The Economic Impact of Climate Change on Farm Decisions and Food Consumption in Ghana

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To my Empress, Nyahans, and Etwireba

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2. Martey, E., **Etwire**, **P. M.,** Wiredu, A. N. and B. D. K. Ahiabor (2017). "Establishing the link between market orientation and agricultural commercialization: Empirical evidence from northern Ghana". *Food Security*, 9(4): 849-866. DOI 10.1007/s12571-017-0688-9

3. **Etwire, P. M.**, Buah, S., Ouédraogo, M., Zougmoré, R., Partey, S. T., Martey, E., Dayamba S. D. and J. Bayala (2017). "An assessment of mobile phone-based dissemination of weather and market information in the Upper West Region of Ghana". *Agriculture & Food Security*, 6 (8): 1-9. DOI 10.1186/s40066-016-0088-y

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Abstract

Climate change poses a serious threat to the growth of developing countries, especially Ghana where the majority of people derive their livelihoods directly from agriculture and related industries. This thesis sets out to examine the economic impact of climate change on agriculture by modelling climate, household, and farm data from Ghana. The impact is assessed through three connected empirical studies.

In our first empirical study, we estimate a multinomial logit (8,700 observations) in order to determine the factors that influence the choice of farming systems in Ghana. Consistent with our expectations, we find that climate is an important determinant of farm selection. Dry conditions (i.e. an increase in temperature or a decline in rainfall) favour the selection of livestock farms and mixed farms (i.e. mixed food-crop and livestock). Wet or cool conditions (i.e. a decrease in temperature or an increase in rainfall) favour the selection of tree-based farms. A decrease in temperature also favours the selection of food-crop farms. Based on the multinomial estimates and various projections of future climate, we simulate the potential impact of climate change and find that farmers will likely adapt by switching from tree-based farms (a highly profitable farming system) to less profitable but climate-resilient farming systems such as livestock farms.

In our second study, we use a flexible structural Ricardian model, SRM (which is a simultaneous two-stage optimisation technique) to estimate the impact of climate change on food-crop production by relying on 6,400 observations. In our version of the SRM, we control for temperature-rainfall interaction in the first stage and then estimate the second stage semi-parametrically. We find that rainfall impacts positively on the productivity of all food-crops except millet. Temperature has a negative effect on the productivity of most food-crops. A simulation of the effects of climate change shows that crop farmers will likely adapt

by replacing high-value crops with millet, a low-value but climate-resilient crop. All things being equal, the results of our first two studies imply a decline in the aggregate value of agricultural output, hence there is the need to invest in research that seeks to improve the climate resilience of high-value food-crops and tree-based farms.

In our final study, we apply a Heckman selection model to 10,200 observations in order to fit Ghanaian farm and non-farm incomes and on that basis, simultaneously estimate the impact of temperature on farm income, non-farm income, and real food consumption. As expected, we find that income determines real food consumption. We find an inverse relationship between farm income and non-farm income. Warming impacts negatively on both farm and non-farm productivity and consequently real food consumption. For a typical adult, a 1°C rise in temperature results in a 4% reduction in real food consumption. This result has important implications for food security and general welfare.

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List of Abbreviations

2SLS	2-Stage Least Squares
3SLS	3-Stage Least Squares
CSIR	Council for Scientific and Industrial Research
FAO	Food and Agriculture Organisation
GSS	Ghana Statistical Service
IIA	Independence from Irrelevant Alternatives
IPCC	Intergovernmental Panel on Climate Change
MoFA	Ministry of Food and Agriculture
OLS	Ordinary Least Squares
SARI	Savanna Agricultural Research Institute
SRM	Structural Ricardian Model
UNFCCC	United Nations Framework Convention on Climate Change

Chapter 1

General Introduction

Abstract

This thesis consists of five chapters. The first and last chapter contain the general introduction and conclusion of the thesis, respectively. The others are three separate, but related, empirical essays.[1] We use the same dataset (climate, household, and farm data from Ghana) for the analyses but examine different aspects of the data for each chapter. The empirical chapters are written in such a way that they can be read together or in isolation.[2] We estimate the effects of climate change on farming system selection in Chapter 2 and find that climate change impacts positively on the selection of specialised[3] livestock farms and mixed food-crop and livestock farms. We find a negative correlation between climate change and the selection of either tree-based farms or specialised food-crop farms. Constrained by data and given that we find a negative correlation between climate change and the selection of specialised food-crop farms, we estimate in some detail the effects of climate change on food-crop production in Chapter 3. We find that climate change favours the production of less profitable but climate-tolerant crops such as millet and impacts negatively on highly profitable but climate-susceptible crops such as yam. In our final empirical chapter (Chapter 4), we highlight how temperature (one of our climate variables) ultimately impacts on food consumption and find that a 1°C increase in temperature results in a 4% decline in real food consumption.

[1] We do not have a separate chapter for literature review. Embedded in each empirical chapter is a review of the relevant literature for that chapter. Chapter 1 contains the general literature of the thesis.

[2] We write an abstract for the first four chapters and provide references for all chapters. We provide notes at the bottom of our tables in order to make each table self-explanatory. The appendices for each chapter are presented after the reference section of that chapter.

[3] Specialised farms are farms that produce only food-crops or livestock (rather than a combination).

1.1 Background

Proof of the occurrence of climate change abounds.[4] Extreme climatic events have been observed since the middle of the 20th century (i.e. following industrialisation). Anthropogenic activity, principally the emission of greenhouse gases (GHGs), has been clearly identified as a major cause of climate change. Given the long shelf-life of these gases, changes in climate would still occur for centuries even if current global emissions were to be curtailed (Intergovernmental Panel on Climate Change, IPCC, 2014a). Future global warming is therefore certain. Global temperature is expected to rise under various climate scenarios. The increase in temperature will lead to the occurrence of drought and heat events that will become more frequent and lengthy. Precipitation and consequently flooding are also expected to become more frequent and intense (IPCC, 2014a).

Climate change has dire consequences for Africa even though the continent contributes little to global carbon emissions (Asafu-Adjaye, 2014). Due to its low adaptive capacity and the interaction of multiple stresses that it already faces (e.g. poor soil fertility, pests and diseases, inadequate access to inputs, and improved seed), Africa is extremely vulnerable to climate change (Boko et al., 2007). The continent already experiences high temperature, low rainfall, and low adoption of modern technology (Kurukulasuriya et al., 2006). Africa is among the hottest places on earth, thus further warming will have damaging ramifications since the region's economic output is determined by agro-climatic conditions (Asafu-Adjaye, 2014; Ringler et al., 2010). Only 5% of the continent's cultivated area is irrigated, compared to 37% in Asia and 14% in Latin America (Ringler et al., 2010).

[4] Climate is defined by the World Meteorological Organisation as the average weather condition (e.g. temperature and rainfall) observed in an area for a long period of time, usually 30 years. Climate differs from weather since the latter is the atmosphere observed in an area for a short period of time, which is a year in our case (see Section 3.3). Climate change is a change in the climate that can be recognised through long-term changes in its properties (IPCC, 2014b).

Climate change does not have a uniform impact on Africa. The effects of climate change vary by country and even for the same country, impacts differ by sector of the economy[5] (Da Cunha et al., 2015). Climate change affects the agricultural sector more than many other sectors. This is especially true for African agriculture where many countries have limited resources to prepare for, adapt to, or recover from extreme climatic events (Thomas and Rosegrant, 2015). Agriculture is an important economic activity in Africa as it serves as the main source of income and employment for over 60% of the people. Improvements in the sector can lead to poverty reduction and vice versa. Additionally, agriculture drives national growth and provides an opportunity for private investment. The sector is the main source of raw materials for agro-industries[6] (Clements et al., 2011).

In spite of the negative impacts that are often highlighted, climate change may have some positive effects. All things being equal, higher emissions of carbon dioxide (CO_2) could lead to improvements in agricultural productivity through increases in the growth rate and water-use efficiency of some food and tree-crops whilst reducing the transpiration rates, a process often referred to as CO_2 fertilisation or global greening (Ausubel, 2015; Aydinalp and Cresser, 2008; Food and Agricultural Organisation, FAO, 2011; Maharjan and Joshi, 2013). Extension of the agricultural season (e.g. in cooler areas) and conversion of non-agricultural lands to productive lands are some other benefits that may result from increased warming and changes in rainfall (Ausubel, 2015; Aydinalp and Cresser, 2008; Fuhrer, et al., 2014; Maharjan and Joshi, 2013). Increases in temperature can facilitate the formation of new soil

[5] In the specific case of Ghana, there is evidence of climate change impacting on agriculture (Mabe et al., 2013; Nkegbe and Kuunibe, 2014; Issahaku and Maharjan, 2014a, b), water resources (Amisigo et al., 2015; Kankam-Yeboah et al., 2013), energy and infrastructure (Arndt et al., 2014; Yaro et al., 2010), human security (Brown and Crawford, 2008), and fisheries (Lam et al., 2012).

[6] Even though the economy of Ghana relies heavily on agriculture, the sector is very vulnerable to climate change since agriculture is mostly weather dependent and is dominated by small-scale operators who have little resources to invest in climate-smart technologies (Ministry of Environment, Science, Technology and Innovation, MESTI, 2013).

by quickening the weathering of parent material (e.g. rocks). Also, warming can enhance microbial soil activity, thereby leading to improvements in soil structure and fertility (Maharjan and Joshi, 2013). Livestock can also benefit from climate change (e.g. CO_2 fertilisation and improved soil fertility) through improvement in pasture production and decline in insect infestation.

There is evidence of climate change in Ghana. Since the second half of the 20th century when weather stations were mounted in the country, the record shows a decreasing trend in rainfall (Nkegbe and Kuunibe, 2014; World Bank, 2010). The World Bank (2010) reports a 2.3mm annual reduction in rainfall since the 1960s. Between latitudes 6° and 9.5^{o}N of the country, Lacombe et al., (2012) also observe a decline in the total number of rainy days. In addition, they detect a delay in the onset of the rainy season in several locations across the nation. Analyses of the rainfall data (1961-2010) from northern Ghana show a high inter-annual variability (Acheampong et al., 2014). A high inter-annual variability was also established in the north-eastern part of the country with the quantity and distribution of rainfall as well as the number of rainy days also found to be on the decline (Assan et al., 2009). Adjei-Nsiah and Kermah (2012) observe a sharp decline in the number of rainy days in the middle portions of the country based on data from 1962-2001. In addition, they find a rapid decline in the amount of rainfall recorded in the driest months. Based on a 40-year data, Boon and Ahenkan (2013) find a general decline (20 to 30%) in the rainfall recorded in the south-western part of Ghana. Owusu and Waylen, (2013a, b) report that the short dry spell usually observed within the rainy season has become wetter.

A rise in temperature has also been observed in Ghana. Analyses of temperature data (1970-2009) show that northern Ghana is becoming warmer (Mabe et al., 2013). Similarly, Acheampong et al., (2014) observe a gradual increase in mean annual temperature with minimal fluctuations for the period between 1991 and 2010. A 2°C increase in temperature

was observed in the north-eastern part of the country between 1960 and 2002 (Assan et al., 2009). Data (1960-2000) from the south-western part show a 1°C increase in temperature (Boon and Ahenkan, 2013). According to Ghana's Ministry of Environment, Science, Technology, and Innovation, MESTI (2013), the average rate of temperature increase (1960-2000) in the country has been 0.21°C per decade. The evidence of climate change in Ghana can therefore be summed up as decreased rainfall, increased variability in both temporal and spatial distribution of rainfall, and increased temperature.

Climate projections for Ghana are not favourable. In the northern parts of Ghana, temperature is expected to increase by 1.7°C to 2.04°C by 2030 (MESTI, 2013). The World Bank (2010) projects that while temperature will increase by 2.4^{o}C, rainfall will decrease by 14% by the year 2050. These changes will result in more frequent and intensive heat, drought, and extreme weather events (World Bank, 2010).

Even though climate change has important implications for agriculture, only a few studies have established a link between climate and the choice of farm type. Most studies tend to focus on how climate change impacts on the choice of crop[7] or livestock type[8] with analysis usually done at the aggregate level (that is, county or municipal). In Chapter 2, we use household, farm, and climate data (8,700 observations) to estimate a multinomial logit in order to determine how climate change impacts on the choice of farming systems in Ghana. We allow for the possibility that the effects of temperature and rainfall may not be separable.

As expected, our microlevel analyses show that climate change impacts on the choice of farm type. An increase in temperature or a decline in rainfall impacts positively on the selection of specialised livestock and mixed food-crop and livestock farms. There is a direct relationship between rainfall and the probability of selecting specialised food-crop farms. A simulation of

[7] For example, Issahaku and Maharjan, 2014a, b; Kurukulasuriya and Mendelsohn, 2008.
[8] For example, Kabubo-Mariara, 2008; Seo and Mendelsohn, 2008.

the effects of climate change (based on the multinomial estimates and possible future climate scenarios) shows that farmers will likely adapt by substituting tree-based farms (a more profitable farming system) with less profitable but climate-resilient farming systems such as specialised livestock and mixed farms. All things being equal, our finding suggests a decline in the aggregate value of Ghana's agricultural output.

Even though Chapter 2 provides useful information on the aggregate effects of climate change, the chapter and other related studies do not reveal how climate change impacts on the individual species that make up a farming system. In Chapter 3, we apply a structural Ricardian model (SRM) to 6,400 observations in order to determine how climate change impacts on specific crop species. The SRM is a simultaneous two-stage optimisation technique where farmers in the first stage are hypothesised to choose the types of crop to produce and based on the crops chosen, revenues are maximised in the second stage (Seo and Mendelsohn, 2008). We estimate a modified SRM. We include a temperature-rainfall interaction term in the first-stage and estimate the second-stage semi-parametrically. Our estimation and subsequent simulation results show that crop producers will likely adapt to climate change by switching from highly profitable but climate-susceptible crops such as yam (*Dioscorea spp*) to the production of less profitable but climate-resilient crops such as millet (*Pennisetum glaucum*).

Empirical studies that examine the effects of climate on agriculture, Chapter 3 inclusive, do not usually extend their analysis to show how the estimated impacts ultimately affect food consumption or other welfare indicators. In Chapter 4, we provide evidence of the effects of temperature on farm income, non-farm income, and food expenditure by estimating a 3-stage least squares model. As expected, we find that income determines food consumption but find an inverse relationship between farm income and non-farm income. Consistent with the literature, we find that warming has a negative effect on farm income, non-farm income, and

real food consumption. The overall estimated effect of a 1°C increase in temperature is a 4% decline in real food consumption. This result has important implications for food security and general welfare.

The remainder of this chapter is structured as follows. We discuss our sources of data in the next section. The study area and associated consumption poverty are described in Section 1.3 and 1.4, respectively. Section 1.5 presents a discussion on agricultural commodities produced in Ghana. We discuss climate change impact assessment models in Section 1.6 and review African farmers' perceptions of climate change in Section 1.7. We conclude this chapter with a listing of previous climate change impact assessments on Ghana.

1.2 Data and Data Sources

Household, climate, and soil are the three types of data that we employ in our analyses. The source of data for each data type is described below.

Household data: Our household data comes from the Sixth Round of the Ghana Living Standards Survey (GLSS-6)[9] which was conducted by the Ghana Statistical Service (GSS). The GLSS-6 sought to generate data that can be used to determine household consumption and expenditure patterns, consumer price index, national account, poverty levels, among others. Prior to the survey, enumerators with at least a Higher National Diploma (Polytechnic degree) were recruited and trained for 21 days. The training included a thorough discussion of the questionnaire, definition of concepts, ethical issues in social research, field practice, and role plays using the major local languages (GSS, 2014a).

In order to capture nationally and regionally representative data, the Ghana Statistical Service relied on a two-stage sampling technique to identify respondents for the GLSS-6. In the first-

[9] The GLSS does not deliberately track individual households over time. Each round of the survey uniquely identifies a nationally representative sample to enumerate.

stage, the 2010 population and housing census was used as a basis to divide the country into 1,200 enumeration areas. In the second stage, 15 households were systematically sampled for interview in each enumeration area. However, as can anticipated, some of the targeted households were unavailable during the field survey. A total of 16,772 households were successfully enumerated out of a target of 18,000 households (i.e. 93.2% response rate). The survey was implemented over a period of 12 months (18th October 2012 to 17th October 2013) and therefore allowed for the continuous capture of household data (GSS, 2014a).

Several mechanisms were put in place to ensure that the data generated will be of a high quality. Even though 30 teams were constituted for the survey, only 25 teams were deployed at any point in time thereby affording the teams the opportunity to take turns to rest. Each team consisted of 8 people (a supervisor, a senior enumerator/editor, 4 enumerators, a data capture staff and a driver). Just like the teams, four enumerators were always at work with the fifth taking a rest. In order to further lessen the burden of enumerators and respondents, the household questionnaire was divided into two parts (A and B) with nearly all parts of the questionnaire pre-coded thus potentially minimising errors associated with slow and tiring coding. The questionnaire was administered in piecemeal. A total of 11 visits were required to enumerate one household. Skips were also employed in the questionnaire to avoid collection of inapplicable data. In addition, supervisors were required to assess the performance of all enumerators during the interviews and examine in detail each completed questionnaire. Finally, a data entry software was installed on microcomputers and enabled to detect discrepancies. The software was used to check completed questionnaires and the errors spotted were corrected by the liable enumerator in consultation with his/her supervisor before leaving the survey area. Note that the survey teams were also sensitised to be punctual, polite, patient, dress decently, and avoid disturbing behavior (GSS, 2014a).

Given that we use survey data, we rely on the bootstrapping technique[10] with 500 replications to estimate our models. Bootstrapping is particularly necessary for Chapters 3 and 4 where we use generated regressors to model our outcome equations.

Climate data: Access to climate data is a major concern for many empirical researchers (Mendelsohn et al., 2004). There are four main types of climate data: ground station, satellite, gridded, and 'reanalysis' (Auffhammer et al., 2013). Except for ground station data, all the other data types can provide climate record covering any location that may be of interest (Auffhammer et al., 2013; Dell et al., 2014). Ground station data are based on weather observations recorded by mounted instruments whereas satellite data are based on satellite readings (Dell et al., 2014). Gridded data is based on extrapolation of existing climate data over a location. Reanalysis combines data from multiple sources (ground stations, satellites, and weather balloons) in order to generate climate variables across a grid (Auffhammer et al., 2013).

In estimating the impact of climate change on agriculture, there is no real reason to choose ground station data over satellite data, or vice versa. Both types of data provide similar insights into the effects of climate change on agriculture (Mendelsohn et al., 2004; Mendelsohn et al., 2007). We generate our climate variables from historical ground station weather data starting from 1973. The historical ground station weather data was obtained from the United States' National Oceanic and Atmospheric Administration, NOAA (2015).

The GLSS6 data does not contain a Global Positioning System (GPS) record so we are unable to match the household data directly with the climate data. However, the GLSS data captured district information thus households in a district are assigned the climate record of

[10] Bootstrapping enables an analyst to compute standard errors and other measures of statistical precision by randomly resampling the observed data several times.

the weather station located in or close to their district capital.[11] Figures 1.1 demonstrates how temperature and rainfall are assigned.

Figures 1.1 shows a contrasting geographical trend in temperature and rainfall. It gets warmer (temperature rises) and drier (rainfall declines) as one moves diagonally from south-western Ghana to the north-eastern parts of the country. The geographical contrast in temperature and rainfall can be linked to the movement of airmasses (Lacombe et al., 2012) and changes in sea surface temperature, natural vegetation processes, and land use (Owusu and Waylen, 2013a). Two airmasses dominate Ghana's climate. These are the rain-bearing south-westerly tropical maritime airmass and the dry north-easterly continental air mass (Lacombe et al., 2012). The former exerts a stronger influence on the south-western parts of Ghana (hence the higher rainfall) whilst the latter is more pronounced in the north-eastern part of the country (thus the higher temperature) (Lyngsie et al., 2011). These two airmasses meet at the Inter-Tropical Convergence Zone (ITCZ). The rainy season begins when the ITCZ passes over a location northward and ends when it retreats southward (and passes over that location a second time). Therefore, there is a general decline in rainfall as one moves from the south to the north (Lacombe et al., 2012). This general trend does not apply to south-eastern Ghana. There is a steep temperature and rainfall gradient as you move along the coast from west to east. The warmer and drier climate in the south-eastern part of the country is likely due to the heavy influence of long-term anthropogenic activities as the colonial capital of Gold Coast (i.e. Cape Coast) and the present-day capital of Ghana (i.e. Accra) are both located along the eastern coast. In northern Ghana, a sharp change in temperature and rainfall is not obvious as that part of the country is relatively homogenous and rural (with less anthropogenic activities).

[11] There were 216 districts in Ghana at the time of the household survey.

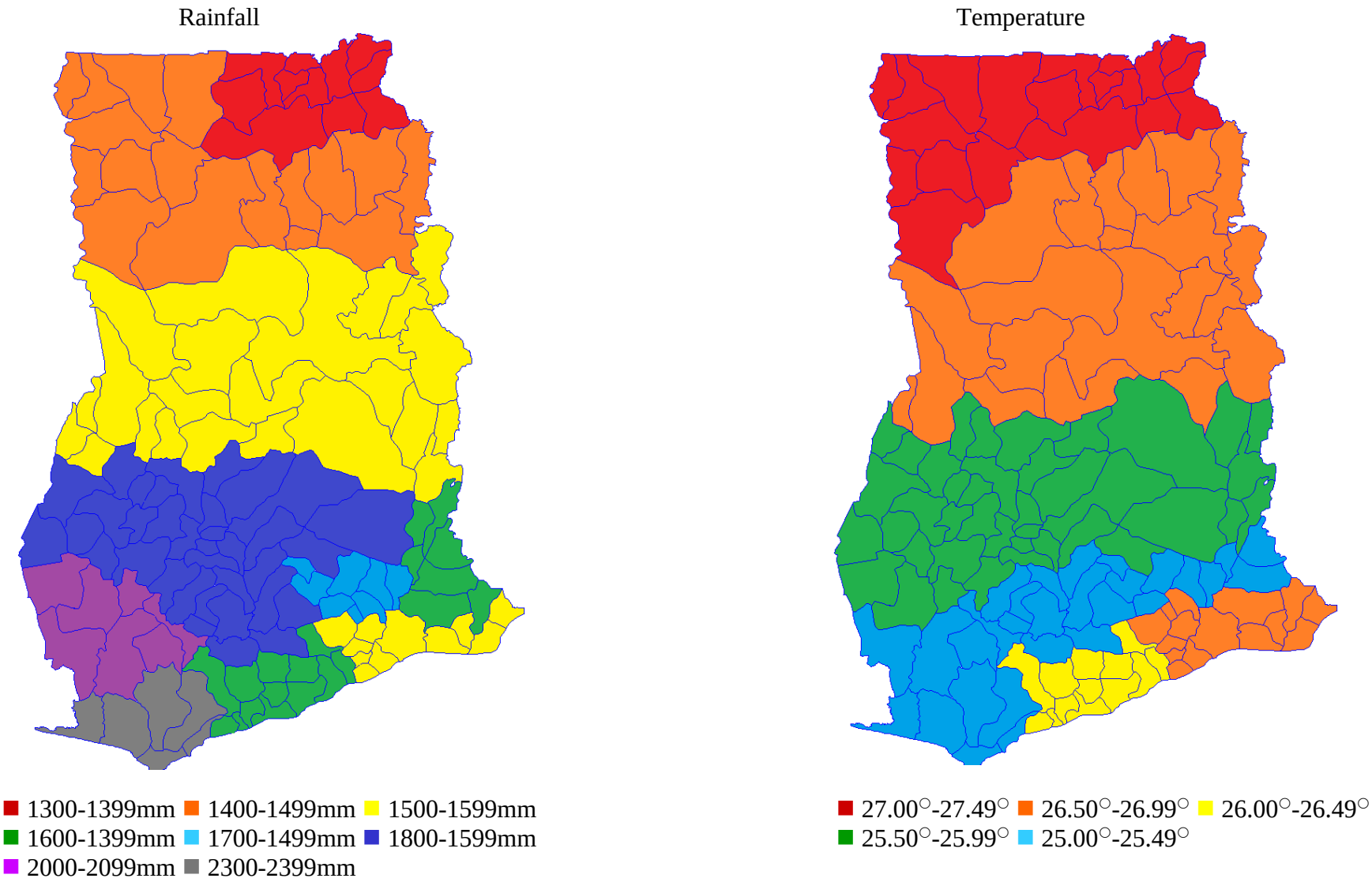

Figure 1.1: Rainfall and temperature in Ghana

Soil data: A comprehensive survey and mapping of soils in Ghana by the nation's Soil Reseach Institute reveal six broad classes of soil in the counry (Ministry of Food and Agriculture, MoFA, 2014). The first class of soil is highly suitable for extensive cultivation of tree and food-crops. These soils are non-gravelly medium to moderately heavy textured. The second class of soil is also suitable for extensive cultivation of tree and food-crops but the texture of the soil may be light with gravelly subsoils. Soil type three is fairly suitable for the production of food-crops. These soils may contain heavy plastic clays that are mostly imperfectly to poorly drained. These are mostly alluvial soils and include gravelly and moderately shallow soils. Soil type four is fairly to marginally suitable for food-crop production. These consist of gravelly, moderately shallow to shallow, and imperfectly drained to loamy sands developed over beaches and may have clay pan beneath the topsoil. The fifth and sixth class of soil are unsuitable for food-crop production. The fifth class of soil consists of poor to very poorly drained soils. These are often terrace-derived alluvial soils, which are dominated by rounded pebbles and an undulated subsoil horizon. These soils are also very shallow, gravelly, and occur on steep slopes. The sixth class of soil is very saline and may be utilised for mining of edible salt (MoFA, 2014). Computing the effect of each soil type poses practical estimation difficulties as some soil types are unpopular. For example, we only have 44 observations on tree-based farms that are cultivated on soil types 5 and 6 (Table 2.2). Given the relatively low cell observations for some individual soil types, we measure soil as a 3-level variable. We label soil types 1 and 2 as 'high-quality soil' and soil types 3 and 4 as 'intermediate soil'. Just like the climate data, households are assigned the soil-type of the district that they belong to.

1.3 Study Area

Our study relies on data from the Republic of Ghana, formerly the Gold Coast. The West African country shares a border with Burkina Faso to the north and is bounded by the Gulf of Guinea (Atlantic Ocean) to the south, Togo to the east, and Ivory Coast to the west (Figure 1.2). The country lies between 4°44'N and 11°11' N and 3°11'W and 1°11' E (MoFA, 2014; Oppong-Anane, 2006). There are 10 administrative regions in Ghana. According to the GSS (2013), the last population and housing census in 2010 put the population of Ghana at 24,658,823 with females constituting 51%. The population is estimated to be growing at an annual rate of 2.5%. The 2010 census shows that people younger than 15 years constitute about 40% of the population while people older than 64 years form about 5% of the population. In 2010, agricultural households accounted for 54.2% of the population (GSS, 2013).

Ghana's climate is influenced by north-east trade winds[12] and tropical maritime air mass (Lyngsie et al., 2011; Oppong-Anane, 2006). Southern Ghana experiences equatorial-type bimodal rainfall while the northern parts of the country experiences tropical monsoon-type unimodal rainfall. Mean annual rainfall decreases from southwest to northeast ranging from about 2000mm in the wettest areas of southwestern Ghana to about 1100mm in the north-eastern parts of the country. (Oppong-Anane, 2006).

We describe the agro-ecology of our study area in this paragraph and the next using information from Oppong-Anane (2006). Ghana's agro-ecology can be zoned into six categories. The forest agro-ecology can be divided into rainforest and semi-deciduous forest. The savannah agro-ecology can also be divided into Guinea, Sudan, and coastal savannahs. The transitional zone located in the middle parts of the country between the northern

[12] The trade wind causes a phenomenon referred to as harmattan, a dry and dusty wind observed in Ghana between November and March (Lyngsie et al., 2011).

savannahs and southern forests[13] can be viewed as a distinct agro-ecology. The forest agro-ecology is characterised by an even tree canopy at 30-40m with emergent trees reaching 60m. Whereas the trees found in the rain forest are evergreen all year round, a good proportion of canopy trees in the semi-deciduous forest shed their leaves in the dry season even though the shrubs and understory trees may remain green. Pasture resources in the forest agro-ecology are relatively scarce compared to those found in the savannah agro-ecologies. Food and tree-crops tend to be more important than ruminant production in the forest agro-ecologies.

The Guinea Savannah is characterised by continuous grassland interspersed with fire-resistant, deciduous, and broad-leaf trees. Sudan savannah has similar characteristics as the Guinea savannah but with shorter grasses and shrubs. The coastal savannah agro-ecology has similar features as the northern savannah. However, rainfall in the former is bimodal whilst that of the latter is unimodal. The coastal savannah is also more humid. The forest-savannah transition zone occurs along the fringes of the forest agro-ecology where forest land is degrading or converting into grassland. Even though rainfall within the zone is often bimodal, it experiences unimodal rainfall in some years.

Ghana is generally not food self-sufficient.[14] The quantity of chicken, rice, wheat, and maize imported into Ghana in 2012 was 73,788.4MT, 508,529MT, 320,000MT, and 151,258MT, respectively (MoFA, 2014). The country is only able to meet half of its meat requirement, 51% of its cereals needs, and 60% of its fish requirements. Less than 30% of the raw materials required by agro-based industries are produced in-country (MoFA, 2007). Agricultural production depends directly on the weather hence agricultural output varies

[13] The forest-savannah transition agro-ecology is located between latitude 7º and 8ºN (Oppong-Anane, 2006).

[14] This is as a result of a number of factors including preference for imported rice and chicken (mostly by urban dwellers) as well as superior performance of cash crops (e.g. cocoa) over food-crops in some areas.

(scarcity, sufficiency, and glut) between seasons (MoFA, 2007; 2014). The traditional system whereby farmers use simple farm implements for production is still widespread (MoFA, 2014). Nevertheless, Ghana's economy depends heavily on the agricultural sector. The average contribution of the agricultural sector to foreign exchange earnings (GDP) averaged 45% (40%) in the latter part of the last millennium but declined to 40% (30%) in the 2000s (GSS, 2013). The importance of agriculture to the economy of Ghana cannot be overstated. The growth of the sector is critical to the economic growth and development of the country (MoFA, 2010).

Figure 1:2 Map of Africa with Ghana highlighted Source: Google image

1.4 Consumption Poverty in Ghana

Poverty in the Ghanaian context generally relates to the inability to meet one's food consumption needs. Individuals that are unable to meet the international consumption standard of US$1.90 a day are classified as poor (World Bank, 2016). Nationally, individuals that are unable to meet their minimum daily calorie requirements (8kcal), which translates into US$1.10, are classified as extremely poor (GSS, 2014b).

Poverty levels in Ghana appear to be on a downward trend following the rapid economic growth experienced in the last three decades. About half (51.7%) of the population were poor in 1991/92. The proportion of poor people decreased to 39.5% just before the turn of the new millennium (1998/99). In 2005/06, 28.5% of the population was estimated to be poor (Government of Ghana, GoG, 2010). The poor constituted 24.2% of the population in 2012/2013. Extreme poverty levels were 36.5%, 26.8%, 16.5%, and 8.4% in 1991/92, 1998/99, 2005/06, and 2012/2013, respectively (GSS, 2014b). Although the trend shows that poverty has dropped significantly over the last 3 decades, poverty is still a major challenge in many areas (Clementi et al., 2016; GoG, 2010; MESTI, 2013).

The gains made in poverty reduction would have been higher but for widening inequality between rural and urban (Food and Agriculture Organisation, FAO, 2012), and perhaps agricultural and non-agricultural, educated and uneducated, and male and female-headed households. Rural, agricultural, uneducated, and female-headed households tend to be poorer. The national Gini coefficient, a measure for inequality, increased from 41.9% in 2005/06 to 42.3% in 2012/13 (GSS, 2014b; World Bank, 2015). Analysis of Ghana's consumption data between 1991 and 2012 shows that the country's middle class is shrinking with a significant proportion moving into the highest quintiles, a clear case of increasing polarisation. Even though the consumption of the 90th quintile has not increased significantly over the period,

the consumption of the bottom 10 has deteriorated significantly (Clementi et al., 2016; World Bank, 2015). Given this background, we examine the effects of warming on food consumption in Chapter 4 as earlier stated.

1.5 Agricultural Commodities Produced in Ghana

This section is written in two parts. We begin with a brief description of the various tree-crops and livestock produced in Ghana and then end with a more detailed discussion of all the food-crops studied in Chapter 3. The absence of a more detailed description of all the tree-crops and livestock produced in Ghana is because we do not estimate how climate change impacts on individual or specific tree-crops and livestock (in this thesis). Note that Chapter 2 estimates the effects of climate change on the selection of aggregate farm types such as livestock, tree-crops, and food-crops.

Figure 1.3 presents livestock population in Ghana between 2004 and 2013. Livestock produced in the country include cattle (*Bos taurus*), sheep (*Ovis aries*), goat (*Capra aegagrus hircus*), pig (*Sus scrofa domesticus*), and poultry such as chicken (*Gallus domesticus*) and Guinea fowl (*Numida meleagris*). Figure 1.2 shows that cattle and pig population (over the period) has been fairly stable with poultry showing a clear increasing trend.

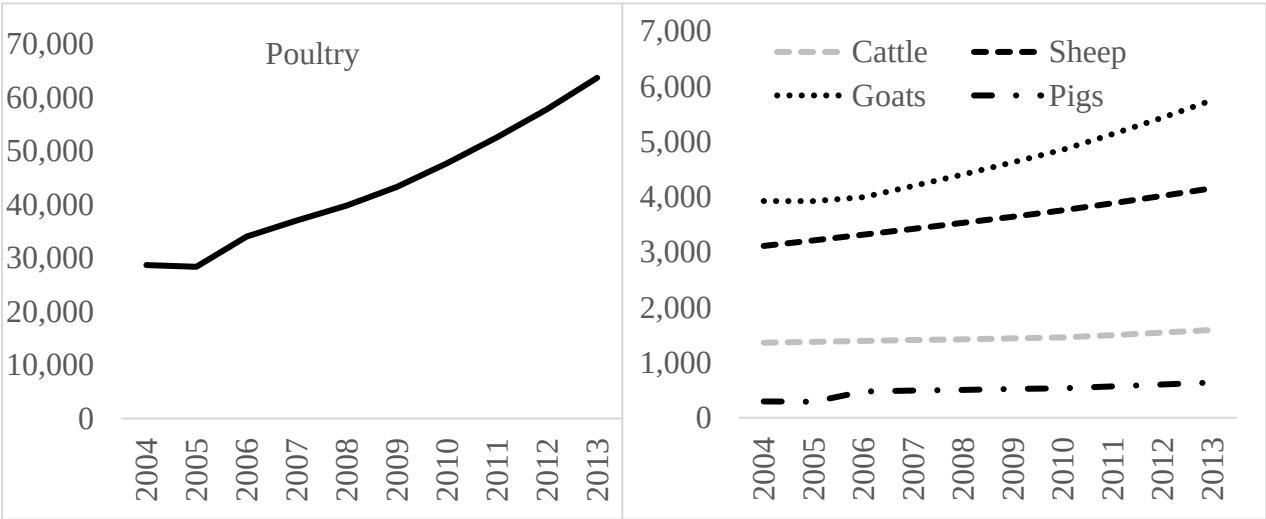

Figure 1.3: Livestock population in Ghana ('000) (MoFA, 2014)

Tree-crops grown in Ghana includes oil palm (*Elaeis guineensis*), cocoa (*Theobroma cacao*), cashew (*Anacardium occidentale*), coffee (*Coffea spp*), and rubber (*Ficus elastica*). Figure 1.4 shows that oil palm is the most produced tree-crop in Ghana followed by cocoa. However, cocoa is (historically) the most valuable tree-crop. In 2010 for example, the price of a metric ton of cocoa was US$3,032 (GSS, 2015) whilst that of oil palm was US$877 (Angelucci, 2013). Even though cocoa attracts a higher price, smallholder farmers may prefer oil palm since its kernels can be processed and consumed at the farm level in case of low demand (as it is already a staple cooking oil). Figure 1.4 shows that cashew production is gaining prominence and will likely become a very important tree-crop in future. Note that cashew production only became significant in the 1990s as there is no official production record before 1987.

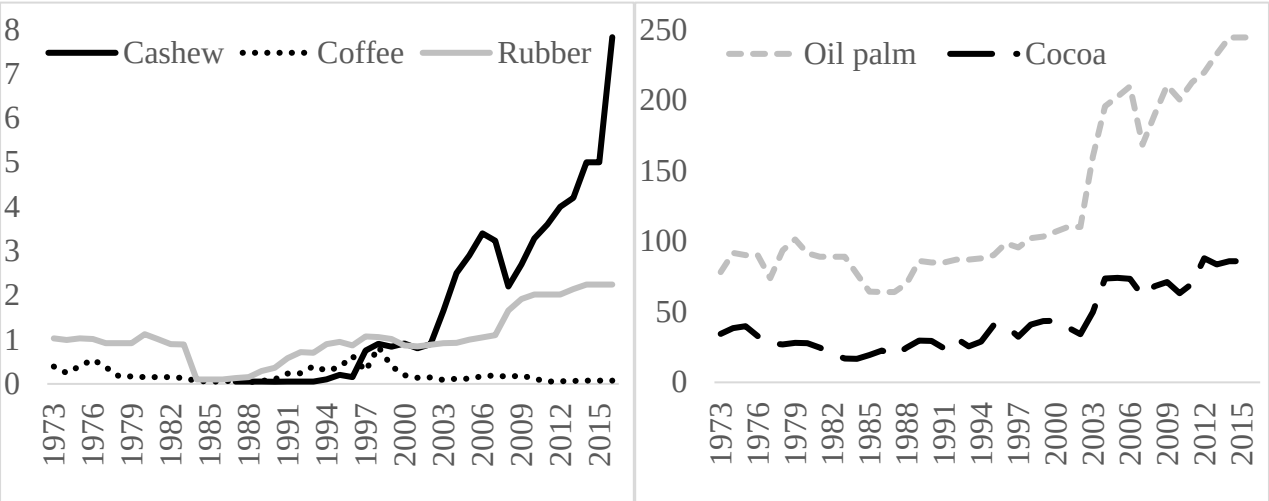

Figure 1.4: Level of production of tree-crops in Ghana (0’000Mt) (FAOSTAT, 2018)

Food-crops cultivated in Ghana include maize, cassava, groundnut, plantain, yam, millet, rice, sorghum, cowpea, sweet potato, and cocoyam. The area kept under cultivation for these crops between 1973 and 2016 is shown in Figure 1.5 whilst volume of production is shown in Figure 1.6. In terms of area under cultivation, Figure 1.5 shows that maize has historically been the most widely produced food-crop in Ghana with cassava being the second most important food-crop even overtaking maize in some years (for example, 2003-2004, 2015-

2016). Apart from maize and cassava, the relative importance of food-crops in terms of area cultivated has changed over time thereby providing evidence of crop substitution behaviour. For example, whereas yam was the third least cropped commodity in 1973, it has since 2009 become the third most cropped commodity. Similarly, plantain that was the fourth least planted crop in 1973 has become the fourth most planted crop after 2012. The area kept under rice cultivation has been increasing steadily since 2007 with sorghum, cocoyam and cowpea witnessing some decline. The official record for sweet potato and cowpea starts later than 1995 thereby suggesting that those food-crops only became significant after 1995.

In terms of output,[15] Figure 1.6 shows that cassava is clearly the most important food-crop followed by yam and plantain. Starting from 2009, maize surpassed cocoyam to become the fourth most produced food-crop. Rice has (since 2012) overtaken groundnut to become the sixth most produced food-crop in Ghana. Since we study how climate change impacts on specific food-crops in Chapter 3, we discuss each food-crop after the graphs.

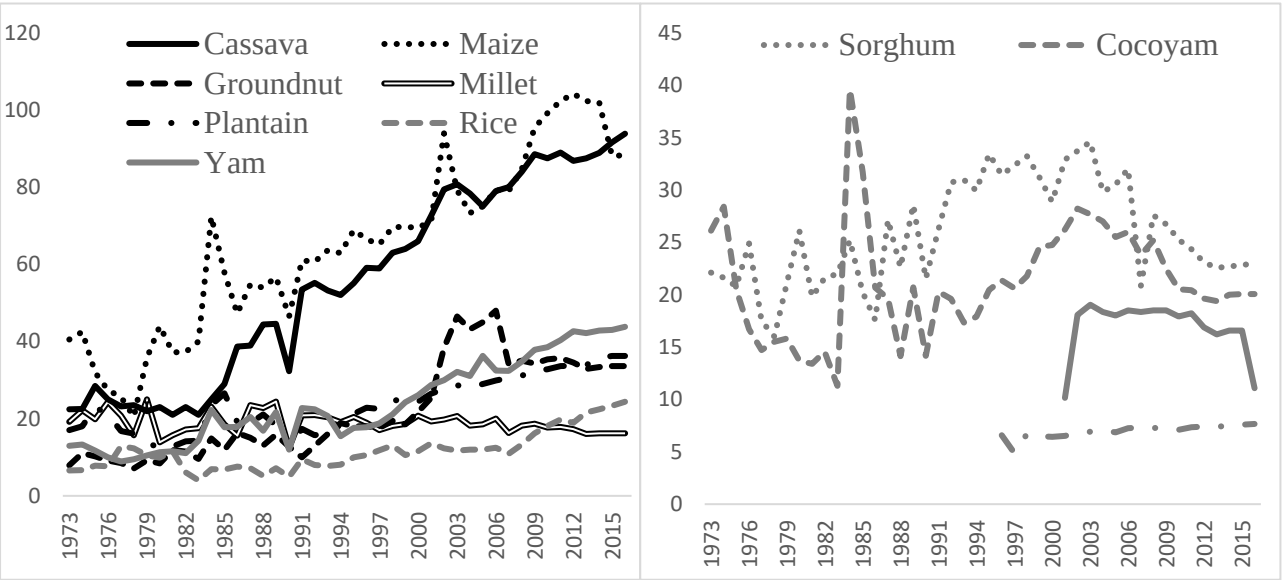

Figure 1.5: Area under cultivation of major food-crops in Ghana ('0,000Ha) (FAOSTAT, 2018)

[15] See Chapter 3 (of this thesis) for a graph of the most valuable crops as opposed to output.

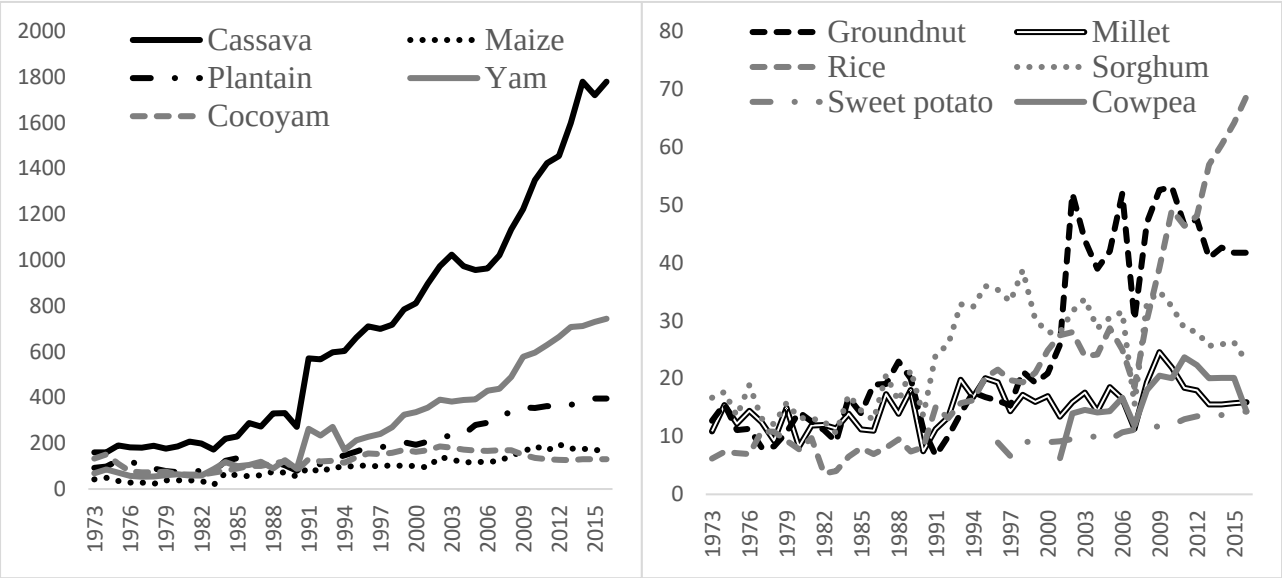

Figure 1.6: Output of major food-crops produced in Ghana ('0,000Mt) (FAOSTAT, 2018)

***Maize* (*Zea mays*)**

Maize originated from Mexico (Bajaj, 1994; Mejia, 2003). It was carried from America to Europe by Christopher Columbus, and then from Europe to Africa by the Portuguese and other Europeans in the 16th and 17th centuries (Mejia, 2003). Maize is a versatile food-crop with great genetic variability that enables it to thrive under diverse climates. It is grown in more places than any other cereal (Mejia, 2003). Maize adapts well to different types of soil including slightly acidic soils (pH range of 5.0 to 7.0). High yields are obtained from fine textured, well aerated, and well drained loamy soils rich in organic matter. The crop requires a lot of nutrients especially nitrogen, phosphorus, and potassium (Kanton et al., 2016). Its productivity tends to decline drastically in poor soils, thus farmers often allocate it to relatively fertile soils. Faced with declining soil fertility and cash constraints, farmers may opt not to produce maize.

In Africa, maize is cultivated mainly as a food-crop and to a lesser extent, as feed for livestock (Bajaj, 1994). It is an important staple food-crop in Ghana accounting for more than 50% of total cereal production (Akramov and Malek, 2012). Maize is cultivated nationwide

(Angelucci, 2012). The crop is replacing millet in some parts of the country (Kanton et al., 2016). Figure 1.7 demonstrates the geographical popularity of the various food-crops that we study. Due to its widespread cultivation coupled with the fact that Ghana is not maize self-sufficient (MoFA, 2010; 2014), the crop can easily be marketed in any part of the country. Maize is often purchased by the National Food Buffer Stock Company of Ghana, World Food Program and other development organisations and programs (Angelucci, 2012).

Maize has some advantages over other crops in Ghana. The crop can be harvested before maturity and used as fodder. Unlike other food-crops, harvested maize can be stored and processed for sale when market conditions are more favourable. The crop can easily be converted (by livestock) into meat, milk, and eggs, and has low fibre but high starch content thereby making it suitable for both livestock and human consumption (Mejia, 2003). Several varieties of the crop, including drought and striga *(hermonthica* weed*)* tolerant varieties, have been developed by two institutes of the Council for Scientific and Industrial Research, CSIR (that is, Savanna Agricultural Research Institute, CSIR-SARI and Crops Research Institute, CSIR-CRI) in collaboration with the International Institute for Tropical Agriculture (IITA) and the International Maize and Wheat Improvement Centre (CYMMIT) (Etwire et al., 2013a). In comparison to other crops, the seed system for maize is quite developed (Etwire el al., 2013b). Further, maize is perhaps the most promoted crop in Ghana in terms of number of years of promotion as well as number of projects or institutions promoting it. Being a priority crop, its input (seed and fertiliser) is subsidised.

