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agricultural impacts and adaptation

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Abstract

Climate and weather extremes generally lead to crop yield, income and consumption losses. Despite their occurrence at the farm level, very little has so far been done to empirically assess weather risks and their effects on welfare at the farm household level, especially, in the West African Sudan Savanna. This thesis analyzes intra-seasonal risk of weather extremes, farmers' adaptation, and impacts of climate shocks on farm households' welfare in the Sudan Savanna of West Africa. The study is based on data from primary and secondary sources and is organized into three main chapters.

Using descriptive techniques, Markov chain model and climatic indices for monitoring weather extremes, it is found that the major climatic threats to crop and livestock production in the regions are rainfall and temperature related. In responding to intra-seasonal climatic threats, some of the farmers practice early planting to take advantage of the first rains, while majority of the farmers either plant late to avoid early-season dry spells or spread their planting to minimize production losses. It is found that for the early planters, the chances for seedlings to be exposed to dry spells of 10 days is estimated at 26.9% to 34.6% in the next 30 days from April 1, while for late planters there is a 36.5% to 48.0% probability for crops to be exposed to dry spells of 21days in the next 30 days from October 28. For the spreaders, there is a high probability for seedlings to be exposed to dry and hot spells and intense precipitation between May and October.

Employing descriptive techniques, Poisson regression and multivariate probit model for analyzing farmers' perception of and adaptation to weather extremes, it is found that farmers' perception of changes in the local climate are in conformity with climatic trends. In adapting to recent changes in the local climate, farmers in the regions implemented a total of 12 adaptation strategies. Although farmers are found to be more likely to adopt a mix of adaptive strategies, they are 7 times more likely to resort to the joint adoption of 6 low-cost measures than adopting 5 capital-intensive measures. This suggests that financial capabilities play major role in farmers adaptation decisions. Institutional and infrastructural measures like distance to markets, access to extension services and credit are found to be the most important determinants of farmers adaptation choices.

Econometric and mathematical programming models are used in the final chapter to simulate the impact of climate shocks on farmers' welfare in the Northern Savanna of Ghana. Farmers were grouped into homogenous units. Three groups of farmers were identified. These are, two poor farmers groups who operate under low input conditions on medium-scale farms (Clusters 1 and 2), and less poor farmers who operate under high input conditions on small-scale farms. It is found that, compared to the current rainfall distribution, a drier future could result in total income loss of about 3.70% (in Cluster 3) to 23.75% (Cluster 1). Under this scenario, the quantity of food available for consumption is predicted to decrease across all the three clusters, although a greater decrease is expected in Cluster 1. Besides the predicted changes in income and consumption, a drier future could result in 13.6%, 5.69% and 3.33% decreases in the shadow price of rainfed lands in Clusters 1, 2 and 3 respectively. It is found that irrigation expansion in the study area could lead to income gains of about 3.98% to 35.32% under the current rainfall distribution, while investment in research and development efforts could lead to income gains of about 10.31% to 33.48%. The poor farmers of Clusters 1 and 2 are expected to benefit the most from these two interventions.

In conclusion, the study shows that policy efforts made to improve farmers access to markets, credit, extension services, and timely and accurate weather forecasts could enhance farmers' adaptation to climate shocks, while the implementation of appropriate adaptation strategies could help to curb the adverse impacts of climate and weather shocks.

Zusammenfassung

Klima- und Wetterextreme rufen generell Verluste in Ernte, Einkommen und Nachfrage hervor. Obwohl sie bereits auf lokaler Ebene sichtbar sind, wurde bisher wenig unternommen, um Wetterrisiken und ihre Auswirkungen auf Lebensbedingungen auf Haushaltlevel empirisch zu erfassen, vor allem in der Westafrikanischen Sudan-Savanne. Diese Arbeit analysiert intrasaisonale Risiken von Wetterrisiken, Anpassung von Bauern und Auswirkungen von Klimaschocks auf Lebensbedingungen von Kleinbauern in der Sudan-Savanne von Westafrika. Die Studie basiert auf primären und sekundären Datenquellen und lässt sich in drei Kapitel gliedern.

Deskriptive Methoden (Markov-Modell sowie klimatische Indizes für das Monitoring von Wetterextremen) ergaben, dass die bedeutsamsten klimatischen Bedrohungen für Land- und Viehwirtschaft in der Region niederschlags- und temperaturbedingt sind. Um intrasaisonale Klimabedrohungen entgegenzuwirken, säen einige Bauern früh aus, um frühe Regenfälle zu nutzen, während die Mehrzahl entweder spät aussät, um den Feldfrüchten frühe Trockenperioden zu ersparen, oder die Aussaat zeitlich verteilen, um das Risiko für Ernteausfälle zu verkleinern. Die Ergebnisse der Gruppe der früh aussäenden Bauern zeigen, dass die Jungpflanzen mit einer Wahrscheinlichkeit von 26,9% und 34,6% in den Tagen ab dem 1. April einer Trockenperiode von 10 Tagen ausgesetzt sind. Für die Gruppe der spät aussäenden Bauern beträgt die Wahrscheinlichkeit 36,5% bis 40,0%, dass die Feldfrüchte Trockenperioden von 21 Tagen in den 30 Tagen ab dem 1. Oktober ausgesetzt sind. In der Gruppe der Bauern, die die Aussaat verteilen, ist die Wahrscheinlichkeit hoch, dass die Jungpflanzen Heiß- und Trockenperioden und intensivem Regen zwischen Mai und Oktober ausgesetzt sind.

Weitere deskriptive Methoden (Poisson-Verteilung und multivariable Probit-Modell für die Analyse der Anpassung an und Wahrnehmung von Wetterextremen der Kleinbauern) zeigten, dass die Wahrnehmung von Veränderungen im Lokalklima mit klimatischen Trends übereinstimmt. Um sich an diese Veränderungen anzupassen, nutzen Bauern insgesamt zwölf Anpassungsstrategien. Obwohl sie tendenziell einen Mix aus verschiedenen Anpassungsstrategien anwenden, ist es siebenmal wahrscheinlicher, dass sie auf eine Kombination aus sechs kostengünstigen Methoden zurückgreifen als auf eine Kombination von fünf kostenintensiven Methoden. Dies deutet darauf hin, dass finanzielle Ressourcen eine wichtige Rolle in der Entscheidungsfindung für Anpassungsmaßnahmen spielen. Institutionelle und infrastrukturelle Maßnahmen wie die Entfernung zu Märkten, Zugang zu staatlichen Leistungen und Krediten sind laut den Ergebnissen die wichtigsten Faktoren im Entscheidungsprozess.

Ökonometrische und mathematische Programmierungsmodelle werden im letzten Teil angewandt, um die Auswirkung von Klimaschocks auf die Lebensbedingungen von Bauern in der nördlichen Savanne in Ghana zu simulieren. Bauern wurden in homogene Einheiten eingeteilt. Drei Gruppen von Bauern wurden identifiziert: zwei Gruppen in hoher Armut, die unter Bedingungen mit geringem Input in Farmen auf mittlerer Skala (Cluster 1 und 2) operieren und eine Gruppe mit geringerer Armut, die unter Bedingungen mit hohem Input in Farmen auf kleiner Skala operiert. Die Ergebnisse zeigen, dass, im Vergleich zu der aktuellen Niederschlagsverteilung, eine trockene Zukunft einen Einkommensausfall von 3,70% (in Cluster 1) bis 23,75% (Cluster 3) hätte. In diesem Szenario kann vorhergesagt werden, dass die Quantität der Nahrung, die für Konsum zur Verfügung steht, in allen drei Clustern sinkt, wobei die größte Abnahme in Cluster 1 erwartet werden kann. Neben den vorausgesagten Veränderungen in Einkommen und Konsum kann eine trockene Zukunft zu einer Abnahme von 13,6%, 5,69% und 3,33% der Schattenpreise von Regenfeldbau in Cluster 1, 2 und 3 führen. Verstärkte Bewässerung in der Studienregion kann bei aktuellen Niederschlagsbedingungen zu Einkommenssteigerungen von 3,98% bis 35,32% führen,

während Investitionen in Forschung und Entwicklungsmaßnahmen das Einkommen von 10,31% bis 33,48% steigern könnte. Die Bauern aus armen Verhältnissen in Cluster 1 und 2 könnten von dieses zwei Eingriffen am meisten profitieren.

Zusammenfassend zeigt diese Studie, dass politische Bemühungen für einen verbesserten Zugang von Bauern zu Märkten, Krediten, staatlichen Leistungen und rechtzeitigen und akkuraten Wettervorhersagen die Anpassung an Klimaschocks verbessern könnte. Die Implementierung von geeigneten Anpassungsstrategien könnte dann dazu beitragen, die nachteiligen Auswirkungen von Klima- und Wetterschocks zu dämpfen.

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Chapter 1

1 Introduction and context of the study

1.1 Introduction

Agriculture contributes immensely towards the attainment of food security, poverty reduction and general human development goals in the West African Sudan Savanna. Through farming, processing of raw materials, and trade, the sector employs between 75 to 90% of the inhabitants of this region (Sanfo and Gérard 2012; MoFA 2013; Knauer *et al* 2017). Despite the major role it plays in the lives of the people, growth of the sector has for decades been hindered by wide crop yield gaps, meagre farm income, land degradation, low innovativeness of production systems, and increasing livestock mortality, among other constraints. Policy measures have been implemented and investment efforts made towards overcoming low productivity of farming systems in this vulnerable region. Despite such efforts, there is not much evidence of success (Terrasson *et al* 2009; Walker *et al* 2016). Increasing frequency, intensity and duration of weather extremes could exacerbate production challenges in this region and other vulnerable regions worldwide (Knox *et al* 2012; Cairns *et al* 2013; Wheeler and von Braun 2013; Haile *et al* 2017). Although increasing incidences and duration of weather extremes are expected globally, impacts could be generally higher on the rural poor, smallholder and subsistence farmers who primarily depend on rainfed agriculture and other weather-sensitve enterprises for their livelihood (Dasgupta *et al* 2014; Sultan and Gaetani 2016). This generally calls for investigation into the current state of farming in areas dominated by these group of people to identify climatic risks to which they have in recent years been subjected, their responses to such risks and effects on farmers' welfare. Findings from such investigations could prove very useful in policy formulation and investment decisions towards enhancing local resilience to weather extremes.

Climate change is documented to have three primary components. These are climatic normals (long-term means), inter- and intra- annual/seasonal variability, and weather extremes (threshold exceedances). The first two components have both positive and negative effects on farming systems depending on location and management conditions (Adams *et al* 1998; Liu *et al* 2004; Kang *et al* 2009), while the latter component has unambiguously negative effect regardless of location (Adams *et al* 1988; Luo 2011; Lobell *et al* 2013). This makes weather extremes much of a worry, yet despite the harm they pose, they are rarely incorporated in climate impact assessments, especially at the farm/village level. Given that most of the rural poor in the Sudan Savanna region of West Africa live as sedentary croppers and to some extent as nomadic pastoralists (Shettima and Tar 2008; Fasona *et al* 2016), dynamics in the evolution of weather extremes could have substantial impact on their primary means of sustenance (agriculture). Identification and documentation of the forms of seasonal climatic risks they face, barriers to effective adaptation, and effects of weather extremes on farm household welfare could guide agricultural planning. In this regard, we assess risks associated with weather extremes in the West African Sudan Savanna. This thesis comprises three related yet independent chapters covering intra-seasonal climatic risks, farmers' adaptation to recent weather extremes, and impacts of extreme weather events on households welfare.

In assessing intra-seasonal risk of weather extremes, farmers' perception of major climatic threats was sought and relevant climatic conditions documented. We make use of a first order Markov chain model and climatic indices for monitoring weather extremes to assess risks to which farming systems have recently been exposed. In analyzing farmers' adaptation to recent exposure, we identify the various measures used, average number of strategies implemented by a representative farm household, determinants of the number and choice of strategies implemented, and probability of marginal and joint adoption of strategies. Having documented climatic risks in the study area and barriers to effective adaptation, a mathematical programming model is used to assess the impacts of climate shocks and adaptation responses on the welfare of farm households. Based on findings from the analyses, relevant recommendations are made towards enhancing resilience of farmers to climate and weather risks.

1.2 Research objectives

Drafting and implementation of pro-active measures to enhance the resilience of vulnerable regions to climate risks has been one of the main priorities of local and global policy formulation processes, especially after the global food crisis in 2007-2008. Efficiency and effectiveness of such measures would, to a greater extent, depend on appropriate identification and documentation of pressing risks, barriers to adaptation and impacts on the welfare of farm households. Making relevant propositions towards formulation and implementation of appropriate measures in this regard is the main goal of the current research. This is achieved through answering of the following research questions:

- Which climatic manifestations do farmers consider major threats to farming in the study area?
- To which intra-seasonal climatic risks have farming systems been recently exposed?
- What are farmers' perception of climatic conditions in the study area?
- Which measures of adaptation have farmers implemented following recent exposure to weather extremes, and what are the determinants of and barriers to adaptation?
- What are the impacts of weather extremes and adaptation responses on farm household welfare?

1.3 Conceptual framework

For every impact assessment, there are drivers, effects and responses (feedbacks). In climate impact studies, the main drivers of relevance to researchers are climate variables, be them long-term means, variability or extremes, controlling for the effects of other relevant non-climatic factors. Efficient assessment, however requires a much clearer understanding of the local climate. Effects of climate variables are yielded via shifts in long-term means for a given location or through climate/weather shocks (Baez *et al* 2012). With the former offering farmers enough time to adjust in order to moderate harm or exploit opportunities, the latter usually comes as a surprise, yielding negative effects on production systems. Shifts in climatic normals, as shown in Figure 1.1, could be changes in a given location's long-term mean or general variability in annual and/or seasonal weather estimates. Changes in weather extremes, are however difficult to define due to their rare occurrence, and lack of a unique definition for such events. The appropriate definition for such events depends basically on the regions and sectors affected (Stephenson 2008), and the issue under investigation, thereby making their definition region-, sector-, and context-specific. In the basic form, the IPCC (2012) defines weather extreme as the occurrence of a value of weather or climate variable above (or below) a threshold value near the upper (or lower) ends of the range of observed values of the variable. Thus, extreme weather events refer to events that have extreme values of certain important meteorological variables (Stephenson 2008). The latter definition of weather extremes by Stephenson (2008) is adopted in this study. A greater number of documentations on these events involve the use of so called "extreme climate indices" and are generally defined for daily temperature and precipitation characteristics (e.g. see Zhang *et al* 2011). Such indices are either used in isolation, or combined to investigate 'extremeness' and the real extent of extremes (Gallant and Karoly 2010; Giorgi *et al* 2011). In their application, these indices have mostly been used to capture probability of occurrence of specified volumes of rainfall, absolute or percentage threshold exceedances for both rainfall and temperature, and complex attributes on duration, intensity and persistence (IPCC 2013). In whichever way extreme weather events are defined, their effects are generally negative (Luo 2011; Lobell *et al* 2013) and much higher without adaptation (Porter *et al* 2014; Palanisami *et al* 2015; Ali and Erenstein 2017).

Climatic and non-climatic drivers impact farming systems in two primary ways: via direct effects on production aspects (including crop yields, livestock mortality, livestock productivity, etc.) and via indirect effects on non-production aspects like farm income, prices, consumption and stock (Porter *et al* 2014). Under favorable climatic conditions, farmers are likely to produce diverse crops to meet subsistence level of household consumption and for cash income generation through selling of surpluses. This could lead to a geneal increase in the welfare of farm households. Under less favorable climatic conditions however, observed yield levels may not be enough to meet subsistence level of consumption and cash requirements. To meet household food needs, farmers may reallocate resources towards the production of low-yielding but stress tolerant traditional staples like sorghum and millet (which serve as major components in the diet of households in the study area), at the expense of high-yielding, profitable, but weather-sensitive crops like maize, rice and groundnut which play vital roles in West African diets. The risk averse nature of most farmers in developing countries and the high uncertainty associated with climate variability makes majority of the farmers in such countries vulnerable and prompts these farmers to generally make decisions that cause substantial income and consumption losses in both favorable and less favorable years (Hansen *et al* 2007). In addition to these and given the subsistence nature of production in majority of the locations of crop production in the study area (Yilma 2005), low yields under less favorable climatic conditions could lead to a general decrease in total food supply, increased output prices, and a potential decrease in household income/consumption. While farmers could compensate for such losses through the sales of livestock or through earning of income from off-farm activities, a limited livestock base or limited off-farm opportunities could lead to a reduced welfare.

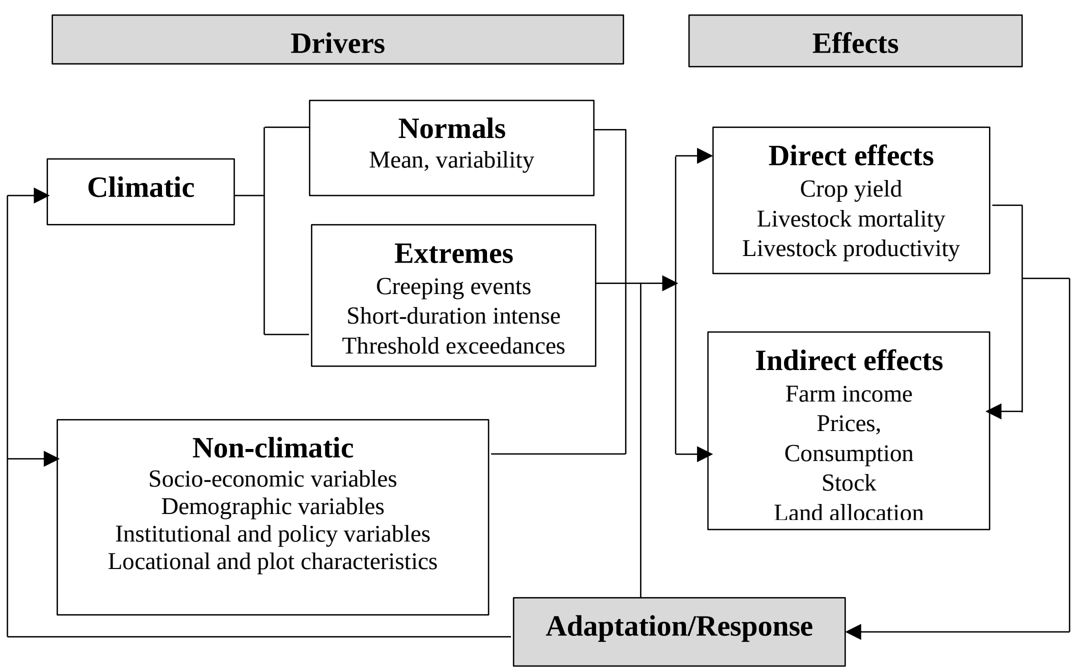


Figure 1. 1 – Conceptual framework
Source: Author's construct

The magnitude of effects of climatic and non-climatic drivers on crop and livestock production depends on whether (or not) farmers already have harm-moderating measures in place (Porter *et al* 2014). Observed effects influence farmers' future adaptation decisions, while sensitivity of farming systems to future weather extremes/conditions depends on effectiveness of implemented adaptive measures (Karfakis *et al* 2012). In assessing such linkages between drivers, effects and adaptation, several approaches have so far been documented in literature, including econometric/Ricardian approaches (Reidsma *et al* 2007; Kurukulasuriya and Mendelsohn 2008; Di Falco *et al* 2011) and programming techniques (with or without risk consideration besides adaptation; static or dynamic; with or without recourse) (e.g Maatman *et al* 2002; Visagie and Ghebretsadik 2005; Lokonon *et al* 2015).

A complete picture of the impact of weather extremes on farming systems depends on a general understanding of the types of weather extremes in a given location, farmers' adaptation to such extremes, and impacts on the welfare/incomes of farm households. In this regard, there is a need to first identify agriculturally-relevant weather extremes in the study area. Choice of appropriate techniques and measures for monitoring and assessing risks from such climatic conditions depends on their manifestation and relevancy in a given location. Similarly, several approaches have been documented for assessing farmers' adaptation to climate change, variability and extremes. In this study, we analyze risk of weather extremes in the study area using a first order Markov chain model and other climatic indices. A combination of descriptive approaches, Poisson regression, and multivariate probit estimation are used in analyzing farmers' adaptation to recent weather extremes. Impacts of climate shocks and adaptation responses on farm household welfare are estimated using mathematical programming.

1.4 Research methods

1.4.1 Study area, data and sampling

This study comprises three primary chapters. The first two chapters are based on data from two sources: a household survey conducted by the author in Upper East Ghana and Southwest Burkina Faso between October 2014 and July 2015, and daily climate data (for the period 1997-2014) extracted from NASA's climatological database. The third chapter is based on data from two secondary sources: a household survey data from the 'Africa Research in Sustainable Intensification for the Next Generation (Africa RISING)' program (Tinonin *et al* 2016) and historical climate data (for 1976-2005) from the CCAFS climate data portal. The Africa RISING program is made up of three research-for-development projects supported by the United States Agency for International Development. These three projects are led by the International Institute of Tropical Agriculture (IITA, in West, East and Southern Africa) and the International Livestock Research Institute (ILRI, in Ethiopian Highlands), with the International Food Policy Research Institute (IFPRI) playing a monitoring and evaluation role. The data used for the third chapter was gathered as part of the evaluation efforts of the Africa RISING program in northern Ghana (baseline survey). The survey covered all the three regions in northern Ghana and involved gathering of data on household characteristics (including demography), agricultural land and production, agricultural input use and prices, agricultural harvest and allocation, data on livestock production activities, prices of crops and livestock by species and age, housing conditions and anthropometry. A stratified two-stage random sampling approach was used in gathering data across the three regions. Although a total of 1,284 households were covered across 50 communities during the baseline survey, this study made use of data from 1,182 households across the regions.

The survey conducted in Upper East Ghana and Southwest Burkina Faso for the first two chapters was based on a multi-stage random sampling technique and covered a total of 450 households across the two regions (300 from Upper East Ghana and 150 from Southwest Burkina Faso). A total of 5 out of the 13 districts in Upper East Ghana and 2 out of the 4 provinces in Southwest Burkina Faso were randomly selected for the study. Data gathered through the household survey comprised the following five primary issues:

1. **Farmers' perception of climatic risks and adaptation**: on this issue, we sought farmers' definition and recent experiences of bad weather and perceived effects, perception of recent changes in local climatic conditions, and adaptation.
2. **Crop production for the 2014 agricultural season**: we placed emphasis on types of crops produced, crop-specific sowing and harvesting plans, non-labor input use, crop yields and prices
3. **Livestock inventory**: we gathered data on the types (species) of livestock kept by the respective farm households, and detailed livestock inventory (*covering units at the beginning of the year, births, purchases, gifts received and made, deaths, sales, consumption, and stock, as well as prices for the respective species by age*)
4. **Household demographics**: this section covered the total number of people in each household by age-group, labor use on farm and sources, number of family members living within 5 km from main residence and number of members abroad (the last two serve as measures of social capital)
5. **Socio-economic, policy and plot-based variables**: data on distance to nearest market, access to formal/informal credits, access to extension services, participation in farmers' organization, farmers' perception on fertility of crop fields, land ownership and size, types and value of farm implements (as indicator of mechanization), and other relevant variables were gathered in this section.

Agriculture is the major source of employment for majority of the population in the four regions covered in this study, and all the four regions are characterized by a unimodal rainfall regime, with a rainy season that extends from May to October, a dry period between November and March, and a period of transition in April. Maize, groundnut, millet, sorghum, rice, chicken, goat, guinea fowl, sheep, cattle, pigs, and donkey are the major crop and livestock species produced across the regions. A map of the study area for the first two chapters is shown in Figure 1.2.

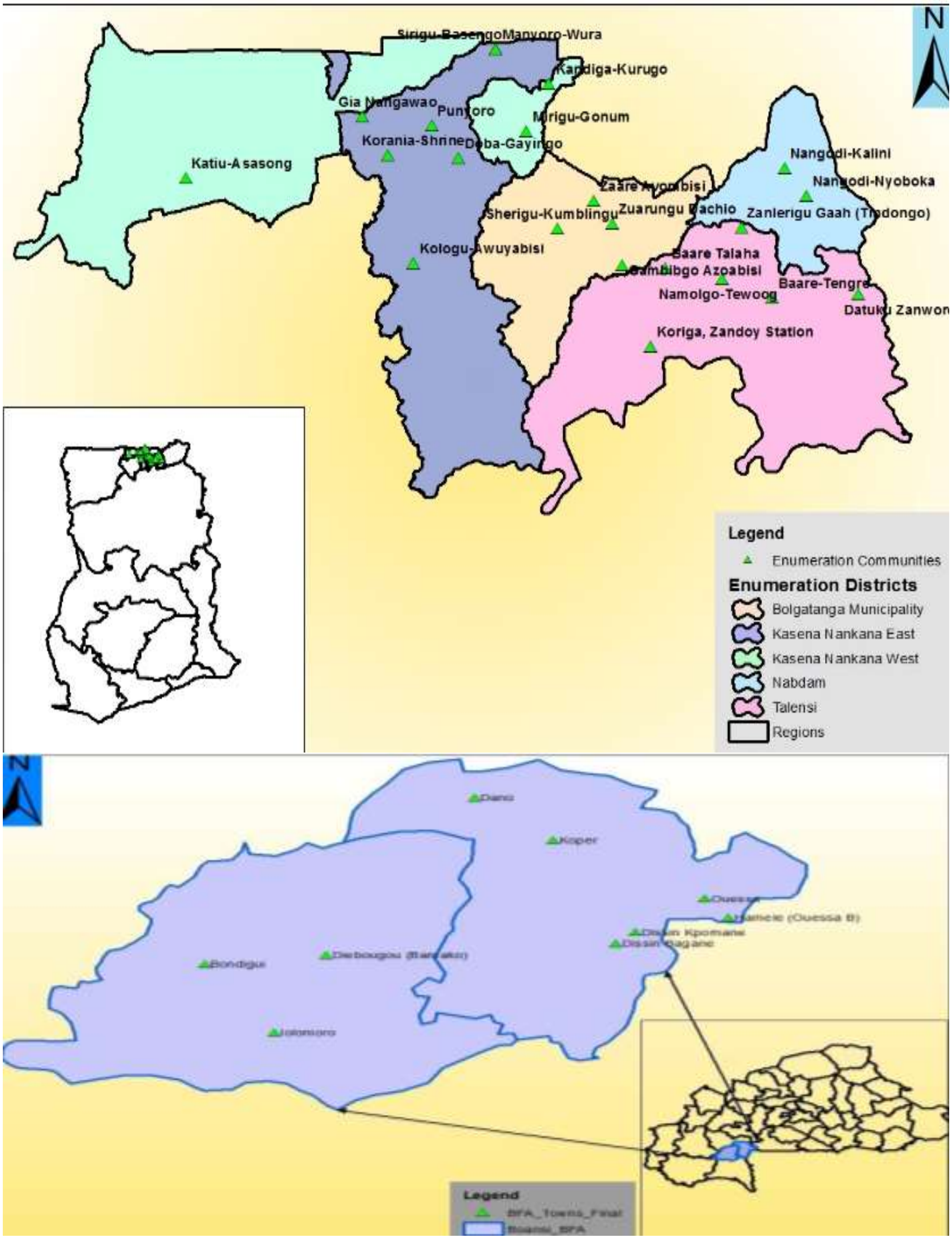


Figure 1. 2- Map of the study area
Source: Author’s construct

1.4.2 Outline of the study

The remainder of the thesis is organized into three main chapters, and a supplementary chapter for general conclusion. In chapter 2, we analyze intra-seasonal risk of agriculturally-relevant weather extremes in the West African Sudan Savanna. In this chapter, we document farmers' definition of a bad weather, their recent experiences and perceived effects, and which among the numerous manifestations of weather extremes they deem more harmful to agriculture. Risks posed by such manifestations are assessed using a first order Markov chain model and other relevant climatic indices. In chapter 3, we document farmers' perceptions of recent changes in the local climate and their adaptation. We as well analyze the determinants of the number and choice of strategies adopted, interdependencies among adopted strategies and the probability of marginal and joint adoption of strategies. Descriptive statistics (percentages), Poisson regression and multivariate probit models are used for the analysis. In the fourth chapter, we estimate the impact of climate/weather shocks and adaptation responses on farm household welfare using mathematical programming. We provide a summary of findings and make vital policy recommendations in the general conclusion.

Chapter 2

2 Intra-seasonal risk of agriculturally-relevant weather extremes in West African Sudan Savanna[1]

2.1 Introduction

Climate variability has been and would continue to be an inherent attribute and a normal element in farming systems worldwide. This is a fact farmers' readily embrace as part of their risk management strategy (Greenhill *et al* 2009; Burlew *et al* 2016). Crossing thresholds in locally relevant climatic conditions, however subject farmers to significant production, consumption and income losses, and unimaginable pressure which coerces some into committing suicide (Nicholls *et al* 2006; Guiney 2012; Hanigan *et al* 2012), defaulting on loan repayment (Shiferaw *et al* 2014) or implementing coping strategies that weaken their ability to appropriately adjust to future shocks (Nelson *et al* 2007; Harvey *et al* 2014). Not only is agriculture in developing countries sensitive to climate variability and extremes, but more importantly, climatic elements remain and would forever be the basic drivers of agricultural production, food availability and stability in such countries (Selvaraju *et al* 2011). For over several decades now, and amidst increasing demographic, economic, social and environmental pressures, sustainable food production in the Sudan Savanna zone of West Africa has been hindered by uncertainty and diverse manifestation of seasonal climatic conditions (Roncoli *et al* 2001; Yiran and Stringer 2016), critical among which are the nature, frequency and intensity of extreme weather events[2]. Be them droughts, floods, heat wave, or in any other form, extreme events manifest either in isolation or in combination, impact negatively on crops, livestock, human health (Yiran and Stringer 2016), 'economic trees' and infrastructure, and consequently yield indirect adverse effects on household income and consumption, reduction in food availability and access, hikes in local and regional commodity prices (Tadesse *et al* 2014), and general retardation in economic growth. Such manifestations and their consequent impacts have in recent decades undermined progress in alleviation of poverty and food insecurity in the current study area and in other developing countries worldwide (Haile 2005; Jeffery 2009). Although increasing globally, by frequency and intensity (IPCC 2014), climate extremes yield worst impact on the rural poor, smallholder and subsistence farmers who primarily depend on rainfed agriculture and other climate-sensitive enterprises (e.g. fishing) for sustenance (Dasgupta *et al* 2014), and have limited access to channels of relief in times of shock (Harvey *et al* 2014; Gautam and Anderson 2016).

Due to the general deleterious effects of extreme weather events on these vulnerable farmers, calls are made worldwide for drafting and implementation of pro-active policies and investments to improve

[1] A version of this chapter has been published in Theoretical and Applied Climatology (https://doi.org/10.1007/s00704-018-2384-x)

[2] Extreme weather events refer to events that have extreme values of certain important meteorological variables (Stephenson 2008)

their current positioning and future resilience to weather shocks. In responding to such calls, several research efforts have been made towards assessing and documenting risks to which farming systems are exposed. Majority of the research efforts made have however, either been founded on general impact assessment and guided by scientific proposition of relevant climatic events (e.g. Salack *et al* 2015) or on farmers' perception of climatic trends and adaptation (e.g. Antwi-Agyei *et al* 2014). Very little effort has so far been made to identify conditions deemed more relevant by farmers given the contextual nature and relevance of extreme weather events, and the actual nature of risks to which farming systems are exposed. With the little effort made so far, emphasis has either been placed solely on qualitative assessment of farmer-perceived effects and causes of climate extremes (e.g. Kusakari *et al* 2014), or on a combination of perception on relevant events and assessment of inter-annual variability of rainfall (e.g. Yengoh *et al* 2010; Yiran and Stringer 2016). Hardly has any of the studies conducted so far critically considered intra-seasonal risk of climate extremes deemed more relevant to farming. Formulation and implementation of effective production and policy measures to promote local resilience to climate change, variability and extremes, however, requires not only information on inter-seasonal and annual trends in climatic conditions, but more importantly intra-seasonal risk of weather extremes (Sivakumar 1992; Hoyos and Webster 2007; Guan *et al* 2014). Besides, majority of the documentations on climatic risks in the study area are based either on a single district or a comparison between few districts within a given region. This precludes appropriate revelation of spatial differences in magnitude and frequency of various climatic extremes. Upon the presumption that farmers have to some extent a better understanding of the local climate (Selvaraju 2012) and do optimize their management practices based on experiences and recent changes in climatic conditions (Madisson 2006), we seek to bridge relevant information gap through identification of climatic conditions deemed agriculturally-relevant by farmers, and assess intra-seasonal risks posed by such conditions in Upper East Ghana and Southwest Burkina Faso.

Selection of these two regions is based on the extreme reliance of the inhabitants on agriculture for sustenance, dominance of rural population in the respective regions, limited use of irrigation facilities, and their recent exposure to various extreme weather events (right from extremely dry conditions in 1997 (Roncoli *et al* 2001), and floods between 1999 and 2012 (Asare-Kyei *et al* 2015; Zoungrana *et al* 2015), to extremely dry and hot conditions in 2013 and 2014). The main objective of this study is to provide answers to the following research questions:

1. Which climatic manifestations do farmers consider major threat to farming in the study area?
2. To which intra-seasonal climatic risks have farming systems been recently exposed?
3. What are the relevant production and policy adjustments needed to moderate harm from weather extremes?

The remaining sections of this chapter are organized as follows. The conceptual framework for this study is covered in section 2.2. In section 2.3, we present the methods, which comprise sampling and data, and analytical framework. We then document climatic conditions deemed major threat to farming systems in the study area, and present results on inter and intra-seasonal risks posed by such conditions in section 2.4. Summary and conclusion are covered in section 2.5.

2.2 Conceptual framework

This study assesses intra-seasonal risk of weather extremes under a Climate risk management framework (Selvaraju 2012). This framework is based on the use of climate information and how better farm management in a changing local climate can help to reduce vulnerability to current and future climatic conditions, including risks of weather extremes. In this regard, climate risk management primarily refers to the use of relevant climate information to cope with and curb potential adverse impacts of climate change on development and management of scarce resources (African Development Forum, 2010). The framework in a broader sense covers different aspects of risk management processes, notable amongst which are "*risk assessments for informed decision-making, risk reduction, planning and preparation, and risk sharing, pooling and transfer in the context of adaptation*" (African Development Forum 2010; Selvaraju 2012). It involves the identification, analysis and response to hydro- and agro-meteorological risks across temporal and spatial scales. In assessing climate risks, greater emphasis is mostly placed on key climatic variables, especially the quantity and distribution of rainfall and the incidence of temperature extremes. Emphasis placed on these two climatic variables is generally attributed to their role in determining the characteristics of the rainy season, farming systems, choice of crop and livestock species and in the implementation of key farm management decisions.

While both inter- and intra-annual/seasonal variability are known to constrain crop production in arid, semi-arid and humid environments, past studies in West Africa and other developing regions have placed more emphasis on inter-annual/seasonal variability (including Yengoh *et al* 2010; Yiran and Stringer 2016) at the expense of intra-annual/seasonal variability (Sivakumar 1992; Selvaraju 2012; Guan *et al* 2014) and from a scientific perspective. This leads to a high degree of disconnect between farmer experiences and perceptions (realities on the grounds) and climatological views expressed by scientists/experts. Intra-seasonal variability is however known to lead to extreme climatic events that have severe impact on both crop production and livelihood opportunities in agriculture. The acceptance and usefulness of weather information by farmers is mostly dependent on whether such information is understood by them and tailored to meet their needs. To improve the acceptance rate, usefulness and efficiency in the use of climate information, emerging/new climate risk assessments (including Yengoh *et* *al* 2010; Selvaraju 2012; Kusakari *et al* 2014; Yiran and Stringer 2016) make effort to bridge the current disconnect between science and local experiences and perceptions of farmers. This helps to identify locally-relevant climatic events and to appropriately apply the right climatological tools to analyze risks, vulnerabilities and impacts of weather extremes on farmers welfare. While the exposure of farmers to climate and weather variability prompts farmers to develop management options to curb adverse impacts of weather extremes, these management options generally serve as inputs for risk analysis and impact simulations to ascertain options that could prove beneficial to farmers. As shown in Figure 2.1, management options that could prove beneficial, based on identified risks, are proposed in the form of advisories to farmers/stakeholders (targeted on key management factors), while the options that could be non-/less-beneficial are either not recommended or re-evaluated.

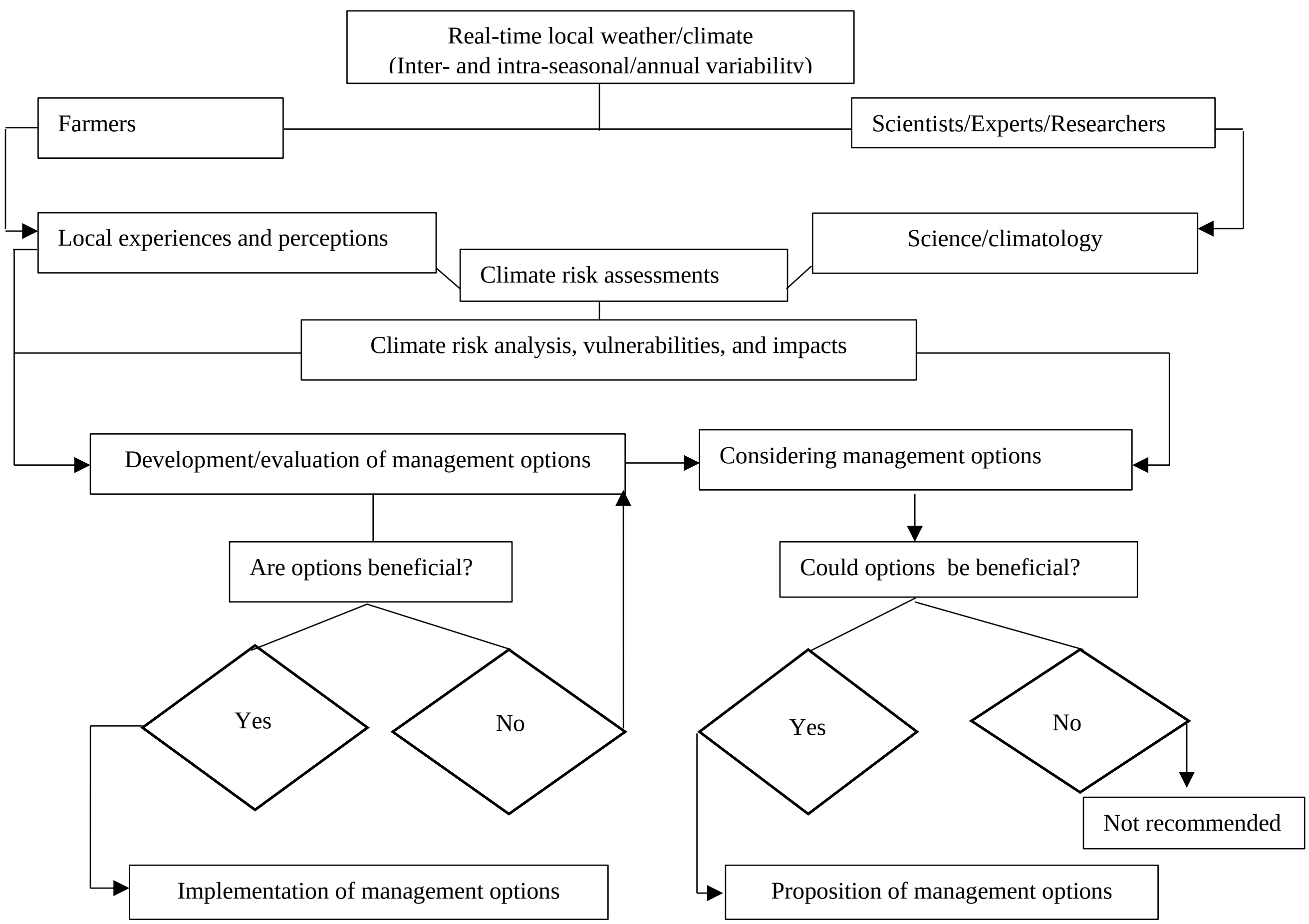


Figure 2. 1-Framework for climate risk analysis at the farm household level

Source: Author's construct

These advisories are options from which farmers/stakeholders could make a choice and implement in effort to reduce the risk of climate and weather shocks. Appropriate seasonal and annual advisory services could enable farmers to reduce risks and minimize crop yield losses. On the other hand, options developed and implemented directly by farmers, based on experiences and perceptions, are mostly implemented to minimize adverse impacts of impending risk as the new rainy season begins. These are mostly implemented based on farmer expectations, and those found to be beneficial are continually implemented, while farmers make some adjustments in their decisions when some options are found to be non-/less-beneficial. This study, under the climate risk management framework documents farmer experiences and perceptions of climate risk in the study area, conditions deemed major threats to farming and use appropriate climatological techniques to analyze risks to which farming systems in the two regions have recently been subjected. Appropriate recommendations are made based on findings from the study. For the analysis, descriptive techniques, Markov Chain modelling and climatic indices for monitoring weather extremes are used.

2.3 Methods

2.3.1 Data and sampling

Two basic types of data are used in this chapter; primary data gathered through a household survey, and daily climate data (1997-2014) extracted (using centroid GPS coordinates for selected communities) from NASA's Climatology Resource for Agroclimatology based on a 1° latitude by 1° longitude grid. Use of extracted data instead of observed field data is due to difficulty in accessing such data and to lack of it in some cases. During the survey, a total of 29 communities were covered across 7 districts/provinces in the two regions. The extracted daily climate data for the respective communities were averaged to obtain district level data and further averaged across districts to obtain regional estimates. As would later be elaborated on, climatic conditions deemed of greater threat by farmers in the study area were basically rain and temperature related. Hence, our extraction of daily climate data was centered on rainfall and temperature for the respective communities. Data gathered through the household survey included farmers cropping and livestock production in the 2014 agricultural season, their perception of climatic conditions deemed major threats to farming in the study area, and some of their recent experiences of such conditions.

A multi-stage random sampling technique was used in gathering data across the two regions. Using pre-tested questionnaires, a total of 450 selected heads of farm households were interviewed by trained research assistants under supervision of the author; 300 in Upper East Ghana and 150 in Southwest Burkina Faso. Of the 13 districts in Upper East Ghana, a total of 5 were randomly selected. The 5 selected districts are Bolgatanga Municipal (90 households), Kassena-Nankana East (70 households), Kassena-Nankana

West (60 households), Nabdam district (40 households) and Talensi district (40 households). Of the 4 provinces in Southwest Burkina Faso, 2 were randomly selected for this study. The two provinces covered are the Ioba province (105 households across Dano, Dissin, Ouessa and Koper departments) and Bougouriba province (45 households across Diébougou, Bondigui and Iolonioro departments). Apportioning across the two regions and districts was based on differences in population density, level of engagement in agriculture and recent exposure to extreme weather events (based on information disclosed by the local Ministry of Agriculture).

2.3.2 Analytical framework

Through qualitative exploration, we discover that farming systems in the study area are exposed to 8 major seasonal climatic threats, namely, droughts (dry spell), low rainfall, short-duration intense precipitation events, flooding, erratic rainfall pattern, extremely high temperatures, delayed rains and early cessation of rains, the latter of which leads to plausible shortening of the effective length of the rainy season. In this study, however, we assess intra-seasonal risk of dry and wet spells, intense precipitation and flooding, inter and intra-seasonal changes in temperature, and recent changes in onset and cessation of rains. In this section, we show the mathematical expressions used in computing climatic indices for monitoring risks from these climatic conditions over the period 1997-2014. We begin with onset and cessation of rains, then to risk of dry and wet spells, indicators of intense precipitation and flooding, and assessment of inter and intra-seasonal changes in temperature. The various indices and graphs used for monitoring recent changes in these climatic indicators were developed in Instat Plus software and in Excel.

2.3.2.1 Measures for monitoring onset, cessation and length of the rainy season

Dates of onset and cessation of rains serve as critical guides in farmers' seasonal planting of crops, while the effective length of the rainy season usually dictates the mix of crops chosen by farmers and spread in their planting. In whichever context these indicators have been used so far in literature, dates of onset of rains are found to be more variable than dates of cessation and the effective length of the rainy season more sensitive to onset than cessation of rains (Omotosho *et al* 2000). Onset and cessation dates are basic indicators of periods within a season where reliable and effective rain falls, and changes/shifts in these indicators have relevant implications for crop choice, mix and yields. Although several definitions have been documented and applied in literature for detecting onset and cessation dates, they all fall under three main categories (Lodoun *et al* 2013), and these are

- Definitions that only place emphasis on amount and distribution of rain (e.g. Stern *et al* 2006)

- Definitions that capture dynamics in soil water balance (e.g. Sivakumar *et al* 1993; Maikano 2006) and
- Definitions that place more emphasis on atmospheric predictors and circulations (e.g. Omotosho *et al* 2000)

In this study, we base our definitions of onset and cessation dates on the first two categories and on respective propositions by Stern *et al* (2006) for onset of rains and Maikano (2006) for cessation of rains, attaching however an ***extra*** precondition in the definition for cessation of rains. We define date of onset of seasonal rains (ORSR) as the first occasion after May 1st with more than 20mm of rain in a 2-day period and with no dry spell of 10 days or more in the next 30 days. That for cessation (CRSR) on the other hand is defined as, the first day after September 1st when soil with a 60mm water holding capacity gets completely depleted, assuming daily evaporation rate of 5mm and ***remains depleted for at least 5 consecutive days without recovering to maximum capacity in the next 15days.*** Effective length of the rainy season[3] (ELRS) is then computed as follows:

$$\mathrm{ELRS_t = CRSR_t - ORSR_t} \qquad (2.1)$$

Where *t* is a representation of year (time).
In defining a dry spell for identification and documentation of the onset and cessation dates, we used a 1mm daily rainfall threshold as in Zhang *et al* (2011) and Schär *et al* (2016), and recommended by the joint CCI/CLIVAR/JCOMM Expert Team on Climate Change Detection and Indices (ETCCDI). By this, we define a dry day (*d*) as a day with less than 1mm of rain, thus $RR_{ij} < 1mm$ and a dry spell as prolonged period of dry days. A wet/rainy day (*r*) is in this study defined also as a day with at least 1mm of rain, thus $RR_{ij} \geq 1mm$. From these expressions, RR_{ij} represents daily precipitation amount (RR) on day *i* in period *j* (monthly or seasonal).

