficient of storage loss by month.

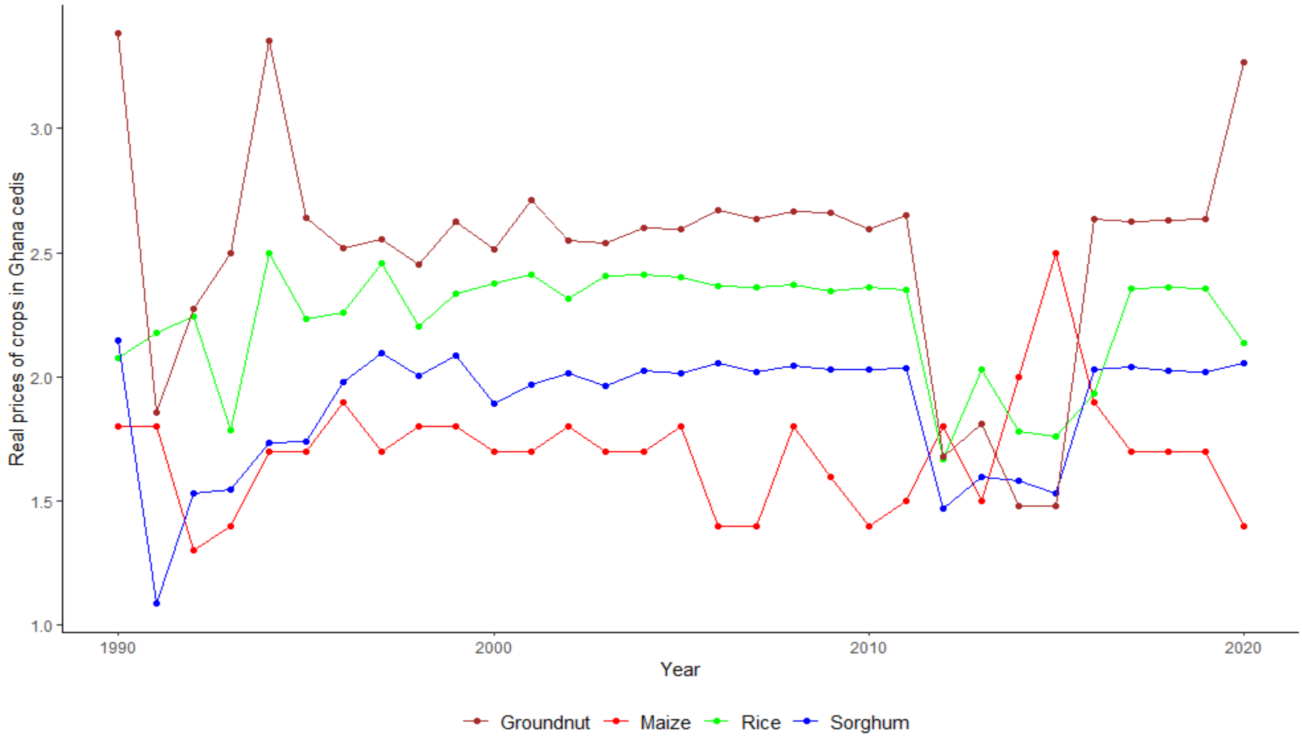
Crop activities	Maize (120KgN)	Maize (80KgN)	Maize (40KgN)	Maize (0KgN)	Rice (100KgN)	Rice (60KgN)	Rice (30KgN)	Rice (0KgN)	Sorghum (100KgN)	Sorghum (80KgN)	Sorghum (40KgN)	Sorghum (0KgN)	Groundnut
Jan	0.88	0.88	0.88	0.88	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.88
Feb	0.85	0.85	0.85	0.85	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.85
Mar	0.82	0.82	0.82	0.82	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.82
Apr	0.79	0.79	0.79	0.79	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.79
May	0.76	0.76	0.76	0.76	0.82	0.82	0.82	0.82	0.82	0.82	0.82	0.82	0.76
Jun	0.73	0.73	0.73	0.73	0.79	0.79	0.79	0.79	0.79	0.79	0.79	0.79	0.73
Jul	0.7	0.7	0.7	0.7	0.76	0.76	0.76	0.76	0.76	0.76	0.76	0.76	0.7
Aug	0.67	0.67	0.67	0.67	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.67
Sep	1	1	1	1	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	1
Oct	0.97	0.97	0.97	0.97	0.67	0.67	0.67	0.67	0.67	0.67	0.67	0.67	0.97
Nov	0.94	0.94	0.94	0.94	1	1	1	1	1	1	1	1	0.94
Dec	0.91	0.91	0.91	0.91	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.91