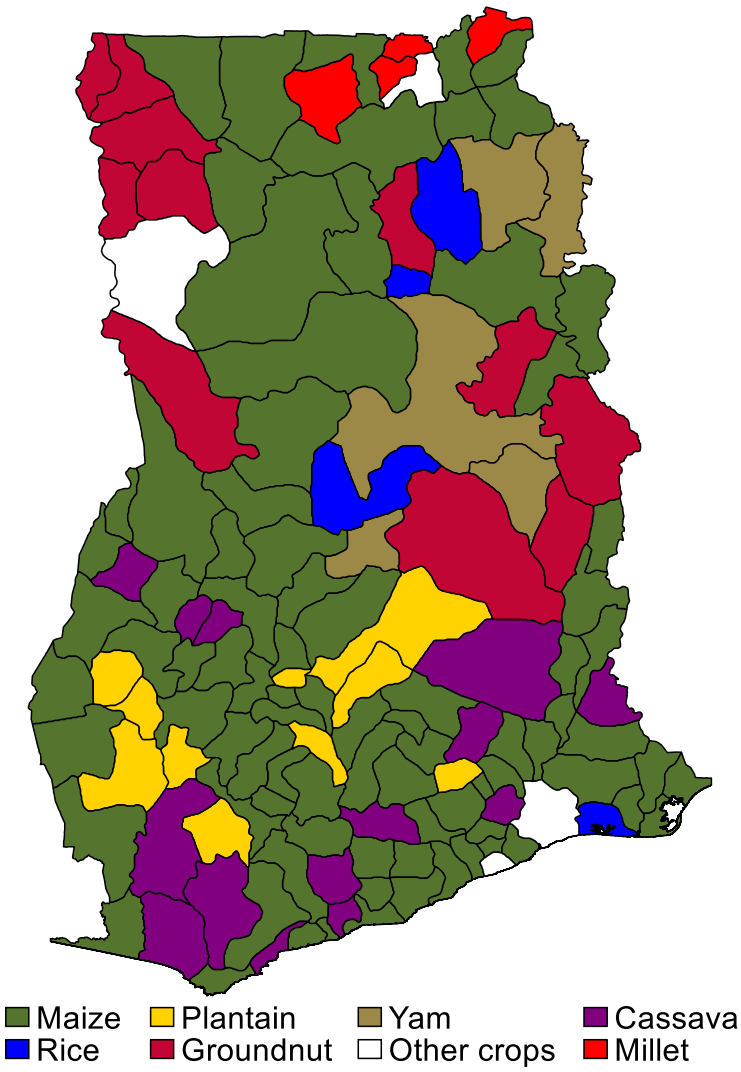

Figure 1.7: Most important food-crop by location

***Cassava* (*Manihot esculenta*)**

Cassava, also known as manioc, yucca or tapioca, was introduced into Africa by colonial governments as a famine-reserve crop by the end of the sixteenth century.[16] The origin of the crop is Latin America, reportedly Brazil (Ceballos et al., 2010; Nweke, 2004). Cassava is now cultivated in over 40 African countries with Nigeria, Congo, and Ghana being the first, second, and third largest producers of the crop in the world, respectively (Nweke, 2004).

[16] Cassava produces a very high output of energy per hectare thereby making it a good crop for overcoming hunger (Nweke, 2004).

In Ghana, cassava was first planted along the coast before eventually moving inland where farmers in the forest and savannah agro-ecologies were already cultivating plantain and pearl millet, respectively (Manu-Aduening et al., 2005). The popularity of the crop soared when it performed better than other crops during the droughts experienced in the 1980s (Nweke, 2004; Manu-Aduening et al., 2005). Figure 1.6 shows that cassava production increased sharply after the 1980s and continues to be on a rising trajectory. The crop is adapted to areas between latitudes 30ºN and 30ºS and can grow on highlands of up to 2000m above sea level. Cassava can be grown in a temperature range of 18ºC to 25ºC, and annual rainfall range of 50mm and 5,000mm (Nweke, 2004). Cassava being a long duration crop is quite hardy and is generally able to tolerate drought better than some crops (Ceballos et al., 2010; Dziedzoave et al., 2006; Nweke, 2004).

Cassava is more important in southern Ghana (Figure 1.7). The crop is mainly grown for its swollen roots even though its leaves are also consumed. The roots contain a lot of starch (60%) with the leaves containing some protein (7%) and significant amount of other minerals, vitamins, and essential amino acids (Dziedzoave et al., 2006; Nweke, 2009). In terms of calories consumed, cassava is the second most important staple food-crop in Africa after maize (Nweke, 2004).

Cassava has features that make it attractive to farmers especially low-income households. It is a cheap source of calorie, feed for livestock, starch for industries, and main ingredient used in the preparation of a wide range of cuisine. Cassava can also be processed into convenient and ready-to-eat products (Kihurani and Kaushal, 2016). Processed cassava can be stored for a long time and may be eaten without further elaborate cooking[17] (Nweke, 2004; 2009). Even though matured roots can be left unharvested underground for up to 2 years, farmers often harvest within the year in order to avoid soil borne pests, free up the land for other purposes

[17] Poorly processed cassava may contain some amount of harmful residual cyanide.

as well as prevent the roots from becoming more fibrous (Kihurani and Kaushal, 2016). Thus, cassava is a perennial crop cultivated as an annual. Cassava grows when conditions are favourable and then assume dormancy when conditions become unfavourable (Ceballos et al., 2010).

Cassava is cultivated vegetatively with planting sets cut from the stem (Nweke, 2009). It requires less care, agro-inputs, and generally tolerates pests and diseases. It can also thrive in a wide range of agro-ecological zones (Ceballos et al., 2010; Dziedzoave et al., 2006; Nweke, 2004). The crop, for example, is capable of suppressing weeds with its canopy. However, harvesting of cassava is labour-demanding. The bulkiness of the harvest makes marketing challenging (Nweke, 2009). Harvested cassava roots have a very short shelf life. This limits its marketing options unless it is processed (Ceballos et al., 2010). The roots begin to deteriorate 2 to 3 days after harvesting (Dziedzoave et al., 2006).

***Yam* (*Dioscorea species*)**

Yams are coiling vine-like annualised crops that are cultivated mainly for the one or more tubers that are usually produced underground. Yam tuber can weigh between 5kg and 10kg. Compared to other root and tubers such as cassava and sweet potatoes, yam has a low yield per hectare. Despite its low multiplicative rate, yam is conventionally propagated by replanting the tubers (main harvest) in prepared mounds or ridges (as opposed to flat land) in order to ensure that the soil is deep and well drained. Yam has a relatively long growth cycle that lasts up to 10 months before it enters a period of dormancy that can take up to 4 months after senescence (Nweke, 2016; Reddy, 2015). The crop can be harvested after its growth cycle or can be left underground during its period of dormancy without much losses just like cassava. The dormancy period occurs in the dry season (Reddy, 2015). In the absence of human intervention/harvesting, the crop is capable of breaking dormancy and restarting the

growth process when conditions become favourable. Yam production is labour intensive because the crop is mostly cultivated using traditional methods (Nweke, 2016; Reddy, 2015).

Yam is well suited to warm and humid conditions but cannot tolerate frost. It requires an annual rainfall of 1200-2000mm (Laxminarayana et al., 2016) and a temperature range of 20-30°C (Mignouna et al., 2007). Ghana produces about 10% of global yam output (Nweke, 2016). Yam is a principal food-crop in the sub humid or forest-savannah transition agro-ecology. Figure 1.7 shows that the crop is more important in the middle-eastern parts of Ghana. Similar to potatoes, fresh tubers of yam can be consumed after boiling, boiling and pounding, frying, or roasting. Yam is more of a commercial crop than a staple crop. After accounting for seed (up to 30% of total harvest (Reddy, 2015)), about 60% of disposable yams are sold by Ghanaian farmers (Nweke, 2016). Yam is a major source of income for farm households since it has a high market value. The price margins on yam in the country is higher than any other priority food-crop. Furthermore, Ghanaian yams are mostly exported to other Sahelian west African countries and are also available for use by African immigrants in Europe, Asia, and the Americas (Nweke, 2016).

***Plantain* (*Musa species*)**

Plantain is believed to have originated from South-East Asia where a great diversity of wild species is found (Price, 1995). It is a giant perennial herb. Uganda, Rwanda, and Ghana are the largest producer of the crop in Africa (Dzomeku et al., 2009). Plantain is the third most important starchy staple in Ghana after maize and cassava (Egyir et al., 2011). Figure 1.7 shows that the crop is more important in the southern parts (forest, semi-deciduous forest, and forest-savannah transition) of the country.

In Ghana, plantain is often grown on relatively fertile soils (Dzomeku et al., 2009). It thrives in deep, well-drained loamy soils with high water holding capacity. Once established, the

crop requires little care and maintenance. Plantain produces harvestable bunches all year round when it reaches maturity thereby guaranteeing continuous flow of food and income (Price, 1995). Even though plantain is a perennial crop, its harvesting is influenced by strong winds and rainfall. Due to its perishable nature, plantain begins to deteriorate after harvesting (Dzomeku et al., 2011).

Plantain has a high carbohydrate and low-fat content. It is a good source of vitamins and minerals. Compared to banana, plantain has more ascorbic acid (Zakpaa et al., 2010). Plantain can be cooked when green or ripe. Plantain peels can be used to feed ruminants or prepare soaps (Danso et al., 2006). Several metric tonnes of plantain from Ghana are exported to countries in the Sahel such as Burkina Faso, Mali, and Niger (Egyir et al., 2011).

Rice (Oryza species)

Rice is an annual grass. The two main species of rice originated from two different places. Whereas *Oryza glaberrima* originated from the Niger River delta in Africa, the more popular species cultivated globally, *Oryza sativa*, is native to Asia (Subudhi et al., 2006). Rice is the only major food-crop that can tolerate various levels of flooding. The amount and distribution of rainfall plays an influential role in the evolution of rice as a food-crop (De Datta, 1981). The crop performs well under appropriate temperature regimes if there is enough water. Its hydromorphic nature is the reason why it is often cropped in low-lying areas, floodplains, and valleys. The crop can grow on a variety of soils ranging from waterlogged to well drained soils (De Datta, 1981). Rain-fed lowland, irrigated, and rain-fed upland ecologies accounts for 78%, 16%, and 6% of the rice-producing area in Ghana, respectively (Kula and Dormon, 2009; MoFA, 2009).

Rice is becoming an important food-crop in Ghana due to several reasons including increasing urbanisation, population growth, and changes in consumer habit (MoFA, 2009).

According to Figure 1.6, rice production increased sharply in 2008 and has since shown an upward trend. Rice output has, since 2012, overtaken groundnut production. Per capita consumption of milled rice in Ghana has been rising with the 2010 levels being twice that of 1985 (MoFA, 2014).

Numerous development interventions have been implemented to improve the competitiveness of the rice subsector in Ghana (MoFA, 2010). For example, the introduction of upland rice varieties means that farmers can now earn returns on their labour in otherwise dry years. However, locally produced rice faces stiff competition from imported rice as only 30-40% of Ghana's demand is met by local production (Angelucci et al., 2013).

***Pearl millet* (*Pennisetum glaucum*)**

Pearl millet originated from central tropical Africa. It is now widely distributed in the drier tropics and India (Department of Agriculture, Forestry and Fisheries, DAFF, 2011). Pearl millet is an erect annual grass adapted to hot climates and tolerates drought even better than sorghum. No cereal performs better than pearl millet in hot and dry regions. Farmers are able to harvest pearl millet from poor sandy soils that cannot support the production of other food-crops (Clottey et al., 2014; Kajuna, 2001). Pearl millet has long roots and can therefore tap into soil nutrients outside the reach of other food-crops. It also attracts few insects. In addition, diseases of pearl millet are not widespread (DAFF, 2011).

Pearl millet is generally sensitive to low temperature at the seedling and flowering stage. High temperature is needed for the grains to mature. Even though pearl millet can grow in areas with annual rainfall of 200-1500mm, it is often cropped in areas with annual rainfall of 250-700mm. Excess rain during the flowering stage can result in crop failure. Optimum soil temperature ranges between 23°C and 30°C. Pearl millet can thrive in acidic soils (pH of 4-5) with high aluminium content (DAFF, 2011).

Demand for pearl millet outside production areas is often low; hence the crop is mostly grown for local consumption (DAFF, 2011; Kajuna, 2001). Pearl millet contains more nutrients than maize. It contains high levels of iron and less gluten. However, maize straw is more palatable than millet straw when utilised as fodder for livestock (Clottey et al., 2014). Pearl millet is used in the preparation of dishes, soups, porridges, alcoholic beverages, and snacks. The plant is also valuable as a source of raw material for fencing, thatching, and basketry (DAFF, 2011).

In Ghana, millet is mostly cultivated in the savannah agro-ecology (Figure 1.7) and on relatively poor soils (Dzomeku et al., 2009; Florkowski and Kolavalli, 2013). Figure 1.5 shows that a lot of land was allocated to millet production in the 1970s but the situation reversed in the 1990s. The decreasing popularity of millet may be as a result of a combination of factors including apparent neglect of the crop. According to Kanton et al., (2015), no new or improved variety of millet has been made available to farmers since Ghana became independent from colonial rule in the 1950s. Millet could assume greater importance if more arid or semi-arid conditions were to arise as a result of climate change.

***Groundnut or peanut* (*Arachis hypogaea*)**

Groundnut is an annual self-pollinating and soil-enriching legume grown in the arid and semi-arid regions of the world (between latitude 40ºN and 40ºS). It is mostly cultivated under warm temperate and equatorial climates (Konlan et al., 2013). Groundnut is believed to have originated from South America even though it has never been found in the wild (Nautiyal, 2002).

In Ghana, groundnuts are mostly grown in the savannah agro-ecology (Figure 1.7). It is an important source of income and protein for many households (Florkowski and Kolavalli, 2013). Groundnuts are a multipurpose crop that are either consumed raw or cooked

(Angelucci and Bazzucchi, 2013). Groundnuts are also used in making local confectionery and in the preparation of soups (Hammons, 1994). According to Naab et al., (2009), groundnuts have a high protein (12–36%) and oil content (36–54%). Groundnut oil can be extracted at the household level using indigenous knowledge. Its press cake contains a high amount of protein (40-50%) and can be used to feed poultry. The vegetative part of the crop can be used to feed ruminants (Hammons, 1994). The haulms can also serve as feed. The pods after shelling can be utilised as a mulch or compost material (Kombiok et al., 2012). The ability of the groundnut plant to fix atmospheric nitrogen (i.e. convert nitrogen in the atmosphere into ammonia) contributes to the maintenance of soil productivity (Naab et al., 2009; Kombiok et al., 2012). The crop can therefore thrive on marginal lands.

Groundnuts are harvested and conditioned by digging, lifting, windrowing, stocking, and threshing. Harvesting is hampered if the land hardens (Nautiyal, 2002). Unlike full-season crops, groundnuts could still be harvested even in years when the rainy season is relatively short. Typical of crops that have their produce underground, matured groundnuts may suffer less from end-of-season climate shocks and wild fires compared to above-field crops like cereals and plantain. The crop is traded widely in the local, regional, and international markets. It tends to attract better prices than other legumes (Naab et al., 2009). Groundnuts are the most commercialised staple crop in Ghana. On average, farmers sell about 70% of their produce (MoFA, 2010).

Cowpea (Vigna unguiculata)

Cowpea is an indigenous African grain legume adapted to the dry savannah climate and is mostly produced and consumed in west Africa. It is quite tolerant to drought and can produce on marginal soils due to its ability to fix atmospheric nitrogen into the soil just like groundnut. Cowpea requires two to three months to mature. With a protein content of 22-

30%, cowpea is a good source of protein for rural dwellers and the urban poor. Cowpea haulms (dried leaves, stems, and pod walls) can be used to prepare feed for livestock (Boukar et al., 2015).

Sorghum (Sorghum bicolor)

In Africa, sorghum is mostly grown in the arid and semi-arid regions of the continent. It is a source of food and feed in those areas. Over the past decade, the global area under sorghum production has been declining at a rate of about 0.15 million hectares (ha) per year. On the contrary, the area under cultivation in Burkina Faso, Ghana's immediate neighbour to the north, has been expanding. Sorghum is mostly consumed in its country of production. It is drought-tolerant and currently a subsistence crop (Hariprasanna and Rakshit, 2016).

***Cocoyam* (*Xanthosoma sagittifolium*)**

Even though cocoyam is not a major food-crop, it is a staple food for some poor people in Africa, Asia, and America. The main product of cocoyam is its corms (underground storage organ). Ghana is the second highest producer of cocoyam after Nigeria with an area of about 0.2 million ha and production of about 1.27 million tonnes (t). The crop performs well under warm and humid climate with a temperature range of 21-27°C and growing season rainfall of about 1000mm. Cocoyam grows in all types of soil and similar to rice, it can also be produced in waterlogged areas. The average yield of cocoyam in Africa is 6.57 t ha^{-1} whilst the global average is 7.68 t ha^{-1} (Laxminarayana et al., 2016).

***Sweet potato* (*Ipomoea batatas*)**

Sweet potato is widely cultivated in the tropics and warm temperate regions of the world. It grows well in a well-drained loamy soil and in a temperature range of 21-26°C (Laxminarayana et al., 2016). Sweet potato is a high-yielding crop that matures between 4-6

months (Reddy, 2015). The yield of sweet potato ranges between 10 t ha^{-1} and 30 t ha^{-1} with a potential of 50 t ha^{-1} (Laxminarayana et al., 2016). At maturity, sweet potato roots can also be left underground and harvested when needed (Laxminarayana et al., 2016).

1.6 Climate Change Impact Assessment Models

Several methods have been developed to assess the impact of climate change on agriculture. The methods vary in terms of data requirement, unit of analysis (the whole economy, a sector or subsector), and discipline (e.g. agronomy or economics) (De Salvo et al., 2013). All methods of analysis have some strengths and weaknesses. The weakness of one approach is often the strength of the other and vice versa (Mendelsohn, 2005; Mendelsohn et al., 2006). General and partial equilibrium models are the broad categories of economic methods available for assessing the impact of climate change (Deressa and Hassan, 2009). General equilibrium models are those models that assess the economy-wide impacts of climate change whilst partial equilibrium models only evaluate the impacts of climate change on a sector of the economy such as agriculture. Following a critical review of the literature as presented below, we opt for the structural Ricardian model (SRM), due to its ability to explicitly capture adaptation to climate change. In addition, the SRM utilises data (i.e. micro-level climate, farmer, and farm observations) which are readily available for Ghana. Compared to other models, the data needs of the SRM are not cumbersome. Moreover, the SRM is relatively easy to compute.

1.6.1 General equilibrium models

General equilibrium models estimate how climate change impacts on the whole economy taking into consideration interlinkages between various sectors (De Salvo et al., 2013; Deressa and Hassan, 2009; Elbehri and Burfisher, 2015). The strength of these models lies in their ability to capture global and sectoral changes. These models are also able to estimate the

impact of climate change on multiple sectors (De Salvo et al., 2013). General equilibrium models are, however, unable to adequately account for local or sectoral specificities. Also, adaptation responses to climate change are not adequately modelled by these models (De Salvo et al., 2013; Mendelsohn and Dinar, 2009b). Further, selection of the most appropriate model, calibration problems, challenges with statistical testing, and the skills required to operationalise general equilibrium models can all be a challenge to researchers (Deressa and Hassan, 2009). Two classes of general equilibrium models are briefly discussed below.

Integrated assessment models (IAMs)

IAMs combine knowledge from different disciplines to estimate the cause and impact of climate change (Ackerman et al., 2009; Dell et al., 2014; De Salvo et al., 2013; Patt et al., 2009; Pindyck, 2013). IAMs usually model long-term impacts of climate change in order to inform current policy decisions. The modelling process typically takes into account activities that generate greenhouse gases, the effect of these gases on climate change and, consequently, the impact of climate change on the economy and the environment (Patt et al., 2009). For any IAM to provide useful evidence for policy decisions, it should be able to show an expected pathway for greenhouse emissions, establish the relationship between greenhouse emission and climate change as well as estimate a damage and welfare function (Dell et al., 2014).

An attractive feature of IAMs is that they allow the analyst to apply the same baseline scenario and discount factor over the same time frame to both climate costs and climate benefits; hence, the analysis is consistent (Mendelsohn, 2008), and results of the various IAMs are comparable. Some examples of IAMs are the Policy Analysis for the Greenhouse Effect (PAGE), the global Dynamic Integrated model for Climate and the Economy (DICE)

and the Regional Integrated model for Climate and the Economy (RICE) (De Bruin et al., 2009).

IAMs tend to overestimate the impact of climate as a result of several uncertainties embedded in the model. For example, finding the appropriate discount factor makes it a challenge in empirical evaluations. The tendency is to use a high discount factor thereby making it economically prudent to delay the adoption of mitigation measures (since the costs and benefits of mitigation do not occur at the same time) (Ackerman et al., 2009). IAMs, being aggregate models, are not able to sufficiently capture uncertainties such as the cost of adaptation, mitigation, and climate damage (De Bruin et al., 2009; Patt et al., 2009; Pindyck, 2013). It is also difficult to value certain costs and benefits, for example, the monetary worth of a human life or an ecosystem (Ackerman et al., 2009). Costs are often estimated as a percentage loss in GDP thereby making it difficult to accurately predict with certainty future costs; for example, the cost associated with technological advancements that could minimise emission of GHGs (Ackerman et al., 2009). Most IAMs either fail to capture or assume optimal adaptation. They tend to impose restrictions that may not hold at the micro level (De Bruin et al., 2009). Also, IAMs cannot be used to reliably predict the potential impact of climate change. Different results can be estimated for the same data given that the modeller has the freedom to determine the functional form, parameters, and other inputs to utilise in the model (Pindyck, 2013). According to Stern (2013), there are grounds to conclude that IAMs produce biased estimates of the impact of climate change.

Computable general equilibrium models (CGEs)

CGE models are economic models that describe some baseline equilibrium situation where economic agents (e.g. farmers and consumers) are satisfied with the equilibrium demand and supply. Climate change, however, destabilises the system leading to increases in the price of

certain production inputs and outputs. Farmers, consequently, are hypothesised to shift from the production of crops with rising input prices to the cultivation of crops with rising output prices. Consumers also adjust their demands accordingly, based on changes in price and income. CGE models are then used to determine the new equilibrium prices and quantities as well as aggregate results for variables such as GDP and trade balance (Elbehri and Burfisher, 2015; Fisher-Vanden et al., 2013). CGE models can be single or multi-country studies, static, or recursive dynamic (Elbehri and Burfisher, 2015).

Examples of CGE models include the Future Agricultural Resources Model (FARM), the World Trade Model with Climate-Sensitive Land (WTMCL), the Modular Applied GeNeral Equilibrium Tool (MAGNET), Conversion of Land Use and its Effects (CLUE), and the Basic Linked System (BLS) (Elbehri and Burfisher, 2015). CGE models are very useful in contributing to trade policies but cannot account for intra-season variability and short-term climatic events, i.e. they are unable to capture intertemporal changes (Fisher-Vanden et al., 2013). CGE models also tend to underestimate the impact of climate change on prices and welfare due to their strict market assumption of full utilisation of capital and labour inputs, which is hardly the situation especially in developing countries (Elbehri and Burfisher, 2015).

1.6.2 Partial equilibrium models

These models hold all other variables of the economy constant except the variable under consideration. Hence, linkages with other sectors of the economy are not considered (Elbehri and Burfisher, 2015). Partial equilibrium models can highlight local or sectoral impacts of climate change. Different types of partial equilibrium models used in assessing the impact of climate change are discussed below.

Crop growth simulation or agronomic models

Crop growth simulation models are used to measure how changes in climate and other agronomic variables (e.g. crop physiology, soil quality) influence crop yields (De Salvo et al., 2013; Elbehri and Burfisher, 2015; Schlenker et al., 2006). Using the latest advancement in agronomic knowledge, these models are able to establish the relationship between crop yields and agronomic and environmental parameters such as crop physiology, soil characteristics, and climate. These models can be used to simulate how crop yields will respond to changes in climate or any other growth parameter (Di Falco et al., 2012; Mendelsohn and Dinar, 2009a). Advantages of the crop simulation models include their ability to capture local climatic effects and plant genetics (Elbehri and Burfisher, 2015) as well as its superior modelling of the agronomic relationship between crop growth and climate change. These models, unlike other partial equilibrium models, are not static and are therefore able to capture dynamic relationships (Elbehri and Burfisher, 2015).

A significant drawback of crop growth simulation models is that farm management is assumed to remain fixed and adaptation is ignored (Mendelsohn and Dinar, 2009a). These models also fail to account for socio-economic constraints (Di Falco et al., 2012). Hence, adjustments in management practices as well as adaptation strategies adopted by farmers in response to climate change are not adequately captured. In addition, crop growth simulation models usually evaluate one crop at a time (Mendelsohn and Dinar, 2009a) and are often calibrated for only the major international crops to the detriment of traditional or local staples (De Salvo et al., 2013; Mendelsohn and Dinar, 2009a). Most models do not consider issues pertaining to pests and diseases, and require lots of data (Elbehri and Burfisher, 2015). Examples of crop growth simulation models include DSSAT (Decision Support System for Agrotechnology), WOFOST (World FOod STudies), PEGASUS (Predicting Ecosystem

Goods and Services Using Scenarios), and MCWLA (Crop-Weather relationship over a Large Area) (Elbehri and Burfisher, 2015).

Production function model

The production function model is based on the principle that agricultural output is determined by a number of inputs such as soil, climate, and management. The relationship between the output and inputs is first established. Based on the estimated production function, changes in output can be simulated using different climate scenarios (De Salvo et al., 2013; Liu et al., 2001; 2004). The model can reliably estimate the impact of climate change on crop yields using controlled experiments (Ahmed and Schmitz, 2011; De Salvo et al., 2013). However, the full set of adjustments that farmers make in response to climate change is not captured and the model usually focuses on a single crop at a time in a single location (De Salvo et al., 2013; Deressa and Hassan, 2009; Mendelsohn and Dinar, 1999). The production function model tends to overestimate the impact of climate change (Closset et al., 2014; Mendelsohn et al., 1994).

Statistical models

These models depend on mathematical or statistical techniques to estimate the effects of climate change. Statistical models can use available data (cross-sectional, time series, or panel) to establish correlation or causation (Elbehri and Burfisher, 2015). These models can be used to estimate the impact of climate change on agriculture at any level be it local, regional, or global, and can be used to measure annual and intra-annual climate variations (Elbehri and Burfisher, 2015). These models tend to be theoretical in nature and are not able to effectively estimate or predict potential impacts of climate change (De Salvo et al., 2013). In spite of the changing climate, statistical models often assume that farmers will continue to cultivate the same crop using the same technology (Mendelsohn and Dinar, 2009a). In

assessing the economic impact of climate change, it is particularly important to jointly model impact and adaptation instead of treating the two concepts separately (Di Falco, 2014). Most statistical and mathematical models are not able to jointly estimate the marginal effects of different adaptation measures. Even when such marginal effects are estimated, findings are either difficult to interpret or cannot be generalised (Elbehri and Burfisher, 2015). Further, these models tend to focus on just a handful of crops (Mendelsohn and Dinar, 2009a).

Ricardian model

Impact assessment models that fail to consider farm-level adaptations overestimate the impacts of climate change. Ignoring adaptation is in effect imposing the assumption that farmers are 'dumb' and will not adjust their practices in response to climate change (Mendelsohn et al., 1994). In contrast, the Ricardian model captures farmers' adaptation responses to climate change. The model is an econometric technique that utilises micro-level data to measure how climate and other factors affect land values or net revenues (Mendelsohn et al., 1994; 1996). The Ricardian model can be applied at any level, be it local, regional or global (Gbetibouo and Hassan, 2005).

The model requires that there is enough variation in the climate observed in the micro-level data such that any future climate will likely fall within this variation (Mendelsohn et al., 2010; Mendelsohn et al., 1996). For example, if a future climate will convert a forest into a savannah agro-ecology, then the micro-level data must include responses from both savannah and forest agro-ecologies. The use of micro-level data enables the researcher to control for a host of non-climatic factors such as socio-economic characteristics and farm-level adaptation (Kurukulasuriya and Ajwad, 2007). Due to the numerous advantages of the Ricardian technique, we rely on its extension, the structural Ricardian model, to estimate the impact of climate change in Chapter 3.

1.7 African Farmers' Perceptions of Climate Change

Appendix 1 summarises the findings of 36 papers[18] that assess African farmers' perceptions of climate change. The summary includes two continent-wide studies, one regional study covering three countries, one cross-country study involving two countries, and 32 separate studies involving 12 countries. Ghana, Ethiopia, Nigeria, Kenya, and South Africa are the most frequently studied countries. Apart from the two continent-wide studies that include observations from Egypt, our review does not include country studies from North Africa. There are a good proportion of studies involving Francophone countries. The sample size for the various studies ranges between 70 and 9,500 observations. Farmers' perceptions about changes in climate is mostly based on a period of recall of 20 years. Some studies ask farmers to base their perceptions on a period of 10, 30, and 40 years.[19] Farmers' perceptions about climate change are often measured using qualitative variables since such responses are easy to capture during surveys. Five common qualitative categorisations include an increase (+), decrease (-), erratic/variable (±), no change (0), and no idea (?).

A review of the studies in Appendix 1 shows that African farmers are of the view that their climate is changing or has changed. The general perception of farmers is that the continent is becoming warmer and rainfall is declining. As expected, disaggregating perception by age shows that older people are more likely to perceive climate change (Debela et al., 2015; Maddison, 2007; Silvestri et al., 2012). There is, however, no significant difference between the views of educated and less educated farmers (Gbetibouo, 2009; Maddison, 2007). Also, men and women's understanding of climate change are similar (Arku, 2013). Compared to

[18] Our review only covers studies published in the English language.

[19] Most farmers do not keep written records of their farm operations and weather observations. Therefore, their perceptions of climate change are usually based on recall from memory.

smallholders, commercial farmers tend to have a better understanding of the science of climate change (Yaro, 2013).

The majority of studies (about 58%) fail to compare farmers' perceptions with real climate data and are therefore unable to verify or validate farmers' claims about changes in climate. Most of the studies that match climate data with farmer observations conclude that perceptions about temperature are in sync with the record. Similarly, the majority of studies[20] conclude that farmers' perception of a decrease in rainfall matches with the precipitation record even though some studies[21] argue that the decline is not statistically significant. In the case of Gbetibouo (2009), farmers' perception about changes in rainfall only matches with the climate record if the analysis is restricted to the recent climate record. There are also instances where the majority of farmers claimed that rainfall was decreasing when in actual fact the climate record showed that rainfall was becoming more variable instead.[22] Mismatch between farmers perceptions and the climate record may be attributable to measurement errors, the tendency for farmers to place additional emphasis on more recent occurrences (Bryan et al., 2009; Debela et al., 2015; Gbetibouo, 2009; Maddison, 2007), or the difficulty in memorising and recollecting long-term changes (Ndamani and Watanabe, 2015).

Farmers tend to base their climate change perceptions on noticeable changes in the environment such as drying up of rivers and streams, delay in the onset of rainfall, drought (Apata, 2011), shortening of harmattan (i.e. cold, dry, and dusty) days (Tambo and Abdoulaye, 2012), and reduction in the number of rainy days (Kassie et al., 2013). In addition to personal observation, farmers may also form their perceptions about climate change through peer interactions and contact with agricultural extension agents. Spatial clustering of

[20] For example, Dossou-Aminon et al., 2014; Gebrehiwot and van der Veen, 2013; Jiri et al., 2015; Mary and Majule, 2009; Nkondze et al., 2014.
[21] For example, Bryan et al., 2009; 2013; Debela et al., 2015; Kassie et al., 2013.
[22] For example, Apata, 2011; Fosu-Mensah et al., 2012; Ndamani and Watanabe, 2015.

farmer perceptions shows that neighbouring farmers tend to have similar views about changes in the climate (Gbetibouo, 2009; Maddison, 2007). African farmers are generally conscious about changes in their climate and adapt accordingly.

1.8 Previous Assessment of Climate Change Impacts on Ghana

A couple of studies have been conducted to assess the economic impacts of climate change in Ghana using diverse methodologies. Arndt et al., (2014) and the World Bank (2010) use a computable general equilibrium model to estimate the impact of climate change on the economy of Ghana.

Arndt et al., (2014) observe that climate change will reduce the welfare of Ghanaians, particularly that of poor and urban households, as well as households in northern (Savannah) Ghana. They find wide variations in the magnitude of climate change impacts. Whereas yields of maize and cassava are projected to increase, those of fruits and vegetables are projected to decline under various scenarios. By 2050, agricultural GDP is estimated to decrease (increase) by 2.1% (1.4%) under the local dry (wet) scenario. Overall, GDP is expected to decline by 0.4% to 1.3% under various scenarios. Climate change is projected to increase the cost of maintaining and replacing road infrastructure thereby resulting in a shorter road network in the country. They also observe that by the middle of the 21st century, 20,100 hectares of land will be lost as a result of sea-level rise. Hydropower is also expected to be negatively affected by climate change (Arndt et al., 2014).

Results from the World Bank (2010) study shows that all regions in Ghana will become warmer by 2050 with a cyclical pattern predicted for rainfall (alternation between high rainfall and drought every 10 years). Whereas the south-western part of the country is expected to experience an increase in surface runoff, other parts of the country are expected to experience significant reductions. Real GDP is expected to fall by 1.9-7.2% by 2050.

Agricultural GDP is also expected to fall by 3-8% within the same period. Damages resulting from sea-level rise are estimated to reach an annual value of US$5.7 million by 2030. Annual losses from agriculture, transport, and hydrology are expected to be US$122 million, US$630 million, and US$70 million, respectively (World Bank, 2010).

In modelling the impacts of coastal inundation arising from climate change, Addo et al., (2011) estimate that the coastline of Ghana will recede by 202 metres in 2100, significantly affecting both life and property. Kankam-Yeboah et al., (2013) use the Soil and Water Assessment Tool (SWAT) to determine the impact of climate change on stream flow in Ghana. They report that by the middle of the 21st century, the mean annual streamflow of the White Volta and Pra basins will decrease by 50% and 46%, respectively. In a similar study, Amisigo et al., (2015), report that the water demand (municipal, hydropower, and agriculture) of Ghana will not be met under any scenario. They also find that climate change will have a negative effect on crop yields.

A couple of studies use micro level data to estimate the impact of climate change on crop production. Amikuzino and Donkoh (2012) conducted a study to establish the relationship between yields of major staple food-crops in northern Ghana and inter-annual variations in temperature or rainfall by employing the co-integration and Granger causality models. They find that annual yields of staple crops are significantly influenced by the total amount of rainfall within the rainy season. Variability in temperature does not have a significant effect on yields. In a study that relies on data from the Northern Region of Ghana, Mabe et al., (2013) observe that a 1°C increase in mean annual temperature results in a per hectare decrease in rice production of 0.15 metric tonnes. De-Graft and Kyei (2012) use the Just and Pope stochastic production function to estimate the influence of climate variables on maize yields in Ghana. They find an inverse relationship between maize yields and rainfall or temperature. They also report that an in increase in temperature will result in an increase in

the variability of maize yields and vice versa for rainfall. None of the studies mentioned above accounted for farm-level adaptation and may therefore be overestimating the impact of climate change.

Nkegbe and Kuunibe (2014) rely on the Ricardian model to estimate the relationship between weather variability and household welfare by employing a three-period panel data from northern Ghana. They conclude that weather variability has a negative influence on farm revenue and household welfare. Though the study by Nkegbe and Kuunibe (2014) provides some insights into the impacts of climate change, they do not show how households would adapt. In addition, their study does not cover central and southern Ghana.[23]

Our study adds to the body of knowledge on climate change impacts in Ghana. To the best of our knowledge, we are the first to estimate the impact of climate change on the choice of farming system in Ghana. The concept of farming systems is key to agricultural research, especially as it relates to the northern part of the country. The Savanna Agricultural Research Institute (SARI), the state institution mandated to conduct research into food and fiber crops in northern Ghana, has over the last two decades undertaken and conducted its research based on the farming systems approach (SARI, 2013). Therefore, a study of the effects of climate change on farming system selection can provide useful information to guide policy on agricultural research and development. In addition, we are not aware of any previous study that simultaneously estimate the impact of climate on farm income, non-farm income, and food consumption. In estimating the impact of climate change on crop production, we control for soil quality and estimate a flexible functional form, two important features that are lacking in previous Ghanaian studies.

[23] Issahaku and Maharjan (2014b) address the limitations of Nkegbe and Kuunibe (2014) by estimating a structural Ricardian model. We discuss Issahaku and Maharjan (2014b) in Chapter 3 (of this thesis).

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Appendix 1: African farmers' perceptions of climate change[24]

#	Country/ Region	Study area	Sample size	Perceived changes in rainfall (Percent of sample)					Perceived changes in temperature (Percent of sample)					Period of recall (Years)	Consistent with climate record?		Authors
				+	-	±	0	?	+	-	±	0	?		Temp	Rain	
1	Ghana	Western Region	98	22	37	30	11		49	33		18					Acquah & Onumah, 2011
2	Ghana	Northern Ghana	296		74				65								Al-Hassan et al., 2013
3	Ghana	Upper East and Ashanti Regions	270	18.2	81.8				78.2	5.2		16.6		40			Antwi-Agyei et al., 2014
4	Nigeria	Southwest	360	0.9	58		0.4		53.4	24		12		10	Y	±	Apata, 2011
5	Ghana	Upper East Region	186	26.5	52.5	20.5			78.5								Badmos et al., 2015
6	Ghana	Upper East and Northern Regions	530		55.9	37.5			80					30			Bawakyillenuo et al., 2014
7	Nigeria	Central Nigeria	150	11.3	58.7				60.7	6.7							Bello et al., 2013
8	South Africa, Ethiopia	Limpopo and Nile basins	1800	6	72	12	10		75	1.5		15		20	Y	NS	Bryan et al., 2009

[24] Temp, Rain, +, -, ±, 0, ?, Y and NS represents temperature, precipitation, increase, decrease, erratic/variable, no change, no idea, yes and not statistically significant, respectively.

#	Country/ Region	Study area	Sample size	Perceived changes in rainfall (Percent of sample)					Perceived changes in temperature (Percent of sample)					Period of recall (Years)	Consistent with climate record?		Authors
				+	-	±	0	?	+	-	±	0	?		Temp	Rain	
9	Kenya		710	6	88				94	2				20	NS	NS	Bryan et al., 2013
10	Nigeria	Niger, Taraba and Oyo States	346	2.3	68.4	19.4	5.5		54.7	12	10.5	6.7					Coster & Adeoti, 2015
11	Ethiopia	Borana	480	2	94				66	1	28			20	Y	NS	Debela et al., 2015
12	Ethiopia	Nile Basin	995	10.4	53		12		50.6	1.9		14.4		20			Deressa et al., 2009
13	Ethiopia	Nile Basin	1000	18	62		20		68	4		28		20			Di Falco et al., 2012
14	Benin	North Eastern Benin	300		50.4	37.7			48.8						Y	Y	Dossou-Aminon et al., 2014
15	Ghana	Ashanti Region	180	12	87.2				88	3.3				20	Y	±	Fosu-Mensah et al., 2012
16	Togo		320		74.6		6.6		72	13		9.7		20	Y	NS	Gadédjisso-Tossou, 2015
17	South Africa	Limpopo River Basin	794	1.7	81	5	2.6	0.4	91	1.5	1	6	0.2	20	Y	NS	Gbetibouo, 2009
18	Ethiopia	Tigray Region	400	12	69		17		78	5		15		20	Y	Y	Gebrehiwot & van der Veen, 2013
19	Africa	11 Countries	8208	5	50		13	4	51	5	16	14	6				Hassan & Nhemachena, 2008

#	Country/ Region	Study area	Sample size	Perceived changes in rainfall (Percent of sample)					Perceived changes in temperature (Percent of sample)					Period of recall (Years)	Consistent with climate record?		Authors
				+	-	±	0	?	+	-	±	0	?		Temp	Rain	
20	Zimbabwe	Masvingo Province	100		85.7	9.2	4.1	1	87					20	Y	Y	Jiri et al., 2015
21	Kenya		816						47	5	18	28					Kabubo-Mariara & Karanja, 2007
22	Ethiopia	Central Rift and Kobo Valleys	200		92.5				97.5						Y	NS	Kassie et al., 2013
23	Africa	10 countries	9500	6.7	48	17.6	15		47.3	9.6	6.4	16.7			±	±	Maddison, 2007
24	Tanzania	Singida Region		0.6	30.2	36	1.6	4.5	68.8	3.5	7.9	2.2	9.9	10	Y	Y	Mary & Majule, 2009
25	Ethiopia	Central Tigray	144		70	20			75	8		4		20			Mengistu, 2011
26	Ghana	Upper West Region	100		87		6		82	6		9	3	10	Y	±	Ndamani & Watanabe, 2015
27	Cameroon	Lake Lagdo watershed	303	12	72		16		77	3		20		20			Ngondjeb, 2013
28	Ghana	Volta Region	70		27	31			24					10			Nhamo et al., 2014
29	Southern Africa	South Africa, Zambia and Zimbabwe	1719	5.2	45	33.3	14	2.4	51.4	5.4	12.2	26.9	4.1				Nhemachena & Hassan, 2007

#	Country/ Region	Study area	Sample size	Perceived changes in rainfall (Percent of sample)					Perceived changes in temperature (Percent of sample)					Period of recall (Years)	Consistent with climate record?		Authors
				+	-	±	0	?	+	-	±	0	?		Temp	Rain	
30	Swaziland	Lubombo Region	323			98			99.4						Y	Y	Nkondze et al., 2014
31	Nigeria	Ekiti State	156							0.6	89.7	9.6					Obayelu et al., 2014
32	Burkina Faso		1530		35.5	37.4											Ouedraogo et al., 2006
33	Kenya		640	6	88.3		3	2.7	94.3	2		0.7	3				Silvestri et al., 2012
34	Nigeria	Borno State	200	2	83.5	12	2	0.5	84	8		6.5	1.5	20			Tambo & Abdoulaye, 2012
35	Ethiopia	Eastern Hararghe Zone	160	2.6	90.3	0.9	6.2		91.2	3.5		5.3		20			Tessema et al., 2013
36	Ethiopia	Nile Basin	1000	18	62		20		68	4		28		20			Yesuf et al., 2008

Chapter 2

The Impact of Climate Change on Farming System Selection in Ghana

Abstract

Farmers are already responding to climate change by adjusting their practices. An important adaptation strategy is the switching of farm types, that is, switching from a vulnerable farming system to one that is more resilient. Using household, farm, and climate data (8,700 observations) from Ghana, we estimate a multinomial logit in order to determine the factors that influence the selection of farm types and the implications of those choices. As expected, we find that climate determines the choice of farming system. Based on the multinomial estimates, a simulation of the effects of climate change shows that farmers will likely adapt by switching from specialised food-crop and tree-based farms to specialised livestock and mixed (food-crop and livestock) farms. All things being equal, a decline in tree-based farms imply a substantial drop in the aggregate value of agricultural output since tree-based farms are the most profitable farm type.

2.1 Motivation

Climate is an important determinant of agricultural productivity (Sejian et al., 2015). Minor changes in climate can have major impacts on agriculture due to its direct dependence on climate and climate-related factors (United Nations Framework Convention on Climate Change, UNFCCC, 2006). Warming and declining rainfall[25] generally affect agricultural production negatively (Thornton et al., 2007). Warm and dry conditions tend to negatively affect soil moisture and nutrients, and consequently crop output (Clements et al., 2011). Similarly, warm and dry conditions usually impact negatively on livestock production by limiting the availability of feed and water, inhibiting growth, reproduction, and milk production as well as facilitating the occurrence of disease (Sejian et al., 2015). Because of the important role that climate plays in agricultural production, farmers tend to respond to changes in climate by adjusting their practices.

Technologies and practices for climate change adaptation[26] already exist (Clements et al., 2011). An important example is the switching of farm types where farmers switch from a vulnerable farming system[27] to one that is less susceptible to a changed climate.[28] Adapting to climate change is non-negotiable since future changes in the climate will occur even if full scale mitigation efforts were to be successfully implemented.[29] Adaptation is particularly

[25] Rainfall and precipitation are used interchangeably since snowfall is not experienced in Ghana, our reference country.

[26] Adaptation is the process of adjusting to real or perceived changes in the climate. It involves adopting measures to either reduce the negative effects or take advantage of the positive effects of climate change (IPCC, 2014; Tol et al., 1998).

[27] Farming system is a term used to refer to a population of farm households that have a broadly similar resource base, production pattern, and face similar constraints to which a single development intervention would be appropriate (Dixon et al., 2001).

[28] For example, there is evidence of farmers in Ghana switching from the production of tree-crops (cocoa) to food-crops (maize/corn, rice and yam) as result of climate change (Antwi-Agyei et al., 2014).

[29] Climate change mitigation is any human intervention aimed at either reducing the source or enhancing the absorption of greenhouse gases (IPCC, 2014). The current changes in climate are attributable largely to anthropogenic emissions released several decades ago (UNFCCC, 2006).

important for African farmers who are already facing multiple stresses (Boko et al., 2007; Hassan and Nhemachena, 2008). According to Boko et al., (2007), it is important to explore the links between biophysical and complex socio-economic systems. Thus, this study seeks to establish the link between climate and choice of farming systems in Ghana.

There are several studies that explore how climate change influences farmer decisions. The majority of these studies estimate the impact of climate change on either crop[30] or livestock[31] selection, with only few studies examining how climate influences the choice of farm type. The few studies that examine farm type either employ aggregate data (for example, Chatzopoulos and Lippert, 2015; Mu et al., 2013) or undertake macro-analysis (for example, Seo, 2010; 2011; 2012; 2015), thereby masking local effects. We rely on a large cross-sectional microeconomic dataset to estimate our model. Most studies that examine farm types[32] often limit their analysis to various combinations of food-crop and livestock production. In addition to food-crops and livestock, tree-crops form part of the mix of farm types considered in this study.

It is important for policy makers to understand the drivers of adaptation in order to design appropriate interventions for the agricultural sector (Bryan et al., 2009; 2013). Therefore, this study provides evidence for policy decisions by identifying the factors that influence the uptake of different farming systems in Ghana. Given that the literature on the effects of temperature and rainfall on farming system selection is limited, this study will provide additional basis for future studies to formulate their apriori expectations. We explicitly model farm decisions in this chapter and the next. We first use the multinomial logit to identify the agricultural subsectors or farming systems that are vulnerable to climate change (in this

[30] For example, Chapter 3 (of this thesis); Issahaku and Maharjan, 2014a; Issahaku and Maharjan, 2014b; Kurukulasuriya and Mendelsohn, 2008.
[31] For example, Kabubo-Mariara, 2008; Seo and Mendelsohn, 2008.
[32] For example, Mu et al., 2013; Seo, 2010; 2011; 2015.

chapter) and on that basis use a structural Ricardian model to specifically determine how the different commodities that make up a vulnerable farming system respond to climate change (Chapter 3).

We estimate a quadratic functional form in this chapter and allow for the possibility that the effects of temperature and rainfall may not be linearly separable (that is, we allow for temperature-rainfall interaction). Simulations based on our multinomial logit estimates and future climate scenarios show that climate change will likely lead to a significant drop in tree-based farms (in all climate scenarios) and a substantial decline in specialised food-crop production (in some climate scenarios). Our finding has important economic implications since tree-based farms are the most profitable farm type.

A review of African farmers' adaptation responses to climate change is presented in the next section. The section also contains a review of factors that influence the uptake of various adaptation measures in Africa. The methodology of the study is discussed in Section 2.3. We present our estimation results in Section 2.4 and conclude in Section 2.5.

2.2 Review of African Farmers' Adaptations to Climate Change

2.2.1 Farm-level adaptations to climate change in Africa

Even though the only climate change adaptation measure that we model in this chapter is the switching of farm types, we nonetheless review a wider range of farm-level adaptation options (employed by African farmers). The benefits of adaptation, as opposed to mitigation, are private and local. Whereas mitigation efforts tend to benefit everyone, adaptation measures are likely to benefit only the implementer. For instance, the benefits arising from a household's greenhouse-gas emission cut will be experienced beyond the household, whilst the benefits resulting from the adoption of an adaptation measure is likely to be experienced

by only the adopting household. Consequently, farmers (in their own best interest) are already adapting to climate change by modifying their practices (Adger et al., 2007; Mendelsohn and Dinar, 1999). The purpose of adaptation is to either reduce vulnerability or enhance resilience to observed (perceived) or expected changes in the climate (Adger et al., 2007). Adaptation can be anticipatory, reactive, private or public (Adger et al., 2007; Fankhauser et al., 1999). Adaptation can also be at various scales (local, national, regional, continental, global) and can be undertaken by various actors (farmers, firms, government) (Gbetibouo, 2009). The climate change adaptation option considered in this study is the switching of farm types (i.e. substituting one farming system for another).