2.3.2.2 Markov chain probability model for occurrence of rain, dry and wet spells

Information on intra-seasonal length of dry and wet spells, their frequencies and probabilities guides proposition and implementation of measures to minimize adverse agricultural impacts of recurrent droughts (Sivakumar 1992). In addition, it helps in seasonal planning of agricultural activities, and in management of water supply systems (Sharma 1996). Although several aspects of dry and wet spells have been studied and documented in literature, for the tropics and sub-tropics, of greater importance among the aspects

[3] We use 'effective' to distinguish this index from the actual length of the season (May 1st to October 31st)

covered so far is the phenomenon of persistent behavior of intra-seasonal dry and wet spells, with Markov chain model being one of the powerful models for describing such behavior (Sharma 1996). Under the domain of stochastic theory, and in Markov chain modelling, the occurrences of daily rainfall are driven by a simple stochastic process founded on the notion that the weather for a given day can only be in one of two states, a wet state or a dry state (Gabriel and Neumann 1962). Definitions for wet and dry days (states) from the preceding section are maintained. The probability of occurrence of a wet or dry day depends on the climatic systems of a given location, and the sequence of these two respective states may be driven either by some trend of persistence or may evolve randomly (Sharma 1996). Processes governed by significant level of dependence are usually and appropriately represented by first-order Markov chain model, while those with insignificant level of dependence are represented by other models beyond the scope of this study.

Based on first-order Markov chain modelling, the degree of persistence in a sequence of occurrence of rain is monitored through estimation of conditional probabilities (Sharma 1996; Barron *et al* 2003). In applying a first order Markov chain model, processes are seen as succession of stages in sequence (Sansom 1998), and the probability of a given state today depends only on the state yesterday and not on that of two or more days ago. This is expressed in the equation below:

$$\Pr[\mathrm{X}_{t+1} = \mathrm{x} | \mathrm{X}_t = \mathrm{i}, \mathrm{X}_{t-1}, \dots \dots, \mathrm{X}_0] = \Pr[\mathrm{X}_{t+1} = \mathrm{x} | \mathrm{X}_t = \mathrm{i}], \quad \mathrm{i}, \mathrm{x} \in \mathrm{Z} \qquad (2.2)$$

In the same way, the probability of a state tomorrow depends only on that of today and not that of yesterday. From equation (2.2), X_t is a day in sequence, *t* is a representation of time (in days, from January 1st to December 31st. Thus, day 1 to 366), x is a revealed state, and *i* is a representation of either of the two plausible states (yet to be revealed/unknown). In this study, the probability of a day being wet given that the previous day was dry is designated as $P_{(rd)}$, wet-given-wet as $P_{(rr)}$, dry-given-wet as $P_{(dr)}$, and dry-given-dry as $P_{(dd)}$. In reporting of findings however, emphasis is placed on $P_{(rd)}$ and $P_{(rr)}$. For a first-order Markov chain model, chances of the respective states can be written in the following transition matrix (Sharma 1996):

$$\mathrm{P} = \begin{pmatrix} \mathrm{pp} & 1 - \mathrm{pp} \\ 1 - \mathrm{qq} & \mathrm{qq} \end{pmatrix} \qquad (2.3)$$

Where $pp = P_{(rr)}$ and $qq = P_{(dd)}$

Probabilities for occurrence of the two primary states of interest to this study are computed with the following expressions (Barron *et al* 2003):

$$P_{(rd)} = \text{prob}(X_t = 1, X_{t-1} = 0) = \frac{\sum_{Q=1}^{Q=m}(X_t = 1, X_{t-1} = 0)}{\sum_{Q=1}^{Q=m}(X_{t-1} = 0)} \qquad (2.4)$$

$$P_{(rr)} = \text{prob}(X_t = 1, X_{t-1} = 1) = \frac{\sum_{Q=1}^{Q=m}(X_t = 1, X_{t-1} = 1)}{\sum_{Q=1}^{Q=m}(X_{t-1} = 1)} \qquad (2.5)$$

With all repeated symbols/letters from equation (2.2) holding their original meanings, from equations (2.4) and (2.5), Q_i is a representation of each year in the dataset, and *m* is a representation of the total number of years covered (18 years in the present case). In arriving at these probability estimates, daily rainfall data were first grouped into 7-day basis, a function fitted to each of the estimated probabilities using Fourier analysis (Barron *et al* 2003; Stern *et al* 2006) and a number of harmonics tested for best fit. For both regions, option for 3-harmonics (which adds a sine and cosine term to the regression equation) was found to be more appropriate. After fitting on 7-day basis, data were interpolated to daily basis and the outcome used in estimating risk (probability) of dry spell. According to Stern *et al* (2006), grouping before fitting and later interpolating to daily basis is deemed a more appropriate technique, in that, the approximate method used in Instat Plus software for fitting the model is more valid when estimation is carried out in this manner. Estimated probabilities for specified (5, 7, 10, and 21 days) dry spell lengths are monitored using graphs on a 10-day ("dekad") step. By this, we monitor the chances for maximum dry spell length to exceed the specified number of days over the next 30 days starting from the first day of each dekad. Monitoring of both shorter and prolonged lengths helps in detecting intra-seasonal risks to which drought-sensitive crops like groundnut, maize, rice, common beans, and cotton, and drought-hardy crops like millet and sorghum are exposed.

In farming and agricultural planning however, farmers and stakeholders are usually not only interested in probabilities, but also in the exact conditional maximum length of dry and wet spells to which farming systems are exposed in the respective months of the season. To provide such useful information, conditional maximum number of consecutive dry days (MCDD) and wet days (MCWD) for each of the seasonal months (May to October) are computed. The conditional maximum length of dry spell (MCDD) in a month, is conceptually defined as the maximum number of consecutive days with $RR_{ij} < 1mm$, conditional on $RR_{ij} \geq 1mm$ on the day prior to the beginning of a spell in that month. The conditional maximum length of wet spell (MCWD) in a month is defined as the maximum number of consecutive days with $RR_{ij} \geq 1mm$, conditional on $RR_{ij} < 1mm$ on the day prior to the beginning of a spell in that month. The use of these conditions helps in identifying risk from planting in each of the seasonal months, assuming each a potential month for planting of drought-sensitive crops. Information on conditional maximum length of dry and wet spells could inform farmers' decision on when to harvest and dry some of the numerous crops they cultivate and in planning of supplemental irrigation.

2.3.2.3 Measures for monitoring incidence of intense precipitation and flooding

Several approaches have been used so far for monitoring incidence of intense precipitation and flooding in various locations across micro and macro-scales. The appropriateness of the respective approaches used depends on the objective of the study and on subsequent use of the processed data. For studies that are aimed at gaining a deeper and clearer understanding of the mechanics behind incidence of flooding, and with a purpose of predicting future precipitation extremes, peak/value-over-threshold method, annual maximum series (Rx1day), Maximum 5-day (Rx5day) and Maximum 7-day (Rx7day) rain totals, and changes in the 95th (R95p) and 99th (R99p) percentile of daily rainfall are often used (e.g see Stern *et al* 2006; Zhang *et al* 2011). For agricultural risk and impact assessment however, Rx1day, Rx5day, and Rx7day, and in few cases R95p and R99p are used (e.g. see Stern *et al* 2006; Preethi and Revadekar 2012). In this study, seasonal risk of intense precipitation and flooding is monitored using both Rx1day and Rx7day rain totals. Rx7day is used instead of Rx5day due to its better representation of periodic accumulation and easy interpretability of outcome to farmers and other stakeholders. Use of both Rx1day (usually perceived to be the cause of flooding) and Rx7day is to draw attention to the fact that, while a single extreme precipitation event in a given season could be destructive to agriculture, harm posed to vulnerable systems through flooding usually arise not only as a result of that single event, but more importantly, by gradual yet consistent accumulation of both moderately and highly intense precipitation events over a short-period of time (Stern *et al* 2006; Yengoh *et al* 2010). This latter case, for example, is believed to be the major cause of the highly documented seasonal flooding in the year 2007 in Northern Ghana (Yengoh *et al* 2010). Having shed some light on the measures used, they are defined as follows:

Let RR_{ij} be the daily precipitation amount on day *i* in period *j* (season). The maximum *1-day* value for period *j* in the respective years is computed as follows:

$$\mathrm{Rx1day_j} = \max\left(\mathrm{RR_{ij}} \geq 1\mathrm{mm}\right) \qquad (2.6)$$

Let RR_{kj} be the precipitation amount for the 7-day interval ending *k*, in period *j* (season). The maximum *7-day* value for period *j* in the respective years is computed as follows:

$$\mathrm{Rx7day_j} = \max\left(\mathrm{RR_{kj}}\right) \qquad (2.7)$$

Given the relatively short period covered by this study, and the risk in extrapolating beyond the scope (18-years) of data (Stern *et al* 2006), 5-year (instead of higher period) return values are computed for these measures. Such computations are done through transformation of probabilities from empirical plots into return periods. Cumulative probability, *F (or P for percent)*, is transformed into return periods, *T*, using either of the following expressions;

$$\mathrm{T} = \frac{1}{(1-\mathrm{F})} \quad \text{or } \mathrm{T} = \frac{100}{(100-\mathrm{P})}\ \text{, for percentages} \qquad (2.8)$$

2.3.2.4 Measures for monitoring changes in temperature and hot spells

In this study, we assess and monitor seasonal risk of extreme temperatures using diurnal temperature range (DTR_j), maximum (Tmx_j), minimum (Tmn_j) and mean ($Tmean_j$) temperatures. In addition to these, it is recommended that changes in the length of hot/warm spells be monitored (Zhang *et al* 2011). In line with such recommendation, several definitions have been proposed for computing indices to monitor hot spells. Majority of the definitions proposed so far are based on the number of consecutive days with temperature of at least 5°C above the mean climatology (Zhang *et al* 2011), while others are based on the continuous stretch of persisting maximum temperature above certain threshold over a specified period (Rasul *et al* 2008). The first definition is not applicable in the current study (due to scope), while the second is also biased towards maximum temperature and ignores changes in minimum temperature, the latter of which has the potential to dictate biomass accumulation in most C_3 plants.

In this study, two major thresholds, $Tmx \geq 32°C \text{ } and \text{ } Tmn \geq 24°C,$ are respectively used in monitoring hot spells. Selection of these two thresholds was based on extensive review of literature on optimum day and night temperature thresholds for majority of the crop and livestock species produced in the study area (e.g. see Thornton and Cramer 2012; Hawkins *et al* 2013; Thornton and Lipper 2014) and on information gathered from private discussions held with extension officers with the local Ministry of Agriculture, opinion leaders, and crop and livestock scientists (experts). We again make use of the conditional clause in this section and place emphasis on maximum consecutive hot day and hot night spells. Accordingly, the conditional maximum length of hot day spell (MCHD) in a month, is defined as the maximum number of consecutive days with $Tmx_{ij} \geq 32°C$, conditional on $Tmx_{ij} < 32°C$ on the day prior to the beginning of a spell in that month. The conditional maximum length of hot-night spell (MCHN) in a month, is defined as the maximum number of consecutive days with $Tmn_{ij} \geq 24°C$, conditional on $Tmn_{ij} < 24°C$ on the day prior to the beginning of a spell in that month. Beside these conceptual definitions for hot day and hot night spells, the following expressions were used in computing diurnal temperature range (DTR) and daily mean temperature (Tmean) over the entire number of days (*I*) in period *j*.

$$\mathrm{DTR_j} = \frac{\sum_{i=1}^{I}\left(\mathrm{Tmx_{ij}} - \mathrm{Tmn_{ij}}\right)}{I} \qquad (2.9)$$

$$\mathrm{Tmean_j} = \frac{\sum_{i=1}^{I}\frac{\mathrm{Tmx_{ij}} + \mathrm{Tmn_{ij}}}{2}}{I} \qquad (2.10)$$

2.4 Results and discussion

In this section, we document farmers' perception of major climatic threats in the study area, and present findings on recent deviations in dates of onset and cessation of rain and consequent effect on the effective length of the rainy season, probability of rain and dry spells, conditional maximum length of dry and wet spells, recent developments in the seasonal measures of intense precipitation and flooding, and recent changes in seasonal temperature indicators. Extracted climate data used in the quantitative part of this study was first explored for oddities[4] using boxplots and other relevant exploratory techniques. Computed monthly estimates for rainfall were also compared with observed rainfall data for some districts in Upper East Ghana where monthly data was available. Through the exploration, we found the extracted data suitable, and hence proceeded with the analysis.

2.4.1 Farmers' perception of major climatic threats

Extremes in seasonal climatic conditions manifest either in isolation or in combination with other events. It is along this same line of reasoning that farmers identify and define agriculturally-relevant weather extremes. Through processing of responses by farmers on their perception of major climatic threats to farming in the study area, we identified a total of 34 different citations/combinations of climatic conditions considered major threat to farming, some founded on isolated events and others on a combination of two or more of these isolated events. While majority of the farmers in Upper East Ghana based their definitions on both isolated and combined events, proposed definitions in Southwest Burkina Faso are mainly founded on isolated events. In this study, however, we place sole emphasis on the highly cited climatic conditions. The most frequently proposed definitions based on combined events in Upper East Ghana are "Combination of low rainfall and extremely high temperature" (29.3% of households), "Low rainfall interspersed with intense precipitation" (10.7% of households) and "Combination of erratic rainfall pattern and drought"

[4] We placed emphasis on detecting instances where minimum temperature was greater than the maximum, monthly rainfall was below 50mm in June, July, August and September, and rainfall regime (unimodal or bimodal) revealed by the extracted climate data

(5.0% of households). Among the highly cited isolated events are “Low rainfall” (18.3% of households), “Incidence of drought” (8.7% of households), “Erratic rainfall pattern” (7.7% of households), and “Incidence of flooding” (3.7% of households). The most frequent definition based on combined events in Southwest Burkina Faso is “Combination of delayed rains and early cessation of rains” (3.3% of households). Among the common propositions based on isolated events are “Incidence of drought” (45.3% of households), “Low rainfall” (14.7% of households), “Incidence of flooding” (11.3% of households), “Early cessation of rains” (8.0% of households), and “Delayed rains” (6.7% of households). From these findings, we deduce that farming systems across the two regions are presumably threatened by 8 major seasonal climatic conditions, namely, drought, low rainfall, short-duration intense precipitation events, flooding, erratic rainfall pattern, extremely high temperatures, delayed rains, and early cessation of rains. Based on farmers’ perception, agriculturally-relevant climatic threat refers to

“*Any incidence of drought*[5] *or low rainfall, intense precipitation or flooding*[6]*, erratic rainfall pattern, extremely high temperatures, delayed rains, and/or early cessation of rains occurring either in isolation or critically in combination*”.

Droughts, floods and intense precipitation were also identified in previous studies by Kusakari *et al* (2014) and Yiran and Stringer (2016) as the major climatic threats in the Sudan Savanna agro-ecological zone of Ghana.

In revealing some of their recent experiences of the climatic threats, a total of 72.3% and 22.7% of households in Upper East Ghana respectively cited 2014 and 2013 as the years in which they experienced majority of the threats. In Southwest Burkina Faso, a total of 20%, 14.7% and 10% of households stated the years 2005, 2014, and 2013 respectively. The years 2003, 2007, 2010, 2011 and 2012 were as well mentioned by 4.7% to 9.3% of households in Southwest Burkina Faso. In assessing perceived effects[7] in the highly-cited years, and as shown in Table 2.1, we found that early millet, rice, and late millet were perceptively the most affected crops in Upper East Ghana, while cotton, groundnut and maize were the most affected in Southwest Burkina Faso. Some farmers also observed major declines in livestock productivity, especially in egg production (a secondary source of income for some households). Although there were reports of livestock mortality, majority of the farmers attributed this to non-climatic causes, while those that believed such deaths were weather-related could not provide adequate information on changes in mortality rates. Based on computed changes in production, we found that egg production in the years 2013 and 2014 decreased respectively by 48% and 47% in Upper East Ghana, while a decrease of

[5] According to the farmers, there is low rainfall when the volumes of rain received are far below their expectation and crops requirement, although they do fall. Drought on the other hand relates to receptive periods of readily evaporable volumes of rain or lack of rains.

[6] Conceptually, intense precipitation refers to the occurrence of high intensity (volume of) rains within a short period of time, while flooding refers to the consequent inundation/submergence of the area receiving such rains as a result of either the high impact (or succession of high and/or moderate intensity rains) or inappropriate percolation triggered by the crusted nature of the surface of soil in the area or poor drainage.

[7] Based on percent change in yields between good and bad years

49.5% was observed in Southwest Burkina Faso in the year 2014. For Upper East Ghana, declines in yields of crops and in egg production in the year 2013 are majorly attributed by farmers to the joint effect of low rainfall and extremely high intra-seasonal temperatures. Declines in the year 2014, are however attributed to the combined effect of drought and low rainfall interspersed with intense precipitation. For Southwest Burkina Faso, losses observed in the year 2005 are mainly attributed to drought, and in the years 2013 and 2014 to drought and erratic rainfall pattern.

Table 2. 1-Farmers' perception on output reductions due to weather extremes

Region	N= C/E	Years	Sorghum N=35:139	L. millet N=45:134	E. millet N=24: 107	Maize N=38:128	Rice N=43:109	Groundnut N=58: 169	-	Egg prod. N=19:149
UER Ghana	68/19 217/149	2013 2014	-42.9% -46.8%	-53.5% -52.9%	-61.5% -56.0%	-42.7% -50.4%	-51.6% -56.8%	-50.4% -49.5%	-	-48.0% -47.0%
	N= C/E	Years	Sorghum N=17:10:18	L. millet N=12:7:6	Maize N=28:15:21	Rice N=15:6:6	Groundnut N=20:9:15	C. beans N=13:9:12	Cotton N=9:3:5	Egg prod. N=0:0:33
Sw Burkina Faso	30/0 15/0 22/33	2005 2013 2014	-49.9% -38.4% -48.6%	-36.3% -43.1% -45.5%	-49.0% -42.5% -46.8%	-40.9% -43.6% -33.8%	-43.8% -49.3% -49.7%	-40.9% -45.2% -48.8%	-55.9% -49.6% -45.8%	- - -49.5%

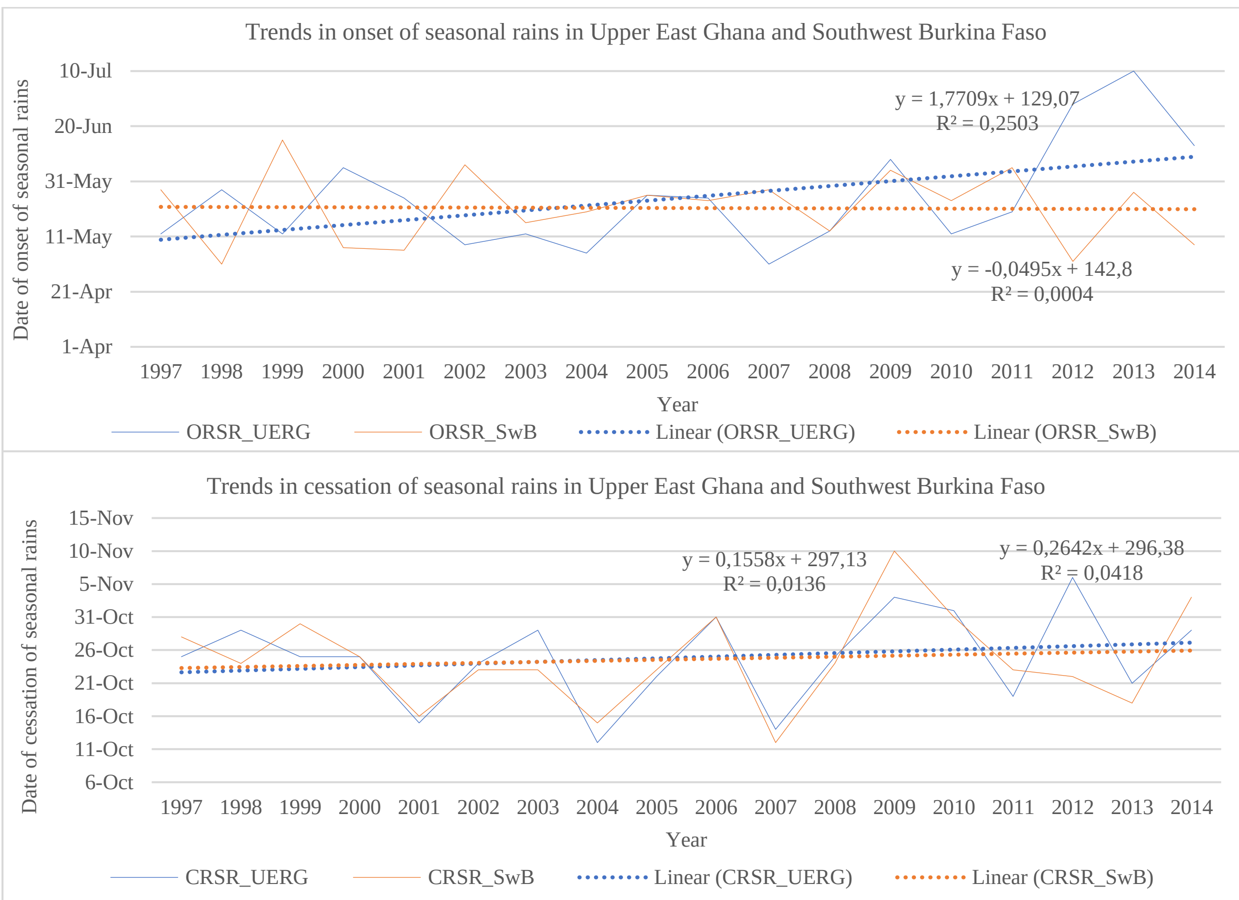
NB: estimates are based on responses from at least 10% of households who experienced bad weather in the years of interest within each region. For, N=X: Y: Z, X-represents number of households that reported low yield for this crop in the first year for a sequence of years in the "Years" column for the respective regions. Y and Z represent the number of households that reported losses in the second and third years if any. For C/E- C refers to total number of households with crop-related experience in the respective years, while E- is the corresponding figure for households with egg production experience.

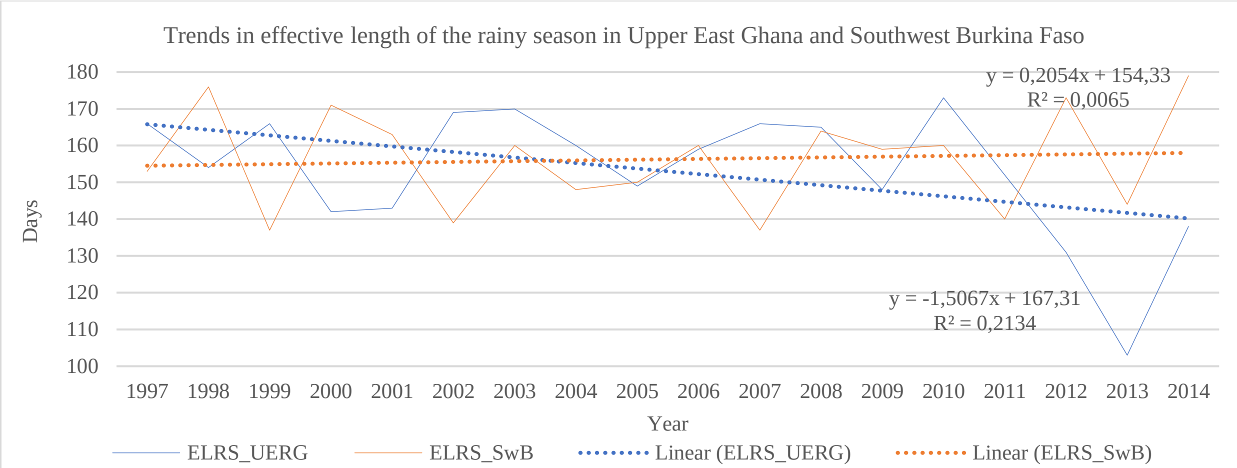
Source: Computed by author with data from farm household survey

2.4.2 Recent changes in dates of onset, cessation and length of the rainy season

As shown in Figure 2.2, the onset dates of seasonal rainfall ranged between May 1st (in 2007) and July 10th (in 2013) in Upper East Ghana, and May 1st (in 1998) and Jun 15th (in 1999) in Southwest Burkina Faso. The cessation dates of seasonal rainfall ranged between October 12th (in 2004) and November 6th (in 2012) in Upper East Ghana, and October 12th (in 2007) and November 10th (in 2009) in Southwest Burkina Faso. The effective length of the rainy season ranged between 103 (in 2013) and 173 days (in 2010) in Upper East Ghana, and 137 (in 2007) and 179 days (in 2014) in Southwest Burkina Faso. Over the period 1997-2014, the onset dates in Southwest Burkina Faso were generally stable, depicting an insignificant trend of 0.050 days decrease per rainy season. In contrast to the generally stable nature of the onset dates in Southwest Burkina Faso, there was an increase in the onset dates by 1.771 days per rainy season (significant at the 5% level) in the Upper East Ghana. Beside this increasing trend, and compared to the 18-year mean, the onset date was on average 16.3 days late during the 2010 to 2014 agricultural seasons in Upper East Ghana, but occurred 1.93 days earlier in Southwest Burkina Faso. While we find no significant trend in the cessation dates in both regions over the period 1997-2014, extensions in cessation dates by 2.71 days and 0.99 days were respectively observed in Upper East Ghana and Southwest Burkina Faso during the period 2010-2014. These changes in onset and cessation dates led to 13.6 days decrease in the effective length of the rainy season in Upper East Ghana during the period 2010-2014, while in Southwest Burkina Faso, an extension of 2.92 days was observed. Over the period 1997-2014, the effective length of the rainy season decreased by 1.507 days per rainy season (significant at the 10% level) in Upper East Ghana, but increased at an insignificant rate of 0.205 days per rainy season in Southwest Burkina Faso.

Due to the recent delay in onset of rains and shortening of the effective length of the rainy season in Upper East Ghana, and as shown in Figure AP 2.1 in the appendix, some farmers in this region have not only started spreading their planting of crops across the first three months of the season, but have mostly shifted their sowing of drought-sensitive crops like maize, rice and groundnut from May (original month for planting, based on information disclosed by farmers and key informants in Upper East Ghana) to June and July.





NB: UERG- Upper East region of Ghana, SwB-Southwest Burkina Faso
Figure 2. 2- Trends in onset, cessation and effective length of the rainy season
Source: Author's construct

Although this may preclude exposure of these crops to risk of prolonged dry spell in the early stage of the season, it may equally expose such crops to risk of prolonged dry spell in the latter part of the season and in the reproductive stage in specific, given that most of these crops have a growth cycle of 3-6 months. Besides spreading of planting across the first three months of the season as observed in Upper East Ghana, some farmers in Southwest Burkina Faso also sowed first seeds of drought-hardy crops like millet and sorghum in April to take advantage of first rains. These adjustments made by farmers in their planting may have some crop growth and yield implications depending on intra-seasonal risk of weather extremes and other production constraints. Through empirical probability plots and computation of return periods and values, we found that in 1 out of 5 years, onset dates exceed June 9th and June 4th respectively in Upper East Ghana and Southwest Burkina Faso, while a 5-year return date for cessation of rains of October 31st is estimated for both regions. For effective length of the rainy season, 5-year return values of 167 days and 171 days are respectively estimated for Upper East Ghana and Southwest Burkina Faso.

2.4.3 Probability of rain and intra-seasonal risk of dry and wet spells

We assess the probability of rain and risk of dry and wet spells from two dimensions. In the first dimension, we monitor chances of the two states (dry or wet) of weather in a day across the 12 months of the year using fitted probabilities for rain-given-dry (in the previous day, 'f_rd') and rain-given-rain (in the previous day, 'f_rr'). The former guides monitoring of persistent behavior of dry spell within a given period, while the latter reveals rainfall regime (unimodal or bimodal nature) for a given location. In the second dimension, we estimate the probability of dry spell of varied lengths across the transitional (April) and seasonal (May-October) periods, and compute conditional maximum lengths of dry and wet spells for each of the seasonal months. Inclusion of the transitional period in the first stage of the second dimension is to aid identification of risks to which farmers who engage in early planting stand facing.

2.4.3.1 Probability of rain

From monitoring of the monthly transition probabilities in Table 2.2, we note that across both regions, intra-annual rainfall reaches a peak between August and September. We as well find low annual probability estimates for both ‘f_rd’ and ‘f_rr’. This implies a general dominance of dry days over wet days over the period 1997-2014. The relatively low ‘f_rd’ estimates for the months of April and October in both regions, compared to that for the other 5 seasonal months indicates a plausible higher persistence of dry spell in these two months. Planting of crops in April without supplemental irrigation could lead to poor emergence, while late planting could lead to exposure of crops to risk of prolonged dry spell in the month of October, which may coincide with the reproductive stage for majority of the late planted crops.

Table 2. 2-Monthly, seasonal and annual transition probabilities

Reg.	Prob.	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Seas	Ann
UER	f_rd	0.011	0.030	0.087	0.246	0.434	0.452	0.450	0.609	0.672	0.335	0.044	0.009	0.491	0.283
	f_rr	0.063	0.091	0.251	0.429	0.430	0.416	0.516	0.618	0.604	0.493	0.311	0.134	0.513	0.364
SwB	f_rd	0.011	0.025	0.087	0.275	0.467	0.519	0.593	0.737	0.721	0.357	0.059	0.013	0.565	0.324
	f_rr	0.067	0.121	0.290	0.436	0.452	0.467	0.551	0.635	0.644	0.532	0.294	0.113	0.547	0.385

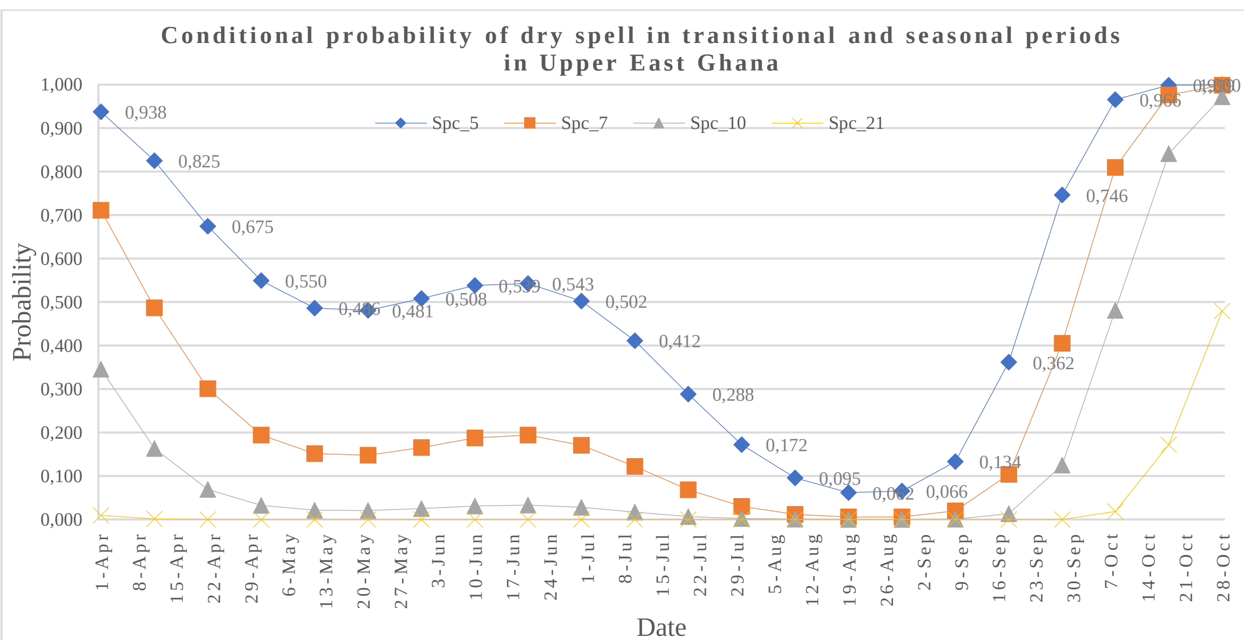
NB: UER-Upper East Region of Ghana; SwB- Southwest Burkina Faso; f_rd – fitted probability of rain-given-dry; f_rr-fitted probability of rain-given-rain; Seas -seasonal estimate; Ann – annual estimate
Source: Computed by author

The seasonal estimates of ‘f_rd’ and ‘f_rr’ for the two regions indicate a relatively higher persistence of dry spell in Upper East Ghana than in Southwest Burkina Faso, and a plausibly higher count of seasonal rainy days in the latter region than in the former.

2.4.3.2 Risk of dry spell

For easy visualization and clarity in presentation of probability estimates for various lengths of dry spell, we display conditional probabilities on a 10-day (dekad) step from the first day of April. By this, each of the estimates in Figure 2.3 for the respective regions represents conditional probability of dry spell lasting for a specified number of days in the next 30 days from first day of a dekad. Across both regions, and in all stages of the season, we detect that the conditional probability of a dry spell lasting for 5 consecutive days far exceeds those for 7, 10 and 21 consecutive days. This implies that, in contrast to the perceived prolonged nature of dry spell in the study area, dry spells are not necessarily prolonged by nature, but rather mostly short-lasting and repetitive in short-intervals. Interspersion of such repetitive spells by high intensity rains could prove harmful to weather-sensitive crops like maize, cotton, and groundnuts.

Conditional probability of a dry spell lasting 5 consecutive days' in the next 30 days from April 1st decreases from as high as 93.8% to 6.60% by August 29th in Upper East, and increases thereafter to 96.6% by October 8th. Within this region, farmers who decide to plant first seeds on April 1st could as well be exposed to dry spells lasting 7 and 10 consecutive days in the next 30 days with respective conditional probabilities of 71.1% and 34.6%. Although drought-hardy crops may survive (but with a possibility of poor emergence and poor seedling growth), drought-sensitive crops may fail to even emerge under such conditions. Late planted crops could as well be exposed to dry spells lasting 7 and 10 consecutive days in the next 30 days from October 8th with respective conditional probabilities of 81.0% and 48.1%. Although chances for a 21-day dry spell is below 2% between April 1st and October 8th, conditional probabilities of 17.2% and 48.0% are respectively estimated for such a prolonged spell in the next 30 days from October 18th and 28th. For Southwest Burkina Faso, conditional probabilities of dry spells lasting 5, 7 and 10 consecutive days in the next 30 days from April 1st decrease from 90.4%, 63.0% and 26.9% respectively to 3.20%, 0.20%, and 0.00% by August 29th, and increase thereafter to 94.2%, 74.0% and 39.3% by October 8th. Like the situation in Upper East Ghana, chances for a 21-day dry spell is below 2% between April 1st and October 8th in Southwest Burkina Faso, but with conditional probabilities of 11.2% and 36.5% in the next 30 days from October 18th and 28th.



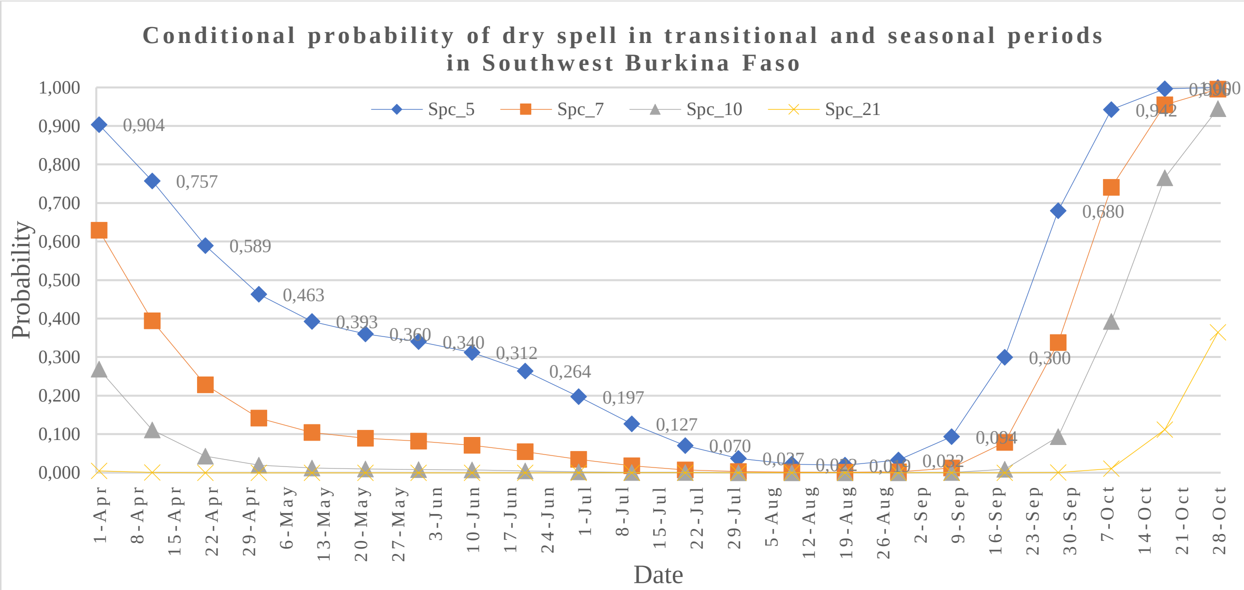


Figure 2. 3-Plots of conditional probability of dry spell of varied lengths
Source: Author's construct

To minimize incidence of poor emergence on crop fields in both regions and any significant shortening of effective length of the rainy season, and as well minimize exposure of drought-sensitive crops to prolonged dry spell in the latter stage of the season, planting of crops around the mean or median onset dates (May 23rd to 25th in Upper East Ghana, and May 21st to 24th in Southwest Burkina Faso) could be a safer option. Should farmers decide to plant first seeds on these dates, conditional probability of 10 consecutive dry days' spell within the next 30 days across the two regions is less than 3.00%. Risk of dry spell lasting 5 to 7 consecutive days could still be high within this period. For appreciable rate of emergence and good seedling growth, there may be a need for supplemental irrigation or use of drought tolerant varieties.

2.4.3.3 Conditional monthly maximum consecutive dry and wet days

In contrast to the situation in the preceding section where both maximum and moderate duration spells were jointly considered in estimating conditional probabilities for varied dry spell lengths, emphasis is in this section placed solely on the longest duration monthly spells (both dry and wet) across the six months of the season. As shown in Table 2.3, and for both regions, relatively longer duration of dry spell is usually observed in the month of October and shorter durations of dry spell in August and September. In contrast, relatively longer durations of wet spell are usually observed in the months of August and September and shorter durations of wet spell in the months of May and June. By this, the need for supplemental irrigation in both regions may be higher in the months of May, June and October than in the other seasonal months.

Besides a 1 in 18 years (5.56% chance) exceedance of a 10-day duration of dry spell in the month of May in Upper East Ghana, length of the longest duration of dry spell never exceeded 10 days in the months of June, July, August and September across the two regions. This threshold was however exceeded in the month of October in 3 out of 18 years (16.7% chance) in Upper East Ghana, and in 2 out of 18 years (11.1% chance) in Southwest Burkina Faso. For Upper East Ghana, the 3 exceedances in the month of October were observed in the years 2001, 2002 and 2006, while in Sud-Ouest Burkina Faso, the 2 exceedances were observed in the years 2001 and 2002.

Through computation of 5-year return values for conditional maximum duration of dry and wet spells, and as shown in Table 2.4, August and September have relatively lower return values for dry spell than the other seasonal months, but higher values for wet spell. Return values for dry spell are relatively higher in May and October than the other seasonal months, while values for wet spell are relatively lower in May and June.

Table 2. 3-Conditional monthly maximum consecutive dry and wet days

Indicators	Upper East Ghana				Southwest Burkina Faso			
	Mean	Median	Max	Std.Dev	Mean	Median	Max	Std.Dev
MCDD_May	5.28	4.50	11.0	2.08	5.22	5.00	9.00	2.10
MCDD_Jun	4.83	4.50	8.00	1.34	4.06	4.00	6.00	1.16
MCDD_Jul	4.17	3.50	9.00	1.98	3.06	3.00	6.00	0.94
MCDD_Aug	3.39	3.00	6.00	0.85	2.28	2.00	4.00	0.57
MCDD_Sep	2.94	2.50	6.00	1.31	2.33	2.00	6.00	0.97
MCDD_Oct	7.78	7.50	20.0	4.28	6.56	6.00	13.0	3.19
MCWD_May	3.33	3.00	5.00	1.14	3.94	3.00	8.00	1.73
MCWD_Jun	3.17	3.00	8.00	1.54	3.67	3.00	12.0	2.28
MCWD_Jul	4.89	5.00	7.00	1.45	5.28	4.50	11.0	2.22
MCWD_Aug	6.17	5.50	12.0	2.90	6.89	5.50	12.0	2.65
MCWD_Sep	5.17	5.00	8.00	1.62	6.56	6.00	13.0	3.17
MCWD_Oct	4.72	4.00	9.00	1.90	4.78	4.00	9.00	2.07
	% >5days	% >7days	% >10 days	% >21 days	% >5days	% >7days	% >10 days	% >21 days
MCDD_May	33.3	16.7	5.56	0.00	33.3	22.2	0.00	0.00
MCDD_Jun	27.8	5.56	0.00	0.00	11.1	0.00	0.00	0.00
MCDD_Jul	22.2	5.56	0.00	0.00	5.56	0.00	0.00	0.00
MCDD_Aug	5.56	0.00	0.00	0.00	0.00	0.00	0.00	0.00
MCDD_Sep	5.56	0.00	0.00	0.00	5.56	0.00	0.00	0.00
MCDD_Oct	66.7	50.0	16.7	0.00	61.1	27.8	11.1	0.00
MCWD_May	0.00	0.00	0.00	0.00	16.7	5.56	0.00	0.00
MCWD_Jun	5.56	5.56	0.00	0.00	11.1	5.56	5.56	0.00
MCWD_Jul	44.4	0.00	0.00	0.00	27.8	11.1	5.56	0.00
MCWD_Aug	50.0	33.3	11.1	0.00	50.0	38.9	16.7	0.00
MCWD_Sep	38.9	11.1	0.00	0.00	55.6	33.3	16.7	0.00
MCWD_Oct	27.8	11.1	0.00	0.00	33.3	16.7	0.00	0.00

NB: MCDD – conditional maximum consecutive dry days; MCWD – conditional maximum consecutive wet days

Source: Computed by author

Table 2. 4-Return values for conditional monthly maximum consecutive dry and wet days

Region	Return period	MCDD_ May	MCDD_ June	MCDD_ July	MCDD_ Aug	MCDD_ Sept	MCDD_ Oct	MCWD_ May	MCWD_ June	MCWD _ July	MCWD _ Aug	MCWD _ Sept	MCWD _ Oct
Upper East GH	1 in 5 years	7.20	6.00	6.20	4.00	4.00	10.2	5.00	4.00	6.00	8.40	7.00	7.00
Southwest BF	1 in 5 years	8.00	5.00	3.20	3.00	2.20	9.20	5.40	4.00	7.00	9.40	9.40	6.40

Source: Computed by author

2.4.4 Recent developments in indicators of intense precipitation and seasonal flooding

For the period 1997-2014, and in Upper East Ghana, seasonal maximum series ranged between 30.10 mm and 51.40 mm, while seasonal maximum 7-day rain ranged between 82.71 mm and 134.38 mm. In Southwest Burkina Faso, a range of 29.25 mm to 71.36 mm is estimated for the seasonal maximum series, while a range of 68.49 mm to 128.08 mm is estimated for seasonal maximum 7-day rain. As shown in Figure 2.4, the highest seasonal maximum series and maximum 7-day rain in Upper East Ghana were both observed in the year 2007, while the lowest seasonal maximum series was recorded in the year 2010 and the lowest maximum 7-day rain in the year 2012. For Southwest Burkina Faso, the highest seasonal maximum series and maximum 7-day rain were both recorded in the year 2008, and the lowest in 2011. Seasonal maximum series and maximum 7-day accumulations are found to be more variable in Southwest Burkina Faso (CoV of 26.43% and 14.69% respectively for Rx1-day and Rx7-day) than in Upper East Ghana (CoV of 15.75% and 13.67% respectively for Rx1-day and Rx7-day). Seasonal maximum series in Upper East Ghana usually occurred as isolated events rather than contributing to the maximum weekly accumulation (Rx7-day).

Over the 18-year period, the two measures of intense precipitation/flooding coincided in only 7 out of 18 years (38.9% chance) in Upper East Ghana, while in Southwest Burkina Faso, they coincided in 11 out of 18 years (61.1% chance). Coincidence in this stance refers to the condition whereby a given seasonal maximum series forms part of 7 daily rainfall records whose accumulation leads to the weekly maximum. From these findings, we deduce that recent incidences of flooding in Upper East Ghana are likely to have been triggered either by a single extreme precipitation event or by maximum weekly accumulation of moderately intense rains. Other hydrological processes and institutional arrangements (e.g. opening of major dams in neighboring Burkina Faso to release excess water) may have also contributed to seasonal flooding in Upper East Ghana. Seasonal incidences of flooding in Southwest Burkina Faso on the other hand, are likely to have been triggered either by a single extreme precipitation event, by maximum weekly accumulation of moderately and/or highly intense precipitation events, or by other hydrological processes.

Based on coincidences across the two measures, we deduce that farming systems and households in the study area are usually exposed to two major threats from flooding, either within a given week in the season or at different points in time during the season, the latter of which could prove more harmful to farmers depending on their ability to recover from whichever among the two measures occurs first. The first threat has to do with the occurrence of a single extreme precipitation event which could lead to lodging or destruction of crop stands, death of livestock (especially birds and small-ruminants), erosion and destruction of parts of farmlands and roads, and as well lead to loss of properties. The second has to do with maximum weekly accumulation, effect of which could be widespread due to gradual weakening of a vulnerable system by accumulation of either moderately intense precipitation events or by both moderately and highly intense precipitation events. Resultant floods from this case could last for relatively longer period, be costlier to deal with, and could cause huge production and income losses through prolonged inundation of crop fields.