Appendix 3: Crop yield per fertiliser application rate



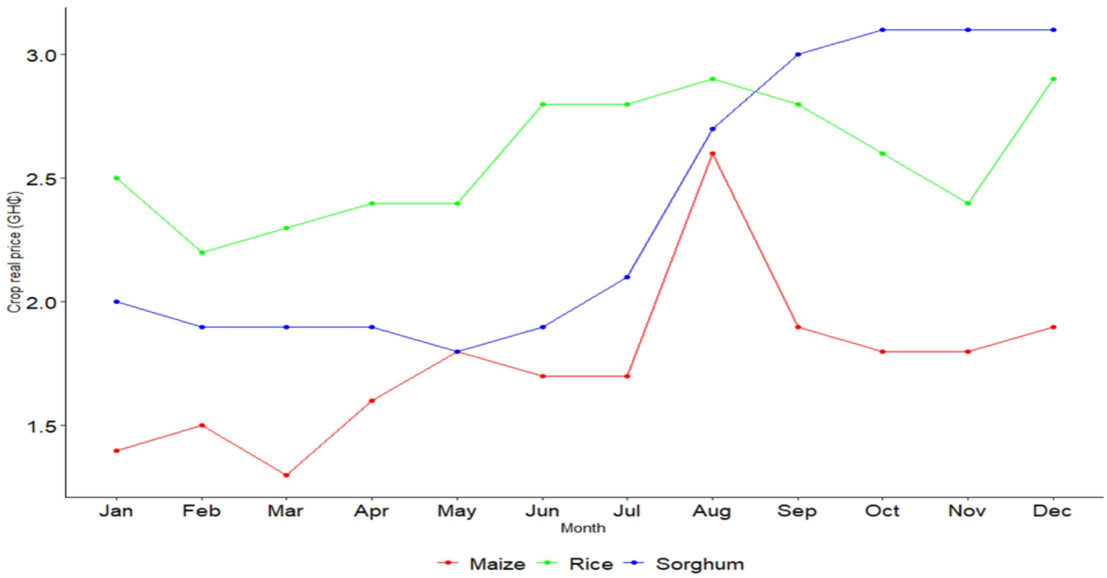
Note: Groundnut was not included in this figure as no fertiliser application rate was employed

Appendix 4: Annual crop prices from 1990 to 2020 for maize, rice, sorghum, and groundnut.



Source: FAO database

Appendix 5: Monthly market selling price for maize, rice, and sorghum.



Source: WFP (2022).

Note: Due to the lack of data availability for groundnut, the 2020 annual price in Appendix 4 was used.

Appendix 6: Subsistence calories consumed per farm type.

Farm type	Food Crop	Household size	Own consumption (kg)	Calories/Kilogram	Annual calories
Farm type 1	Maize		955.9	3,590	3,431,681
	Rice	12	204.2	3,330	679,986
	Sorghum		0	3,430	0
	Groundnut		64.5	5,720	368,940
Total					**4,480,607**
Farm type	**Food Crop**	**Household size**	**Consumption (kg)**	**Calories/Kilogram**	**Annual calories**
Farm type 2	Maize		504.3	3,590	1,810,437
	Rice	9	55	3,330	183,150
	Sorghum		0	3,430	0
	Groundnut		28.8	5,720	164,736
Total					**2,158,323**
Farm type	**Food Crop**	**Household size**	**Consumption (kg)**	**Calories/Kilogram**	**Annual calories**
Farm type 3	Maize		445.7	3,590	1,600,063
	Rice	8	0	3,330	0
	Sorghum		193.2	3,430	662,676
	Groundnut		0	5,720	0
Total					**2,262,739**

Appendix 7: Subsistence protein consumed per farm type.