Empirical studies on farm-level adaptations to climate change are plentiful. Our review considers only the actual[33] farm-level adaptation practices undertaken by African farmers. Whereas some studies[34] disaggregate adaptation strategies according to climate variable, the majority of studies do not.[35] Appendix 2.1 presents a summary of adaptation measures undertaken by African farmers and the reasons why some farmers fail to either adopt or scale-up adoption.

Even though we discuss the adaptation measures individually, it should be noted that farmers tend to adopt a combination of strategies. Hence, the majority of studies allow for multiple responses. Some adaptation measures are agriculture and productivity related whilst others

[33] For potential climate change adaptation measures, see Clements et al., 2011; Thornton and Herrero, 2014.

[34] For example, Bryan et al., 2009; Di Falco et al., 2012; Dossou-Aminon et al., 2014; Fosu-Mensah et al., 2012; Gbetibouo, 2009; Kabubo-Mariara and Karanja, 2007; Maddison, 2007; Nhamo et al., 2014; Nhemachena and Hassan, 2007; Ouedraogo et al., 2006; Tambo and Abdoulaye, 2012; Yesuf et al., 2008.

[35] For example, Acquah and Onumah, 2011; Al-Hassan et al., 2013; Antwi-Agyei et al., 2014; Apata, 2011; Apata et al., 2011; Bello et al., 2013; Bryan et al., 2013; Coster and Adeoti, 2015; Debalke, 2014; Deressa et al., 2009; Etwire et al., 2013; Gadédjisso-Tossou, 2015; Gebrehiwot and van der Veen, 2013; Jiri et al., 2015; Kassie et al., 2013; Ndamani and Watanabe, 2015; Ngondjeb, 2013; Obayelu et al., 2014; Silvestri et al., 2012; Tambo, 2016; Tessema et al., 2013; Yegbemey et al., 2013.

are off-farm and unrelated to yields. Some adaptation measures are targeted specifically at crops, whereas others are meant for livestock production. Adaptation measures can be implemented before, during, or after the production season.[36]

The rest of the section (i.e. a review of climate change adaptations and barriers to adaptation) is based on Appendix 2.1. The appendix shows that some African farmers adapt to climate change by adopting different varieties of the same crop. Whereas some farmers prefer newly improved early-maturing or drought-tolerant crop varieties (Etwire et al., 2013; Nhemachena and Hassan, 2007; Tambo, 2016; Tambo and Abdoulaye, 2012), there are also farmers who prefer full-season traditional varieties that are perceived to be hardy and already adapted to harsh weather conditions (Al-Hassan et al., 2013). A desirable attribute of early-maturing varieties is their ability to escape drought (grow past their critical stages of development before a drought occurs) while that of drought-tolerant varieties is their ability to produce a good harvest in spite of drought. According to Kassie et al., (2013), the choice of variety depends on the timing of rainfall. Farmers tend to select improved early-maturing or drought-tolerant varieties when the rains are delayed but cultivate traditional full-season varieties when the rain starts early or as expected.

Instead of switching varieties, some farmers choose to change crops. As a result of climate change, farmers are substituting perennial crops for short-duration crops (Al-Hassan et al., 2013). In the savannah region of Nigeria, farmers are switching from millet, sorghum, and cotton cultivation to the production of early-maturing maize (corn), cowpea, and vegetables because of warming and shortening of the rainy season/reduction in the number of rainy days (Tambo and Abdoulaye, 2012). However, farmers in the savannah zone of Ghana are switching to the cultivation of millet and Sorghum (Tambo, 2016).

[36] For example, farming system selection, irrigation, and temporal migration can be undertaken before, during, and after the production season, respectively.

Crop diversification is another strategy often employed by farmers in order to adapt to climate change. Cultivating different types of crop on the same piece of land or on different plots of land within the same season reduces the risk of total crop failure when faced with an extreme climatic event (Al-Hassan et al., 2013; Gebrehiwot and van der Veen, 2013; Nhemachena and Hassan, 2007; Tambo, 2016). Different crops have different weather requirements (Al-Hassan et al., 2013; Gebrehiwot and van der Veen, 2013); hence, if one crop fails due to inadequate rainfall or warming, the farmer can rely on yields from another crop to compensate for the loss (Antwi-Agyei et al., 2014). The different crops can be planted at the same time or at different times within the season (Kassie et al., 2013).

Crop rotation is another adaptation option. It involves alternating the production of a predetermined set of crops on the same piece of land over several seasons. If a crop is not produced in a particular season, it does not mean that the crop has been abandoned as is the case in crop substitution. Crop rotation usually involves cereals and legumes and, in some instances, root and tuber crops. Crop rotation enables farmers to adapt to declining soil fertility and pests and diseases arising from changes in the climate (Al-Hassan et al., 2013).

Some farmers also vary their production calendar as a response to climate change. These farmers vary their cropping calendar by either planting early or late so as to ensure that the sensitive stages of crop growth (for example, flowering) do not coincide with harsh climatic events such as mid-season or terminal drought, flood, pests, and diseases, (Al-Hassan et al., 2013; Gebrehiwot and van der Veen, 2013; Nhemachena and Hassan, 2007; Tambo, 2016; Tambo and Abdoulaye, 2012). According to Al-Hassan et al., (2013), some farmers depend on indigenous knowledge to determine if, after sporadic periods of rainfall, the rainy season has established.

Water and soil conservation adaptation techniques are undertaken in order to conserve moisture and replenish soil nutrients. These techniques include mulching, making mounds or ridges, creating drainage channels, applying inorganic fertilisers or manure (Al-Hassan et al., 2013), using stones to build terraces across slopes (Tambo and Abdoulaye, 2012), minimum tillage, and building of soil and stone bunds (Al-Hassan et al., 2013; Kassie et al., 2013). Water and soil conservation techniques do not only improve vegetative cover and control erosion, they are also important in protecting farming systems against extreme rainfall events and intermittent drought (Al-Hassan et al., 2013; Gebrehiwot and van der Veen, 2013; Nhemachena and Hassan, 2007).

Some farmers adjust to climate change by reducing their farm size. Farmers are better-off concentrating their resources on a manageable piece of land than producing inefficiently on a large piece of land (Etwire et al., 2013). Apart from improvement in efficiency and consequent maximisation of returns, farmers with small farms tend to suffer less damage from extreme climatic events compared to those with large farms, all other things being equal. Closely related to reduction of farm size is destocking, where livestock producers reduce the size of their stocks.

Irrigation is the means by which some farmers adapt to rising temperature and erratic rainfall. It is an important source of additional water that can be used to lengthen the farming season (Nhemachena and Hassan, 2007). Some farmers irrigate their farms by relying on small dug-outs with canals, shallow wells, lakes, rivers, and tributaries. The water is extracted manually with buckets or mechanically with motor pumps (Bawakyillenuo et al., 2014; Kassie et al., 2013; Laube et al., 2012). Some farmers also divert flood water from seasonal rivers to their farms by building earth embankments before the commencement of the rainy season (Kassie et al., 2013).

Some farmers perceive crop production to be more sensitive to changes in climate than livestock production (Al-Hassan et al., 2013). Therefore, it is not uncommon for such farmers to switch from crop to livestock production as an adaptation response to climate change (Al-Hassan et al., 2013).

Some farmers adapt to climate change by switching from specialised food-crop or livestock production to mixed food-crop and livestock production. That is, some food-crop (livestock) producers adapt by adding livestock (food-crops) to their portfolio. Food-crops and livestock are complimentary commodities and can therefore be produced together. Manure from livestock can be utilised for food-crop fertilisation. Profits from food-crop production can be invested in livestock production and vice versa. This arrangement can serve as a social safety net for climate induced scarcity or stress (Bawakyillenuo et al., 2014).

Another adaptation response to climate change is the switching to or introduction of tree-crops to existing portofolios. Tree-cropping is a beneficial adaptation strategy that can be undertaken alone or in combination with either food-crops or livestock or both. Some farmers plant trees in order to shade their crops and livestock from rising temperature or serve as windbreaks (Tambo, 2016; Tambo and Abdoulaye, 2012). In addition to being an adaptation strategy, tree planting is also a climate change mitigation strategy as it enhances carbon sequestration (Gebrehiwot and van der Veen, 2013).

A few farmers insure their farms against extreme climate events. An example is a drought index insurance scheme where insured farmers are entitled to cash payments if there is less than 2.5mm of rain for more than 16 consecutive days during the germination or crop growth stages, or if there is less than 125mm of rain during the flowering stage (Bawakyillenuo et al., 2014). Some farmers adapt to climate change by either switching to, or diversifying into non-farm activities that are less climate dependent. Non-farm activities include processing or

marketing of food-crops and livestock, petty trading, and marketing of agro-inputs (Antwi-Agyei et al., 2014).

Temporal migration is a non-farm strategy employed by some farmers as an adaptation response to climate change (Antwi-Agyei et al., 2014; Bawakyillenuo et al., 2014; Kassie et al., 2013; Ouedraogo et al., 2006; Yegbemey et al., 2013; Yesuf et al., 2008). Temporal migration does not only ease the pressure on available resources, it also presents an opportunity to generate extra income for consumption or investment expenditures (Laube et al., 2012). According to Laube et al., (2012), temporal migration either takes place during the dry season (i.e. farmers migrate after harvest and then return at the beginning of the rainy season) or within the rainy season (i.e. farmers migrate after planting and then return for harvesting). Temporal migrants are often willing to undertake a wide range of menial jobs. Other farm-level adaptation measures identified in the literature include replanting and shifting cultivation (Dossou-Aminon et al., 2014) as well as moving livestock to a different site (Silvestri et al., 2012).

The studies in Appendix 2.1 show that even though farmers are aware that the climate is changing, some of them are unable to adopt adaptation measures due to a number of constraints. Farmers often cite lack of credit as the main constraint to adaptation. Some adaptation practices require a significant level of investment. With increased access to credit, farmers can likely procure improved seeds, livestock and agro-chemicals, as well as undertake irrigation (Fosu-Mensah et al., 2012). Even though some farmers have access to credit, they cite high cost of adaptation as the main disincentive to adopting some strategies such as water and soil conservation techniques (Kassie et al., 2013). Irrespective of the cost involved, farmers in remote areas are often constrained by their lack of, or limited access to location-related adaptation measures such as irrigation facilities.

Another barrier to climate change adaptation is the inadequacy or lack of climate information. Climate awareness is a necessary condition for climate adaptation (Maddison, 2007). Some farmers report that they do not have access to adequate climate information and when such information is available, it is either delivered too late or is too general and unsuitable for making strategic decisions at the farm-level (Kassie et al., 2013). Weak institutions and the failure to include climate change issues in agricultural extension delivery are part of the underlying causes (Tessema et al., 2013). Related to lack of climate information is lack of adaptation knowledge. Other constraints include lack of markets, labour and land shortages, and insecure property rights.

2.2.2 Factors that influence adaptation to climate change

The literature on the determinants of farm-level adaptation to climate change in the African context is voluminous. We used four criteria to determine the relevant literature to review. To begin with, we exclude from our review past African studies that fail to include climate variables as covariates or determinants of farm-level adaptation[37] since climate is our main variable of interest. We also exclude studies that capture climate as a qualitative variable (farmers' perceptions) instead of a quantitative variable (climate observations) because climate is measured as a quantitative variable in this study.[38] In addition, since it is helpful to know the specific factors that determine uptake of individual adaptation options, we exclude studies that treat adaptation as a binary choice. Such studies often employ the Heckman model (where farmers perceive changes in climate in the first stage and then adopt adaptation measures in the second stage),[39] binary logit[40] or binary probit.[41] Finally, our review does not

[37] For example, Gadédjisso-Tossou, 2015; Obayelu et al., 2014; Silvestri et al., 2012; Tazeze et al., 2012; Tessema et al., 2013; Yegbemey et al., 2013.
[38] For example, Al-Hassan et al., 2013; Atinkut and Mebrat, 2016; Debalke, 2014; Etwire et al., 2013; Jiri et al., 2015; Shongwe et al., 2014; Tambo, 2016.
[39] For example, Apata, 2011; Maddison, 2007; Mandleni and Anim, 2011.

cover studies that use multiple binary logits for their estimation.[42] Relying on multiple binary logits, instead of a qualitative response model, is inappropriate since each estimate is based on a different sample (Long and Freese, 2014). For a response variable that has more than two categories, estimating several binary logits in a pairwise manner means that for each estimate, data on all the other categories are dropped except the pair being estimated. In addition, multiple binary estimates have larger standard errors and are less efficient (Agresti, 2013).

By relying on data from 8,208 farmers from 11 countries, Hassan and Nhemachena (2008) employ a multinomial logit to estimate the determinants of uptake of adaptation measures in Africa. Their analysis suggests that a warmer winter or spring promotes the use of crop diversification, mixed farming, and irrigation as adaptation options. Farmers are more likely to irrigate and less likely to engage in specialised farming with warming in summer or autumn. With increases in summer or autumn precipitation, there is a higher probability of farmers moving away from specialised farms. Male-headed households are more likely to adapt to climate change through specialised farming, irrigation, crop diversification, and mixed farming. Household size favours the selection of mixed farms over specialised farms. Age is not a significant determinant.

In order to identify the determinants of choice of farm-level adaptation strategies in southern Africa, Nhemachena and Hassan (2007) estimate a multivariate probit using 1,719 observations from three southern African countries (South Africa, Zambia, and Zimbabwe). They observe that farmers adapt to increasing temperature by cultivating drought-tolerant crops or varieties, varying planting dates, cultivating several crops, diversifying into non-

[40] For example, Mandleni and Anim, 2012; Fosu-Mensah et al., 2012.
[41] For example, Bryan et al., 2009; Yesuf et al., 2008.
[42] For example, Bryan et al., 2013; Mabe et al., 2014; Taruvinga et al., 2013.

farm activities, using water and soil conservation techniques, and irrigating their farms. A decrease in precipitation increases the probability of farmers adopting water and soil conservation techniques. Female-headed households are also more likely to take up farm-level adaptation measures. Additional farm labour favours the adoption of crop diversification, irrigation, and water conservation techniques. Age does not play a major role in determining the uptake of climate change adaptation measures.

Farm households in South Africa are more likely to switch crops, irrigate, and change planting dates in response to increasing temperatures. Farmers are also likely to change their planting dates in response to decreasing rainfall. As expected, large family size favours the selection of labour intensive adaptation measures such as soil conservation techniques. Sex and education are not significant determinants of the choice of climate change adaptation strategies. These conclusions were reached by using a multinomial logit to model data from 794 farmers in the Limpopo River Basin (Gbetibouo, 2009).

In the Tigray Region of Ethiopia, Gebrehiwot and van der Veen (2013) analyse the factors that influence farmers' choice of adaptation measures. They estimate a multinomial logit with data from 400 households. The probability of farmers adopting crop diversification, soil and water conservation, as well as irrigation, increases with an increase in either temperature or education. A decrease in precipitation increases the probability of farmers changing planting dates and using different crop varieties. Age has a positive influence on the adoption of crop diversification, irrigation, and changing of planting dates. Household size favours afforestation. As an adaptation response to climate change, male-headed households are more likely to adopt different crop varieties, soil and water conservation techniques, afforestation, and irrigation.

Deressa et al., (2009) estimate the factors that affect the choice of adaptation methods in the Nile Basin of Ethiopia by using a multinomial logit to model 995 observations. The probability of farmers adopting water and soil conservation, different crop varieties, irrigation, and changing planting date increases (decreases) with an increase in temperature (precipitation). Older farmers are more likely to adopt water and soil conservation techniques, change crop varieties, and plant trees. Male-headed households are also more likely to plant trees and change planting dates. Education increases the probability of selecting soil conservation techniques and switching of planting date. Household size does not have a significant effect on the adoption of climate change adaptation measures.

Only two of the studies that we reviewed (Deressa et al., 2009; Gebrehiwot and van der Veen, 2013) considered tree-cropping as a possible adaptation response to climate change. Except for Gbetibouo (2009), none of the studies accounted for soil type, an important factor that is likely to influence farm-level adaptation. All the studies reviewed used household data and therefore controlled for farmer characteristics. Based on the literature, Table 2.1 shows the explanatory variables utilised in our study.

Table 2.1: Definition of explanatory variables

Variable	Definition
Temperature	Temperature (degree Celsius) is one of the variables we use to operationalise climate, the other being precipitation. Temperature is defined as the long-term mean annual[43] temperature observed between 1973 and 2011.
$(\text{Temperature})^2$	Square of temperature.[44]
Precipitation	Precipitation (Millimetres) is defined as the long-term mean annual rainfall computed from data spanning 38 years.
$(\text{Precipitation})^2$	Square of precipitation.
Temperature* Precipitation	Interaction between temperature and rainfall.
Soil	A 3-level qualitative variable that measures the productivity or fertility of the land, i.e. low, intermediate, and high-quality soil.[45]
Age	Age of the household head measured in years.
Sex	Sex of the household head. A value of one is assigned to males and zero for females.
Education	A 3-level qualitative variable that measures the educational attainment of the head of household, i.e. no, primary, and secondary education.
Household size	The number of people that make up the household.

2.3 Methodology

2.3.1 Multinomial logit

Our dependent variable, farming system, is captured as a qualitative variable. Since farm types cannot be arranged in any natural order or rank, we treat farming system as a nominal outcome or an unordered response. Several methods are available for modelling unordered qualitative responses. The most common methods include multinomial logit, multinomial probit, and multivariate probit. These methods of analysis are discussed in many econometric

[43] Our definition of the climate variables is informed by the popular literature (for example, Chatzopoulos and Lippert, 2015, Deressa et al., 2009; Gbetibouo, 2009; Gebrehiwot and van der Veen, 2013; Nhemachena and Hassan, 2007)

[44] Following Mendelsohn et al., (1994), subsequent studies control for the quadratic form of the climate variables.

[45] See Chapter 1 (of this thesis) for details on how the soil variable is constructed.

textbooks (see Cameron and Trivedi, 2009; Greene, 2003; Train, 2009). We prefer the multinomial logit because of its ease of computation and wide use for empirical analysis. Unlike the multivariate probit, multinomial logit provides a convenient closed form for the underlying choice probabilities. Additionally, the multinomial logit is computationally simple[46] and converges quickly due to its globally concave likelihood function (Hausman and McFadden, 1984).

In deciding the type of farming system to adopt, agricultural households in Ghana essentially have four mutually exclusive options to choose from. These are (I) specialised food-crop production; (II) specialised livestock production; (III) mixed food-crop and livestock production; and (IV) tree-based production system. Specialised food-crops and specialised livestock consists solely of food-crops and livestock, respectively. Mixed farming is a combination of food-crops and livestock (no trees). Tree-based farming system is any production system that involves the cultivation of trees. A household cannot belong to more than one farming system at any point in time (e.g. a household that belongs to the tree-based farming system cannot belong to another farming system at the same time). Additional description of the four choice sets is presented in Section 2.4.1.

It can be shown that the probability that household *i* will adopt farming system *j* is given by (McFadden, 1973; Train, 2009):

$$Prob(Y_i = j) = \frac{e^{\boldsymbol{\beta}_j' \boldsymbol{X}_i}}{\sum_{k=1}^{4} e^{\boldsymbol{\beta}_k' \boldsymbol{X}_i}}, j = 1, \dots, 4. \tag{2.1}$$

where $\boldsymbol{X}$ is a vector of covariates that determine the choice of farming system including climate, soil, and farmer characteristics. The vector of parameters to be estimated is $\boldsymbol{\beta}$. Our

[46] We also considered estimating a multivariate probit using the algorithm developed by Roodman (2011) but had to abandon it after it became apparent that we will need more than 6 months (of computational time) to derive the marginal effects of all possible combinations.

model (Equation 2.1) is identified by setting the mixed food-crop and livestock farming system as the base outcome. The parameter estimates of the multinomial logit cannot be interpreted directly (Alauddin and Sarker, 2014; Cameron and Trivedi, 2009; Hassan and Nhemachena, 2008). It is often tempting and misleading to associate the β_j with the jth outcome (Greene, 2003; Hassan and Nhemachena, 2008). The marginal effects are, however, more meaningful and interpretable (Alauddin and Sarker, 2014; Cameron and Trivedi, 2009). We therefore report and discuss the marginal effects in this study. Two types of marginal effects are estimated namely population-averaged and partial marginal effects. We compute partial marginal effects for our climate variables (in order to plot the results as well as capture temperature-rainfall interaction) but estimate population-averaged marginal effects for all other variables. We evaluate the partial marginal effects at the sample means of the variables. The population-averaged marginal effects and corresponding coefficients may have different signs or directions because the signs on the marginal effects depend on the signs of all the coefficients of all the categories and not just the category under consideration (Hassan and Nhemachena, 2008). Mathematically, the population-averaged marginal effect is (Greene, 2003):

$$\delta_j = \frac{\partial P_j}{\partial \boldsymbol{X}_i} = P_j\left[\boldsymbol{\beta}_j - \sum_{k=0}^{J} P_k \boldsymbol{\beta}_k\right] = P_j\left[\boldsymbol{\beta}_j - \bar{\boldsymbol{\beta}}\right] \tag{2.2}$$

Since our climate and soil variables are measured at the district level, the standard errors associated with Equation (2.2) are computed at the district level with the Huber-White sandwich estimator. Our empirical model is specified as:

$$\begin{aligned} ln\Omega_{\mathrm{F|B}} = {} & \beta_{0,\mathrm{F|B}} + \beta_{1,\mathrm{F|B}} Temperature + \beta_{2,\mathrm{F|B}} (Temperature)^2 + \beta_{3,\mathrm{F|B}} Rainfall + \\ & \beta_{4,\mathrm{F|B}} (Rainfall)^2 + \beta_{5,\mathrm{F|B}} Temperature * Rainfall + \beta_{6,\mathrm{F|B}} Soil + \beta_{7,\mathrm{F|B}} Age + \\ & \beta_{8,\mathrm{F|B}} Sex + \beta_{9,\mathrm{F|B}} Education + \beta_{10,\mathrm{F|B}} Household\ size + e \end{aligned} \tag{2.3}$$

where B is the base outcome (mixed food-crop and livestock production system) and F are the remaining farming systems. Inclusion of the quadratic and interaction terms is informed by literature and the need to increase flexibility of our models. A quadratic relationship has already been established between agricultural revenue and climate. Initial and further increases in temperature and rainfall tend to have varying impact on agricultural productivity (Coster and Adeoti, 2015; Di Falco et al., 2012; Kurukulasuriya and Mendelsohn, 2008; Mendelsohn et al., 1994; Ouedraogo, et al., 2006; Seo and Mendelsohn, 2008). Moreover, the effects of temperature and rainfall are often additively inseparable as the impact of warming depends on mean rainfall and vice versa (Fezzi and Bateman 2015).

Note that we estimate a reduced model. Therefore, our analysis does not explicitly show how famers switch from one farming system to another. Even though our dataset does not capture transition costs, we do not expect those costs to be prohibitive because the majority of farmers depend on simple farm implements to cultivate their farms. Farm holdings in Ghana are typically (90%) less than 2 hectares (MoFA, 2014). Additional information on effects of transitional costs and limitations of cross-sectional models are presented in Section 3.2.1. There is evidence that some farmers in Africa and Ghana adapt to climate change by switching farm and crop types (Section 2.2.1).

2.3.2 Independence of irrelevant alternatives

The main limitation of the multinomial logit is its assumption of independence from irrelevant alternatives (IIA). This assumption implies that estimates of the multinomial logit will not change with the introduction of a new category or elimination of an existing category from the choice set or outcome variable (Hausman and McFadden, 1984). Violation of the IIA assumption renders estimates of the multinomial logit biased and inconsistent (Alauddin and Sarker, 2014). Two well-known tests for detecting violation of the IIA assumption are the

Hausman-McFadden and Small-Hsiao tests (Hausman and McFadden, 1984; Small and Hsiao, 1985).[47] The former and latter is a Hausman specification test and likelihood ratio (LR) test, respectively (Cheng and Long, 2007; Fry and Harris, 1998; Hausman, 1978; Long and Freese, 2014).

2.4 Results and Discussion

2.4.1 Description of the dependent variable

Figure 2.1 shows the relative popularity of the main farming systems[48] in Ghana. These farming systems are distributed nationwide. Although some tree-crops, food-crops, and livestock are more popular in some regions than others, analysis of the data shows that tree-crops, food-crops, and livestock are produced in all agro-ecologies, hence these commodities will likely persist into the future. The most common farm type is mixed food-crop and livestock production (51%). As discussed, mixed farming is one of the climate change adaptation strategies utilised by farmers (see Section 2.2.2). Mixed farming ensures food security, continuous flow of income, as well as efficient utilisation of a household's resources (Bawakyillenuo et al., 2014). The two enterprises (food-crops and livestock) tend to be complementary as residues or output from crop production can be utilised as input for livestock production and vice versa. According to the Ministry of Food and Agriculture, MoFA (2010), livestock production in Ghana is mostly undertaken as an addition to crop production.

[47] See Cheng and Long (2007:188-190) for a description of how Hausman-McFadden and Small-Hsiao tests are implemented in the STATA software.

[48] Seven farming systems were initially identified but due to low cell observations and similarity in practices, four categories were merged. That is, specialised tree-crop production was combined with mixed tree-crop and food-crop production, mixed tree-crop and livestock production, and mixed tree-crop, food-crop, and livestock production to form the combined category, tree-based production system. Our results do not change when we omit the specialised tree-crop production system (i.e. 94 observations) from the tree-based category, that is, when we consider only mixed tree-crop systems as a category. See Appendix 2.8 (Model 8).

About a quarter of farm households are engaged in tree-based production. Due to the level of capitalisation involved in tree-crop production, farmers that opt for the tree-based production system tend to be commercial producers. Unlike food-crops or livestock, tree-crops take a longer time to yield dividends. Tree-crops such as cashew and cocoa provide their best output only after 10 years (Coates et al., 2011). In the event that production losses are incurred towards maturity, tree-crop producers are more likely to suffer higher damages than food-crop or livestock producers, hence risk-averse and less endowed households will likely prefer other farm types to the tree-based system. However, all things being equal, returns from tree-based farms are likely to be higher than other farm types (Obiri et al., 2007; Wongnaa and Awunyo–Vitor, 2013).

Even though the tree-based system is the second most popular farm type, it is undoubtedly the most economically important farm type (even if the additional income obtained from its associated food-crops or livestock are disregarded). The value of cocoa beans export (a proxy for production) amounted to US$1.6 billion. The value of cashew export also amounted to 813.7 million dollars. Cocoa alone accounted for about 10% of agricultural GDP (Ghana Statistical Service, GSS, 2015). It is not obvious how the other farm types compare to each other in terms of value.

The remaining quarter of farm households engage in the specialised production of either food-crops (17%) or livestock (8%). Specialised farms tend to require less resources than mixed or tree-based farms. Analysis of the data shows that food-crops cultivated in Ghana include maize, millet, cassava, rice, groundnut (peanut), yam, and plantain. Households also produce livestock such as cattle, sheep, goat, pig, chicken, and Guinea fowl. The main livestock production systems in Ghana are extensive, semi-intensive, and intensive systems. Livestock are confined and catered for under the intensive system whilst livestock are left to

fend for themselves under the extensive system. The semi-intensive system is the intermediate case with varying degrees of confinement and feed supplementation. Cattle are mostly reared under the extensive system whereas farmers of small ruminants (sheep and goats) are increasingly transitioning from the extensive to the semi-intensive system. The majority of poultry (mostly undertaken in rural areas) and pig production is semi-intensive (MoFA, 2016).

Cashew, millet, groundnut, and Guinea fowl are commonly produced in northern Ghana or the Guinea and Sudan savannahs. Commodities commonly produced in southern Ghana or in the semi-deciduous and rainforest areas include cocoa, oil palm trees, and plantain. Maize and chicken are produced throughout the country by all categories of farmers (MoFA, 2010). Oil palm, cassava, and poultry are the most produced tree-crop, food-crop, and livestock, respectively.[49] In terms of revenue, cocoa is the most valuable tree-crop and yam is the most valuable food-crop (MoFA, 2014).

[49] See Chapter 1 (of this thesis) for the trend in livestock and food-crop production in Ghana.

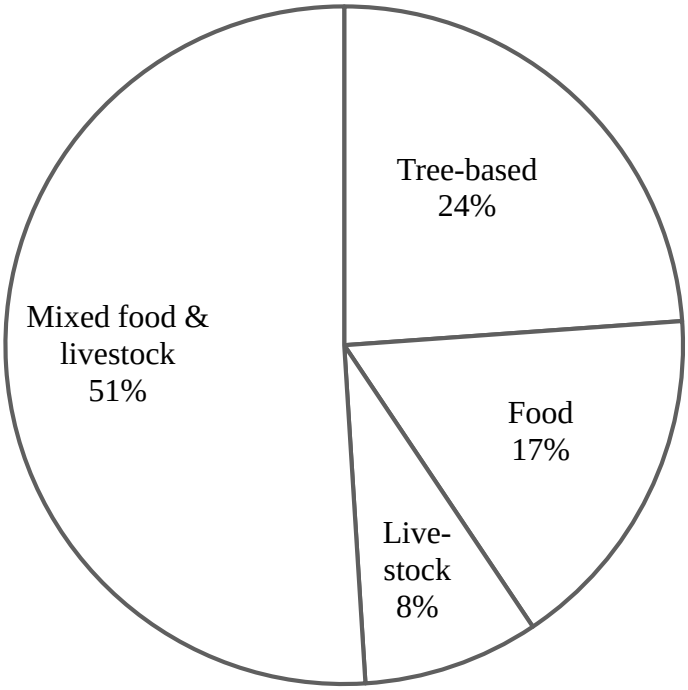

Figure 2.1: Relative popularity of different farming systems in Ghana. Note that the tree-based farming system is an aggregation of specialised tree-crop, mixed tree-crop and food-crop, mixed tree-crop and livestock, and mixed tree-crop, food-crop, and livestock production systems.

2.4.2 Description of the explanatory variables

Table 2.2 shows a description of the explanatory variables disaggregated by farming system. Mean temperature is about 26°C and the average household head is in his or her late forties. Tree-based and specialised food-crop farms are associated with areas with slightly higher levels of rainfall while specialised livestock and mixed farms are associated with areas with slightly lower levels of rainfall.

Specialised farms (either food-crop or livestock production) are associated with slightly smaller households (about 4 members) whilst tree-based and mixed farms are associated with slightly larger households (about 5 members). High-quality soils are frequently allocated to either tree-based or specialised food-crop production. Even though male-headed household dominate all farm types, an appreciable proportion of specialised farms (about a third) are cultivated by female-headed households. Tree-based and specialised livestock production

systems are associated with education. Household heads with primary (but not secondary) education mostly choose the tree-based farm type whilst those with secondary or higher education typically opt for specialised livestock production.

We test if the differences in the means of the variables (disaggregated by farming system) are statistically significant at conventional levels. Quantitative explanatory variables are compared using the one-way analysis of variance (ANOVA) test, or more specifically, the Bonferroni multiple-comparison test. Similarly, qualitative explanatory variables are compared by applying the chi square (χ^2) test. Table 2.1 shows that the variation in temperature, rainfall, age of household head, and household size is statistically significant. The χ^2 test also reveals a statistically significant difference in the sex, level of education, and type of soil associated with the different farming systems.

Table 2:2: Description of explanatory variables disaggregated by farming system

Variable	Tree-based	Food	Livestock	Mixed food & livestock	*F*	Prob > *F*
	Mean and standard deviation (in italics)				ANOVA (Bonferroni) test	
Temperature (ºC)	25.93	26.24	26.53	26.47	647.18	0.000
	0.49	*0.57*	*0.47*	*0.48*		
Rainfall (mm)	1774.7	1711.1	1623.5	1693.7	464.54	0.000
	151.5	*172.1*	*134.9*	*179.0*		
Age (Years)	49.6	46.7	48.5	48.1	10.28	0.000
	14.4	*16.1*	*16.2*	*15.8*		
Household size (Number)	4.8	4.0	4.2	5.5	136.34	0.000
	2.6	*2.5*	*2.4*	*3.0*		
	Frequency and percentage (in italics)				Chi square test	
Soil 1 (High-quality)	1,662	730	267	1,697		
	79.9	*50.0*	*36.5*	*38.2*	1400.00	0.000
Soil 2 (Intermediate)	374	326	164	971		
	18.0	*22.3*	*22.4*	*21.8*		
Male	1,652	964	457	3,713	304.55	0.000
	79.4	66.1	62.4	83.5		
Education 1 (Primary)	1,419	678	401	1,607		
	68.2	*46.5*	*54.8*	*36.2*	831.68	0.000
Education 2 (≥Secondary)	165	161	140	325		
	7.9	*11.0*	*19.1*	*7.3*		
Observations	2,080	1,459	732	4,445		

Notes: The tree-based farming system is any production system that involves the cultivation of trees such as specialised tree-crop, mixed tree-crop and food-crop, mixed tree-crop and livestock, and mixed tree-crop, food-crop, and livestock. Temperature and rainfall represent the mean weather conditions observed from 1973-2011. No education, female, and low-quality soil serve as the base category for their respective variables.

2.4.3 Modelling the impact of climate change on choice of farming system

Table 2.3 shows the marginal effects[50] of all the explanatory variables (Equation 2.3) except our main variables of interest (temperature and rainfall) which are discussed afterwards. Note that Table 2.2 presents unconditional associations (descriptive statistics) whilst Table 2.3 reflects conditional associations. Unlike the unconditional associations, the marginal effect of each variable is conditioned on all the other explanatory variables.

Farmers who have access to high-quality soils are more likely to choose the tree-based farming system (Table 2.3). Being perennial trees, tree-crops utilise soil nutrients all year round unlike food-crops that are mostly annuals. Allocating tree-crops to productive soil could be a farmer's strategy to minimising fertiliser costs. Moreover, soil productivity is likely to be more important for tree-crops than livestock since the latter do not depend directly on the soil (Seo and Mendelsohn, 2008).

Age and education have a positive effect on the selection of specialised livestock and tree-based farms but a negative effect on specialised food-crop and mixed farms selection.[51] Unlike food-crops (produced alone or in combination with livestock), tree-crops and livestock permit flexible management since they do not have binding harvesting or maturity period. This feature, perhaps, makes tree-crops and livestock more attractive to older and educated farmers.

Households with fewer members as well as those headed by females are more likely to cultivate specialised farms (either food-crops or livestock). Females tend to have limited

[50] The marginal effects of the multinomial logit show how a unit change in each explanatory variable will affect the outcome variable in terms of magnitude and direction. For example, the probability of selecting a tree-based production system increases by about 28% if a household has access to high-quality soil (Table 2.3).

[51] The practical effect of age is negligible. For example, a 1000-year increase in age will only result in a 2% increase in the probability of selecting the tree-based farming system.

access to resources such as land, labour, extension services, and formal credit (African Development Fund, 2008). These resources are needed for tree-based and mixed farms since both farm types require relatively high initial investments which includes farm labour.

Table 2.3: Population-averaged marginal effects of the multinomial logit model

Variable	Tree-based	Food	Livestock	Mixed food & livestock
Soil 1 (High-quality)	0.28***	-0.048***	-0.048***	-0.19***
	0.0086	*0.011*	*0.0082*	*0.013*
Soil 2 (Intermediate)	0.16***	-0.026**	-0.0030	-0.13***
	0.010	*0.013*	*0.010*	*0.015*
Age (Years)	0.0020***	-0.0013***	5.85×10^{-4}***	-0.0012***
	2.45×10^{-4}	2.61×10^{-4}	1.84×10^{-4}	3.15×10^{-4}
Male	0.034***	-0.096***	-0.079***	0.14***
	0.0091	*0.011*	*0.0083*	*0.012*
Education 1 (Primary)	0.13***	-0.0066	0.069***	-0.19***
	0.0085	*0.0086*	*0.0059*	*0.011*
Education 2 (≥Secondary)	0.045***	0.029	0.15***	-0.23***
	0.014	*0.015*	*0.014*	*0.018*
Household size	5.60×10^{-4}	-0.020***	-0.0050***	0.024***
	0.0014	*0.0018*	*0.0011*	*0.0018*

Notes: Normal type values are the marginal effects while values in italics are the associated standard errors clustered at the district level. ** and *** signify significance levels at 5% and 1%, respectively. The tree-based farming system is any production system that involves the cultivation of trees such as specialised tree-crop, mixed tree-crop and food-crop, mixed tree-crop and livestock, and mixed tree-crop, food-crop, and livestock. No education, female, and low-quality soil serve as the base category for their respective variables. Wald Chi^2 (36) = 2593.2; Prob > Chi^2 = 0.000; Count R^2 = 0.624; Pseudo R^2 = 0.2314; Log pseudo likelihood = -7977.8.

Figures 2.2 and 2.3 show how our main variables of interest, temperature and rainfall, influence the selection of farming systems in Ghana (partial marginal effects). Note that our inclusion of the quadratic terms of temperature and rainfall allows the response function to be either hill-shaped or U-shaped. The effect of temperature (rainfall) is evaluated at the mean value of rainfall (temperature) and the other variables. The relationship between temperature and the probability of selecting the tree-based system is hill-shaped. Initial increases in temperature favours selection but further increases above 25.7^{o}C affects selection negatively.

Whereas food-crop selection is decreasing in temperature, livestock and mixed farm selections are increasing in temperature (Figure 2.2).

As temperature increase from 25°C to 26°C, the proportion of households selecting tree-based, mixed, and specialised livestock farms increases from about 29% to 36%, 35% to 44%, and 3% to 6%, respectively. On the contrary, the proportion of households selecting specialised food-crop farms decreases from about 30% to 19%. At 27°C, the proportion of households selecting the tree-based system declines to 2% and that of the food-crop system further declines to 14% with more households now opting for specialised livestock production (18%) and mixed farms (66%). This result suggests that farmers will likely adapt to warming by switching into mixed farms or specialised livestock production. Resource-poor farmers may switch to livestock production with relatively better-off farmers opting for mixed farms as temperature increases.

Figure 2.3 shows that selection of the tree-based system responds positively to rainfall while mixed farms respond negatively to rainfall. Increases in rainfall up to 1600mm favours livestock selection but further increases after that are detrimental. The probability of selecting the food-crop system does not vary much with increases in rainfall. At 1450mm, mixed farms are selected by about 65% of households with tree-based and specialised livestock farms also separately chosen by about 10% of households. The proportion of households that select specialised food-crop farms throughout the range of rainfall fluctuates between 15% and 20%. Whereas the selection of specialised farms (food-crops or livestock) at 1750mm is similar to selection at 1450mm, the selection of tree-based (mixed) farms increases (drops) by more than 10 percentage points. The selection of the tree-based system at 1900mm is 27 percentage points higher than the 1450mm selection. Within the same range, the portion of households that choose mixed and specialised farms drop by about 17 and 8 percentage points, respectively. There is further substitution into the tree-based system as rainfall

increases with the system becoming the most popular farm type (more than 40% of households) at 2020mm. The confidence bands presented in Figures 2.2 and 2.3 suggest that our temperature and rainfall estimates are precise.[52] Therefore, we expect that climate change simulations based on those estimates would be reliable.

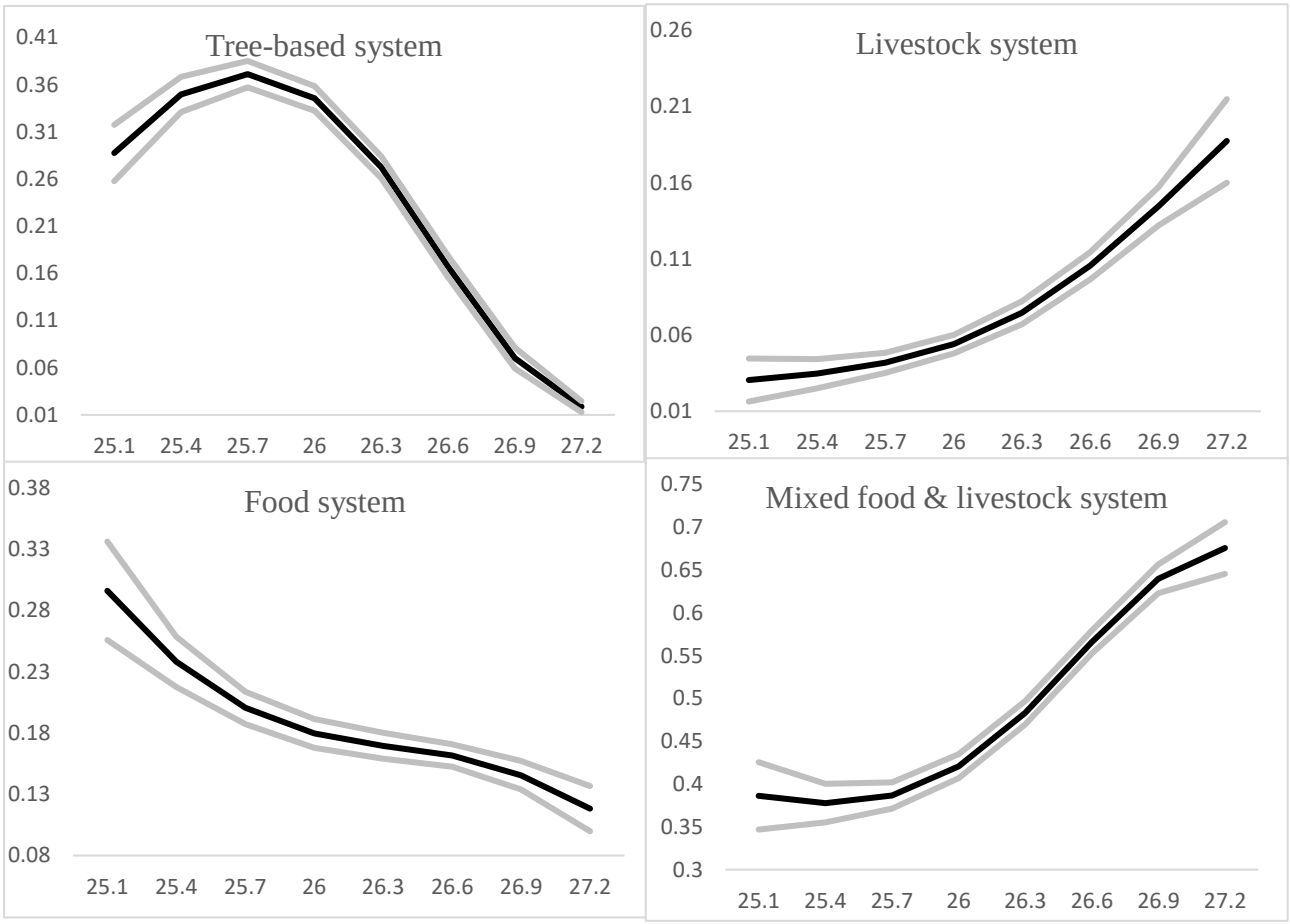

Figure 2.2: Effect of temperature on farming system selection

Notes: The response function in black and grey represent the point estimates and the 95% confidence band, respectively. The 95% confidence intervals are generated using the delta method (Long and Freese, 2014; StataCorp, 2017). The delta method uses a Taylor approximation to expand the fitted values around its mean before deriving the variance (StataCorp, 2017). The vertical axis measures the probability of selection and the horizontal axis measures the 38-year average temperature (ºC). Estimates are evaluated at the mean value of all the other covariates including rainfall (partial marginal effects).

[52] Note that none of the confidence bands include a zero probability of selection. In addition, the lower and upper limits are very close to the point estimates at most temperature and rainfall values.

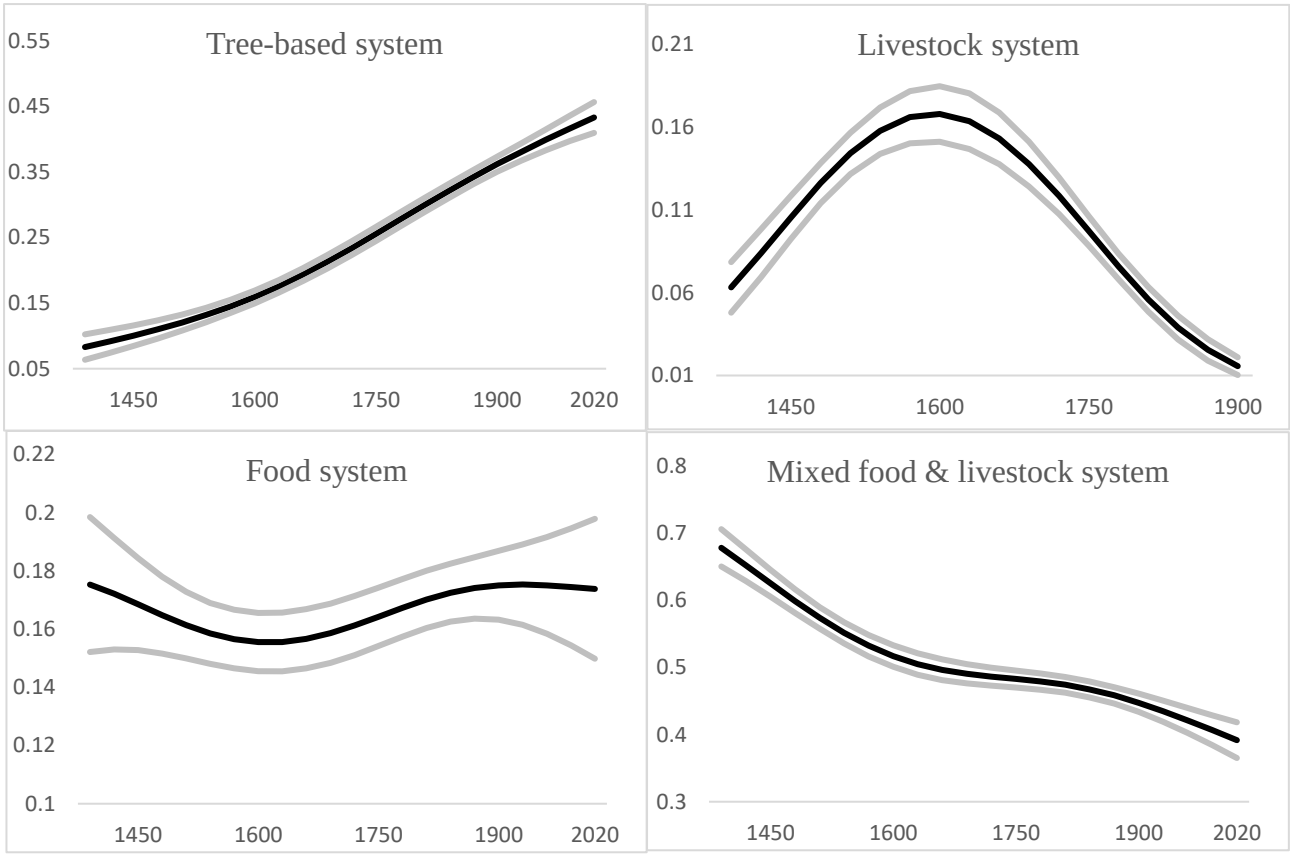

Figure 2.3: Effect of rainfall on farming system selection

Notes: The response function in black and grey represent the point estimates and the 95% confidence band, respectively. The 95% confidence intervals are generated using the delta method (Long and Freese, 2014; StataCorp, 2017). The delta method uses a Taylor approximation to expand the fitted values around its mean before deriving the variance (StataCorp, 2017). The vertical axis measures the probability of selection and the horizontal axis measures the 38-year average rainfall (mm). Estimates are evaluated at the mean value of all the other covariates including temperature (partial marginal effects).

2.4.4 Robustness check

We subject our results to several diagnostic and robustness checks. To begin with, we test for possible violation of the IIA assumption. Results of the Hausman-McFadden and Small-Hsiao tests are presented in Appendix 2.2 and 2.3, respectively. In each case, we do not find evidence to reject the hypothesis that the various farming systems are independent of each. Wald's test[53] also confirms that it is inappropriate to further combine the various farming

[53] Cheng and Long (2007:185) describes how Wald's test is implemented in the STATA software.

systems considered. The null hypothesis that various alternatives can be combined is strongly rejected (Appendix 2.4). Therefore, our choice of the multinomial logit for analysis is justified since the various farming systems are truly independent. Additionally, we do not find evidence to support the hypothesis that all coefficients associated with the explanatory variables are zero (Appendix 2.5 and 2.6).