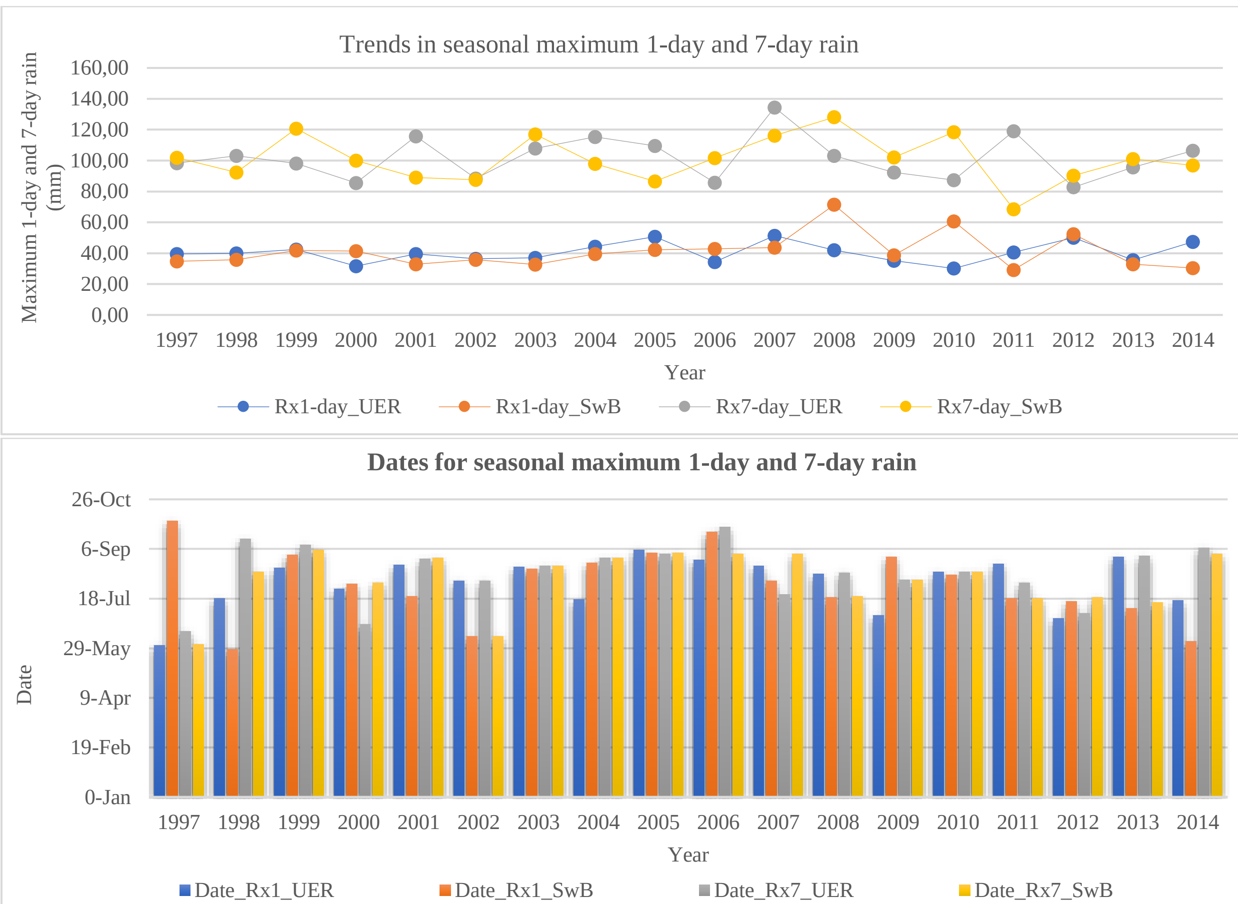


Figure 2. 4-Recent trends and dates for seasonal indicators of intense precipitation and flooding
NB: Rx1-day -seasonal maximum series; Rx7-day -seasonal maximum 7-day rain;
Source: Author's construct

In assessing intra-seasonal risk posed by these two measures of flooding, and as shown in Figure 2.4, we find the months of July and August to be the riskiest months for incidence of seasonal maximum series across both regions, and August and September the riskiest for maximum weekly accumulation. For Upper East Ghana, and based on dates for the two measures of flooding, we estimate a 27.8% chance of the seasonal maximum series occurring in July and 55.6% chance of it occurring in August. For seasonal maximum weekly accumulation, a 50.0% chance is estimated for the month of August and 27.8% chance for the month of September. For Southwest Burkina Faso, we estimate a 27.8% chance of seasonal maximum series occurring in July and 38.9% chance of it occurring in August. For seasonal maximum weekly accumulation, a 38.9% chance is estimated for the month of August and 27.8% chance for the month of September. From these findings, and adjustments made by farmers in their planting (as shown in Figure AP 2.1 in the appendix), farmers who plant late to escape early season dry spell, are likely to have some of their seeds (if not all) washed away by either extreme precipitation events within July and August, or by high weekly accumulation of moderately and/or highly intense rains in August and September. A significant number of crop stands could as well be subjected to lodging and destruction.

Table 2. 5-Return values for seasonal maximum 1-day and maximum 7-day rain

Indicator	Return period	Upper East Ghana	Southwest Burkina Faso
Rx1-day (mm)	1 in 5 years	47.95	45.45
Rx7-day (mm)	1 in 5 years	115.4	117.3

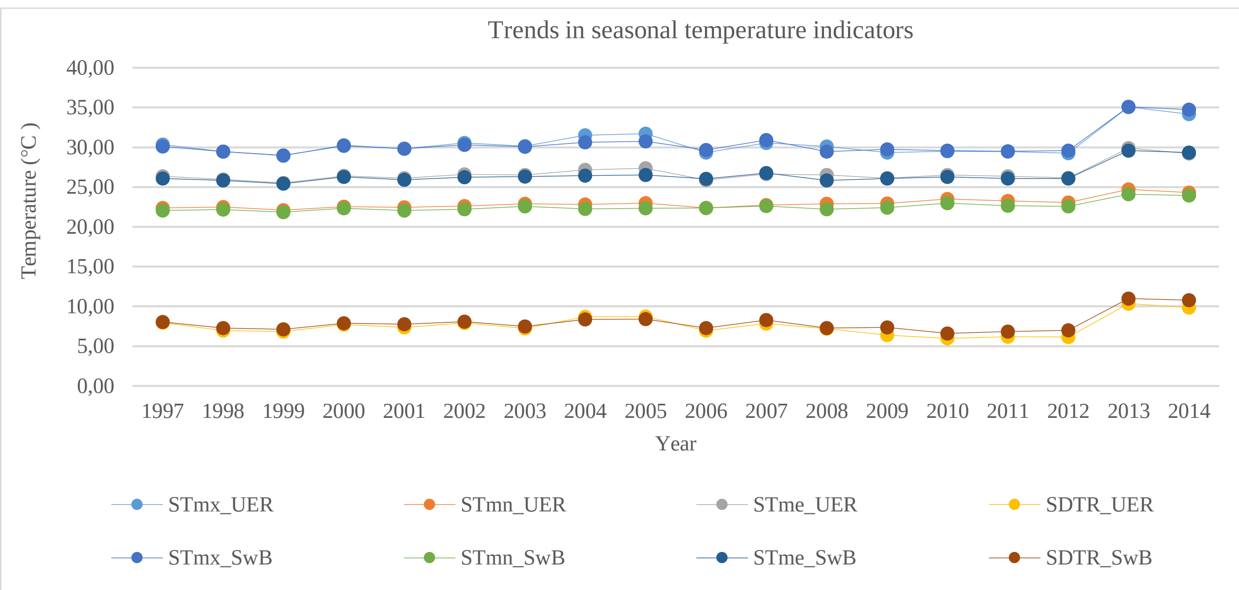
Source: Computed by author

Through computation of 5-year return values, and as shown in Table 2.5, it is found that Rx1-day threshold of at least 45 mm and Rx7-day threshold of at least 115 mm are exceeded in both regions in 1 out of 5 years.

2.4.5 Recent developments in seasonal temperatures

In assessing recent changes in seasonal temperatures, and based on Figure 2.5, we detect an increase in both normal temperature indicators (maximum, minimum, mean and diurnal temperature range) and indicators of extreme hot days (Tmx $\geq 32°C$) and hot nights (Tmn $\geq 24°C$). Increments in each of these seasonal temperature indicators over the period 2010-2014 are however majorly driven by extreme rise in each of the indicators over the period 2013-2014. For example, compared to the 18-year (1997-2014) mean estimate of 44 seasonal hot-days and 29 seasonal hot-nights, a total of over 90 extra seasonal hot-days and over 62 extra seasonal hot-nights were observed over the period 2013-2014 in Upper East Ghana. Compared to the mean estimates of 45 seasonal hot-days and 20 seasonal hot-nights for Southwest Burkina Faso, a total of over 95 extra seasonal hot-days and over 66 extra seasonal hot-nights were observed for the aforementioned period. Across both regions, besides a consistently increasing trend for seasonal minimum temperature, the other three normal temperature indicators remained generally stable between the years 1997 and 2012, but all four indicators rose sharply over the period 2013-2014. In Upper East Ghana for example, absolute deviations of 4.08°C, 1.55°C, 2.81°C, and 2.53°C from the 18-year mean estimates for seasonal maximum temperature (30.53°C), minimum temperature (22.95°C), mean temperature (26.74°C) and diurnal temperature range (7.58°C) were observed over the period 2013-2014. In Southwest Burkina Faso, respective deviations of 4.44°C, 1.48°C, 2.96°C, and 2.95°C from the 18-year mean for maximum temperature (30.48°C), minimum temperature (22.54°C), mean temperature (26.51°C) and diurnal temperature range (7.94°C) were observed.

In analyzing risk of hot day and hot night spells, we find May and October to be the riskiest months for long duration of hot day spell, and the month of May the riskiest for hot night spell (see Table 2.6). For Upper East Ghana, we estimate 22.2% and 38.9% chances for hot day spell to exceed 10 days in the months of May and October, respectively. For Southwest Burkina Faso, we estimate 33.3% and 38.9% chances respectively for May and October. August is found the least risky month for hot spell. Although risk of hot night spell is generally low across majority of the seasonal months, we estimate 38.9% and 16.7% chances for a 10-day duration of hot night spell to be exceeded in the month of May in Upper East Ghana and Southwest Burkina Faso, respectively.



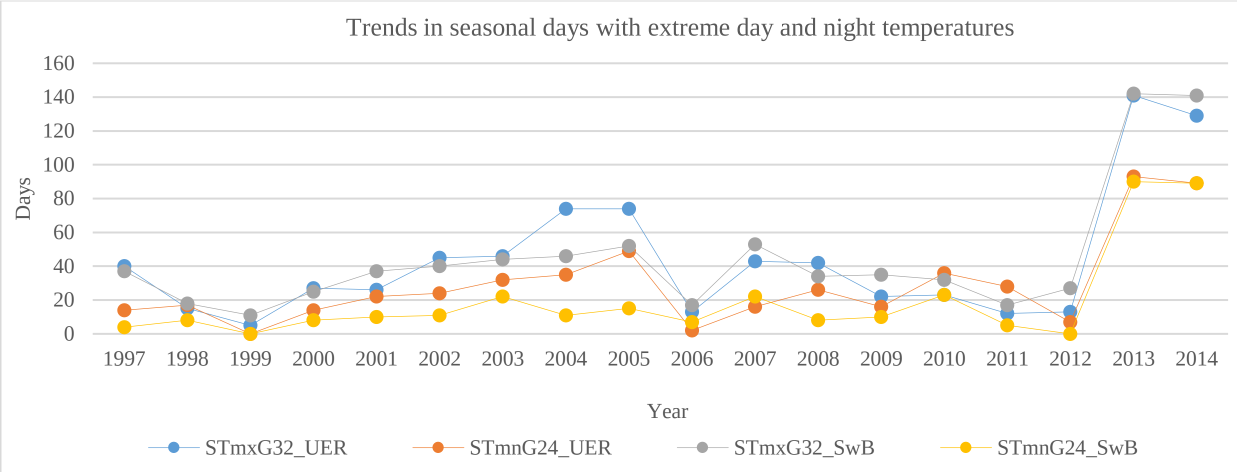


Figure 2. 5-Recent trends in indicators of seasonal temperature

NB: UER- Upper East Region of Ghana, SwB – Southwest Burkina Faso; STmx – seasonal maximum temperature; STmn – seasonal minimum temperature; STme -seasonal mean temperature; SDTR- seasonal diurnal temperature range; STmxG32 - seasonal hot days (Tmax≥32°C); STmnG24 -seasonal hot nights (Tmin≥24°C)

Source: Author's construct

Through computation of 5-year return values for hot spell, it is found that, July and August have relatively lower return values for hot day spell than the other seasonal months, while return values are relatively higher in May and October across both regions (see Table 2.7). Hot night spells are rarely observed in July, August and September. For the month of May however, 5-year return values of 14 days and 10 days are respectively estimated for Upper East Ghana and Southwest Burkina Faso.

Table 2. 6-Conditional monthly maximum consecutive hot days and hot nights

Indicators	Upper East Ghana				Southwest Burkina Faso			
	Mean	Median	Max	Std.Dev	Mean	Median	Max	Std.Dev
MCHD_May	7.78	4.50	31.0	7.39	9.72	7.50	30.0	7.95
MCHD_Jun	4.11	1.00	30.0	7.50	4.17	2.00	30.0	7.51
MCHD_Jul	1.89	0.00	15.0	4.80	1.56	0.00	14.0	3.91
MCHD_Aug	0.61	0.00	6.00	1.54	0.44	0.00	4.00	1.15
MCHD_Sep	1.61	0.50	7.00	2.03	1.61	1.00	9.00	2.33
MCHD_Oct	8.00	4.00	26.0	8.57	10.0	7.50	30.0	10.2
MCHN_May	7.61	6.00	19.0	6.07	5.28	3.00	19.0	5.31
MCHN_Jun	4.50	1.00	30.0	9.38	2.89	0.00	24.0	7.35
MCHN_Jul	1.11	0.00	11.0	2.85	0.83	0.00	8.00	2.28
MCHN_Aug	0.28	0.00	2.00	0.57	0.06	0.00	1.00	0.24
MCHN_Sep	0.06	0.00	1.00	0.24	0.06	0.00	1.00	0.24
MCHN_Oct	2.94	1.00	15.0	4.14	1.50	0.00	10.0	2.75
	% >5days	% >7days	% >10 days	% >21 days	% >5days	% >7days	% >10 days	% >21 days
MCHD_May	44.4	38.9	22.2	5.56	66.7	50.0	33.3	11.1
MCHD_Jun	11.1	11.1	11.1	5.56	16.7	11.1	11.1	5.56
MCHD_Jul	11.1	11.1	11.1	0.00	11.1	11.1	5.56	0.00
MCHD_Aug	5.56	0.00	0.00	0.00	0.00	0.00	0.00	0.00

MCHD_Sep	5.56	0.00	0.00	0.00	5.56	5.56	0.00	0.00
MCHD_Oct	44.4	44.4	38.9	5.56	55.6	50.0	38.9	16.7
MCHN_May	50.0	44.4	38.9	0.00	33.3	22.2	16.7	0.00
MCHN_Jun	11.1	11.1	11.1	11.1	11.1	11.1	11.1	11.1
MCHN_Jul	11.1	5.56	5.56	0.00	11.1	5.56	0.00	0.00
MCHN_Aug	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
MCHN_Sep	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
MCHN_Oct	16.7	16.7	5.56	0.00	11.1	5.56	0.00	0.00

NB: MCHD – conditional maximum consecutive hot days; MCHN – conditional maximum consecutive hot nights

Source: Computed by author

Table 2. 7-Return values for conditional monthly maximum consecutive hot days and hot nights

Region	Return period	MCHD_ May	MCHD_ June	MCHD_ July	MCHD_ Aug	MCHD_ Sept	MCHD_ Oct	MCHN_ May	MCHN_ June	MCHN _ July	MCHN_ Aug	MCHN_ Sept	MCHN_ Oct
Upper East GH	1 in 5 years	14.2	4.20	1.20	1.00	3.20	16.2	14.2	4.00	1.00	1.00	0.00	5.60
Southwest BF	1 in 5 years	15.4	3.60	2.00	0.20	3.00	22.0	9.80	1.20	0.20	0.00	0.00	2.20

Source: Computed by author

2.5 Summary and conclusion

Extreme weather events yield major adverse impacts on farming systems and households, notable amongst which are decreasing yields, income and consumption, and degradation of croplands. Despite research efforts made so far in the West African Sudan Savanna to inform production and policy decisions on measures needed to moderate harm from weather extremes, hardly has emphasis been placed on intra-seasonal risk of weather extremes. To bridge information and knowledge gap, we, through farm household survey, identified agriculturally-relevant weather extremes in Upper East Ghana and Southwest Burkina Faso, and using statistical and modelling techniques assessed intra-seasonal risk posed by such events.

Based on farmers' perception of major climatic threats to farming systems in the study area, we found drought, low rainfall, intense precipitation, flooding, erratic rainfall pattern, extremely high temperatures, delayed rains and early cessation of rains to be the major threats. Through assessment of recent changes in onset and cessation of rains, we found approximately 16 days' delay in onset of rains, 3 days' extension in cessation of rains, and 14 days decrease in effective length of the rainy season in Upper East Ghana over the period 2010-2014 compared to mean estimates for the period 1997-2014. In Southwest Burkina Faso however, onset occurred 2 days earlier, cessation dates remained generally stable and the effective length of the rainy season was extended by 3 days. To minimize chances of a shortened growth cycle for some of the crops, preclude exposure of drought-sensitive crops to risk of prolonged dry spell in the early stage of growth, and minimize general adverse yield implications of intra-seasonal risk of extreme weather events, farmers in both regions have not only started spreading their planting across the first three months of the season, but have generally resorted to late planting of drought-sensitive crops like maize, rice and groundnut to avoid exposing them to prolonged early season dry spell. Some of the farmers in Southwest Burkina Faso have also resorted to planting of first seeds of drought-hardy crops like sorghum and millet in April to take advantage of early rains. Each of these decisions stand yielding general adverse effects on crop growth and yields due to inherent nature of climatic risk in the rainy season. For farmers who sow in April in both regions, the conditional probabilities of their crops being exposed to 10 consecutive dry days in the next 30 days, assuming sowing is done on April 1st, is estimated at 34.6% and 26.9% respectively for Upper East Ghana and Southwest Burkina Faso. For those who engage in late planting, besides the high chances of seeds being washed away by intense precipitation events or flooding in July, August, or September, there is a high probability for exposure of late-planted crops to prolonged dry and hot day spells in the month of October, which may possibly coincide with the reproductive stage of such crops, bearing in mind a 3-6 months' growth cycle.

Across the two regions, and for the seasonal months, we found the months of May, June and October to be the most prone to relatively longer duration of dry and hot spells, while July, August and September were found the most prone to intense precipitation and seasonal flooding. From these, we conclude that, climatic risk is a general inherent attribute of the transitional (April) and seasonal (May-October) periods in the West African Sudan Savanna. Through monitoring of mean and median onset dates, and the probability of varied dry spell lengths, we recommended planting of crops between 23rd and 25th May in Upper East Ghana, and between 21st and 24th May in Southwest Burkina Faso. Although planting on these dates is deemed relatively safer due to minimized chances of prolonged dry spell, the probability of dry spell lasting 5 to 7 consecutive days is still high. It was found that dry spells across majority of the seasonal months are not necessarily prolonged by nature, but rather short-lasting and repetitive. Interspersion of such repetitive spells by high intensity rains, especially in the months of July and August could prove harmful to crop growth, as these months generally coincide with the early vegetative, late vegetative and/or reproductive stages for majority of the crops grown in the area. For observance of appreciable yields or moderation of harm from weather extremes across the two regions, farmers need to adopt a mix of risk management strategies. These may include adjusting their cropping calendar, planting appropriate crop varieties (*based on production and environmental conditions in the respective locations and on anticipated weather conditions, founded either on seasonal weather forecasts or traditional knowledge*), and implementing soil and water management practices. This would help to minimize exposure and sensitivity of crops to prolonged dry and hot spells in the early and latter stages of the season, reduce evaporation and minimize effects of recurrent flooding between July and September. Efforts made by researchers to provide farmers with accurate and timely weather forecasts may help to minimize adverse effects of weather extremes (Sivakumar and Motha 2007). Weather forecasts could guide farmers in their crop and variety selection, timing of planting, input management, and harvesting among other cultural practices (Crane *et al.* 2010). In addition to these, there may be a need for supplemental irrigation to ensure availability of enough water to meet crop requirements in the early and latter stages of growth. We recommend that policy makers and other stakeholder invest in/install low cost irrigation facilities to enhance the practice by farmers. This could help to moderate harm from diverse manifestations of weather extremes, especially dry and hot spells.

Chapter 3

3 Analysis of farmers' perception of and adaptation to weather extremes in West African Sudan Savanna[8]

3.1 Introduction

Agricultural productivity in the Sudan Savanna zone of West Africa has in recent decades been hindered by diverse technological, institutional, and infrastructural constraints. These constraints have already taken a toll on production outcomes and is reflected by low productivity of farming systems and high yield gaps for the major crop species cultivated in the area (Chauvin *et al* 2012; MoFA 2013). Despite policy and research efforts made to overcome low productivity of crop fields, there is not much evidence of success (Walker *et al* 2016). While investors, policy makers and researchers continue to battle with production challenges posed by persisting constraints, increasing frequency, intensity and duration of weather extremes stand further reducing the already low observed yields and meagre farm incomes. This could, in the medium to long-term, lead to a reduction in food availability and access, and increased poverty. Enhancing farmers adaptive capacity, could, to a greater extent help to minimize adverse agricultural impacts of weather extremes. Adaptive capacity enhancement, however, requires appropriate identification of barriers to adaptation and the implementation of pro-active measures to overcome such barriers. In this study, we analyze farmers' adaptation to recent weather extremes in West African Sudan Savanna, and make policy recommendation on measures needed to build resilience in the region and other regions that share similar attributes with the current study area.

Farming in the study area is dominated by the rural poor, small-scale and subsistence farmers (Terrasson *et al* 2009). These farmers produce mostly on marginal lands with inherent terrain and poor soil fertility constraints (Laube *et al* 2012). Majority of the farmers have limited access to input and output markets, limited access to credit (Tambo and Abdoulaye 2013), limited access to weather-related information and water resources, and do face high cost of production (Ndamani and Watanabe 2015). Above all these, farmers in the study area rely heavily on rain for appreciable yields (CGIAR 2013). Given these attributes, increasing incidence of extreme weather events, amidst low adaptive capacity of farmers (Tambo and Abdoulaye 2013), could at the farm-level, exacerbate production and livelihood challenges by causing further reduction in crop yields and current meagre farm incomes. Besides this, climatic shocks could impact on the limited asset base of farmers and trigger distress sale of productive assets, thereby reducing future investment capacity (Nelson *et al* 2007; Bryan *et al* 2009). Such localized impacts could yield regional and national ramifications. Among the likely macro-level effects are reduced regional and national agricultural production, increasing food prices due to reduced supply, increasing land values due

[8] A version of this chapter has been published in Weather and Climate Extremes (http://dx.doi.org/10.1016/j.wace.2017.03.001)

to scarcity of fertile lands, general modification of trade and investment patterns, depletion of savings, and increasing hunger (FAO 2016).

A number of studies have been conducted in the study area to assess farmers' adaptation to changing local climatic conditions, and recommendations made towards minimizing potential effects of climate change, variability and extremes at local, regional and national levels (e.g. see Tambo and Abdoulaye 2013; Antwi-Agyei *et al* 2014). Besides being generally qualitative in nature, majority of the studies conducted so far have either looked at on-farm and off-farm (coping) strategies (e.g. Antwi-Agyei *et al* 2014), or jointly documented adaptation strategies and barriers without placing emphasis on dimensions[9] (e.g. Tambo and Abdoulaye 2013). With the few that placed emphasis on dimensions, hardly were the differences in resource requirements considered in formulating such dimensions. Plausible interdependencies among strategies were as well not explored. With the few that explored interdependencies among adaptation strategies (e.g. Tambo 2016), emphasis was placed on establishing spatial differences in resilience to climate extremes using climate resilience index, and in generally assessing determinants of the number and choice of adaptation strategies. In the global literature, although a lot of research has been done to inform policy decision on measures needed to enhance farmers' adaptive capacity (e.g. see Hassan and Nhemachena 2008; Bryan *et al* 2009; Deressa *et al* 2009; Harvey *et al* 2014; Uddin *et al* 2014; Ngigi *et al* 2017), to the best of our knowledge, very little (if any) has been done to identify adaptation strategies, analyze determinants, predict joint and marginal probabilities of adoption of strategies, and explore interdependencies along critical dimensions. In addition, very little[10] has been done to capture the effect of weather extremes on farmers' adaptive behaviour. Bridging of this research gap could prove very useful for policy and investment decisions in the study area and at the global level.

In this study, and to complement efforts made so far (e.g. Antwi-Agyei *et al* 2014; Tambo 2016; Mulwa *et al* 2017), we identify and assess adaptation strategies, their determinants, probabilities and interrelations under two primary headings; direct measures and supportive measures. Conceptually, direct measures refer to varietal and crop-related adjustments made by farmers, which generally demand low cash outlay in the medium to long-term, but with a probable high initial investment in required inputs and with a high potential for preserving majority of such inputs for future use. Supportive measures on the other hand refer to insurance based and/or stress-reducing measures implemented by farmers, which generally demand relatively high cash outlay in the medium to long-term, with both low and high probability of high initial investment, and may require repeated application both within and between seasons for effectiveness.

[9] Dimension in this context refers to analysis of adaptation and interpretation of outcomes in a particular direction, placing emphasis either on time, place, input requirements, or costs on a broader perspective

[10] Besides the use of perception on experienced climatic shocks as proxy for incidence of weather extremes (e.g Bryan *et al* 2009; Rakib 2015; Ngigi *et al* 2017)

Adoption of strategies under the respective measures could be enhanced through the undertaking of initiative, or collective action (joint effort) (Ringler *et al* 2014; Rakib 2015; Ngigi *et al* 2017), or both.

Upon the presumption that adaptation involves a multistage process of signal detection and response (Maddison 2006), we first analyze farmers' perceptions of recent changes in climatic conditions (and validate this with climate data), and assess the factors that influence their perceptions. We then explore farmers' adaptation to changes in the local climate, analyze determinants of the number and choice of adaptation strategies implemented, joint and marginal probabilities of adoption within and between measures, and explore prevailing within-measure and between-measures complementarities and substitutions. We analyze the determinants of farmers' perceptions, adaptation strategies, probabilities, and interdependencies using a multivariate probit model, and analyze determinants of the number of strategies implemented using a Poisson regression. This study uses data obtained from 450 heads of farm households in Upper East Ghana and Southwest Burkina Faso. These two regions were selected due to extreme reliance of the inhabitants on agriculture for sustenance, dominance of rural population in the respective regions, their limited use of irrigation facilities, and their recent exposure to various extreme weather events. In this study, we define extreme weather events as events that have extreme values of certain important meteorological variables (e.g. rainfall and temperature, Stephenson 2008). We make use of both primary data (gathered through a household survey between October 2014 and July 2015) and historical daily climate data extracted from NASA's Climatological database. In all, 29 communities were covered across 7 districts in the two regions. To effectively address the goals of this research, we aimed at answering the following research questions:

1. What are farmers' perceptions of climatic conditions in the study area, and which factors influence these perceptions?
2. Which direct and supportive measures of adaptation have farmers implemented following recent exposure to weather extremes?
3. Are there significant within-measure and between-measures interdependencies among the strategies used?
4. What are the relevant determinants of the number and choice of adaptation strategies used?
5. What are the chances for the average farm household to adopt each of the revealed adaptation strategies, all adaptation strategies, strategies deemed direct measures, and strategies deemed supportive measures?

The remaining sections of this chapter are organized as follows. In section 3.2, we provide a review of relevant literature on adaptation to climate change, variability and extremes, and explicitly state contribution of the current study. We then provide a conceptual framework on which this study is founded in section 3.3. Methods are covered in section 3.4. Under methods, we provide brief information on sampling and data, analytical framework, and descriptive statistics on variables. We then present results and discuss relevant findings in section 3.5. In section 3.6, we draw conclusion and make relevant policy and stakeholder recommendations.

3.2 Literature review and contributions of the study

3.2.1 Adaptation to climate change, variability and extremes: a review

Climate change is a reality and adaptation a necessity (Porter *et al* 2014). As a complex, multidimensional and multi-scale process, adaptation to a changing climate has been studied at local, regional, national and global scales (e.g. see Biagini *et al* 2014; Robinson 2017). From a global perspective, adaptation strategies have been analyzed based on the timing relative to stimulus (as anticipatory, concurrent, or reactive), intent (autonomous or planned), spatial scope (local, regional or national), form (technological, behavioral, financial, or institutional) and degree of change (gradual (incremental) or transformational) (Biagini *et al* 2014). At the national, regional and community levels, other researchers (including Smit *et al* (2000) and Cutter *et al* (2008)) have analyzed adaptation based on the driver of action (disaster, climate variability, and climate change), while at the household and/or group levels, emphasis has been placed so far on documenting farmers' perceptions of changes in local climatic conditions, responses (adaptation) and barriers to effective adaptation (Deressa *et al* 2009; Harvey *et al* 2014). Given the objectives of this study, we focus more on findings from adaptation studies at the household and/or group levels, as the latter contributes towards enhancing adaptation at the former level (Ringler *et al* 2014; Ngigi *et al* 2017). We place emphasis on farmers' adaptation strategies and constraints due to presumed higher vulnerability of farmers to climate change, variability and extremes.

Climate change adaptation at the household level is enhanced through the undertaking of initiative by the household head or through collective (joint) efforts by members of the household (Rakib 2015). Besides this, participation in farmers' and other community-based organization facilitates adoption of relevant adaptation strategies, especially in terms of adoption of high cost measures like irrigation and soil and water conservation practices (Sidibe 2005; Rakib 2015). Through research efforts, diverse strategies implemented by farmers to moderate harm from prevailing and anticipated climatic conditions have been identified and documented. Among the common strategies identified in sub-Saharan Africa and other developing regions worldwide are crop production strategies like changing planting dates, crop diversification, adoption of improved crop varieties, soil and water conservation, water drainage, small-and large-scale irrigation, and agroforestry (e.g. see Barbier *et al* 2009; Deressa *et al* 2009; Bryan *et al* 2013).

A study by Below *et al* (2010) found a total of 104 climate change adaptation practices across Africa, the Americas, Europe and Asia. Although very little has been documented so far on adaptation strategies in relation to livestock production, studies by Benhin (2006) in South Africa, Rakib (2015) in Bangladesh and Ngigi *et al* (2017) in Kenya found changes in livestock breed, changes in livestock feeding practices, de-stocking, changes in animal portfolio, and veterinary interventions to be the major strategies adopted by livestock producers.

Adaptation is generally preceded by perception and/or awareness of changes in the local climate (Maddison 2006), and strategies implemented by farmers are influenced by diverse climatic, socio-economic, institutional, cognitive, locational, plot-level, and infrastructural measures (Deressa *et al* 2009; Nhemachena *et al* 2014; Ngigi *et al* 2017). A common perception held by farmers across majority of the adaptation studies on observed changes in the local climate are increasing temperature, decreasing rainfall and erratic rainfall pattern (e.g. see Bryan *et al* 2009; Tambo and Abdoulaye 2013). Whereas strategies like changing planting dates, crop diversification and use of improved crop varieties are generally regarded as low cost measures (e.g see Harvey *et al* 2014; Fisher *et al* 2015), others like irrigation, soil and water management practices (e.g. subsurface drainage) and agroforestry are regarded high cost measures (e.g see Bryan *et al* 2013; Palanisami *et al* 2015). Among the major constraints to farmers adoption of climate change adaptation strategies are limited availability of accurate climate forecasts, limited access to extension services, insecure land tenure, limited access to credit, limited access to markets, limited supply of labor, small farm size, poor soil fertility, poor management, lack of capital, high transaction cost, and lack of awareness and technical skills (Fisher *et al* 2015; Palanisami *et al* 2015; Mulwa *et al* 2017).

In analyzing farmers adaptation to a changing local climate, some researchers make use of perceptions held by farmers on their experience of climatic shocks as proxy for weather variables (e.g. see Bryan *et al* 2009; Ngigi *et al* 2017), others make use of either long-term average climate estimates or mean temperature and rainfall for the agricultural season preceding the survey (e.g. Deressa *et al* 2009; Asfaw *et al* 2015), while in other studies (including Belay *et al* 2017), effects of climate/weather variables are completely ignored. Whereas the use of perceptions as proxy for weather variables is flawed by a potential distortion of farmers' memory of changes in local climatic conditions (Hansen *et al* 2004), the use of long-term means or average weather conditions precludes appropriate identification of farmers' adaptation to relevant weather attributes like changes in the frequency and variability of rainfall, timing and intensity of seasonal rains, and extremes in seasonal temperatures among other climatic conditions. Although given limited attention so far in adaptation studies, incidences of weather extremes (including temperature extremes and the frequency and distribution of rainfall within a season) influence farmers' adaptive behavior (Bryan *et al* 2009). While adaptation involves incurrence of costs, thereby limiting adaptive capacity of majority of the poor and already vulnerable farmers, expected cost for non-adoption is reportedly higher (Porter *et al* 2014; Palanisami *et al* 2015).

3.2.2 Contributions of the study

Temperature extremes, decreasing rainy days and variability in intra-seasonal rainfall are well known threats to food crop production in developing countries due to high dependence of such countries on rain-fed agriculture. Yet, effects of these weather indicators on adaptation decisions are rarely captured in farm-level and regional adaptation studies in these countries. In this study, we assess the effects of extremes in daily maximum temperature, changes in rainy days, intra-seasonal rainfall variability and other relevant plot characteristics, socio-economic, institutional and infrastructural, and location variables on the intensity and choice of adaptation strategies adopted by farmers. Although adaptation to climate change holds at the individual/farm household, group[11] (or community/village), regional, national[12] and/or global levels[13], emphasis is placed in this study on farm household adaptation to weather extremes. We focus on adaptation strategies implemented by the entire farm household, as expressed by the head of the household. Conceptually, a household refers to a group of people "*who share the same living accommodation, pool some or all of their income and wealth, and consume certain types of goods and services collectively, mainly, housing and food*" (UNECE/FAO/OECD/World Bank/Eurostat 2007). A farm household consequently refers to a household that is attached to a farm where some farm income is earned for upkeep of the household. Through this analysis, the present study contributes to literature on climate change adaptation in four key ways.

- We go beyond the usual analysis of adaptation to changes in long-term climatic conditions, and focus more on recent incidence of weather extremes and erratic nature of intra-seasonal rainfall.
- In addition, and per experience and evidence in literature on differences in input requirements and potential costs involved in implementing alternative adaptation strategies (e.g. Barbier *et al* 2009; Lybbert and Sumner 2012; Harvey *et al* 2014; Fisher *et al* 2015; Palanisami *et al* 2015), we analyze farmers' adaptation to weather extremes under two primary headings; direct measures and supportive measures. This enables grouping of implemented strategies based on their nature (varietal/crop related adjustment or not), presumed cost[14] of implementation, and frequency of application. This as well enables identification of differential effects of climatic, socio-economic, plot-level, locational, and institutional and infrastructural variables on the respective strategies

[11] Based on collective action
[12] Based on government initiatives, research (e.g. breeding) and other public and private (donor) investment efforts
[13] Through international negotiations
[14] Due to our inability to access accurate information on strategy-specific administrative, investment and transaction costs from farmers (as in Palanisami *et al* 2015), we depend on literature for the cost-based grouping

implemented under the two primary measures. Through this grouping, we can identify common factors that inhibit (or enhance) adoption of potential low cost measures or high cost measures or both. Although livestock adaptation strategies like changes in livestock breeds, changes in livestock feeding practices, de-stocking, changes in animal portfolio, and veterinary interventions are reported in other studies (e.g. Benhin 2006; Rakib 2015; Ngigi *et al* 2017), there are no reports of such measures in the current study area. Hence, more emphasis is placed on adaptation strategies that are related to crop production.

- Whereas most studies focus on adaptation within a single country or region, two vulnerable regions in two different (but neighboring) countries are considered in this study
- To the best of our knowledge, this is the first study conducted in West Africa where adaptation is analyzed along cost-related dimensions, interdependencies among strategies explored, and joint and marginal probabilities of adoption estimated at the same time.

3.3 Conceptual framework

In a given location, farmers usually adjust to gradual changes in climatic conditions with a mindset of either moderating harm from such changes or exploiting beneficial opportunities. When exposed to extreme events, adjustments made are primarily aimed at reducing the actual adverse effects from current exposure or anticipated effects from future exposition (Smith *et al* 2000). Given the focus of this study, we define adaptation as the implementation of measures by farmers based on their recent exposure to weather extremes and with a purpose of reducing actual and/or anticipated effects of future weather extremes. Farming systems are generally exposed to two distinct climatic challenges: challenges related to changing dynamics of weather shocks and challenges related to long-term shifts in relevant climatic indicators for a given location (temperature, rainfall patterns, etc.) (Baez *et al* 2012). Impacts of climate change, variability and extremes on farming systems are therefore yielded either through shifts in long term means or climatic shocks. We place emphasis however on the latter.

Depending on exposure and sensitivity of farming systems to such shocks, low crop yields and farm incomes are usually observed, farm lands are in some cases destroyed or degraded, access to input and output markets becomes limited, changes in water supply for production and for domestic use are usually observed by virtue of either overflow (in times of intense precipitation and/or flooding) or scarcity (in times of droughts and extreme heat), and prices of inputs and outputs become highly volatile. Effects are usually more pronounced on the poor rural households, who are more vulnerable to climatic shocks and have limited access to safety nets and other channels of relief. Vulnerability of farming systems to recent and anticipated shocks however depends on cropping patterns and species, innovativeness of farming systems, and prevailing economic, demographic, production, marketing, terrain, and institutional constraints. Based on needs of the respective farm households, available resources, availability of institutions and infrastructure, changing trends in critical climatic variables, geographic pressures (location, elevation, etc.), and plot characteristics, farmers make relevant adjustments in their production to help moderate harm. At the farm-household level, and as shown in Figure 3.1, the main production-related adjustments made by farmers can be categorized into direct and supportive measures.

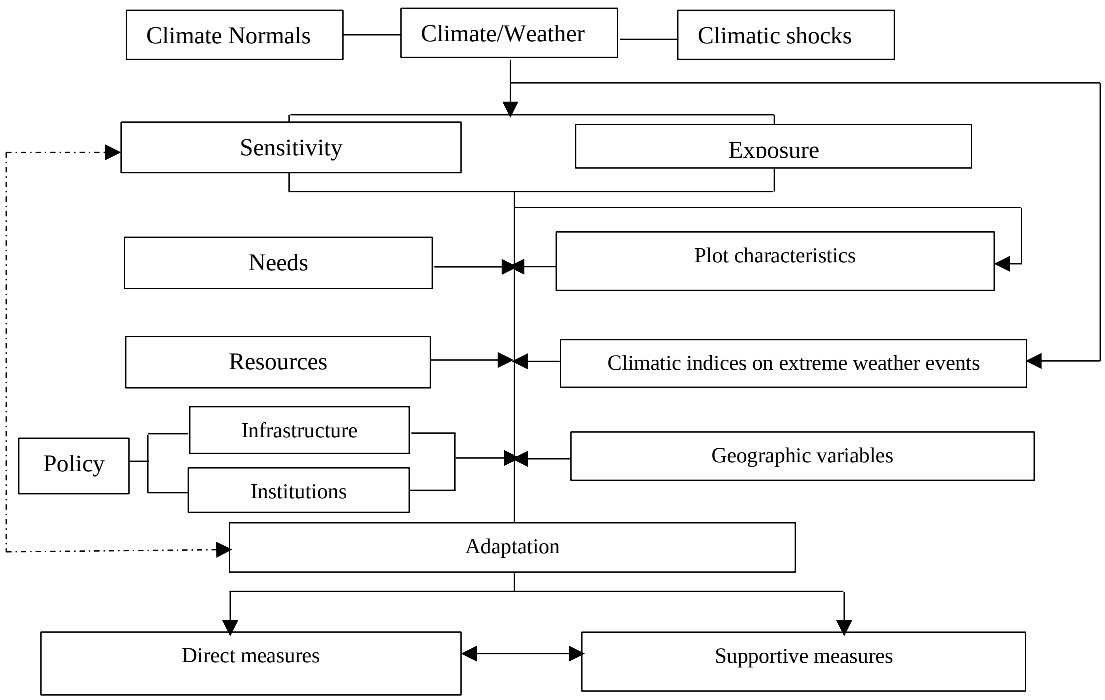


Figure 3. 1-Drivers of farmers' adaptation to weather events
Source: Author's construct

In contrast to the mutual exclusivity assumption held by various researchers regarding choice of farmers' adaptation to climate change (e.g. Hassan and Nhemachena 2008; Deressa *et al* 2009), farmers tend to implement multiple strategies that serve multiple purposes and are strongly interrelated (Smit and Skinner 2002; Mulwa *et al* 2017). Farmers' sensitivity to recent weather extremes influences their decision on whether (or not) to adapt and the number and choice of strategies employed, while their sensitivity to future climatic shocks depends on effectiveness of current measures implemented (Karfakis *et al* 2012).

3.4 Methods

3.4.1 Data and sampling

Upper East region of Ghana and Southwest Burkina Faso are the two regions covered in this study. The study is based on data gathered through a household survey between October 2014 and July 2015 across the two regions, and daily climate data (for 1997-2014) extracted from NASA's Climatological database. For data extraction, we made use of centroid GPS coordinates for each of the 29 communities covered across the two regions. We focused on daily temperature and rainfall data. Data gathered through the survey include farmers' perception of changes in climatic conditions over the period 2005-2014, socio-economic and demographic attributes, institutional and infrastructural constraints, farm (plot) characteristics, cropping and livestock production during the 2014 agricultural season, and farmers' adaptation to recent weather extremes. A multi-stage random sampling technique was used in gathering data across the regions. A total of 5 districts were randomly selected from the 13 in Upper East Ghana and 2 out of 4 provinces in Southwest Burkina Faso. Using pre-tested questionnaires, heads of 300 selected households in Upper East Ghana and 150 in Southwest Burkina Faso were interviewed by trained research assistants under supervision of the author. Apportioning across the regions and districts was based on differences in population density, level of engagement in agriculture and recent exposure to extreme weather events (based on information obtained from the local Ministry of Agriculture). The 5 districts covered in Upper East Ghana are Bolgatanga Municipal (90 households), Kassena Nankana East (70 households), Kassena-Nankana West (60 households), Nabdam district (40 households) and Talensi district (40 households). The two provinces covered in Southwest Burkina Faso are the Ioba province (105 households across Dano, Dissin, Ouessa and Koper departments) and Bougouriba province (45 households across Diébougou, Bondigui and Iolonioro departments)

3.4.2 Analytical framework

Climate and weather risks are among the leading threats to the agriculture sector in most of the countries in sub-Saharan Africa due to high dependence of majority of the rural households in this location on rainfed agriculture for sustenance (Haile 2005). While productivity of farming systems in this vulnerable region is deemed low due to high yield gaps for the dominant crops (Nin-Pratt *et al* 2011; Tittonel and Giller 2013), increasing variability of seasonal distribution of rainfall and incidences of seasonal temperature extremes could trigger further reduction in the already low yields and farm incomes due to an increase in the risk of moisture stress among other inter- and intra-seasonal climatic perturbations (Lobell *et al* 2008). This could have dire consequences on farmers' welfare, and the entire rural and urban population. In effort to minimize the adverse effects of weather-related risks on farm household welfare, several risk-minimizing strategies have been promoted over the years, although their adoption by farmers has been generally low due to limited resources and capacity (Ranganathan *et al* 2010; Harvey *et al* 2014). Adoption of climate change adaptation strategies by farmers depends not only on the availability of the strategies, but also on their accessibility and affordability (Komba and Muchapondwa 2015). These three factors (availability, accessibility, and affordability) generally dictate farmers' awareness, adoption and intensity of adoption, and benefits derived from adopting various adaptation strategies. Thus, a given farmer is likely to adopt a technology only if that technology is available, accessible, affordable and beneficial (de Janvry *et al* 2010).