Farm type	Food Crop	Household size	Own consumption (kg)	Grams/kilogram	Annual protein (grams)
Farm type 1	Maize	12	955.9	62	59,265.8
	Rice		204.2	70.4	14,375.68
	Sorghum		0	82.7	0
	Groundnut		64.5	232	14,964
Total					**88,605.48**
Farm type	**Food Crop**	**Household size**	**Consumption (kg)**	**Calories/Kilogram**	**Annual calories**
Farm type 2	Maize	9	504.3	62	31,266.6
	Rice		55	70.4	3,872
	Sorghum		0	82.7	0
	Groundnut		28.8	232	6,681.6
Total					**41,820.2**
Farm type	**Food Crop**	**Household size**	**Consumption (kg)**	**Calories/Kilogram**	**Annual calories**
Farm type 3	Maize	8	445.7	62	27,633.4
	Rice		0	70.4	0
	Sorghum		193.2	82.7	15,977.64
	Groundnut		0	232	0
Total					**43,611.04**

Appendix 8: Average values from literature sources and extrapolated data

Average value from literature source			Aquacrop average yield	Extrapolated values	
Maize Data-Source for extrapolation is Wongnaa et al. 2019					
Yield (kg/Ha)	Labour (person days/Ha)	Total cost/Ha (GH₵)	Kg/ha	Labour (person days/Ha)	Total cost/Ha (GH₵)[1]
1,800	64	1,236	914 (0 kgN)	32.5	589
			2,251 (40 kgN)	80.5	968
			3,221 (80 kgN)	114.5	1,244
			3,622 (120 kgN)	128.8	1,358
Rice Data-Sources for extrapolation are Akolgo et al. (2021), and Jakada and Ifyalem (2023)					
1,270	80.3	1,811.4	1,498 (0 kgN)	47.4	1,132
			3,276 (30 kgN)	103	1944
			4,637 (60 kgN)	146.6	2580
			4,962 (100 kgN)	156.9	2731
Sorghum Data-Sources for extrapolation are Akuriba and Brempong et al. (2012), and Sienso et al. (2021)					
1,163	46.05	1,117	783 (0 kgN)	30.9	737
			2652 (40 kgN)	104.8	1,505
			3069 (80 kgN)	121.3	1741
			3274 (100 kgN)	129.4	1,858

[1]The total cost/Ha (GHC) is less seed, transportation, and fertiliser cost for maize. A ploughing cost of GH₵ 250 obtained from an informant in the study area was added as it was not included in Wongnaa et al. (2019). For rice, the total cost is total variable cost in Akolgo et al. (2021) without seed, transplanting, fertiliser, and water levy costs, and the sorghum total cost was taken from Akuriba and Brempong (2012) less seed and fertiliser cost.

A total of 783.1 hours of labour without transplanting hours (as most smallholder farmers do not transplant), from Jakada and Ifyale (2023) was converted to person days at 1 person day equals 8 hours of work. Also, average yield for Jakada and Ifyalem (2023) was calculated by dividing the average yield by the average land size in the study area. Yield and labour requirements for sorghum from Sienso et al. (2021), were converted from acres to hectares respectively.