In order to check the reliability of our results, we estimate 7 other models and then compare the marginal effects of those models with that of our preferred model. The results are presented in Appendix 2.7. Model 1 is our preferred multinomial logit model (lowest AIC/N or highest R^2). Model 2 is the corresponding multinomial probit estimates.[54] Models 3-8 are all multinomial logit estimates. We assume in Model 3 that the effects of temperature and rainfall are separable (i.e. no interaction term). We estimate unconventional equations for Models 4-6. Contrary to the popular literature that estimate quadratic climatic effects (see Section 3.3.1), we estimate simple temperature and rainfall effects in model 4 by omitting quadratic and interaction terms. Instead of controlling for both temperature and rainfall as usual, we control for only temperature and its square (one climate variable) in Model 5 and focus on only rainfall and rainfall^2 in Model 6. Model 7 shows the exclusive effects of the climate variables (i.e. temperature and rainfall) without the household and soil characteristics. In our final model (8), we re-estimate our preferred model but slightly alter our dependent variable by omitting specialised tree farms from the tree-based category. Appendix 2.7 shows that in all cases, the magnitude, direction, and statistical significance of our variables of interest (temperature and rainfall) do not change markedly between models.

[54] The multinomial probit, unlike the multinomial logit, does not impose the IIA assumption (Cameron and Trivedi, 2009; Greene, 2003; Hausman and Wise, 1978; Wooldridge, 2010).

2.4.5 Simulating the impact of climate change on choice of farming system

We rely on the latest projections of the IPCC (Christensen et al., 2013) to simulate the impact of climate change on choice of farm type in Ghana.[55] Temperature and precipitation output from the CMIP5 (Coupled Model Intercomparison Project Phase 5) served as the basis for IPCC's projection. CMIP5 collates results from 39 global models. We utilise all the three projections for West Africa for the year 2035. Under the first IPCC scenario which we designate as 'scenario 2', temperature and precipitation are projected to increase by 0.7^{o}C and 8%, respectively. In the second IPCC scenario designated 'scenario 3', temperature and precipitation increase by 0.9^{o}C and 1%, respectively. In the third IPCC scenario which we label as 'scenario 4', temperature increases by 1.5^{o}C and precipitation declines by 4%. In order to further disentangle the potential impacts of temperature and rainfall, we also considered four additional scenarios. Scenario 1 is a very optimistic scenario where temperature and rainfall increase by 0.5^{o}C and 15%, respectively. The fifth and least optimistic scenario entails a 2°C increase in temperature and a 10% reduction in rainfall. In Scenario 6, temperature increases by 0.5^{o}C and rainfall declines by 10%. In the last scenario, temperature and rainfall increase by 2°C and 15%, respectively. These 7 climate scenarios are summarised in Chapter 3 (of this thesis) as Table 3.4. These scenarios are applied uniformly to all parts of Ghana.

The simulation results show that the selection of tree-based and specialised food-crop farms decline in all scenarios (Table 2.4). The proportion of households cultivating tree-based farms falls considerably from 24% to 2% or less under scenarios 4, 5, and 7. The selection of mixed-farms increases in all scenarios except scenario 5 where there is no change in selection

[55] The simulations are based on our multinomial logit estimates (Equation 2.3). We first apply the expected changes in temperature and rainfall before predicting the percentage change in probability of selection.

despite the 10% reduction in rainfall and 2ºC increase in temperature. Similarly, the selection of specialised livestock farms increases in all scenarios except the very optimistic scenario (scenario 1 or +15% rainfall and +0.5ºC) where selection declines. The simulation results seem more aligned to the temperature effects than the rainfall effects thereby suggesting that temperature has a stronger influence than rainfall. Consistent with the earlier temperature effects (Figure 2.2), the simulation results also show that farmers will likely adapt to different climate scenarios by switching from tree-based and specialised food-crop farms to mixed and specialised livestock farms. All things being equal (i.e. assuming changes in climate and other factors do not drastically change the relative value of the various farming systems), this adaptation response implies a fall in the total value of agricultural output since the tree-based system, which produces commercial commodities such as cocoa and cashew, is clearly the most profitable farm type.

Appendix 2.8 shows the simulated change in the probability of selecting a farming system relative to the existing variation in climate at each latitude. Note that our simulation exercise is a static analysis (because all the non-climatic explanatory variables are held at their mean value[56]) and therefore intended to serve only as a guide since it does not capture factors that could change over time (e.g. technology).

[56] Apart from the climate variables (temperature and precipitation), we do not have reliable projections on how other variables will change in future.

Table 2.4: Estimated changes[57] in the probability of selecting each farming system under different climate scenarios[58] (with 95% confidence bands)

	Estimate	95% confidence interval			Estimate	95% confidence interval	
Baseline: Tree-based	0.24			Baseline: Food	0.17		
Change in scenario 1	-0.012	-0.016	-0.008	Change in scenario 1	-0.001	-0.003	0.001
Change in scenario 2	-0.093	-0.10	-0.089	Change in scenario 2	-0.031	-0.032	-0.029
Change in scenario 3	-0.15	-0.15	-0.15	Change in scenario 3	-0.06	-0.062	-0.060
Change in scenario 4	-0.22	-0.22	-0.21	Change in scenario 4	-0.11	-0.11	-0.11
Change in scenario 5	-0.23	-0.24	-0.23	Change in scenario 5	-0.14	-0.14	-0.14
Change in scenario 6	-0.15	-0.15	-0.14	Change in scenario 6	-0.042	-0.044	-0.041
Change in scenario 7	-0.23	-0.24	-0.23	Change in scenario 7	-0.10	-0.10	-0.095
Baseline: Livestock	0.08			Baseline: Mixed food & livestock	0.51		
Change in scenario 1	-0.022	-0.024	-0.019	Change in scenario 1	0.035	0.032	0.038
Change in scenario 2	0.022	0.019	0.025	Change in scenario 2	0.10	0.10	0.11
Change in scenario 3	0.081	0.078	0.084	Change in scenario 3	0.13	0.13	0.13
Change in scenario 4	0.23	0.23	0.23	Change in scenario 4	0.10	0.093	0.10
Change in scenario 5	0.37	0.37	0.38	Change in scenario 5	0.00	-0.007	0.006
Change in scenario 6	0.074	0.071	0.078	Change in scenario 6	0.12	0.11	0.12
Change in scenario 7	0.081	0.076	0.086	Change in scenario 7	0.25	0.24	0.25

[57] The change is the percentage point difference between the predicted and baseline probabilities.

[58] The tree-based farming system is any production system that involves the cultivation of trees such as specialised tree-crop, mixed tree-crop and food-crop, mixed tree-crop and livestock, and mixed tree-crop, food-crop, and livestock. Scenario 1 corresponds to an increase in temperature and rainfall by 0.7°C and 8%, respectively. Scenario 2 represents an increase in temperature and rainfall by 0.9°C and 1%, respectively. Scenario 3 shows an increase in temperature by 1.5°C and a 4% reduction in rainfall. Scenario 4 represents an increase in temperature by 0.5°C and a 15% increase in rainfall. Scenario 5 shows a 2°C increase in temperature and a 10% reduction in rainfall. In scenario 6, temperature increases by 0.5°C and rainfall declines by 10%. Scenario 7 represents a 2°C increase in temperature and a 15% increase in rainfall.

2.5 Summary and Conclusions

The agronomic literature shows that climate plays an important role in determining the types of farms that are established in an area. In this study, we use the multinomial logit to estimate the relationship between climate and the choice of farming systems by modelling climate, farmer, and farm data from Ghana. The dominant farm types in Ghana are specialised food-crop, specialised livestock, mixed food-crop and livestock, and tree-based production systems. We find that climate, soil, and household characteristics all influence the choice of farm-type. For example, households with access to high-quality soils and headed by educated males are more likely to select a tree-based system. An uneducated male that heads a large family but produces on a low-quality soil is more likely to select mixed farms. Female-headed households are more likely to select specialised farms (either food-crop or livestock production).

We find substantial substitution of tree-based and food-crop farms for livestock and mixed farms when we rely on the multinomial logit estimates to simulate the impact of climate change on farm type selection. Switching into livestock production would likely be because of its flexibility rather than profitability as livestock in Ghana is mostly produced on an extensive (pastoralism) and semi-intensive basis[59] (MoFA, 2016). The large decline in tree-based farms has important policy implications since tree-crops such as cocoa and cashew contribute significantly to employment, foreign exchange, and overall GDP. Therefore, it is important to undertake research to improve the climate resilience of tree-based productions as well as implement measures to safeguard the profitability of the system.

[59] Unlike tree-crops and food-crops that cannot be moved once planted, livestock can be moved to more favourable areas for feed and water as the need be. Even if the livestock are not moved and produced under the intensive or sedentary system, a withered livestock can be consumed at home unlike a withered crop.

Even though we have shown that climate change is likely to be detrimental to tree-based and food-crop production, different types of tree-crops and food-crops may respond differently to temperature and rainfall. It is therefore necessary to undertake a more detailed study in order to determine how different tree-crops and food-crops are impacted by climate change. Since we only have access to reliable food-crop production data, we use the structural Ricardian model to estimate how climate impacts on different food-crops (Chapter 3 of this thesis). A detailed analysis of the effects of climate on the production of specific tree-crops is a subject for future research that will involve a carefully planned survey.

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Appendices 2

Appendix 2.1: Adaptation measures and constraints[60]

No	Country	Study area	Sample size	Percent that adapts	Adaptation measures (%)*	Barriers/constraints to adaptation (%)*	Authors
1	Ghana	Western Region	98	60.2	Different varieties (93.9) Different planting dates (92.9) Prayers (74.5) Irrigation (73.5) Tree planting (33.7) Water and soil conservation (30.6)	Lack of credit (93.9) Lack of access to inputs (91.8) Insecure property rights (87.8) Adaptation not cost effective (82.7) Lack of climate information (77.6) Lack of adaptation knowledge (71.4) No access to water (41.8)	Acquah & Onumah, 2011
2	Ghana	Northern Ghana	296		Different planting dates (36.8) Water and soil conservation (19.3) Crop diversification (12.8) Different varieties (3.4) Crop rotation (3.0) Livestock production (1.4)		Al-Hassan et al., 2013
3	Ghana	Upper East and Ashanti Regions	270		Different planting dates (92.2) Different varieties (69.3) Crop diversification (79.3) Tree planting (15.9) Irrigation (6.7) Crop rotation (44.8) Diversifying to non-farm activity (46.3) Temporal migration (45.6)		Antwi-Agyei et al., 2014

[60] *Multiple responses allowed

No	Country	Study area	Sample size	Percent that adapts	Adaptation measures (%)*	Barriers/constraints to adaptation (%)*	Authors
4	Nigeria		650	80.8	Crop diversification Irrigation Livestock production Mixed farming Diversifying to non-farm activity	Lack of climate information Lack of credit Labour shortage Land shortage No access to water	Apata et al., 2011
5	Nigeria	Southwest	360	57.6	Crop diversification (57.4) Different planting dates (44.6) Mixed farming (29.7) Water and soil conservation (20.9) Tree planting (13.7)	Lack of adaptation knowledge Lack of credit Labour shortage Land shortage No access to water	Apata, 2011
6	Ghana	Upper East Region	186			Lack of credit Lack of access to inputs Lack of climate information Land shortage Labour shortage	Badmos et al., 2015
7	Ghana	Upper East and Northern Regions	530		Water and soil conservation (96) Mixed farming (87) Diversifying to non-farm activity (29.6) Temporal migration (29.2) Irrigation (8.3) Insurance (2.7)	Lack of credit Lack of adaptation knowledge	Bawakyillenuo et al., 2014
8	Nigeria	Central Nigeria	150		Different varieties (53.3) Tree planting (52.7) Crop diversification (48) Different planting dates (46.7)	Lack of credit Lack of climate information Insecure property rights Lack of markets	Bello et al., 2013

No	Country	Study area	Sample size	Percent that adapts	Adaptation measures (%)*	Barriers/constraints to adaptation (%)*	Authors
					Water and soil conservation (25.3) Irrigation (22) Insurance (3.3)		
9	South Africa, Ethiopia	Limpopo and Nile basins	1800	50.5	Water and soil conservation Different varieties Tree planting Different planting dates Irrigation Livestock production Different varieties (33) Reduce farm size Different planting dates (20) Crop diversification	Lack of climate information Lack of credit Land shortage Labour shortage Lack of access to inputs No access to water Insecure property rights Lack of markets	Bryan et al., 2009
10	Kenya		710	81	Crop substitution (18) Water and soil conservation (12) Tree planting (7) Destocking (7)		Bryan et al., 2013
11	Nigeria	Niger, Taraba and Oyo States	346	92.4	Different planting dates (77) Mixed farming (51.5) Different varieties (47.9) Crop diversification (44.5) Water and soil conservation (35.5) Prayers (30.6) Diversifying to non-farm activity (24.4)	Lack of credit (84.8) Lack of climate information (79.7) Lack of adaptation knowledge (59.5) Lack of access to inputs (59.5) Insecure property rights (49.4) No access to water (15.2)	Coster & Adeoti, 2015

No	Country	Study area	Sample size	Percent that adapts	Adaptation measures (%)*	Barriers/constraints to adaptation (%)*	Authors
					Irrigation (16.2)		
12	Ethiopia	Amhara Region	225		Livestock production Water and soil conservation Irrigation Different planting dates Crop diversification	Lack of climate information (34.6) Lack of credit (23.9) Land shortage (20.4) No access to water (11.5) Labour shortage (5.6)	Debalke, 2014
13	Ethiopia	Nile Basin	995	58	Tree planting (21) Water and soil conservation (15) Different varieties (13) Different planting dates (5) Irrigation (4)	Lack of climate information (44) Lack of credit (24) Labour shortage (16) Land shortage (10)	Deressa et al., 2009
14	Ethiopia	Nile Basin	1000	50.6	Water and soil conservation Different varieties Tree planting Irrigation	Lack of credit Lack of climate information Labour shortage No access to water	Di Falco et al., 2012
15	Benin	North Eastern Benin	300		Shifting cultivation Different varieties Different planting dates Water and soil conservation Replanting Crop rotation		Dossou-Aminon et al., 2014
16	Ghana	Northern Ghana	320		Water and soil conservation (56.2) Different varieties (6) Tree planting (3.1) Irrigation (3.1) Reduce farm size (0.9)		Etwire et al., 2013
17	Ghana	Ashanti	180	44.4	Different planting dates	Lack of climate information	Fosu-Mensah

No	Country	Study area	Sample size	Percent that adapts	Adaptation measures (%)*	Barriers/constraints to adaptation (%)*	Authors
		Region			Crop diversification Crop substitution Reduce farm size Different varieties Diversifying to non-farm activity	Poverty Lack of adaptation knowledge	et al., 2012
18	Togo		320	58.3	Different varieties (20.4) Different planting dates (17.9) Crop diversification (9.7) Diversifying to non-farm activity (3.8) Reduce farm size (1.9)		Gadédjisso-Tossou, 2015
19	South Africa	Limpopo River Basin	794		Crop substitution Irrigation Reduce farm size Different planting dates Livestock production Different varieties Crop diversification		Gbetibouo, 2009
20	Ethiopia	Tigray Region	400	53	Crop diversification (24) Water and soil conservation (10) Irrigation (8) Tree planting (6) Different planting dates (5)	Lack of climate information (42) Lack of credit (23) Land shortage (17) Labour shortage (10)	Gebrehiwot & van der Veen, 2013
21	Zimbabwe	Masvingo Province	100		Prayers (83.8) Diversifying to non-farm activity (83.7) Livestock production (82.5)		Jiri et al., 2015

No	Country	Study area	Sample size	Percent that adapts	Adaptation measures (%)*	Barriers/constraints to adaptation (%)*	Authors
					Irrigation (80.4) Tree planting (74.2) Mixed farming (74.2) Different planting dates (68) Crop diversification (63.9) Water and soil conservation (63.4) Different varieties (51.6)		
22	Kenya		816	69	Crop diversification Different planting dates Livestock production Irrigation Water and soil conservation Tree planting	Lack of credit (59) Lack of adaptation knowledge (19) Lack of climate information (8) No access to water (8) Lack of access to inputs (5)	Kabubo-Mariara & Karanja, 2007
23	Ethiopia	Central Rift and Kobo Valleys	200		Crop substitution Different varieties Different planting dates Crop diversification Water and soil conservation Irrigation Diversifying to non-farm activity Destocking Temporal migration	Lack of markets Adaptation not cost effective Lack of climate information Lack of credit Land shortage Labour shortage Risk averse behaviour	Kassie et al., 2013
24	Tanzania	Iringa, Morogoro, Dodoma and Tanga	534	65.6	Irrigation (5.6) Different varieties (41.4) Tree planting (7.4) Different planting dates (11.3)	Lack of credit (25.9) No access to water (27.3) Lack of access to inputs (3.2)	Komba & Muchapondwa, 2015
25	Africa	10 countries	9500	83	Different varieties (20.4)	Lack of credit (28.4)	Maddison,

No	Country	Study area	Sample size	Percent that adapts	Adaptation measures (%)*	Barriers/constraints to adaptation (%)*	Authors
					Crop diversification (12.2) Different planting dates (9.8) Diversifying to non-farm activity (7.9) Irrigation (9.8) Water and soil conservation (25.2) Tree planting (14.1) Insurance (8.2) Prayers (3.8)	Lack of adaptation knowledge (8.8) Lack of climate information (6.3) No access to water (6) Lack of access to inputs (4.6) Adaptation not cost effective (4.3) Insecure property rights (1.9)	2007
26	Tanzania	Singida Region			Water and soil conservation Different planting dates Crop diversification		Mary & Majule, 2009
27	Ghana	Upper West Region	100	67	Crop diversification (41) Crop rotation (10) Different varieties (12) Different planting dates (23) Diversifying to non-farm activity (6) Reduce farm size (3)	Adaptation not cost effective Lack of climate information No access to water Lack of credit Poor soil fertility Lack of markets Labour shortage Land shortage	Ndamani & Watanabe, 2015
28	Cameroon	Lake Lagdo watershed	303	61	Water and soil conservation (29) Different varieties (13) Different planting dates (11) Tree planting (5) Irrigation (3)	Insecure property rights (43) Lack of credit (22) Labour shortage (16) Lack of climate information (13) No access to water (6)	Ngondjeb, 2013
29	Ghana	Volta	70	33.6	Different planting dates	Poverty	Nhamo et al.,

No	Country	Study area	Sample size	Percent that adapts	Adaptation measures (%)*	Barriers/constraints to adaptation (%)*	Authors
		Region			Water and soil conservation Different varieties		2014
30	Southern Africa	South Africa, Zambia and Zimbabwe	1719	>60	Different planting dates (17) Different varieties (11) Crop diversification (9) Irrigation (9) Diversifying to non-farm activity (8) Water and soil conservation (5) Crop substitution (4)	Lack of credit (29.2) Lack of climate information (14.5) Lack of access to inputs (7.3) Lack of adaptation knowledge (5.6) No access to water (3.4) Lack of markets (2.5) Adaptation not cost effective (1.6)	Nhemachena & Hassan, 2007
31	Nigeria	Ekiti State	156		Water and soil conservation (42.9) Different planting dates (20.5) Mixed farming (10.3) Reduce farm size (10.3) Diversifying to non-farm activity (8.3) Different varieties (7.7)		Obayelu et al., 2014
32	Burkina Faso		1530		Water and soil conservation Different varieties Tree planting Crop diversification Prayers Temporal migration		Ouedraogo et al., 2006
33	Kenya		640		Mixed farming Destocking Move livestock to a different site	Poverty (55) Lack of credit (12) Lack of markets (8) Lack of access to inputs (5)	Silvestri et al., 2012

No	Country	Study area	Sample size	Percent that adapts	Adaptation measures (%)*	Barriers/constraints to adaptation (%)*	Authors
34	Nigeria	Borno State	200		Crop diversification Different varieties Different planting dates Tree planting Crop substitution Irrigation Diversifying to non-farm activity	Lack of climate information Lack of credit Lack of adaptation knowledge	Tambo & Abdoulaye, 2012
35	Ethiopia	Eastern Hararghe Zone	160		Tree planting (89.1) Different planting dates (20) Irrigation (18) Prayers (9.2)	Lack of climate information (22.5) Lack of access to inputs (20.7) Land shortage (17.1) Lack of credit (14.4) No access to water (8) Labour shortage (4)	Tessema et al., 2013
36	Benin	Northern Benin	308		Crop diversification Different planting dates Reduce farm size Diversifying to non-farm activity Temporal migration Prayers		Yegbemey et al., 2013
37	Ethiopia	Nile Basin	1000	50.6	Water and soil conservation Different varieties Tree planting Diversifying to non-farm activity Different planting dates Temporal migration	Lack of climate information Lack of credit No access to water Labour shortage Land shortage	Yesuf et al., 2008

Appendix 2.2: Hausman test for IIA assumption

Farming system	Chi^2	df
Tree-based	-22	14
Food	-99	17
Livestock	-2	14
Mixed food & livestock	-824	14

H_o: Odds (Outcome-J vs Outcome-K) are independent of other alternatives. A negative result is evidence against rejection of the null hypothesis.

Appendix 2.3: Small-Hsiao test for IIA assumption

Farming system	lnL(full)	lnL(omit)	Chi^2	df
Tree-based	-2479	-7978	-11000	39
Food	-2250	-4026	-3551	39
Livestock	-2969	-4026	-2114	39
Mixed food & livestock	-1601	-4026	-4849	39

H_o: Odds (Outcome-J vs Outcome-K) are independent of other alternatives.

Appendix 2.4: Wald test for combining alternatives

Combination of farming system	Chi^2	df
Tree-based & Food	905***	12
Tree-based & Livestock	1092***	12
Tree-based & Mixed food and livestock	1662***	12
Food & Livestock	498***	12
Food & Mixed food and livestock	662***	12
Livestock & Mixed food and livestock	646***	12

H_o: All coefficients except intercepts associated with a given pair of alternatives are 0 (i.e., alternatives can be combined). *** represents statistical significance at the 1% level.

Appendix 2.5: Wald test for independent variables

Explanatory variables	Chi^2	df
Temperature	184***	3
$(Temperature)^2$	171***	3
Rainfall	77***	3
$(Rainfall)^2$	168***	3
Temperature*Rainfall	43***	3
Soil 1	355***	3
Soil 2	159***	3
Age	82***	3
Male	244***	3
Education 1	409***	3
Education 2	255***	3
Household size	213***	3

H_o: All coefficients associated with given variable(s) are 0. *** represents statistical significance at the 1% level.

Appendix 2.6: LR test for independent variables

Explanatory variables	Chi^2	df
Temperature	209***	3
$(Temperature)^2$	194***	3
Rainfall	79***	3
$(Rainfall)^2$	210***	3
Temperature*Rainfall	43***	3
Soil 1	659***	3
Soil 2	231***	3
Age	83***	3
Male	243***	3
Education 1	434***	3
Education 2	250***	3
Household size	234***	3

H_o: All coefficients associated with given variable(s) are 0. *** represents statistical significance at the 1% level.

Appendix 2.7: Different estimates of the effect of climate on choice of farm type[61]

Variable	Farming system	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Temperature (oC)	Tree-based	-0.15***	-0.16***	-0.14***	-0.16***	-0.14***		-0.29***	-0.15***
		0.0066	*0.0064*	*0.0067*	*0.006*	*0.0066*		*0.006*	*0.0066*
	Food	-0.080***	-0.076***	-0.080***	-0.058***	-0.067***		-0.057***	-0.081***
		0.008	*0.0079*	*0.008*	*0.0073*	*0.008*		*0.0078*	*0.008*
	Livestock	0.078***	0.070***	0.078***	0.058***	0.058***		0.087***	0.078***
		0.0074	*0.0073*	*0.0073*	*0.0067*	*0.0077*		*0.007*	*0.0074*
	Mixed food & livestock	0.15***	0.16***	0.15***	0.16***	0.15***		0.26***	0.15***
		0.01	*0.01*	*0.01*	*0.0092*	*0.01*		*0.01*	*0.01*
Rainfall (mm)	Tree-based	$5.80x10^{-4}$***	$5.70x10^{-4}$***	$5.63x10^{-4}$***	$5.43x10^{-4}$***		$4.90x10^{-4}$***	$6.73x10^{-4}$***	$5.73x10^{-4}$***
		$2.12x10^{-5}$	*$2.14x10^{-5}$*	*$2.20x10^{-5}$*	*$2.22x10^{-5}$*		*$2.31x10^{-5}$*	*$2.28x10^{-5}$*	*$2.11x10^{-5}$*
	Food	$5.40x10^{-6}$	$6.92x10^{-6}$	$1.19x10^{-5}$	$2.94x10^{-5}$		$1.71x10^{-5}$	$-4.63x10^{-5}$**	$8.82x10^{-6}$
		$2.35x10^{-5}$	*$2.27x10^{-5}$*	*$2.40x10^{-5}$*	*$2.28x10^{-5}$*		*$2.29x10^{-5}$*	*$2.35x10^{-5}$*	*$2.36x10^{-5}$*
	Livestock	$-1.44x10^{-4}$***	$-1.59x10^{-4}$***	$-1.47x10^{-4}$***	$-2.14x10^{-4}$***		$-1.67x10^{-4}$***	$-1.51x10^{-4}$***	$-1.41x10^{-4}$***
		$9.77x10^{-6}$	*$9.55x10^{-6}$*	*$9.38x10^{-6}$*	*$1.45x10^{-5}$*		*$9.21x10^{-6}$*	*$1.06\ x10^{-5}$*	*$9.98x10^{-6}$*
	Mixed food & livestock	$-4.42x10^{-4}$***	$-4.19x10^{-4}$***	$-4.27x10^{-4}$***	$-3.59x10^{-4}$***		$-3.40x10^{-4}$***	$-4.76x10^{-4}$***	$-4.41x10^{-4}$***
		$2.74x10^{-5}$	*$2.67x10^{-5}$*	*$2.78x10^{-5}$*	*$2.69x10^{-5}$*		*$2.82x10^{-5}$*	*$2.88x10^{-5}$*	*$2.76x10^{-5}$*

[61] Normal type values are the marginal effects while values in italics are the associated standard errors clustered at the district level. Model 1 is our preferred multinomial logit model. Model 2 is the corresponding multinomial probit estimates. Models 3-8 are all multinomial logit estimates. We assume in Model 3 that the effects of temperature and rainfall are separable (i.e. no interaction term). Models 4-6 contradict the literature. We estimate simple climate effects by dropping the quadratic and interaction terms in model 4. In Model 5 (Model 6), we control for only one climate variable, that is, temperature and its square (rainfall and rainfall2). Model 7 shows the exclusive effects of the climate variables (i.e. temperature and rainfall) without the household and soil characteristics. In our final model (8), we re-estimate our preferred model but slightly alter our dependent variable by omitting specialised tree farms from the tree-based category. ** and *** signify significance levels at 5% and 1%, respectively. The tree-based farming system is any production system that involves the cultivation of trees such as specialised tree-crop, mixed tree-crop and food-crop, mixed tree-crop and livestock, and mixed tree-crop, food-crop, and livestock. Temperature and rainfall represent the mean weather conditions observed from 1973-2011. No education, female, and low-quality soil serve as the base category for their respective variables.

Variable	Farming system	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Soil 1 (High-quality)	Tree-based	0.28***	0.27***	0.29***	0.28***	0.29***	0.34***		0.27***
		0.0086	*0.0091*	*0.0083*	*0.0081*	*0.0083*	*0.0073*		*0.0086*
	Food	-0.048***	-0.042***	-0.047***	-0.050***	-0.043***	-0.0067		-0.043***
		0.011	*0.01*	*0.011*	*0.011*	*0.011*	*0.0093*		*0.011*
	Livestock	-0.048***	-0.051***	-0.047***	-0.050***	-0.053***	-0.080***		-0.047***
		0.0082	*0.0083*	*0.0079*	*0.0079*	*0.0086*	*0.0076*		*0.0082*
	Mixed food & livestock	-0.19***	-0.18***	-0.19***	-0.18***	-0.20***	-0.25***		-0.18***
		0.013	*0.013*	*0.013*	*0.013*	*0.013*	*0.012*		*0.013*
Soil 2 (Intermediate)	Tree-based	0.16***	0.15***	0.16***	0.18***	0.18***	0.19***		0.15***
		0.01	*0.01*	*0.01*	*0.01*	*0.01*	*0.0098*		*0.01*
	Food	-0.026**	-0.016	-0.024*	-0.031**	-0.017	0.014		-0.023
		0.013	*0.012*	*0.013*	*0.013*	*0.013*	*0.012*		*0.013*
	Livestock	-0.003	-0.015	-0.0019	-0.014	-0.018*	-0.029***		-0.0015
		0.01	*0.0098*	*0.01*	*0.0099*	*0.01*	*0.0099*		*0.01*
	Mixed food & livestock	-0.13***	-0.12***	-0.13***	-0.14***	-0.14***	-0.18***		-0.12***
		0.015	*0.015*	*0.015*	*0.015*	*0.015*	*0.014*		*0.015*
Age (Years)	Tree-based	0.0020***	0.0021***	0.0021***	0.0021***	0.0022***	0.0023***		0.0019***
		$2.45x10^{-4}$	*$2.46x10^{-4}$*	*$2.46x10^{-4}$*	*$2.48x10^{-4}$*	*$2.63x10^{-4}$*	*$2.60x10^{-4}$*		*$2.45x10^{-4}$*
	Food	-0.0013***	-0.0013***	-0.0014***	-0.0014***	-0.0015***	-0.0014***		-0.0013***
		$2.61x10^{-4}$	*$2.59x10^{-4}$*	*$2.61x10^{-4}$*	*$2.64x10^{-4}$*	*$2.66x10^{-4}$*	*$2.62x10^{-4}$*		*$2.63x10^{-4}$*
	Livestock	$5.85x10^{-4}$***	$5.07x10^{-4}$***	$5.86x10^{-4}$***	$5.54x10^{-4}$***	$5.94x10^{-4}$***	$5.81x10^{-4}$***		$5.98x10^{-4}$***
		$1.84x10^{-4}$	*$1.86x10^{-4}$*	*$1.84x10^{-4}$*	*$1.92x10^{-4}$*	*$1.94x10^{-4}$*	*$1.92x10^{-4}$*		*$1.86x10^{-4}$*
	Mixed food & livestock	-0.0012***	-0.0012***	-0.0013***	-0.0013***	-0.0014***	-0.0014***		-0.0012***
		$3.15x10^{-4}$	*$3.15x10^{-4}$*	*$3.16x10^{-4}$*	*$3.17x10^{-4}$*	*$3.21x10^{-4}$*	*$3.27x10^{-4}$*		*$3.18x10^{-4}$*
Male	Tree-based	0.034***	0.034***	0.032***	0.036***	0.039***	0.019**		0.036***
		0.0091	*0.0093*	*0.0092*	*0.0094*	*0.0097*	*0.01*		*0.0091*
	Food	-0.096***	-0.095***	-0.095***	-0.095***	-0.091***	-0.098***		-0.098***
		0.011	*0.011*	*0.011*	*0.011*	*0.011*	*0.011*		*0.011*
	Livestock	-0.079***	-0.080***	-0.079***	-0.084***	-0.088***	-0.075***		-0.080***
		0.0083	*0.0085*	*0.0082*	*0.0088*	*0.0091*	*0.0084*		*0.0084*
	Mixed food & livestock	0.14***	0.14***	0.14***	0.14***	0.14***	0.15***		0.14***
		0.012	*0.012*	*0.012*	*0.012*	*0.012*	*0.013*		*0.012*

Variable	Farming system	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Education 1 (Primary)	Tree-based	0.13***	0.13***	0.13***	0.14***	0.13***	0.18***		0.12***
		0.0085	*0.0085*	*0.0085*	*0.0085*	*0.0089*	*0.0084*		*0.0085*
	Food	-0.0066	-0.0062	-0.0076	-0.011	-0.012	-0.0067		-0.0059
		0.0086	*0.0086*	*0.0086*	*0.0087*	*0.0087*	*0.0085*		*0.0087*
	Livestock	0.069***	0.068***	0.069***	0.068***	0.073***	0.065***		0.070***
		0.0059	*0.0059*	*0.0059*	*0.006*	*0.0062*	*0.006*		*0.006*
	Mixed food & livestock	-0.19***	-0.19***	-0.19***	-0.20***	-0.20***	-0.24***		-0.19***
		0.011	*0.0108*	*0.011*	*0.011*	*0.011*	*0.011*		*0.011*
Education 2 (≥Secondary)	Tree-based	0.045***	0.046***	0.049***	0.052***	0.058***	0.070***		0.042***
		0.014	*0.014*	*0.014*	*0.014*	*0.015*	*0.014*		*0.014*
	Food	0.029	0.029	0.028	0.026	0.024	0.029		0.030**
		0.015	*0.015*	*0.015*	*0.015*	*0.015*	*0.015*		*0.015*
	Livestock	0.15***	0.15***	0.15***	0.16***	0.16***	0.16***		0.16***
		0.014	*0.014*	*0.014*	*0.015*	*0.015*	*0.015*		*0.014*
	Mixed food & livestock	-0.23***	-0.23***	-0.23***	-0.24***	-0.24***	-0.26***		-0.23***
		0.018	*0.018*	*0.018*	*0.018*	*0.018*	*0.018*		*0.018*
Household size	Tree-based	5.60×10^{-4}	6.24×10^{-4}	5.70×10^{-4}	9.36×10^{-4}	0.0025	0.0012		0.0018
		0.0014	*0.0014*	*0.0014*	*0.0014*	*0.0015*	*0.0015*		*0.0014*
	Food	-0.020***	-0.019***	-0.020***	-0.020***	-0.020***	-0.020***		-0.021***
		0.0018	*0.0017*	*0.0018*	*0.0018*	*0.0018*	*0.0018*		*0.0018*
	Livestock	-0.0050***	-0.0052***	-0.0050***	-0.0050***	-0.0057***	-0.0052***		-0.0051***
		0.0011	*0.0011*	*0.0011*	*0.0012*	*0.0012*	*0.0012*		*0.0012*
	Mixed food & livestock	0.024***	0.023***	0.024***	0.024***	0.023***	0.023***		0.024***
		0.0018	*0.0018*	*0.0018*	*0.0018*	*0.0018*	*0.0019*		*0.0019*
Log-likelihood Model		-7978	-8025	-7999	-8215	-8505	-8524	-8983	-7887
Wald Chi^2		2593***	2621***	2424***	2544***	2322***	2009***	1398***	2553***
Count R^2		0.624	0.623	0.621	0.615	0.597	0.594	0.619	0.627
AIC		16034	16128	16070	16489	17070	17107	18001	15851
AIC/N		1.84	1.85	1.85	1.9	1.96	1.97	2.07	1.84
BIC		16309	16404	16325	16702	17282	17319	18129	16127

Appendix 2.8: Estimated changes in the probability of selecting each crop at different latitudes under different climate scenarios[62]

Scenario	Latitude	Tree-based	Food	Livestock	Mixed food & livestock
Baseline	Below 6° N	0.40	0.16	0.088	0.36
	6-7° N	0.35	0.17	0.056	0.38
	7-8° N	0.34	0.21	0.072	0.38
	8-9° N	0.16	0.17	0.051	0.62
	9-10° N	0.14	0.15	0.055	0.65
	Over 10° N	0.046	0.15	0.096	0.71
Scenario 1	Below 6° N	-0.13	0.00	0.044	0.087
	6-7° N	0.034	-0.050	0.122	-0.040
	7-8° N	0.12	-0.024	-0.043	-0.057
	8-9° N	-0.038	0.049	-0.048	0.037
	9-10° N	-0.050	0.040	-0.052	0.062
	Over 10° N	-0.035	0.025	-0.095	0.10
Scenario 2	Below 6° N	-0.27	-0.024	0.14	0.16
	6-7° N	-0.063	-0.057	0.15	-0.0021
	7-8° N	-0.016	-0.030	-0.010	0.056
	8-9° N	-0.11	-0.0029	-0.038	0.15
	9-10° N	-0.11	-0.0063	-0.038	0.16
	Over 10° N	-0.043	-0.028	-0.079	0.15
Scenario 3	Below 6° N	-0.35	-0.049	0.19	0.21
	6-7° N	-0.15	-0.063	0.27	0.062
	7-8° N	-0.14	-0.054	0.058	0.14
	8-9° N	-0.14	-0.051	-0.012	0.20
	9-10° N	-0.13	-0.053	0.011	0.18
	Over 10° N	-0.045	-0.075	0.017	0.10
Scenario 4	Below 6° N	-0.39	-0.097	0.28	0.21
	6-7° N	-0.30	-0.093	0.33	0.12
	7-8° N	-0.30	-0.11	0.20	0.20
	8-9° N	-0.16	-0.11	0.070	0.20
	9-10° N	-0.14	-0.11	0.15	0.10
	Over 10° N	-0.046	-0.13	0.25	-0.076

[62] The tree-based farming system is any production system that involves the cultivation of trees such as specialised tree-crop, mixed tree-crop and food-crop, mixed tree-crop and livestock, and mixed tree-crop, food-crop, and livestock. Scenario 1 corresponds to an increase in temperature and rainfall by 0.7°C and 8%, respectively. Scenario 2 represents an increase in temperature and rainfall by 0.9°C and 1%, respectively. Scenario 3 shows an increase in temperature by 1.5°C and a 4% reduction in rainfall. Scenario 4 represents an increase in temperature by 0.5°C and a 15% increase in rainfall. Scenario 5 shows a 2°C increase in temperature and a 10% reduction in rainfall. In scenario 6, temperature increases by 0.5°C and rainfall declines by 10%. Scenario 7 represents a 2°C increase in temperature and a 15% increase in rainfall.

Scenario	Latitude	Tree-based	Food	Livestock	Mixed food & livestock
Scenario 5	Below 6° N	-0.40	-0.12	0.26	0.25
	6-7° N	-0.34	-0.13	0.011	0.14
	7-8° N	-0.34	-0.15	0.32	0.17
	8-9° N	-0.16	-0.15	0.27	0.041
	9-10° N	-0.14	-0.14	0.37	-0.094
	Over 10° N	-0.046	-0.14	0.52	-0.33
Scenario 6	Below 6° N	-0.29	0.00	-0.012	0.30
	6-7° N	-0.18	-0.020	0.253	0.19
	7-8° N	-0.17	-0.031	0.053	0.15
	8-9° N	-0.13	-0.054	0.059	0.12
	9-10° N	-0.12	-0.058	0.10	0.077
	Over 10° N	-0.042	-0.083	0.18	-0.057
Scenario 7	Below 6° N	-0.40	-0.11	0.31	0.20
	6-7° N	-0.34	-0.072	-0.040	0.16
	7-8° N	-0.33	-0.077	0.029	0.38
	8-9° N	-0.16	-0.11	-0.038	0.31
	9-10° N	-0.14	-0.11	-0.044	0.29
	Over 10° N	-0.046	-0.11	-0.09	0.25

Chapter 3

The Impact of Climate Change on Crop Selection and Revenue in Ghana: A Structural Ricardian Analysis

Abstract

Several methods have been used in studies to estimate the economic impact of climate change on agriculture. Many of these methods do not explicitly consider adaptation and thereby tend to produce biased estimates. We estimate the impact of climate change on crop production by applying a flexible form of the structural Ricardian model[63] to climate data (1973-2011) and farm observations (6,404) from Ghana. Based on our estimates, we simulate the potential impact of climate change and find that crop producers will likely adapt by switching from more profitable crops to the production of drought-tolerant crops such as millet. Our findings imply a significant decrease in aggregate revenue since millet is a low-value crop.

[63] The structural Ricardian model (SRM) is a simultaneous two-stage technique that analyses how climate impacts on farmers' crop selection decisions (in the first stage), and consequently estimates the conditional revenue function for each selected crop (in the second stage). In order to ensure increased flexibility, we include quadratic and interaction terms in the first-stage and estimate the second stage semi-parametrically.

3.1 Background

Climate change affects food production and vice versa[64] (Amikuzino and Donkoh, 2012; Asafu-Adjaye, 2014; Mendelsohn and Dinar, 2009a). The extent to which a country's food production is impacted by climate change depends on a combination of factors such as the level of development (Mendelsohn et al., 2001); adaptation capacity, technological capabilities, and location or latitude (Fleischer et al., 2008; Mendelsohn et al., 2006). Compared to developed countries, developing countries are often more adversely affected by climate change, because they are usually located in low latitudes where temperatures are already high and suboptimal for climate-sensitive food-crops (Da Cunha et al., 2015; Kurukulasuriya et al., 2006; Mendelsohn et al., 2006).

Climate change is both an environmental and a developmental challenge (Di Falco, 2014; Ministry of Food and Agriculture, MoFA, 2010). As a result of climate change, Sub-Saharan Africa's crop yields, food security, and economic growth may be hampered or even reversed due to its over-reliance on the weather coupled with limited human, capital, and technological capacities (Acheampong et al., 2014; Di Falco, 2014; Roudier et al., 2011; Thomas and Rosegrant, 2015). The region is already facing multiple stresses including limited use of technology (resulting in low productivity) and limited access to structured markets (Di Falco, 2014; Kurukulasuriya et al., 2006).

In Ghana for instance, productivity enhancing facilities such as screen houses, irrigation, and improved seed are either inadequate or non-existent (Amikuzino and Donkoh, 2012). The ability of the country to meet its food production targets depends chiefly on the vagaries of the weather (MoFA, 2007; 2014). Food-crop production in Ghana is mainly a rain-fed

[64] Agriculture impacts positively and negatively on climate change through carbon sequestration and greenhouse gas (GHG) emissions, respectively. The sector was responsible for 14% of the GHG emissions in 2010 (Intergovernmental Panel on Climate Change, IPCC, 2014).

activity since less than 1% of land is irrigated (MoFA, 2010; 2014; World Bank, 2010). The impact of climate change on Ghana's food-crops subsector is therefore expected to be higher than in other parts of the world. The threat is further aggravated by declining soil fertility arising from a myriad of factors including continuous cropping without adequate nutrient replacement, inadequate access to chemical fertilisers, soil erosion, and climate change-induced reduction of soil microbial activity (Kanton et al., 2016).

Given Ghana's vulnerability to climate change, we rely on a rich set of data to empirically evaluate the impact of climate change on food-crop production[65] using a two-stage micro-econometric model known as the structural Ricardian model (SRM). The first stage of the model involves estimating a crop selection equation. Conditioned on the selection estimates, the revenue function for each food-crop is then computed in the second stage. The estimated model can be used to simulate the potential impact of climate change under various climate scenarios. An attractive feature of the SRM is its ability to explicitly account for climate change adaptation such as switching of crop types. We avoid functional form misspecification by estimating a flexible SRM. Specifically, we estimate a semiparametric revenue equation conditioned on a flexible selection equation with quadratic and interaction terms. To the best of our knowledge, this study is the first to flexibly estimate the SRM with data from a developing country. Previous flexible estimations of the Ricardian model, a precursor to the SRM, include De Salvo et al., (2013b) who used data from Italy to estimate a Box-Cox model and Fezzi and Bateman (2015) who estimated a semiparametric model with data from Great Britain.

In addition to the functional form contribution, our study also provides evidence for policy decisions. Arndt et al., (2014) observe that a major impediment to incorporating climate

[65] The food-crops subsector contributes significantly to employment and GDP.

change issues in development planning in Ghana can be attributed to the absence of empirical evidence of the impacts of climate change. Even though global and regional models are useful in predicting the general effects of climate change on food-crop production, they fall short of providing detailed information of the impacts at the micro level. Micro level estimations are important since the impact of climate change varies from country to country (Mendelsohn et al., 2004). According to Asafu-Adjaye (2014), the effects of climate change on individual African economies is often inappropriately estimated or concealed in global studies. We, therefore, empirically evaluate the impact of climate change on food-crop production in Ghana. This chapter differs from the previous chapter in that we evaluate the impact of temperature and rainfall on both crop selection and crop revenue whereas we focused entirely on farm selection in Chapter 2.

In the next section, we present the concept behind the Ricardian method and show how our preferred method of analysis, the SRM, extends the Ricardian model. We end the section with a review of previous structural Ricardian papers. Our empirical strategy and variables are discussed in Section 3.3. We present our findings in Section 3.4. Section 3.5 concludes the study.

3.2 Ricardian Model and Its Extension

3.2.1 Conceptual framework of the Ricardian model

Even though the Ricardian model can be traced to Mendelsohn et al., (1994), it was named after David Ricardo due to his earlier proposition that the value of land reflects its best use (both current and potential). Thus, land values reflect the present value of all future annual revenue discounted at an appropriate rate (Darwin, 1999a; Mendelsohn et al., 1994; 1996).

The intuition behind the Ricardian model is presented in Figure 3.1 (Mendelsohn and Dinar, 1999; Mendelsohn et al., 1994). There is an optimal climate (temperature and rainfall) beyond which the performance of any food-crop will become sub-optimal. The Ricardian model argues that under unfavourable climatic conditions (e.g. rising temperature) when it is no longer optimal to produce rice but rather favourable to produce maize (corn), farmers in their own interest will shift from the cultivation of rice to maize. A further increase in temperature might make maize production sub-optimal but optimal for millet production in which case farmers will once again shift from maize to millet production. The same principle can be extended to substitutions between different varieties of the same food-crop and can be further extended to different environmental variables such as rainfall. Hence, the value of land will always reflect its best use even in the face of climate change and other external constraints (as represented by the farmer opportunity or broken function). In Ghana, there is evidence of crop switching as an adaptation response to climate change. For instance, some farmers in mid-Ghana are adapting to climate change by shifting from cocoa production to the cultivation of food-crops such as maize and cassava (Adjei-Nsiah and Kermah, 2012). In the far arid north, some farmers adapt to climate change by producing millet (Tambo, 2016).

Ignoring adaptation or treating farm management as a constant, as is often assumed by other models (e.g. the production function model), will result in a biased estimate of impact as farmers are hypothesised to continue to produce the same food-crop (no adaptation) instead of switching to the production of a different food-crop that performs optimally under the changed climate.

A distinctive feature of the Ricardian model is its ability to estimate the impact of climate change on both a change and a shift in the production function (Mendelsohn et al., 1994). Changes in production decisions (for example, substitution of inputs and farm enterprises) and productivity enhancements will result in a change and shift of the production function,

respectively. The Ricardian model, therefore, implicitly captures farmers' adaptation responses to climate change (Mendelsohn et al., 1994).

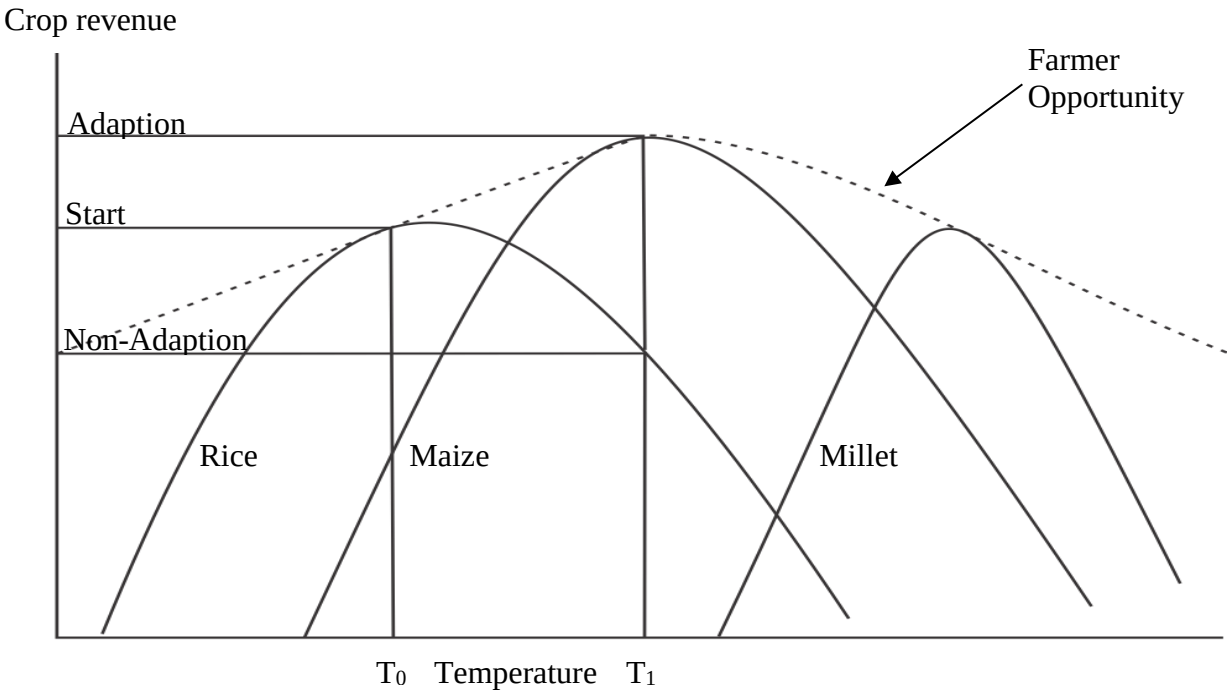

Figure 3.1: Intuition behind the Ricardian model (Mendelsohn and Dinar, 1999)

Assumptions of the Ricardian model

The Ricardian model, just like any other economic model, reflects complex reality by making a number of assumptions. Consistent with Ricardo's preposition as stated earlier, the Ricardian model assumes that farmers will select the best food-crop for their land when faced with climate change and other constraints (Mendelsohn and Dinar, 1999; Mendelsohn et al., 1994; 1996). Farmers are expected to notice or feel the impacts of climate change, identify appropriate adaptation options given market conditions and thereby modify their practices to maximise farm profits (Polsky, 2004). This assumption is plausible as there is overwhelming evidence that farmers are aware of climate change and have being modifying their practices to deal with the effects of climate change (see Chapter 2 of this thesis).