A farmer's adaptation decision is therefore governed by a utility maximization framework in the presence of risk, whereby the farmer is assumed to implement a strategy only if the expected utility minus the cost of adoption exceeds the expected utility for non-adoption of the strategy (Finger and Schmid 2007). Thus,

$$A_i = \begin{cases} 1 & if\ E\big(U(\pi_{I=1})\big) - V_c > E\big(U(\pi_{I=0})\big) \\ 0 & otherwise \end{cases} \qquad (3.1)$$

Where A_i represents farmer's adoption decision regarding strategy i, V_c is a representation of variable costs of adoption, and π_I, the quasi-rent (revenue minus variable costs). Presented with alternative strategies however, a risk-averse farmer may choose a strategy, Q, that yields higher expected utility than any of the other alternatives, say R. i.e.

$$E\big(U_Q\big) - M_Q > E(U_R) - M_R \qquad (3.2)$$

From equation (3.2), $E\big(U_Q\big)$ represents the expected utility of implementing strategy Q and the associated costs M_Q, while $E(U_R)$ and M_R are the corresponding representations for strategy R. As pointed out by Cameron and Trivedi (2005) however, the utility function for each of the strategies is only partially observed, and the partially observable utility attached to each of the adaptation strategies $s = 0,1, \dots, S$ by a farmer can be expressed as

$$\begin{aligned} U_0 &= \varepsilon_0 \\ U_1 &= X\beta_1 + \varepsilon_1 \\ U_2 &= X\beta_2 + \varepsilon_2 \qquad (3.3) \\ &\dots\dots\dots \\ U_S &= X\beta_S + \varepsilon_S \end{aligned}$$

Where $s = 0$ indicates non-adoption of any of the strategies by the farmer, and $s = 1,2, \dots, S$ indicates the alternative strategies from which the farmer chooses; X is a vector of factors that influence the farmer's choice of a particular strategy, $\beta's$ are unknown parameters to be estimated, and $\varepsilon's$ are error terms assumed to be independent from each other. Whereas majority of the earlier studies presume farmers' adaptation decisions to be mutually exclusive, the adoption of adaptation strategies could in general be path dependent (Mulwa *et al* 2017), whereby earlier adopted strategies inform decisions on subsequent practices. Thus, instead of choosing a single strategy among alternatives, farmers usually adopt a mix of strategies in a substitutive or complementary manner, the latter of which is reported to yield synergistic effect[15] (e.g. see Teklewold *et al* 2016; Asayehegn *et al* 2017; Leal Filho *et al* 2017) and the adoption of a relatively higher

[15] The interaction of two or more strategies so that their combined effect is greater than the sum of their individual effects.

number of strategies reported to yield greater benefits (in terms of income, food security, poverty reduction,etc.) than adoption of fewer strategies (Ali and Erenstein 2017). The synergistic effects from adoption of multiple strategies have been attributed among other things to differences in the nature of risks to which the alternative strategies are purposed on minimizing (curbing). For example, farming systems could be exposed to both dry and hot spells at the same time, or to interspersion of successive dry periods by high intensity rain. Similarly, crop fields could be exposed to drought, extreme heat and flooding within the same season, leading to major yield, income and consumption losses. The joint occurrence of such events necessitates the adoption of diverse strategies to help minimize losses to the poor rural households who strongly depend on agriculture. For example, whereas a farmer could adopt drought tolerant varieties, heat tolerant varieties or practice irrigation to help minimize drought and heat stress, implementation of water drainage and soil conservation techniques or adoption of flood tolerant varieties could prove useful in minimizing adverse effects of seasonal flooding and waterlogging. In addition, joint adoption of some (or all) of the aforementioned strategies with water conservation techniques could as well prove beneficial in times of seasonal rainfall deficit, although this may involve the incurrence of a relatively high cost. Joint adoption of beneficial strategies could help to minimize adverse effects of overlapping weather-related constraints to production (Khanna 2001; Teklewold *et al* 2016). This indicates a need to promote the adoption of multiple strategies (as a package) rather than emphasizing the adoption of individual strategies. Promoting adoption of diverse strategies requires identification of the determinants of the choice of strategies implemented by farmers, as well as the drivers of the number of strategies implemented.

In identifying major determinants of the number of strategies implemented by the respective farm households in the study area, we employed a Poisson regression model due to the count-nature of the dependent variable. The model used is expressed as follows (Tambo 2016):

$$\mathrm{A_{NSi}} = \beta \mathrm{X_i} + \varepsilon_\mathrm{i} \qquad (3.4)$$

Where A_{NSi} is the number (N) of adaptation strategies (S) implemented by household i, X_i is a vector of socio-economic, plot level, institutional and infrastructural, climatic, and location variables, and ε_i represents the corresponding random errors. The variables considered in this study are gender, age and education of household head, percent of household income from non-farm sources, potential labor capacity of household, group membership, number of family members (18-65 years) living within 5km from main residence, number of family members abroad, land ownership, access to credit, access to crop-related extension services, distance to nearest market, total cropland area, perceived fertility of crop fields, units of livestock owned at the beginning of the year 2014, total value of farm implements, average seasonal rainy days, intra-seasonal rainfall variability, average seasonal days with maximum temperature of at least 32°C, and a regional dummy. In contrast to the use of total seasonal (or annual) rainfall in other studies (e.g. see Deressa *et al* 2009; Asfaw *et al* 2015), we made use of rainy days and intra-seasonal rainfall variability as indirect measures of persistence of dry spell and uncertainty with monthly rainfall accumulations and seasonal distribution of rains. Increasing rainy days indirectly mean decreasing dry days and consequent decrease in persistence of dry spell. On the other hand, high coefficient of variation for intra-seasonal rainfall distribution reveals a more erratic nature of intra-seasonal rainfall and increasing chances for incidence of drought and flooding in the same season. This could lead to a reduction in efficiency of nutrient utilization by crops and increased chances of crop failure. Farmers' are usually more concerned about the number of days on which they receive rain and in the distribution of seasonal rainfall. Having high seasonal rainfall and intensity, but with poor distribution yields no major benefit to farmers. All the explanatory variables are grouped into seven broad categories, namely: household characteristics; social capital; institutional and infrastructural variables; plot characteristics; physical and financial assets; climatic variables; and location variables.

For a deeper insight into farmers' adaptation to extreme weather events, we also analyze determinants of the specific strategies implemented by the respective households. Based on presumed interdependencies among adopted strategies, we use a multivariate probit model. The model can be specified as follows:

$$\mathrm{A_{is}}^* = \beta_s \mathrm{X_{is}} + \varepsilon_{\mathrm{is}}\,, \qquad s = 1, \ldots\ldots, S$$

$$\mathrm{A_{is}} = \begin{cases} 1 \text{ if } \ \mathrm{A_{is}}^* > 0 \\ 0 \quad \text{otherwise} \end{cases} \qquad (3.5)$$

From equation (3.5), A_{is} is the adoption of strategy *s* by household *i*, while $A_{is}{}^*$ represents the latent propensity for the respective households to adopt strategy *s* (Tambo 2016). Using multivariate probit model, we estimate influence of the explanatory variables on each of the adaptation strategies, and at the same time account for systematic correlations of unobserved and unmeasured factors across identified strategies. Failure to account for this, as noted in univariate probit and multinomial logit models, could lead to biased and inefficient estimates whenever significant correlations exist (Lin *et al* 2005). From equation (3.5), positive correlations between the ε_{is} over adaptation strategies indicate complementarity between strategies, while negative correlations reveal substitutability. The error term, ε_{is}, has a multivariate normal distribution, with zero mean, unitary variance and an $n\times n$ correlation matrix (Mulwa *et al* 2017). In analyzing the determinants of adaptation strategies, we estimate three models; one for direct measures, one for supportive measures, and a joint model for both measures. The latter is however used as the primary model for this study, as it facilitates exploration of both within- and between-measures complementarities and substitutions. Estimation of three different models facilitates the prediction of joint and marginal probabilities for adoption of direct measures, supportive measures, and both measures.

Prior to estimating the respective models on farmers' adaptation strategies and intensity however, we first explore the perceptions held by farmers on recent changes in the local climate and analyze the determinants of such perceptions. Descriptive statistics are used for the exploration, while the determinants are analyzed using a multivariate[16] probit model. Based on findings from an extensive review of literature on farmers' perception of climate change (including Gbetibouo 2009; Deressa *et al* 2011), a subset of the explanatory variables from equations 3.4 and 3.5 are used for the perception analysis.

3.4.3 Descriptive statistics on variables

In this section, we provide a brief description of both the explanatory and explained variables. A total of 12 adaptation strategies were reported by farmers across the two regions; 6 direct measures and 6 supportive measures. The reported direct measures are crop diversification, planting of drought tolerant, flood tolerant, heat tolerant, and early maturing varieties, and changing planting dates (see Table 3.1). The reported supportive measures are practice of crop-livestock mix, purchase of crop and livestock insurance, practice of irrigation, and the use of water conservation, water drainage, and soil conservation techniques. Across the 12 strategies however, soil conservation techniques, changing planting dates, crop-livestock mix, crop diversification and planting of early maturing varieties are found to be the major adaptation strategies implemented by farmers. With regards to the number of strategies implemented by a representative household, a mean of 7.27 strategies (with standard deviation of 2.09) is estimated for the two regions; 6.80 (std. dev 1.80) and 8.22 (std. dev 2.31) for Upper East Ghana and Southwest Burkina Faso respectively. Approximately 88% of the interviewed heads of the respective households were males. A representative household head in the study area is about 50 years old, with 3 years of schooling, and earns about 31% of household income from non-farm sources. Composition of the average household is equivalent to 5 men. Farmers have weak social capital/network on which they can rely in times of shock. As shown in Table 3.1, the average number of relatives between 18-65 years old living within 5km from the main residence on whom a farmer can depend for cash and/or in-kind support when need arises is estimated at approximately 2 people, with similar approximate value estimated for the number of family members abroad from whom household receives remittances. In this study, family members living abroad refers to the number of relatives living either outside of the country or in a city in the country from whom household receives remittances. Beside these, approximately 41% of the interviewed farmers claimed membership in farmer organizations.

[16] This is based on the presumption that perceptions held by farmers regarding the respective weather variables could be correlated (Gbetibouo 2009).

Table 3. 1-Descriptive statistics on variables

Variable	Units	Mean	Std Dev
Dependent variables			
Number of strategies implemented (Numb. strategies)	Count of strategies	7.273	2.094
Direct measures			
Crop diversification (Crop Diver)	Dummy=1 if yes, 0 otherwise	0.838	0.369
Planting of drought tolerant varieties (Drought TV)	Dummy=1 if yes, 0 otherwise	0.596	0.491
Planting of flood tolerant varieties (Flood TV)	Dummy=1 if yes, 0 otherwise	0.413	0.493
Planting of heat tolerant varieties (Heat TV)	Dummy=1 if yes, 0 otherwise	0.369	0.483
Planting early maturing varieties (Early MV)	Dummy=1 if yes, 0 otherwise	0.831	0.375
Changing planting dates (Change PD)	Dummy=1 if yes, 0 otherwise	0.918	0.275
Supportive measures			
Crop-livestock mix (C-L Mix)	Dummy=1 if yes, 0 otherwise	0.904	0.294
Crop and livestock insurance (C-L Insurance)	Dummy=1 if yes, 0 otherwise	0.176	0.381
Practice of irrigation (Irrigation)	Dummy=1 if yes, 0 otherwise	0.180	0.385
Use of water conservation techniques (Water Con)	Dummy=1 if yes, 0 otherwise	0.531	0.500
Use of water drainage techniques (Water Drain)	Dummy=1 if yes, 0 otherwise	0.580	0.494
Use of soil conservation techniques (Soil Con)	Dummy=1 if yes, 0 otherwise	0.940	0.238
Explanatory variables			
Household characteristics			
Gender of household head	Dummy 1=male, 0 otherwise	0.876	0.330
Age of household head	Years	50.03	13.76
Education of household head	Years	3.022	3.969
Percent of income from non-farm sources	%	30.81	21.01
Potential labour capacity of household	Man-Equivalent[18]	4.549	2.655
Social capital			
Group membership (Agricultural union/cooperative)	Dummy=1 if yes, 0 otherwise	0.407	0.492
Family members 18-65 years living within 5km from resid.	Count	1.513	2.818
Number of family members abroad	Count	1.640	4.080
Institutional and infrastructural variables			
Land ownership	Dummy=1 if full/part ownership, 0 otherwise	0.938	0.242
Access to credit	Dummy=1 if yes, 0 otherwise	0.313	0.464
Access to crop-related extension services	Dummy=1 if yes, 0 otherwise	0.804	0.397
Distance to market	Km	6.189	6.813
Plot characteristics			
Soil fertility	Dummy=1 if fertile to very fertile, 0 otherwise	0.651	0.477
Cropland area	Hectares	2.846	2.628
Physical and financial Assets			
Livestock holding at the beginning of year 2014	Tropical Livestock Unit[19]	4.629	4.619
Total value of farm implement (after depreciation)	US$/Household	52.84	174.21
Climatic variables			
Average seasonal rainy days (2013-2014) (Rainy days)	Count of seasonal days with daily rain ≥ 1mm	76.42	4.475
Intra-seasonal rainfall variability[17] (2013-2014)	Coefficient of variation, %	48.75	7.710
Average seasonal days with Tmax ≥32°C (2013-2014) (Hot days)	Count of seasonal days with Tmax ≥32°C	137.5	9.040
Location variables			
Region	Dummy=1 if Upper East Ghana, 0 otherwise	0.667	0.472

NB: (n=450 across all variables, except "Livestock holding at the beginning of year 2014" which has n=439)

Source: computed by author with data from household survey

[17] This is measured as the standard deviation of the monthly (months in the season) means expressed as a percentage of their respective seasonal means (Kahsay and Hansen 2016)

[18] Computed using the following conversion factors; for Females: 0-5years (0.00), 6-10 years (0.05), 11-17years (0.40), 18-65 years (0.50), > 65 years (0.10); for males 0-5years (0.00), 6-10 years (0.10), 11-17years (0.80), 18-65 years (1.00), > 65years (0.70); (modified version of age range proposed by Runge-Metzger and Diehl 1993)

[19] Computed using the following conversion factors (Runge-Metzger and Diehl 1993; Ghirotti, 1993); Cattle (Bullock (0.80), Bull (0.70), Cow (0.70), Calf (0.35)), Sheep (Ram (0.10), Ewe (0.10), Lamb (0.05)), Goat (Billy goat (0.10), Nanny goat (0.10), Kid (0.05)), Pig (Boar (0.20), Sow (0.20), Piglet (0.10)), Chicken (0.01), Guinea fowl (0.01) Duck (0.01), Turkey (0.02), Horse (0.80), Donkey (0.50)

Of the 450 farmers, only 31.3% have access to credit. The average farm household is about 6.19 km from the nearest market. These figures reveal limited access to both credit and markets across the two regions. Majority of the households cultivate on own or partially-owned land, but with low scale of cropland cultivation. The average household cultivates approximately 2.85 hectares of cropland and majorly use rudimentary techniques (as indicated by the low mean value of farm implements used by a representative household). An average of 4.63 tropical livestock units was held by households in the study area at the beginning of the year 2014. For the period 2013-2014, besides observance of a fairly high intra-seasonal rainfall variability (coefficient of variation estimate of 48.75%), we estimate an average of 76 seasonal rainy days across the two regions, and 138 seasonal hot days. Definition of a hot day is based on a daily maximum temperature threshold of 32°C. This threshold was used based on advice by crop and livestock scientists in the study area, extensive literature review on critical temperature thresholds for the major crop and livestock species produced in the area (e.g. see Thornton and Cramer 2012; Hawkins *et al* 2013; Thornton and Lipper 2014) and based on suggestions from discussions held with extension officers of the Ministry of Agriculture in the respective districts covered in this study.

3.5 Results and discussion

3.5.1 Farmers' perceptions and empirical validation of recent trends in climatic conditions

Farmers' across the two regions were generally unanimous in their perception on predictability of climatic conditions over the past 10 years. A total of 97.5% of households either agreed or strongly agreed that the weather has become more unpredictable in recent years. Approximately 72% held a perception that average seasonal temperature has either increased or increased and with high temperature extremes. With about 57% reporting of an increase in average seasonal temperature without stressing on an increase in frequency of high (day or night) temperature extremes, a total of about 15% stressed that recent increments observed in seasonal temperature are driven by increasing frequency of high daily temperature extremes. Majority of the respondents who perceived an increase in temperature however revealed their observance of extreme seasonal temperatures and low rainfall over the 2013 and 2014 agricultural seasons. Based on estimates in Table 3.2, a total of about 87% of households in the study area perceived either a decrease in seasonal rainfall or a decrease and with more dry days (reflecting a decrease in rainy days or increasing persistence of dry spell). Across both regions however, a general decrease in incidence of seasonal flooding is perceived. These results are in conformity with earlier discovery by Antwi-Agyei *et al* (2014) in the Upper East region of Ghana, where approximately 86% of the respondents perceived decreasing rainfall and about 81% perceived increasing temperature in recent years. Based on the revealed perceptions of farm households, we deduce that farming systems in the study area have plausibly been exposed over the past 10 years to erratic climatic conditions, steered by increasing seasonal temperature and decreasing seasonal rainfall and rainy days. These changes in the local climate have the potential to adversely affect farming through increasing evaporative losses, decreasing water supply for crop and livestock production, and wilting of plants whenever extreme temperatures and dry days coincide with critical growth stages. These perceived conditions could also lead to a decrease in crop yields, livestock productivity, agricultural income and consumption.

Table 3. 2-Farmers' perceptions on climate variability and extremes

Indicator	Perception	Region surveyed		Total [n=450]
		Upper East [n=300]	Southwest [n=150]	
The weather becomes more unpredictable from year to year	Strongly agree	70.3	72.7	71.1
	Agree	26.3	26.7	26.4
	Not sure	3.3	0.0	2.2
	Disagree	0.0	0.7	0.2
	Strongly disagree	0.0	0.0	0.0
Changes observed in seasonal temperature over the past 10	Decreased	17.0	28.7	20.9
	Increased	57.0	57.3	57.1
	No change	8.3	0.0	5.6
	Increased and with (high temp.) extremes	17.0	11.3	15.1
	Decreased and with (low temp.) extremes	0.7	2.7	1.3
Changes observed in seasonal rainfall over the past 10 years	Decreased	79.0	66.0	74.7
	Increased	2.7	19.3	8.2
	No change	4.7	0.0	3.1
	Increased and with extremes	2.3	0.0	1.6
	Decreased and with more dry days	11.3	14.7	12.4
Changes observed in seasonal flooding over the past 10 years	Decreased	74.3	56.0	68.2
	Increased	7.3	18.0	10.9
	No change	18.3	26.0	20.9

Source: computed by author with data from household survey

In ascertaining the magnitude of change in seasonal temperature and rainfall attributes, regional estimates were computed from the extracted climate data for the respective communities and districts. Based on the number of districts covered in each of the regions, observed seasonal values were averaged across districts and used as a representation of regional values. For example, in Upper East Ghana where a total of 5 districts were covered, seasonal estimates for each of the districts were averaged across all 5 districts and used as a representation of regional values. Same was done for Southwest Burkina Faso. In line with the perceptions held by farmers in the study area, we detect an increase in both normal temperature indicators (maximum, minimum, mean and diurnal temperature range) and indicators of hot days ($\mathrm{Tmx} \geq 32°\mathrm{C}$) and hot nights ($\mathrm{Tmn} \geq 24°\mathrm{C}$). Increments in each of these seasonal temperature indicators over the last 10 years were however, majorly driven by extreme rise in each of the indicators over the period 2013-2014. For example, compared to the 18-year (1997-2014) mean estimate of 43.5 seasonal hot days and 28.64 seasonal hot nights, a total of 90.07 extra seasonal hot days and 63.06 extra seasonal hot nights were observed over the period 2013-2014 in Upper East Ghana. Compared to the mean estimates of 44.8 seasonal hot days and 20.53 seasonal hot nights for Southwest Burkina Faso, a total of 95.10 extra seasonal hot-days and 66.72 extra seasonal hot-nights were observed over the 2013-2014 agricultural seasons. Across both regions, besides a consistently increasing trend for minimum seasonal temperature, the other three normal temperature indicators remained generally stable between the years 1997 and 2012, but all four indicators rose sharply over the period 2013-2014 (see Figure AP 3.1 in the appendix).

In Upper East Ghana for example, deviations of 4.08°C, 1.55°C, 2.81°C, and 2.53°C from the 18-year mean estimates for seasonal maximum temperature (30.53°C), minimum temperature (22.95°C), mean temperature (26.74°C) and diurnal temperature range (7.58°C) were observed over the period 2013-2014. In Southwest Burkina Faso, respective deviations of 4.44°C, 1.48°C, 2.96°C, and 2.95°C from the 18-year mean for maximum temperature (30.48°C), minimum temperature (22.54°C), mean temperature (26.51°C) and diurnal temperature range (7.94°C) were observed. From these estimates, we note relatively higher increment in maximum temperature than in the other indicators. Given the fact that farmers undertake most of their farming operations during day-time, their adaptation to recent extremes in temperature could generally be towards changes in daily maximum temperature extremes. From Figure AP 3.2 in the appendix, we also observe a decreasing trend for rainfall since the year 2007 and rainy days since the year 2009 in Upper East Ghana, but generally increasing trends for both rainfall and rainy days in Southwest Burkina Faso until the period 2013-2014, where both regions observe declines in rainfall and rainy days. During this period, rainfall and rainy days decreased respectively by 164.29 mm and 12.11 days compared to the 18-year averages (893.85mm and 92.11 days) for Upper East Ghana, while in Southwest Burkina Faso, respective deviations of -40.53 mm and -6.22 days were observed (compared to averages of 937.24 mm and 101.22 days). Beside these, we note an increase in both inter- and intra-seasonal rainfall variability in recent years, especially in Upper East Ghana. Emphasis is however placed in this study on intra-seasonal variability as this is found to be comparatively higher among the two measures of erratic nature of seasonal rainfall. Increment in days with extreme temperatures, decreasing rainfall and rainy days, and increasing intra-seasonal rainfall variability reveals exposure of farming systems to both heat and moisture stress over the 2013 and 2014 agricultural seasons, and farmers' adjustment to recent weather extremes could have been towards moderating harm from these changes.

From these findings, we note that farmers' perceptions about recent changes in the local climate are in conformity with climatic trends. Pro-adaptation response to the perceptions held by farmers could therefore be appropriate and helpful in policy efforts undertaken to reduce adverse effects of weather extremes and in building local resilience to climate shocks.

3.5.2 Determinants of farmers' perceptions on recent changes in the local climate

Having explored perceptions held by farmers regarding recent changes in the local climate, we present results on the determinants of these perceptions. As shown in Table 3.3, an increase in the years of schooling (education) increases the likelihood that a farmer will perceive an increase in temperature (with or without extremes). More educated farmers are in a better position to acquire, understand and interpret information on the local climate to which they are exposed.

Table 3. 3-Determinants of farmers' perceptions of recent changes in the local climate

Variables	Output for multivariate probit					
	1 Increasing Temperature		2 Decreasing Rainfall		3 Increasing flooding	
	Coeff.	Rob SE.	Coeff.	Rob SE.	Coeff.	Rob SE.
Gender	-0.0530	0.2149	0.2664	0.2169	-0.0397	0.2940
Age	0.0072	0.0050	0.0057	0.0072	-0.0054	0.0073
Education	0.0427**	0.0188	0.0044	0.0214	-0.0276	0.0264
Per. Inc. non-farm	-0.0061*	0.0033	-0.0111**	0.0046	0.0024	0.0048
Group membership	-0.2616*	0.1395	-0.3425*	0.1787	0.5839***	0.1896
Fam mem 18655K	0.0258	0.0261	0.0751**	0.0337	-0.0897**	0.0398
Fam mem abroad	0.0165	0.0171	0.0439	0.0342	-0.0454	0.0408
Land ownership	-0.3906	0.2833	0.1389	0.2940	0.2324	0.4353
Extension	-0.3345*	0.1991	0.0160	0.2245	0.2453	0.2469
Credit	-0.2523*	0.1408	-0.6821***	0.1808	0.1876	0.1838
Distance to market	-0.0075	0.0101	0.1052***	0.0390	-0.1039***	0.0255
Total cropland area	-0.0083	0.0351	-0.0445	0.0410	0.0017	0.0412
Livestock holding	0.0102	0.0153	0.0171	0.0197	0.0241	0.0202
Region	0.0980	0.2244	0.1378	0.3006	-0.5645*	0.3260
Constant	1.0906**	0.5128	0.5710	0.6229	-0.8324	0.7054
Number of obs	439					
Wald chi2	102.61					
Prob>chi2	0.0000					
Log pseudolikelihood	-484.180					

NB: significance level ***1%, **5%, *10%
Increasing Temperature: either an increase in temperature or an increase and with extremes=1, 0 otherwise
Decreasing Rainfall: either a decrease in rainfall or a decrease and with more dry days=1, 0 otherwise
Increasing flooding: an increase in seasonal flooding=1, 0 otherwise

Farmers with a high percentage of household income from non-farm sources, belong to a farmers' organization, and/or have access to credit are less likely to perceive an increase in seasonal temperature or a decrease in seasonal rainfall. This generally implies that farmers that are relatively less financially constrained or less dependent on agriculture are less likely to perceive an increase in temperature and/or a decrease in rainfall. Farmers with more family members within the ages of 18 to 65 years living at most 5 km from the main residence are less likely to perceive an increase in seasonal flooding, but more likely to perceive a decrease in seasonal rainfall. Farmers who live farther from markets, may plausibly have limited access to non-farm opportunities, could be more reliant on rainfed agriculture, and are more likely to perceive a decrease in seasonal rainfall and a decrease/no change in seasonal flooding, the latter of which could be due to potential investments made by such farmers in flood-risk management strategies.

Table 3. 4-Correlation matrix for perception on changes in the local climate

	Increasing Temperature	Decreasing Rainfall	Increasing flooding
Increasing Temperature	1.0000		
Decreasing Rainfall	0.3616*** (0.0876)	1.0000	
Increasing flooding	-0.1724* (0.0897)	-0.5101*** (0.0995)	1.0000

Likelihood ratio of rho21=rho31=rho32=0: chi2(3)=30.469 Prob>chi2=0.0000; significance level ***1%, *10%

In line with our a-priori expectation that perceptions held by farmers regarding the respective weather variables could be correlated, and as shown in Table 3.4, farmers who perceive an increase in seasonal temperature are more likely to perceive a decrease in seasonal rainfall, but less likely to perceive an increase in seasonal flooding.

3.5.3 Regional adaptation and empirical documentations

Prior to analyzing the determinants of the number and choice of strategies implemented by farmers, we assess regional similarities and differences in the choice of strategies used and document empirical evidences in the study area and other locations in sub-Saharan Africa and the developing world on a broader perspective. Following recent exposure to increasing seasonal hot days, decreasing rainy days, and increasing intra-seasonal rainfall variability, majority of the farmers in Upper East region of Ghana responded by majorly using at least one form of soil conservation technique[20] (98.7%), crop-livestock mix (93.3%), changing planting dates (92.3%), planting early maturing varieties (81.3%), engaging in crop-diversification (78.0%), and planting drought tolerant varieties (62.3%). This is in conformity with an earlier documentation by Antwi-Agyei *et al* (2014) for Upper East region of Ghana where majority of the farmers stated changing planting dates and crop diversification as the major on-farm adaptation strategies used in responding to decreasing rainfall and increasing temperature. For this same region, Tambo (2016) reported changing planting dates, planting of drought tolerant/early maturing varieties, and mixed cropping as the major adaptation measures used by farmers. In Southwest Burkina Faso, farmers responded by engaging more in crop diversification (95.3%), changing planting dates (90.7%), planting early maturing varieties (86.7%), crop-livestock mix (84.7%), use of soil conservation techniques (84.7%), and use of water conservation techniques (basically, water harvesting, 82.7%).

[20] Farmers were instructed to indicate whether they made use of any of 8 soil conservation measures presented to them. Farmers who made use of at least one of these strategies were given 1 and 0 for using none. The 8 individual strategies considered under soil conservation are crop rotation, cover-cropping and mulching, cross-slope farming, intercropping, application of manure, fallowing, use of physical anti-erosive measures, and reduced tillage

Table 3. 5-Farmers' adaptation to recent weather extremes

Adaptation strategies	Total (n=450)	Southwest (n=150)	Upper East (n=300)	Documented examples in study area and other locations in SSA and developing economies
Crop diversification	83.8	95.3	78.0	Antwi-Agyei *et al* (2014) (Upper East, Ghana); Uddin *et al* (2014) (Bangladesh); Zampaligré *et al* (2014) (Burkina Faso)
Planting of drought tolerant varieties	59.6	54.0	62.3	Benhin (2006) (South Africa); Antwi-Agyei *et al* (2014) (Upper East, Ghana); Uddin *et al* (2014) (Bangladesh); Tambo (2016) (Upper East, Ghana);
Planting of flood tolerant varieties	41.3	49.3	37.3	Harlan and Pasquereau (1969) (Mali); Pandey *et a*l (2012) (South Asia)
Planting of heat tolerant varieties	36.9	60.7	25.0	Benhin (2006) (South Africa)
Planting early maturing varieties	83.1	86.7	81.3	Tambo and Abdoulaye, (2013) (Nigerian savanna); Antwi-Agyei *et al* (2014) (Upper East, Ghana)
Changing planting dates	91.8	90.7	92.3	Deressa *et al* (2009) (Ethiopia); Tambo (2016) (Upper East, Ghana)
Crop-livestock mix	90.4	84.7	93.3	Zampaligré *et al* (2014) (Burkina Faso)
Crop and livestock insurance	17.6	20.0	16.3	Benhin (2006) (South Africa)
Use of irrigation	18.0	37.3	8.3	Deressa *et al* (2009) (Ethiopia); Laube *et al* (2012) (Northern Ghana); Rakib (2015) (Bangladesh); Ngigi *et al* (2017) (Kenya);
Use of water conservation techniques	53.1	82.7	38.3	Laube *et al* (2012) (Northern Ghana); Zampaligré *et al* (2014) (Burkina Faso); Ngigi *et al* (2017) (Kenya)
Use of water drainage techniques	58.0	76.7	48.7	Wester and Bron (1998) (Bangladesh); Benhin (2006) (South Africa); Ngigi *et al* (2017) (Kenya)
Use of soil conservation techniques	94.0	84.7	98.7	Sidibe (2005) (Northern Burkina Faso); Deressa *et al* (2009) (Ethiopia); Mulwa *et al* (2017) (Malawi); Ngigi *et al* (2017) (Kenya)

NB: figures represent percent of households

Source: Data from farm household survey and documented evidence in literature

This is in conformity with earlier documentation by Zampaligré *et al* (2014) for Burkina Faso where farmers stated crop diversification, crop-livestock mix, water harvesting, and use of physical anti-erosive measures such as half-moon or stone dikes as the major adaptation strategies used in responding to recent climatic changes.

Although there are differences in the magnitude of adoption of the various strategies across regions, we note that soil conservation techniques, changing planting dates, crop-livestock mix, crop diversification and planting of early maturing varieties are the leading strategies across both regions and farmers are making extensive use of both direct and supportive measures. This is an indication that farmers have realized that, given recent changes in the local climate, and anticipated changes in the near future, relying on a single measure may not be enough to moderate harm. Across the two regions, the use of irrigation is the least adopted strategy in Upper East Ghana, while the purchase of crop and livestock insurance is found the least in Southwest Burkina Faso. Although one would have anticipated extensive use of irrigation across both regions due to the recurrent nature of dry spell and heat wave, and erratic nature of rainfall pattern in the study area, we observe low practice of irrigation as an adaption strategy. The low use of irrigation in the study area could have severe implications for crop and livestock production in the near future. Based on documented evidences in the study area, in sub-Saharan Africa in general and in developing economies on a broader perspective, and as shown in Table 3.5, we note that adapting to a changing climate is not new to farmers, but the measures used and magnitude of their use are generally contextual. Understanding local adaptation to weather extremes could therefore guide the proposition of relevant production and policy prescriptions that could help build local resilience to future weather/climatic shocks.

3.5.4 Intensity of adaptation and determinants

We began our analysis in this section with an exploration, through descriptive techniques, of the visual correlation between the number of strategies adopted and net income[21] from crop production (due to emphasis placed on crop-related strategies in this study). As shown in Figure 3.2, majority of the farmers adopted between 6 (19.11% of farmers) to 8 (12.44% of farmers) strategies. While none of the farmers implemented 2 strategies, the proportion of farmers that implemented either 1 or 3 strategies was below 1%. This is a general confirmation that farmers adopt a mix of strategies in their adaptation to climate and weather shocks rather than choosing a single strategy as presumed in previous studies (e.g. Deressa *et al* 2009). In assessing the correlation between the intensity of adaptation and income from crop production, it is found that, although the association between these two variables appears to be non-linear[22], income from crop production generally increases with the number of strategies implemented. Through a pairwise correlation analysis, we find a significant positive correlation (correlation coefficient (r)= 0.1239, p-value=0.0086) between the number of strategies implemented and net income from crop production. This indicates that, although in a non-linear fashion, the response of net income from crop production to the number of strategies implemented is generally positive. Having analyzed the correlation between the number of strategies implemented and net crop income[23], we now present and discuss results on the determinants of the number of strategies adopted.

Access to extension services and credit are found to be the major determinants of the number of strategies adopted by farmers. Beside these, variables for distance to market, number of family members abroad, total cropland area, seasonal hot days, intra-seasonal rainfall variability and the regional dummy also have significant effects on the number of strategies implemented by the farmers.

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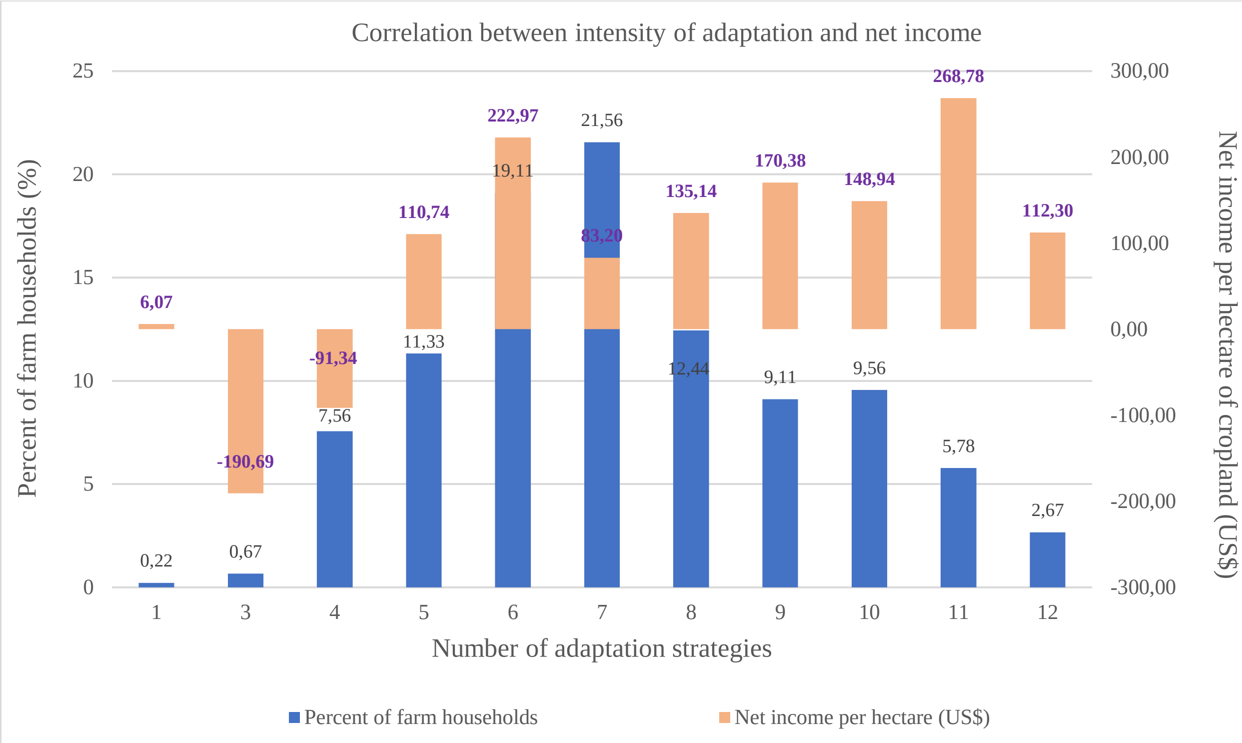
[21] Net income = Gross income –total variable cost (i.e. cost of seeds, fertilizer, pesticides, agrochemical application charges, and total labor (family and hired/communal) cost)

[22] Due to a potential increase in the cost of adaptation with the implementation of a higher number of strategies. This could erode net revenues if the strategies adopted as a package (portfolio of actions) are majorly capital-intensive.

[23] Maximization of which is presumed to be one of the goals of farmers in the study area.



NB: Correlation coefficient (r) =0.1239 (p-value= 0.0086)

Figure 3. 2-Correlation between number of adaptation strategies and net income from crop production
Source: Author's construct

Farmers with access to credit are likely to use 0.568 additional adaptation strategies. Regardless of the nature of a given adaptation strategy, implementation of it may involve the incurrence of some cost (either in cash or kind), which could preclude its adoption by some cash-constrained farmers. Adoption of an adaptation strategy (either in isolation or as a package) requires the strategy being available, accessible, affordable and beneficial. Thus, even when strategies are available, accessible, and beneficial, yet unaffordable, farmers may still find it difficult to implement them. Limited access to credit makes farmers in locations prone to weather risks more vulnerable to adverse shocks and in most cases force them to forgo income-generating-but-risky strategies (Morduch 1994). Having access to credit relaxes liquidity constraints, increases financial resources of farmers and enhance their ability to meet transaction costs associated with the implementation of diverse strategies. Thus, with more financial resources at their disposal, farmers could make vital managerial adjustments in response to a changing local climate and make vital use of information available to them. Farmers with access to crop-related extension services are likely to use 1.205 additional adaptation strategies (see Table 3.6). Adaptation requires awareness and application of relevant skills. Awareness is founded on access to information, while application of various strategies requires at least some level of knowledge and skills in their implementation.

Table 3. 6-Determinants of the number of strategies adopted by farmers

Variable	Dependent variable: Numb. strategies		
	Coefficient	Robust SE	Marginal Effects
Household characteristics			
Gender	-0.0011	0.0374	-0.0082
Age	-0.0004	0.0009	-0.0031
Education	0.0010	0.0033	0.0075
Per Inc. non-farm	0.0006	0.0006	0.0045
Pot. Labour cap	-0.0021	0.0047	-0.0155
Social capital			
Group membership.	0.0028	0.0260	0.0205
Fam mem 18655K	-0.0008	0.0041	-0.0058
Fam mem abroad	-0.0078**	0.0032	-0.0568
Institutional and infrastructural variables			
Land ownership	0.0436	0.0482	0.3185
Credit	0.0778***	0.0269	0.5679
Extension	0.1652***	0.0371	1.2054
Distance to market	-0.0055***	0.0019	-0.0398
Plot characteristics			
Soil fertility	0.0209	0.0263	0.1522
Cropland area	0.0194***	0.0049	0.1417
Physical and financial assets			
Livestock holding	-0.0037	0.0027	-0.0270
Value of farm implement	0.00006	0.00004	0.0004
Climatic variables			
Rainy days	-0.0013	0.0048	-0.0093
Intra-seasonal rainfall variability	-0.0056**	0.0028	-0.0407
Hot days	0.0053**	0.0021	0.0384
Location variables			
Region	-0.1183**	0.0509	-0.8635
Constant	1.5047**	0.6019	
Wald Chi2 (20)	234.25	Observations	439
Prob >Chi 2	0.0000	Pseudo R-sq.	0.0377
Log pseudolikelihood	-928.47		

NB- Significance level: ***1%, **5%

Through extension services, farmers are updated on changing climatic conditions and accompanying risks, improved production techniques, and are trained on how to efficiently and effectively implement various technologies. This promotes the adoption of diverse strategies in a changing local climate. The observed positive effect of extension services on the number of adaptation strategies implemented by farmers is in conformity with earlier report by Tambo (2016) for Upper East Ghana. Increasing access to remittances and limited access to markets are associated with the adoption of fewer strategies. Whereas increasing seasonal hot days is associated with an increase in the number of strategies adopted, increasing uncertainty with monthly accumulations and distribution of rains leads to the adoption of fewer strategies. Farmers in the Upper East region of Ghana are likely to use 0.864 strategies less the number used by their counterparts in Southwest Burkina Faso.

3.5.5 Determinants of the choice of adaptation strategies

In this section, we present results and discuss findings on the determinants of the choice of adaptation strategies under the seven broad categories of explanatory variables. Due to limitation in the estimation of a high number of equations with multivariate probit, we could include only 11 of the 12 adaptation strategies in the joint model, (dependent variable for the use of soil conservation techniques was dropped). We therefore analyzed 11 strategies in the joint model, 6 strategies in the equation for direct measures, and 5 strategies in the equation for supportive measures. In conformity with previous study by Tambo (2016) in Upper East Ghana, we discover that, the major determinants of the number of strategies implemented by farmers' also have significant effects on majority of the direct and supportive measures. Besides this, we observe differences in the magnitude and direction of effects for the respective explanatory variables on each of the 11 strategies. This indicates a need to investigate effects on the individual strategies rather than resorting to the assessment of the determinants of adoption or non-adoption behavior as observed in Maddison (2006). Prior to presenting and discussing implications of the estimated coefficients as shown in Table 3.7, we first assess (non-) appropriateness of the use of multivariate probit model instead of single equation binary models or multinomial logit model. The likelihood ratio test results ($\chi 2=425.89$, $P<0.0000$; as shown beneath Table 3.8) indicate a significant correlation between error terms of the 11 equations estimated in the joint model. This indicates that multivariate probit model is the right model for this study. We hereby proceed with the presentation and discussion of the results.

3.5.5.1 Household characteristics

Older farmers are less likely to adapt through crop diversification, but more likely to adapt through changing planting dates. Based on accumulated farming and climatic-risk experiences, older farmers usually know periods within the season where planting could be safer and usually adjust their decisions in a changing climate to minimize risk. Relatively low use of crop diversification by older farmers could be attributed to the labor-intensive nature of the practice. Increasing share of non-farm income in total household income enhances the adoption of drought tolerant varieties and the purchase of crop and livestock insurance. Potential labour capacity has significant effects on the adoption of both direct and supportive measures. For direct measures, it leads to increased adoption of flood tolerant varieties through income effect, but leads to a decrease in the adoption of changing planting dates. Increased potential for the energetic men/women of the household to generate income for upkeep of the household reduces the likelihood of engaging in crop-livestock mix, purchase of crop and livestock insurance, and the use of water conservation techniques, but stimulates the practice of irrigation through both income and labour effects.

3.5.5.2 Social capital

Farmers who belong to farmer organizations are likely to adopt flood tolerant varieties and practice irrigation, the latter of which is usually enhanced through joint investment (collective efforts) by group members in irrigation facilities to help minimize drought risk. They are however less likely to adopt heat tolerant varieties and changing planting dates. Farmers with higher number of energetic relatives around (on whom they can rely in times of shock) are less likely to invest in flood tolerant varieties, purchase crop and livestock insurance or practice irrigation. They are however more likely to engage in changing planting dates to assist neighboring relatives (with hope of them returning the favor in due time-*principle of reciprocity*) during planting, and to engage in crop-livestock mix to shield both the immediate household and neighboring relatives in times of shock. Farmers with increased access to remittances are less likely to adapt through crop diversification, use of improved varieties, or practice irrigation, but are more likely to change planting dates to suit their seasonal schedule of operation.

3.5.5.3 Institutional and infrastructural variables

Ownership of land incites the adoption of changing planting dates and the practice of crop-livestock mix. Having right to the land on which a farmer cultivates, puts less pressure on the farmer on when to plant, and adjusting the timing of planting is less costly to such a farmer than one cultivating on a rented/leased land. The farmer can equally produce some species of livestock alongside his/her cropping activities. This may however be forbidden in situations where a farmer crops on a rented/leased land. Increased access to credit stimulates adoption of changing planting dates, practice of crop-livestock mix, purchase of crop and livestock insurance, and the practice of irrigation. The last three strategies are presumed cost-intensive strategies. Having access to low interest credit reduces financial burden of farmers, but increases their capacity to meet the costs involved in implementing these capital-intensive strategies. Increasing access to credit also enables farmers to meet labour cost during peak and off-peak periods of labour demand, and this enables them to change planting dates to suit their seasonal planting schedule. Through provision of information and advisory services, increasing access to extension services stimulates adoption of all 6 direct measures, and the practice of irrigation. It however reduces the adoption of water drainage techniques. Farmers living farther from market centers are less likely to adopt drought, flood and heat tolerant varieties, and practice irrigation. They are however more likely to change planting dates due to limited access to markets for timely purchase of inputs, practice crop-livestock mix, and use water drainage techniques as precautionary measures. Whereas fartherness from markets increases the cost of adoption of improved seeds and limits farmers access to vital information on improved crop varieties and production techniques (thereby precluding their adoption of new crop varieties), limited access of farmers in remote areas to non-farm opportunities may prompt them to engage in crop-livestock mix as an insurance mechanism and to invest in water drainage techniques as a potential flood-risk management strategy. Risk mitigation through the adoption of improved crop varieties could as well be a risky gamble with a possibility of negative payoffs under unfavorable weather conditions, and given limited access to output markets, farmers in more remote areas may rather forgo the adoption of such strategies for safety reasons (Mulwa *et al* 2017). These effects of institutional and infrastructural variables are in conformity with findings from previous studies (e.g. see Deressa *et al* 2009; Nhemachena *et al* 2014; Mulwa *et al* 2017).

3.5.5.4 Plot characteristics

Increasing farm size increases the chances of adopting early maturing varieties and investing in all five supportive measures (the effect on the purchase of crop and livestock insurance is however not significant). Whereas the adoption of early maturing varieties may be attributed to a more market-oriented nature of large-scale producers, large farms are more likely to be equipped with more capital and resources that enable them to invest in capital-intensive strategies. In addition, uncertainty and fixed transaction and information costs associated with innovation may limit the adoption of cost-intensive strategies by small-scale farmers, whereas the availability of higher capital and resources on large-scale farms could enable large-scale producers to invest in costly yet beneficial strategies (Daberkow and McBride 2003). Farmers with positive perception about fertility status of their crop fields are likely to adopt more direct measures and less supportive measures. Fertile croplands usually require less investment in capital-intensive practices (Mulwa *et al* 2017), since such lands could achieve similar yields as less fertile lands with much investment. This is the likely notion held by farmers with affirmative perception about fertility status of their crop fields and this reduces incentive for them to invest in capital-intensive technologies. They are rather more likely to plant improved crop varieties for higher yields and less likely to change planting dates.

3.5.5.5 Physical and financial assets

More mechanized farms are likely to change planting dates to suit their schedule of operation, and use water conservation techniques to ensure availability of water throughout the season. Interestingly, we find a negative effect of mechanization on the practice of irrigation, which contradicts expectation and documented evidence in literature (e.g. see Nhemachena *et al* 2014). Farmers with higher livestock holding are less likely to adopt flood tolerant varieties, water drainage techniques and practice irrigation.