Appendix 9: Optimal allocation for input, sales, and consumption variables

Variable per farm type	Optimal value for the longest distance metric (L_1)	Optimal value for the shortest distance metric (L_∞)
FT1*		
Operating cost	GH₵ 7,285	GH₵ 10,967
Own seed used	Maize-24.7 kg, Rice-47.7 kg, Groundnut-17.3 kg	Rice-54.08 kg, Sorghum-7.83 kg, Groundnut-12.52 kg
Own consumption	Maize-979.6 kg, Groundnut-168.5 kg	Groundnut-783.3 kg
Total food and non-food expenditure	Food- GH₵ 2,173 Non-Food- GH₵ 2,699	Food- GH₵ 3,140 Non-Food- GH₵ 3,882
Fertiliser	None	Sorghum-Urea (63.9 kg), Compound (65.3 kg)
Quantities sold	Rice-2,809 kg (Sold in December), Groundnut-914 kg (Sold in September)	Rice-3187 kg (Sold in December), Sorghum-2589 kg (Sold in November)
FT2*		
Operating cost	GH₵ 2,525	GH₵ 4,027
Own seed used	Maize-12.1 kg, Rice-10.9 kg, Sorghum1.5 kg, Groundnut-1.2 kg	Maize-11.2 kg, Rice-9.1 kg, Sorghum-2.4 kg, Groundnut-1.6 kg
Own consumption	Maize-478.2 kg, Groundnut-77.2 kg	Maize-444 kg, Groundnut-98.7 kg
Total food and non-food expenditure	Food-GH₵1,011 Non-Food- GH₵ 961	Food-GH₵ 1,411 Non-Food- GH₵ 1,412
Fertiliser	Sorghum-Urea (12.4 kg), Compound (12.7 kg)	Sorghum-Urea (19.2 kg), Compound (19.7 kg). Rice -Urea (23.6 kg), Compound (24.1 kg)
Quantities sold	Rice-645.2 kg (Sold in Dec.), Sorghum-503.3 kg (Sold in Nov.)	Rice-1177 kg (Sold in Dec.), Sorghum-779.5 kg (Sold in Nov.)
FT3*		
Operating cost	GH₵ 2,184	GH₵ 3,891
Own seed used	Maize-9.1 kg, Rice-8.6, Sorghum-0.7 kg, Groundnut-0.54	Maize-10.7 kg, Rice-17.1 kg, Sorghum-1.6 kg, Groundnut-0.5 kg
Own consumption	Maize-576.1 kg, Groundnut-34 kg	Maize-576.1 kg, Groundnut-34 kg
Total food and non-food expenditure	Food- GH₵1,102 Non-Food- GH₵ 661.2	Food- GH₵1,582 Non-Food- GH₵ 1,137
Fertiliser	Sorghum-Urea (6.5 kg), Compound (6.7 kg)	Sorghum(40kg N)-Urea (15.2 kg), Compound (15.6 kg)
Quantities sold	Maize-242 kg (Sold in Sept.), Rice-509 kg (Sold in Dec.), Sorghum-265 kg (Sold in Nov.)	Maize-390 kg(Sold in September), Rice-1005 kg (Sold in December), Sorghum-617 kg (Sold in Nov.)

**For each FT, the fertiliser application rates for all crops are the same as Figures 6.2 to 6.4*

Chapter 7 Conclusion

7.1 Introduction

This chapter comprehensively summarises the research journey undertaken to explore how farm household risk and income decision making under climate variability in northern Ghana could be optimised. It serves as a culmination of the preceding chapters, providing a clear overview of the study's objectives, the significance of each chapter, and the contributions of the developed model.

7.2 Research overview

This research examines climate variabilities in northern Ghana and its implications for smallholder farmers in the context of farm typologies. The study reflects heterogeneity in farming systems, potential climate smart technologies smallholder farmers could employ to enhance resilience, and how these farmers could minimise the effect of climate risk by growing a combination of crops that offer a more stable income. To begin with the modelling process, the study identified the research gap, reviewed previous literature in the research context, and discussed the significance of the research. The review revealed a lack of research on the use of bio-economic modelling for on-farm decision making under risk to improve the adaptability of smallholder farmers to climate variabilities in northern Ghana. Based on this, research questions were formulated. The findings of the chapters in this study, contributed to answering the research questions and achieving the research objectives mentioned in Chapter 1.