The approach also assumes that farmers are aware of the characteristics of their land[66] and that there is a unified land market. This assumption is also plausible since most food-crops are traded on the national markets thereby making the integration of land markets a possibility (Maddison, 2000). The approach further assumes that there is a perfectly competitive input and output market, with climate variables not having a direct influence on market prices (Ahmed and Schmitz, 2011; Benhin, 2008; Maddison, 2000; Maharjan and Joshi, 2013). Prices are therefore assumed to be stable and land values are expected to have attained a long-run equilibrium (Mendelsohn et al., 1994; 1996).

Criticisms of the Ricardian model

Since the pioneering work of Mendelsohn et al., (1994), the Ricardian model has been critically scrutinised, thereby leading to improvements in the original model. The approach has been criticised for capturing the cost of adaptation while failing to account for transitional cost (Apata et al., 2011; Closset et al., 2014; Darwin, 1999a; Maddison, 2000). As is common with reduced form models, the Ricardian analysis does not show how a farmer moves from an old state to a new state in adapting to climate change (Reilly, 1999). For example, if, as a result of climate change, a farmer adopts a new food-crop after testing it, the Ricardian model will capture the cost of producing the new food-crop. The model will not account for the cost of testing the new food-crop before full scale adoption. Similarly, if a farmer suddenly shifts to the cultivation of a new food-crop that requires new equipment, the Ricardian analysis will not capture the cost of disposing the old equipment associated with the abandoned food-crop.

In response, Mendelsohn and Nordhaus (1996) argue that the Ricardian analysis seeks to estimate long-term equilibrium effects and not short-term transitional cost. Also, transitional

[66] This assumption is plausible since farmers would usually make enquires about a parcel of land before purchasing it or, in instances where the land is inherited, they would have worked on it for a while before formally inheriting it, in which case they would have learnt about the characteristics of the land prior to inheritance.

cost may not be a problem where the cost of shifting from one adaptation practice to another does not involve heavy capital (Kurukulasuriya and Mendelsohn, 2006; Mendelsohn et al., 2010). This is mostly the case for smallholder peasant farmers in developing countries such as Ghana who deal with relatively small farm implements and machinery as compared to commercial farmers or farmers who use large machines. For smallholder farmers, transitional costs are likely to be negligible in the long-run (Mendelsohn and Nordhaus, 1999). Timmins (2006) concludes that ignoring transitional cost may be appropriate since his study in Brazil yield similar estimates for two transitional cost scenarios, that is, zero adjustment cost and prohibitive adjustment cost.

The Ricardian model has also been criticised for not accounting for changes in prices (Cline, 1996; Darwin, 1999a) and has even been labelled by Darwin (1999a) to be a good qualitative but poor quantitative measure of the impact of climate change on food production. The assumption of constant prices has been criticised to be a rather strict one, since farm-level adaptation may result in an increase in production which could lead to a reduction in prices due to increased supply. In addition, production changes in other countries may influence world prices; hence, the model is likely to exaggerate both the quantitative benefits and costs of climate change thereby resulting in a net positive bias (Darwin, 1999a). In response, it has been argued that welfare biases associated with climate induced changes will be marginal if the difference between global supply and demand is small (Mendelsohn and Dinar, 1999; Mendelsohn and Schlesinger, 1999; Mendelsohn and Nordhaus, 1996; Mendelsohn et al., 1994). In addition, it is often difficult to empirically estimate price changes since such changes depend on the global market. According to Kurukulasuriya and Mendelsohn (2006), studies that attempt to take price changes into consideration have had to make several other assumptions about how production will change with climate change; hence it is not unusual for partial equilibrium models to assume constant prices.

The Ricardian model is a static analysis (De Salvo et al., 2013b) and as is common with all static models, the approach has been criticised for failing to measure variables that do not vary over space, for example, the effect of carbon fertilisation[67] (Kurukulasuriya and Mendelsohn, 2006; Mendelsohn and Dinar, 2009a; Mendelsohn and Schlesinger, 1999), as well as variables that could change drastically over time such as technology (Closset et al., 2014; Gbetibouo and Hassan, 2005; González and Velasco, 2008; Kurukulasuriya and Mendelsohn, 2006), taxes, and trade policies (Kurukulasuriya and Mendelsohn, 2006; Mendelsohn and Dinar, 2009a). Darwin (1999a) also argues that the Ricardian model does not show how benefits and losses could be transferred from one region to another through trade. These are valid criticisms common with static models and are important considerations for future extensions of the model.

Future changes in climate that do not resemble any existing conditions cannot be estimated by the Ricardian model (Darwin, 1999a; Stern, 2013). Hence, the model cannot accurately estimate the impact of climate change if there are little or no variations in the climate of the study area (Kurukulasuriya and Mendelsohn, 2006). We avoid this criticism by utilising data from six major agro-ecologies that have different climatic conditions.

Earlier Ricardian studies were criticised for not explicitly accounting for irrigation even though irrigation can have an influence on the extent to which food production will be impacted by climate change (Cline, 1996; Darwin, 1999b). The response to this criticism has been varied. Some studies respond by including an irrigation variable[68] or estimating

[67] Elevation of carbon dioxide levels could be beneficial for plant growth and yields since carbon dioxide is needed for photosynthesis. Increased carbon dioxide could enlarge the world's biosphere leading to the so called global greening phenomenon (Ausubel, 2015).

[68] For instance, Coster and Adeoti, 2015; Dung and Phuc, 2012; Gbetibouo and Hassan, 2005; Kar and Das, 2015; Kumar, 2011; Kurukulasuriya and Ajwad, 2007; Mano and Nhemachena, 2007; Mendelsohn et al., 2010; Mishra and Sahu, 2014; Molua, 2008; 2009; Ngondjeb, 2013; Nhemachena, 2014; Polsky and Easterling, 2001; Seo and Mendelsohn, 2008b; Wang et al., 2009; 2014.

different Ricardian models for dryland and irrigated farms.[69] Other studies capture irrigation using surface runoff as a proxy variable.[70] Empirical results from these studies have been mixed. While some studies have found a positive relationship between irrigation and farm values, other studies have found either a negative or insignificant effect (Mendelsohn, 2005; Mendelsohn and Williams, 2004). In Ghana, less than 1% of land is under irrigation (MoFA, 2010; 2014; World Bank 2010). We therefore focus our analyses on dryland or unirrigated food-crop production.

Overall, the Ricardian model has been found to be a good tool for empirically estimating the impact of climate change (De Salvo et al., 2013b; Timmins, 2006). Because of the criticisms and widespread empirical applications, the model has been improved over the last two decades. According to De Salvo et al., (2013a), the Ricardian model is the most used empirical micro-econometric tool. Its strength lies in its ability to incorporate farm-level adaptation whilst utilising micro-level data. It is also easy to compute and yields geographically reliable estimates.

Improvements in the Ricardian model

The Ricardian approach to estimating the economic impact of climate change on food-crop production has been evolving since the pioneering work of Mendelsohn et al., (1994). Even though earlier Ricardian analysis implicitly accounts for whole-farm adaptation, it does not specify the exact adaptation responses used to adjust to climate change as well as the impact of each adaptation response on land value or net revenue (Chatzopoulos and Lippert, 2015; González and Velasco, 2008). A recent Ricardian model, referred to as the structural Ricardian model (SRM) in the literature, explicitly accounts for adaptation and its consequent

[69] For instance, Ajetomobi et al., 2010; Benhin, 2008; Deressa et al., 2005; Kurukulasuriya and Mendelsohn, 2006; Seo et al., 2005.
[70] For instance, Benhin, 2006; Kurukulasuriya et al., 2006; Ouedraogo et al., 2006; Seo et al., 2009.

effect on land value or net revenue (Chatzopoulos and Lippert, 2015). We utilise the SRM to assess the impact of climate change on Ghana's food-crop production. The model is discussed in Section 3.3.3.

Further improvements in the Ricardian model have been in the area of dealing with estimation and econometric problems,[71] choice of functional form (De Salvo et al., 2013b; Fezzi and Bateman, 2015), and choice and measurement of climate variables (Auffhammer et al., 2013; Dell et al., 2014; Mendelsohn et al., 2004; Mendelsohn et al., 2007a, b). This study contributes to the literature in terms of flexible estimation of the SRM. In that regard, we are among the first to utilise data from a developing country.

3.2.2 Theoretical framework of the Ricardian model

The Ricardian model, which is the foundation of the SRM, is derived below. Farmers are hypothesised to maximise profits under the Ricardian model. Following Mendelsohn et al., (1996), the output (Equation 3.1), cost (Equation 3.2) and profit maximising (Equation 3.3) functions can be specified as:

$$Q_j = Q_j(\boldsymbol{K_j}, \boldsymbol{E}), j = 1, \dots, J, \tag{3.1}$$

$$C_j = C_j(Q_j, \boldsymbol{R}, \boldsymbol{E}), \tag{3.2}$$

$$max_{Q_j} P_j Q_j - C_j(Q_j, \boldsymbol{R}, \boldsymbol{E}) - \rho_{LE} L_j\,(E), \tag{3.3}$$

where Q_j is the output from food-crop j; $\boldsymbol{K_j}$ is a vector of the inputs used in producing food-crop j excluding land; $\boldsymbol{E}$ is a vector of exogenous climate and environmental variables, which could be the same for the production of different food-crops within the same locality; $\boldsymbol{R}$ is a

[71] See Ahmed and Schmitz, 2011; Benhin, 2008; Chatzopoulos and Lippert, 2015; Da Cunha et al., 2015; De Salvo et al., 2013b; Di Falco et al., 2012; Fleischer et al., 2008; Fisher et al., 2012; Kurukulasuriya and Ajwad, 2007; Mano and Nhemachena, 2007; Ngondjeb, 2013; Seo, 2008; Schlenker et al., 2006; Timmins, 2006; Reinsborough, 2003.

vector of input prices excluding land rent; C_j is the cost of producing food-crop j excluding the value of land; P_j is the output price for food-crop j; $\rho_{LE}$is the yearly cost or rent of land; and $L_j\ (E)$ is the amount of land used in producing food-crop j. Climate affects land in two ways. It affects both the value (productivity) and the amount of land that can be used for production (Mendelsohn et al., 1996).

Under competitive conditions, pure profits will be driven to zero, hence:

$$P_j Q_j(\boldsymbol{K_j}, \boldsymbol{E}) - C_j(Q_j, \boldsymbol{R}, \boldsymbol{E}) - \rho_{LE} L_j(E) = 0, \tag{3.4}$$

Solving for ρ_{LE} results in:

$$\rho_{LE} = \frac{P_j Q_j(\boldsymbol{K_j}, \boldsymbol{E}) - C_j(Q_j, \boldsymbol{R}, \boldsymbol{E})}{L_j(E)}, \tag{3.5}$$

It can be deduced from Equation (3.5) that for each hectare of land, its rent will be equal to the net revenue from its most productive use. Mathematically, the present value of land can be calculated by relying on the future streams of net revenue to compute the integral expression:

$$V_{LE} = \int_0^\infty \rho_{LE} e^{-rt} dt = \int_0^\infty \frac{[P_j Q_j(\boldsymbol{K_j}, \boldsymbol{E}) - C_j(Q_j, \boldsymbol{R}, \boldsymbol{E})] e^{-rt}}{L_j(E)} dt, \tag{3.6}$$

where V_{LE} is the present value of land, and r is the discount rate. Equation (3.6) summarises the key idea of the Ricardian model in that changes in environmental conditions affect food-crop production and thus costs, which in turn affect the land value. Formally, a change in the annual land value resulting from a change in climate can be represented by:

$$\Delta V_{LE}(\boldsymbol{E}_B - \boldsymbol{E}_A) = \int_0^{Q_B} \frac{[P_j Q_j(\boldsymbol{K_j}, \boldsymbol{E}) - C_j(Q_j, \boldsymbol{R}, \boldsymbol{E})] e^{-rt}}{L_j(E)} dQ - \int_0^{Q_A} \frac{[P_j Q_j(\boldsymbol{K_j}, \boldsymbol{E}) - C_j(Q_j, \boldsymbol{R}, \boldsymbol{E})] e^{-rt}}{L_j(E)} dQ, \tag{3.7}$$

where $\boldsymbol{E}_A$ is the baseline climate, and $\boldsymbol{E}_B$ is the changed climate. If farmers' expectations of future prices are not different from the baseline prices, Equation (3.7) then becomes:

$$\Delta V_{LE}(\boldsymbol{E}_A - \boldsymbol{E}_B) = \left[\boldsymbol{PQ}_B - \sum C_j\left(Q_j, \boldsymbol{R}, \boldsymbol{E}_B\right)\right] - \left[\boldsymbol{PQ}_A - \sum C_j\left(Q_j, \boldsymbol{R}, \boldsymbol{E}_A\right)\right] = \Delta W, \quad (3.8)$$

where ΔW is the change in welfare resulting from the change in land value due to climate change. Rearranging Equation (3.5) results in:

$$\rho_{LE} L_j(E) = P_j Q_j\left(\boldsymbol{K_j}, \boldsymbol{E}\right) - C_j\left(Q_j, \boldsymbol{R}, \boldsymbol{E}\right), \quad (3.9)$$

Substituting Equation (3.9) into Equation (3.8) yields:

$$\Delta W = W(\boldsymbol{E}_A - \boldsymbol{E}_B) = \sum_j (V_{LEB} L_{jB} - V_{LEA} L_{jA}), \quad (3.10)$$

The present value of welfare change is (Mendelsohn et al., 1996):

$$\int_0^\infty W(\boldsymbol{E}_A - \boldsymbol{E}_B) e^{-rt} dt = \sum_j \left(V_{LEB} L_{Bj} - V_{LEA} L_{Aj}\right), \quad (3.11)$$

Equation (3.11) shows that, given prices, the value of environmental change is captured by the change in aggregate land values. Depending on the data available, the Ricardian model can be estimated using Equation (3.10) or (3.11) as the dependent variable. Equation (3.11) is used when data on capitalised land values ($V_{LE}L$) are available. These are normally not available in developing countries hence agricultural net revenues (Equation (3.9)) are often utilised to assess the impact of climate change by estimating the regression:

$$\rho_{LE} L_j(E) = P_j Q_j - C_j\left(Q_j, \boldsymbol{R}, \boldsymbol{E}\right) = \pi_j = \boldsymbol{\beta X} + \boldsymbol{u}, \quad (3.12)$$

where π_j is net revenue from food-crop j; $\boldsymbol{\beta}$ is a vector of Ricardian parameter estimates; $\boldsymbol{X}$ is a vector of climate, farm, and farmer characteristics; and $\boldsymbol{u}$ is the error term of the Ricardian model. We employ the SRM (which builds on the Ricardian model) to estimate impact of climate change on food-crop production in Ghana.

3.2.3 The structural Ricardian model (SRM)

The SRM is a simultaneous two-stage optimisation procedure that analyses farm-level adaptation choices in the first stage and conditional net revenue functions in the second stage (Elbehri and Burfisher, 2015; Kurukulasuriya and Mendelsohn, 2008; Seo, 2015; Seo and Mendelsohn, 2008a). Empirically, a multinomial logit model is estimated in the first stage in order identify the types of food-crop that are used by farmers to adapt to climate change and, in the second stage, a 'traditional' Ricardian model is estimated whilst accounting for selection bias.

As shown by McFadden (1973), the probability that farmer i will choose food-crop j among J alternatives in the face of climate and other constraints, assuming that the error term is independently and identically distributed and drawn from a Gumbel distribution (in order to invoke the IIA hypothesis), can be expressed as:

$$Prob(Y_i = j) = \frac{\exp(\beta_j x_i)}{\sum_{k=1}^{J} \exp(\beta_k x_i)}, j = 1, \dots . J, \tag{3.13}$$

Equation (3.13) is the standard multinomial logit model and serves as the first stage in the estimation of the SRM. Because the second stage is only estimable if a particular food-crop is selected in the first stage, the model is likely to suffer from selection bias since the choice of a food-crop will be correlated with its conditional net revenue, i.e. the error terms of the first (multinomial) and second ('traditional' Ricardian model) stages will be correlated. Least squares estimate of the SRM without correcting for this selection bias can lead to inconsistent results (Bourguignon et al., 2007). The bias can be corrected by using Lee's or Dahl's or Dubin and McFadden's method.[72] The Dubin–McFadden method, which we use, has been

[72] See Bourguignon et al., (2007) for a review and the theoretical underpinnings.

found to be superior to other methods (Bourguignon et al., 2007). For food-crop 1, the selection correction term is shown on the right-hand side of Equation (3.14):

$$\pi_1 = \beta_1 X_1 + \delta \frac{\sqrt{6}}{\pi} \sum_{j=2....M} r_j \left(\frac{P_j ln(P_j)}{1-P_j} + ln(P_1) \right) + w_1, \qquad (3.14)$$

where π_1 is the net revenue from food-crop 1, X_1 is a vector of climate, farm, and farmer characteristics associated with the production of food-crop 1, δ is the standard error of the second stage net revenue equation, r is the correlation coefficient between the conditional net revenue and multinomial equations, and w is the error term from the conditional net revenue equation. The selection correction term is the obvious difference between Equation (3.14) and the Ricardian model (Equation 3.12), hence the simultaneous estimation of Equations (3.13) and (3.14) has become known as the SRM. OLS can provide unbiased estimates of Equation (3.14).[73]

3.2.4 Ricardian data types

Even though the Ricardian analysis was developed as a cross-sectional technique, a couple of studies use panel data to estimate the model.[74] Both types of data can be used to estimate the model provided there is sufficient variation in the dataset, i.e sufficient cross-sectional or time variation in the cross-sectional or panel dataset. Each data type has some advantages and disadvantages. Whereas modelling panel data will potentially eliminate omitted variable bias, time variability in panel datasets is often negligible compared to cross-sectional variability (Fezzi and Bateman, 2015). Short-term panel data (less than 30 years) measure the effects of weather whilst cross-sectional climate data measure the effects of climate. It is unlikely that

[73] Note that we did not estimate the conventional second stage net revenue equation (3.14), instead, we treated the functional relationship of climate differently from the other explanatory variables (see Section 3.4).

[74] For example, Hanif et al., 2010; Kumar, 2011; Kumar and Sharma, 2014; Nkegbe and Kuunibe, 2014.

the climate at any location will change significantly within a short period of time in order to make it possible for a short panel data to capture its effects.

Due to limited variability, Dell et al., (2014) observe that short-term panel data often result in the estimation of the impact of a weather shock on an economic variable. Similar views are expressed by Kurukulasuriya and Mendelsohn (2008) who report that short-term panel data usually measure the impact of climate 'surprise' and not climate change. Changes in weather are surprises to farmers, hence they may not have enough opportunities (for example, time and technology) to adequately adapt to such weather changes (Massetti and Mendelsohn, 2011). According to Massetti and Mendelsohn (2011), short-term panel data measure intertemporal variation and are therefore not very suitable in measuring the impact of climate change. Inter-annual changes in weather are a poor proxy for climate and are not a good measure for long-term climatic impacts. Intertemporal analysis of weather may therefore result in a very good estimate but of the wrong phenomenon (Massetti and Mendelsohn, 2011). Since cross-sectional variation in climate can be used to estimate the SRM, we match cross-sectional farm data with long-term climate to estimate our model.[75]

The Ricardian model and its extension, the SRM, can be estimated with data at the household or higher level (community, district/county, or region). Analysts that rely on data from developed or emerging economies, or from multiple countries, usually estimate the model with aggregate data[76] whilst researchers who study developing countries and single country studies often use household data.[77]

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[75] See Chapter 1 (of this thesis) for a description of our data sources.

[76] For example, Aurbacher et al., 2010; Chatzopoulos and Lippert, 2015; Chen et al., 2013; Fezzi and Bateman, 2015; Kar and Das, 2015; Kumar, 2011; Maddison, 2000; Mendelsohn and Reinsborough, 2007; Mendelsohn et al., 2007a, b; Mendelsohn et al., 2001; Mendelsohn et al., 1994; 1996; Mishra and Sahu, 2014; Polsky and Easterling, 2001; Reinsborough, 2003; Sanghi and Mendelsohn, 2008; Seo et al., 2009; Seo et al., 2005; Timmins, 2006; Van Passel et al., 2014.

[77] For example, Ajetomobi et al., 2010; Benhin, 2006; Closset et al., 2014; Coster and Adeoti, 2015;

3.2.5 Previous estimations of the structural Ricardian model

The Ricardian model has been used to evaluate the impact of climate change on agriculture in various parts of the world. See Mendelsohn and Dinar (2009b) for a review of previous Ricardian studies. Since our study employs the SRM, we review only the structural Ricardian studies in this section. Empirically, the SRM has been applied to estimate the impact of climate change on food-crop production, livestock production, and farming systems. None of the studies reviewed explicitly address issues of model specification. This section only highlights the key findings and gaps of studies that apply the SRM. The intuition behind past results are discussed along with our findings (Section 3.4).

We begin our review with structural Ricardian estimates of the impact of climate change on crop production. In Ghana, Issahaku and Maharjan (2014) use the technique to assess the impact of climate change on net revenues of five food-crops. They report that temperature has a positive (negative) effect on sorghum (maize) selection and revenue. Temperature also impacts positively on the selection of rice and yam but has a negative effect on their resulting revenues. The reverse holds for cassava. Apart from sorghum and maize, rainfall has a negative effect on revenue as well as the probability of selecting any other crop. Rainfall has a positive (negative) influence on the selection of maize (sorghum) but a negative (positive) influence on its revenue. They find that even though age and sex do not significantly influence revenue from food-crops, they are important in determining which food-crops are selected for production. Compared to maize, older and female-headed households are less likely to select rice and sorghum. Household size has a positive effect on the selection and consequently net revenues from all food-crops. Education has a positive (negative) effect on

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Da Cunha et al., 2015; Dung and Phuc, 2012; Fleischer et al., 2008; Fonta et al., 2011; Issahaku and Maharjan, 2014; Kurukulasuriya and Ajwad, 2007; Mano and Nhemachena, 2007; Mendelsohn et al., 2010; Molua, 2009; Nkegbe and Kuunibe, 2014; Onoja and Achike, 2014; Ouedraogo et al., 2006; Seo, 2015; Seo and Mendelsohn 2007a, b; 2008a, b; Shakoor et al., 2011; Tibesigwa et al., 2015.

cassava (rice) selection but a negative (positive) effect on its revenue. Larger farms are associated with rice and yam selection and vice versa for cassava. Unlike many related studies, Issahaku and Maharjan (2014) fail to control for soil type, a very important determinant of crop productivity. They also did not consider non-linear influences of the climatic variables (squared terms). In addition, they relied on data from limited amount of weather stations (10) and households (3718) for their estimation. Finally, their choice of crop price as an instrument (for model identification) can be problematic since crop price is a likely determinant of crop revenue hence its exclusion from the revenue equation may not be valid.

Eleven African countries were studied by Kurukulasuriya and Mendelsohn (2008). Their analyses of 7,296 observations show that an increase in temperature reduces the probability of farmers cultivating sorghum, fruits-vegetables, maize-beans, and maize-groundnut (peanut) but increases the probability of selecting all other crops (cowpea, cowpea-sorghum, maize-millet, and millet-groundnut). Warming has a positive impact on revenues from maize, fruits-vegetables, maize-groundnut, maize-millet, and millet-groundnut. Increases in precipitation reduces the probability of farmers selecting cowpea, sorghum, cowpea-sorghum and millet-groundnut, but increases the probability of selecting fruits-vegetables, maize-beans, maize-groundnut, and maize-millet. Precipitation has a positive impact on net revenues from all crop types except maize-groundnut, and maize-millet combination. Soil type also influences crop choice. Compared to maize, farmers with steep farmlands and fine-textured soils are more likely to choose millet-groundnut but less likely to choose cowpea, sorghum, cowpea-sorghum, maize-beans, and fruits-vegetables. Although household size influences the selection of all farm types positively, it significantly impacts on net revenue from only the maize-groundnut combination.

The study of Kurukulasuriya and Mendelsohn (2008) suffers a few limitations. Their findings are too broad since they combined data from several countries without accounting for individual country effects. Culture is one variable that could be an important determinant of cross-country heterogeneity. For example, the cultivation of certain crops is gender-specific in some countries (e.g. yam is perceived as a male crop in Nigeria), but this is a cultural phenomenon that varies a lot more across countries than it does within countries. In addition to undertaking aggregate analysis, they dropped some observations without stating how they dealt with the resulting loss of information or potential sample selection bias. Only crop combinations with at least 100 observations were retained for their analysis. The crop combinations that were dropped could become important under a changed climate. Instead of omitting those 'minor' crops, aggregation of those crops into an 'other crops' category could have been valuable. Finally, Kurukulasuriya and Mendelsohn (2008) failed to control for farmer characteristics even though the data was available.

Seo and Mendelsohn (2008a) apply the SRM to study the impact of climate change on livestock production by utilising data from 5,000 African livestock farmers. Conditioned on climate, they find that livestock that are frequently chosen also have the highest net revenues and vice versa. As temperature increases, farmers switch from beef cattle, dairy cattle, and chicken production to small ruminant production (goat and sheep). The relationship between net revenue and temperature is inverse for beef cattle but direct for sheep and goat. As rainfall increases, farmers switch from beef cattle, dairy cattle, and sheep production to goat and chicken production. Net revenue from beef cattle, dairy cattle, and sheep decreases whilst that of goat and chicken increases with increases in rainfall. Whereas the influence of soil variables on livestock choice and income is weakly significant, that of age and sex is insignificant. Seo and Mendelsohn (2008a) suffer the same limitations as Kurukulasuriya and Mendelsohn (2008). Indeed, both studies rely on the same dataset for their analysis. In

addition to the limitations already highlighted, Seo and Mendelsohn (2008a) controlled for a new explanatory variable (sale price) in the outcome/net revenue equation. According to Wooldridge (2012), the outcome variables should be a subset of the selection variables. Omission leads to large standard errors since variables that are excluded from the selection equation cannot be factored in the derivation of the selection terms. Lastly, even though the SRM is a static analysis, Seo and Mendelsohn (2008a) generate predictions far into the future (2100). These predictions maybe unreliable if technology and policy changes.

In Germany, Chatzopoulos and Lippert (2015) depend on data from 9,684 observations to estimate the structural Ricardian impact of climate change on farm types. Compared to forage farms (grazing livestock), temperature favours the selection of all other farm types (cash crops, i.e. wheat, barley, potato, sugar beer; livestock fattening, i.e. pigs, poultry; permanent crops, i.e. fruit trees, vine, hop; horticultural crops, i.e. vegetables, floriculture, tree nursery; and mixed farms). Temperature also has a positive effect on rents from all farm types except horticultural farms. Precipitation has a positive effect on rents from all farm types. Compared to forage cultivation, productive soils are more likely to be allocated to cash and permanent crop production. Less productive soils are more likely to be allocated to mixed farm and livestock production. Higher soil productivity translates into higher rents for all farm types except permanent crops. Land-extensive crops are more likely to be allocated to larger farms and labour-intensive (horticultural) crops are more likely to be allocated to smaller farms. The study of Chatzopoulos and Lippert (2015) also has some weaknesses. Although it is well documented that the selection and outcome equations of the SRM are likely to be correlated (Bourguignon et al., 2007; Issahaku and Maharjan, 2014; Seo and Mendelsohn, 2008a, b; Seo, 2015), they failed to account for selection bias. Also, it is not clear how they dealt with possible loss of information after they discarded some observations or farm types.

Seo and Mendelsohn (2008b) measure the impact of climate change on choice of farm type by using 7,965 observations from 10 African countries. Except for irrigated crop production, estimates of the SRM show that temperature has the same effect on choice of farm type (rain-fed crop production, rain-fed mixed farming, irrigated mixed farming and livestock production) and net revenues. A 1°C increase in temperature results in farmers switching from specialised crop and livestock production to mixed farming. An increase in rainfall favours the selection and revenue from rain-fed crop production. The influence of soil on choice of farm type is mixed. Farmers are more likely to choose mixed rain-fed farms when soils are lithosol (i.e. with lots of pebbles). Rain-fed crop farms earn lower incomes if soils are lithosol. Similarly, both rain-fed and irrigated crop farms earn lower incomes when soils are vertisol (i.e. with lots of clay). The study of Seo and Mendelsohn (2008b) has the same drawbacks as their earlier paper (Seo and Mendelsohn, 2008a) except that the covariates of the outcome equation are a subset of the selection equation as expected.

In South America, Seo (2010) and (2015) estimate the impact of climate change on choice of farm type using 2,000 observations from 7 countries. Their results show that a marginal increase in temperature or precipitation results in farmers moving from crop production to mixed farm and livestock production. The relationship between summer temperature and land value is U-shaped for mixed farm; whereas the relationship between summer temperature and crop or livestock production is hill-shaped. The relationship between summer precipitation and land value is hill-shaped for all farm types. The response function between winter precipitation and crop production is U-shaped. Crops are more likely to be cultivated on lithosols or phaeozems soils. Kastanonzem soils favour the selection of mixed farms. Phaeozem soils have positive influence on the land value of crop and mixed farms but not livestock farms. Older farmers avoid specialising in livestock production and female farmers prefer crop production to mixed farming. Household size and education impact positively on

land values from specialised and mixed farms, respectively. However, both variables do not significantly influence selection. The main limitations of Seo (2010) and (2015) are that simulations are too far into the future and the findings are too general (for several countries).

Our review shows that climate, farm, and farmer characteristics are important in explaining the types of crops that are produced and the income that results from production. Covariates do not always have the same effect on crop selection and revenue. For the same crop, a variable can have a positive effect on selection but a negative effect on revenue (see Section 3.4.2 for possible explanations of this observation). The effect of temperature, rainfall, soil, education, sex, age, household size, and farm size on crop production varies between locations/countries and production systems. Based on our review, we control for farm and farmer characteristics in addition to our main variables of interest (temperature and rainfall).

3.3 Estimation Procedure

3.3.1 Choice of functional form

Functional form misspecification can result in misleading conclusions. Different functional forms can result in different predictions of the effects of climate change (De Salvo et al., 2013b). Yet, the majority of Ricardian studies assume that the response function between agricultural revenue and climate is quadratic (with all the variables measured in levels,[78] or

[78] See for example, Ahmed and Schmitz, 2011; Ajetomobi et al., 2010; Amassaib et al., 2015; Apata et al., 2011; Benhin, 2008; Chen et al., 2013; Closset et al., 2014; Coster and Adeoti, 2015; Deressa et al., 2005; Di Falco et al., 2012; Firdaus et al., 2012; Fleischer et al., 2008; Gbetibouo and Hassan, 2005; Hanif et al., 2010; Kar and Das, 2015; Kumar, 2011; Kumar and Sharma, 2014; Kurukulasuriya and Ajwad, 2007; Liu et al., 2001; 2004; Mano and Nhemachena, 2007; Mendelsohn and Reinsborough, 2007; Mendelsohn et al., 1996; Mikémina, 2013; Mishra and Sahu, 2014; Ngondjeb, 2013; Reinsborough, 2003; Sanghi and Mendelsohn, 2008; Seo and Mendelsohn, 2007b; 2008a; Seo et al., 2008; Shakoor et al., 2011; Tibesigwa et al., 2015; Wang et al., 2009; 2014; Wood and Mendelsohn, 2015; Zainal et al., 2012; 2014.

with the dependent variable log-transformed[79] or with one independent variable log transformed (household size)[80]).

Although the quadratic transformation of the climate variables seems to be reasonable, there is no theoretical justification for assuming such a strict representation except for the ease of computation (Fezzi and Bateman, 2015). Therefore, it is important to estimate a flexible model that allows the data to suggest the most appropriate functional form. In that regard, there are several techniques that can be used to estimate a flexible functional form. One option is to estimate a fully nonlinear model where all the explanatory variables are jointly determined nonparametrically.[81] The drawbacks of this approach are its computational difficulty, (Keele, 2008; StataCorp, 2017), lack of parameters for precise interpretation (Keele, 2008), requirement for a relatively large dataset, and the well-known problem of the 'curse of dimensionality'[82] (Fezzi and Bateman, 2015; StataCorp, 2017). The availability of modern computers and the ability to generate functional relationships with confidence bands make it possible to deal with some of the limitations of nonparametric regressions (Keele, 2008).

Another option is to estimate an additive model as in Fezzi and Bateman (2015) where all the explanatory variables are separately determined nonparametrically. This approach avoids the problem of dimensionality but requires all the explanatory variables to be continuous (Keele, 2008). Since some of our explanatory variables are categorical, we estimate a semiparametric (partially linear) model instead. A semiparametric regression combines the attractive feature

[79] For example, Chatzopoulos and Lippert, 2015; Fezzi and Bateman, 2015; Mendelsohn et al., 2010; Miah et al., 2014; Van Passel et al., 2014.

[80] For example, Kurukulasuriya and Mendelsohn, 2006; Kurukulasuriya et al., 2006; Molua 2009; Nhemachena 2014; Ouedraogo et al., 2006.

[81] Nonparametric regression makes it possible to robustly estimate the relationship between variables when the functional form is unknown (Keele, 2008; StataCorp, 2017).

[82] It is difficult to obtain local fits as well as interpret (visualise) the results when more than 2 variables (3 dimensions) are jointly estimated nonparametrically (Keele, 2008).

of precise interpretation from parametric models and the flexibility of nonparametric models (Robinson, 1988). The model yields consistent results even in the presence of heteroscedasticity[83] (Keilegom and Wang, 2010). Following Robinson (1988), we estimate Equation (3.14) semi-parametrically as;

$$\pi = f(Z) + \beta O \tag{3.15}$$

Where Z represents the climate variables and O represents all the other explanatory variables including the selection terms (estimated from the first stage/multinomial equation). The Z variables are modelled nonparametrically whilst the O variables are modelled parametrically. The parameter estimates associated with O are β.

In order to capture possible nonlinear effects, a smooth estimator is required to determine the functional relationship between π and Z (i.e. $f(.)$). For this study, we use the kernel estimator. Although there are several smooth estimators, the kernel estimator is the most popular (Lee, 1996) and has been shown to be superior to many widely used methods such as histograms, box plots, cumulative distributions, and raw plot[84] (Cox, 2007). There are different types of kernel estimators/functions including Epanechnikov, biweight, cosine trace, Gaussian, Parzen, rectangle, and triangle (StataCorp, 2017). Due to its robustness to outliers, we used the Epanechnikov kernel function to determine the relative weight to allocate to each observation (in computing the average conditional revenue at each climate observation).

All smooth estimators (including the Kernel-based estimator) require an optimal bandwith selector that minimises the trade-off between bias and variance (Keele, 2008; StataCorp, 2017). An optimal bandwith selector uses the data to determine the right amount of

[83] Semiparametric regression textbooks include Härdle et al., (2004); Keele (2008); Ruppert et al., (2003). See Ruppert et al., (2009) for a review of semiparametric studies published between 2003 and 2007. Ruppert et al., (2003) review studies published before 2003.

[84] See Keele (2008) for a discussion on the merits and demerits of the various smooth estimators such as kernel, local polynomial, and splines.

smoothing required to fit the model thereby ensuring that the analyst does not deliberately choose to either underfit or overfit the model (Keele, 2008). Examples of kernel-based optimal bandwith selectors include cross-validation (Li and Racine, 2004) and improved Akaike information criterion (AICc) (Hurvich et al., 1998). Compared to cross-validation or the earlier Akaike information criterion, AICc performs better in avoiding large variance and undersmoothing (Hurvich et al., 1998). Therefore, we use the AICc bandwith selector to determine the number of observations that is required to optimally estimate the conditional mean revenue at each climate and on that basis, identify the appropriate functional form. The procedure outlined above is formally referred to as the local-linear kernel regression (StataCorp, 2017). The local-linear kernel regression has been shown to be superior to an alternate procedure known as the local-constant kernel regression (Li and Racine, 2004).

Having shown that our version of the SRM entails a first-stage multinomial logit and a second-stage semiparametric regression, it is worth stating the empirical model explicitly. Our empirical selection (Equation 3.13) model is:

$$P(Y_{\mathrm{F|B}}) = \beta_{0,\mathrm{F|B}} + \beta_{1,\mathrm{F|B}} Selection\ temperature + \beta_{2,\mathrm{F|B}} (Selection\ temperature)^2 + \beta_{3,\mathrm{F|B}} Selection\ rainfall + \beta_{4,\mathrm{F|B}} (Selection\ rainfall)^2 + \beta_{5,\mathrm{F|B}} Selection\ temperature * Selection\ rainfall + \beta_{6,\mathrm{F|B}} Farm\ size + \beta_{7,\mathrm{F|B}} Soil\ type + \beta_{8,\mathrm{F|B}} Household\ size + \beta_{9,\mathrm{F|B}} Age + \beta_{10,\mathrm{F|B}} Sex + \beta_{11,\mathrm{F|B}} Education + e_{\mathrm{F|B}} \quad (3.16)$$

where B is the base outcome (maize) and F are the remaining food-crops. Note that the selection model is fully parametric.[85] The quadratic and interaction terms, however, allow for some flexibility in the selection equation.[86]

[85] To the best of our knowledge, no semiparametric estimator for an unordered multinomial response model has yet been developed.

[86] Fezzi and Bateman (2015) observe that least squares estimate of a traditional Ricardian model with

Even though non-linearities associated with the first-stage selection terms (inverse Mills ratio, IMR) can be used to identify the SRM (Heckman, 1979; Madden, 2008; Wilde, 2000; Wooldridge, 2012), the model is identified more concretely via an exclusion restriction (Bourguignon et al., 2007; Madden, 2008; Wooldridge, 2010). Therefore, we identify our model by including additional (production) weather covariates to Equation (3.16) (to form Equation 3.17b) and by excluding the selection climate from the outcome or semiparametric equation (Equation 3.17a). Since the production weather is observed only after selection, it does not have an intuitive interpretation when included in the selection equation except for the sole purpose of identification.[87] Hence, the results of Equation 3.17b are not reported in the main text but presented as Appendix 3.1 (Model 2). Our empirical outcome or semiparametric (Equation 3.15) equation is specified as:

$$Net\ revenue_j = f(Production\ temperature, Production\ rainfall) + \beta_2 Farm\ size + \beta_3 Soil\ type + \beta_4 Household\ size + \beta_5 Age + \beta_6 Sex + \beta_7 Education + \alpha \sum_{J=2\ldots8} Selection\ terms + w_j \quad (3.17a)$$

conditioned on

$$P(Y_{\mathrm{F|B}}) = \beta_{0,\mathrm{F|B}} + \beta_{1,\mathrm{F|B}} Selection\ temperature + \beta_{2,\mathrm{F|B}} (Selection\ temperature)^2 + \beta_{3,\mathrm{F|B}} Selection\ rainfall + \beta_{4,\mathrm{F|B}} (Selection\ rainfall)^2 + \beta_{5,\mathrm{F|B}} Selection\ temperature * Selection\ rainfall + \beta_{6,\mathrm{F|B}} Production\ temperature + \beta_{7,\mathrm{F|B}} (Production\ temperature)^2 + \beta_{8,\mathrm{F|B}} Production\ rainfall + \beta_{9,\mathrm{F|B}} (Production\ rainfall)^2 + \beta_{10,\mathrm{F|B}} Production\ temperature *$$

quadratic and interaction terms yield similar results as a semiparametric model.

[87] In order to identify the model via exclusion restriction, variables in the outcome equation should be drawn from the selection equation. Incorrectly excluding a variable from the selection equation is costly (since the excluded variables do not contribute to the formulation of the selection/IMR terms) and can lead to inconsistent results (Wooldridge, 2012).

$$Production\ rainfall + \beta_{11,\mathrm{F|B}} Farm\ size + \beta_{12,\mathrm{F|B}} Soil\ type + \beta_{13,\mathrm{F|B}} Household\ size +$$

$$\beta_{14,\mathrm{F|B}} Age + \beta_{15,\mathrm{F|B}} Sex + \beta_{16,\mathrm{F|B}} Education + e_{\mathrm{F|B}} \quad (3.17b)$$

3.3.2 Choice of variables

Dependent variable

Net revenue from food-crop production is the dependent variable for our outcome equation. We define net revenue (converted to US dollars) as the reported total value of food-crop produced by a household less its cost of production. Due to practical estimation difficulties in modelling all the various combinations of food-crops grown in Ghana, we restrict our analysis to just the most important food-crop per household even though multiple food-crop production is common (our data reveal more than 1,000 different food-crop combinations/cropping systems in Ghana). We focus our analysis on 7 main food-crops that contributed 94% to national food-crop revenue (of about US$11 billion) in 2013 as shown in Figure 3.2 (Ghana Statistical Service, GSS, 2015). The 7 food-crops that we study are maize/corn (*Zea mays*), rice (*Oryza spp*), cassava (*Manihot esculenta*), yam (*Dioscorea spp*), plantain (*Musa spp*), groundnut/peanut (*Arachis hypogaea*), and millet (*Pennisetum glaucum*). Since it is possible that some other food-crop could become important with future climate change, we created an 'other crops' category that aggregates the average net revenue from food-crops such as cocoyam (*Xanthosoma sagittifolium*), cowpea (*Vigna unguiculata*), sorghum (*Sorghum bicolor*), and sweet potato (*Ipomoea batatas*).[88] Tree/beverage crops such as cocoa and oil palm as well as fruits and vegetables are not considered in this study. As earlier indicated in Section 2.5, our next project will be a carefully planned survey that will collect sufficient data for the analysis of the effects of climate change on tree-crop production.

[88] See Chapter 1 (of this thesis) for a detailed description of the crops studied.

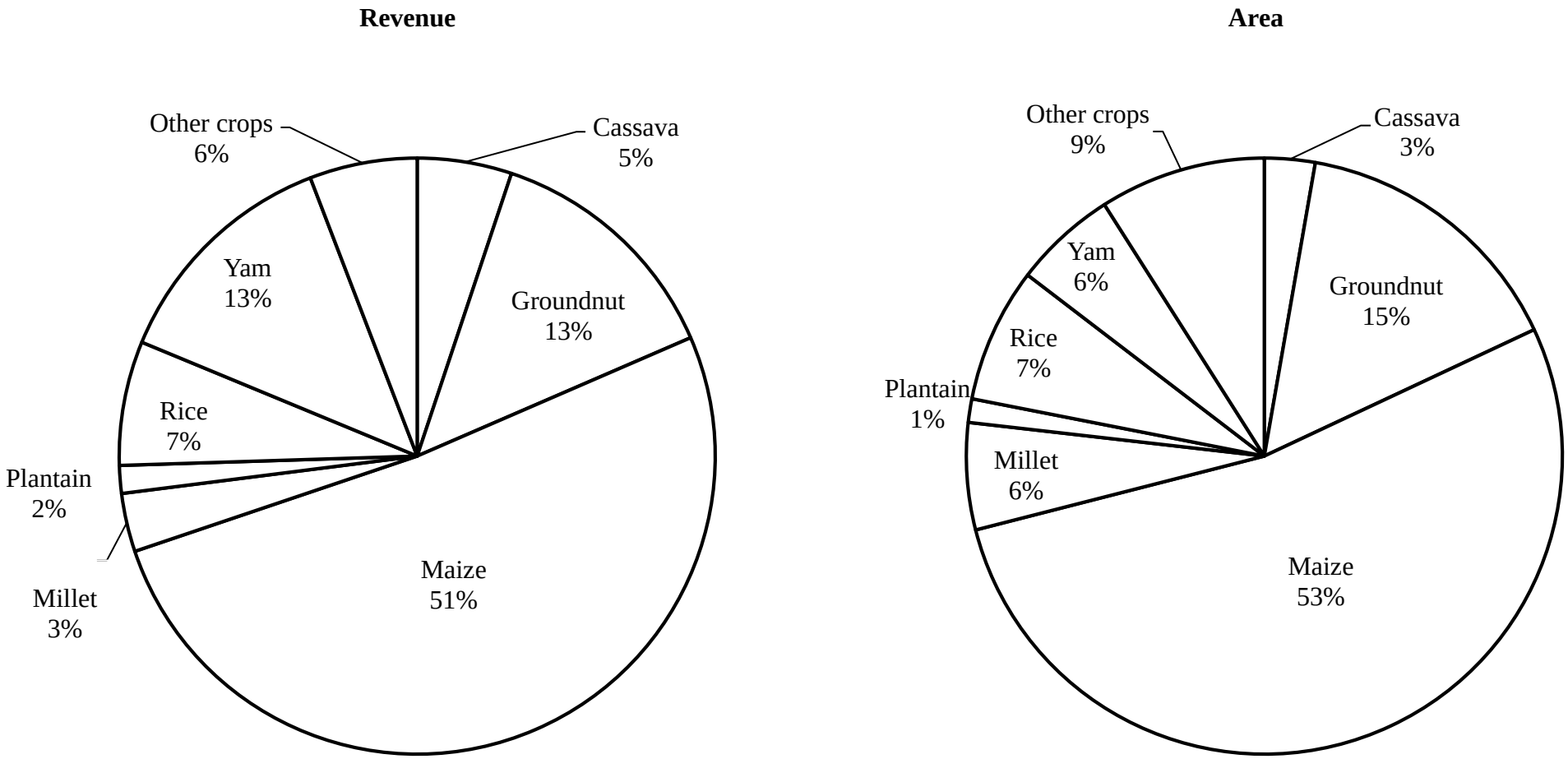

Figure 3.2: Contribution of each crop to national crop revenue and area under cultivation (GSS, 2015)

Table 3.1 shows the descriptive statistics of the dependent and explanatory variables. Yam producers earn the highest net revenue per hectare with the crop being 5 times more profitable than millet, the crop with the lowest net revenue.[89] The other two highest earning food-crops are rice and maize. Groundnut and cassava represent an intermediate case. Millet appears to have little commercial value as the crop is only produced in northern Ghana (MoFA, 2014) and is usually cultivated as a staple crop meant for local consumption unlike yam that has an additional export market (Nweke, 2016), or rice and maize that are produced and consumed nationwide (MoFA, 2014).

Explanatory variables

Climate variables are the main variables of interest in Ricardian analysis. As already indicated, a review of the literature also shows that farm attributes and socio-economic characteristics are important in explaining differences between farms. These control variables tend to improve the climate estimates when they are included in a Ricardian model (Mendelsohn and Dinar, 1999).