3.5.5.6 Climatic variables

In locations with higher seasonal rainy days, farmers are less likely to adopt drought tolerant, flood tolerant, and heat tolerant varieties, but are more likely to engage in crop-livestock mix, and to use water conservation and water drainage techniques. In times of increasing rainy days, farmers try to store/harvest rainwater for use during dry spell. Increasing rainy days however makes systems also vulnerable to flooding, and as farmers' store water for future use, they also use water drainage techniques to divert excess water from their fields to minimize chances of waterlogging and flooding. Crop-livestock mix is a system that demands high availability of water for both crops and livestock. Although this system is usually practiced as insurance against unexpected shocks, increasing availability of water enhances its adoption. For the observed negative effects, increasing rainy days increases the potential for indigenous varieties to produce appreciable yields, and this demotivates farmers from adopting improved (new) varieties which may involve incurrence of comparatively higher costs. Similarly, increasing intra-seasonal rainfall variability discourages farmers from adopting improved crop varieties, practicing irrigation and using water conservation techniques. This effect of intra-seasonal rainfall variability on farmers' adaptation decisions indicates in general that, increasing uncertainty with intra-seasonal rainfall distribution makes farmers more risk averse (Di Falco *et al* 2014) and demotivates them from investing in these adaptation strategies. Due to increased chances of high accumulation of rains in some few months, low accumulation in others, and increased potential for waterlogging/flooding however, farmers adopt water drainage techniques in locations with relatively higher intra-seasonal rainfall variability. These significant effects of rainy days and intra-seasonal rainfall variability affirm a presumption held by Bryan *et al* (2009) of a potential for seasonal frequency, intensity and distribution of rains to influence farmers' adaptive behaviour. Farmers located in areas with higher seasonal hot days are more likely to practice irrigation, and adopt water conservation and water drainage techniques, but are less likely to purchase crop and livestock insurance. This indicates a realization by farmers that the use of direct measures alone may not be enough to shield them from adverse effects of extreme temperatures, and when exposed to such extremes, they generally invest in water management techniques (as supportive measures) to minimize evaporative losses and heat stress. Their adoption of water drainage techniques may be related to incidences of high intensity rains and flooding usually observed after prolonged periods of hot days.

3.5.5.7 Location variables

Effect of the regional dummy on the choice of adaptation strategies is found to be significant across 7 of the 11 strategies. This indicates that strategies adopted and the magnitude of their use depend on regional conditions. Farmers in Southwest Burkina Faso appear to have adapted better to recent manifestations of weather extremes than those in Upper East Ghana.

3.5.6 Interdependencies among strategies

From Table 3.8, we note that farmers adaptation decisions are correlated instead of being mutually exclusive. Farmers generally adopt direct measures in a complementary manner, while the degree of complementarity among the supportive measures is relatively low. For example, besides a significant negative correlation observed between planting of early maturing varieties and changing planting dates, and a non-significant positive correlation between planting of heat tolerant varieties and changing planting dates, all other correlations among the direct measures are positive and significant. This is in conformity with findings by Mulwa *et al* (2017) on correlations among strategies covered under direct measures in this study. Among the supportive measures, we find a positive correlation between the practice of crop-livestock mix and the use of water conservation techniques, although this correlation is significant only at the 10% level. All other correlations between crop-livestock mix and the other supportive measures are not significant. This indicates that the practice of crop-livestock mix is generally adopted as an isolated supportive measure. We as well find a complementary association between the purchase of crop and livestock insurance and the use of water conservation techniques, while water drainage techniques and the purchase of crop and livestock insurance are adopted as substitutes. We observe complementary use of water conservation techniques, water drainage techniques, and the practice of irrigation. In exploring correlations between measures, we find a positive correlation between the adoption of crop diversification as a direct measure and the adoption of crop-livestock mix, water conservation and water drainage techniques as supportive measures. Farmers who plant drought tolerant varieties also tend to adopt water conservation techniques. Farmers who plant flood tolerant varieties tend to adopt water conservation and water drainage techniques, and practice irrigation. We find a significant negative correlation between planting of heat tolerant varieties and the adoption of water drainage techniques. Farmers who plant early maturing varieties tend to use more of water conservation techniques to minimize drought stress in the early stages of the season. As shown in Table 3.8, farmers who adopt changing planting dates as a direct measure usually purchase crop and livestock insurance, use water conservation techniques, water drainage techniques, and practice irrigation as supportive measures.

3.5.7 Probability of marginal and joint adoption of strategies

From Table 3.9, the joint probability of adoption of all 11 strategies by a farmer in the study area is estimated at 1.11%, while probabilities for adoption of all 6 direct measures and 5 supportive measures are estimated at 17.32% and 2.53% respectively. From these estimates, we deduce that the probability for farmers in the study area to resort to the adoption of all 6 direct measures to moderate harm from weather extremes is about 6.85 times higher than their probability of resorting to the use of all 5 supportive measures. This result shows that farmers in the study area favour the adoption of direct measures as complements. This could be attributed to the presumably low cost of implementing such strategies, while the low probability for joint adoption of supportive measures may be attributed to the resource- and capital-intensive nature of these strategies (in terms of time and money). In addition, whereas majority of the direct measures stand yielding benefits in the short-run, benefits derived from most of the supportive measures may materialize only in the long-run while requiring current investment efforts (Shikuku *et al* 2017). Given however that farmers' planning horizons are usually short (Shiferaw and Holden 1998), joint adoption of strategies that generally yield benefits in the short-run may seem more appropriate to the farmers. The relatively low probability estimates (less than 50%) for sole adoption of either measures however indicates that, instead of resorting to strategies under one of the measures, farmers are more likely to use a mix of strategies under both measures. Marginal predictions for the respective strategies by the joint and individual models are shown in Table 3.9.

Table 3. 7-Determinants of farmers' choice of adaptation strategies

	Direct measures						**Supportive measures**				
Variable	Crop Diver	Drought TV	Flood TV	Heat TV	Early MV	Change PD	C-L Mix	C-L Insurance	Irrigation	Water Con	Water Drain
Gender	0.0214	0.0213	-0.2193	-0.0141	-0.1259	0.0541	-0.4836	-0.1828	0.5829	-0.1367	0.2667
	(0.2365)	(0.1987)	(0.1836)	(0.2340)	(0.2168)	(0.3097)	(0.5631)	(0.2326)	(0.3800)	(0.2126)	(0.1917)
Age	-0.0131**	-0.0030	-0.0010	0.0052	-0.0011	0.0177**	-0.0073	0.0020	0.0044	0.0046	-0.0068
	(0.0062)	(0.0054)	(0.0052)	(0.0062)	(0.0059)	(0.0070)	(0.0077)	(0.0054)	(0.0079)	(0.0058)	(0.0054)
Education	-0.0087	0.0319	0.0237	-0.0256	0.0085	0.0059	-0.0655***	0.0120	0.0045	0.0218	-0.0083
	(0.0218)	(0.0196)	(0.0178)	(0.0210)	(0.0214)	(0.0294)	(0.0243)	(0.0217)	(0.0253)	(0.0189)	(0.0179)
Per Inc. non-farm	0.0006	0.0062*	0.0047	0.0049	0.0011	0.0026	-0.0073	0.0083**	0.0077	-0.0027	-0.0037
	(0.0043)	(0.0037)	(0.0034)	(0.0039)	(0.0041)	(0.0049)	(0.0050)	(0.0036)	(0.0055)	(0.0036)	(0.0035)
Pot. Labour cap	0.0378	-0.0185	0.0444*	-0.0216	-0.0065	-0.1649***	-0.1101***	-0.0500*	0.0938***	-0.0510*	0.0203
	(0.0347)	(0.0272)	(0.0264)	(0.0289)	(0.0327)	(0.0398)	(0.0347)	(0.0301)	(0.0307)	(0.0266)	(0.0261)
Group membership	0.1002	-0.0979	0.2419*	-0.4566***	0.0367	-0.5396***	0.3276	-0.0744	0.3539*	0.2308	0.0308
	(0.1717)	(0.1455)	(0.1348)	(0.1604)	(0.1595)	(0.2027)	(0.2146)	(0.1625)	(0.1826)	(0.1534)	(0.1374)
Fam mem 18655K	0.0577	3.34e-06	-0.0481**	0.0095	0.0370	0.1220**	0.1036***	-0.1160***	-0.0681*	0.0144	0.0017
	(0.0395)	(0.0307)	(0.0235)	(0.0270)	(0.0287)	(0.0544)	(0.0395)	(0.0390)	(0.0349)	(0.0324)	(0.0261)
Fam mem abroad	-0.0589***	-0.0504**	0.0231	-0.0432**	-0.0375*	0.1257*	0.0437	-0.0039	-0.0914**	-0.0011	0.0227
	(0.0172)	(0.0206)	(0.0161)	(0.0215)	(0.0214)	(0.0711)	(0.0314)	(0.0247)	(0.0411)	(0.0241)	(0.0158)
Land ownership	0.5641	0.2710	0.2391	-0.3819	-0.0601	1.0684***	0.8933**	0.0907	0.1778	-0.2264	-0.1725
	(0.3970)	(0.2918)	(0.2714)	(0.3473)	(0.3341)	(0.4021)	(0.3714)	(0.3308)	(0.3338)	(0.3000)	(0.2815)
Credit	0.2240	0.2499	0.2417	0.2626	0.0059	0.8548***	0.6690**	0.5281***	0.3382*	0.1973	-0.0855
	(0.2131)	(0.1631)	(0.1470)	(0.1666)	(0.1724)	(0.3129)	(0.3003)	(0.1705)	(0.1917)	(0.1839)	(0.1511)
Extension	0.4978**	0.9893***	0.7804***	0.6151***	0.4946**	0.6964**	0.1371	0.1333	0.9572***	-0.0720	-0.4834***
	(0.2049)	(0.1914)	(0.1962)	(0.2072)	(0.2033)	(0.2796)	(0.2470)	(0.2037)	(0.2531)	(0.2046)	(0.1792)
Distance to market	0.0146	-0.0461***	-0.0398***	-0.0928***	-0.0160	0.0314*	0.0303**	-0.0158	-0.0392***	-0.0025	0.0377***
	(0.0207)	(0.0148)	(0.0145)	(0.0169)	(0.0142)	(0.0188)	(0.0147)	(0.0140)	(0.0128)	(0.0126)	(0.0131)
Soil fertility	0.2407	0.5694***	0.2267	0.8296***	0.6262***	-0.5854**	-0.0792	-0.5871***	0.0282	-0.6553***	-0.1508
	(0.1855)	(0.1613)	(0.1479)	(0.1847)	(0.1603)	(0.2599)	(0.2351)	(0.1749)	(0.1797)	(0.1704)	(0.1482)
Cropland area	0.0471	-0.0297	0.0032	0.0416	0.1495**	0.0072	0.2853***	0.0206	0.1490***	0.1048**	0.1244***
	(0.0576)	(0.0405)	(0.0370)	(0.0408)	(0.0600)	(0.0632)	(0.0889)	(0.0411)	(0.0368)	(0.0480)	(0.0407)
Livestock holding	0.0213	0.0019	-0.0259*	-0.0079	-0.0022	-0.0069	0.0359	0.0225	-0.0399*	-0.0069	-0.0394**
	(0.0220)	(0.0157)	(0.0157)	(0.0166)	(0.0212)	(0.0250)	(0.0287)	(0.0185)	(0.0239)	(0.0201)	(0.0155)
Value of farm implement	0.0003	0.0014	0.0002	0.0005	0.0005	0.0032*	-0.0003	-0.0001	-0.0025**	0.0031*	0.0011
	(0.0005)	(0.0009)	(0.0003)	(0.0008)	(0.0010)	(0.0017)	(0.0004)	(0.0003)	(0.0010)	(0.0017)	(0.0009)
Rainy days	0.0369	-0.1087***	-0.0566**	-0.0744**	0.0143	0.0251	0.0793*	0.0104	-0.0155	0.1386***	0.1225***
	(0.0495)	(0.0315)	(0.0268)	(0.0319)	(0.0364)	(0.0515)	(0.0439)	(0.0325)	(0.0306)	(0.0439)	(0.0314)
Intra-seasonal rainfall var.	0.0102	-0.0361**	-0.0247*	-0.0501***	-0.0237	-0.0144	0.0059	0.0235	-0.0440**	-0.0369*	0.0444***
	(0.0225)	(0.0163)	(0.0149)	(0.0170)	(0.0180)	(0.0276)	(0.0221)	(0.0189)	(0.0187)	(0.0193)	(0.0152)
Hot days	0.0229	-0.0161	0.0155	-0.0039	0.0123	0.0372	0.0167	-0.0598***	0.0489***	0.0360**	0.0459***
	(0.0168)	(0.0123)	(0.0116)	(0.0132)	(0.0140)	(0.0239)	(0.0201)	(0.0158)	(0.0174)	(0.0142)	(0.0134)
Region	-0.7506	-0.8875***	-0.6061*	-1.8140***	-0.0054	0.9480	1.9530***	-0.7928**	-0.7542**	0.0616	0.5737*
	(0.4771)	(0.3254)	(0.3101)	(0.3563)	(0.3614)	(0.5915)	(0.5180)	(0.3706)	(0.3538)	(0.3665)	(0.2974)
Constant	-5.7900	11.955***	2.5933	9.1818**	-1.4583	-7.2209	-8.9475	5.9061	-6.4988	-13.173**	-17.572***
	(5.9874)	(4.0101)	(3.3867)	(4.0403)	(4.5120)	(6.7041)	(5.9556)	(4.3385)	(4.3758)	(5.1020)	(4.1891)

Log pseudolikelihood = -1771.47; Number of obs = 439; Wald chi2 (220) = 2053.42, Prob > chi2 =0.0000; (*) – robust standard error

Table 3. 8-Correlation matrix for multivariate probit model

Measures	Strategies	Direct measures						Supportive measures				
		Crop Diver	Drought TV	Flood TV	Heat TV	Early MV	Change PD	C-L Mix	C-L Insurance	Irrigation	Water Con	Water Drain
Direct measures	Crop Diver	1.0000										
	Drought TV	0.3350***	1.0000									
		(0.0817)										
	Flood TV	0.3451***	0.5418***	1.0000								
		(0.0918)	(0.0650)									
	Heat TV	0.2008*	0.5948***	0.2176**	1.0000							
		(0.1083)	(0.0637)	(0.0872)								
	Early MV	0.2472**	0.5926***	0.5134***	0.5111***	1.0000						
		(0.1218)	(0.0733)	(0.0891)	(0.0891)							
	Change PD	0.3261**	0.1927*	0.3422***	0.0386	-0.2194*	1.0000					
		(0.1370)	(0.1059)	(0.0940)	(0.1159)	(0.1135)						
Supportive measures	C-L Mix	0.3168**	0.0229	0.0463	-0.0060	-0.0359	0.2683	1.0000				
		(0.1430)	(0.0972)	(0.1123)	(0.1073)	(0.1445)	(0.1670)					
	C-L Insurance	-0.1157	0.0374	-0.0671	0.1263	-0.1462	0.2148*	0.1143	1.0000			
		(0.1184)	(0.0986)	(0.0940)	(0.1183)	(0.1041)	(0.1138)	(0.1253)				
	Irrigation	0.1095	0.1573	0.4836***	-0.1425	0.1304	0.2899*	-0.1825	0.0251	1.0000		
		(0.1242)	(0.1012)	(0.0849)	(0.1092)	(0.1304)	(0.1730)	(0.1359)	(0.1557)			
	Water Con	0.2659*	0.2475***	0.5874***	0.0900	0.2148**	0.5361***	0.2927*	0.3657***	0.3674***	1.0000	
		(0.1539)	(0.0929)	(0.0845)	(0.1035)	(0.1090)	(0.1510)	(0.1669)	(0.1227)	(0.1143)		
	Water Drain	0.2369***	-0.1080	0.4471***	-0.1731**	0.1399	0.2410**	-0.1334	-0.1632*	0.2530**	0.2123**	1.0000
		(0.0898)	(0.0824)	(0.0672)	(0.0859)	(0.0858)	(0.1031)	(0.1136)	(0.0894)	(0.1056)	(0.0892)	

Likelihood ratio test of rho21=rho31=rho41=rho51=rho61=rho=71=rho81=rho91=rho101=rho111=rho32=rho42=rho52=rho62=rho72=rho82=rho92=rho102=rho112=rho43=rho53=rho63=rho73=rho83 =rho93=rho103=rho113=rho54=rho64=rho74=rho84=rho94=rho104=rho114=rho65=rho75=rho85=rho95=rho105=rho115=rho76=rho86=rho96=rho106=rho116=rho87=rho97=rho107=rho117=rho98=rho108=rho118=rho109=rho119=rho1110=0 ; chi2(55) = 425.89 Prob > chi2= 0.0000

Table 3. 9-Joint and marginal predictions for probability of adoption of strategies

			Joint Model				Model for direct measures		Model for supportive measures	
Model	Predictions	Strategies	Obs.	Mean	Std. Dev	Predictions	Mean	Std. Dev	Mean	Std. Dev
Joint	pall1s	All	439	0.0111	0.0320	pall1s	0.1732	0.1829	0.0253	0.0580
	pall0s	None	439	0.0003	0.0011	pall0s	0.0032	0.0078	0.0097	0.0189
Direct measures	pmargm1	Crop Diver	439	0.8374	0.1436	pmargm1	0.8366	0.1434		
	pmargm2	Drought TV	439	0.5881	0.2257	pmargm2	0.5965	0.2263		
	pmargm3	Flood TV	439	0.4181	0.2154	pmargm3	0.4119	0.2026		
	pmargm4	Heat TV	439	0.3709	0.2645	pmargm4	0.3722	0.2640		
	pmargm5	Early MV	439	0.8397	0.1221	pmargm5	0.8371	0.1247		
	pmargm6	Change PD	439	0.9183	0.1277	pmargm6	0.9138	0.1383		
Supportive measures	Pmargm7	C-L Mix	439	0.9215	0.1261	pmargm1			0.9203	0.1271
	Pmargm8	C-L Insurance	439	0.1785	0.1382	pmargm2			0.1779	0.1376
	Pmargm9	Irrigation	439	0.1774	0.2429	pmargm3			0.1806	0.2463
	Pmargm10	Water Con	439	0.5466	0.2822	pmargm4			0.5346	0.2797
	Pmargm11	Water Drain	439	0.5905	0.2030	pmargm5			0.5819	0.2162

3.6 Conclusion

For a deeper insight into farmers' adaptation to climatic shocks, this study documented farmers' perceptions of recent changes in the local climate, and identified factors that influence the number and choice of adaptation strategies implemented. Interdependencies among strategies were explored and joint and marginal probabilities of adoption estimated. Upper East Ghana and Southwest Burkina Faso were used as the case study regions due to their recent exposure to climatic shocks and extreme reliance of the inhabitants on agriculture for their livelihood. Under two primary headings of 'direct measures' and 'supportive measures', we document a total of 12 adaptation strategies implemented by farmers. Under these headings, strategies were grouped based on presumed cost-dimensions, where direct measures refer to low-cost measures covering varietal and crop-related adjustments, while supportive measures refer to high-cost measures covering insurance and other stress-reducing measures that help to minimize risk on farm.

From the perception analysis, it was found that farmers' perceptions of changes in the local climate are in conformity with climatic trends. Pro-adaptation response to the perceptions held by farmers could therefore be appropriate and helpful in policy efforts undertaken to reduce the adverse effects of weather risks. It was found that perceptions of farmers are significantly influenced by the level of education of the farmers, share of household income from non-farm sources, group membership, number of family members within the ages of 18 to 65 years living at most 5 km from the main residence, access to credit and distance to input and output markets. Perceptions held by farmers, regarding changes in the local climatic conditions, were found to be correlated. Farmers who perceived an increase in seasonal temperature were more likely to perceive a decrease in seasonal rainfall, but less likely to perceive an increase in seasonal flooding. This observation is in conformity with documented evidences in literature (e.g. Gbetibouo 2009, Bryan *et al* 2009; Tambo and Abdoulaye 2013).

Given their perception on the local climate and recent experience of weather shocks, farmers have made some adjustments in their production activities through crop diversification, planting of drought tolerant, heat tolerant, flood tolerant, and early maturing varieties, and changing planting dates under direct measures. Under supportive measures, farmers practiced crop-livestock mix, irrigation, purchase of crop and livestock insurance, and adoption of soil conservation, water conservation, and water drainage techniques. It was found through visual and pairwise correlation analysis that, although the association between intensity of adaptation and net crop income is non-linear, income from crop production generally increases with the number of strategies implemented. We identified the major determinants of the number and choice of strategies implemented by farmers through estimation of a Poisson regression and multivariate probit model. It was found that the number of strategies adopted by farmers increases with increasing access to extension services and credit, farm size, and seasonal hot days, but decreases with increasing access to remittances, remoteness, and increasing intra-seasonal rainfall variability. Farmers in Southwest Burkina Faso appeared to have adapted better to recent changes in the local climate than their counterparts in Upper East Ghana. Through estimation of the multivariate probit model, we discovered differential effects of various socio-economic, institutional and infrastructural, plot-based, climatic and location variables on farmers adoption of strategies under direct and supportive measures. Increased access to information and advisory services via extension officers and positive perception about fertility status of crop fields enhanced the adoption of majority of the strategies under direct measures. The adoption of direct measures was however inhibited by increased access to remittances, limited access to markets, increasing rainy days, increasing intra-seasonal rainfall variability and participation in farmers' organization. Farmers with access to credit, larger farm size, but with limited access to markets tend to adopt majority of the strategies under supportive measures. Adoption of majority of the supportive measures is as well enhanced by increasing rainy days, increasing seasonal hot days and group membership (although significant only in the case of irrigation). Farmers with positive perception about fertility status of their crop fields, high livestock inventory, and high potential labour capacity are less likely to invest in supportive measures. Of all the weather variables considered in this study, we note that increasing intra-seasonal rainfall variability has the greatest disincentive effect on farmers' adaptive behaviour.

Across all the estimated models, institutional and infrastructural measures like access to credit, extension services and distance to markets, plot characteristics (namely cropland area and fertility status of crop fields) and weather variables were found to be the major determinants of farmers' adaptation to weather extremes. This indicates that farmers' adaptation to weather extremes depends on functioning institutions that could improve farmers access to cash, information and skills, and markets for timely purchase of vital inputs for production. Increasing farmers access to credit could reduce financial burden, enhance timely purchase of inputs and incite investment in appropriate technologies. Increasing farmers access to information on climatic conditions, input and output prices, and skills via extension services could keep farmers updated on yield enhancing techniques, impending risks and on appropriate risk management practices. Improving farmers access to markets enables timely purchase of relevant inputs for production, and draws them closer to new developments on the local market. While larger farm size has a potential to instill economies of scale, thereby motivating large-scale producers to invest in stress-reducing measures, perceptions held by farmers on fertility status of their crop fields inform their decision on appropriate adaptive strategies to implement. Enlightening farmers on soil fertility issues could guide them in making appropriate decisions in this regard.

It was found that farmers are more likely to adopt a mix of direct and supportive measures to moderate harm from weather extremes, although their preference is more towards the adoption of direct measures, plausibly due to the relatively low cost incurred in implementing such measures and to their ability to yield benefits in the short-run. Direct measures implemented by farmers are generally adopted as complementary strategies. The degree of complementarity in the adoption of supportive measures is relatively low. Farmers are found to be approximately 7 times more likely to resort to the adoption of 6 direct measures than adopt 5 supportive measures to moderate harm from climate shocks.

Based on results from the respective analysis, we conclude that farmers have a good knowledge of their local environment and adapt to changes by implementing diverse strategies, although their preference is generally towards low-cost strategies that are likely to yield benefits in the short-run. Uncertainty with intra-seasonal rainfall distribution and with the potential outcome from the adoption of improved varieties under unfavorable conditions could incite a more risk-averse attitude in farmers, prompting them to forgo potential income-generating-but-risky strategies. Policy efforts purposed on providing farmers with timely weather-related information (forecasts) and enlightening them on risk management under unfavorable climatic conditions could incite the adoption of appropriate adaptation strategies to help minimize agricultural losses. Farmers adaptation to weather extremes could be enhanced through awareness creation (via extension officers), improving their access to markets and vital resources (including land) for production, and improving their access to credit (to ease liquidity constraints). Although in a non-linear fashion, income from crop production is found to increase with the number of strategies adopted. This implies that policy and research efforts to promote the adoption of risk management strategies as a package (diverse strategies) could prove beneficial to farmers.

Chapter 4

4 Impact of climate shocks on farm households' welfare in the Northern Savanna of Ghana

4.1 Introduction

There is undoubtedly a consensus that increasing frequency, intensity and duration of weather extremes inhibit agricultural growth in both developed and developing countries (Dercon and Krishnan 2000; Hawkins *et al* 2013; Thornton *et al* 2014; Wossen *et al* 2014; Haile *et al* 2017; Wineman *et al* 2017). In whichever form weather extremes manifest, they trigger major reduction in crop yields, incite soil and land related degradations, reduce food availability and access, and consequently enhance malnutrition, poverty and hunger especially in agriculture-reliant economies (Lobell and Field 2007; Schlenker and Lobell 2010; Thornton *et al* 2014; Wossen *et al* 2014). For example, in a study by Dercon *et al* (2005) in Ethiopia, it is reported that an experience of drought of at least one in five years leads to about a 20% decrease in per capita consumption. From the results of a research conducted by Wossen *et al* (2014), it is found that severe dry spells in the Upper East region of Ghana could reduce total production by about 38% and increase the rate of poverty by at least 10%. A study by Lokonon *et al* (2015) also report of a decrease in farm income by 17.43% to 69.48% with increasing risk of droughts and floods in the Niger basin of Benin. Beside these, extreme weather events have been linked to decreasing livestock productivity, high livestock mortality and general economic losses (Nardone *et al* 2010; Rojas-Downing *et al* 2017). These documented findings from previous research works indicate that vulnerable rural economies that are founded on sedentary crop farming and to some extent on nomadic pastoralism could be the most affected under current and anticipated climatic conditions (Berhe *et al* 2017; Cabot 2017). In such vulnerable locations where access to non-farm opportunities is highly limited (Barrett *et al* 2001; 2005), increasing incidences of weather extremes could paralyze the primary means of sustenance (agriculture) for majority of the inhabitants and drive most people into poverty trap.

Besides the direct localized effects of extreme weather events, indirect and second-round effects from decreases in production at the local level yield regional, national and global ramifications through forward and backward linkages of the agricultural sector with other sectors of the economy (Pandey *et al* 2007). This makes climate and weather extremes potential threats to national development. While climatically induced, the overall impact of weather extremes depends greatly on the susceptibility and adaptive capacity of the exposed system (Kelly and Adger 2000). With poor rural households and farmers in general, being likely to be the most affected by climate and weather shocks (Devereux 2008; Dasgupta *et al* 2014; Porter *et al* 2014), gaining a deeper insight into the impact of such shocks and adaptive responses on the welfare of this group of people, could guide the drafting and implementation of effective policies to promote resilience. Given the general adverse effects of extreme weather events, especially in developing countries, several research efforts have been made to assess the effects of climate shocks on agriculture and to inform policy decisions on relevant measures needed to mitigate, adapt and/or curb the adverse implications of weather extremes (e.g. see Lobell and Field 2007; Schlenker and Lobell 2010; Lobell *et al* 2011; Hawkins *et al* 2013; Haile *et al* 2017; Wineman *et al* 2017). Majority of these studies analyzed effects at a more macro-scale using either time series or panel data (e.g. Schlenker and Lobell 2010; Haile *et al* 2017), and in some cases based on experimental outputs (e.g. Lobell *et al* 2011). Very little effort (except for Wossen *et al* 2014; Lokonon *et al* 2015; Powell and Reinhard 2016; Wineman *et al* 2017) has so far been made at the farm level to assess the effects of weather shocks on farm households' welfare (income). With the researches done at both the micro- and macro-scales, greater emphasis has been placed on the impacts on crop production (e.g. see Powell and Reinhard 2016; Haile *et al* 2017), thereby ignoring effects on total income (from crop, livestock and off-farm activities).

Using secondary data from a farm household survey conducted across the three northern regions of Ghana by the Africa RISING program (Tinonin *et al* 2016) and historical climate data (1976-2005) from the CCAFS[24]-Climate data portal, we estimate the impact of climate shocks on the welfare of farm households in the Northern Savanna of Ghana. This zone was selected for the study due to high dependence of the inhabitants on rainfed agriculture for their livelihood, recent incidences of extreme weather events across the regions (Kusakari *et al* 2014; Yiran and Stringer 2016) and vulnerability of the farmers to weather shocks due to their low adaptive capacity (Antwi-Agyei *et al* 2012; 2014). Analyzing the impact of climate shocks on households' welfare could provide vital insights to guide the proposition of relevant policy recommendations. Econometric and mathematical programming models are used for the analysis.

In the remaining sections of the study, we shed some light on the theory of agricultural household model, the conceptual framework for this study, methods (data and analytical framework), present and discuss results for the study, draw conclusions, and make vital policy recommendations.

4.2 Theory of agricultural household model

Treated either as a single entity or a collective decision-making unit, an agricultural household model (AHM) deems a farm household as an entity that is jointly engaged in production, consumption and labor supply (Singh *et al* 1986) to optimize a set of household goals. Three economic theories have so far been documented in literature on the behavior of agricultural (farm) households. These are "profit maximization theory"[25] (Schulz 1964; Choi and Helmberger 1993; Moore *et al* 1994), "utility maximization theory"[26]

[24] CGIAR's Research Program on Climate Change, Agriculture and Food Security
[25] Where farmers are treated as entrepreneurs and profit maximizers, with the aspect of household consumption overlooked in decision-making processes (Schultz, 1964)
[26] This theory incorporates production and consumption goals of farm households

(Chayanov 1966; Singh *et al* 1986) and "risk aversion theory"[27] (Roumasset 1976; Morduch 1993). Based on these three theories, goals of farm households have been generally analyzed using either econometric models, (normative or positive) mathematical programming, dynamic simulation, agent-based modelling (Schreinemachers and Berger 2006; van Wijk *et al* 2012; Wineman *et al* 2017) or an appropriate combination of these approaches (Herrero *et al* 1999; Popp *et al* 2009), and in separable or non-separable frameworks depending on assumptions made about markets, prices and/or risk. While quite a high number of studies assume that households operate in a separable framework[28] (including Yotopoulos and Lau 1974; Choi and Helmberger 1993; Moore *et al* 1994), in majority of the developing countries where agricultural households can only consume what they produce (due to limited access to trade) or produce partly for own consumption and partly for sale, the use of a non-separable[29] framework is usually deemed more appropriate (Singh *et al* 1986; Yilma 2005; de Janvry and Sadoulet 2006; Louhichi *et al* 2013). In the latter case where farm households operate as semi-commercial entities, surpluses from production are sold on the market to raise income to meet household expenses, while excess labor is supplied off-farm to earn income. Whereas complete and perfectly operating markets (for labour and products) are assumed for the adoption of a separable framework (Delforce 1994), this assumption is usually relaxed (due to imperfect information or potential market failures) or refuted in models based on a non-separable framework. In addition, in a separable framework, farm household income is primarily assumed to be the only mediating variable between production and consumption, while a complex interaction is assumed between the two variables in a non-separable framework.

Founded on logical assumptions, agricultural/farm household models facilitate the analysis of the impact of household behavior/decisions (production and consumption decisions) on key economic variables likes households' welfare (income, food security, poverty, etc.), inter and intra-household resource allocations, sustainability issues, and market exchange and prices among other variables (Barnum and Squire 1979; Singh *et al* 1986; Taylor and Adelman 2003; Louhichi *et al* 2013; van Wijk *et al* 2014; Wossen *et al* 2014). In its simplest form, an agricultural household model optimizes an assumed objective (e.g. profit maximization, utility maximization, risk minimization, or cost minimization) subject to a set of constraints (key among which are resource and/or budget/cash constraints). Assuming a profit/utility maximization framework, a basic agricultural household model can be expressed as follows:

[27] Under this theory, a farm household's primary goal is to secure the survival of its members by avoiding risk. This may include a tradeoff between profits (by forgoing profitable-but-risky options) and survival (opting for less profitable but certain (less risky) alternatives)
[28] In a separable framework, production, consumption and labor supply decisions are independently made and the household is assumed to behave as a profit maximizing producer (de Janvry and Sadoulet 2006). Under this framework, farmers are assumed to be neutral to risks (Barnum and Squire 1979), and it is generally impossible to accommodate risk in a separable model (Delforce 1994).
[29] In a non-separable framework, production, consumption and labor supply decisions are made simultaneously or sequentially but with a greater degree of dependency between the three variables in the latter case (e.g. consumption depends on production and on income earned from production) (Singh *et al* 1986).

$$\max Z \qquad (4.1)$$

$$s.t \quad R_j \geq \sum_{i=1}^{I} a_{ij} X_i \qquad (4.2)$$

Where Z is the objective to be maximized, R_j is the total quantity of resource *j* (e.g. fertilizer, labor, land,) available to the household, a_{ij} represents the input use coefficients for crop *i*, and the area allocated to the respective crops is represented by X_i. While the use of each of the three aforementioned economic theories has been justified on various grounds in economic literature, in locations where households play a dual role as producers and consumers of food, a high degree of interdependency is mostly assumed between production, consumption and labor allocation decisions. This precludes the use of a profit maximization theory. Risk aversion and utility maximization theories are the noted theories mostly used in the analysis of household behavior/decision making in settings where the separability assumption fails. However, while the former is generally used in analyzing portfolio selection decisions (e.g. see Telser 1955; Gandorfer *et al* 2011; Hardaker *et al* 2015), the latter has been extensively applied to and is deemed most appropriate for analyzing household behavior in rural areas where consumption and production decisions are interdependent and where households make effort in diverse ways to smoothen income (ex-ante) or consumption (ex-post) before/after a shock (Singh *et al* 1986; Lovo 2011; Louhichi *et al* 2013). Although variants of mathematical programming models based on a utility maximization theory have been specified and used to analyze the behavior of agricultural/farm households, the basic form of the utility function used in this study can be expressed as follows (Chen *et al* 2014; Louhichi and Gomez y Paloma 2014; Lokonon *et al* 2015):

$$maximize\ U = \sum_{e=1}^{E} \sum_{c=1}^{C} Prob_e \times Y_{c,e}(Z, X_f) \times a_c \times Pr_c - \sum_{c=1}^{C} CS_c - ONetI \qquad (4.3)$$

- Resource constraints

$$IC_{c,f} a_c \leq R_f + b_f - s_f \qquad (4.4)$$

- Commodity balance

$$Q_c + B_c = Sold_c + Cons_c + OU_c \qquad (4.5)$$

- Cash constraints[30] and other relevant constraints

[30] This constraint states that the value of inputs and other tradable factors that a household purchases is constrained by the households' total cash income from production and off-farm income

From Eq. (4.3), e represents the states of weather conditions, c is an index for crops produced, $Prob_e$ represents the probability of weather conditions, Y is the yield of the respective crops expressed as a function of weather/climate variables (*Z*) and the rate (*X*) of factors of production (*f*) used in producing each crop. The index 'a' represents the amount of land allocated to each crop, '*Pr*' is the observed/expected crop prices, '*CS*' is the total cost of crop production, while '*ONetI*' is an index for net income from livestock production and off-farm activities. From the constraints in equations 4.4 and 4.5, '$IC_{c,f}$' is the input cofficients for factor f used in the production of each crop, R is the initial resource endowment of the household, *b* is a vector of rented-in tradable factors (including land and labor), while *s* is a vector of rented-out tradable factors. The quantity of each crop produced by the household is represented by Q, with *B* representing the quantities bought. *S* and *C* are the quantities of each crop sold and consumed respectively. The index 'OU' represents other components of a commodity balance, including losses and/or stocks.

Expressing yield as a function of weather variables and inputs of production, and accounting for the risk of different states of weather conditions facilitates the estimation of the impact of different levels of a given weather variable on crop yields, while permitting farmers traditional adaptation (land re-allocation and adjustments in input use) in a changing local climate. Based on historical weather data and projections or Monte Carlo simulation, this approach allows the estimation of the impact of both minor and major weather shocks on production in cross-sectional, panel and time series analysis, thereby accounting for the impact of climate change, variability and extremes on agriculture.

4.3 Conceptual framework

Agriculture is inherently a risky business, subjected to business[31] and financial risks[32] (Hardaker *et al* 2015) and findings from agricultural-related risk assessments serve as a useful guide in the formulation of vital local, regional and national resilience building policies and in agribusiness investment decision-making. Seen either as a single entity or a collective unit, in meeting some set goals (including income and basic food needs), the household devotes resources including land, labour and other vital agronomic inputs to the production of crop and livestock and to off-farm activities to earn supplementary income for upkeep of the household. A farm household's decision-making process and realization of set goals are presumed to be driven by a set of variables that fall under four primary modules; namely a supply module, a household module, a climate/weather risk[33] module, and an adaptation module (reflecting autonomous adaptation

[31] Business risks include production (weather risks and uncertainty about performance of crops and livestock due to pests and diseases), market (price) risks, and institutional and personal/human risks (Hardaker *et al* 2015)
[32] This type of risk results from the method of financing operations and activities on the farm firm
[33] Due to the inherent nature of climate risks in the environment in which farmers operate

and/or policy interventions). Under the supply module and given input and expected[34] output prices, farmers engage in the production of an appropriate (based on household's goals and needs) combination of crop and livestock species, on a limited land area (self-owned and/or rented-in), using some amounts of vital inputs of production within the constraints of the household's resource base. The latter phrase implies that the resources allocated to various activities on a farm cannot exceed that available (self-supplied and/or purchased) to the household. Among the inputs deemed vital to the production activities of the farm household are labor, seeds and other agronomic inputs like fertilizer, pesticides and herbicides, feed for livestock, and veterinary services.

Variables under the household module are primarily related to the households' food consumption needs and entails the influence of household size on the quantity of total output and market-purchased foods consumed and/or stored by the household, a reference consumption level that reveals the lower bound of output required to meet the food needs of the household, estimated income (coefficients) elasticities[35], post-harvest losses and the role of off-farm incomes. Given the inherent nature of climate and weather risks in the environment in which farmers operate, meeting of a household's set goals is contingent on the states of nature to which farm operations are subjected. Under favorable climatic conditions, farmers are likely to meet set targets through observance of appreciable crop yields and livestock output, complemented by off-farm incomes. Under unfavorable conditions however, there is a greater likelihood of a negative deviation of observed outcomes from planned (expected). The effects of climate and weather risks on production are basically revealed through deviations in crop yields from the norm (observed yields under normal climatic conditions) (Visagie *et al* 2004; Yilma 2005; Pandey *et al* 2007; Lokonon *et al* 2015). The risk of climate and/or weather shocks can be appropriately incorporated into agricultural household models as discrete states of nature with assigned probabilities (Visagie *et al* 2004; Hardaker *et al* 2015; Lokonon *et al* 2015). These probabilities could be based on subjective elicitation by farmers (Hardaker *et al* 2015; Lokonon *et al* 2015) or computed from historical weather data and Monte Carlo approach (Djanibekov 2014; Bocher 2016). The latter approach is used in this study to analyze the impact of increasing frequency of weather extremes on farmers' welfare in the Northern Savanna of Ghana. The approach based on farmers subjective elicitation of weather risks is flawed by a potential distortion of farmers' memory of experienced weather shocks (Hansen *et al* 2004; Hardaker *et al* 2015).

Operating in an environment where risks and uncertainty abound in several dimensions (Hazell and Norton 1986; Hardaker *et al* 2015), and access to infrastructural and institutional services are limited, farmers are subjected to input and output price risks, credit constraints, and market access limitations among

[34] The true prices of commodities (produce) are only revealed at the end of the harvest period when farmers engage in selling of market surpluses. As price-takers however, farmers have limited control over the prices they receive for their produce and mostly base their expectations on prevailing prices (which may not necessarily be different from the true prices) at the time production decisions are made.

[35] Obtained from the estimation of appropriate consumption (demand) models; such as linear expenditure system (LES), Engel functions, etc.

other challenges (Hazell and Norton 1986; Singh *et al* 1986; de Janvry and Sadoulet 2006). In such settings, autonomous adaptation by farmers to a changing local climate and policy interventions stand playing key roles in enhancing and sustaining households' welfare. While farmers adapt via the implementation of diverse strategies, governments do intervene through various channels to either curb adverse effects of climate/weather risks on farmers' welfare or improve production conditions. Among the channels used by governments are the use of pricing policies[36], investment in research and development, improving farmers access to credit (to ease liquidity constraints), or a combination of the interventions (Louhichi *et al* 2013; Mosnier *et al* 2017). Guided by the four primary modules in which it operates, a farm household makes effort to optimize an objective (or objectives) subject to a set of constraints.

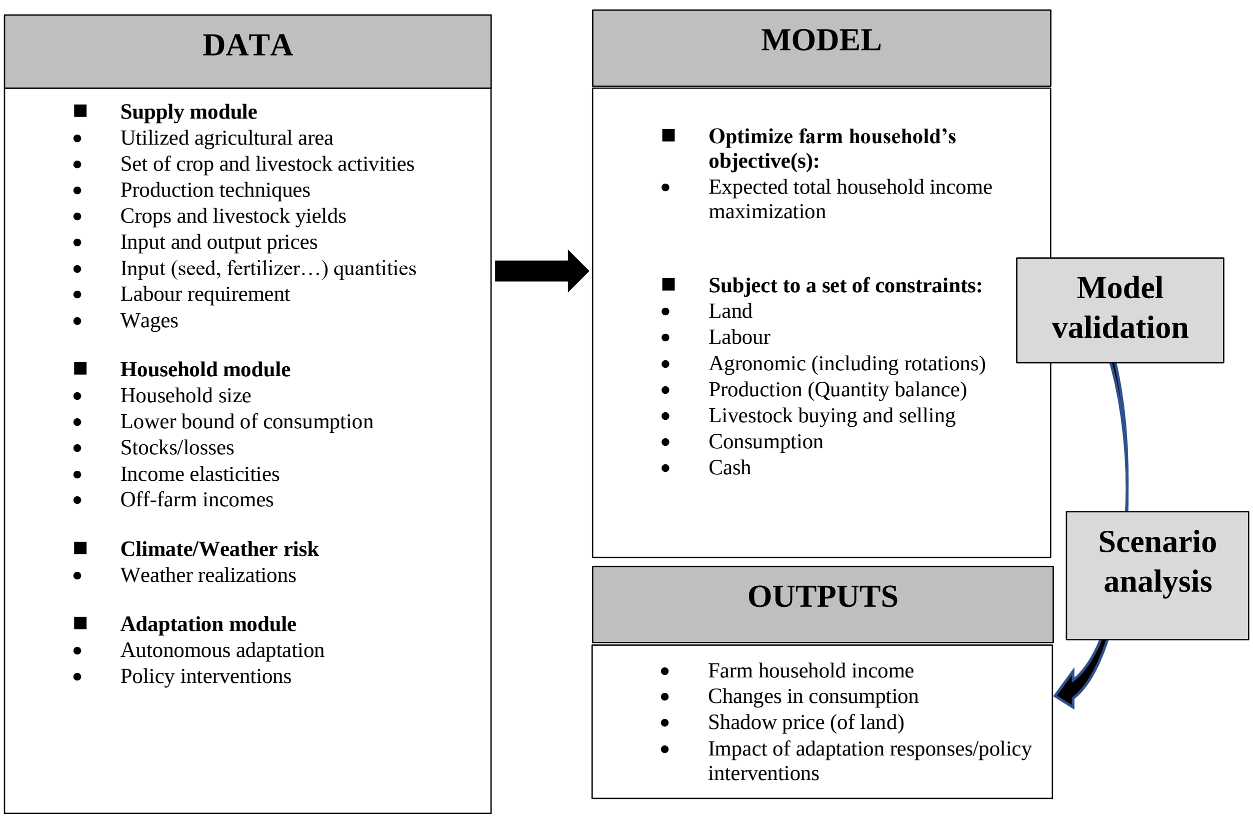


Figure 4. 1-An overview of agricultural household model for assessing the impact of weather risks
Source: Modified version of FSSIM-Dev[37] model (Louhichi *et al* 2016)

As shown in Figure 4.1, and in line with the goals of this study, households in the study area are assumed to maximize expected total income subject to land, labour, agronomic, quantity balance, livestock buying and selling, consumption, and cash constraints. Conceptually, farm household income refers to the total net income from crop and livestock production plus off-farm income minus cost of food purchased from

[36] Including the levying of input price subsidies and/or increasing output prices
[37] Farm System Simulator for Developing Countries

the market and the value of post-harvest losses. Although outputs from the analysis of farm household behavior could be numerous, outcomes of interest to this study are the total household income, changes in the quantity of food available for human consumption, shadow price of land and the impact of adaptation responses/policy interventions.

4.4 Methods

4.4.1 Data

The datasets used for this study originate from two secondary sources; a household survey data from the Africa RISING program (Tinonin *et al* 2016) and historical climate data (1976-2005) extracted from the CCAFS-Climate data portal. The Africa RISING program comprises three research-for-development projects supported by the United States Agency for International Development. The three research projects are led by the International Institute of Tropical Agriculture (IITA, in West, East and Southern Africa), and the International Livestock Research Institute (ILRI, in Ethiopian Highlands), with the International Food Policy Research Institute (IFPRI) playing a monitoring and evaluation role. The data used in this study was gathered as part of the evaluation efforts of the Africa RISING program in northern Ghana (baseline survey[38]). The survey, which covered all the three regions[39] in northern Ghana, was conducted using a stratified two-stage random sampling procedure. In all, a total of 1,284 households in 50 communities were covered across 9 districts in the three regions. This study however makes use of data from 1,182 households across the three regions. The 9 districts covered are Tolon/Kumbungu, Salvelugu and West Mamprusi for the Northern region, Kassena-Nankana East, Talensi-Nabdam, and Bongo for the Upper East region, and Wa West, Wa East and Nadowli for the Upper West region. The Ghana Africa RISING Evaluation Survey (GARBES) was conducted between May 13th and July 3rd 2014, and basically covered production and household activities for the year 2013. All the interviewed households were farming households that rely on agriculture at various degrees for their livelihood. Areas covered by the survey include household characteristics (including demography), agricultural land and production, agricultural input use and prices, agricultural harvest and allocation, data on livestock production activities, and prices of crops and livestock by species and age.