7.3 Model building process and findings

7.3.1 Bio-economic modelling process

Based on the modelling framework in Chapter 3, the model building process began by employing data on climate, soil, and crop parameters. Due to the difficulty in generating field data for crop parameters, literature sources were employed for each crop. From Figure 7.1, data on climate, soil, and crop parameters for each crop was used as inputs in Aquacrop to generate crop yield (Chapter 3). Further, crop simulations from Aquacrop were used to produce crop yield variabilities which were converted to income variabilities to select risk efficient climate smart technologies (Chapter 4). Although adopting climate smart technologies could contribute to minimising risk on farms, the approach does not consider the socio-economic conditions of smallholder farmers and the interaction effect of resource endowments. Also, the findings in Chapter 4 recommends changing planting date for maize and sorghum, and transplanting for rice as the most risk efficient climate smart technologies. However, relatively poor rice farmers may not be able to adopt transplanting as a climate smart technology due to the high cost involved. In addition, maize and sorghum farmers are forced to plant earlier to be able to outsource tractor services which are only available during the start of the season. In such instances, adopting the recommended planting date may be difficult. This implies that the timeliness of resource availability and the cost associated with employing climate smart technologies may affect the smallholder farmers' decision to adopt climate smart technologies. In order to account for the effect of resource endowments, plus the challenges associated with minimising risk using climate smart technologies, the study proceeded to Chapter 5 to investigate farm typologies by exploring the heterogeneity of farming systems, and used the findings in combination with yield variabilities from Aquacrop simulations to develop a mixed-integer quadratic compromise risk programming model (Chapter 6). The model provides information on market participation decisions, consumption, income-risk trade-offs, and risk resilient cropping patterns suitable for each farm type (Figure 7.1).