Climate variables

Temperature and rainfall are the two main climate variables estimated in most Ricardian studies. Different authors measure their climate variables differently. The main types of measurement include monthly observations (that is, monthly values averaged over years for each calendar month), quarterly (monthly values averaged over years for a single month in winter, spring, summer, and autumn), biannual, and growing-season climate. Monthly data is often used to capture the influence of every month (Da Cunha et al., 2015). Quarterly, biannual, or growing-season climate is used to minimise multicollinearity since observations

[89] In addition to the large inter-crop variation, there is also a large intra-crop variation as shown by the standard deviations.

for successive months tend to be collinear (Closset et al., 2014; Kurukulasuriya and Ajwad, 2007). We define our climate variables based on the growing-season. In that regard, the growing-season for perennial or late-maturing crops such as plantain, cassava, and yam is the whole year. The growing season for the rest of the crops depends on the location of the farm. The growing-season for farms located in northern Ghana is May-November whilst that of farms located in southern Ghana is April-October. Temperature is measured in degree Celsius (^{o}C). Rainfall is measured in Millimetres (mm). For the purposes of identifying our model, we make a distinction between selection climate and production weather as indicated in Section 3.3.1. Selection climate (temperature and rainfall) is the prevailing weather condition (mean weather station observation) recorded over a period of 38 years (1973-2011) whereas production weather refers to the average weather condition observed in the production year (2012-2013). We anticipate that past climate plays a key role in determining the types of crops that are selected whilst productivity is likely determined by the weather observed in the production year.

Table 3.1 shows that cassava and plantain are cultivated under a climate of low temperature and high rainfall while groundnut and millet are produced under relatively high temperature and low rainfall. Rice, yam, and maize are grown in-between those two-contrasting climates and could therefore be regarded as midway crops. Regional data from MoFA (2014) shows that production of millet and groundnut is concentrated in northern Ghana where the weather conditions are relatively warm and dry while cassava and plantain are largely produced in southern Ghana where the weather conditions are relatively cool and wet. Rice and maize are produced nationwide under all the various weather conditions thereby representing an intermediate case. Similarly, the production of yam is concentrated in the forest-savannah transitional zone (middle portions of the country) and therefore literally represents the midway between the dry north and the wet south. A comparison of the selection temperature

and rainfall with the production temperature and rainfall shows that the survey year (2012-2013) was warmer and drier than the prevailing climate prior to the survey year (1973-2011).

Soil attributes

Soil type has been found to influence crop revenue (see Section 3.3.5). We measure the soil variable qualitatively in this study on a scale of three, i.e. high, intermediate, and low-quality soils. Maize, cassava, and plantain are mostly cultivated on relatively productive soils whereas groundnut and millet are often allocated to relatively unproductive soils. Yam and rice represent an intermediate case (Table 3.1). Cassava and plantain being full-year crops (Ceballos et al., 2010; Dzomeku et al., 2009) and maize being a heavy feeder (Coster and Adeoti, 2015; Kanton et al., 2016) naturally require higher levels of soil fertility to produce a good harvest unlike millet and groundnut that can thrive under poor conditions (Clottey et al., 2014; Kombiok et al., 2012). Households, on average, allocate about a hectare of land to the various food-crops except cassava and plantain, which receives about half a hectare. Food-crop production in Ghana is typically on a smallholder basis with about 90% of farmers cultivating less than 2 hectares (MoFA, 2014).

Socio-economic characteristics

Consistent with the literature, we also control for household size and the age, sex, and educational attainment of the household head. The age of the household head is measured in years whilst educational attainment is measured on a scale of three. No, primary, and secondary education applies to a household head with no, basic (1-9 years), and secondary education (≥ 10 years), respectively. There is relatively little variation among households in terms of household size and the age of the head. A typical household has four or five members with the head being between 45 and 50 years old (Table 3.1). Male-headed households tend to dominate the cultivation of all food-crops. However, a substantial

proportion of female-headed households (48%) are involved in the production of plantain. For resource-constrained households (in terms of land and labour for example), the majority of whom are usually headed by females, a perennial food-crop like plantain permits flexible management and multiple harvests. Males tend to have better access to resources (for example, productive lands, agro-inputs, machinery, and agricultural extension) required for production (African Development Fund, 2008). The majority of farmers with formal education cultivate cassava and plantain.

Table 3.1: Descriptive statistics[90]

Variable	Cassava	Groundnut	Maize	Millet	Plantain	Rice	Yam	Other crops
				Mean and standard deviation (in italics)				
Net revenue per hectare (US$)	507	502.96	645.1	301.43	380.75	615.25	1525.91	411.28
	796.83	*740.7*	*7393.83*	*523.73*	*682.43*	*1072.72*	*2809.29*	*622.18*
Selection temperature (^oC)	26.09	26.68	26.46	27.07	25.89	26.29	26.31	26.48
	0.65	*0.56*	*0.67*	*0.55*	*0.73*	*0.68*	*0.69*	*0.58*
Production temperature (^oC)	26.68	28.13	27.51	28.7	26.41	27.21	27.19	27.88
	0.69	*0.8*	*1.05*	*0.79*	*0.66*	*1.06*	*1.04*	*0.82*
Selection rainfall (mm)	1853	1720.7	1737.1	1621.9	1850.3	1839.1	1827.9	1722.2
	85.4	*173.6*	*162.6*	*162.3*	*97.5*	*113.3*	*141.7*	*163.3*
Production rainfall (mm)	1597.4	1260.8	1273.3	1102.2	1492.7	1516.3	1228.9	1286.6
	342	*363.2*	*358.1*	*256.3*	*362.4*	*382.3*	*279.5*	*376.3*
Farm size (Hectares)	0.5	1.06	1.23	1.01	0.6	1.23	1.22	1.17
	0.52	*1.5*	*1.74*	*1.45*	*1.07*	*2.11*	*1.12*	*2.33*
Household size (Number)	4.4	5.5	4.9	5.5	4.1	5.3	5.7	5.8
	2.5	*3*	*2.9*	*2.9*	*2.3*	*2.6*	*3*	*3*
Age (Years)	49.7	46.7	47.8	49.5	47.2	45.9	47.2	48.2
	14.8	*16.3*	*15.4*	*16.7*	*13.5*	*16.1*	*16.2*	*15.7*
				Frequency and percentage (in italics)				
Soil 1 (High-quality)	297	110	1,599	156	143	84	102	149
	75%	*11%*	*52%*	*38%*	*93%*	*20%*	*31%*	*27%*
Soil 2 (Intermediate)	49	224	703	30	10	127	164	94
	12%	*22%*	*23%*	*7%*	*6%*	*30%*	*50%*	*17%*
Male	280	845	2473	341	89	350	296	469
	71%	*82%*	*80%*	*83%*	*58%*	*82%*	*90%*	*85%*

[90] Notes: The "Other crops" category includes cowpea, cocoyam, sorghum, and sweet potato. Tree/beverage crops such as cocoa and oil palm as well as fruits and vegetables are not considered in this study. Selection temperature and rainfall represent the long-term climate observed prior to cultivation (1973-2011) whilst production temperature and rainfall represent the weather observed during the production year (2012-2013). No education, female, and low-quality soil serve as the base category for their respective variables.

Variable	Cassava	Groundnut	Maize	Millet	Plantain	Rice	Yam	Other crops
Education 1 (Primary)	246	284	1360	97	99	119	84	161
	62%	*27%*	*44%*	*24%*	*64%*	*28%*	*25%*	*29%*
Education 2 (≥ Secondary)	25	77	269	19	16	30	24	35
	6%	*7%*	*9%*	*5%*	*10%*	*7%*	*7%*	*6%*
Sample size	394	1036	3100	410	154	427	330	553

3.4 Results and Discussion

3.4.1 The selection equation

Having already discussed the unconditional associations in Section 3.4.2, we now present and discuss conditional associations beginning with the non-climatic variables. Table 3.2 shows the population-averaged marginal effects of the multinomial crop selection equation (Equation 3.16).[91] The size of the population-averaged marginal effects is generally small.

Farm size has a statistically significant positive effect on the selection of maize and the other crops aggregate but a negative effect on yam and cassava selection. Whereas an additional hectare of land increases the probability of selecting maize and the other crops category by about 5%, it also decreases the probability of selecting yam and cassava by 0.6% and 4%, respectively. This result suggests that households with additional plots will likely allocate them to early-maturing food-crops as opposed to full-season or perennial food-crops.

High-quality soils are associated with maize and longer-season food-crops such as cassava, yam, and plantain. Farmers tend to select groundnut, millet, and rice for low-quality soils. This result is expected since maize requires fertile soils to yield optimally (Coster and Adeoti, 2015; Kanton et al., 2016) unlike millet that can be produced on marginal lands (Clottey et al., 2014; Kajuna, 2001) or groundnut that can improve soil fertility by fixing atmospheric nitrogen (Naab et al., 2009; Kombiok et al., 2012). Farmers may opt to minimise soil amendment costs by allocating maize and longer-season crops to high-quality soils.

Older farmers are more likely to select cassava and maize but less likely to select groundnut and rice. Production objectives could vary for different age groups. Elderly farmers may

[91] The earlier Ghanaian study by Issahaku and Maharjan (2014) only reported the coefficient estimates (for non-climate variables) and not the marginal effects as we do. Nevertheless, our coefficient effects (Appendix 3.2) are similar to theirs. Note that we capture sorghum as part of the 'other crops' aggregate.

prefer to cultivate staple food-crops such as cassava and maize in order to feed their families whilst younger farmers may be seeking to accumulate wealth and thereby favour the selection of commercial food-crops such as groundnut and rice.

Female farmers are more likely to cultivate plantain but less likely to produce millet and yam. Plantain require some post-harvest processing prior to preservation. These processing tasks are often undertaken by women (African Development Fund, 2008). The crop is also able to improve soil structure with their rooting system and can absorb soil nutrients and moisture that may be out of reach of annual food-crops. Being a perennial crop, plantain producers do not have to compete with other farmers for tractor and labour at the beginning of the season (Dziedzoave et al., 2006; Nweke, 2009; Price, 1995). These features tend to make plantain attractive to vulnerable farmers, the majority of whom are usually female.

Household size favours the selection of yam and groundnut but not cassava. The production of yam and groundnut is labour intensive (Nweke, 2016), hence availability of additional family labour might favour their selection. There is evidence of household size impacting positively on crop selection in 10 other African countries (Kurukulasuriya and Mendelsohn, 2008). Education is positively associated with the selection of maize, cassava, and plantain but negatively associated with the selection of yam, rice, millet, and groundnut. Overall, our findings show that farmer and farm characteristics are important in explaining the types of food-crops that are cultivated in Ghana.

Appendix 3.1 (Model 2) shows the marginal effects of the selection equation when we include production temperature and rainfall as additional covariates (Equation 3.17b). We find that both production temperature and rainfall are significant indicating that they are not weak instruments. Similar conclusions are reached when we replace production temperature and rainfall with an alternate instrument, non-farm income (Appendix 3.1, Model 3).

Table 3.2: Population-averaged marginal effects of the crop selection equation

Variable	Cassava	Groundnut	Maize	Millet	Plantain	Rice	Yam	Other crops
Farm size (Ha)	-0.040***	-0.0050	0.051***	-0.00037	-0.0071	0.0031	-0.0061**	0.0051**
	0.0055	*0.0045*	*0.0076*	*0.0029*	*0.0052*	*0.0034*	*0.0025*	*0.0047*
Soil 1 (High-quality)	0.067***	-0.24***	0.26***	-0.014**	0.041***	-0.070***	0.013**	-0.064***
	0.0064	*0.010*	*0.014*	*0.0068*	*0.0036*	*0.0079*	*0.0054*	*0.0092*
Soil 2 (Intermediate)	0.017**	-0.13***	0.17***	-0.055***	0.0093***	-0.018	0.081***	-0.073***
	0.007	*0.013*	*0.017*	*0.0068*	*0.0032*	*0.010*	*0.0089*	*0.010*
Household size	-0.0016	0.0031**	-0.0078***	0.0011	-0.00092	0.00017	0.0026***	0.0034***
	0.0012	*0.0016*	*0.0023*	*0.0010*	*0.00083*	*0.0010*	*0.00083*	*0.0012*
Age (Years)	0.00065***	-0.0012***	0.0013***	3.64×10^{-5}	-0.00012	-0.00059***	-8.7×10^{-5}	-4.5×10^{-5}
	0.00019	*0.00030*	*0.00040*	*0.00019*	*0.00013*	*0.00022*	*0.00018*	*0.00024*
Male	0.0037	-0.016	-0.022	0.016**	-0.015***	-0.0054	0.022***	0.017
	0.0067	*0.012*	*0.016*	*0.0068*	*0.0053*	*0.0087*	*0.0061*	*0.0094*
Education 1 (Primary)	0.038***	-0.051***	0.118***	-0.040***	0.014***	-0.026***	-0.024***	-0.028***
	0.0069	*0.010*	*0.014*	*0.0062*	*0.0042*	*0.0070*	*0.0060*	*0.0079*
Education 2 (≥Secondary)	0.00081	-0.034**	0.134***	-0.045***	0.016	-0.024**	-0.018	-0.030**
	0.010	*0.016*	*0.0234*	*0.0095*	*0.0081*	*0.011*	*0.010*	*0.013*

Notes: Robust standard errors in italics. ** and *** signify significance levels at 5%, and 1%, respectively. The "Other crops" category includes cowpea, cocoyam, sorghum, and sweet potato. No education, female, and low-quality soil serve as the base category for their respective variables. Number of observations = 6404; Wald Chi^2 (60) = 2234.62; Prob > Chi^2 = 0.000; Count R^2 = 0.504; Pseudo R^2 = 0.1777; Log pseudo likelihood = -8087.77.

We now turn our attention to the impact of climate on crop selection (partial marginal effects). Figure 3.3 shows the effect of temperature on crop selection at the mean value of all the other covariates (including rainfall). Similarly, Figure 3.4 shows the effect of rainfall on crop selection at the mean value of all the other covariates (including temperature). Inclusion of the square terms of temperature and rainfall allows the estimated probability function to assume a hill or U-shape.

Figure 3.3 shows that the relationship between temperature and maize selection is hill-shaped with a turning point at 25.5^{o}C. Therefore, initial increases in temperature (up to the turning point) favours selection but further increases in temperature (above the turning point) discourages selection. Millet selection has a U-shaped relationship with temperature. Initial increases in temperature (up to 26°C) has a negative effect on selection but further warming favours selection. Whereas warming impacts negatively on the selection of cassava, plantain, rice, and yam, it generally favours the selection of groundnut.

At 25°C, nearly half of all farms (about 47%) are allocated to maize with rice occupying about a tenth (13%) of farms and full-season or late-maturing crops (cassava, plantain, and yam) covering more than a quarter of farms (28%). Only 8% of farms are allocated to drought-tolerant crops (millet and groundnut) at 25°C. The proportion of farms allocated to full-season crops declines with warming. At 26°C, about 15% of farms are allocated to full-season crops. The figure drops to only 9% at 27°C suggesting that farmers adapt to warming by switching out of the production of full-season or late-maturing crops. Farmers continue to allocate about 50% of their farms to maize within the range of temperature reported. The selection of groundnut increases with warming. About 21% of farms are allocated to the crop at 27°C.

At 1400mm (Figure 3.4), about 88% of farms are allocated to maize (53%) and drought-tolerant crops such as groundnut (21%) and millet (14%). As rainfall increases, farmers switch from these crops to longer-season and water-loving crops such as cassava, plantain, yam, and rice. Whereas the proportion of farms allocated to millet decreases as rainfall increases, the reverse holds for yam. At 2000mm, less than 2% of farms are allocated to millet whereas yam increases to about 10% from a proportion of 1% at 1400mm. Rainfall has a general negative effect on the selection of groundnut and millet but a positive effect on the selection of rice, plantain, and yam. Initial increases in rainfall favours cassava selection but further increases (after 1950mm) has a negative effect. Similarly, initial increases in rainfall impacts positively on maize selection but further increases (after 1600mm) has a negative effect. Except for the extreme upper levels of rainfall, the 95% confidence band shows that our climate variables are precise determinants of crop selection.

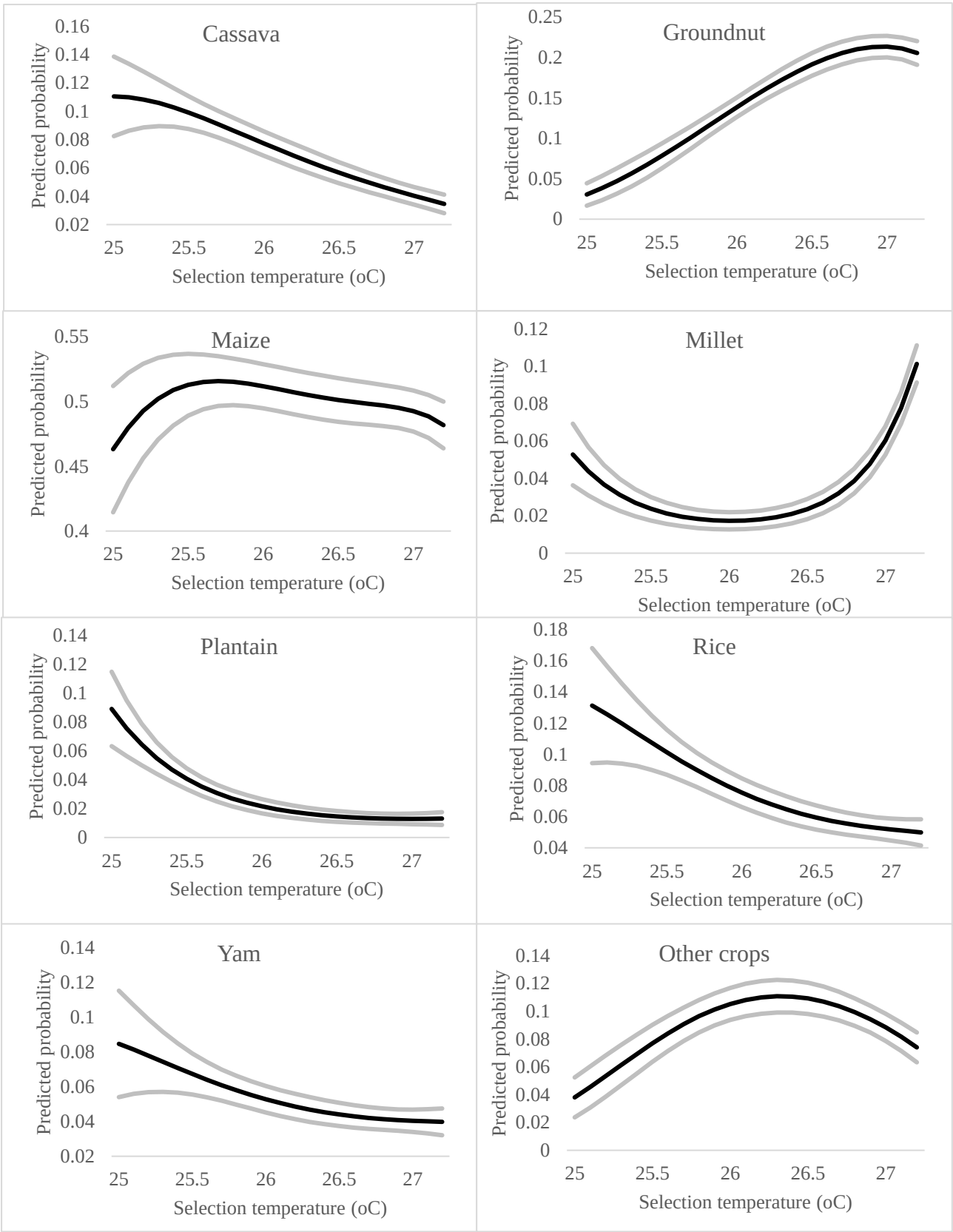

Figure 3.3: Effect of temperature on crop selection at the mean value of all the other covariates (partial marginal effects). The grey curves represent the 95% confidence band

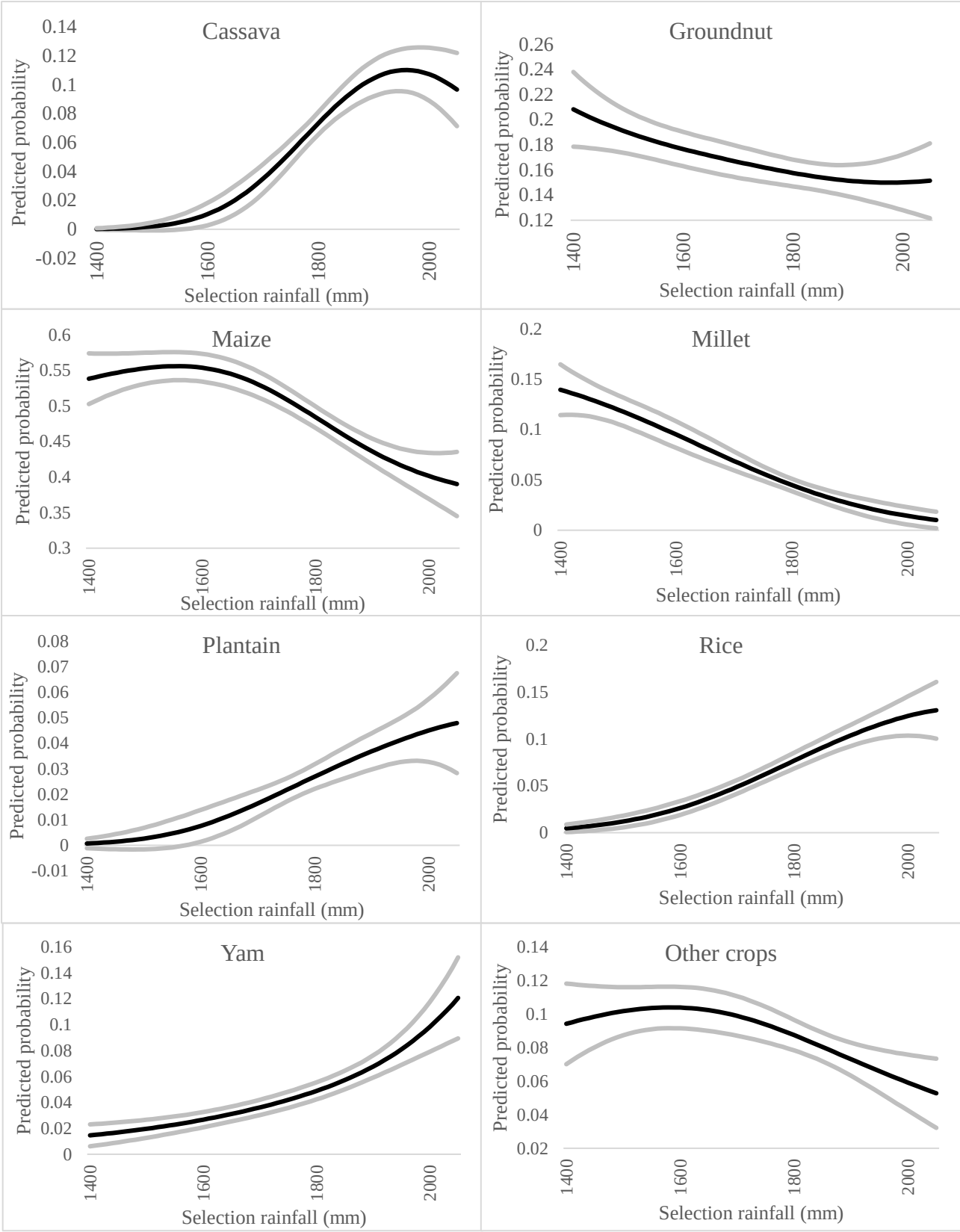

Figure 3.4: Effect of rainfall on crop selection at the mean value of all the other covariates (partial marginal effects). The grey curves represent the 95% confidence band

3.4.2 The revenue equation

We discuss estimates of the revenue equation (Equation 3.17a) in two parts. We discuss the non-weather variables first and then show the temperature and rainfall effects afterwards. Table 3.3 presents the semiparametric estimates of the revenue equation. The corresponding parametric estimates are presented in Appendix 3.3. The non-weather variables have the expected signs. For example, farm size impacts positively on crop revenues. An additional hectare of land (i.e. doubling of the average farm, Table 3.1) increases maize revenues by 47%, rice revenues by 24%, and groundnut and yam revenues by 30%. Similarly, high-quality soils improve rice revenues. Household size also has a positive effect on revenue from maize, groundnut, and yam. Additionally, education impacts positively on maize revenues whilst age has a negative effect on revenues from cassava and yam. Male-headed households tend to earn higher revenues than their female counterparts.

A comparison of our revenue and selection results (Table 3.3 and 3.2) shows that except for four cases, a variable that increases the selection of a particular crop also increases revenue from that crop and vice versa. The four cases that differ are highlighted as follows. Firstly, farm size has a small negative effect on yam selection (0.6%) but a large positive effect on yam revenue (30%). The relatively high production cost associated with yam cultivation (Nweke, 2016) could be a reason why resource-constrained households would choose to allocate their extra farmlands to other crops despite the opportunity cost that may arise from foregoing yam. Secondly, high-quality soils have a positive effect on rice revenue but a negative effect on rice selection. Rice is a water-loving crop.[92] Therefore, rice farmers may opt to produce the crop on water-guaranteed or water-induced low-quality soils (e.g. lowlands or flooded areas) even though high-quality soils could possibly increase revenues. Thirdly, an

[92] Rice is often cultivated in low-lying areas because of its hydromorphic nature (De Datta, 1981). In Ghana, 78% of rice farms are lowlands (MoFA, 2009).

increase in household size does not favour maize selection but impacts positively on maize revenue. Since maize is a staple crop (MoFA, 2014), it is possible that a typical household already produces some amount of maize. Hence, an additional household member may opt to produce a more profitable crop such as yam. Finally, age has a positive effect on cassava selection but a negative effect on cassava revenue. Cassava is a very high-yielding crop. In 2013, the average yields of cassava, maize, and millet were 18.3Mt/Ha, 1.7Mt/Ha, and 1.0Mt/Ha, respectively (MoFA, 2014). Older farmers may be more concerned about food for domestic consumption and therefore choose to cultivate cassava because of its high yields even though its revenue may be falling with age.

Table 3.3 also presents results of the selection terms. For the maize conditional regression, the selection term for groundnut (cassava) is positive (negative) implying that farmers who are predicted by the selection model to choose groundnut (cassava) but who actually choose maize will earn higher (lower) than expected revenues from maize. Several of the individual selection effects are significantly different from zero, suggesting that direct estimation of the revenue equation (Equation 3.17a) without the selection terms will produce biased parameter estimates.

Table 3.3: Semiparametric estimates of the crop revenue equation[93]

Variable	Log(Cassava)	Log(Groundnut)	Log(Maize)	Log(Millet)	Log(Plantain)	Log(Rice)	Log(Yam)	Log(Other crops)
Farm size (Ha)	0.35	0.30***	0.47***	0.069	0.14	0.24**	0.29**	0.22
	0.19	0.08	0.047	0.12	0.36	0.11	0.12	0.13
Soil 1 (High-quality)	-0.072	-0.21	-0.051	0.4	2.5	1.91***	-0.064	0.92**
	0.83	0.21	0.2	0.86	2.6	0.61	0.56	0.45
Soil 2 (Intermediate)	0.77	-0.31	-0.27	-0.2	4.65	-0.71	-0.077	0.54
	0.68	0.2	0.15	0.56	2.43	0.46	0.36	0.33
Household size (Number)	-0.027	0.065***	0.037***	0.057	0.04	0.0085	0.11***	0.04
	0.059	0.019	0.014	0.038	0.1	0.053	0.035	0.034
Age (Years)	-0.021**	-0.002	0.0038	0.0021	0.014	0.0064	-0.016***	0.0024
	0.0094	0.0041	0.0027	0.009	0.016	0.0067	0.0054	0.0055
Male	-0.038	0.48***	0.42***	1.37***	0.98	0.91***	0.31	0.86***
	0.26	0.17	0.091	0.45	0.63	0.34	0.23	0.19
Education 1 (Primary)	-0.031	-0.1	0.24**	-0.37	0.9	0.54	-0.072	0.31
	0.43	0.16	0.11	0.4	1.05	0.39	0.22	0.24
Education 2 (Secondary)	0.85	-0.03	-0.07	0.92	-0.2	0.41	-0.56	0.37
	0.62	0.24	0.15	1.44	1.24	0.5	0.33	0.37
Cassava selection			-0.84**	-0.71	-5.53***	-7.58***	-0.34	0.86
		0.92	0.37	1.92	1.45	1.69	0.79	1.3
Groundnut selection	1.22		0.65**	-0.61	-13.32	2.12	0.97	0.54
	1.52		0.29	1.09	7.56	1.17	0.81	0.62
Maize selection	-0.12	0.029		-0.077	-1.00***	-0.2	0.13	-0.07
	0.1	0.063		0.12	0.35	0.12	0.14	0.08
Millet selection	-6.61	-1.33	0.48		14.1	-5.28	5.53***	1.46

[93] Dependent variable is the logarithm of net revenue from each crop. The "Other crops" category includes cowpea, cocoyam, sorghum, and sweet potato. No education, female, and low-quality soil serve as the base category for their respective variables. Figures in italics are bootstrapped (500 replications) standard errors (that provides corrected variances given that the selection terms in our outcome or 2nd-stage equation are generated regressors from our 1st-stage or multinomial equation). ** and *** signify significance levels at 5% and 1%, respectively. Note that for each crop equation, we control for the probability of selecting all other crops (all other selection terms) except the crop under study since that is observed (i.e. for farmers who are already involved in cassava production as evidenced by revenue, it will be redundant to predict or control again for the probability of cultivating cassava).

Variable	Log(Cassava)	Log(Groundnut)	Log(Maize)	Log(Millet)	Log(Plantain)	Log(Rice)	Log(Yam)	Log(Other crops)
	4.7	0.76	0.6		12.51	3.92	1.92	1.41
Plantain selection	-2.50***	3.24**	1.06**	0.085		3.17**	-2.49***	0.79
	0.63	1.27	0.43	3.81		1.46	0.96	1.53
Rice selection	-4.01	-1.02	0.41	4.49**	-3.05		-2.53**	3.06**
	3.38	1.11	0.61	2.26	7.85		1.25	1.33
Yam selection	-0.45	1.01	0.51	-2.05	-6.41	0.53		-1.15
	1.66	0.52	0.3	1.27	4.57	1.03		0.97
Other crops selection	-0.68	0.52	-0.53	-0.55	14.31	-0.36	-3.79***	
	2.91	0.52	0.42	1.22	12.23	1.81	1.48	

Figures 3.5 and 3.6 show the flexible estimation of the revenue-weather function (semiparametric estimation of Equation 3.17a). The corresponding parametric graphs are presented in Appendix 3.4. Note that temperature is evaluated at the mean value of rainfall and vice versa. We only present rainfall and temperature effects for ranges that are somewhat precisely estimated (Figures 3.5 and 3.6). The 95% confidence bands of our initial plots showed that the response function between revenue and rainfall is imprecisely estimated after 1800mm. For a significant number of food-crops, temperature effects below 26°C are imprecisely estimated. A strong selection effect means there is little variation to precisely estimate the revenue equation. For example, a large proportion of households in drier areas select millet so there is less variability (farmers in wetter areas) to estimate the revenue equation precisely in our sample.

A critical comparison of Figures 3.5 and 3.6 with Figures 3.4 and 3.3 shows that farmers are generally making consistent choices (within the range of values presented). The only notable exception which we discuss later is the effect of temperature on plantain revenue. Consistent with the selection effects, revenues from cassava, plantain, yam, and rice all increase with increases in rainfall (for the range 1380mm-1800mm). Maize revenue is also increasing in rainfall even though its selection declines with additional rain. Note that as rainfall increases from 1380mm to 1800mm, revenue from cassava, plantain, yam, rice, and maize increases by 20% (i.e. US$104/Ha),[94] 42% (US$159/Ha), 63% (US$961/Ha), 37% (US$230/Ha), and 13% (US$86/Ha). The lower percentage increase in maize revenue could be the reason why farmers gradually switch out of maize production as rainfall increases (Figure 3.4). Consistent with the selection effects, Figure 3.5 also shows that millet revenue decreases with

[94] The figures in bracket, i.e. the increase in revenue per hectare, can be computed by multiplying a crop's average revenue per hectare (Table 3.1) with its percentage loss in revenue per hectare caused by the increase in rainfall from 1380mm to 1800mm (Figure 3.5).

increases in rainfall. Groundnut selection and revenue does not change much as rainfall increases from 1380mm to 1800mm.

Warming impacts negatively on both the selection and revenues from cassava, rice, yam, and maize. Temperature also has a negative effect on millet revenue. Under already warm conditions, a further rise in temperature from 27.5^{o}C to 28°C decreases revenue from cassava, rice, yam, maize, and millet by 29% (US$146/Ha), 42% (US$256/Ha), 32% (US$483/Ha), 6% (US$38/Ha), and 10% (US$30/Ha). The relatively small per hectare revenue reduction in millet could be the reason why the crop is frequently selected after 26.5^{o}C.

The one unexpected weather effect is temperature increasing plantain revenue even though warming harms its selection (as expected). This result requires further research. However, additional exploration of the data suggests that the unexpected result may be arising from an omitted variable that is possibly a function of temperature and farm size. Appendix 3.5 shows results of a base structural Ricardian model for plantain where climate and weather are the only explanatory variables. The appendix also presents temperature effects when we add the other covariates individually to the base model. The base model shows that temperature impacts negatively on both plantain selection and revenue as expected. We get similar results when we introduce most of the other covariates. Farm size is a notable exception thereby suggesting that there may be some association between plantain revenue, temperature, and farm size.

For many of the variables, results of our revenue equation are similar to those of Issahaku and Maharajan (2014). The few cases that we find different effects are highlighted as follows. Firstly, we estimate different effects for farm size. While we find a positive effect, they report that farm size impacts negatively on revenue from maize, cassava, and yam. Note that we measure farm size in levels (since 90% of farmers in Ghana cultivate less than 2 hectares of

land, MoFA, 2014) whilst Issahaku and Maharajan (2014) measure farm size in logarithm. Additionally, we find that male-headed households earn higher rice revenues whilst Issahaku and Maharajan (2014) find the opposite. Finally, whereas we find a positive relationship between rainfall and maize revenue, a negative effect is reported by Issahaku and Maharajan (2014). Note that Issahaku and Maharajan (2014) estimated a fully parametric linear model without quadratic and interaction terms.

Our results generally show that crop selection decisions are influenced by the climate observed before production whiles crop productivity is determined by the weather observed in the production year. Climate and weather tend to have consistent effects on crop selection and revenue. Warming impacts negatively on the revenue of all food-crops except groundnut and oddly plantain. Rainfall has a positive effect on the productivity of all food-crops except millet.

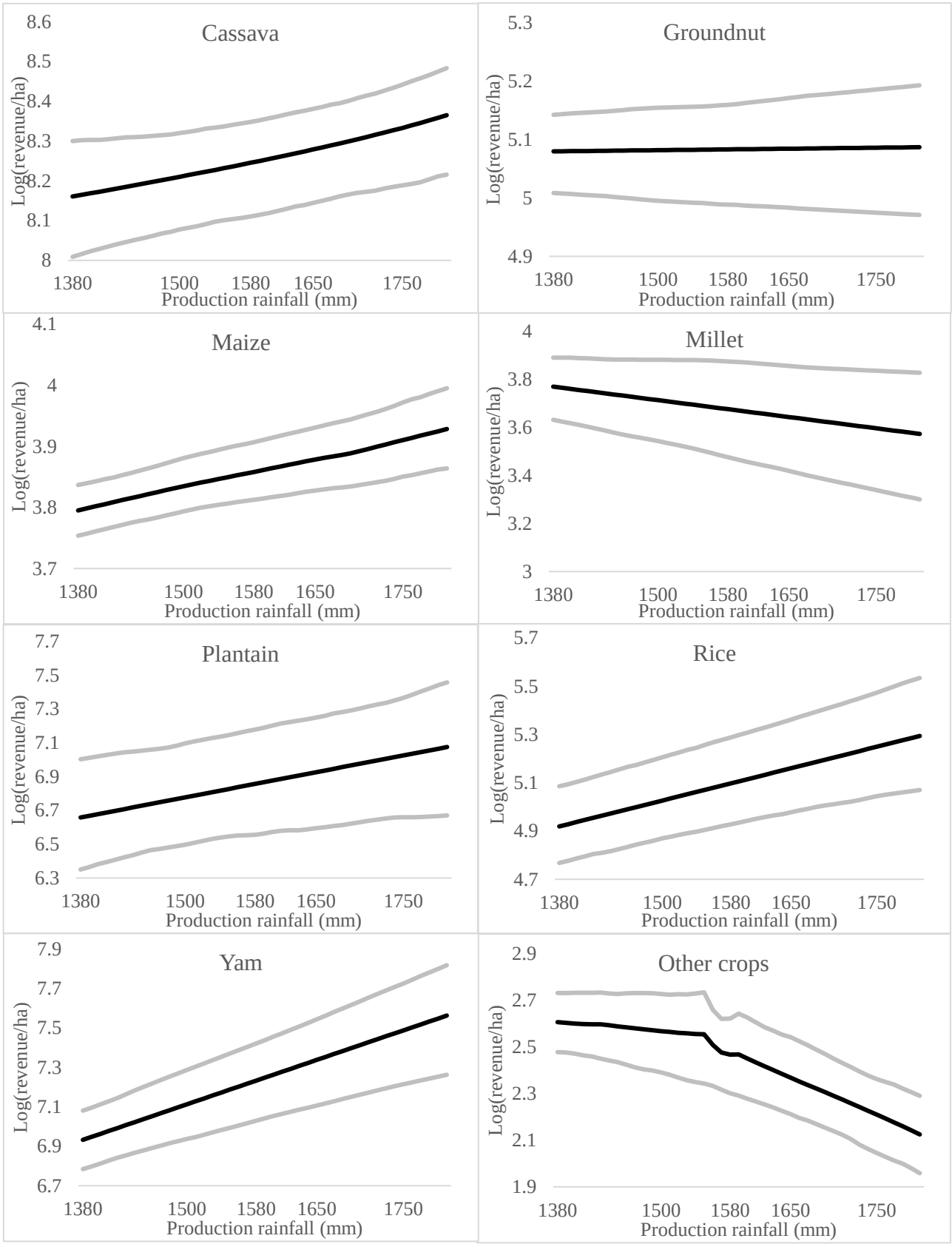

Figure 3.5: Effect of rainfall on log(crop revenue/ha) at mean temperature showing the 95% confidence interval in grey (semiparametric estimates)

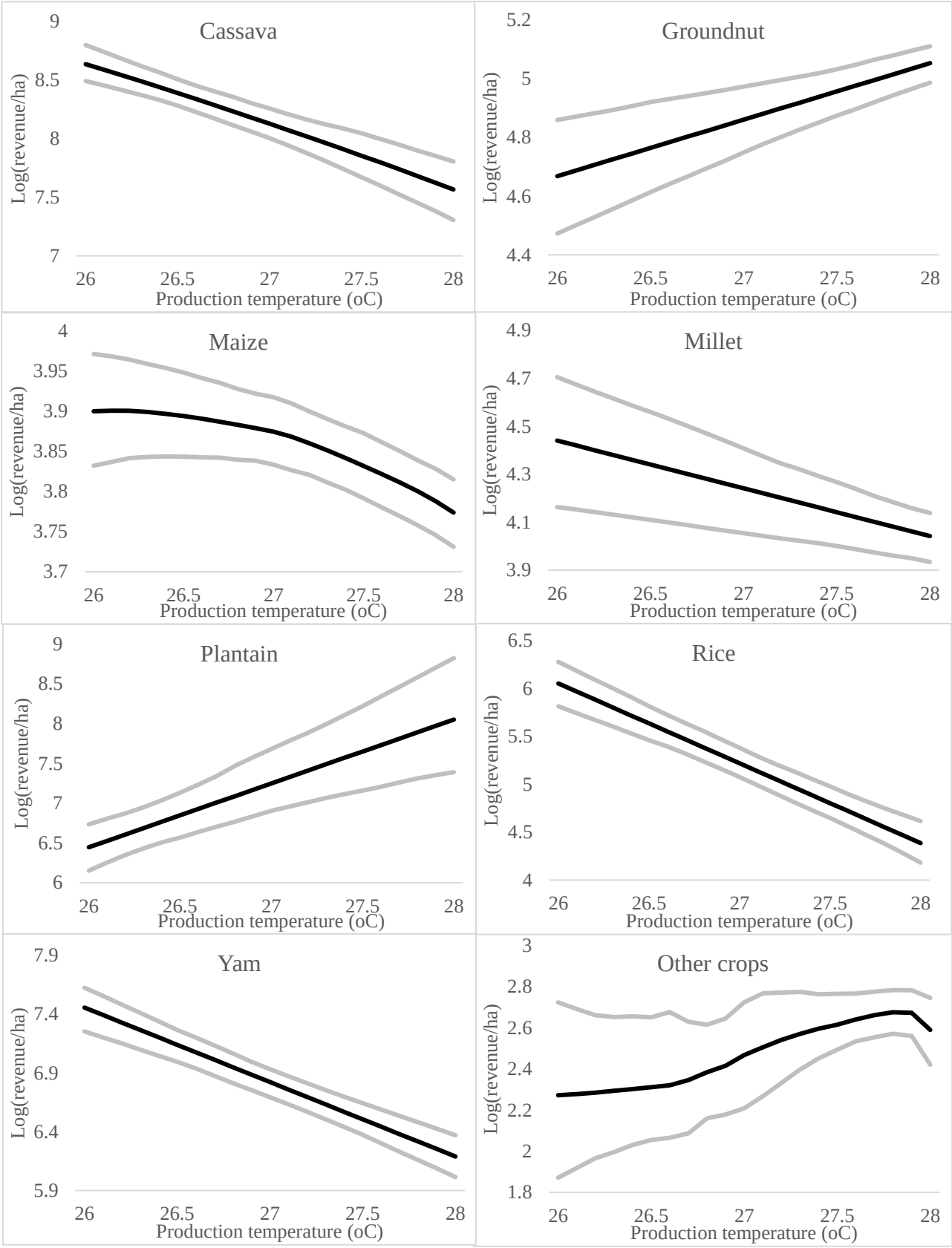

Figure 3.6: Effect of temperature on log(crop revenue/ha) at mean rainfall showing the 95% confidence interval in grey (semiparametric estimates)

3.4.3 Sensitivity and robustness checks

In order to generate robust results, we computed unconventional standard errors in all our models. For the selection equation, we estimated Huber/White/sandwich standard errors clustered at the district level (Fleischer et al., 2008; Reinsborough, 2003). For the second stage equations (both semiparametric and parametric), we estimated bootstrapped standard errors replicated 500 times.

The econometric problem of the Independence of Irrelevant Alternatives (IIA) associated with multinomial estimation does not affect estimates of the SRM. Monte Carlo experiments conducted by Bourguignon et al., (2007) show that violation of the IIA hypothesis in the first stage does not adversely affect estimates of the net revenue regressions in the second stage. Nevertheless, we tested for possible violation of the IIA assumption using the test proposed by Small and Hsiao (1985). We did not find evidence against the IIA assumption (Appendix 3.6).

Consistent with earlier structural Ricardian studies, we re-estimate our semiparametric model using the same climate variables[95] for both the selection and revenue equations. Following Chatzopoulos and Lippert (2015), we use non-farm income as an alternate instrument.[96] Apart from semiparametric models, power transformations can also reasonably approximate the functional relationship between variables in some cases.[97] As already indicated, we estimated fully parametric versions of our alternate models where we assumed, consistent with the literature, that temperature and rainfall have a quadratic effect on crop revenue. We

[95] Climate is now measured as the average growing season weather observed from 1973-2012.

[96] This was our initial model until two anonymous reviewers suggested that the use of non-farm income might be problematic since non-farm income could be correlated with the availability of funds to purchase farm inputs or acquire education (and therefore influence crop revenue).

[97] Power transformations have some flaws including the fact that they fit global model as opposed to local fits and the choice of power or degree of transformation is often arbitrary (Keele, 2008).

also controlled for temperature-rainfall interaction. Results of the semiparametric and parametric estimations of the alternate models are presented in Appendix 3.3. The results do not differ significantly across models. Parametric estimates of the Ricardian model with quadratic and interaction terms have been shown to be similar to semiparametric estimates (Fezzi and Bateman, 2015).

3.4.4 Simulating the impact of climate change on food-crop production

The climate scenarios used in this section are the same as those in Chapter 2. Table 3.4 provides a summary of these scenarios. We rely on our selection and revenue equation estimates and a uniform application of the climate scenarios to all farms in order to simulate the impact of climate change on food-crop selection and revenue.

Table 3.4: The different climate scenarios considered

	change in rainfall	change in temperature
scenario 1	+15%	+0.5^{o}C
scenario 2	+8%	+0.7^{o}C
scenario 3	+1%	+0.9^{o}C
scenario 4	–4%	+1.5^{o}C
scenario 5	–10%	+2.0^{o}C
scenario 6	–10%	+0.5^{o}C
scenario 7	+15%	+2.0^{o}C

Appendix 3.7 presents the simulation results based on the parameter estimates of the revenue equation (parametric). Since the parameter estimates of the weather variables (that serve as the basis for the simulations) are largely insignificant (Appendix 3.3, Model 2), the resulting predictions are also insignificant (Appendix 3.7). We, therefore, focus our discussion on simulations based on parameter estimates of the selection equation (Table 3.2). Appendix 3.8 disaggregates the simulation results by latitude. The appendix highlights the probability of selection relative to the existing regional variation in climate. Table 3.5 shows that climate change will clearly favour millet selection. The proportion of farmland allocated to millet

production increases in all scenarios. In the very extreme case of scenario 5 for instance (+2°C and -10% rainfall), 68.5% of farms (representing a 62% increment) is allocated to millet production. Simulations based on scenarios 1-3 show that the proportion of farms allocated to millet proportion will increase by 13% to 47% under those climatic conditions. Based on current value and all things being equal, this substantial substitution into millet suggest a decline in the aggregate value of agricultural production since millet is currently the least profitable crop (Table 3.1).

Climate change will likely affect maize, plantain, and yam production adversely as the simulation results show a decline in the proportion of farms allocated to these crops in all scenarios. The proportion of farms allocated to rice and cassava production will likely decline in all other scenarios except for scenario 4 (+1.5^{o}C and -4% rainfall). Our results show that crop substitution is an apparent adaptation response to climate change.

Table 3.5: Simulated changes in the probability of selecting each crop under different climate scenarios[98]

Variable	Estimate	95% confidence interval		Variable	Estimate	95% confidence interval	
Cassava: Baseline	0.063			Groundnut: Baseline	0.16		
Change in scenario 1	-0.004	-0.0059	-0.0021	Change in scenario 1	0.01	0.0069	0.013
Change in scenario 2	-0.014	-0.017	-0.012	Change in scenario 2	0.0038	$6.7x10^{-6}$	0.0077
Change in scenario 3	-0.04	-0.042	-0.038	Change in scenario 3	-0.042	-0.047	-0.037
Change in scenario 4	0.0036	0.0021	0.0052	Change in scenario 4	0.009	0.0067	0.011
Change in scenario 5	-0.057	-0.059	-0.054	Change in scenario 5	-0.082	-0.088	-0.077
Change in scenario 6	-0.013	-0.014	-0.011	Change in scenario 6	0.0092	0.0069	0.012
Change in scenario 7	-0.053	-0.055	-0.050	Change in scenario 7	-0.072	-0.077	-0.066
Maize: Baseline	0.48			Millet: Baseline	0.065		
Change in scenario 1	-0.16	-0.17	-0.16	Change in scenario 1	0.19	0.19	0.2
Change in scenario 2	-0.19	-0.2	-0.19	Change in scenario 2	0.26	0.26	0.27
Change in scenario 3	-0.29	-0.29	-0.28	Change in scenario 3	0.47	0.47	0.48
Change in scenario 4	-0.13	-0.14	-0.13	Change in scenario 4	0.13	0.12	0.13
Change in scenario 5	-0.36	-0.37	-0.35	Change in scenario 5	0.62	0.61	0.63
Change in scenario 6	-0.097	-0.10	-0.094	Change in scenario 6	0.14	0.14	0.15
Change in scenario 7	-0.36	-0.37	-0.35	Change in scenario 7	0.58	0.57	0.59
Plantain: Baseline	0.025			Rice: Baseline	0.066		
Change in scenario 1	-0.014	-0.015	-0.013	Change in scenario 1	-0.02	-0.021	-0.019
Change in scenario 2	-0.017	-0.018	-0.016	Change in scenario 2	-0.034	-0.035	-0.033
Change in scenario 3	-0.023	-0.024	-0.021	Change in scenario 3	-0.05	-0.051	-0.0481
Change in scenario 4	-0.011	-0.012	-0.01	Change in scenario 4	0.0028	0.0019	0.0038
Change in scenario 5	-0.024	-0.026	-0.023	Change in scenario 5	-0.057	-0.059	-0.056

[98] The "Other crops" category includes cowpea, cocoyam, sorghum, and sweet potato. Scenario 1 corresponds to an increase in temperature and rainfall by 0.7°C and 8%, respectively. Scenario 2 corresponds to an increase in temperature and rainfall by 0.9°C and 1%, respectively. Scenario 3 shows an increase in temperature by 1.5°C and a 4% reduction in rainfall. Scenario 4 represents an increase in temperature by 0.5°C and a 15% increase in rainfall. Scenario 5 represents a 2°C increase in temperature and a 10% reduction in rainfall. In scenario 6, temperature increases by 0.5°C and rainfall declines by 10%. Scenario 7 represents a 2°C increase in temperature and a 15% increase in rainfall.