[38] Ghana Africa RISING Evaluation Survey (GARBES) conducted by the Pan African Field Services Limited on behalf of the Monitoring and Evaluation team at IFPRI

[39] Northern region, Upper East region and Upper West region

4.4.2 Characteristics of annual rainfall and temperature for the study area

Located in the semi-arid Northern Ghana, the three regions have a unimodal rainfall regime, with a rainy/growing period between May and October and relatively drier conditions between November and April. Annual mean temperature for the study area ranges between a minimum of 27.27°C and a maximum of 29.06 °C (based on the average for all 9 districts). Temperatures are however found to be relatively higher in the Upper East region and comparatively lower in the Upper West region. As shown in Table 4.1, although there are noted differences in the district level rainfall ranges, annual rainfall for the study area ranges between 730.73mm and 1274.8 (mm).

Table 4. 1-Characteristics of annual rainfall and temperature (1976-2005) for the Northern Savanna of Ghana

Districts	Rain (mm)					Temperature (°C)			
	Mean	Std	CoV,%	Min	Max	Mean	Std	Min	Max
Tolon-Kumbungu	1053.83	125.65	11.92	767.32	1375.4	28.230	0.402	27.22	29.18
Salvelugu-Nanton	1060.79	150.48	14.19	727.35	1410.4	28.231	0.414	27.20	29.23
West-Mamprusi	991.72	149.68	15.09	753.26	1328.2	28.668	0.397	27.67	29.60
Kassena-Nankana E.	933.69	142.84	15.30	695.70	1201.2	28.348	0.350	27.47	29.10
Talensi-Nabdam	961.52	129.82	13.50	782.94	1275.0	28.511	0.408	27.47	29.40
Bongo	924.53	127.82	13.83	754.69	1187.9	28.550	0.385	27.57	29.35
Wa West	1014.80	105.81	10.43	770.09	1223.9	27.658	0.314	26.98	28.52
Wa East	1022.71	127.75	12.49	716.37	1308.1	27.950	0.345	27.13	28.88
Nadowli	982.02	142.67	14.53	593.18	1203.2	27.452	0.314	26.75	28.27
Zone (Average)	993.96	118.26	11.90	730.73	1274.8	28.176	0.359	27.27	29.06

Source: Computed by author based on historical weather data from CCAFS-Climate data portal

The year 1987 is found to be the hottest for the study area, while the year 1976 is found to be the coldest. The lowest annual rainfall estimate was recorded in the year 1983 and the highest in the year 1999.

4.4.3 Production and livelihood indicators for the semi-arid Northern Ghana

Although predominantly on a smallholder basis, agriculture has been the major source of livelihood for majority of the inhabitants of the Northern Savanna of Ghana. In this zone, over 90% of the rural households and approximately 80% of the total households are employed by the agriculture sector (MoFA 2013). Agricultural activities in the zone comprise direct production of crops and livestock, processing of farm produce and marketing of both raw and processed products from the farm. Besides this, some farmers participate in other activities like selling of charcoal, firewood and other forest products, selling of wild foods, grain milling, and local beer brewing to raise extra income to complement that earned from crop and livestock production. Incomes from non-farm enterprises, remittances from family members or friends, renting of non-farm properties, and pension also do play vital roles in the upkeep of households in the study area. Although farmers in the three regions produce several crops and livestock species, approximately 72%

of the total cropland area is allocated to the production of maize, millet, sorghum and rice, while about 24% of the cropland area is used to produce legumes/pulses (see Table 4.2). Only 1.61% of the farmers in the three regions practice irrigation and this is mainly done on rice farms. The average household cultivates about 3.291 hectares of cropland, with the cropland per man-equivalent for the regions estimated at 0.894 hectares.

Table 4. 2-Production and livelihood indicators for the Northern Savanna of Ghana

Indicators	Mean	Indicators	Mean
Diversification (N=1,182)		TLU of goat at beginning of year 2013 (TLU/hh)	0.9553
Number of crops produced	2.658	TLU of sheep at beginning of year 2013 (TLU/hh)	0.6357
Number of livestock groups prod.	2.020	TLU of pig at beginning of year 2013 (TLU/hh)	0.2274
Number of off-farm income sources	0.960	TLU of poultry at beginning of year 2013 (TLU/hh)	0.3309
		TLU of livestock at beginning of year 2013 (TLU/hh)	3.9153
Plot-level variables and technology		Yield of maize (Kg/ha) (N=1,042)	765.87
Total cropland area (ha)	3.291	Yield of millet (Kg/ha) (N=294)	506.87
Cropland area under rainfed production (ha)	3.277	Yield of sorghum (Kg/ha) (N=110)	509.94
Irrigated cropland area (ha)	0.014	Yield of rice (Kg/ha) (N=420)	992.95
Practice of irrigation (1=Yes, 0 otherwise)	0.016	Yield of common beans (Kg/ha) (N=315)	277.80
Area of cropland under cereals, %	71.83	Yield of soybean (Kg/ha) (N=111)	671.42
Area of cropland under legumes/pulses, %	24.22	Yield of groundnut (Kg/ha) (N=460)	618.49
Area of cropland under root and tubers, %	3.442	Yield of bambara nuts (Kg/ha) (N=138)	362.54
Cropland per man-equivalent[40] (ha/ME)	0.894	Yield of yam (Kg/ha) (230)	4284.1
Crop and livestock production (N=1,182)		Cash income[41] to gross income[42] ratio for livestock, %	45.06
Produced maize (1=Yes, 0=No)	0.8816	Cash income to gross income ratio for crops, %	21.45
Produced millet (1=Yes, 0=No)	0.2487		
Produced sorghum (1=Yes, 0=No)	0.0931	**Off-farm income sources (N=1,182)**	
Produced rice (1=Yes, 0=No)	0.3553	Access to off-farm income (% of households (hh))	69.46
Produced common beans (1=Yes, 0=No)	0.2665	Access to agricultural off-farm income (% of households)	36.97
Produced soybean (1=Yes, 0=No)	0.0939	Access to non-agricultural off-farm income (% of hh)	43.40
Produced groundnut (1=Yes, 0=No)	0.3892		
Produced bambara nuts (1=Yes, 0=No)	0.1168	Income from non-farm enterprise (1=Yes, 0=No)	0.3283
Produced yam (1=Yes, 0=No)	0.1946	Income from firewood and forest prod. (1=Yes,0=No)	0.1574
Produced crop (1=Yes, 0=No)	0.9949	Income from sale of charcoal (1=Yes,0=No)	0.1591
Produced draught cattle (1=Yes, 0=No)	0.0296	Income from sale of wild foods (1=Yes,0=No)	0.0144
Produced bull (1=Yes, 0=No)	0.0660	Income from grain milling (1=Yes,0=No)	0.0152
Produced cow (1=Yes, 0=No)	0.1464	Income from local beer brewing/malting (1=Yes,0=No)	0.0753
Produced calf (1=Yes, 0=No)	0.1066	Income from agric. processing business (1=Yes,0=No)	0.0533
Produced donkey (1=Yes, 0=No)	0.0550	Income from pension (1=Yes,0=No)	0.0059
Produced goat (1=Yes, 0=No)	0.7064	Income from remittances (1=Yes,0=No)	0.1210
Produced sheep (1=Yes, 0=No)	0.4687	Income from other assistance (1=Yes,0=No)	0.0144
Produced pig (1=Yes, 0=No)	0.1235	Income from property non-farm rental (1=Yes,0=No)	0.0161
Produced poultry (1=Yes, 0=No)	0.8773		
Produced livestock (1=Yes, 0=No)	0.9712		
TLU of draught cattle at beginning of 2013 (TLU/hh)	0.1692		
TLU of bull at beginning of year 2013 (TLU/hh)	0.2221		
TLU of cow at beginning of year 2013 (TLU/hh)	1.2792		
TLU of calf at beginning of year 2013 (TLU/hh)	0.0447		
TLU of donkey at beginning of year 2013 (TLU/hh)	0.0508		

Source: Computed by author with GARBES (Ghana Africa RISING Evaluation Survey data)

[40] Computed using the following conversion factors; for Females: 0-5years (0.00), 6-10 years (0.05), 11-17years (0.40), 18-65 years (0.50), > 65 years (0.10); for males 0-5years (0.00), 6-10 years (0.10), 11-17years (0.80), 18-65 years (1.00), > 65years (0.70); (modified version of age range proposed by Runge-Metzger and Diehl 1993)

[41] Defined as the sum of income from direct sales of livestock and earnings from secondary products (e.g. eggs, draught services, milk, etc.)

[42] Defined as the sum of the cash income from livestock production and the value of self-consumed stocks (herds)

The common livestock species raised in the regions are poultry (chicken), goat, sheep, cattle and pigs. Less than 6% of the farm households produce equines (horse, donkeys and mules). Donkeys are however the common equines found in the study area. The average farmer produces about 3 crops, 2 livestock groups (large ruminants, small ruminants, poultry, pigs and equines), and earns off-farm income from a single source. A total of about 69.5% of the farmers have access to off-farm income. While crops are produced mostly on a subsistence basis (*the ratio of cash income to gross income for crops is less than 25%*), livestock producers in the regions earn more than 40% of their annual gross livestock income from the direct sales of livestock and secondary livestock products like egg, milk and draught services. With regards to farmers' access to off-farm income, it is found that majority of the farmers who claim to have access to off-farm income earn income mostly from non-farm enterprises, selling of charcoal, firewood and forest products, remittances from relatives, and from local beer brewing and malting.

4.4.4 Classification of farm households

4.4.4.1 Factor analysis

Farmers are regularly exposed to various risks and challenges and are subjected to diverse policy interventions to either curb adverse effects of prevailing and persistent risks or improve their welfare. The effects of external influence on farm households do generally differ due to prevailing heterogeneity across farm households, in terms of their endowments/wealth, access to vital infrastructure and institutional supports, and their adaptive capacity in the midst of risks (among other factors). To gain a deeper and much clearer insight into the effect of various socio-economic, environmental and policy-related variables on farmers, there arises a need to first cluster farmers into homogenous groups. This grouping is mostly done through appropriate clustering techniques. Such techniques segment an entire dataset of records on a given population into relatively homogenous subgroups, through maximization of the similarity of records within a given subgroup and minimization of similarity of records between subgroups (Larose 2005). For clustering techniques to appropriately reveal typologies of farms/farm households, there is a need to first define what a homogenous farm group is. Farm households that may be homogenous in terms of one variable may be heterogenous in terms of other variables (Yilma 2005). For appropriate clustering of farmers into subgroups, varying numbers of indicator variables have been used in previous studies to define a homogenous group.

Common variables used for such grouping are mostly related to household demographics, endowment/wealth, access to markets, labour availability and use, technology/innovation and access to credit (e.g. Yilma 2005; Bidogeza *et al* 2009; Lokonon 2015; Weltin *et al* 2017). Whereas the use of a relatively higher number of variables is preferred to the use of one variable for defining a homogenous group, some variables in the former case could be highly correlated, thereby inducing collinearity /multicollinearity problems. To address this problem, the precedence of a cluster analysis with a factor analysis has been proposed and applied in earlier studies to reduce the number of variables into manageable and meaningful size through extraction of factors that are non-collinear to one another (Woelcke 2003; Larose 2006; Weltin *et al* 2017). The common methods for extraction of factors include principal components analysis (PCA, or principal component factoring, PCF), principal axis factoring, and maximum likelihood. Factor analysis basically groups similar variables into dimensions known as factors (Hair *et al* 1998). For depiction of more meaningful and interpretable factors, the extracted factors are rotated after extraction using either orthogonal rotations[43] or oblique rotations[44]. Saved factor scores after rotation are used to cluster the given population or sample of interest. This can be achieved using either hierarchical or non-hierarchical clustering techniques or both. For this study and based on documented indicator variables in literature for clustering farm households, a total of 10 variables are used for the factor analysis and in subsequent grouping of farm households into homogenous groups based on saved factor scores. The 10 variables used are listed in Table 4.3.

Table 4. 3-Descriptive statistics of variables used for cluster analysis

Variables (N=1,182)	Units	Mean	Std. Dev
Income per man-equivalent per day	GHS/ME	1.521	2.224
Share of cereals in total acreage of cropland cultivated	%	71.83	28.59
Irrigation dummy	Dummy (1=Yes, 0 otherwise)	0.0161	0.1258
Value of non-land assets	GHS/household	4488.5	9121.2
Labor input for crop production	Person-days per hectare	88.36	62.10
Quantity of fertilizer applied on farm	Kg/hectare	92.15	98.08
Total cropland area cultivated	Hectares	3.291	3.8930
Total number of adult males in household	Count of people	2.0482	1.3587
Total number of adult females in household	Count of people	2.2690	1.5283
Total number of children in household	Count of people	4.3646	3.1359

Source: Computed by author with GARBES (Ghana Africa RISING Evaluation Survey data)

A total of four factors were extracted from the 10 variables. These factors jointly explain about 64.9% of the total variance in the variables used for the factor analysis (see Table 4.4). The factor analysis was based on a principal component factoring and an orthogonal varimax rotation with Kaiser/Horst normalization.

[43] This type of rotation ensures that the extracted factors remain uncorrelated and at the same time preserve variable communalities. Orthogonal rotations include varimax rotation, quartimax rotation, and equimax rotation, although varimax is the commonly used orthogonal rotation technique (Abdi 2003).

[44] This type of rotation allows factors to lose their uncorrelatedness if that would lead to the production of a clearer simple structure. Oblique rotations include promax rotation and oblimin rotation, although the promax is the commonly used technique due to its advantage of being fast and conceptually simple (Abdi 2003)

The use of Kaiser normalization ensures that all rows have the same weight during computation of the optimal rotation (Horst 1965).

The first factor has the largest loadings from the variables 'Total number of adult males in household', 'Total number of adult females in household', and 'Total number of children in household'. These three variables are indicators of the demographic attributes of the farm households. This factor is hereby named '***Household demographics***". The highest loadings on the second factor are from the variables 'Irrigation dummy', 'Quantity of fertilizer applied on farm', and 'Share of cereals in total acreage of cropland cultivated'. These three variables are indicators of production technology. Farms with a greater share of land allocated to the production of cereals are more likely to use higher quantity of fertilizer than farms with a smaller share of land under cereals. These farmers are as well more likely to practice irrigation, as this is done mainly on cereal farms, especially rice. The second factor is dubbed '***production technology***'. The third factor has more factor loadings from the variables 'Income per man-equivalent per day', and 'value of non-land assets'. With these two variables being general indicators of wealth, the second factor is dubbed '***wealth/asset endowment***'.

Table 4. 4-Rotated factor loadings

Variables (N=1,182)	Factors			
	1	2	3	4
Income per man-equivalent per day			**0.8097**	
Share of cereals in total acreage of cropland cultivated		**0.7037**		
Irrigation dummy		**0.5496**		
Value of non-land assets			**0.6283**	
Labor input for crop production				**-0.8768**
Quantity of fertilizer applied on farm		**0.8030**		
Total cropland area cultivated				**0.5601**
Total number of adult males in household	**0.7290**			
Total number of adult females in household	**0.8668**			
Total number of children in household	**0.8383**			
Summary				
Eigenvalues	2.3978	1.4771	1.3287	1.2862
Percent trace	23.98	14.77	13.29	12.86

NB: percent of total variance extracted= 64.90
Threshold: abs (loadings)> 0.45
Rotation: orthogonal varimax rotation with Kaiser normalization
Bartlett test of sphericity: Chi-square= 2170.54, Degrees of freedom=45, p-value=0.000
H_0: variables are not intercorrelated
Kaiser-Meyer-Olkin measure of sampling adequacy=0.677; Determinant of the correlation matrix= 0.158
Source: Author's construct based on output of factor analysis in Stata15

The fourth factor is named '***scale of production and labor intensity***' due to the relatively higher loadings from the variables 'Total cropland area cultivated' and 'labor input for crop production'. Per the factor loadings for these variables, large scale farmers are likely to use less labour input per hectare of cropland than small-scale farmers. Majority of the small-scale farmers mostly rely on family labor input for production, and use labor intensively per a given area. After the factor analysis, scores for the respective factors were saved and used to group farm households into appropriate clusters.

4.4.4.2 Cluster analysis

Although clustering procedure comprise hierarchical, non-hierarchical (partitioning), and/or two-step clustering techniques, a partitioning method (specifically, the k-means clustering) is used in this study. In contrast to the use of distance measures like Euclidean or city-block distance by the hierarchical methods, k-means clustering uses the within-cluster variation as a measure to form homogenous clusters (Mooi and Sarstedt 2011). The procedure aims at segmenting the data to minimize the within-cluster variation. It starts by randomly assigning objects to a specified number of clusters. These objects are reassigned to other clusters to minimize the squared distance from each observation to the center of the associated cluster. The approach is less affected by outliers and the presence of irrelevant clustering variables, and can be applied to large datasets (and is the recommended choice for sample sizes above 500) (Mooi and Sarstedt 2011). While factor analysis tells us which variables are similar to one another and how they should be grouped, cluster analysis tells us which people (objects) are similar and how they should be grouped. The saved factor scores from the factor analysis were used in place of the 10 indicator variables from the previous section for the cluster analysis. The objects were initially grouped into clusters of 2 to 6, and based on distinctness and unequal size problem (number of people in each cluster), a cluster of 3 was found to be more appropriate. Thus, the 1,182 households were grouped into 3 clusters. Cluster 1 is made up of 663 households (56.09%), Cluster 2 has 427 households (36.13%), while Cluster 3 has 92 households (7.78%),

4.4.4.3 Characteristics of the identified clusters

In this section, we provide a brief description of farmers in each of the clusters. As shown in Table 4.5, farmers of Clusters 1 and 2 earn less than US$1.25/day (international poverty line), while farmers of Cluster 3 earn approximately US$1.75/day[45]. Besides this, the total value of non-land assets held by farmers of Cluster 3 is significantly higher than the value held by farmers of Clusters 1 and 2. Based on these information, farmers of Clusters 1 and 2 are deemed poor, while the farmers of Cluster 3 are deemed less poor. Fertilizer application rate (kg/ha) is found to be very high on farms owned by farmers of Cluster 3 (approximately 301kg/ha), and comparatively lower on farms owned by farmers of Clusters 1 (less than 100kg/ha) and 2 (less than 50kg/ha). The share of cereals in the total cropland cultivated is however found to be higher in Clusters 3 and 1, than in Cluster 2. Irrigation is practiced solely by farmers in Cluster 3. The

[45] Below a US$2/day international poverty line, but above US$1.25/day

labor input for crop production is found to be higher in Cluster 3 than in Clusters 1 and 2. By this information, farms owned by farmers of Cluster 3 are deemed high input farms, while those owned by farmers of Clusters 1 and 2 are deemed low input farms. Per the scale of production, farmers of Clusters 1 and 2 are found to cultivate relatively larger acreages than farmers of Cluster 3. By the observed acreages (>3ha for Clusters 1 and 2, and <2 ha in Cluster 3) cultivated, farms in Cluster 3 are regarded as small-scale farms, while the farms in the other two clusters are regarded as medium-scale farms. In regards to the household demographics however, no major differences in the household size are found.

Table 4. 5-Characteristics of the identified clusters

Variables (N=1,182)	Cluster 1	Cluster 2	Cluster 3
	Poor farmers (G70%C[46]) (N=663)	Poor farmers (L70%C[47]) (N=427)	Less poor farmers (G70%C) (N=92)
Income per man-equivalent per day	1.1002 [US$ 0.563]	1.7638 [US$ 0.9026]	3.4248 [US$ 1.7526]
Share of cereals in total acreage of cropland cultivated	87.45	42.70	94.49
Irrigation dummy	0.00	0.00	0.2065
Value of non-land assets	3,273.49	5,089.39	10,456.1
Labor input for crop production	75.968	100.44	121.59
Quantity of fertilizer applied on farm	93.860	44.426	301.297
Total cropland area cultivated	3.4479	3.3770	1.7585
Total number of adult males in household	2.1765	1.9555	1.5543
Total number of adult females in household	2.3167	2.2225	2.1413
Total number of children in household	4.6018	4.0632	4.0543
Total household size	9.1237	8.2482	7.7826

Note: [*] -equivalent in US dollars, Exchange rate for 2013: 1 USD =GHC 1.9541

Source: Author's construct based on output of factor analysis in Stata15

With these information, we deem the farmers of Cluster 1 as 'poor farmers who operate under low input conditions on medium-scale farms and allocate more than 70% of the total cropland area to the production of cereals". The farmers of Cluster 2 are considered as 'poor farmers who operate under low input conditions on medium-scale farms and allocate less than 70% of the total cropland area to the production of cereals". Finally, farmers of Cluster 3 are referred to as 'less poor farmers who operate under high input conditions on small-scale farms and allocate more than 70% of the total cropland area to the production of cereals. All the three clusters are considered in this study.

[46] At least 70% of the total cropland area is under cereals
[47] The share of cropland area under cereals is less than 70%

4.4.5 Analytical framework

In this study, econometric and mathematical programming techniques are used to estimate the impact of climate shocks on farm households' welfare. Emphasis is placed on simulating the impact of future rainfall variability/distribution on households welfare, using historical/current variability/distribution as a reference for comparison. While the use of historical climate data enables the assessment of risk to which current farming systems are subjected, the consideration of future climate (which brings an element of uncertainty into climate impact assessment) facilitates the identification of potential risks that farmers are likely to face in the near future, and to ascertain which group of farmers are likely to be affected the most under diverse rainfall distributions. By this, we seek to simulate the effect of climate shocks on farmers welfare and production decisions by generating random rainfall distributions (based on statistics for the historical climate data) using Monte Carlo simulation, predicting crop yields for each distribution, and maxiziming household income given the predicted yields and other production outcomes. The analysis involves

- The estimation of a yield response function
- Prediction of crop yields for different levels of rainfall based on the historical climate data
- Constructing anomalies using the historical time series rainfall distribution and assigning each year to a corresponding anomaly based on definitions for five considered states of rainfall
- Repetition of the process for random rainfall distributions (based on defined scenarios) and
- Estimation of welfare changes by comparing estimates under the historical and future rainfall distributions.

Thus, emphasis is placed on estimating the impact of increasing frequency of years with extreme rainfall conditions on farmers' welfare (Bocher 2016). To guide the identification and assigning of years into rainfall states, anomaly incidences are computed from the historical time series climate data using Standardized Anomaly Index (SAI), and rainfall grouped into five states, namely very dry, dry, normal, wet, and very wet. As defined by Bordi *et al* (2001), SAI is computed as:

$$SAI_t = \frac{R_t - \bar{R}}{\sigma} \qquad (4.6)$$

Table 4. 6- Definitions for the states of rainfall conditions

Rainfall realizations	Definition
Very dry	SAI ≤ -1.5
Dry	-1.49 ≤ SAI < -0.5
Normal	-0.5 ≤ SAI ≤ 0.5
Wet	0.5 < SAI≤ 1.49
Very wet	SAI ≥ 1.5

Source: Author's construct

Where t is an index for each year in the rainfall series, R is the annual rainfall for a particular year, while $\bar{R}$ and σ are the long-term average rainfall and standard deviation respectively. Based on the constructed anomalies, the years in the series are classified as in Table 4.6. In line with earlier studies, including Visagie *et al* (2004), Yilma (2005) and Lokonon *et al* (2015), it is presumed that climate shocks affect households' production decisions and outcomes through crop yields, and the rate of decrease/increase in yields amidst such shocks depends on technology and management conditions of the exposed farms (Rockström and Falkenmark 2000; Chang 2002). Given the technology and management conditions of farms and estimated yields for the diverse crops produced by each of the households, incomes are maximized subject to a set of constraints faced by the farmers. Details of the constraints considered, production technology assumed and assumptions on which the optimization model is founded are provided in the subsequent sections. A static optimization model is used for the study.

Although farmers in the study area produce diverse crops and livestock species, the current analysis is based only on the most frequently found activities. This is to minimize complications in the estimation process. Besides, and as stressed on by Börner (2005), "*defining production activities for linear programming involves tradeoff between model size and the representation of reality*". A total of 9 crops are considered in this study. These are maize, millet, sorghum, rice, common beans, soybean, groundnut, bambara nuts and yam. The livestock species considered are draught cattle, bull, cow, calf, donkey, goat, sheep, pig and chicken.

4.4.5.1 Assumptions for the production function and optimization model

Farm households decision-making is a complex process that is influenced by a mix of agronomic, market, financial, policy, and other biotic and abiotic factors. The ability for analysts to accurately predict such a process and the consequent outcomes using models is to some extent limited by a potential information gap between the decision-maker and the modeler. To represent the decision-making process, it is essential to include some assumptions to guide the model building and subsequent predictions. The following assumptions are made for this study:

1. The weather conditions under which farmers in the study area operate are categorized into five states: 'very dry', 'dry', 'normal', 'wet', and 'very wet'. The risk of crop production that results from unpredictability of rainfall levels is reflected by the variability of crop yields under the five states of rainfall, given the level of technology and management for the farming systems considered.

2. Food commodities produced by the households are for self-consumption (human consumption + seeds + gift/exchange) or sold on the market to generate cash income. There could be post-harvest losses and farmers could purchase food items from the market to meet food supply deficits resulting from low crop harvests or high household food demand. Thus, food consumption needs of the farm households can be met from domestic production and/or through purchases from the market. Stocks of food crops are not considered in this study because the surveyed households are generally net purchasers of food.
3. To meet the food and income needs of the households, farmers allocate various inputs to the production of crops and livestock species. These inputs are either supplied by the households, rented-in from the market or both. For example, land used for the cultivation of the respective crops comprises self-owned/communal land and/or rented-in land. Similarly, in each cropping year, farm households have a total labor endowment, which could be used on the household's farm or supplied to the labor market for income generation. These households could hire-in labor from the market when the need arises. Inputs like fertilizer, pesticides and herbicides which are not produced within the household could be purchased from the market.
4. With regards to the use of labor on farm, family and hired labor are assumed to be imperfect substitutes in the farm production. While hired labor is valued at the reported wage rates by farmers, a reservation wage rate (set at 25% of the hired labor wage) is used in costing family labor input on farm. This is in line with the 0 to 50% range proposed by Yilma (2005) for the study area. Besides, given the scarcity of land in the study area, limited access to off-farm wage income, and limited access to diverse non-wage off-farm opportunities, the opportunity cost for using family labor on farm could be very low (Louhichi *et al* 2013).
5. Farmers in the study area are assumed to be price-takers in the input, output and labor markets.
6. Although it is well documented in literature (e.g see Owusu *et al* 2011; Senadza 2012) that farmers in the study area participate in non-farm work to generate income, opportunities for off-farm employment are limited in the three regions (Yilma 2005; Wossen *et al* 2014). This is as well confirmed by the statistics in Table 4.2, which reveals that the average household has access to only 1 off-farm employment opportunity. Thus, it is assumed that the three regions have a relatively working labor market that enables farmers to both hire-in and hire-out labor. There are however constraints on access of farmers to off-farm labor market/opportunities. To account for such constraints, we set an upper bound (a ceiling) on the amount of labor the household can hire-out to the off-farm market (Yilma 2005). For this study, and for each cluster, the bound is set at the average persondays of off-farm employment from the survey data for the respective clusters.

7. Given exogenous prices of fertilizer, it is assumed that the quantity of fertilizer applied on a farm is only constrained by the farmers budget/cash constraint and that the total quantity of fertilizer applied is a choice made by the farmers to maximize total household income.

Besides the above-mentioned assumptions, the study hypothesizes that:
‘*drier climatic conditions would result in reduced crop yields, lower household income and food consumption. Wetter conditions can result in higher or lower yields depending on the level of rainfall and crop types*’.

4.4.5.2 Production function

While crop production is influenced by a complex mix of factors, this study assumes crop yield (*Y*) to be a function of labor input (*L*), seed (*Sd*), new agricultural technologies used by the farmers (*T*) (including fertilizer application, irrigation, etc), and natural endowment (*E*) (specifically, climate (rainfall and temperature)):

$$Y = f(L, Sd, T, E) \qquad (4.7)$$

Although several explicit functional forms have been used to analyze yield responses, recent studies (including Makowski and Wallach 2002; Amon-Armah *et al* 2014) have shown that there exists little or no consensus among applied economists on the right choice of estimation approach. This is based on the presumption that functional forms that may accurately describe underlying biological relationship and technologies in one instance may fail to do so in another (Diwert and Wales 1989; Driscoll and Boisvert 1991; Amon-Armah *et al* 2014). Among the common functional forms used for analyzing yield response of crops to climatic and non-climatic factors are quadratic functions (e.g. Martinez and Albiac 2006; Jalota *et al* 2007), log-linear specifications (Lobell and Burke 2010), and Cobb-Douglas specifications (Lokonon *et al* 2016; Mendelsohn and Wang 2017; Amare *et al* 2018). While the debate on the appropriate choice of function to use is ongoing, research generally suggests that production functions tend to be multiplicative rather than being additive (Mendelsohn and Wang 2017) and the Cobb-Douglas specification is the commonly used multiplicative production function. A Cobb-Douglas specification is hereby used for this study. In this regard, equation (4.7) is rewritten as follows:

$$Y = CL^{\propto} Sd^{\beta} T^{\gamma} E^{\varphi} \qquad (4.8)$$

Where $\propto, \beta, \gamma, and\ \varphi$ represent estimated coefficients and *C* the intercept term. In linearizing this function, we obtain

$$Ln(Y) = Ln(C) + \propto Ln(L) + \beta Ln(Sd) + \gamma Ln(T) + \varphi Ln(E) \quad (4.9)$$

The specification in equation (4.9) implies that the explanatory variables affect crop yields in a proportional manner and that the effectiveness of labor, seeds, and agricultural technologies depends on advantageous weather conditions (Mendelsohn and Wang 2017). Yield response functions are estimated for each of the 9 crops considered in this study. In the case of rice, where some farmers practice irrigation, two separate yield response functions were estimated. One for purely rainfed farms and the other for all rice farms with an irrigation dummy included to capture the effect of irrigation (Bocher 2016). The estimation of two separate yield response functions for rice is based on the presumption that rainfed and irrigated rice farms are likely to face different intercepts (and possibly different coefficients for the explanatory variables). The yield predictions for each of the crops are compared with the observed to assess the goodness-of-fit of the model (using Percent Absolute Deviation, see Table AP 4.1 in the Appendix for details). Only fertilizer application is considered for the variable T[48]. Fertilizer application is expressed in kg/ha. The variable T was however omitted from the regression function for yam, where none of the households applied fertilizer. Equation (4.9) was estimated as a cross sectional regression using a maximum likelihood optimization (under Generalized Linear Models).

Although we are unable to directly include other adaptation measures (in the regression) used by farmers due to lack of information, estimation of the cross-sectional regression and using the long-term (1976-2005) weather averages helps to implicitly capture adjustments that farmers are likely to make under the five states of weather conditions (Mendelsohn and Wang 2017). Thus, other climate adaptations that farmers are making are implicitly captured through estimation of the cross sectional regression. To endogenize management decisions made by the farmers, crop yields are predicted for combinations of five levels of fertilizer (namely 0, 25, 50, 100, 150) with each of the 30 historical/future weather observations. Predicted yields for each of these combinations are averaged for each of the five states of weather conditions and the outcome used in the static optimization model. Given the average yields for the respective combinations of fertilizer levels and weather realizations, and input costs, the model chooses the optimal linear combination of model activities (Börner 2005). Thus, the underlying production function is introduced into the static optimization model through a piecewise linearization of the Cobb-Douglas function. To assess the impact of the different weather realizations on crop yields under the historical/current rainfall distribution, predictions were also made for the five states of weather conditions keeping all other inputs at the mean values from the survey.

[48] Due to lack of information on other adaptation measures used by farmers in the regions

4.4.5.3 Static optimization model

The goal of this study is to estimate the impact of increasing frequency of weather extremes on farm households' welfare in the Northern Savanna of Ghana. To achieve this goal, a utility maximization framework was adopted, placing emphasis on the maximization of expected farm household income (Z) under the risk ($Prob_e$) of five rainfall conditions (*e*) ('very dry', 'dry', 'normal', 'wet' and 'very wet'). Household income refers to the difference between the sum of revenue generated from all activities and the total cost incurred on all activities. Households in the region can generate revenue from the production[49] ($Y_{c,s,F,e} * a_{c,s,F}$) of crops (c) on land type 's' (rainfed or irrigated) at fertilizer levels 'F', hiring out labor (L^o) at a wage rate of w_{Ol} per person per day, selling of livestock (SL_{ls}) at a price $prliv_{lsS}$ and earning secondary income per head of livestock species (Vsp_{ls}). Secondary income comprises income earned from livestock products (milk, egg, draught services, etc.) and the value of livestock slaughtered and consumed by the household. Crops produced can be sold, consumed or partly lost ($PHLoss_c$) and in either case valued at a price 'Pr_c'. For every hectare of cropland, farmers apply a chosen (based on farmers decision) kg of fertilizer (*fer*) at a cost of '*prf*' per kg and incur other non-labor expenses (specifically, cost of seed, pesticides and herbicides) (*CSPOnl*). Using family labor ($\bar{L} - L^o$) on farm[50], farmers incur an indirect labor cost valued at a reservation wage rate of w_R per person per day.

$$\begin{aligned}
Max\ Z = {} & \sum_{c=1}^{n}\sum_{s=1}^{2}\sum_{F=1}^{5}\sum_{e=1}^{5} Prob_e \times Y_{c,s,F,e} \times Pr_c \times a_{c,s,F} - \sum_{c=1}^{n}\sum_{s=1}^{2}\sum_{F=1}^{5} prf_c \times fer_{c,s,F} \times a_{c,s,F} \\
& - \sum_{c=1}^{n}\sum_{s=1}^{2}\sum_{F=1}^{5} CSPOnl_c \times a_{c,s,F} - w_R * (\bar{L} - L^o) - w_{Hl} * L^H - int * CRED + w_{Ol} * L^o \\
& - \sum_{c=1}^{n}\sum_{e=1}^{5} Pr_c * PHLoss_{c,e} - \sum_{c=1}^{n}\sum_{e=1}^{5} Pr_{pc} * Bfood_{c,e} - \sum_{s=1}^{2} CR * RLand_s \\
& + \sum_{ls=1}^{n} prliv_{lsS} \times SL_{ls} - \sum_{ls=1}^{n} prliv_{lsB} \times BO_{ls} + \sum_{ls=1}^{n} Vsp_{ls} \times [BGY_{ls} + BO_{ls} - SL_{ls}] \\
& - \sum_{ls=1}^{n} CFV_{ls} \times [BGY_{ls} + BO_{ls} - SL_{ls}] \qquad (4.10)
\end{aligned}$$

[49] Defined as the product of crop yields (Y) and the area (a) allocated to each crop
[50] Defined as the difference between the total household labor endowment and off-farm labor

In times of labor deficit or high labor demand, farmers can readily hire-in labor (L^H) from the market, but at a wage rate of w_{Hl} per person per day. Credit (CRED) may be accessed by farmers to ease liquidity constraints if need be, but at an interest charge of 'int'. The interest charge is set at 25%.[51] In times of food supply deficit, farmers purchase food ($Bfood_c$) from the market to help meet consumption needs and these food items are bought at a price of 'Pr_{pc}' per kg. Besides cultivating on self-owned/communal land ($OLand$), there exists a relatively working land market that permits farmers to rent-in additional land ($RLand$) at a cost of 'CR' per hectare. In producing livestock as one of the enterprises from which farm households generate income, farmers may choose to buy (BO) any species of livestock (ls) at a price ($prliv_{lsB}$) and in the production process incur costs on feed and veterinary services. The total cost incurred depends on the cost per head (CFV_{ls}) and the total number of each livestock species held. The total number of livestock species held is defined as the sum of the number of species at the beginning of the year (BGY_{ls}) and the number bought (BO_{ls}) minus the number sold (SL_{ls}). With these avenues of income generation and cost incurrence, the households are assumed to maximize the expected total net income (Z) from all activities subject to the following constraints:

Land constraint:

Land in the study area is split into two types: rainfed and irrigated lands. The sum of the area allocated to the production of each of the crops for each land type and across the five levels of fertilizer application cannot exceed the total cropland area cultivated, the latter of which comprises self-owned and /or rented-in land.

$$\sum_{c=1}^{n}\sum_{s=1}^{2}\sum_{F=1}^{5} a_{c,s,F} \leq OLand_s + RLand_s \qquad (4.11)$$

c, *s*, and *F* are indices of the crops, land types, and levels of fertilizer application respectively, *a* is the modeled land size (ha) for each crop, *Oland* and *RLand* are self-owned and rented-in land area

Labor constraint:

The total labor used for crop production is expected to be less than or equal to the sum of family labor input on farm plus hired-in labor, where the total family labor used on farm is defined as the difference between the household's total labor endowment and its hired-out labor for off-farm work.

$$\sum_{c=1}^{n}\sum_{s=1}^{2}\sum_{F=1}^{5} Lab_{c,s} \times a_{c,s,F} \leq \bar{L} - L^o + L^H \qquad (4.12)$$

[51] The minimum interest rate approved by the government of Ghana for financial institutions in the country

$$L^{o} \leq Upper.L^{o} \qquad (4.13)$$

To account for labor market imperfections, regarding farmers' access to off-farm employment, the model sets an upper bound on the amount of labor the farm household can hire-out. From equations (4.12) and (4.13), $Lab_{c,s}$, $\bar{L}$, L^{o}, L^{H} are the persondays of labor per hectare for the production of each crop (c) on the two land types ('s'), the households total labor endowment, hired-out labor and hired-in labor input respectively.

Quantity balance at farm household level:

The sum of the total quantity (kg) of food consumed (*CONS*) by the households plus the quantity (kg) sold (*SOLD*) and the quantity (kg) lost after harvest ($PHLoss$) cannot exceed the sum of food crops production (*Prod*, in kg) and market purchases of food (*Bfood*, in kg) for the household's consumption. Due to infrastructural challenges in the three regions (*including lack/limited number of appropriate long-term storage facilities, and other flaws in farmers' post-harvest management of crops*), it is assumed that the total quantity of post-harvest losses (during drying and storage) would be proportional to the total harvest. Thus, we expect no/limited changes in farmers post-harvest management of crops under current and future rainfall distributions. Losses are thereby expected to be comparatively higher in times of good harvest and lower in times on bad harvest. To account for this assumption in the model, the quantity lost is defined as a product of food loss index ($Lossi$) (*ratio between quantity lost and quantity produced for the year 2013*) and the total harvest for each crop (see equation 4.16).

$$Prod_{c,e} + Bfood_{c,e} = CONS_{c,e} + SOLD_{c,e} + PHLoss_{c,e} \qquad (4.14)$$

$$Prod_{c,e} = \sum_{c=1}^{n}\sum_{s=1}^{2}\sum_{F=1}^{5}\sum_{e=1}^{5} Prob_{e} \times Y_{c,s,F,e} \times a_{c,s,F} \qquad (4.15)$$

$$PHLoss_{c,e} = Lossi_{c} * \ Prod_{c,e} \qquad (4.16)$$

$$CONS_{c1,e} - \beta_{1,c1} \times Z - \beta_{2,c1} \times HHSIZE - \beta_{0,c1} \geq 0 \qquad (4.17)$$

Equation (4.17) is a consumption constraint, the $\beta's$ in which are estimated through Engel functions (Sadoulet and de Janvry 1995) for self-consumed crops ($c1$) (maize, millet, sorghum, rice, common beans and groundnut). From equation (4.17), $\beta_{1,c1}, \beta_{2,c1}, \beta_{0,c1}\ and\ HHSIZE$ represent the marginal propensity to consume crop out of total income, coefficient for the variable household size, the minimum consumption requirement, and the size of the households respectively. The results for the Engel functions are shown in Table 4.7. The total consumption of each of the crops is expected to increase at higher income levels and with household size (except for sorghum). Increasing income in the regions is mostly associated with an increase in output for majority of the crops. This increases the availability of food and the capacity for farmers to also purchase food from the markets to meet domestic supply deficits resulting from high demand for food. Larger households are also more likely to have higher demand for food than smaller households.

Table 4. 7-Coefficients for the Engel functions

	Maize (N=1,042)	Millet (N=294)	Sorghum (N=110)	Rice (N=420)	Common beans (N=315)	Groundnut (N=460)
Total income (Z)	0.244404*** (0.018236)	0.017507*** (0.006275)	0.0487626*** (0.0124782)	0.038766*** (0.0093416)	0.009068*** (0.002460)	0.008813** (0.00401)
Household size	112.6434*** (12.91769)	13.74215*** (4.221851)	-7.602822 (7.132358)	32.5392*** (7.822589)	2.8118 (1.818649)	17.0768*** (3.10503)
Constant ($\beta_{0,c1}$)	-311.928** (130.5715)	149.6389*** (40.06917)	217.9439*** (55.94164)	197.208** (79.609)	87.98864*** (15.52896)	124.1055*** (30.2997)
R-squared	0.2433	0.0766	0.1280	0.0926	0.0646	0.0851
F-stat [Prob]	167.06 [0.000]	12.07 [0.000]	7.850 [0.0007]	21.28 [0.000]	10.77 [0.000]	21.25 [0.000]

NB: (*) – standard errors; ***1%, **5%

Source: Author, based on regression output in Stata15

Livestock balance/inventory constraint:

Earlier studies (including Visagie *et al* 2004 and Lokonon *et al* 2015) accounted for livestock buying and selling decisions using minimum and maximum carrying capacity bounds. In the current study, where we have no information on these bounds, an inventory (accounting) balance is used to capture farmers livestock production decisions. From equation (4.18), the number of livestock species (ls) at the beginning of the year (BGY_{ls}) plus the number bought (BO_{ls}) minus the number sold (SL_{ls}) is expected to be greater than or equal to zero.

$$BGY_{ls} + BO_{ls} - SL_{ls} \geq 0 \quad (4.18)$$

Cash constraint:

The total expenditure (cost incurred) on all activities is expected to be less than or equal to the total cash income from all activities plus available own funds (CAP)[52] at the beginning of the production year. All sets, parameters and variables hold their original definitions as in equations (4.10) to (4.18)

[52] Set at 10% of the value of household's non-land assets (Yilma 2005)

$$\sum_{c=1}^{n}\sum_{s=1}^{2}\sum_{F=1}^{5} prf_c \times fer_{c,s,F} \times a_{c,s,F} + \sum_{c=1}^{n}\sum_{s=1}^{2}\sum_{F=1}^{5} CSPOnl_c \times a_{c,s,F} + w_{Hl} * L^H + int * CRED$$
$$+ \sum_{c=1}^{n}\sum_{e=1}^{5} Pr_{pc} * Bfood_{c,e} + \sum_{s=1}^{2} CR * RLand_s + \sum_{ls=1}^{n} prliv_{lsB} \times BO_{ls}$$
$$+ \sum_{ls=1}^{n} CFV_{ls} \times [BGY_{ls} + BO_{ls} - SL_{ls}]$$
$$\leq CAP + CRED + w_{Ol} * L^o + \sum_{ls=1}^{n} prliv_{lsS} \times SL_{ls}$$
$$+ \sum_{ls=1}^{n} Vsp_{ls} \times [BGY_{ls} + BO_{ls} - SL_{ls}] + \sum_{c=1}^{n} SOLD_c \qquad (4.19)$$

Crop rotation strategies constraints:

$$\sum_{c=1}^{n}\sum_{s=1}^{2}\sum_{F=1}^{5} a_{c,s,F,j} \geq \gamma * \sum_{c=1}^{n}\sum_{s=1}^{2}\sum_{F=1}^{5} a_{c,s,F,k} \quad , \quad j \neq k \qquad (4.20)$$

γ represents cropland ratios for crops considered in the crop rotation strategies[53]. The incorporation of rotational constraints helps to account for temporal interactions between crops (Sorrentino *et al* 2011). Crop rotations also help in the control of pest and diseases in the study area and in the management of soil fertility.

Fertilizer use:

The sum of fertilizer applied on the respective crops (*c*) for the two land types (*s*) across the five levels of fertilizer application is expected to be equal to the total quantity of fertilizer available, the latter of which is assumed variable in this study. This constraint facilitates monitoring of the potential adjustments farmers could make in their fertilizer application decisions under a changing climate.

$$\sum_{c=1}^{n}\sum_{s=1}^{2}\sum_{F=1}^{5} fer_{c,s,F} \times a_{c,s,F} = FERT \qquad (4.21)$$

Non-negativity constraint:

$$a, L^H, L^o, CRED, BO, SL, Prod, Bfood, SOLD, CONS, PHLoss, FERT \geq 0 \qquad (4.22)$$

[53] The rotations are based on documented evidences in agronomic and economic literature for the study area and other developing regions in Sub-Saharan Africa, including Jones 1974; Kipo 1993: Braimoh 2004; Kombiok *et al* 2012; Lokonon *et al* 2015

4.4.6 Model validation

Farm households decision-making is a complex process that is influenced by several factors and one of the challenges in modeling farm household behavior and decision outcomes is building an appropriate model that represents observed decision processes. A model is generally deemed useful and acceptable only when it can portray a system under investigation to an appreciable degree. The level deemed appreciable is however quite subjective. While a percentage absolute deviation (less than 15%) measure is used to validate models based on positive mathematical programming, the validation process for other types of models is subjective in diverse days. For these models, the modelers subjectively choose the validation tests, criteria for passing those tests, the model outputs to validate, and the data to use among other measures (McCarl and Apland 1986). Whereas a ***perfect*** model is expected to replicate each empirical observation, information gap between the modeler and the decision maker precludes such perfect prediction. A more realistic condition is for a model to be able to reproduce certain model outputs of policy and research interest to an appreciable degree. The model for this study was validated through the acreages allocated to the respective crops. This involved regressing the simulated cropland area (Sim_a) on the observed acreages (Obs_a) (with and without intercepts, Wossen 2014; Lokonon *et al* 2015) as follows:

$$Sim_a = f(Obs_a) \qquad (4.23)$$

For perfect validation, the regressions are expected to have slope coefficients of one and R^2 values of one (McCarl and Apland 1986)

4.4.7 Scenarios for simulation experiments

Given the extensive reliance of farmers in West Africa on rainfed agriculture and their vulnerability to high intra- and inter-annual climate variability, quite a high number of research works have been conducted in the region on future risk of weather (precipitation and temperature) extremes (including Niang *et al* 2014; Riede *et al* 2016; Sultan and Gaetani 2016; Sylla *et al* 2016). In contrast to the consistency in projections for temperature, there have been some contradictions in projections for precipitation. For example, while Riede *et al* (2016) report of increased annual and seasonal rainfall conditions between the mid to the end of the 21^{st} century for West Africa, Sylla *et al* (2016) report of a possibility for West African farmers to be exposed to drier rainfall conditions. These contradictions have been attributed among other things to large uncertainties that affect simulations of future West African Climate, especially the summer precipitation (Sultan and Gaetani 2016) and to discrepancies between different observed precipitation datesets (Niang *et al* 2014). Projections for the current study area (Northern Savanna of Ghana) also reveal both increments and declines in annual and seasonal rainfall in the range of -28% to +30% with an overall ensemble prediction of a slight decrease in rainfall (Stanturf *et al* 2011). These projections indicate a possibility for both wetter and drier annual rainfall conditions in the future. Another issue debated on in climate risk assessments is how frequent extreme events could be observed in the future and how intense these events could be. With these uncertainties surrounding the nature of future rainfall distribution, there arises a need to simulate the impact of annual rainfall shocks across a broad range of scenarios. This could help to determined and document the worst that could happen to farmers in the regions. Besides the historical/current distribution of rainfall (base condition), a total of 5 potential future rainfall distributions are considered for this study. Details of these are provided in Table 4.8. Due to the uncertainty associated with potential future accumulation of annual rainfall, a total of 5 randomly simulated 30 years rainfall observations (that conform with defined scenarios) are considered for each distribution (scenario) and the average yield for each rainfall state across the 5 simulated random distributions used as a representative estimate for each crop in the optimization process.