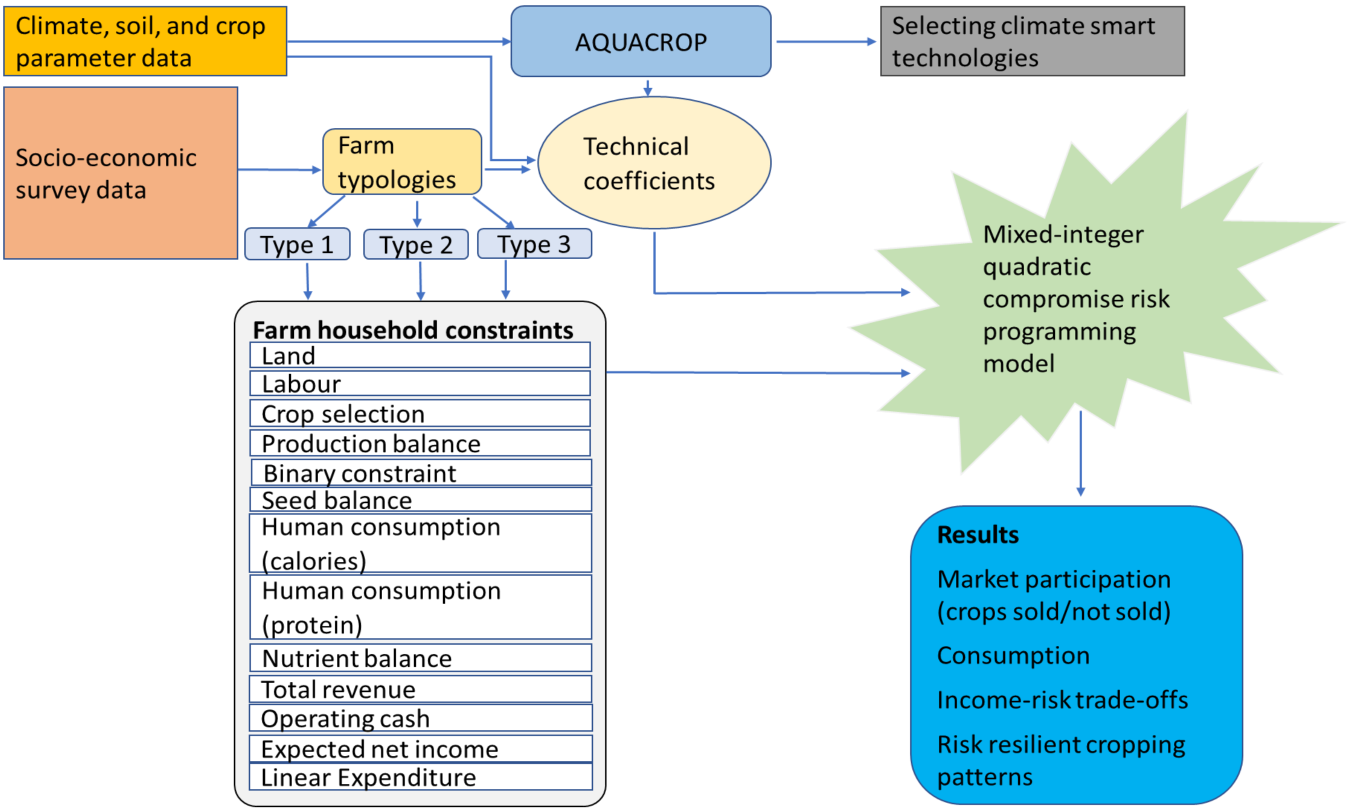


Figure 7.1. Model development process.

7.3.2 General discussion on findings

The study reveals that climate variabilities play a significant role in the variabilities observed in crop yields from 1990 to 2020. Higher crop yields are generally associated with increased soil nutrient status, but this relationship exhibits diminishing returns and is accompanied by greater variability across all crops. This suggests that increasing fertiliser application rates may lead to diminishing returns on crop yields, coupled with a potential rise in variability. One of the strategies to mitigate yield variability is the adoption of climate-smart technologies (CSTs), which conserve water, allowing plants to effectively harness the benefits of increased fertility. Chapter 4 emphasizes that applying CSTs, especially when adjusting planting dates for maize and sorghum and transplanting rice seedlings, helps minimise the variability in crop yield. This underscores the notion that CSTs contribute to climate risk resilience and helps mitigate the adverse impacts of climatic variability (Yahaya et al., 2023). Furthermore, sorghum exhibited the lowest yield variability compared to maize, possibly attributed to its drought-tolerant characteristics (Chadalavada et al., 2021). This implies that the crop is not highly affected by water stress, resulting in minimal impact from CSTs in reducing yield variability.

In Chapters 5 and 6, the study narrows down on the effect of yield variabilities on the socio-economic conditions of specific farm types in the study area. The results in Chapter 5 indicate that crop yields from well-endowed and less risk-averse farm types were better than the less-endowed ones. Additionally, impoverished farmers tend not to store a significant portion of their harvest, due to lack of storage facilities and immediate cash needs. Consequently, they opt to sell or consume their produce immediately after harvesting to avoid post-harvest and cash losses. This practice leaves them with limited options for acquiring food throughout the rest of the year (Tittonell, 2014), perpetuating a cycle of entrenched poverty and hindering any potential for welfare improvement. Moreover, these economically disadvantaged farmers are compelled to accept low prices, as they are unable to capitalise on potential future price increases during off-seasons when market supply is low. Interventions aimed at enhancing yield productivity, and providing reliable storage facilities for these farmers would serve as crucial economic relief, fostering resilience to climate risks.

In Chapter 5, the study reaffirms that the predominant approach to managing climate risk as a result of droughts or floods among households across different farm types involves opting for low-risk, less-income activities. Poorer farm types attach more weight to low-risk, less-income activities which involves prayers, divine consultation, doing nothing, receiving unconditional help from relatives, altering eating habits, migration, finding alternative work, or other similar activities. In contrast a lesser percentage of these households pursue higher-risk options, such as selling assets, crop stock, livestock, or relying on their savings. This pattern is mirrored across all farm types in the study area. As a result the study confirms that the majority of households tend to adopt less risky activities as a strategy for managing climate risks. This inclination is primarily attributed to the overall scarcity of resources, limiting farmers' ability to engage in higher-risk, more income-generating activities. The study's observations align with the perspectives of Barr and Genicot (2008), Binswanger (1980), Binswanger (1981), Bezuneh (1991), Kisaka-Lwayo and Obi (2012), and Wik et al. (2004) who attribute the risk averse behaviour of farmers in developing countries to insufficient resource endowments and a limited capacity to mitigate risks.