Variable	Estimate	95% confidence interval		Variable	Estimate	95% confidence interval	
Change in scenario 6	-0.011	-0.012	-0.011	Change in scenario 6	-0.028	-0.029	-0.027
Change in scenario 7	-0.024	-0.026	-0.023	Change in scenario 7	-0.049	-0.051	-0.048
Yam: Baseline	0.048			Other crops: Baseline	0.087		
Change in scenario 1	-0.022	-0.023	-0.0216	Change in scenario 1	0.017	0.016	0.019
Change in scenario 2	-0.025	-0.026	-0.025	Change in scenario 2	0.014	0.012	0.016
Change in scenario 3	-0.035	-0.036	-0.034	Change in scenario 3	0.0031	-0.00042	0.0065
Change in scenario 4	-0.019	-0.02	-0.018	Change in scenario 4	0.018	0.017	0.019
Change in scenario 5	-0.041	-0.042	-0.04	Change in scenario 5	0.0007	-0.0037	0.0051
Change in scenario 6	-0.014	-0.015	-0.013	Change in scenario 6	0.013	0.012	0.014
Change in scenario 7	-0.042	-0.043	-0.041	Change in scenario 7	0.018	0.013	0.022

3.5 Summary and Conclusions

We use the structural Ricardian model to estimate the impact of climate change on food-crop production by modelling farm-level data from Ghana. Our study is among the first semiparametric estimations of a SRM with data from a developing country.

Our findings can be summarised as follows: millet and yam are the least and highest income generating food-crops, respectively. The survey year was generally hotter and drier than the historical mean. An average household has five members that is headed by a 48-year-old male with some form of formal education and allocates about a hectare of land to their most important food-crop. The probability of a household cultivating a maize farm increases with advances in age, educational level, access to high-quality soils and access to additional farmlands. Farm size is not associated with the selection of cassava and yam. In addition to maize, high-quality soils are associated with the selection of longer-season crops such as cassava, plantain, and yam but not groundnut and millet. As opposed to cassava and plantain, food-crops such as groundnut, millet, and rice are more likely to be selected by household heads with no formal education.

Households consider their climate (temperature and rainfall) before deciding what food-crops to cultivate. At mean rainfall, warming favours the selection of drought-tolerant crops such groundnut and millet. At mean temperature, increases in rainfall favours the selection of water-loving and longer-season crops such as yam.

Large households with access to large farmlands and headed by males earn higher revenues from groundnut and maize. Higher rice revenues are earned by large households with access to high-quality soils and headed by males. Younger household heads earn higher revenues from cassava and yam production. Within a rainfall range of 1380mm-1800mm, rainfall has a positive effect on revenue from all crops except millet. Within a temperature range of 26°C-

28°C, temperature has a negative effect on revenue from all crops except groundnut and oddly plantain.

A simulation of the potential impact of climate change suggests that crop producers will likely adapt to various climate scenarios by switching mostly to the production of millet. Holding all factors constant, substantial substitution into millet implies aggregate reduction in agricultural value since millet is currently the least profitable food-crop. Therefore, the government of Ghana and relevant stakeholders need to invest in plant breeding and adaptation programs that seek to improve the climate resilience of high-value food-crops such as yam, maize, and rice. In the short term, the Ministry of Food and Agriculture and other organisations involved in agricultural extension should promote millet in warm areas whilst promoting yam and rice in wet areas for maximum adoption and impact.

We end the chapter by recalling the caveats of the SRM (see Section 3.2.1). The model does not account for variables that do not vary over space, for example, the effect of carbon fertilisation. The model (cross-sectional application) does not also factor variables that could change drastically over time such as technology, taxes, and trade policies. Finally, note that our simulation results will not hold if future changes in climate do not resemble any existing conditions in our baseline data.

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Appendices 3

Appendix 3.1: Marginal effects of the crop selection equation with different sets of covariates (1/4)

Variable	Cassava			Groundnut		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Selection temperature (°C)	-0.032***	-0.0059		0.022***	-0.069***	
	0.004	*0.012*		*0.0065*	*0.025*	
Selection rainfall (mm)	0.00022***	2.0×10^{-4}***		-8.8×10^{-5}***	-6.67×10^{-5}	
	2.63×10^{-5}	*3.98×10^{-5}*		*2.81×10^{-5}*	*3.6×10^{-5}*	
Production temperature (°C)		-2.78×10^{-4}			0.070***	
		0.011			*0.019*	
Production rainfall (mm)		6.11×10^{-5}***			2.14×10^{-5}	
		1.09×10^{-5}			*2.39×10^{-5}*	
Long-term temperature (°C)			-0.032***			0.022***
			0.004			*0.0065*
Long-term rainfall (mm)			2.26×10^{-4}***			-8.77×10^{-5}***
			2.6×10^{-5}			*2.8×10^{-5}*
Non-farm income (US$)			-9.01×10^{-8}			-3.80×10^{-8}
			4.68×10^{-7}			*1.06×10^{-6}*
Farm size (Ha)	-0.040***	-0.035***	-0.040***	-0.005	-0.0067	-0.005
	0.0055	*0.0048*	*0.0054*	*0.0045*	*0.0044*	*0.0045*
Soil 1 (High-quality)	0.067***	0.052***	0.067***	-0.24***	-0.21***	-0.24***
	0.0064	*0.0063*	*0.0064*	*0.01*	*0.0055*	*0.01*
Soil 2 (Intermediate)	0.017**	0.0067	0.017**	-0.13***	-0.099***	-0.13***
	0.007	*0.0073*	*0.0074*	*0.013*	*0.013*	*0.013*
Age (Years)	0.00065***	5.65×10^{-4}***	6.53×10^{-4}***	-0.0012***	-0.0010***	-0.0012***
	0.00019	*1.77×10^{-4}*	*1.90×10^{-4}*	*0.0003*	*2.92×10^{-4}*	*3.03×10^{-4}*
Male	0.0037	0.0025	0.0038	-0.016	-0.018	-0.016
	0.0067	*0.0064*	*0.0067*	*0.012*	*0.012*	*0.012*
Education 1 (Primary)	0.038***	0.031***	0.038***	-0.051***	-0.044***	-0.050***
	0.0069	*0.0063*	*0.0069*	*0.01*	*0.0095*	*0.0099*

Variable	Cassava			Groundnut		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Education 2 (≥Secondary)	0.00081	-0.0016	0.0013	-0.034**	-0.023	-0.030
	0.01	*0.0093*	*0.0098*	*0.016*	*0.016*	*0.017*
Household size	-0.0016	-9.21×10^{-4}	-0.0014	0.0031**	0.0025	0.0033**
	0.0012	*0.0011*	*0.0012*	*0.0016*	*0.0015*	*0.0016*

Notes: Model 1 is our preferred crop selection equation. In order to identify the second-stage revenue equation, we control for production temperature and rainfall in Model 2 even though those variables do not have an intuitive interpretation (since they only observed after selection). We replaced production temperature and rainfall we non-farm income in Model 3. The "Other crops" category includes cowpea, cocoyam, sorghum, and sweet potato. Production temperature and rainfall refer to the growing season weather observed in the production year whilst selection temperature and rainfall refer to a 38-year average growing season climate observed prior to production. Long-term temperature and rainfall refer to the average growing season climate observed over a period of 39 years. No education, female and low-quality soil serve as the base category for their respective variables. Figures in italics are robust standard errors. ** and *** signify significance levels at 5% and 1%, respectively.

Appendix 3.1: Marginal effects of the crop selection equation with different sets of covariates (2/4)

Variable	Maize			Millet		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Selection temperature (ºC)	-0.043***	0.22***		0.141***	-0.14***	
	0.01	*0.029*		*0.012*	*0.044*	
Selection rainfall (mm)	-0.00032***	-2.60×10^{-4}***		-0.00020***	-2.30×10^{-4}***	
	4.27×10^{-5}	*5.3×10^{-5}*		*1.53×10^{-5}*	*2.6×10^{-5}*	
Production temperature (ºC)		-0.19***			0.19***	
		0.021			*0.032*	
Production rainfall (mm)		-1.87×10^{-4}***			5.50×10^{-5}***	
		3.22×10^{-5}			*1.65×10^{-5}*	
Long-term temperature (ºC)			-0.042***			0.14***
			0.01			*0.012*
Long-term rainfall (mm)			-3.19×10^{-4}***			-1.95×10^{-4}***
			4.3×10^{-5}			*1.5×10^{-5}*
Non-farm income (US$)			7.62×10^{-6}***			-3.88×10^{-6}**
			1.50×10^{-6}			*1.65×10^{-6}*
Farm size (Ha)	0.051***	0.046***	0.0503***	-0.00037	-0.0011	-2.92×10^{-4}
	0.0076	*0.0074*	*0.0077*	*0.0029*	*0.0029*	*0.0028*
Soil 1 (High-quality)	0.26***	0.24***	0.26***	-0.014**	-0.0071	-0.013
	0.014	*0.014*	*0.014*	*0.0068*	*0.0063*	*0.0067*
Soil 2 (Intermediate)	0.17***	0.14***	0.16***	-0.055***	-0.050***	-0.055***
	0.017	*0.017*	*0.017*	*0.0068*	*0.0063*	*0.0068*
Age (Years)	0.0013***	0.0013***	0.0013***	3.64×10^{-5}	6.57×10^{-5}	3.62×10^{-5}
	0.0004	*3.96×10^{-4}*	*4.02×10^{-4}*	*0.00019*	*1.82×10^{-4}*	*1.84×10^{-4}*
Male	-0.022	-0.021	-0.023	0.016**	0.015**	0.016**
	0.016	*0.016*	*0.016*	*0.0068*	*0.0068*	*0.0068*
Education 1 (Primary)	0.118***	0.12***	0.11***	-0.040***	-0.037***	-0.035***
	0.014	*0.0134*	*0.0138*	*0.0062*	*0.006*	*0.0062*
Education 2 (≥Secondary)	0.134***	0.13***	0.11***	-0.045***	-0.043***	-0.036***
	0.0234	*0.023*	*0.024*	*0.0095*	*0.0092*	*0.01*
Household size	-0.0078***	-0.0078***	-0.0095***	0.0011	0.0011	0.0018

Variable	Maize			Millet		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
	0.0023	*0.0023*	*0.0023*	*0.001*	*0.001*	*0.0011*

Appendix 3.1: Marginal effects of the crop selection equation with different sets of covariates (3/4)

Variable	Plantain			Rice		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Selection temperature (ºC)	-0.025***	0.0046		-0.028***	0.034***	
	0.004	*0.0087*		*0.0048*	*0.0094*	
Selection rainfall (mm)	8.3 x10^{-5}***	7.05 x 10^{-5}***		2.15 x 10^{-4}***	1.53 x 10^{-4}***	
	1.66 x 10^{-5}	*2.46* x 10^{-5}		*2.37* x 10^{-5}	*3.05* x 10^{-5}	
Production temperature (ºC)		-0.022**			-0.047***	
		0.01			*0.0065*	
Production rainfall (mm)		6.32 x 10^{-6}			6.24 x 10^{-5}***	
		6.18 x 10^{-6}			*1.34 x 10^{-5}*	
Long-term temperature (ºC)			-0.025***			-0.028***
			0.004			*0.0048*
Long-term rainfall (mm)			8.16 x 10^{-5}***			2.15 x 10^{-4}***
			1.66 x 10^{-5}			*2.38* x 10^{-5}
Non-farm income (US$)			6.07 x 10^{-7}***			1.32 x 10^{-6}**
			2.07 x 10^{-7}			*5.53 x 10^{-7}*
Farm size (Ha)	-0.0071	-0.0052	-0.0067	0.0031	0.0035	0.0028
	0.0052	*0.0049*	*0.0052*	*0.0034*	*0.0034*	*0.0034*
Soil 1 (High-quality)	0.041***	0.038***	0.041***	-0.070***	-0.078***	-0.070***
	0.0036	*0.0032*	*0.0036*	*0.0079*	*0.0082*	*0.008*
Soil 2 (Intermediate)	0.0093***	0.0078***	0.0094***	-0.018*	-0.022**	-0.019
	0.0032	*0.0028*	*0.0032*	*0.01*	*0.01*	*0.01*
Age (Years)	-0.00012	-1.53 x 10^{-4}	-1.24 x 10^{-4}	-5.9 x 10^{-4}***	-6.13 x 10^{-4}***	-5.89 x 10^{-4}***
	0.00013	*1.31 x 10^{-4}*	*1.32 x 10^{-4}*	*2.2 x 10^{-4}*	*2.14 x 10^{-4}*	*2.20 x 10^{-4}*
Male	-0.015***	-0.015***	-0.015***	-0.0054	-0.0031	-0.0053
	0.0053	*0.0053*	*0.0054*	*0.0087*	*0.0085*	*0.0087*
Education 1 (Primary)	0.014***	0.013***	0.013***	-0.026***	-0.028***	-0.028***
	0.0042	*0.0041*	*0.0043*	*0.007*	*0.007*	*0.0071*
Education 2 (≥Secondary)	0.016*	0.015*	0.013*	-0.024**	-0.028***	-0.028***
	0.0081	*0.0078*	*0.0079*	*0.011*	*0.011*	*0.011*
Household size	-0.00092	-6.19 x 10^{-4}	-0.0013	0.00017	-5.80 x 10^{-5}	-1.82 x 10^{-4}

Variable	Plantain			Rice		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
	0.00083	*8.08×10^{-4}*	*8.61×10^{-4}*	*0.001*	*9.77×10^{-4}*	*0.001*

Appendix 3.1: Marginal effects of the crop selection equation with different sets of covariates (4/4)

Variable	Yam			Other crops		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Selection temperature (ºC)	-0.015***	0.030***		-0.019***	-0.078***	
	0.0042	*0.0082*		*0.0037*	*0.014*	
Selection rainfall (mm)	0.00016***	1.88×10^{-4}***		-8.2×10^{-5}***	-5.49×10^{-5}**	
	2.28×10^{-5}	2.69×10^{-5}		2.13×10^{-5}	2.7×10^{-5}	
Production temperature (ºC)		-0.033***			0.039***	
		0.0057			*0.011*	
Production rainfall (mm)		2.01×10^{-6}			-2.15×10^{-5}	
		1.80×10^{-5}			2.15×10^{-5}	
Long-term temperature (ºC)			-0.015***			-0.020***
			0.0042			*0.0037*
Long-term rainfall (mm)			1.60×10^{-4}***			-8.09×10^{-5}***
			2.27×10^{-5}			2.1×10^{-5}
Non-farm income (US$)			-1.20×10^{-6}			-4.34×10^{-6}***
			7.84×10^{-7}			1.04×10^{-6}
Farm size (Ha)	-0.0061**	-0.0057**	-0.0061**	0.0051**	0.0035	0.0053
	0.0025	*0.0025*	*0.0025*	*0.0047*	*0.0047*	*0.0047*
Soil 1 (High-quality)	0.013**	0.0093	0.013**	-0.064***	-0.047***	-0.062***
	0.0054	*0.0055*	*0.0054*	*0.0092*	*0.0088*	*0.0091*
Soil 2 (Intermediate)	0.081***	0.072***	0.081***	-0.073***	-0.061***	-0.073***
	0.0089	*0.0084*	*0.0088*	*0.01*	*0.0092*	*0.0094*
Age (Years)	-8.7×10^{-5}	-8.42×10^{-5}	-8.15×10^{-5}	-4.5×10^{-5}	-3.45×10^{-5}	-3.05×10^{-5}
	0.00018	1.82×10^{-4}	1.84×10^{-4}	*0.00024*	2.33×10^{-4}	2.33×10^{-4}
Male	0.022***	0.022***	0.022***	0.017	0.016	0.017
	0.0061	*0.006*	*0.0061*	*0.0094*	*0.0093*	*0.0094*
Education 1 (Primary)	-0.024***	-0.025***	-0.022***	-0.028***	-0.026***	-0.022***
	0.006	*0.0058*	*0.006*	*0.0079*	*0.0078*	*0.0079*
Education 2 (≥Secondary)	-0.018	-0.018	-0.012	-0.030**	-0.027**	-0.017
	0.01	*0.0094*	*0.011*	*0.013*	*0.013*	*0.014*
Household size	0.0026***	0.0028***	0.0029***	0.0034***	0.0030**	0.0044***

Variable	Yam			Other crops		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
	0.00083	*8.56×10^{-4}*	*8.61×10^{-4}*	*0.0012*	*0.0012*	*0.0012*

Appendix 3.2: Coefficient estimates of the crop selection equation[99]

Variable	Cassava	Groundnut	Millet	Plantain	Rice	Yam	Other crops
Selection temperature (ºC)	1.36	26.99***	-63.64***	-32.41***	-7.95	-11.20	29.17***
	6.13	*5.88*	*6.17*	*8.78*	*6.38*	*6.85*	*5.98*
(Selection temperature)^2	-0.048	-0.51***	1.21***	0.58***	0.15	0.18	-0.55***
	0.11	*0.11*	*0.12*	*0.16*	*0.12*	*0.13*	*0.11*
Selection rainfall (mm)	0.071**	-0.021	-0.0092	0.031	0.029	-0.027	0.0033
	0.029	*0.012*	*0.018*	*0.031*	*0.021*	*0.019*	*0.015*
(Selection rainfall)^2	$-1.94\text{x}10^{-5}$***	$2.23\text{x}10^{-6}$	$-3.48\text{x}10^{-6}$	$-1.00\text{x}10^{-5}$	$-6.20\text{x}10^{-6}$**	$2.16\text{x}10^{-6}$	$-1.56\text{x}10^{-6}$
	$5.12\text{x}10^{-6}$	*$1.29\text{x}10^{-6}$*	*$2.76\text{x}10^{-6}$*	*$6.67\text{x}10^{-6}$*	*$2.43\text{x}10^{-6}$*	*$2.04\text{x}10^{-6}$*	*$1.86\text{x}10^{-6}$*
Selection temperature x selection rainfall	$2.23\text{x}10^{-4}$	$4.97\text{x}10^{-4}$	$6.29\text{x}10^{-4}$	$4.47\text{x}10^{-4}$	$-8.58\text{x}10^{-5}$	$8.94\text{x}10^{-4}$	$5.49\text{x}10^{-5}$
	0.0010	*$3.97\text{x}10^{-4}$*	*$6.20\text{x}10^{-4}$*	*0.0011*	*$7.06\text{x}10^{-4}$*	*$6.70\text{x}10^{-4}$*	*$5.04\text{x}10^{-4}$*
Farm size (Ha)	-0.88***	-0.10**	-0.067	-0.56**	-0.060	-0.25***	-0.022
	0.11	*0.041*	*0.058*	*0.25*	*0.062*	*0.060*	*0.066*
Soil 1 (High-quality)	0.98***	-2.47***	-0.98***	3.90**	-1.69***	-0.14	-1.33***
	0.18	*0.12*	*0.12*	*1.01*	*0.15*	*0.18*	*0.11*
Soil 2 (Intermediate)	0.31	-1.08***	-1.81***	2.51**	-0.51***	1.13***	-1.28***
	0.23	*0.10*	*0.22*	*1.06*	*0.13*	*0.17*	*0.14*
Age (Years)	0.010***	-0.012***	-0.0039	-0.0047	-0.013***	-0.0054	-0.0050
	0.0038	*0.0027*	*0.0038*	*0.0062*	*0.0040*	*0.0044*	*0.0033*
Male	0.061	-0.026	0.37**	-0.58***	-0.022	0.61***	0.27
	0.14	*0.11*	*0.16*	*0.21*	*0.15*	*0.20*	*0.14*
Education 1 (Primary)	0.57***	-0.75***	-1.10***	0.70***	-0.72***	-0.77***	-0.68***
	0.14	*0.091*	*0.14*	*0.23*	*0.13*	*0.15*	*0.11*
Education 2 (≥Secondary)	-0.14	-0.62***	-1.22***	0.60	-0.70***	-0.64***	-0.71***
	0.25	*0.15*	*0.26*	*0.35*	*0.22*	*0.24*	*0.20*
Household size	-0.021	0.047***	0.044**	-0.038	0.026	0.074***	0.064***

[99] Maize is the base outcome. The "Other crops" category includes cowpea, cocoyam, sorghum, and sweet potato. Selection temperature and rainfall refer to a 38-year average growing season climate observed prior to production. No education, female and low-quality soil serve as the base category for their respective variables. Figures in italics are robust standard errors. ** and *** signify significance levels at 5% and 1%, respectively.

Variable	Cassava	Groundnut	Millet	Plantain	Rice	Yam	Other crops
	0.025	*0.015*	*0.021*	*0.039*	*0.019*	*0.020*	*0.017*

Appendix 3.3: Different estimates of the revenue (second-stage) equation[100] (1/4)

Variable	Log(Cassava)				Log(Groundnut)			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Production temperature (°C)		-0.085				-0.017		
		0.15				*0.068*		
Production rainfall (mm)		2.3×10^{-4}				-3.10×10^{-5}		
		5.1×10^{-4}				*0.00013*		
Long-term temperature (°C)				-0.077				0.1
				0.13				*0.1*
Long-term rainfall (mm)				5.30×10^{-4}				0.0018
				0.0016				*0.0011*
Farm size (Ha)	0.35	0.39***	0.24	0.35***	0.30***	0.29***	0.23***	0.25***
	0.19	*0.14*	0.13	0.14	*0.08*	*0.068*	*0.074*	*0.076*
Soil 1 (High-quality)	-0.072	-0.21	-0.53	-0.47	-0.21	0.04	-0.021	0.2
	0.83	*0.59*	0.97	0.92	*0.21*	*0.17*	*0.24*	*0.26*
Soil 2 (Intermediate)	0.77	-0.81	-1.22	-0.89	-0.31	0.034	0.0072	0.071
	0.68	*0.44*	0.76	0.75	*0.2*	*0.11*	*0.27*	*0.27*
Household size	-0.027	0.070***	0.048	0.053	0.065***	0.038***	0.044***	0.043***
	0.059	*0.027*	0.031	0.027	*0.019*	*0.012*	*0.016*	*0.016*
Age (Years)	-0.021**	-0.0005	0.0022	2.80×10^{-4}	-0.002	-0.0012	-7.49×10^{-4}	0.0021
	0.0094	*0.0056*	0.0069	0.0066	*0.0041*	*0.0019*	*0.0025*	*0.0028*

[100] Notes: Model 1 is our preferred/semiparametric model with selection climate as instrument. Model 2 is the parametric version of model 1. Model 3 is estimated semi-parametrically with non-farm income as instrument. Model 4 is the parametric version of model 3. Dependent variable is the logarithm of net revenue from each crop. The "Other crops" category includes cowpea, cocoyam, sorghum, and sweet potato. Production temperature and rainfall refer to the growing season weather observed in the production year whilst long-term temperature and rainfall refer to the average growing season climate observed over a period of 39 years. No education, female and low-quality soil serve as the base category for their respective variables. Figures in italics are bootstrapped (500 replications) standard errors (that provides corrected variances given that the selection terms in our outcome or 2nd-stage equation are generated regressors from our 1st-stage or multinomial equation). ** and *** signify significance levels at 5% and 1%, respectively. Note that for each crop equation, we control for the probability of selecting all other crops (all other selection terms) except the crop under study since that is observed (i.e. for farmers who are already involved in cassava production as evidenced by revenue, it will be redundant to predict or control again for the probability of cultivating cassava).

Variable	Log(Cassava)				Log(Groundnut)			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Male	-0.038	0.33**	0.16	0.25	0.48***	0.53***	0.61***	0.64***
	0.26	*0.16*	0.22	0.2	*0.17*	*0.092*	*0.12*	*0.12*
Education 1 (Primary)	-0.031	-0.17	0.12	-0.07	-0.1	0.022	-0.08	0.057
	0.43	*0.24*	0.31	0.29	*0.16*	*0.086*	*0.11*	*0.12*
Education 2 (≥Secondary)	0.85	-0.3	0.03	-0.17	-0.03	-0.045	-0.27	-0.16
	0.62	*0.33*	0.42	0.37	*0.24*	*0.13*	*0.16*	*0.17*
Cassava selection					-2.25**	-1.5	-4.22***	-3.77***
					0.92	*1.01*	*1.02*	*1*
Groundnut selection	1.22	0.45	-1.3	-0.39				
	1.52	*0.75*	1.55	1.46				
Maize selection	-0.12	-0.086	-0.18	-0.089	0.029	-0.026	-0.13	-0.24**
	0.1	*0.1*	0.2	0.14	*0.063*	*0.083*	*0.088*	*0.11*
Millet selection	-6.61	1.04	3.25	1.76	-1.33	-0.15	-0.69***	-0.67**
	4.7	*5.46*	1.88	1.61	*0.76*	*0.19*	*0.27*	*0.28*
Plantain selection	-2.50***	-1.34***	-1.46	-1.28	3.24**	4.33	3.26**	3.73**
	0.63	*0.47*	1.32	0.86	*1.27*	*2.37*	*1.41*	*1.85*
Rice selection	-4.01	0.84	-0.017	-0.74	-1.02	0.12	-2.88***	-0.89
	3.38	*1.39*	1.61	1.84	*1.11*	*0.47*	*1.04*	*0.86*
Yam selection	-0.45	0.055	2.21	1.18	1.01	-0.13	-1.09	-1.03
	1.66	*0.66*	1.77	1.91	*0.52*	*0.42*	*0.89*	*0.83*
Other crops selection	-0.68	-4.47**	-2.6	-2.08	0.52	0.083	-1.42	-1.34
	2.91	*2.25*	2.24	2.58	*0.52*	*0.44*	*0.87*	*0.91*

Appendix 3.3: Different estimates of the revenue (second-stage) equation (2/4)

Variable	Log(Maize)				Log(Millet)			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Production temperature (^oC)		-0.027				0.17		
		0.035				*0.15*		
Production rainfall (mm)		2.3 x 10^{-4}**				-6.50 x 10^{-5}		
		9.89 x 10^{-5}				*0.00022*		
Long-term temperature (^oC)				0.021				0.26
				0.049				*0.36*
Long-term rainfall (mm)				8.28 x 10^{-4}				-0.0019
				5.51 x 10^{-4}				*0.0022*
Farm size (Ha)	0.47***	0.353***	0.30***	0.34***	0.069	0.13	0.20***	0.18***
	0.047	*0.026*	0.037	0.035	*0.12*	*0.048****	*0.06*	*0.07*
Soil 1 (High-quality)	-0.051	-0.23**	-0.37	-0.22	0.4	-0.29	-0.23	-0.3
	0.2	*0.11*	0.29	0.2	*0.86*	*0.29*	*0.46*	*0.51*
Soil 2 (Intermediate)	-0.27	-0.34****	-0.29	-0.30	-0.2	0.3	-0.29	0.083
	0.15	*0.076*	0.22	0.16	*0.56*	*0.31*	*0.43*	*0.5*
Household size	0.037***	0.031***	0.040***	0.036***	0.057	0.032	0.014	0.02
	0.014	*0.0079*	0.011	0.0091	*0.038*	*0.014***	*0.021*	*0.023*
Age (Years)	0.0038	-0.0012	-0.0034	-7.21 x 10^{-4}	0.0021	-0.0035	-1.08 x10^{-4}	-7.47 x 10^{-4}
	0.0027	*0.0014*	0.002	0.0018	*0.009*	*0.0035*	*0.0041*	*0.0043*
Male	0.42***	0.54***	0.56***	0.58***	1.37***	0.49	0.44***	0.45***
	0.091	*0.057*	0.074	0.071	*0.45*	*0.12****	*0.15*	*0.16*
Education 1 (Primary)	0.24**	0.017	-0.11	0.02	-0.37	-0.46	-0.26	-0.29
	0.11	*0.053*	0.1	0.078	*0.4*	*0.13****	*0.15*	*0.15*
Education 2 (≥Secondary)	-0.07	-0.14	-0.29**	-0.16	0.92	-0.1	0.12	0.13
	0.15	*0.083*	0.12	0.11	*1.44*	*0.26*	*0.27*	*0.31*
Cassava selection	-0.84**	-0.74***	-1.29***	-1.00***	-0.71	-3.13	-1.39	-1.48
	0.37	*0.19*	0.34	0.3	*1.92*	*3.62*	*1.44*	*1.49*
Groundnut selection	0.65**	0.18	0.012	0.17	-0.61	0.16	-0.2	-0.33
	0.29	*0.18*	0.45	0.32	*1.09*	*0.4*	*0.7*	*0.77*
Maize selection					-0.077	0.21**	-0.0012	0.018

Variable	Log(Maize)				Log(Millet)			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
					0.12	*0.10*	*0.069*	*0.081*
Millet selection	0.48	-0.022	-0.13	0.11				
	0.6	*0.088*	0.24	0.15				
Plantain selection	1.06**	0.91***	0.25	1.14**	0.085	6.93	6.70***	6.60***
	0.43	*0.32*	0.61	0.55	*3.81*	*7.33*	*2.27*	*2.52*
Rice selection	0.41	-0.26	-1.48**	-0.12	4.49**	-1.93	1.54	0.78
	0.61	*0.21*	0.64	0.47	*2.26*	*1.37*	*1.77*	*2.04*
Yam selection	0.51	0.50**	-0.33	0.27	-2.05	1.09	1.44	0.83
	0.3	*0.21*	0.58	0.6	*1.27*	*0.92*	*1.75*	*1.92*
Other crops selection	-0.53	-0.19	-0.48	-0.47	-0.55	-0.26	0.36	0.36
	0.42	*0.23*	0.54	0.5	*1.22*	*0.62*	*1.5*	*1.56*

Appendix 3.3: Different estimates of the revenue (second-stage) equation (3/4)

Variable	Log(Plantain)				Log(Rice)			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Production temperature (^oC)		0.17				-0.25**		
		0.51				*0.12*		
Production rainfall (mm)		0.0006				0.00022		
		0.0009				*0.00025*		
Long-term temperature (^oC)				0.0081				-0.11
				0.31				*0.13*
Long-term rainfall (mm)				-0.0014				-1.61×10^{-4}
				0.0043				*0.0015*
Farm size (Ha)	0.14	0.18	0.0015	0.086	0.24**	0.21***	0.21**	0.20**
	0.36	*0.24*	*0.3*	*0.35*	*0.11*	*0.063*	*0.084*	*0.09*
Soil 1 (High-quality)	2.5	6.58	0.85	2.94	1.91***	0.32	0.8	0.24
	2.6	*320.45*	*2.07*	*235.63*	*0.61*	*0.32*	*0.53*	*0.48*
Soil 2 (Intermediate)	4.65	6.85	0.82	2.57	-0.71	0.35	0.18	-0.11
	2.43	*320.23*	*2.24*	*235.02*	*0.46*	*0.18*	*0.45*	*0.47*
Household size	0.04	-0.039	0.063	0.051	0.0085	0.011	0.015	0.021
	0.1	*0.063*	*0.056*	*0.064*	*0.053*	*0.023*	*0.027*	*0.028*
Age (Years)	0.014	-0.0027	-0.0015	-0.0023	0.0064	0.00084	0.0061	0.0034
	0.016	*0.0098*	*0.0091*	*0.013*	*0.0067*	*0.0041*	*0.0048*	*0.0049*
Male	0.98	-0.41	0.089	0.22	0.91***	0.70***	0.86***	0.82***
	0.63	*0.36*	*0.29*	*0.35*	*0.34*	*0.14*	*0.17*	*0.18*
Education 1 (Primary)	0.9	0.97	0.2	-0.14	0.54	0.29	0.43**	0.24
	1.05	*0.71*	*0.49*	*0.75*	*0.39*	*0.15*	*0.2*	*0.18*
Education 2 (≥Secondary)	-0.2	0.87	0.16	-0.32	0.41	0.025	-0.06	-0.21
	1.24	*0.76*	*0.6*	*0.72*	*0.5*	*0.25*	*0.28*	*0.29*
Cassava selection	-5.53***	0.66	0.44	0.24	-7.58***	-1.71***	-3.10***	-3.53***
	1.45	*0.79*	*1.15*	*0.95*	*1.69*	*0.47*	*0.87*	*0.9*
Groundnut selection	-13.32	-1.13	0.6	2.06	2.12	0.33	0.89	0.17
	7.56	*7.43*	*2.73*	*8.53*	*1.17*	*0.46*	*0.74*	*0.67*
Maize selection	-1.00***	-0.24	0.24	-0.05	-0.2	-0.13	-0.2	-0.2

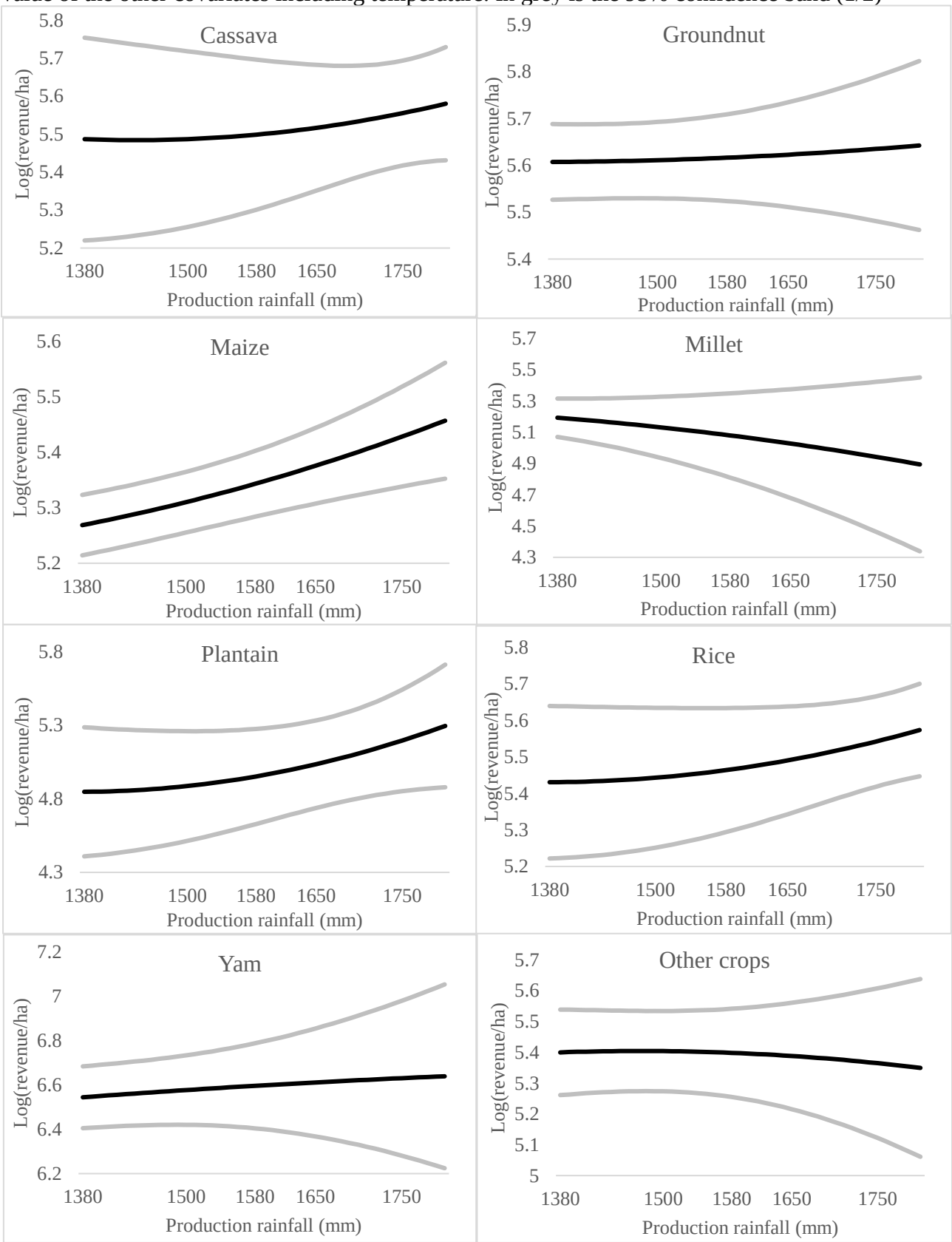
Variable	Log(Plantain)				Log(Rice)			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
	0.35	*0.24*	*0.31*	*0.32*	*0.12*	*0.1*	*0.17*	*0.23*
Millet selection	14.1	10.09	1.77	-0.63	-5.28	0.11	-2.07***	-1.85**
	12.51	*15.52*	*3.32*	*4.18*	*3.92*	*0.62*	*0.68*	*0.76*
Plantain selection					3.17**	1.15	2.68**	2.90**
					1.46	*0.85*	*1.23*	*1.36*
Rice selection	-3.05	-1.48	0.89	-0.05				
	7.85	*3.96*	*1.86*	*4.59*				
Yam selection	-6.41	3.08	-0.51	1.08	0.53	-0.3	-0.24	-0.16
	4.57	*2.61*	*5.51*	*7.22*	*1.03*	*0.41*	*1.01*	*1.16*
Other crops selection	14.31	22.12**	2.17	-0.77	-0.36	-0.7	-2.13	-2.28
	12.23	*9.71*	*5.31*	*8.32*	*1.81*	*0.67*	*1.47*	*1.71*

Appendix 3.3: Different estimates of the revenue (second-stage) equation (4/4)

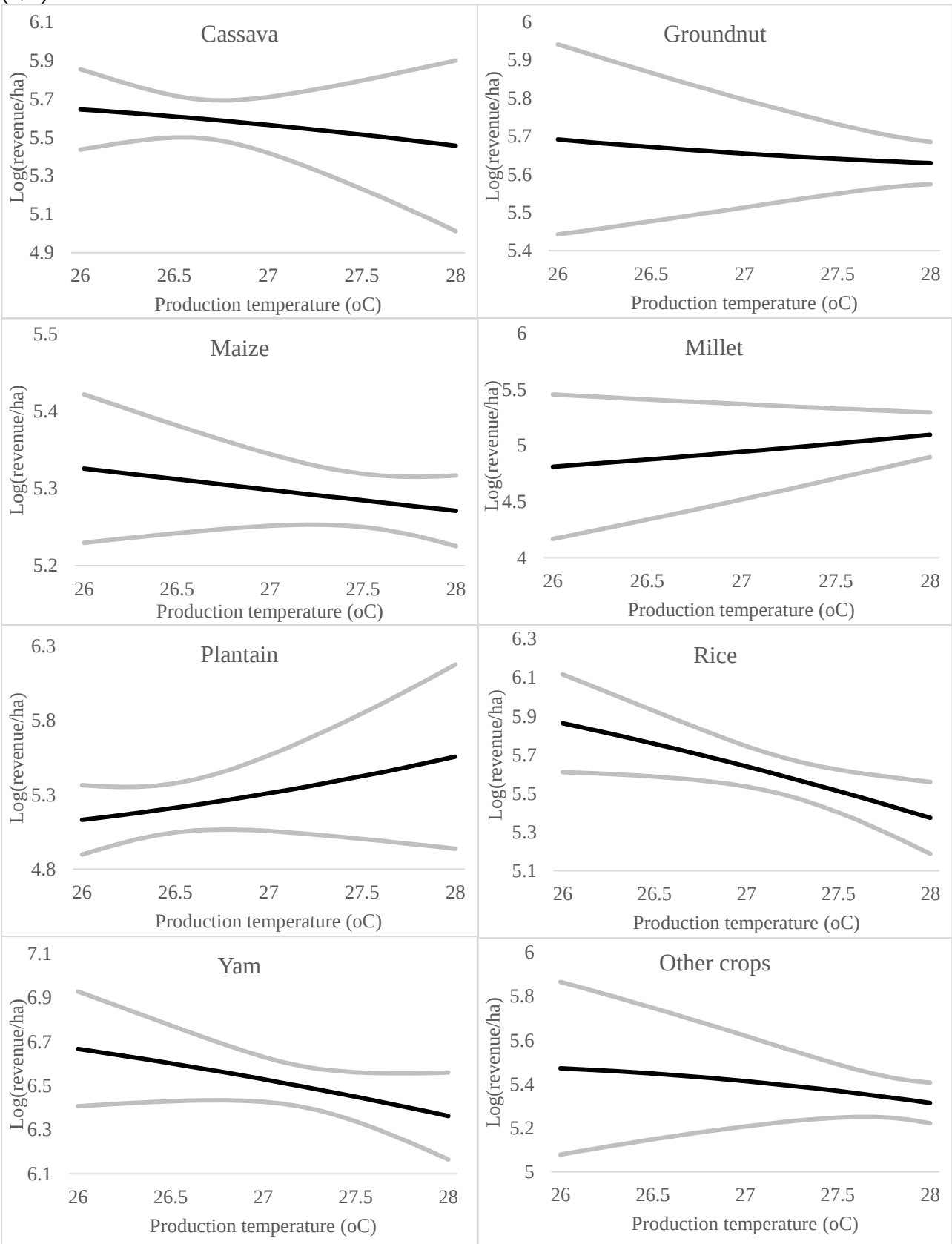
Variable	Log(Yam)				Log(Other crops)			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Production temperature (^{o}C)		-0.16				-0.11		
		0.11				*0.12*		
Production rainfall (mm)		0.00034				0.00019		
		0.00023				*0.00023*		
Long-term temperature (^{o}C)				0.038				0.17
				0.13				*0.15*
Long-term rainfall (mm)				7.21×10^{-4}				0.0024
				0.0014				*0.0019*
Farm size (Ha)	0.29**	0.47***	0.40***	0.40***	0.22	0.1	0.12	0.12
	0.12	*0.068*	*0.084*	*0.078*	*0.13*	*0.13*	*0.14*	*0.15*
Soil 1 (High-quality)	-0.064	0.32	-0.78	0.18	0.92**	0.13	0.72	0.2
	0.56	*0.38*	*0.65*	*0.68*	*0.45*	*0.39*	*0.69*	*0.72*
Soil 2 (Intermediate)	-0.077	0.12	-0.98**	-0.02	0.54	0.18	1.11**	0.55
	0.36	*0.24*	*0.41*	*0.42*	*0.33*	*0.23*	*0.45*	*0.43*
Household size	0.11***	0.044***	0.043	0.051**	0.04	0.060***	0.050	0.063**
	0.035	*0.017*	*0.023*	*0.023*	*0.034*	*0.023*	*0.029*	*0.027*
Age (Years)	-0.016***	-0.0062	-0.010**	-0.0071	0.0024	-0.0086**	-0.0083	-0.0094
	0.0054	*0.004*	*0.0047*	*0.005*	*0.0055*	*0.0036*	*0.0057*	*0.0062*
Male	0.31	0.24	0.24	0.23	0.86***	0.67***	0.65***	0.63***
	0.23	*0.19*	*0.19*	*0.21*	*0.19*	*0.13*	*0.15*	*0.16*
Education 1 (Primary)	-0.072	-0.18	-0.45**	-0.13	0.31	0.12	0.17	0.04
	0.22	*0.16*	*0.22*	*0.22*	*0.24*	*0.16*	*0.27*	*0.28*
Education 2 (≥Secondary)	-0.56	-0.069	-0.52	-0.1	0.37	-0.1	0.028	-0.085
	0.33	*0.22*	*0.27*	*0.3*	*0.37*	*0.3*	*0.37*	*0.38*
Cassava selection	-0.34	0.9	-1.72**	-0.14	0.86	-1.91**	-2.49**	-2.33
	0.79	*0.61*	*0.82*	*1.01*	*1.3*	*0.8*	*1.16*	*1.4*
Groundnut selection	0.97	0.22	-1.16	-0.52	0.54	-0.71	-0.24	-1.19
	0.81	*0.62*	*0.88*	*0.81*	*0.62*	*0.47*	*0.92*	*1.03*
Maize selection	0.13	0.017	-0.1	-0.019	-0.07	-0.22**	-0.31**	-0.33**

Variable	Log(Yam)				Log(Other crops)			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
	0.14	*0.045*	*0.1*	*0.11*	*0.08*	*0.1*	*0.15*	*0.16*
Millet selection	5.53***	0.75	-2.06**	0.96	1.46	-0.08	0.083	-0.45
	1.92	*0.64*	*1.02*	*0.83*	*1.41*	*0.34*	*0.56*	*0.61*
Plantain selection	-2.49***	-2.52**	-0.86	-2.43	0.79	3.48	-0.56	-0.17
	0.96	*1.14*	*1.54*	*2.08*	*1.53*	*2.04*	*1.7*	*2*
Rice selection	-2.53**	-0.48	-3.03**	-0.27	3.06**	-0.29	-2.57	-1.26
	1.25	*0.69*	*1.3*	*1.19*	*1.33*	*0.79*	*1.33*	*1.57*
Yam selection					-1.15	-1.37	-3.65**	-3.09
					0.97	*0.92*	*1.58*	*1.65*
Other crops selection	-3.79***	0.088	-1.32	-0.28				
	1.48	*0.82*	*1.17*	*1.44*				

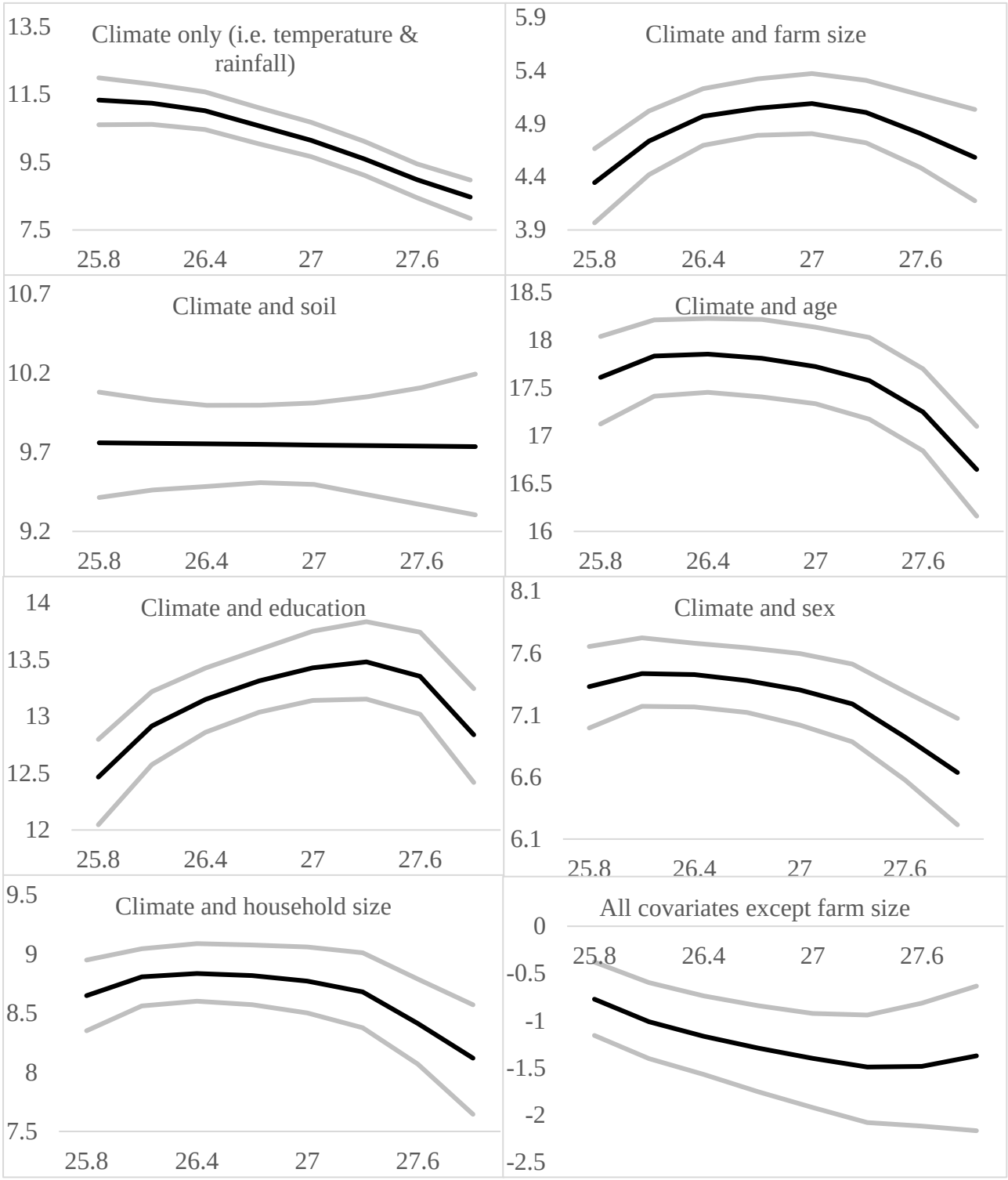
Appendix 3.4: Parametric estimates of the effect of rainfall on log(revenue/ha) at the mean value of the other covariates including temperature. In grey is the 95% confidence band (1/2)



Appendix 3.4: Parametric estimates of the effect of temperature on log(revenue/ha) at the mean value of the other covariates including rainfall. In grey is the 95% confidence band (2/2)



Appendix 3.5: The effect of different covariates on the relationship between temperature (ºC) and log(plantain revenue/ha).[101]



[101] The "climate only" graph is the base semiparametric structural Ricardian model for plantain where climate and weather are the only explanatory variables. The other graphs show the temperature effects when we add the other covariates individually to the base model or when we omit farm size from the full model. The response function in black and grey represent the point estimates and the 95% confidence band, respectively. The vertical axis measures log(plantain revenue/ha) and the horizontal axis measures production temperature (ºC). Estimates are evaluated at the mean value of the other covariates.