Table 4. 8-Rainfall scenarios for simulation experiments

Scenarios	Definitions	Number of rainfall series considered in yield predictions	Probability of states of rainfall (0 to 1)				
			Very dry	Dry	Normal	Wet	Very wet
Historical/ current distribution	This represents the distribution for the time series data used in estimating the yield response for the base run	1 (30 years obs.)	0.0333	0.3333	0.2667	0.3333	0.0333
Drier future	This scenario assumes an increase in the frequency of very dry years, no change in the frequency of dry years, and a decrease in the frequency of normal and wet years	5 (30 years obs.)	0.2000	0.3333	0.2333	0.2000	0.0333
Dry future	This scenario assumes no change in the frequency of very dry and normal years, an increase in the frequency of dry years, and a decrease in the frequency of wet years	5 (30 years obs.)	0.0333	0.4667	0.2667	0.2000	0.0333
Normal future	This scenario assumes no change in the frequency of very dry and very wet years, but a decrease in the frequency of dry and wet years	5 (30 years obs.)	0.0333	0.2000	0.5333	0.2000	0.0333
Wet future	This scenario assumes no change in the frequency of very wet and normal years, an increase in the frequency of wet years, and a decrease in the frequency of dry years.	5 (30 years obs.)	0.0333	0.2000	0.2667	0.4667	0.0333
Wetter future	This scenario assumes an increase in the frequency of very wet years, no change in the frequency of wet years, and a	5 (30 years obs.)	0.0333	0.2000	0.2333	0.3333	0.2000

	decrease in the frequency of normal and dry years						

Source: Author's construct

This exercise helps to ascertain the welfare implications of the 5 potential future rainfall distributions in the regions.

After the assessment, simulation experiments are carried out for two primary interventions (irrigation expansion and investment in research and development). Farmers in the three regions are vulnerable to climate variability and shocks due to their extensive reliance on rain-fed agriculture under low-input conditions for their livelihood, high yield gaps for the dominant crops (maize and rice in terms of land area and dietary energy supply) and the high sensitivity of these crops to changing local climatic conditions (Roudier *et al* 2011; Tittonell and Giller, 2013; Sultan and Gaetani 2016). For example, with MoFA (2013) reporting achievable yields of 6000kg/ha and 6500kg/ha respectively for maize and rice, observed yields for these crops in the study area are estimated at 765.87kg/ha and 992.95kg/ha, indicating that maize and rice currently meet only 12.77% and 15.28% of the achievable yields. At the national level, yields for these crops are only about 31.67% (for maize) and 38.5% (for rice) of the achievable (MoFA 2013). Despite the high yield gap, the three regions together with the Volta region account for more than 80% of total national rice output in Ghana (Amanor-Boadu 2012). In these three regions where climate and weather shocks pose risks for farmers, irrigation development/expansion (in the case of rice) and research and development intervention (in the case of maize and rainfed rice production) are deemed potential measures that offer a promise of greater food security and household welfare (Yilma 2005; Namara *et al* 2011; Sanfo and Gérard 2012). Gaining an insight into the potential impact of these interventions on the different farmer groups could guide the proposition of appropriate policy/stakeholder recommendations. Details of the two primary interventions used for the simulation experiments are shown in Table 4.9. These simulation exercises are performed for each rainfall scenario to ascertain how the effectiveness of the interventions changes with climatic conditions. Following each of the simulations, impacts of the respective interventions on household income and food consumption are computed based on the following mathematical expression:

$$Impact_I = ((Vw_I - V_w)/V_w) \times 100 \quad (4.24)$$

Where V is an index for the measures of household welfare (income and food consumption)

$Impact_I$ is the impact of the intervention (I) expressed as a percentage

Vw_I is welfare after introducing the intervention(s)

V_w is welfare without the intervention(s)

Table 4. 9-Adaptation responses for simulation experiments

Scenarios	Interventions	Description of interventions
1	Irrigation development / expansion	Converting 50% (half) of the cultivated area under rain-fed rice production to irrigated rice production. For the clusters where some farmers already practice irrigation, this would be an expansion of irrigation, while for the clusters in which none of the farmers practice irrigation, this would be an introduction of/development of irrigation. For this initiative, farmers are assumed to face only additional (or reduced) operational charges including charges related to fertilizer application, labor, and other non-labor expenses besides cost of water.
2	Investment in Research and Development (R&D):	25% increase in the yield of maize and rainfed rice
3	Scenario 1 + Scenario 2	Irrigation expansion + Investment in Research and Development

Source: Author's construct

4.5 Results and discussion

Before presenting and discussing results for the respective analyses, we first assess the performance of the optimization model to be sure it is valid for simulation experiments.

Table 4. 10-Model validation based on cropland area

Indicators	Cluster 1		Cluster 2		Cluster 3	
	Obs.	Sim.	Obs.	Sim.	Obs.	Sim.
Maize	2.2037	1.876	1.2580	0.999	1.0676	1.230
Millet	0.2436	0.207	0.1833	0.145	0.0562	0.064
Sorghum	0.0701	0.369	0.0938	0.440	0.0405	0.134
Rice rainfed	0.4857	0.618	0.2567	0.534	0.3198	0.044
irrigated	0.000	0.000	0.0000	0.000	0.1800	0.180
Common beans	0.0747	0.064	0.3755	0.298	0.0141	0.016
Soybean	0.0805	0.068	0.1749	0.139	0.0066	0.007
Groundnut	0.2142	0.182	0.7842	0.623	0.0519	0.059
Bambara nut	0.0156	0.013	0.0939	0.075	0.0018	0.002
Yam	0.0599	0.051	0.1568	0.124	0.0198	0.023

Source: Author, based on output from GAMS and household survey data

Estimates used in assessing the validity of the model are presented in Tables 4.10 and 4.11. From the regression results in Table 4.11, we observe slope coefficients that are close to one for each cluster and R-squared values that are close to one. Based on the reported estimates, it is noted that the model has a good fit of the data and can be used for the current analyses.

Table 4. 11-Regression results for the model validation

Clusters		With intercept		Without intercept	
		Coefficients	P>|t|	Coefficients	P>|t|
Cluster 1	X-observed	0.8374	0.000	0.8744	0.000
	Cons	0.0561	0.221		
	Adj. R-squared	0.9577		0.9637	
Cluster 2	X-observed	0.7097	0.000	0.8415	0.000
	Cons	0.0980	0.170		
	Adj. R-squared	0.7627		0.8693	
Cluster 3	X-observed	1.0922	0.000	1.0701	0.000
	Cons	-0.0161	0.706		
	Adj. R-squared	0.9083		0.9259	
Joint	X-observed	0.8530	0.000	0.8930	0.000
	Cons	0.0420	0.148		
	Adj. R-squared	0.9042		0.9296	

Source: Author, based on regression output in Stata15

4.5.1 Effects of weather conditions on crop yields

From the estimation of the production function in equation (4.9) and subsequent prediction of crop yields for the five states of rainfall (*based on the production function coefficients in Table AP 4.1 in the Appendix)*, it is found that while wetter climatic conditions are beneficial for majority of the crops grown in the three regions, drier conditions have adverse implications for crop productivity. This observation is consistent with findings from a study by Wossen *et al* (2014) in the study area. Except for sorghum and common beans, yields of all the other 7 crops increase under 'Wet' and 'Very wet' rainfall conditions. Crops with the greatest decreases in yields under drier conditions, benefit the most under wetter conditions. Yields of maize, millet and groundnut decrease by more than 45% under 'Very dry' climatic conditions and increase by more than 55% for maize and groundnut and 44% for millet under 'Very wet' conditions. Besides this, yield of rainfed rice is found to decrease by approximately 42% under drier rainfall conditions and increases by approximately 40% under wetter conditions (Table 4.12). This indicates that farms that allocate a greater portion of the cultivated cropland area to the production of cereals could experience greater decreases in gross (and/or net) crop income under less favorable climatic conditions. Yields of sorghum and common beans however increase under drier conditions, and this makes them strategic crops for overcoming hunger during less favorable climatic conditions. Following this assessment, yields were predicted for different combinations of the five levels of fertilizer application (mentioned in previous sections) and the 30 historical/potential future climate observations. Average yields for the respective combinations under the six rainfall scenarios (including the historical/current distribution) were used in the static optimization model to assess the impact of increasing frequency of weather extremes on the welfare of farm households.

Table 4. 12-Effects of rainfall conditions on crop yields under historical rainfall distribution

Crops	Yields for normal conditions (kg/ha)	% change in yields			
		Very dry	Dry	Wet	Very wet
Maize	798.62	-48.13	-14.94	32.69	57.41
Millet	558.52	-47.75	-13.17	25.04	44.51
Sorghum	602.25	13.33	-0.740	-10.19	-10.80
Rice (rainfed)	1041.0	-41.66	-16.14	19.08	39.95
Rice (Irrigated)	2723.60	-35.91	-12.77	17.03	33.26
Rice (rainfed+Irrigated)	1099.5	-41.16	-15.85	18.91	39.38
Common beans	286.02	54.73	10.99	-18.50	-26.29
Soybeans	603.98	-39.64	-12.14	23.69	41.31
Groundnut	607.29	-45.23	-9.620	38.55	55.21
Bambara nuts	480.73	-44.70	-20.12	16.02	39.48
Yam	3876.70	-20.73	-3.740	13.74	18.70

Source: Computed by Author

4.5.2 Impacts of climate shocks on the welfare of farm households

Per the output of the static optimization model for each of the clusters, it is found that increasing frequency of drier climatic conditions will have the greatest adverse impact on the poor farmers of Cluster 1 who operate on medium-scale farms under low input conditions and allocate more than 70% of the total cropland area to the production of cereals. For these farmers, total household income is predicted to decrease by about 23.75% under increasing risk of very dry rainfall conditions. With comparatively higher livestock base and operating on a relatively smaller scale, farmers of Clusters 2 and 3 can compensate for crop income losses with the sales of livestock and income from off-farm employment opportunities (by allocating surplus labor to the off-farm labor market). Due to the relatively stronger asset base of farmers of Cluster 3 and the high input system under which they operate, income loss under a drier future scenario for these farmers is estimated at 3.70%, while for the poor farmers of Cluster 2 (who allocate less than 70% of the cropland area to cereals), income loss is estimated at 6.76%. In contrast to this observation however, the more vulnerable farmers of Cluster 1 are likely to benefit the most under the wet and wetter future scenarios. Under the latter scenario, income gain for these farmers is estimated at 24.19%, while for Clusters 2 and 3, these gains are estimated at 7.77% and 3.85% respectively (see Table 4.13). It is noted that compared to the dry future scenario, the adverse impact of rainfall risk more than doubles under the drier future scenario, while for the wet and wetter scenarios, this is not the case. This indicates that, while farmers can compensate for crop income losses under minor negative deviations in rainfall from the norm, their ability to compensate for losses under extremely dry rainfall conditions is limited. This makes drier rainfall conditions more harmful to agriculture in the study area. Although practiced on a very small scale, irrigated rice production is also found to play a major role in the generation of crop income for farmers of Cluster 3 and plays a key role in reducing the overall crop income loss arising from adverse weather conditions.

Table 4. 13-Impact of potential future rainfall distributions on household income

Clusters	Income under historical/current rainfall variability (base)	Percent change in income from base, %				
		Dry future	Drier future	Normal future	Wet future	Wetter future
Cluster 1	1,029.7	-9.768	-23.75	8.792	16.61	24.19
Cluster 2	2,188.6	-3.207	-6.755	1.192	4.348	7.770
Cluster 3	3,989.0	-1.329	-3.698	1.801	2.297	3.854

Source: Author's construct based on output from GAMS

It is as well noted that increasing probability of a rainfall distribution with more normal rainfall conditions than the historical/current distribution could prove beneficial to farmers in the regions. Farmers of Cluster 1 are however likely to benefit the most from such a distribution, with a potential income gain of 8.79%.

Besides the impact of the respective rainfall distributions on household income, outputs for the simulation experiments show major decreases in production (harvest) for majority of the crops under dry and drier rainfall scenarios. Although it is predicted that farmers in all the three clusters could bridge production deficits with food purchases from the market, their ability to appropriately meet consumption requirements of the households decreases with increasing risk of drier rainfall conditions. Across all the three clusters, consumption losses are predicted to be higher for maize, sorghum, rice and common beans, and the vulnerable farmers of Cluster 1 are expected to experience the greatest decreases in the quantity of food available for human consumption. These farmers are however likely to witness the greatest consumption gains under normal, wet and wetter rainfall distributions (see Figure 4.2).

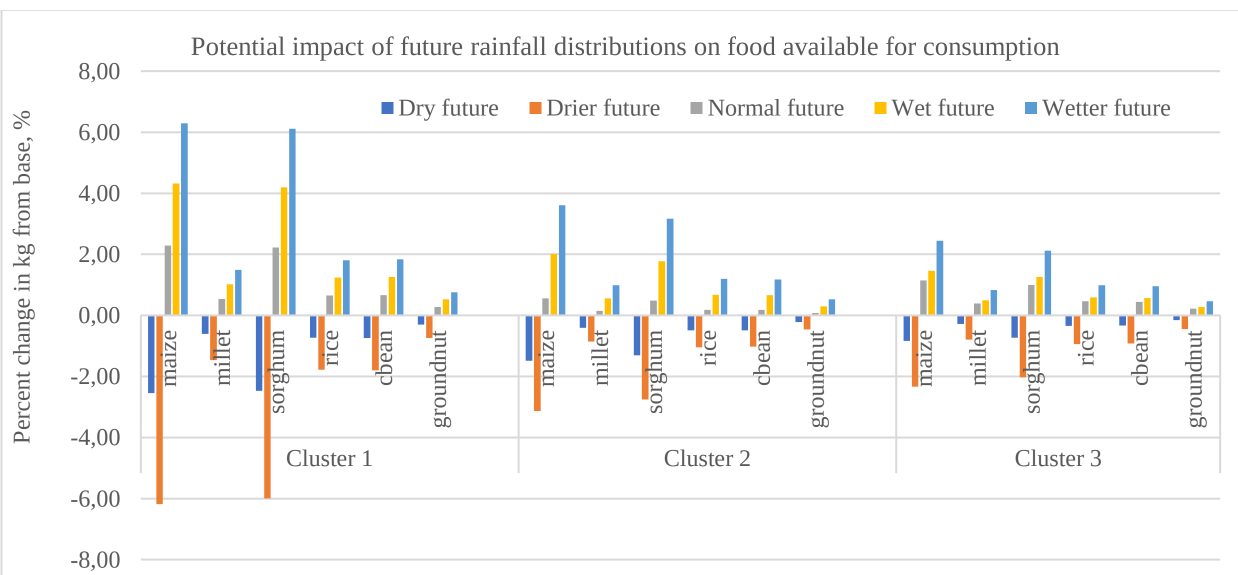


Figure 4. 2-Impact of potential future rainfall distributions on household food consumption
Source: Author's construct based on output from GAMS

For the farmers of Cluster 1, consumption losses are estimated at -6.18%, -6.00%, -1.78% and -1.80% for maize, sorghum, rice and common beans under a drier future scenario. Consumption gains for these farmers under a wetter future scenario are estimated at 6.29%, 6.11%, 1.81% and 1.84% for maize, sorghum, rice and common beans. The less poor farmers of Cluster 3 would experience the least changes in their consumption levels under dry, drier, wet and wetter future rainfall distributions. The results for the simulation experiments show a relatively low responsiveness of the less poor farmers to changing local climatic conditions. This indicates that differences in the farmers asset and resource base, and input use intensity do play major role in curbing the impact of adverse rainfall conditions on the welfare of farmers in the regions.

Table 4. 14-Potential impact of rainfall distributions on the shadow price of land

For rainfed land	Price (GHC/ha) under historical/current variability (base)	Dry future	Drier future	Normal future	Wet future	Wetter future
Cluster 1	456.28	429.44 (-5.88)	394.14 (-13.6)	491.97 (7.82)	505.09 (10.7)	530.87 (16.4)
Cluster 2	628.48	610.66 (-2.84)	592.7 (-5.69)	683.64 (8.78)	699.52 (11.3)	721.93 (14.9)
Cluster 3	1053.8	1042.6 (-1.06)	1018.8 (-3.327)	1033.7 (-1.91)	1062.6 (0.84)	1062.6 (0.83)
For irrigated land						
Cluster 3	3523.3	3511.03 (-0.35)	3464.4 (-1.67)	3509.8 (-0.38)	3555.87 (0.92)	3544.30 (0.60)

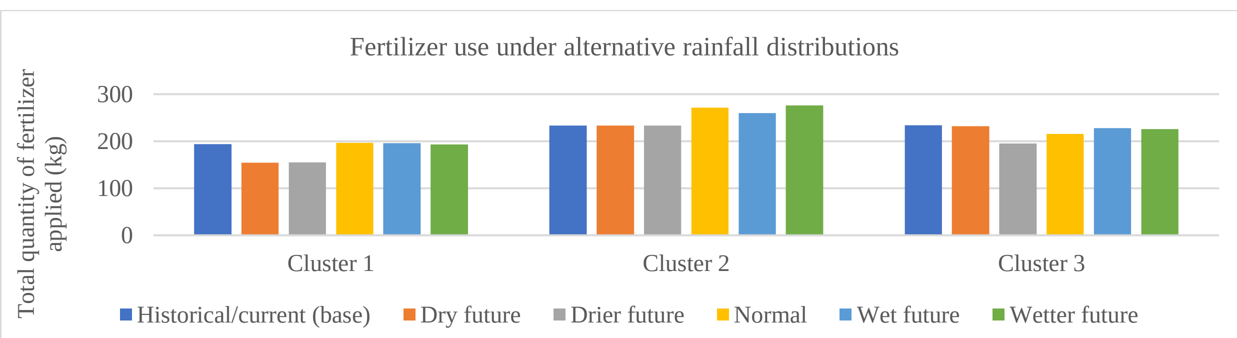
(*)- % change from base

Source: Author's construct based on output from GAMS

In addition to the impact of weather conditions on household income and food consumption, the shadow prices of land are found to decrease with increasing risk of drier rainfall conditions and to increase under wetter rainfall conditions (see Table 4.14). These prices indicate the maximum amounts by which total household income could increase with additional units of the scarce resources. The greatest decrease in the shadow price of land is expected on the low input medium-scale farms operated by the poor farmers of Cluster 1, while the least decrease is expected on the high input small-scale farms operated by the less poor farmers of Cluster 3. This indicates that, besides documented arguments on the effect of economies of scale (increasing returns to land on large farms) on shadow prices (Lokonon *et al* 2015), differences in input use also have a role to play in determining the shadow price of land. In addition, although operating under low input conditions but on a medium-scale, the shadow price of land under rainfed conditions is also found to be higher in Cluster 2 than in Cluster 1. This indicates that the production system (share of cereals in total cropland) under which the two farms operate may also play a role in determining the shadow price of land. Under a drier future rainfall distribution, the shadow price of rainfed land could decrease by about 13.6%, 5.69% and 3.33% in Clusters 1, 2 and 3 respectively. Compared to the impact on rainfed lands, it is noted that all the five potential future rainfall distributions would have minimal impact on the shadow price of irrigated land area. Minor increases in the shadow price of irrigated land are however expected under wet and wetter conditions and minor decreases under drier conditions. The observed negative impacts of drier rainfall scenarios on income, consumption and the shadow prices of land are in conformity with documented evidences in literature (e.g see Wossen 2014; Lokonon *et al* 2015; Bocher 2016)

4.5.3 Farmers traditional adaptation under alternative future rainfall distributions

Having estimated the impact of the alternative rainfall distributions on farmers welfare, effort was made to assess farmers traditional adaptation under the alternative distributions, placing emphasis on the use of fertilizer as an input that has the potential to increase crop yields and income under diverse rainfall conditions (Komarek *et al* 2017). While the low use of fertilizer is reported to be a major cause of the high crop yield gaps documented for the regions (Martey *et al* 2014; Chapota *et al* 2015), it is found in the current study that drier climatic conditions could lead to further decreases in the current rate of fertilizer application (see Figure 4.3). This could result in further decreases in crop yields, income and consumption. The quantity of fertilizer applied is however predicted to increase under more favorable rainfall conditions, indicating that increasing access to appreciable volumes of water could enhance farmers fertilizer application (Yilma 2005). Given the low use of fertilizer under less favorable climatic conditions and the potential implications of this for farmers welfare, there arises a need to explore other adaptation responses/policy interventions that could help curb the adverse impact of weather risks. Two interventions are considered in this study, namely, irrigation expansion and improvement in the yield of maize and rainfed rice through investment in research and development efforts. The results from the simulation of the impact of these two interventions on farmers welfare are presented in the subsequent section.



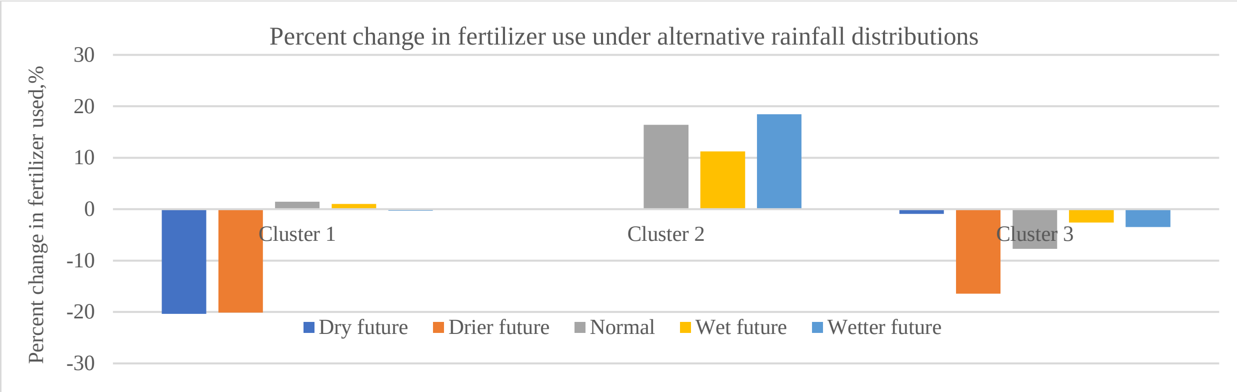


Figure 4. 3-Fertilizer use under alternative rainfall distributions
Source: Author's construct based on output from GAMS

4.5.4 Impact of policy responses on farm households' welfare

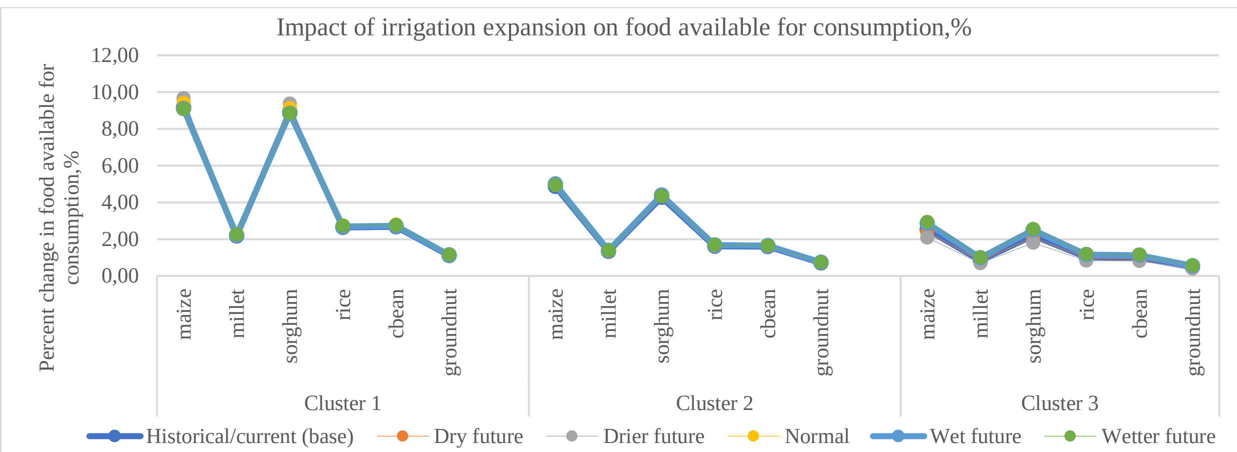
In simulating the impact of irrigation expansion and research and development intervention on household income, it is found that the poor and vulnerable farmers of Cluster 1 would derive the greatest benefit from the two interventions. The greatest benefits are however expected under a drier future rainfall distribution (see Table 4.15). Under such a distribution, irrigation expansion is predicted to increase household income by 45.78%, while research and development intervention could increase income by 40.01% in Cluster 1. For the less poor farmers of Cluster 3, the two interventions could increase income by 3.33% and 10.24% under a drier future scenario. The observed positive impacts of the two interventions on household income are in conformity with reports by Sanfo and Gérard (2012) and Lokonon *et al* (2015). For example, while the current study estimates income gains of 3.98% (in Cluster 3) to 35.32% (Cluster 1) for irrigation expansion under the historical/current rainfall distribution, a range of 17% to 21% is found by Sanfo and Gérard (2012) for the Plateau Central area of Burkina Faso. Similarly, while this study estimates income gains of 10.31% (Cluster 3) to 33.48 (Cluster 1) for a 25% increase in the yields of maize and rainfed rice, Lokonon *et al* (2015) report income gains of 2.34% to 51.80% for a 25% increase in the yields of maize, sorghum, millet and rice in the Niger Basin of Benin.

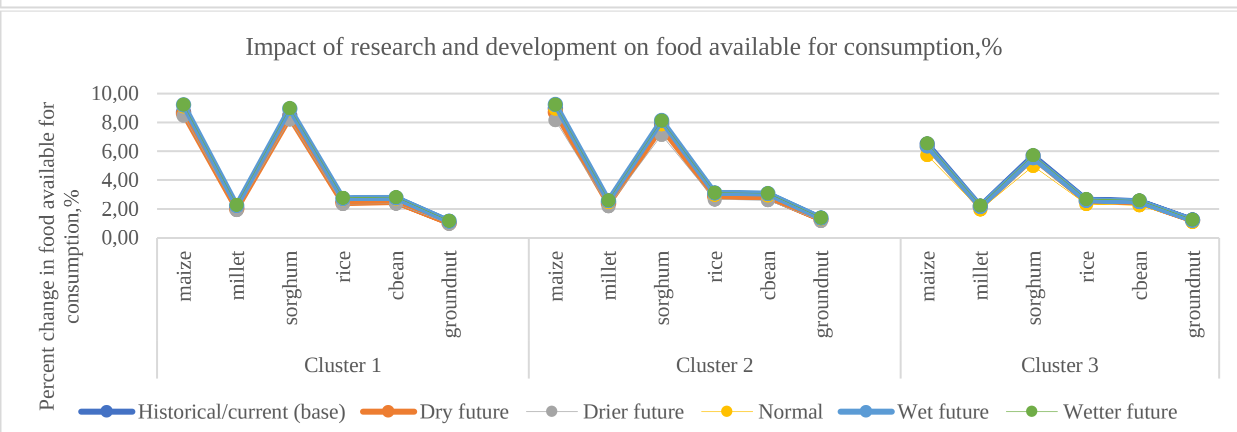
Although the two policy interventions are implemented to reduce risk of income losses under adverse climatic conditions, these initiatives have the potential to also affect food consumption quantities and patterns, although emphasis is placed on the former in this study. As shown in Figure 4.4, besides increasing household income, the two interventions lead to increases in the quantity of food available for human consumption across all the six rainfall scenarios. Based on the joint impact of the two interventions, it is noted that the poor farmers of Clusters 1 and 2 would experience greater consumption gains from these two potential policy responses.

Table 4. 15- Potential impact of policy responses on farmers welfare

Adaptation responses/ Interventions	Income under historical/current rainfall variability (base)	Dry future	Drier future	Normal future	Wet future	Wetter future
Cluster 1						
No intervention, GHC	1,029.7	929.11	785.17	1,120.2	1,200.7	1,278.7
Percent change, %						
Irrigation exp.	35.32	38.90	45.78	34.00	31.27	29.86
R& D	33.48	35.71	40.01	32.90	31.68	30.42
Both interventions	59.23	64.13	73.79	57.00	54.25	52.07
Cluster 2						
No intervention, GHC	2,188.6	2,118.5	2,040.8	2,214.7	2,283.8	2,358.7
Percent change, %						
Irrigation exp.	10.87	11.22	11.68	11.03	10.88	10.57
R& D	19.32	19.10	18.23	19.16	19.45	19.11
Both interventions	27.30	27.37	26.96	27.46	27.39	26.84
Cluster 3						
No intervention, GHC	3,999.3	3,946.2	3,851.6	4,071.4	4,091.0	4,153.3
Percent change, %						
Irrigation exp.	3.980	3.780	3.330	4.530	4.470	4.560
R& D	10.31	10.08	10.24	8.970	9.980	10.21
Both interventions	14.28	14.01	13.84	13.41	14.50	14.50

Source: Computed by author based on output from GAMS





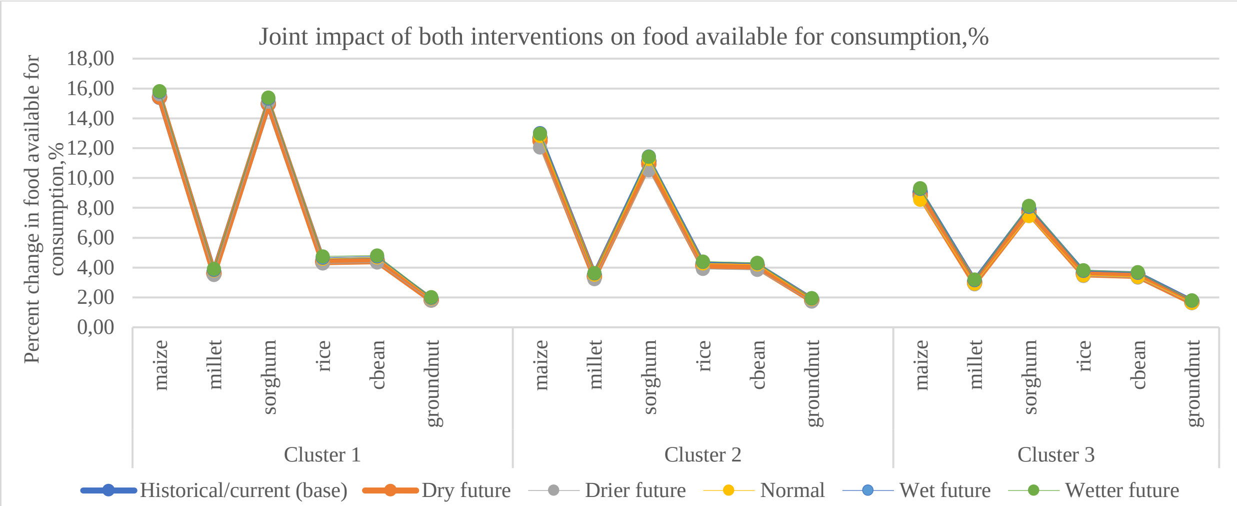


Figure 4. 4-Potential impact of policy responses on households' food consumption
Source: Author's construct based on output from GAMS

For example, the joint implementation of the two interventions could lead to 15.41%, 12.67% and 9.05% increases in maize consumption in Clusters 1, 2 and 3 respectively under the historical/current rainfall distribution. With the poor farmers likely to benefit the most from the two interventions, the implementation of these measures could go a long way to help reduce the incidence of poverty in the study area, improve food security and farmers' welfare on a broader perspective, and contribute towards minimizing income inequality.

4.6 Conclusion

Weather extremes manifest at the local (farm/village) level and yield impacts that extend to regional, national and global scales. Despite this, very little has so far been done to estimate the impact of climate and weather shocks on farm households, especially in the West African Sudan Savanna, where majority of the farmers depend on agriculture for their livelihood. An insight into the local production conditions and how different weather realizations impact on the welfare of farm households could guide the proposition of relevant political and production strategies to promote resilience. Using Ghana Africa RISING Evaluation Survey (GARBES) data, historical climate data from the CCAFS climate data portal, and Monte Carlo simulation of random rainfall distributions, this study analyzed the impacts of climate shocks and adaptation responses on the welfare of farmers in the Northern Savanna of Ghana. A total of 1,182 households were covered across the three northern regions of Ghana. Due to potential heterogeneity across farm households, which could consequently influence their responses to external shocks, farmers in the study area were clustered using a combination of factor analysis and K-means clustering. Three groups of farmers were identified. These are

- Poor farmers who operate under low input conditions on medium-scale farms and allocate more than 70% of the total cropland to the production of cereals
- Poor farmers who operate under low input conditions on medium-scale farms and allocate less than 70% of the total cropland to the production of cereals and
- Less poor farmers who operate under high input conditions on small-scale farms and allocate more than 70% of the total cropland to the production of cereals.

To estimate the impact of weather conditions on the welfare of the different farmer groups, econometric and mathematical programming (static optimization) models were used for the study. These models were used to predict/simulate the impact of annual rainfall distributions (scenarios) and adaptation responses on crop yields, activity levels for the respective farms, farm household income, food consumption, and the shadow prices of land. A total of six rainfall scenarios were considered in this study. These are the 'historical/current rainfall distribution', 'dry future', 'drier future', 'normal future', 'wet future' and 'wetter future' scenarios. In addition to these, the impacts of two potential policy interventions on households' welfare were estimated. The interventions considered are 'Irrigation expansion/development' and investment in 'Research and development'.

Based on the results for the respective analyses/estimations, it was found that drier climatic conditions would lead to reduced crop yields (except for sorghum and common beans), lower household income and food consumption losses. Yields for crops like maize, millet, and groundnut could decrease by more than 45% under 'Very dry' rainfall conditions and increase by more than 55% for maize and groundnut and 44% for millet under 'Very wet' rainfall conditions. Total household income and food available for consumption are predicted to decrease with increasing frequency of drier rainfall conditions (a 'drier future' scenarios), and to increase with increasing frequency of normal to very wet rainfall conditions ('normal future', 'wet future' and 'wetter future' scenarios). The poor farmers of Cluster 1 are expected to experience the greatest adverse impact from a drier future scenario. For these farmers, total income is predicted to decrease by 23.75%. For farmers of Clusters 2 and 3, income losses of 6.76% and 3.70% are estimated. The poor and vulnerable farmers of Cluster 1 are however expected to benefit the most under the 'wetter future' scenario, where total income of these farmers could increase by about 24.19%. Under this scenario, income gains for farmers of Clusters 2 and 3 are estimated at 7.77% and 3.85%. The quantity of food available for human consumption is predicted to decrease with increasing risk of drier rainfall conditions. Across all the three clusters, higher consumption losses are predicted for maize, sorghum, rice and common beans. The poor farmers of Cluster 1 could experience the greatest decreases in consumption. Beside these, drier rainfall conditions are found to reduce the shadow prices of both rainfed and irrigated lands, although the impact on the latter is very minimal. In exploring farmers traditional adaptation under the six rainfall scenarios, it was found that drier rainfall conditions could lead to further decreases in fertilizer application by farmers in the regions. This could lead to crop yield, income and consumption losses.

In estimating the impact of 'irrigation expansion' and investment in 'research and development' on farmers welfare, it was found that the former intervention could lead to income gains of 3.98% to 35.32% under the historical/current rainfall scenario, while the latter intervention could lead to income gains of about 10.31% to 33.48%. These two interventions could as well lead to increases in the quantity of food available for human consumption, and the poor farmers of Clusters 1 and 2 are expected to benefit the most from these policy responses. These measures could hereby contribute towards reducing the incidence of poverty, improve food security and farmers welfare, and reduce income inequality in the study area.

Chapter 5

5 Conclusions

Majority of the inhabitants of the Savanna belt of West Africa live either as sedentary croppers or nomadic pastoralists (Callo-Concha *et al* 2013; Larbi *et al* 2014). These group of farmers earn a living and meet household expenses and other necessities of life through crop and livestock production (and to a minor extent from other non-farm sources). Growth in these two areas of agriculture has for more than two decades now been hindered by technological, institutional, soil infertility, and socio-economic constraints. Pressure imposed on farming systems in the region by these constraints has already taken a toll on production outcomes, as reflected in low productivity of crop fields and livestock (Chauvin *et al* 2012; MoFA 2013). Despite research and policy efforts made to boost productivity, there is not much evidence of success (Walker *et al* 2016). While investors, policy makers and researchers continue to battle with production challenges posed by persisting constraints, increasing frequency, intensity and duration of weather extremes stand further reducing the already low observed yields and meagre farm incomes. This could, in the medium to long-term lead to a reduction in food availability and access, and increased poverty. To enhance farmers resilience to weather extremes, amidst other production challenges, there is a need to identify risks in farming, the primary means of livelihood for over 75% of the inhabitants of the Savanna belt of West Africa (Sanfo and Gérard 2012; MoFA 2013; Masumbuko and Somda 2014; Knauer *et al* 2017). Using household survey data from primary and secondary sources, and historical daily climate data from NASA's climatological database and the CCAFS-climate data portal, we analyzed intra-seasonal risk of weather extremes, farmers' adaptation to such shocks, and the impact of climate shocks on farm households' welfare in the Sudan Savanna of West Africa. The first two chapters on intra-seasonal risk of weather extremes and farmers' adaptation covered households in Upper East Ghana and Southwest Burkina Faso, while the final chapter covered households in the Northern Savanna zone (Upper East, Upper West and Northern regions) of Ghana.

In analyzing intra-seasonal risk of weather extremes in the study area, we identified climatic conditions deemed major threats to farming based on farmers' perception, and analyzed risks posed by such conditions using a first order Markov chain model and other relevant indices for monitoring extremes in climatic conditions. Based on suggestions by farmers, we found drought (emphasis on dry spell), low rainfall, intense precipitation, flooding, erratic rainfall pattern, extremely high temperatures, delayed rains and early cessation of rains to be the major threats. Through analysis of risks posed by these conditions, we found approximately 16 days delay in onset of rains, 3 days extension in cessation of rains, and 14 days decrease in effective length of the rainy season in Upper East Ghana over the period 2010-2014 (compared to estimates for the period 1997-2014). In Southwest Burkina Faso however, onset of rains occurred 2 days earlier, with cessation dates remaining generally stable, while the length of the rainy season increased on average by 3 days.

In responding to these changes, farmers across the two regions made some adjustments in their seasonal planting of crops. Some of the farmers practiced early planting to take advantage of the early/first rains, while majority of the farmers engaged in late planting to avoid early-season dry spells or spreading of their plantings to minimize production losses. It was however found that each of these planting options have risk implications. For planting as early as 1st April, the early planters stand a 26.9% to 34.6% chance of exposing their seedlings to dry spells of 10 days in the next 30 days, while for the late planters, there is a 36.5% to 48.0% chance for their crops to be exposed to dry spells of 21 days in the next 30 days from October 28. For the spreaders, seedlings could be exposed to dry and hot spells in April, May, June and October, and to intense precipitation/flooding between July and August. This indicates that there is no 'best time' for planting in the regions as the respective months of the transitional and seasonal periods are prone to diverse climatic threats. Through monitoring of mean and median onset dates however, it was found that planting around these dates (*23rd and 25th May in Upper East Ghana, and between 21st and 24th May in Southwest Burkina Faso*) could be a safer option, although with a 36.0% to 48.0% probability for crops to be exposed to dry spells of 5 days. The implication is that, even with the supposed safer planting options, farmers in the regions may have to practice supplemental irrigation for appreciable rate of emergence/germination and good seedling stands. Policy and stakeholder efforts to improve farmers' access to low-cost irrigation facilities could thereby prove helpful to farmers in the regions. In addition, although adjustments made by farmers in their plantings were based on past experiences, held perceptions and future expectations, it was found that majority of these farmers still reported major production losses at the end of the 2013 and 2014 production years. This indicates that their expectations concerning weather conditions may have been different from the observed and that their planting schedules were not better suited to the local climate. Policy and research efforts made to provide the farmers with timely and accurate weather forecasts that are easily understandable and tailored to meet their needs could help farmers adjust their cropping calendar appropriately, enable them to plant the right varieties of crops (depending on environmental/suitability conditions) and implement appropriate soil and water management practices to moderate harm.

Having analyzed intra-seasonal risk of weather extremes in the study area, we subsequently analyzed farmers perceptions of recent changes in the local climate and their adaptation to observed changes. Farmers in the study area generally perceived increasing seasonal temperatures (with some incidences of extreme values), decreasing rainfall and rainy days, and increasing erratic nature of rainfall in recent years. These perceptions held by farmers are in conformity with climatic trends, indicating that pro-adaptation response to the perceptions held by farmers could be appropriate and helpful in policy efforts undertaken to reduce agricultural losses from climate and weather risks. Perceptions held by farmers were found to be significantly influenced by the level of education of the farmers, share of household income from non-farm sources, group membership, number of family members within the ages of 18 to 65 years living at most 5 km from the main residence, access to credit and access to markets. Although in a non-linear fashion, net income from crop production was found to increase with the number of adaptation strategies implemented by farmers in response to their recent exposure to weather shocks. This implies that policy and research efforts made to promote the adoption of diverse strategies could prove beneficial to farmers. Through estimation of a Poisson regression, it was found that the number of adaptation strategies implemented by farmers increases with increasing access to credit and extension services, farm size and increasing frequency of seasonal hot days, but decreases with increasing access to remittances, remoteness, and increasing intra-seasonal rainfall variability. Through estimation of a multivariate probit model to assess the determinants of farmers' choice of adaptation strategies, it was found that institutional and infrastructural variables like access to credit, extension services and markets, as well as plot characteristics (like cropland area and fertility status of crop fields) and weather variables are the major determinants of farmers' adaptation to weather extremes. Of all the weather variables considered in this study, it was found that increasing intra-seasonal rainfall variability has the greatest disincentive effect on farmers' adaptive behaviour. These results imply that any noted reluctance in farmers' adaptation to climate shocks may be attributed to the high uncertainty surrounding intra-seasonal accumulation and distribution of rains, the erratic nature of weather conditions, liquidity constraints resulting from the limited access of farmers to credit, limited access of farmers to input and output markets (remoteness), and the limited access of farmers to vital information and skills on productivity enhancing innovations/strategies. Policy efforts made to improve farmers access to credit, input and output markets, extension services, and timely and accurate weather forecasts could enhance farmers' adaptation to climate and weather shocks.

Although farmers were found to be more likely to adopt a mix of adaptation strategies, their preference was more towards the adoption of low-cost measures that are likely to yield benefits in the short-run. Among such measures are the adoption of improved crop varieties, changing planting dates, and crop diversification. This implies that financial capabilities play major role in dictating farmers' choice of adaptation strategies. Farmers' preference for the low-cost measures could as well be associated with their short-term planning horizon. Thus, while majority of these low-cost measures stand yielding benefits in the short-run, benefits derived from most of the capital-intensive measures mostly materialize only in the long-run while requiring current investment efforts. The adoption of capital-intensive strategies like crop-livestock mix, crop and livestock insurance, irrigation, water conservation and water drainage techniques was enhanced by increasing access to credit, larger farm size, and limited access to markets, while the adoption of the aforementioned low-cost measures was enhanced by increasing access to extension services and positive perception of farmers about the fertility status of their crop fields.

In the fourth chapter of this thesis, econometric and mathematical programming models were used to estimate the impact of climate shocks on the welfare of farm households in the Northern Savanna of Ghana. Emphasis was placed on predicting the impact of five potential future rainfall distributions (scenarios) and adaptation responses on crop yields, farm household income, food consumption and the shadow prices of land. Due to potential heterogeneity across farm households which could influence farmer responses to external shocks, farmers in the study area were grouped into homogenous units. A total of three groups of farmers were identified. These are

- Poor farmers who operate under low input conditions on medium-scale farms and allocate more than 70% of the total cropland area to the production of cereals (Cluster 1)
- Poor farmers who operate under low input conditions on medium-scale farms and allocate less than 70% of the total cropland area to the production of cereals (Cluster 2) and
- Less poor farmers who operate under high input conditions on small-scale farms and allocate more than 70% of the total cropland area to the production of cereals. (Cluster 3).