To contribute to minimising risk among risk averse smallholder farmers, Chapter 6 considers farmers' limitations in resource endowments, income variabilities and weight attached to income targets and risk management derived from the Chapter 5 farm typologies. As poor farmers attached more weight to risk than income, the findings indicate that to remain resilient such farmers should produce a combination of crops using less resources which eventually amounts to lower net income targets and vice versa for wealthier farmers. Off the four crops investigated in this study, maize featured prominently as an ideal crop for relatively poor farmers whereas rice was suitable for wealthier farmers (Chapter 6). This research posits that smallholder farmers' decision to remain resilient under climate variability is firmly tied to farmers ability to trade off more risk for a more stable income. However, due to the lack of resource endowment, smallholder farmers in the study area rather produce less to cater for their subsistence needs first before sales; hence are unable to trade-off more risk for a more stable higher income level. This further affects the expenditure, consumption and cropping patterns of smallholder farm households. In brief, this research advocates for the prioritisation of efforts by both governmental and non-governmental organisations towards enhancing the resource endowments of farm households. This involves providing assistance in the form of inputs and other essential farm resources to increase productivity, and help improve the overall livelihood conditions of smallholder farmers. Furthermore, supporting farmers by strengthening their resource endowments and productivity can lead to an increase in income levels, a reduction in the dependence on own produce consumption and the diversification in the consumption patterns from less to more nutritious food.

7.4 Model assumptions, future use, and limitations

Given the risk minimisation approach employed in developing the model, the study assumed that all smallholder farmers are risk averse due to reasons previously discussed. Also, since the compromise region on each frontier in Chapter 6 is the closest to the ideal point, this research accepts that, the compromise region is the landing point of the utility curve for smallholder farmers in each farm type. In terms of limitations, the study confirms Aquacrop's limitation in modelling soil fertility with specific nutrient elements. It rather employs a soil fertility stress approach (Chapter 3), hence, soil fertility rates per crop were proxied for nitrogen application rates from literature sources. No field experiments were conducted in this study to generate yield variabilities, rather, secondary experimental data from literature sources were employed. Since the model results are as good as the data used, future use of the model by researchers should consider employing practical field experiments to generate yield variabilities overtime in order to provide more accurate results. Further, the model does not include livestock activities as a determinant of on-farm decision making under climate risk among smallholder farmers. Future research could investigate the effect of a crop-livestock interaction on farmers risk and income decision making and the consequences thereof in terms of farm households' livelihood systems.

7.5 Overall conclusion

Climate variability in northern Ghana is a key challenge for smallholder farmers seeking to make farm level risk efficient decisions to improve their economic wellbeing. This study examines the sources of risk in terms of variabilities in yield and income and proposes a bio-economic model developed to address farmers' risk management concerns in the study area The results of this research suggest that policymakers should avoid uniform implementation of agriculture support interventions. Rather, they should develop tailor-made intervention programs for specific farm types. These interventions could include various strategies such as promoting better farming techniques to enhance crop yields and minimise risks, establishing connections to markets to boost household incomes, and offering affordable agricultural inputs along with welfare assistance to small-scale farmers. Further, the model developed could be employed as a decision-making model to improve smallholder farmers' ability to minimise the risk associated with climate variabilities without violating the resource constraints of farm households. By this approach, farmers are capable of surviving under harsh climatic conditions given that they cultivate a combination of crops that align with their risk and income preferences. Finally, this research is novel given the fact that risk indices were generated based on farm types and integrated into a bio-economic model developed in the form of a mixed integer quadratic compromise risk programming model. Further, the model captures the complex interaction of socio-economic and biophysical processes that influence risk and income decision making of smallholder farmers. Under changed climate scenarios, the model could be updated to generate cropping patterns to further analyse the economic implications of such scenarios in the context of smallholder farmers. The study concludes that the findings of this research will be beneficial to agricultural risk management organisations operating in arid/semi-arid regions with similar socio-economic conditions as northern Ghana.

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