It is found that, compared to the current rainfall distribution, a drier future could result in total income loss of about 3.70% (in Cluster 3) to 23.75% (Cluster 1). Under this scenario, the quantity of food available for consumption is predicted to decrease across all the three clusters, although a greater decrease is expected in Cluster 1. Besides this, it was found that predicted decrease in income and consumption could more than double under a drier future scenario compared to a dry future. This indicates that, while farmers could compensate for crop income losses with income from the livestock enterprise and from off-farm sources, their ability to compensate for such losses is highly limited under extremely dry rainfall conditions. A relatively lower adverse impact of extremely dry rainfall conditions is predicted for the high input farms with a stronger asset base and for the farms that allocate relatively lower share of cropland to the production of cereals. These results indicate that while the diversification of crop production may help to minimize crop income losses under adverse weather conditions, specialization (in terms of allocation of cropland to cereals, legumes, roots and tubers) under low input conditions could prove harmful to farmers in the regions (as is found in Cluster 1). In addition, efforts to promote asset accumulation in the regions and to improve farmers input use intensity (especially regarding fertilizer) may prove beneficial to farmers in the regions, as this could help to minimize production and income losses under drier rainfall conditions, and enhance productivity under normal to wetter rainfall conditions. Besides the predicted changes in income and consumption, a drier future could result in 13.6%, 5.69% and 3.33% decreases in the shadow price of rainfed lands in Clusters 1, 2 and 3 respectively. It is found that irrigation expansion in the study area could lead to income gains of about 3.98% to 35.32% under the current rainfall distribution, while investment in research and development efforts could lead to income gains of about 10.31% to 33.48%. This implies that, while climate and weather shocks would continue to pose threats to farming systems in the regions, policy and stakeholder efforts made to promote the practice of irrigation and to bridge current yield gaps for majority of the weather sensitive crops could prove worthwhile. Such efforts could help to improve farmers' welfare by increasing their incomes and food available for human consumption. The poor and more vulnerable farmers of Clusters 1 and 2 are expected to however benefit the most from such interventions. This could thereby lead to reduced incidence of poverty and income inequality in the regions.

In conclusion, the study shows that policy and stakeholder efforts made to improve farmers' access to (formal/informal) credits, input and output markets, extension services, and timely and accurate weather forecasts could enhance farmers' adaptation to climate shocks, while the implementation of appropriate adaptation strategies could help to curb the adverse impacts of climate and weather shocks

While findings from this study are deemed relevant for agricultural and food policy formulation, and for drafting of measures to promote resilience, the study is not without limitations. Majority of the limitations of this study are statistical or data related. Due to difficulty in accessing observed climate data from the field and to lack of such data in most cases, we resorted to the extraction of climate data from NASA's climatological database for the first two chapters. This limited the scope of our analysis to the period 1997-2014, thereby precluding identification of other devastating climatic shocks beyond this period. The limited scope of the study also precluded identification of other climatic risks whose definition are primarily based on climatic normals (long-term averages for the study area). The use of observed field data or bias-corrected data for a much longer period could prove more useful (beneficial). In addition, although some recent studies (including Ringler *et al* 2014; Rakib 2015; Ngigi *et al* 2017) report of gender differences in farmers' adaptation to climate shocks, the current study focused solely on adaptation by the entire farm household as expressed by the head of the household without placing emphasis on gender aspects. Although we analyzed farmers' adaptation to weather extremes based on cost dimensions, we made no computation of the actual costs of adoption of the individual strategies implemented by farmers as in Palanisami *et al* (2015), but rather, we based our groupings on documented evidences in literature. This was due to our inability to gather accurate data on strategy-specific costs. Efforts made in future research works to address this flaw could provide greater insight into the differential rates of adoption of the strategies under direct and supportive measures, and on the differential effects of the explanatory variables on strategies within and between measures. In addition to these, the study assumed fixed output and input prices. This may however not always be the case with a changing local climate and implementation of interventions.

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Publications

- Intra-seasonal risk of agriculturally-relevant weather extremes in West African Sudan Savanna

- Analysis of farmers' adaptation to weather extremes in West African Sudan Savanna: Weather and Climate Extremes, 16: 1-13

Appendices

Appendix A: Tables and Figures

Tables

(dependent variable: Log(Yield), Optimization: ML
Table AP 4. 1-Production function coefficients

Explanatory variables	Maize (N=1,042)	Millet (N=294)	Sorghum (N=110)	Rice (rainfed) (N=401)	Rice (general) (N=420)
Log (Rain)	2.2633***	1.8833*	-0.3561	1.9344**	1.5906**
Log (Temperature)	0.6499	1.8060	6.1745	7.3485**	4.7389
Log (Fertilizer)	0.0776***	0.0006	0.0135	0.0526***	0.0663***
Log (Labor)	0.2405***	0.2380***	0.1616*	0.2675***	
Log (Seed)	0.0309	0.2641***	0.2555***	0.1128**	0.0905*
Irrigation dummy					0.9298***
Intercept	-12.62**	-14.617	-13.395	-32.995**	-20.629
Observed Yield	765.87	506.87	509.94	917.4	2587.43 (for irrig)
Predicted Yield	863.11	553.99	558.96	1053.45	2786.84 (for irrig)
PAD	12.70%	9.297%	9.613%	14.83%	7.707%
Variables	Common beans (N=315)	Soybean (N=111)	Groundnut (N=460)	Bambara nuts (N=138)	Yam (N=230)
Log (Rain)	-1.5203	1.7553	1.9525**	2.1488	0.7572
Log (Temperature)	0.427	1.2791	-7.4504***	12.653***	-3.0578
Log (Fertilizer)	-0.032	0.0401	0.0366	-0.0529	
Log (Labor)	0.236***	0.0505	0.2205***	0.2064**	0.1671**
Log (Seed)	0.0644	0.2660**	0.1146***	0.2474***	0.1558**
Intercept	13.448	-11.41	16.226*	-52.913**	11.273
Observed Yield	277.80	671.42	618.49	362.54	4284.10
Predicted Yield	273.71	665.48	702.52	369.28	4222.64
PAD	1.473%	0.884%	13.59%	1.858%	-1.434%

NB: ***1%, **5%, *10%; (for irrig) – observed and predicted yields for irrigated rice production

Figures

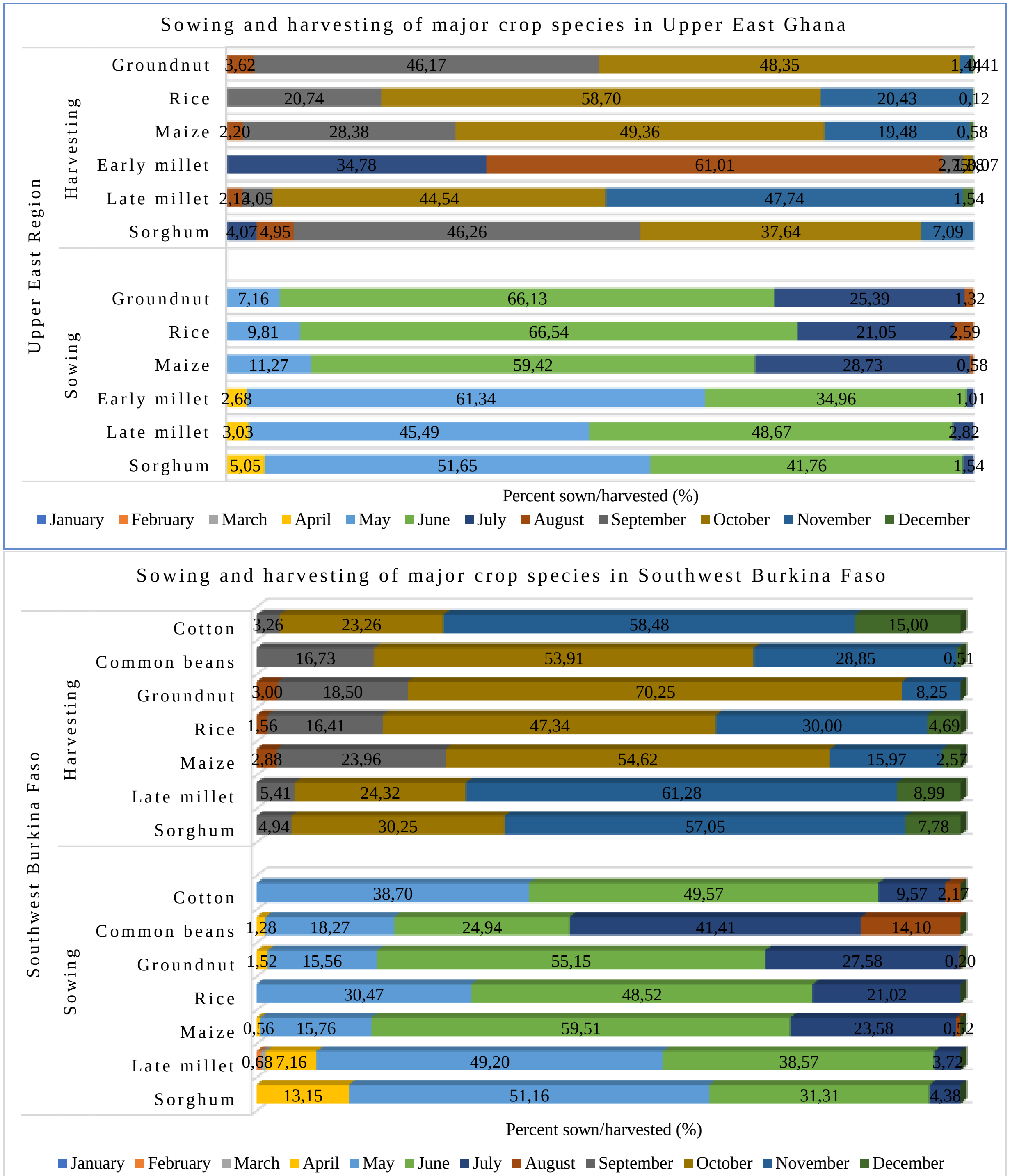
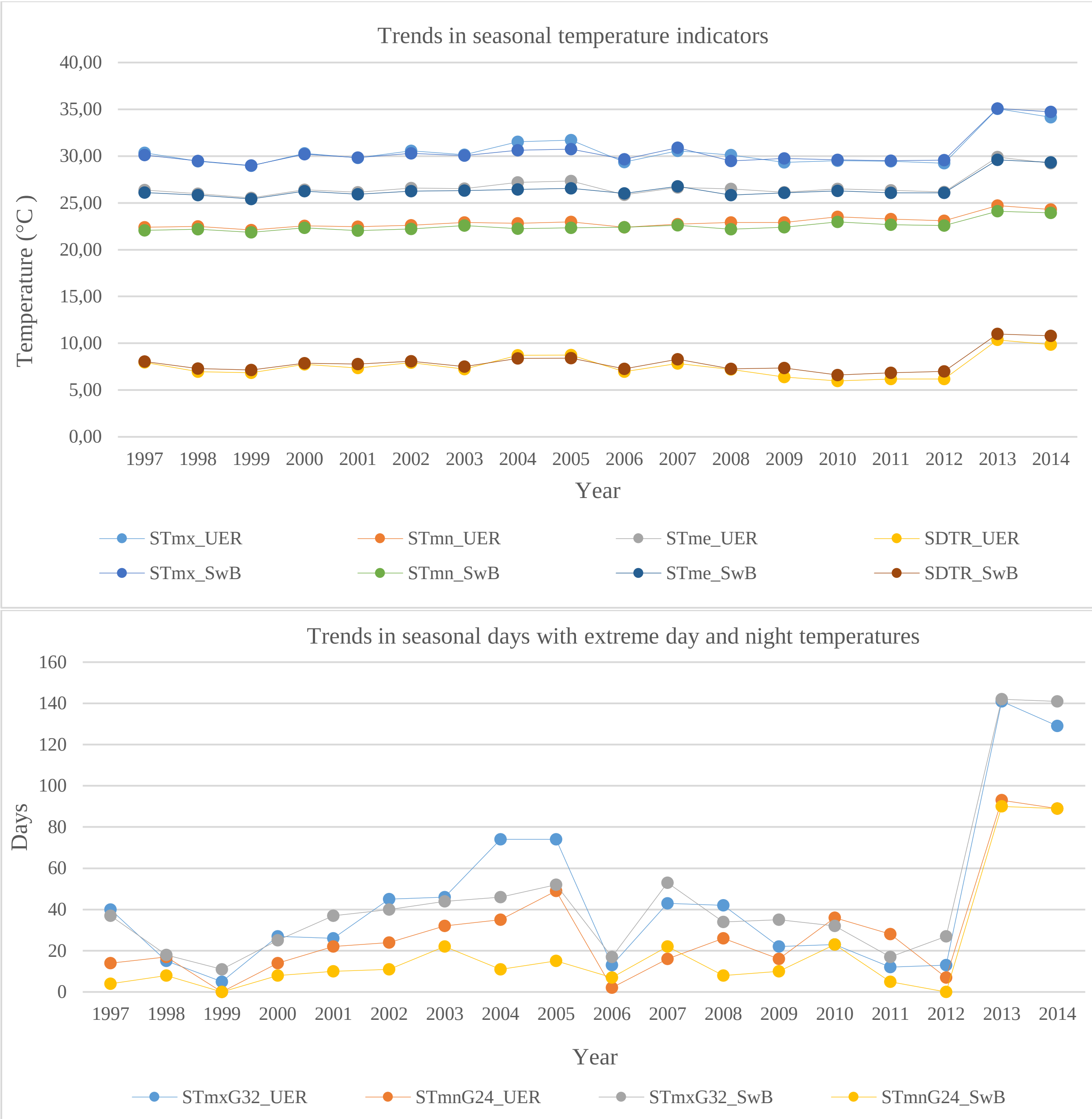


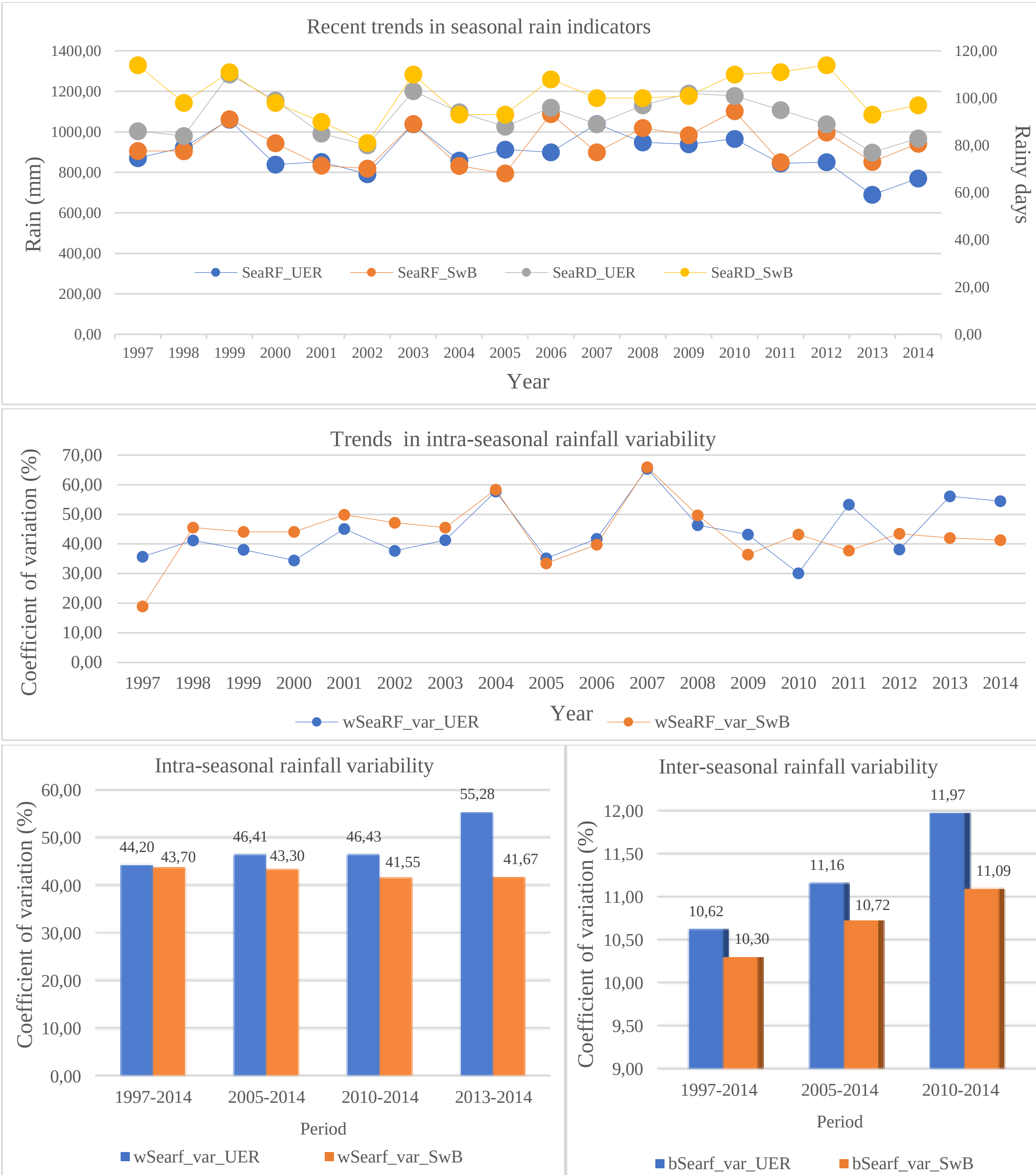
Figure AP 2. 1-Cropping calendar for major crops in the study area
Source: Author’s construct with data from household survey



NB: UER- Upper East region of Ghana, SwB – Southwest Burkina Faso; STmax – seasonal maximum temperature; STmin – seasonal minimum temperature; STmean -seasonal mean temperature; SeaDTR- seasonal diurnal temperature range; SeTmx32 - seasonal hot days (Tmax≥32°C); SeTmn24 -seasonal hot nights (Tmin≥24°C)

Figure AP 3. 1-Recent trends in seasonal temperature

Source: Author's construct



NB: UER- Upper East region of Ghana, SwB – Southwest Burkina Faso; SeaRF- seasonal rainfall; SeaRD- seasonal rainy days; wSeaRF_var – intra-seasonal rainfall variability; bSeaRF_var – inter-seasonal rainfall variability;

Figure AP 3. 2-Recent trends in seasonal rainfall, rainy days and variability in rainfall

Source: Author’s construct

Appendix B: Questionnaire for chapters 2 and 3

Extreme weather events in Sudan Savanna Region of West Africa: agricultural impacts and adaptation
Questionnaire for household survey

Department of Economic and Technological Change
Center for Development Research, University of Bonn, Germany

Purpose of the survey

The purpose of the survey is to identify the types of extreme weather events to which farmers in the study area have been recently exposed, which among the numerous manifestations of climatic conditions they deem a threat to farming, their adaptation to recent changes in the local climate and perceived impacts of weather extremes. Data from the survey would be used for a study on climatic risks in the study area. Findings from the study would be used as a guide to inform policy decisions on measures needed to promote resilience to climate and weather risks.

Voluntary participation and confidentiality

In the course of answering this questionnaire, you have every right to stop me and ask questions whenever a question/ or an issue is unclear. Your participation in this interview is voluntary and you can back out whenever you like (***nobody can and must force you to provide any confidential information***). Any interactions between us would be kept confidential.

For further questions please contact:

Name: Boansi David
Email: boansidavid@rocketmail.com
Mobile:
Home address: Apostolic Faith Church, P.O.Box RY49, Railways, Kumasi, Ghana
Address abroad: Center for Development Research, Walter-Flex-Strasse 3, D-53113, Bonn, Germany

Participation

I agree to ***voluntarily*** participate in this interview

_________________________________ _________________________________

Signature of respondent Signature of interviewer

- **Structure of the household**

Household (HH) ID	
Name of household head	
Sex of household head	Male = 1 Female = 0
Age of household head	
Total number of people in household • Male 0-5 years 6-10 years 11-17 years 18-65 years > 65 years • Female 0-5 years 6-10 years 11-17 years 18-65 years > 65 years	
Number of family members 18-65 years living within 5km from main residence	
Number of family members abroad	
Primary occupation of household head	1. Crop farming 2. Livestock production 3. Other (Specify):
Secondary occupation(s) of household head	
% of household income from non-farm sources	
Schooling of household head	1. No schooling 2. Primary level 3. Junior High 4. Secondary level 5. Tertiary level
How long have you been living in this community/village?	1. < 1year 2. 1-5years 3. 6-10 years 4. 11-20 years 5. > 20years
How long have you been farming?	Crops 1. < 1year 2. 1-5years 3. 6-10 years 4. 11-20 years 5. > 20years Livestock 1. < 1year 2. 1-5years 3. 6-10 years 4. 11-20 years 5. > 20years
Did any of your parents ever engage in farming activities?	Yes= 1 No = 0
Ownership of land for agriculture	1. Own land 2. Rented / leased
Total Size of land owned/ leased Cropland in total land owned/leased	Size: owned: leased: Size: owned: leased:
Participation in agricultural union/group	Yes= 1 No = 0
Have you any access to credit (formal or informal)	Yes= 1 No = 0

- **Farmer cropping decisions**

When do you usually make a decision on which crops to grow in a season?	1. About six months to the next rainy season 2. About 3 months to the next rainy season 3. About two months to the next rainy season 4. About a month to the next rainy season 5. Other (Specify):
What are the main factors that influence your decision on which crops to grow?	1. Household food needs 2. Prevailing market and producer prices 3. Previous year's income from a specific crop 4. Weather conditions from the previous season 5. Expectation about weather in the impending season 6. Labour availability 7. Access to market 8. Other (Specify):
Which crop(s) did you begin your farming activity with?	List: a) e) b) f) c) g) d)
Do you still produce all these crops?	Yes = 1 No = 0
If No, which crops have you stopped producing?	List:
What are the main reasons for not producing them anymore?	1. More rains/floods 2. Less rains/droughts 3. Rising production costs 4. Labour challenges 5. Issues with pests and diseases 6. Financial constraints 7. other (Specify):
Do you now produce other crops beside the ones you started with? Which crops if yes?	Yes = 1 No = 0 List:
Which of the crops you produce do you allot most of your time, inputs and money on? Why?	List: Reason(s):

- **Crop allocation, management and challenges in production**

Total Cropland (Area)	
Share of crop per land area Crop A Crop B Crop C Crop D Crop E Crop F Crop G	Size (Units - ……………………)
Crop mix if mixed-cropping	List of crops in sequence:
Source(s) of water for production	1. Rain 2. Tap system at home/nearby 3. Tap system/far away 4. River/lake 5. Boreholes/well 6. Other (specify):

Which crops do you irrigate if any?	List:
During which periods in the growing season do you irrigate these crops? (Select all that apply)	Periods 1. From sowing to emergence 2. From emergence to pre-flowering 3. During flowering 4. Post-flowering to maturity stage
Total area of respective crops under irrigation	Size (Units……) Crop A Crop B Crop C Crop D Crop E Crop F Crop G
Do you cultivate old variety or new variety of the respective crops you grow? Old variety =1 New variety= 2 *If 2, state the variety*	Crop A 1 2 Crop B 1 2 Crop C 1 2 Crop D 1 2 Crop E 1 2 Crop F 1 2 Crop G 1 2

	Strong Agree =1	Agree = 2	Not sure = 3	Disagree = 4	Strongly Disagree = 5
It is very difficult to access adequate land for crop production in this location					
It is very difficult to access enough hired labour (farm hands) for crop production during the main season					
It is very difficult to access chemical inputs from this location					
We receive low prices for our crops due to distance from the market and bad roads					
We observe high post-harvest losses due to lack of storage facilities					
We observe high post-harvest losses due to bad weather during storage					
Financial constraint and access to credit are major challenges for production					

Crops	Seed per unit area	Seed price (LCU/kg)	Seed cost (LCU)
Crop A Crop B Crop C Crop D Crop E Crop F Crop G			

Sowing date (% sown)

Crops	JAN	FEB	MARCH	APRIL	MAY	JUNE	JULY	AUG	SEP	OCT	NOV	DEC
A												
B												
C												
D												
E												
F												
G												

Harvesting date (% harvested)

Crops	JAN	FEB	MARCH	APRIL	MAY	JUNE	JULY	AUG	SEP	OCT	NOV	DEC
A												
B												
C												
D												
E												
F												
G												

Labour supply and sources

Labour used	Sowing			Weeding			Harvesting		
Crops	Total Num.	Household	Hired/Com L	Total Num.	Household	Hired/Com L	Total Num.	Household	Hired/Com L
A									
B									
C									
D									
E									
F									
G									

Time and wages	Sowing			Weeding			Harvesting		
Crops	Days	Hours/day	Wages/hour	Days	Hours/day	Wages/hour	Days	Hours/day	Wages/hour
A									
B									
C									
D									
E									
F									
G									

Use and cost of agro-chemicals

Time and wages Crops	Fertilizer application Days	 Hours/day	 Wages/hour	Pesticide application Days	 Hours/day	 Wages/hour
A						
B						
C						
D						
E						
F						
G						

What quantity of fertilizer do you apply on the respective crops during the following stages (if any)?	During emergence After emergence but before flowering During flowering Post-flowering Crop A Crop B Crop C Crop D Crop E Crop F Crop G
What extra costs do you incur in accessing fertilizer for your cropping activities (besides the actual price)?	**Narration**:
What quantity of pesticide do you apply on the respective crops during the following stages?	During emergence After emergence but before flowering During flowering Post-flowering Crop A Crop B Crop C Crop D Crop E Crop F Crop G
What extra costs do you incur in accessing pesticide for your cropping activities (besides the actual price)?	**Narration**:
Name and price of agrochemicals applied on the respective crops	Name of Fertilizer Price (LCU/…………) Name of Pesticide Price (LCU/…………) Crop A Crop B Crop C Crop D Crop E Crop F Crop G

Access to market

How far is your residence from the nearest town?	
How far is your residence from the nearest market?	
How does the distance factor (to the nearest market) affect price you receive for your produce?	

- **Soil conditions and management**

How would you rate the general fertility of your crop field?	1. Very fertile 2. Fertile 3. Non-fertile 4. Very non-fertile
How often do you till your soil/land?	1. At the beginning of every growing season 2. Once in two seasons 3. Once in three seasons 4. Never 5. Other (Specify):
What forms of soil and water conservation measures do you employ in your cropping? Crop rotation Reduced tillage Cover cropping and mulching Cross-slope farming Fallowing Physical anti-erosive measures (stone bunds) Intercropping Manure application	 Yes = 1 No = 0 Yes = 1 No = 0 Yes = 1 No = 0 Yes = 1 No = 0 Yes = 1 No = 0 Yes = 1 No = 0 Yes = 1 No = 0 Yes = 1 No = 0
How often does your crop field get water-logged?	1. Never 2. Once in three seasons 3. Once in two seasons 4. Once in a season 5. Twice in a season 6. More than twice in a season
How often do you experience erosion on your crop field?	1. Never 2. Once in three seasons 3. Once in two seasons 4. Once in a season 5. Twice in a season 6. More than twice in a season

- **Farmer perception about weather and sources of weather related information**

The weather becomes more unpredictable from year to year	1. Strongly Agree 2. Agree 3. Not sure 4. Disagree 5. Strongly Disagree
What changes have you observed in seasonal temperature over the past 10 years?	1. A decrease in seasonal temperature 2. An increase in seasonal temperature 3. No change in seasonal temperature 4. An increase in seasonal temperature and extremes 5. A decrease in seasonal temperature and extremes
What changes have you observed in seasonal rainfall over the past 10 years?	1. A decrease in seasonal rainfall 2. An increase in seasonal rainfall 3. No change in seasonal rainfall 4. An increase in seasonal rainfall and extremes (extreme wet days) 5. A decrease in seasonal rainfall and extremes (extreme dry days)
What changes have you observed in seasonal flooding over the past 10 years?	1. A decrease in seasonal floods 2. An increase in seasonal floods 3. No change in seasonal floods
Source(s) of climate change information (select all those that apply)	1. On television 2. In the newspaper 3. On radio 4. On the internet 5. From extension agents and experts

	6. From fellow farmers 7. Other (Specify):
Have you any extension contact in relation to Crop production? Livestock production?	 Yes = 1 No= 0 Yes = 1 No= 0
If yes, how often do you get in touch with extension officers?	1. Once in three seasons 2. Once in two seasons 3. Once in a season 4. More than once in a season 5. Other (Specify):

- **Farmer description of a bad cropping year and experiences from the past**

How would you define a bad weather in relation to your cropping activities?	
What previous experience(s) have you had in relation to your definition of a bad weather above?	
How did that affect your crop yields? Crop A Crop B Crop C Crop D Crop E Crop F Crop G	Perceived decrease in yield compared to norm (%)

- **Yield and yield allocations between household consumption and sales**

Yield of crops

Crops	Observed yield (If harvested)	Expected yield (If not harvested yet)	Prevailing prices (LCU) /Kg
Crop A			
Crop B			
Crop C			
Crop D			
Crop E			
Crop F			
Crop G			

Output allocations

Share of crop output for		
Crops	**Household consumption (%)**	**Sale on the market (%)**
Crop A		
Crop B		
Crop C		
Crop D		
Crop E		
Crop F		
Crop G		

- **Livestock inventory**

Livestock at beginning of the year	Number	Price/Unit	Born	Bought	Gift received	Died	Sold	Consumed	Gift made	Current stock (number)
Cattle Bullock, trained Male adult Female adult Calves										
Sheep Male adult Female adult Young										
Goats Male adult Female adult Young										
Pigs Male adult Female adult Young										
Chicken										
Guinea fowls										
Ducks										
Turkeys										
Horses										
Donkeys										

- **Reasons for keeping livestock**

	Household consumption and income generation through sales									
	Bullock/draft services Yes = 1 No = 0	Meat: Sale Yes = 1 No = 0	Meat: HH Yes = 1 No = 0	Milk: Sale Yes = 1 No = 0	Milk: HH Yes = 1 No = 0	Eggs: Sale Yes = 1 No = 0	Eggs: HH Yes = 1 No = 0	Leather Yes = 1 No = 0	Marriage rites Yes = 1 No = 0	Insurance against unexpected weather events Yes = 1 No = 0
Cattle Bullock, trained Male adult Female adult Calves										
Sheep Male adult Female adult Young										
Goats Male adult Female adult Young										

Pigs Male adult Female adult Young										
Chicken										
Guinea fowls										
Ducks										
Turkeys										
Horses										
Donkeys										

- **Animal products**

Products produced	Total Value (LCU) / year
Bullock services offered to other farmers per season	
Milk production	
Leather production per month	
Eggs produced	

- **Husbandry practices and costs**

Livestock at beginning of the year	Vaccination against relevant diseases		Indoor system =1 Outdoor system = 2	Frequency of feeding per day		Frequency of watering per day		Labour (production) cost per month
	Yes=1, No=0	Share (%) if yes		Rainy Season	Dry Season	Rainy Season	Dry Season	
Cattle Bullock, trained Male adult Female adult Calves								
Sheep Male adult Female adult Young								
Goats Male adult Female adult Young								
Pigs Male adult Female adult Young								
Chicken								
Guinea fowls								
Ducks								

Turkeys								
Horses								
Donkeys								

- **Experience with bad weather**

How do extreme events	
Influence mortality rate of your livestock? Kindly give examples of how they affected your livestock in the past	Narration:
Affect egg production from your birds (Poultry)? Kindly give examples of how they affected egg production in the past	Narration:
Affect leather production from your livestock? Kindly give examples of how they affected leather production in the past	Narration:
Affect bullock services from your livestock? Kindly give examples of how they affected bullock services in the past	Narration:
Affect meat production from your livestock? Kindly give examples of how they affected meat production in the past	Narration:

- **Farm implements / other entitlements/ assets**

Implement / asset	Purchase price (LCU)	Price at end of useful period	Expected use	Number of units	Average age
Hoes Cutlasses					
Bullock implement - Plough - Harrow - Cart					
Tractor - Tractor - Plough - Harrow - Cart					
Stores					

Farmers' adaptation to and coping with extreme weather events

What immediate steps do you take following yield and income losses due to extreme events (Coping strategies)?	1. Selling of livestock and other assets 2. Reducing household consumption 3. Borrowing from friends 4. Borrowing from family members around 5. Taking loan from the banks 6. Migration of some energetic members of the household to the city to seek jobs 7. Look for other job opportunities around while we continue farming 8. Rely on family members abroad for remittances 9. Laying off some laborers 10. Other (Specify)
Why the selected steps and not the others?	Narration:
In case you do lay off some laborers (farm-hands) in response to unexpected weather shocks, how many people do you usually lay off?	
How many meals per day does your household consume in the absence of extreme events?	1. Once per day 2. Twice per day 3. Thrice per day 4. More than thrice per day
How many meals per day does your household consume in the midst of extreme events?	1. Once per day 2. Twice per day 3. Thrice per day 4. Less than once per day
Farmers' adaptation to recent incidences of weather extremes • Crop diversification • Planting of drought tolerant crops • Planting of flood tolerant crops • Planting of heat tolerant crops • Planting of early maturing crops • Changing planting dates • Crop-livestock mix • Purchase of crop and livestock insurance • Practice of irrigation • Use of water conservation techniques (wat. Harvesting) • Use of soil conservation techniques • Use of water drainage techniques • Other (specify)	 Yes = 1 No= 0 Yes = 1 No= 0 Yes = 1 No= 0 Yes = 1 No= 0 Yes = 1 No= 0 Yes = 1 No= 0 Yes = 1 No= 0 Yes = 1 No= 0 Yes = 1 No= 0 Yes = 1 No= 0 Yes = 1 No= 0 Yes = 1 No= 0 Yes = 1 No= 0
What factors determine which adaptive strategy you employ in the midst of extreme events?	1. Weather information 2. Access to credit 3. Access to irrigation facilities

Aside: for interviewer *(Thick according to voluntary answer provided by respondent)*	4. Ownership of livestock and agricultural implements 5. Availability of labor 6. Availability of land 7. Availability of inputs for production 8. Access to information on prices 9. Access to market 10. Household food needs 11. Effectiveness of previous response to specific extreme events 12. Free extension services 13. Other (Specify)

How would you rank the following factors/conditions in terms of their influence on your adaptation decisions?				
Conditions	1= extremely important	2= Important	3=Unimportant	4= extremely unimportant
Access to critical field inputs .e.g. improved seeds, fertilizer, agrochemicals, etc				
Access to low interest credit				
Access to irrigation water				
Access to land				
Access to labor				
Historical climatic conditions, especially evolvement of extreme events				
Information on prevailing climatic conditions				
Information on anticipated (future) climatic conditions				
Ownership of livestock and other assets				
Being part of a farmer's organization				
Being covered by insurance (crop and livestock insurance)				
Household food needs				
Access to market				
Prevailing farm-gate prices for produce				
Previous farm-gate prices for produce				
Expected (future) farm-gate prices for produce				
Adverse weather-related experiences from the past				
Beneficial weather-related experiences from the past				
Access to free extension services				
Indigenous knowledge in designing and implementing farm activities				
Energetic family members abroad and in high paid jobs (abroad or in Ghana) – Remittances				

Appendix C: Programming script

```
**********************General script
OPTION LIMROW = 0
 OPTION LIMCOL = 0
 option iterlim =1500

sets  c crops/maize,mill,sorg,rice,cbean,sbean,grou,bbnut,yam/
      c1(c) self-consumed crops  /maize,mill,sorg,rice,cbean,grou/
      s farming systems /s1 rainfed agriculture, s2 irrigated agriculture/
      F fertilizer application levels  /F1*F5/
      ls livestock species /draughtcattle,localbull,localcow,localcalf,donkey,localgoat,sheep,localpig,chicken/
      FIXED      FIXED INPUTS /LAN/
      e rainfall conditions /e1 very dry, e2 dry, e3  normal, e4 wet, e5  very wet/  ;

parameter prob(e) probability of occurrence of states of nature
        /e1    , e2    ,   e3    , e4      , e5      /              ;

table y(c,s,F,e)  yield of crops in kg per hectare
                              e1        e2        e3        e4        e5
maize.s1.F1
maize.s1.F2
maize.s1.F3
maize.s1.F4
maize.s1.F5
mill.s1.F1
mill.s1.F2
mill.s1.F3
mill.s1.F4
mill.s1.F5
sorg.s1.F1
sorg.s1.F2
sorg.s1.F3
sorg.s1.F4
sorg.s1.F5
rice.s1.F1
rice.s1.F2
rice.s1.F3
rice.s1.F4
rice.s1.F5
rice.s2.F1
rice.s2.F2
rice.s2.F3
rice.s2.F4
rice.s2.F5
cbean.s1.F1
cbean.s1.F2
cbean.s1.F3
cbean.s1.F4
cbean.s1.F5
sbean.s1.F1
sbean.s1.F2
sbean.s1.F3
```

```
sbean.s1.F4
sbean.s1.F5
grou.s1.F1
grou.s1.F2
grou.s1.F3
grou.s1.F4
grou.s1.F5
bbnut.s1.F1
bbnut.s1.F2
bbnut.s1.F3
bbnut.s1.F4
bbnut.s1.F5
yam.s1.F1
yam.s1.F2
yam.s1.F3
yam.s1.F4
yam.s1.F5

;



table fer(c,s,F)  rate of fertilizer application in kg per hectare
              F1     F2     F3     F4     F5
maize.s1      0      25     50     100    150
mill.s1       0      25     50     100    150
sorg.s1       0      25     50     100    150
rice.s1       0      25     50     100    150
rice.s2       0      25     50     100    150
cbean.s1      0      25     50     100    150
sbean.s1      0      25     50     100    150
grou.s1       0      25     50     100    150
bbnut.s1      0      25     50     100    150
yam.s1        0      0      0      0      0
;

TABLE      Ld(FIXED,c,s,F) FIXED INPUT USAGE BY PRODUCTION
                  F1     F2     F3     F4     F5
LAN.maize.s1      1      1      1      1      1
LAN.mill.s1       1      1      1      1      1
LAN.sorg.s1       1      1      1      1      1
LAN.rice.s1       1      1      1      1      1
LAN.rice.s2       1      1      1      1      1
LAN.cbean.s1      1      1      1      1      1
LAN.sbean.s1      1      1      1      1      1
LAN.grou.s1       1      1      1      1      1
LAN.bbnut.s1      1      1      1      1      1
LAN.yam.s1        1      1      1      1      1
;
```

```
parameter pr(c) unit price of crop per kg in GHC
/
maize
mill
sorg
rice
cbean
sbean
grou
bbnut
yam
 /;

parameter  prf(c) price per kg of fertilizer used on crop in GHC
/
maize
mill
sorg
rice
cbean
sbean
grou
bbnut
yam
 /;

parameter Labpha(c,s) labor requirement per crop in person-days per hectare
/
maize.s1
mill.s1
sorg.s1
rice.s1
rice.s2
cbean.s1
sbean.s1
grou.s1
bbnut.s1
yam.s1
 /;

parameter csponl(c,s) other crop-related costs per hectare in GHC
/
maize.s1
mill.s1
sorg.s1
rice.s1
rice.s2
cbean.s1
sbean.s1
grou.s1
bbnut.s1
yam.s1
```

```
 /;

parameter beta0(c1) lower bound of produce consumption requirement in kg
/
maize     -311.928
mill       149.6389
sorg       217.9439
rice      197.208
cbean      87.98864
grou       124.1055

/;

parameter beta1 marginal propensity to consume crop out of income in kg per GHC
/
maize      0.244404
mill      0.017507
sorg      0.0487626
rice      0.038766
cbean      0.009068
grou      0.008813
/;

parameter beta2 coefficient of variable household size within Engel function in kg per person
/
maize   112.6434
mill     13.74215
sorg    -7.602822
rice      32.5392
cbean    2.8118
grou    17.0768
/;

parameter L1 post-harvest loss to output ratio from base year
/
maize
mill
sorg
rice
cbean
sbean
grou
bbnut
yam
 /;

parameter prli(ls) price of livestock species in GHC per head
/
draughtcattle
localbull
localcow
localcalf
```

```
donkey
localgoat
sheep
localpig
chicken
/;

parameter cfdvetph(ls) cost of feed and veterinary services per head of livestock type in GHC
/
draughtcattle
localbull
localcow
localcalf
donkey
localgoat
sheep
localpig
chicken
/;

parameter vspph(ls) income from selling secondary livestock product per head in GHC
/
draughtcattle
localbull
localcow
localcalf
donkey
localgoat
sheep
localpig
chicken
/;

parameter bgy(ls) number of livestock species at beginning of year in head
/
draughtcattle
localbull
localcow
localcalf
donkey
localgoat
sheep
localpig
chicken
/;


$ontext
parameter Sland(s) self-owned land area per farming system in ha
/   s1
    s2
/
```

```
;


parameter Rland(s) rented-in land area per farming system in ha
/   s1
    s2
/
;

parameter Land(s) total land area per farming system in ha
/   s1
    s2
/
;

$ontext
************Irrigation expansion_50%
parameter Sland(s) self-owned land area per farming system in ha
/   s1
    s2
/
;

parameter Rland(s) rented-in land area per farming system in ha
/   s1
    s2
/
;

parameter Land(s) total land area per farming system in ha
/   s1
    s2
/
;


$offtext

scalar CRland cost of rented in land per ha /70 /;
scalar int interest rate /0.25/;
scalar CAP available own fund / /;
scalar HHSIZE total household size /  /  ;
Scalar Upperhirout upper bound of hirout labor / /;
scalar wageout off-farm wage rate GHC per day/10 /;
scalar wFlab wage rate for family labor on farm /  / ;
scalar h1 wage rate for hired  labor /  /;
scalar familynofflab total household labor endowment  /335.8549/;


variables
Z expected total household income
X cropland area in hectare
```

```
Hlab person-days of hired labor
offlab person-days of off-farm labor
farmlab total farm labor use per season
CRED credit
FERT  optimal quantity of fertilizer to apply across farm in kg
SL number of livestock species sold
BO number of livestock species bought
CONS self-consumption
SOLD crop sold
BouC quantity of food crops bought from the market in kg
PHLoss post-harvest losses
produce


positive variables X,Hlab,offlab,farmlab,CRED,FERT,SL,BO,CONS,SOLD,BouC, PHLoss,produce;

equations
THINC total household income
lland land constraint
llabor2   farm labor constraint
lfarmlab persondays of labor input on farm
lfert fertilizer use constraint
lquant production
lquant2 commodity balance
lPHLoss output loss function
lcons consumption constraint
llbs livestock buying and selling constraint
lcash cash constraint
lrot1   rotation maize-groundnut
lrot2   rotation groundnut-yam
lrot3   rotation maize-commonbean
lrot4   rotation maize-millet
lrot5   rotation groundnut-bambaranuts
lrot6   rotation groundnut-soybean

;

THINC.. sum((c,s,F,e),prob(e)*y(c,s,F,e)*pr(c)*X(c,s,F))-sum((c,s,F),prf(c)*fer(c,s,F)*X(c,s,F))-
sum((c,s,F),csponl(c,s)*X(c,s,F))-wFlab*(familynofflab-offlab)-(h1*Hlab)
         -int*CRED+ sum(ls,prli(ls)*SL(ls))-sum(ls,1.05*prli(ls)*BO(ls))+sum(ls,vspph(ls)*(bgy(ls)+BO(ls)-SL(ls)))-
sum(ls,cfdvetph(ls)*(bgy(ls)+BO(ls)-SL(ls)))+ wageout*offlab -sum((c,e),pr(c)*PHLoss(c,e))-
sum(s,CRland*Rland(s))-sum((c,e),1.05*pr(c)*BouC(c,e)) =e= Z;

*lland
lland(s)..   sum((c,F,FIXED),Ld(FIXED,c,s,F)*X(c,s,F))=l=Sland(s)+Rland(s) ;
*lland(s)..   sum((c,F,FIXED),Ld(FIXED,c,s,F)*X(c,s,F))=l=land(s) ;

llabor2.. sum((c,s,F),Labpha(c,s)*X(c,s,F))=l=familynofflab-offlab +Hlab;

lfarmlab..  sum((c,s,F),Labpha(c,s)*X(c,s,F))=e=farmlab;

offlab.up=upperhirout;
```

```
*lfert
lfert..   sum((c,s,F),fer(c,s,F)*X(c,s,F)) =l= FERT    ;

*lquant
lquant(c,e) ..sum((s,F),y(c,s,F,e)*X(c,s,F))=e=produce(c,e);
lquant2(c,e) ..produce(c,e)+Bouc(c,e)=e=CONS(c,e)+SOLD(c,e)+PHLoss(c,e);

lPHLoss(c,e).. PHLoss(c,e)=e= L1(c)*produce(c,e)   ;

*lcons
lcons(c1,e)..  CONS(c1,e)-beta1(c1)*Z-beta2(c1)*(HHSIZE)-beta0(c1)=g=0;

*llbs
llbs(ls).. bgy(ls)+BO(ls)-SL(ls)=g= 0;

lcash.. sum((c,s,F),prf(c)*fer(c,s,F)*X(c,s,F))+sum((c,s,F),csponl(c,s)*X(c,s,F))+(h1*Hlab)
+sum((c,e),pr(c)*BouC(c,e))+sum(s,CRland*Rland(s))
        +int*CRED +sum(ls,prli(ls)*BO(ls))+sum(ls,cfdvetph(ls)*(bgy(ls)+BO(ls)-
SL(ls)))=l=sum((c,e),pr(c)*SOLD(c,e))+sum(ls,vspph(ls)*(bgy(ls)+BO(ls)-SL(ls)))+ sum(ls,prli(ls)*SL(ls))+
CAP+ CRED +wageout*offlab;


lrot1(s)..  sum(F,X('grou','s1',F)) =e=   *sum(F,X('maize','s1',F));
lrot2(s)..  sum(F,X('yam','s1',F))  =e=   *sum(F,X('grou','s1',F));
lrot3(s)..  sum(F,X('cbean','s1',F)) =e=  *sum(F,X('maize','s1',F));
lrot4(s).. sum(F, X('mill','s1',F)) =e=    *sum(F,X('maize','s1',F));
lrot5(s)..   sum(F, X('bbnut','s1',F))  =g=  *sum(F, X('grou','s1',F));
lrot6(s)..   sum(F,  X('sbean','s1',F))  =g=  *sum(F, X('grou','s1',F));


********************research and development
**********maize
*y('maize',s,F,e)=1.25*y('maize',s,F,e)   ;
*********rice
*y('rice','s1',F,e)=1.25*y('rice','s1',F,e) ;


model farm /all/    ;

solve farm using lp maximizing Z;
```