Appendix 3.6: Small-Hsiao test for IIA assumption

Variable	Model 1				Model 2				Model 3			
	lnL(full)	lnL(omit)	chi2	df	lnL(full)	lnL(omit)	chi2	df	lnL(full)	lnL(omit)	chi2	df
Cassava	-3607	-8088	-8962	98	-3290	-7518	-8456	133	-3445	-8053	-9216	105
Groundnut	-3005	-4093	-2175	98	-2651	-3682	-2061	133	-2863	-3972	-2217	105
Maize	-2203	-4093	-3780	98	-1887	-3682	-3589	133	-2144	-3972	-3655	105
Millet	-3611	-4093	-963	98	-3267	-3682	-830	133	-3511	-3972	-921	105
Plantain	-3858	-4093	-470	98	-3498	-3682	-368	133	-3777	-3972	-389	105
Rice	-3474	-4093	-1238	98	-3144	-3682	-1074	133	-3431	-3972	-1080	105
Yam	-3636	-4093	-913	98	-3269	-3682	-825	133	-3572	-3972	-798	105
Other crops	-3301	-4093	-1584	98	-2932	-3682	-1499	133	-3216	-3972	-1512	105

Notes: H_o = Odds (Outcome-J vs Outcome-K) are independent of other alternatives. We do not find evidence against the null hypothesis. N = 6404. Model 1 is our preferred crop selection equation. In order to identify the second-stage revenue equation, we control for production temperature and rainfall in Model 2 even though those variables do not have an intuitive interpretation since they only observed after selection. We replaced production temperature and rainfall we non-farm income in Model 3.

Appendix 3.7: Simulated changes in log(revenue) under different climate scenarios (parametric estimates)[102]

Variable	Estimate	95% confidence interval		Variable	Estimate	95% confidence interval	
Log(cassava): Baseline	5.59			Log(groundnut): Baseline	5.63		
Change in scenario 1	-1.1×10^{-5}	-0.0087	0.0087	Change in scenario 1	1.73×10^{-6}	-0.004	0.004
Change in scenario 2	-1.10×10^{-5}	-0.01	0.01	Change in scenario 2	5.81×10^{-6}	-0.0043	0.0044
Change in scenario 3	-3.0×10^{-5}	-0.014	0.014	Change in scenario 3	3.54×10^{-6}	-0.0047	0.0047
Change in scenario 4	-1.23×10^{-5}	-0.0078	0.0078	Change in scenario 4	-8.95×10^{-8}	-0.0036	0.0036
Change in scenario 5	-3.5×10^{-5}	-0.015	0.015	Change in scenario 5	5.15×10^{-6}	-0.0054	0.0054
Change in scenario 6	-7.92×10^{-6}	-0.0093	0.0093	Change in scenario 6	-4.13×10^{-6}	-0.0035	0.0035
Change in scenario 7	-4.30×10^{-5}	-0.016	0.016	Change in scenario 7	1.15×10^{-6}	-0.0057	0.0057
Log(maize): Baseline	5.28			Log(millet): Baseline	5.22		
Change in scenario 1	-4.30×10^{-5}	-0.0033	0.0032	Change in scenario 1	1.0×10^{-5}	-0.01	0.0096
Change in scenario 2	-3.20×10^{-5}	-0.0034	0.0033	Change in scenario 2	6.93×10^{-6}	-0.01	0.01
Change in scenario 3	-9.67×10^{-6}	-0.0036	0.0036	Change in scenario 3	-1.10×10^{-5}	-0.012	0.012
Change in scenario 4	-4.46×10^{-5}	-0.003	0.0029	Change in scenario 4	8.58×10^{-6}	-0.0084	0.0084
Change in scenario 5	-7.81×10^{-6}	-0.0036	0.0036	Change in scenario 5	-1.60×10^{-5}	-0.013	0.012
Change in scenario 6	-3.80×10^{-5}	-0.0028	0.0028	Change in scenario 6	2.19×10^{-6}	-0.0094	0.0094
Change in scenario 7	-1.30×10^{-5}	-0.0038	0.0037	Change in scenario 7	-1.80×10^{-5}	-0.013	0.013
Log(plantain): Baseline	5.21			Log(rice): Baseline	5.56		
Change in scenario 1	-2.90×10^{-5}	-0.03	0.03	Change in scenario 1	-1.13×10^{-4}	-0.016	0.015
Change in scenario 2	-4.80×10^{-5}	-0.034	0.034	Change in scenario 2	-6.20×10^{-5}	-0.016	0.016
Change in scenario 3	-4.90×10^{-5}	-0.039	0.039	Change in scenario 3	-2.50×10^{-5}	-0.016	0.016
Change in scenario 4	-1.39×10^{-5}	-0.026	0.026	Change in scenario 4	-1.14×10^{-4}	-0.015	0.015
Change in scenario 5	-4.0×10^{-5}	-0.046	0.046	Change in scenario 5	-4.70×10^{-5}	-0.018	0.018
Change in scenario 6	-2.80×10^{-5}	-0.031	0.031	Change in scenario 6	-7.10×10^{-5}	-0.015	0.015
Change in scenario 7	-4.30×10^{-5}	-0.049	0.049	Change in scenario 7	-4.50×10^{-5}	-0.018	0.018

[102] The "Other crops" category includes cowpea, cocoyam, sorghum and sweet potato. Scenario 1 corresponds to an increase in temperature and rainfall by 0.7°C and 8%, respectively. Scenario 2 corresponds to an increase in temperature and rainfall by 0.9°C and 1%, respectively. Scenario 3 shows an increase in temperature by 1.5°C and a 4% reduction in rainfall. Scenario 4 represents an increase in temperature by 0.5°C and a 15% increase in rainfall. Scenario 5 represents a 2°C increase in temperature and a 10% reduction in rainfall. In scenario 6, temperature increases by 0.5°C and rainfall declines by 10%. Scenario 7 represents a 2°C increase in temperature and a 15% increase in rainfall.

Variable	Estimate	95% confidence interval		Variable	Estimate	95% confidence interval	
Log(yam): Baseline	6.49			Log(other crops): Baseline	5.31		
Change in scenario 1	-1.77×10^{-6}	-0.013	0.013	Change in scenario 1	-1.0×10^{-5}	-0.017	0.017
Change in scenario 2	7.14×10^{-6}	-0.015	0.015	Change in scenario 2	-6.48×10^{-6}	-0.018	0.018
Change in scenario 3	4.39×10^{-6}	-0.019	0.019	Change in scenario 3	-7.09×10^{-6}	-0.018	0.018
Change in scenario 4	-6.86×10^{-6}	-0.011	0.011	Change in scenario 4	-1.94×10^{-5}	-0.017	0.017
Change in scenario 5	-4.20×10^{-5}	-0.023	0.023	Change in scenario 5	-2.15×10^{-5}	-0.019	0.019
Change in scenario 6	2.32×10^{-5}	-0.011	0.011	Change in scenario 6	1.36×10^{-5}	-0.014	0.014
Change in scenario 7	-2.60×10^{-5}	-0.022	0.022	Change in scenario 7	-3.20×10^{-5}	-0.019	0.019

Appendix 3.8: Estimated changes in the probability of selecting each crop at different latitudes under different climate scenarios[103]

	Latitude	Cassava	Groundnut	Maize	Millet	Plantain	Rice	Yam	Other crops
Baseline	districts below 6 ^{O} N	0.21	0.01	0.67	0	0.07	0.01	0.01	0.03
	districts 6-7 ^{O} N	0.14	0.02	0.68	0	0.09	0.01	0.03	0.03
	districts 7-8 ^{O} N	0.11	0.07	0.61	0.01	0.03	0.03	0.09	0.06
	districts 8-9 ^{O} N	0.05	0.31	0.32	0.02	0	0.08	0.17	0.04
	districts 9-10 ^{O} N	0	0.24	0.36	0.04	0	0.13	0.1	0.12
	districts over 10 ^{O} N	0	0.24	0.37	0.15	0	0.1	0.01	0.13
Scenario 1	districts below 6 ^{O} N	-0.02	0.03	-0.11	0.13	-0.04	-0.01	-0.02	0.02
	districts 6-7 ^{O} N	-0.01	0.03	-0.13	0.13	-0.03	-0.01	-0.02	0.03
	districts 7-8 ^{O} N	0	0.03	-0.16	0.16	-0.02	-0.01	-0.02	0.03
	districts 8-9 ^{O} N	0	0.02	-0.15	0.16	0	-0.03	-0.04	0.04
	districts 9-10 ^{O} N	0	0.02	-0.16	0.17	0	-0.03	-0.05	0.05
	districts over 10 ^{O} N	0	0	-0.19	0.27	0	-0.03	-0.02	-0.03
Scenario 2	districts below 6 ^{O} N	-0.05	0.04	-0.12	0.18	-0.04	-0.01	-0.02	0.03
	districts 6-7 ^{O} N	-0.03	0.03	-0.15	0.18	-0.04	-0.02	-0.02	0.04
	districts 7-8 ^{O} N	-0.01	0.03	-0.2	0.22	-0.03	-0.02	-0.02	0.03
	districts 8-9 ^{O} N	-0.01	0.02	-0.18	0.23	0	-0.05	-0.04	0.04
	districts 9-10 ^{O} N	0	0.02	-0.2	0.24	0	-0.05	-0.05	0.04
	districts over 10 ^{O} N	0	-0.01	-0.22	0.35	0	-0.04	-0.02	-0.05

[103] The "Other crops" category includes cowpea, cocoyam, sorghum, and sweet potato. Scenario 1 corresponds to an increase in temperature and rainfall by 0.7°C and 8%, respectively. Scenario 2 corresponds to an increase in temperature and rainfall by 0.9°C and 1%, respectively. Scenario 3 shows an increase in temperature by 1.5°C and a 4% reduction in rainfall. Scenario 4 represents an increase in temperature by 0.5°C and a 15% increase in rainfall. Scenario 5 represents a 2°C increase in temperature and a 10% reduction in rainfall. In scenario 6, temperature increases by 0.5°C and rainfall declines by 10%. Scenario 7 represents a 2°C increase in temperature and a 15% increase in rainfall.

	Latitude	Cassava	Groundnut	Maize	Millet	Plantain	Rice	Yam	Other crops
Scenario 3	districts below 6 ^{O} N	-0.13	0.06	-0.2	0.35	-0.05	-0.02	-0.02	0.03
	districts 6-7 ^{O} N	-0.07	0.04	-0.26	0.37	-0.05	-0.03	-0.03	0.03
	districts 7-8 ^{O} N	-0.04	0.03	-0.33	0.43	-0.04	-0.03	-0.03	0.02
	districts 8-9 ^{O} N	-0.02	0.01	-0.29	0.47	0	-0.07	-0.06	-0.03
	districts 9-10 ^{O} N	0	0	-0.3	0.49	0	-0.07	-0.07	-0.02
	districts over 10 ^{O} N	0	-0.04	-0.3	0.57	0	-0.06	-0.02	-0.12
Scenario 4	districts below 6 ^{O} N	0.01	0.03	-0.1	0.08	-0.03	0.01	-0.01	0.02
	districts 6-7 ^{O} N	0.01	0.03	-0.11	0.08	-0.02	0.01	-0.02	0.02
	districts 7-8 ^{O} N	0.01	0.03	-0.13	0.1	-0.02	0.01	-0.02	0.02
	districts 8-9 ^{O} N	0	0.02	-0.12	0.1	0	0	-0.03	0.03
	districts 9-10 ^{O} N	0	0.02	-0.13	0.1	0	0.01	-0.04	0.04
	districts over 10 ^{O} N	0	0.01	-0.15	0.19	0	0	-0.01	-0.02
Scenario 5	districts below 6 ^{O} N	-0.16	0.07	-0.31	0.49	-0.06	-0.03	-0.03	0.02
	districts 6-7 ^{O} N	-0.1	0.05	-0.36	0.53	-0.05	-0.04	-0.03	0.02
	districts 7-8 ^{O} N	-0.07	0.04	-0.43	0.59	-0.04	-0.04	-0.04	-0.01
	districts 8-9 ^{O} N	-0.02	0	-0.36	0.63	0	-0.08	-0.08	-0.09
	districts 9-10 ^{O} N	0	-0.02	-0.37	0.67	0	-0.09	-0.09	-0.09
	districts over 10 ^{O} N	0	-0.05	-0.34	0.69	0	-0.07	-0.03	-0.17
Scenario 6	districts below 6 ^{O} N	-0.03	0.02	-0.04	0.09	-0.03	-0.01	-0.01	0.02
	districts 6-7 ^{O} N	-0.02	0.02	-0.06	0.09	-0.02	-0.02	-0.01	0.02
	districts 7-8 ^{O} N	-0.01	0.02	-0.09	0.11	-0.02	-0.02	-0.01	0.02
	districts 8-9 ^{O} N	-0.01	0.03	-0.09	0.11	0	-0.04	-0.03	0.02
	districts 9-10 ^{O} N	0	0.04	-0.1	0.11	0	-0.04	-0.03	0.02
	districts over 10 ^{O} N	0	-0.02	-0.13	0.2	0	-0.03	-0.01	0

	Latitude	Cassava	Groundnut	Maize	Millet	Plantain	Rice	Yam	Other crops
Scenario 7	districts below 6 ^{O} N	-0.15	0.02	-0.32	0.46	-0.06	-0.02	-0.03	0.1
	districts 6-7 ^{O} N	-0.1	0.02	-0.37	0.48	-0.05	-0.03	-0.03	0.07
	districts 7-8 ^{O} N	-0.07	0	-0.43	0.55	-0.04	-0.03	-0.04	0.06
	districts 8-9 ^{O} N	-0.02	-0.07	-0.36	0.59	0	-0.07	-0.08	0.02
	districts 9-10 ^{O} N	0	-0.07	-0.37	0.62	0	-0.08	-0.09	0
	districts over 10 ^{O} N	0	-0.16	-0.34	0.66	0	-0.06	-0.03	-0.04

Chapter 4

The Impact of Warming on Food Consumption in Ghana

Abstract

We provide new evidence on the effects of temperature on farm income, non-farm income, and real food expenditure. We first apply a Heckman model to a large household dataset (10,200 observations) from Ghana in order to fit farm and non-farm income and then subsequently estimate a 3-stage least squares model. Consistent with our expectations, we find that income determines real food consumption. The elasticity of consumption of farm income (0.44) and non-farm income (0.33) are both positive and less than one. The difference in elasticities is statistically insignificant. We find an inverse relationship between the two types of income. Compared to non-farm income, we find that temperature has a larger negative effect on farm income. Warming also impacts negatively on real food consumption. For a typical adult, a 1°C increase in temperature results in a 4% decline in real food consumption. The decline in food consumption can be attributed to the negative effect of temperature on land and labour productivity. In the absence of microlevel adaptation, our results show that general welfare levels in Ghana will likely decline with warming.

4.1 Background

It has long been established that income affects consumption.[104] In the last decade, a substantial number of empirical studies have also shown that temperature has a direct effect[105] on food consumption.[106] This strand of literature appears to be developing separately from the strand of literature that estimates the impact of global warming on agriculture. Even though changes in agriculture (resulting from changes in the climate) have, among others, implications for food consumption (Food and Agricultural Organisation, FAO, 2008; Mirzabaev, 2015; Rosenzweig and Binswanger, 1993), most researchers (see Chapters 2 and 3 of this thesis) who study the impacts of global warming on agriculture do not extend their analysis to include how the estimated impacts ultimately (or indirectly) affect food consumption. We add to the very few studies that attempt to link these two strands of literature by simultaneously estimating the direct and indirect effects of warming on food consumption.

In establishing the indirect effects of temperature on food consumption, we make a distinction between farm income and non-farm income for two reasons. Firstly, a survey of the literature shows that temperature, our main variable of interest, has differential impacts on farm and non-farm income (Amisigo, et al., 2015; Hsiang and Deryugina, 2014; Jones and Olken, 2010; Thomas and Rosegrant, 2015; World Bank, 2010). Consistent with the literature, we expect warming to impact farm income more than non-farm income and therefore test that hypothesis. Secondly, we anticipate that the elasticity of consumption of farm income will be higher than non-farm income since the cost of consuming own

[104] See Friedman, 1957; Hall, 1978; Keynes, 1936; Laibson, 1997; Modigliani, 1966; 1986.

[105] A negative relationship between warming and metabolism, energy expenditure and food intake has already been reported (Lichtenbelt et al., 2001; Westerterp-Plantenga et al., 2002).

[106] E.g. Asfaw et al., 2015; Asiimwe and Mpuga, 2007; Bandyopadhyay and Skoufias, 2012; FAO, 2016; Foltz et al., 2013; Hirvonen, 2016; Lazzaroni and Bedi, 2014; Mirzabaev, 2015; Nkegbe and Kuunibe, 2014; Rosenzweig and Binswanger, 1993; Safir et al., 2013; Skoufias and Vinha, 2013; Skoufias et al., 2012; Zhou and Turvey, 2015.

production is likely to be lower than the cost of consuming purchased food. That is, farmers may find it easier to increase their consumption (as farm productivity increases) as compared to non-farmers who may still to have overcome some constraints (e.g. transaction costs) in order to increase consumption (as non-farm productivity increases).

For our empirical strategy, we first use a large micro-level dataset (10,200 observations) from Ghana to fit farm and non-farm income and since a simultaneous (reverse causality) relationship between farm and non-farm income is plausible, we subsequently estimate a 3-Stage Least Squares (3SLS) model. Our estimation results show a negative relationship between real food consumption and temperature. This implies that an average adult will likely compensate for any warming-related decline in productivity by reducing real food consumption. We also observe an inverse relationship between farm income and non-farm income suggesting that households are more likely to specialise in either agriculture or non-farm operations (depending on climatic and other constraints). The elasticity of consumption of both farm income (0.44) and non-farm income (0.33) is positive and less than one (indicating that food is a necessity as expected). The 0.11 difference in elasticity is not statistically significant. Additionally, we find that farm income and non-farm income are both impacted negatively by temperature with farm income affected the most.

The detailed results are presented and discussed in Section 4.4. We review related empirical studies in the next section. The methodology of the study which is made of the conceptual framework and empirical strategy is presented in Section 4.3. We summarise and conclude the study in Section 4.5.

4.2 Previous Assessments of the Impacts of Global Warming on Food Consumption

Having already reviewed how climate change impacts on farm income (see Chapter 3 of this thesis), we now turn our attention to the impacts of global warming on food consumption.

Our review covers applied economic (partial equilibrium) studies only. We did not review studies that apply multidisciplinary or data intensive methods such as general equilibrium models.[107] Also excluded from our review are studies that examine the impacts of warming on the consumption of non-food items such as energy (Fikru and Gautier, 2015; Kaufmann et al., 2013), tobacco (Govind et al., 2014) and water (Chang et al., 2014).

There is no unanimity among practitioners on the environmental variable that influences food consumption. Nonetheless, weather-related studies[108] seem to outnumber climate-related studies.[109] The type of environmental variable that is estimated appears to depend on the type of data that is available to the researcher and the estimation technique utilised. Studies that estimate the impact of weather and weather variability on consumption usually depend on pooled cross-sectional or panel data (ranging from 2 to 8 waves) and either estimate a random or fixed effects model. The time difference between the first and last panel is typically less than 30 years, therefore, those weather observations cannot technically be used to represent climate change. Papers that estimate the impact of warming on food consumption, including this study, usually match long-term weather observations with cross-sectional data. Even though panel data enables the researcher to control for unobserved characteristics, the cost involved (in collecting such data over the required length of time) makes it difficult for practitioners interested in estimating climate effects to adopt panel methods.

Our review shows that the majority of studies estimate a reduced model that only highlights the overall impacts of climate or weather without explicitly revealing the mechanism(s)

[107] E.g. Arndt et al., 2012; Thurlow et al., 2009; Wiebelt et al., 2013; Winters et al., 1998; Wossen and Berger 2015; Wossen et al., 2014.
[108] See Asfaw et al., 2015; Asiimwe and Mpuga, 2007; FAO, 2016; Foltz et al., 2013; Hirvonen, 2016; Lazzaroni and Bedi, 2014; Nkegbe and Kuunibe, 2014; Rosenzweig and Binswanger, 1993; Safir et al., 2013; Skoufias and Vinha, 2013; Zhou and Turvey, 2015.
[109] See Bandyopadhyay and Skoufias, 2012; Mirzabaev, 2015: Skoufias et al., 2012.

through which food consumption is affected.[110] In addition to the direct effects, a few studies recognise that climate or weather variables can also impact on food consumption indirectly through occupational choices (Bandyopadhyay and Skoufias, 2012) or agricultural income (Mirzabaev, 2015; Rosenzweig and Binswanger, 1993; Zhou and Turvey, 2015). The studies that analyse the direct and indirect effects of climate or weather estimate their model in either two-stages (Bandyopadhyay and Skoufias, 2012; Mirzabaev, 2015; Rosenzweig and Binswanger, 1993) or three-stages (Zhou and Turvey, 2015). Our model is similar to Zhou and Turvey (2015) except that we treat non-farm income (other income) as a response variable instead of an exogenous variable since it determines food consumption (Babatunde and Qaim, 2010; Imai et al., 2015; Seng, 2015; Zereyesus et al., 2017) and is also influenced by climate, farm income, and other covariates (D'haen et al., 2014; Nagler and Naudé, 2017).

Climate and weather have mixed effects on food consumption. While some authors do not observe any significant relationship between weather and consumption (because households are able to adapt or smoothen out consumption), the majority of studies find a significant relationship between weather and food consumption since households are not always able to smooth out their consumption (because weather shocks can either increase or decrease income). Hirvonen (2016) establishes that a one standard deviation increase in temperature lowers per capita consumption in Tanzania. In the case of rural Uganda, Lazzaroni and Bedi (2014) also observe that higher than normal temperature affects food consumption negatively. According to Foltz et al., (2013), temperature impacts positively on household consumption because heat-loving crops grown in the highlands of rural Ethiopia benefit from warming. Nkegbe and Kuunibe (2014) estimate a non-linear relationship between weather and total consumption based on data from northern Ghana. They find that the relationship between

[110] See Asfaw et al., 2015; Asiimwe and Mpuga, 2007; FAO, 2016; Foltz et al., 2013; Hirvonen, 2016; Lazzaroni and Bedi, 2014; Nkegbe and Kuunibe, 2014; Safir et al., 2013; Skoufias and Vinha, 2013; Skoufias et al., 2012.

total consumption and temperature is hill-shaped suggesting that initial increases in temperature favours agriculture and the elimination of mosquitoes (improve health), respectively, whilst further increases in temperature results in drought.

Although rainfall effects are not the main focus of our study (rainfall turns out to have a practically insignificant effect on food consumption as shown in Appendix 4.4), a review of the literature shows that the empirical relationship between food consumption and rainfall is varied. A statistically insignificant effect is found in Uganda (Asfaw et al., 2015; Skoufias et al., 2012), Indonesia (Lazzaroni and Bedi, 2014), and China (Zhou and Turvey, 2015). A positive relationship is found in Ethiopia (Foltz et al., (2013), Uganda (Skoufias and Vinha (2013), and Mexico (Asiimwe and Mpuga (2007), whereas a negative effect is established in Tanzania (FAO, 2016) and Bangladesh (Bandyopadhyay and Skoufias, 2012).

Studies that estimate differential impacts of climate generally find that poor households or households in the lower income quintiles tend to be more sensitive to changes in climate.[111] According to Foltz et al., (2013), a household located in a vulnerable area is more likely to be worse-off than a poor household located in a non-vulnerable area. Whereas poor households in central Asia are expected to reduce consumption by 0.52% with a 1% decline in income, rich households are expected to reduce consumption by only 0.04% (Mirzabaev, 2015).

The papers that we review have some limitations. Some studies use interpolated climate data (i.e. gridded and reanalysis) in order to avoid the problem of missing data often associated with weather station observations.[112] However, interpolated climate data are liable to measurement error and its consequences (Auffhammer et al., 2013). A few studies do not state how their climate and survey data are matched (e.g. Mirzabaev, 2015; Nkegbe and Kuunibe, 2014; Zhou and Turvey, 2015), and some studies do not control for income, a very

[111] See Asfaw et al., 2015; FAO, 2016; Hirvonen, 2016; Mirzabaev, 2015; Zhou and Turvey, 2015.
[112] E.g. Asfaw et al., 2015; FAO, 2016; Foltz et al., 2013; Hirvonen, 2016.

important determinant of consumption (e.g. Hirvonen, 2016; Lazzaroni and Bedi, 2014; Skoufias et al., 2012).

Some papers fail to account for heterogeneity among households since they neither control for household size and sex nor take those factors into consideration in the computation of household consumption (e.g. Hirvonen, 2016; Rosenzweig and Binswanger, 1993). On the other hand, Skoufias et al., (2012) and Nkegbe and Kuunibe (2014) control for household composition (i.e. household size, age and sex) even though those variables are already factored in the computation of their dependent variable (consumption per capita or adult equivalence).

It is well known that the effect of climate on agriculture is non-linear (Mendelsohn et al., 1994). This notwithstanding, Zhou and Turvey (2015) only control for the linear effects of climate in their agricultural production equation. Rosenzweig and Binswanger (1993) estimate a farm income regression with rainfall as one of the covariates and instead of deriving the fitted values of farm income; the residuals are rather derived and used as an explanatory variable for their consumption regression.

Safir et al., (2013) utilise a qualitative measure for weather variability where households are assigned a value of one if their rainfall is more than one standard deviation above the long-term mean, and zero for otherwise. They then proceed to log transform food consumption and interpret the coefficients on the rainfall variability variable as percentage changes implying that a computation of the derivative of a qualitative regressor is possible contrary to the findings of Halvorsen and Palmquist (1980) and Kennedy (1981).[113]

[113] The qualitative regressor can be converted to percentage using the formuale $100(exp(c) - 1)$ rather than $100(c)$, where c is the coefficient of the regressor (Halvorsen and Palmquist, 1980).

Although the literature provides useful information on how temperature impacts on food consumption, there is limited information on how warming simultaneously impacts on farm income, non-farm income, and food consumption. This study provides new evidence on the impacts of temperature by estimating a 3SLS model with farm income, non-farm, and food consumption as our response variables.

4.3 Methodology

4.3.1 Conceptual framework

Figure 4.1 presents our conceptual framework. The study assumes that households prefer more consumption to less consumption. Households face some constraints including environmental (climate), institutional, and demographic constraints. Given these limitations, households must allocate their resources optimally to produce outputs that will lead to their desired outcome of increased consumption. Households can allocate their resources to agriculture, non-farm activities, or various combinations of farm and non-farm enterprise (D'haen et al., 2014; Hsiang and Deryugina, 2014; McNamara and Weiss, 2005; Nagler and Naudé, 2017; Reardon et al., 1994; Skoufias et al., 2017).

Temperature has already been identified as a direct determinant of food consumption.[114] Temperature can impact on food consumption directly by biologically altering the food needs of individuals. Controlled experiments have shown that the human body autonomously adapt to warming by decelerating metabolism and energy expenditure (Lichtenbelt et al., 2001; Westerterp-Plantenga et al., 2002). Warming can also impact on food consumption indirectly

[114] See, for example, Asfaw et al., 2015; Asiimwe and Mpuga, 2007; Bandyopadhyay and Skoufias, 2012; FAO, 2016; Foltz et al., 2013; Hirvonen, 2016; Lazzaroni and Bedi, 2014; Mirzabaev, 2015; Nkegbe and Kuunibe, 2014; Rosenzweig and Binswanger, 1993; Safir et al., 2013; Skoufias and Vinha, 2013; Skoufias et al., 2012; Zhou and Turvey, 2015.

by influencing agricultural productivity (see Chapter 3 of this thesis) and non-farm income (D'haen et al., 2014; Nagler and Naudé, 2017). Specifically, we hypothesise that temperature affects food consumption through 3 indirect channels. Firstly, warming influences households' decision to participate in non-farm operations and consequently non-farm income and food consumption. A second channel involves households that use non-farm income (farm income) to support the generation of additional farm income (non-farm income) for consumption. Households that do not earn any non-farm income (farm income) and therefore depend solely on farm income (non-farm income) for food consumption constitute a third channel.

Regardless of the channel, we expect temperature to ultimately have a negative effect on food consumption. Yet, we anticipate that household that depend solely on farm income will be worst affected by warming followed by those that depend on only non-farm income with households that have both farm and non-farm income being the least affected. In order to model the multiple channels through which temperature can likely impact on food consumption, a plausible estimation strategy would be to compute a system of equations rather than a single equation.

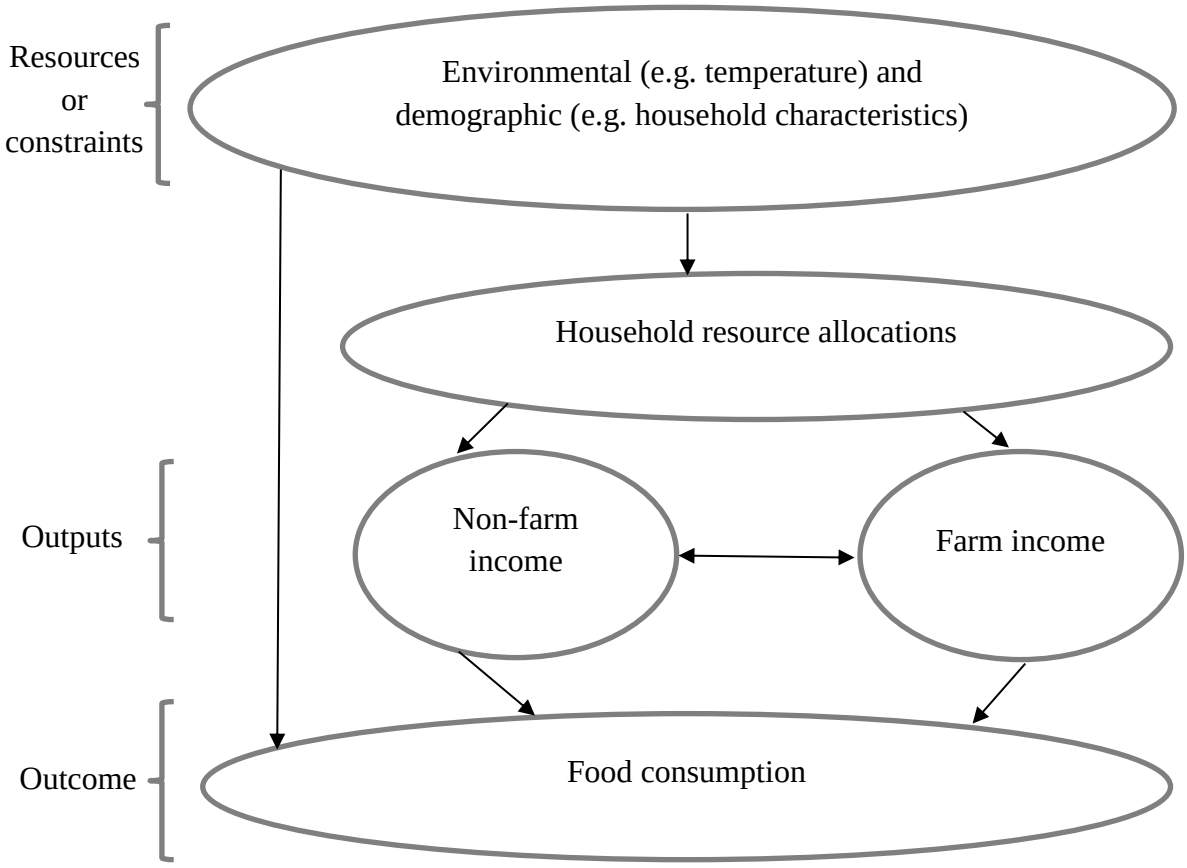


Figure 4.1: Conceptual framework

4.3.2 Empirical strategy

A couple of methods are available for estimating a system of equations including the Ordinary Least Squares (OLS), Zellner's Seemingly Unrelated Regression Equations (SURE) and 3-Stage Least Squares (3SLS). OLS can be used if the equations in the system are recursive and unrelated. There is loss of efficiency when the equations are correlated in which case SURE performs better (Cameron and Trivedi, 2009; Greene, 2012; Zellner, 1962). Even in the absence of cross-equation correlations, SURE still performs better than OLS if the equations do not contain the same covariates (Cameron and Trivedi, 2009; StataCorp, 2017). Furthermore, SURE makes it possible to jointly test for cross-equation significance since a construction of the variance-covariance matrix of the entire system is possible (Cameron and Trivedi, 2009; StataCorp, 2017).

OLS and SURE are inappropriate when there is simultaneity or reverse causality (i.e. when the response variables in a system of equations are endogenous or interdependent). On the contrary, the 3SLS technique is appropriate for modelling simultaneity (Greene, 2012; Wooldridge, 2012). Similar to the SURE, the 3SLS technique allows for cross-equation tests (StataCorp, 2017). 2SLS can also be used to estimate a simultaneous model but are generally less efficient than the 3SLS when the model contains more than 2 identified equations (StataCorp, 2017; Wooldridge, 2012). However, 2SLS is computationally easier to estimate and performs better in the presence of heteroskedasticity (Cameron and Trivedi, 2009). Based on its attractive features and because our response variables are probably interdependent,[115] we estimate a 3SLS model and present the corresponding OLS and 2SLS estimates as Appendix 4.3.

Variables and Identification

There is evidence that food consumption, our main response variable, is determined by farm income and non-farm income (our other two response variables).[116] Non-farm income tends to be correlated with farm income (Reardon et al., 1994). The correlation is positive when income from one enterprise is used to improve the productivity or returns of the other enterprise (e.g. financing farm operations at the beginning of the production season with non-farm income). An inverse relationship is also possible if one of the enterprises is undertaken as an adaptation strategy such that attention is switched from the main source of income to the secondary source of income under unfavourable conditions and vice versa. Therefore, a reverse relationship between farm and non-farm income is possible. We expect to find a positive farm and non-farm income elasticity of less than one since food consumption is a necessity.

[115] For example, non-farm income can be used to finance farm operations and vice versa.
[116] See Babatunde and Qaim, 2010; Imai et al., 2015; Seng, 2015, Zereyesus et al., 2017.

As already indicated, we account for possible simultaneity by estimating a 3SLS model. The model is identified through exclusion restrictions. Consistent with the literature, we consider warming (temperature) and education as exogenous variables since it has already been established that those variables have a unilateral effect on farm income (see Chapter 3 of this thesis), non-farm income,[117] and food consumption.[118] In making income allocation decisions, households are more likely to prioritise the education of younger (other) members over the education of the head. Therefore, a reverse causality between income and educational attainment of the head of household is quite unlikely (since household heads with primary or no education will have to enroll with children or teenagers if they were to further their education following an increase in income). Nonetheless, we omit education in another version of our model (See Section 4.4.2). The other three variables that we consider as exogenous are distance to drinking water (an indicator for level of development), soil type, and general price level.

We expect households with access to water (or those in more developed areas) to also have access to varied non-farm vocational training opportunities and consequently income. We do not control for distance to drinking water in our farm income equation because such a relationship is not obvious for our study area, i.e. domestic water use (i.e. drinking water) and agricultural water use differ in Ghana. Whereas all households have access to drinking water,[119] agricultural water (irrigation) contributes less than 1% to total agricultural production (MoFA, 2010; 2014; World Bank, 2010). Since agriculture in Ghana is basically

[117] See Dell et al., 2012; Hsiang, 2010; Hsiang and Deryugina, 2014; Jones and Olken, 2010.

[118] See Asfaw et al., 2015; Asiimwe and Mpuga, 2007; Bandyopadhyay and Skoufias, 2012; FAO, 2016; Foltz et al., 2013; Hirvonen, 2016; Lazzaroni and Bedi, 2014; Safir et al., 2013; Skoufias et al., 2012; Skoufias and Vinha, 2013; Zhou and Turvey, 2015.

[119] All households consume water because it is an essential commodity. However, there is variation among households in terms of quality of drinking water and ease of access.

rain-fed, we do not anticipate a correlation between access to drinking water and agricultural productivity.

Due to several deliberate national agricultural interventions, we do not expect a direct relationship between agriculture productivity and proximity to a city (or the level of development of a community). Examples of deliberate national agricultural interventions include the fertiliser subsidy program, livestock development project, rice sector support project, drought-tolerant maize for Africa program, root and tuber improvement and marketing program, West African agricultural productivity program, agriculture services sub-sector investment program among others (Etwire et al., 2013; MoFA, 2010). In addition to these projects and programs, the Ministry of Food and Agriculture has an office in every district of the country where agricultural extension officers are assigned to various communities. Apart from the district offices, the Ministry also has a couple of specialised livestock stations. Ghana's national agriculture research council, the Council for Scientific and Industrial Research, has a research institute responsible for the development of agricultural commodities in every region of the country (MoFA, 2010). Given these institutions, projects, and programs, we do not anticipate a correlation between agricultural productivity and the level of development of a community (or proximity to a city).

Soil type has already been found to be a determinant of farm income (see Chapter 3 of this thesis). We expect to find a positive relationship between high-quality soil and farm income. We exclude soil type from the non-farm equation. We expect soil type and distance to drinking water to influence food consumption only through farm income and non-farm income, respectively. We also include a household price index as a covariate for all our response variables. Our price index is computed using household level data. By assuming that individual households are price-takers, we treat the household price index as an exogenous variable. Our empirical model is specified as;

$$Log(nonfarm\ income) = \alpha_0 + \alpha_1 \text{Log}(farm\ income) + \alpha_2 Temperature + \alpha_3 (Temperature)^2 + \alpha_4 Distance\ to\ water\ + \alpha_5 Education + \alpha_6 Log(price\ index) + u_1 \quad (4.1a)$$

$$Log(farm\ income) = \beta_0 + \beta_1 \text{Log}(nonfarm\ income) + \beta_2 Temperature + \beta_3\ (Temperature)^2 + \beta_4 Soil + \beta_5 Education + \beta_6 Log(price\ index) + u_2 \quad (4.1b)$$

$$Log(food\ consumption) = \gamma_0 + \gamma_1 \text{Log}(nonfarm\ income) + \gamma_2 \text{Log}(farm\ income) + \gamma_3 Temperature + \gamma_4 (Temperature)^2 + \gamma_5 Education + \gamma_6 \text{Log}(price\ index) + u_3 \quad (4.1c)$$

Note that the indirect effects of warming are captured by controlling for temperature in Equations 4.1a and 4.1b. The temperature variable in Equation 4.1c shows the direct effects of warming. A plot of the relationship between temperature and food consumption is shown in Appendix 4.1.

We only observe farm income and non-farm income for 59% and 24% of our sample.[120] The relatively large number of observations with zero farm and non-farm income implies that any least squares estimate with those two variables as response variables would be inappropriate (Cameron and Trivedi, 2009; Greene, 2012; StataCorp, 2017; Wooldridge, 2012). Failure to explicitly model the decision to participate in either farm on non-farm operation will likely result in a biased estimate since we do not observe any farm income for non-farm households and vice versa.[121] Therefore, the farm and non-farm income that we rely on to estimate our 3SLS model (Equations 4.1a-c) are fitted based on the following Heckman selection model (Heckman, 1976);

[120] Given that only 59% (24%) of our sample engage in farm (non-farm) operations, the non-farm (farm) income of these farm (non-farm) households can be treated as missing.

[121] The decision to participate and the income from participation are likely to be correlated.

$$Nonfarm\ income = \acute{\alpha}_0 + \acute{\alpha}_1 Farm\ income + \acute{\alpha}_2 Temperature + \acute{\alpha}_3 (Temperature)^2 + \acute{\alpha}_4 Distance\ to\ water + \acute{\alpha}_5 Education + \acute{\alpha}_6 \text{Log}(price\ index) + v \quad (4.2a)$$

Conditioned on;

$$Nonfarm\ selection = \acute{\alpha}_0 + \acute{\alpha}_1 Farm\ income + \acute{\alpha}_2 Temperature + \acute{\alpha}_3 (Temperature)^2 + \acute{\alpha}_4 Distance\ to\ water + \acute{\alpha}_5 Education + \acute{\alpha}_6 \text{Log}(price\ index) + \acute{\alpha}_7 Population\ density + w \quad (4.2b)$$

$$Farm\ income = \text{ƀ}_0 + \text{ƀ}_1 Nonfarm\ income + \text{ƀ}_2 Temperature + \text{ƀ}_3 (Temperature)^2 + \text{ƀ}_4 Soil + \text{ƀ}_5 Education + \text{ƀ}_5 \text{Log}(price\ index) + e \quad (4.3a)$$

Conditioned on;

$$Farm\ selection = \text{ƀ}_0 + \text{ƀ}_1 Nonfarm\ income + \text{ƀ}_2 Temperature + \text{ƀ}_3 (Temperature)^2 + \text{ƀ}_4 Soil + \text{ƀ}_5 Education + \text{ƀ}_6 \text{Log}(price\ index) + \text{ƀ}_7 Population\ density + f \quad (4.3b)$$

We use population density as an indicator variable for access to land,[122] a fundamental unit of production. We expect a higher population density to have a negative effect on the probability of selecting agriculture but a positive influence on non-farm selection. An increase in population density or a decrease in land size per capita will likely reduce (increase) the probability of selecting agriculture (non-farm operations). That is, we expect higher diminishing marginal returns to agriculture as population density increases. We exclude population density from the outcome equation because we do not expect farm and non-farm productivity to depend on access to land but rather the quality of land and labour.

[122] Note that population density may not be a particularly good measure for level of development or proximity to a city as less developed areas in Ghana can also have high population densities due to large families arising from polygamy or the need for family labour. We use access to water as a proxy for level of development as stated earlier on in this section.

We define population density as the number of people per square kilometre. Farm income is measured as the market value of total farm produce less the cost of production. Non-farm income is the net income obtained from all non-farm operations. Real food consumption is the nominal value of food consumed deflated by the price index. Note that for the estimation model (descriptive statistics), farm income, non-farm income, and food consumption are a year's (day's) observation divided by adult equivalence.[123] Farm and non-farm income and are expressed in the United States Dollars (US$). We transform our income variables into their natural logarithms thus the coefficients of farm and non-farm income can be interpreted as elasticities since real consumption is also log-transformed. The logarithm transformation is intuitive since the effect of income tends to depend on the baseline condition. For example, a 1% increase in income will likely impact the consumption of poor and non-poor individuals differently.

Price index is a weighted average of food prices computed from the household survey. Our price index is akin to a consumer price index (CPI)[124] for a single period and is log-transformed. Specifically, the price index for a farm household is the CPI for the basket of food-crops and livestock consumed by that household.[125] Non-farm households are assigned

[123] The adult equivalence for males aged 11-14, 15-18, 19-50, and 51+ is 0.86, 1.03, 1, and 0.79, respectively. The equivalence for females aged 11-50 and 51+ is 0.76 and 0.66, respectively. The equivalence for children below 10 years ranges between 0.22 and 0.69 (Ghana Statistical Service, GSS, 2014).

[124] We do not make a distinction between producer price and consumer price. It seems reasonable to assume that the two are the same at the farm level.

[125] The price index of a farm household is $FPI_j = \frac{P_j^1 Q_j^1}{\sum_{k=1}^{n} P_j^k Q_j^k} P_j^1 + \cdots + \frac{P_j^n Q_j^n}{\sum_{k=1}^{n} P_j^k Q_j^k} P_j^n$ where P is the price and Q is the quantity of food-crops and livestock consumed, k is the number of commodities consumed from 1 to n. As it is to be expected, the composition of food-crops and livestock consumed varies across the country. A total of 43 crop types and 19 livestock types were captured by the household survey.

the CPI reported by their closest farm neighbour.[126] Thus, none of the households studied have a unique price index value.

Temperature, measured in degree Celsius (^{o}C), is the average weather conditions recorded over a period of 38 years (1973-2011).[127] Distance to drinking water is the time it takes to access drinking water and is measured in minutes for the descriptive statistics but hours for the estimation model. Soil quality (high, intermediate, and low) and education (no, primary, and secondary) are measured qualitatively on a 3-level scale. Education refers to the educational attainment of the household head. The other variables refer to the entire household. Following Halvorsen and Palmquist (1980) and Kennedy (1981), we transform the marginal effects of our qualitative explanatory variables to reflect percentages since all our response variables are log-transformed. See Chapter 1 (of this thesis) for a description of our sources of data.

4.4 Results and Discussion

4.4.1 Description of variables

Table 4.1 describes our endogenous and explanatory variables. An average adult spends about US$2.90 on food every day. The corresponding standard deviation shows that there is a large variation between individuals. A comparison of the consumption levels in 1991 and 2012 reveals a 30% increment in the consumption gap between the 10th and 90th quintiles (Clementi et al., 2016).

The daily earning of an average adult is about US$3.00, i.e. US$1.80 from farm income and US$1.20 from non-farm sources. Farm enterprises include tree-crop, food-crop, and livestock

[126] We are unable to construct a household level price index for non-farm households because our data does not capture non-farm food prices and quantities. Unlike farm households who report food quantities and food expenditure, non-farm households only report food expenditure.

[127] The temperature variable is the same as the selection temperature variable in Chapter 3 of this thesis.

production. Non-farm enterprises include agro-processing, hair dressing, carpentry, building and construction, bicycle and motorbike repairs, metal fabrication, dress making, shoe and leatherworks, driving, weaving, and others. Note that we evaluate only farm and non-farm income. We do not consider transitory income (e.g. donation, dowry, and occasional remittance) and fixed income (e.g. pension, government support, and public pay). Transitory income is irregular and can be sent from outside the locality whilst fixed income are constant inflows (often received from outside the locality) hence both types of income are not likely to be affected by changes in the local temperature.

The mean annual temperature for the period 1973-2011 is 27°C. Located near the equator, Ghana is a fairly warm country. The average temperature seems to be just about optimal for the production of most agricultural commodities currently produced as future changes are projected to impact negatively on Ghana's agriculture (Chapter 3 of this thesis; Mabe et al., 2013; Nkegbe and Kuunibe, 2014).

Table 4.1 also shows that an average household travels about seven minutes to access drinking water. The standard deviation of our price index variable shows a large difference in price across the country. The descriptive statistics also show that farm households often produce their commodities on good quality soils. A typical household head has some form of education.

We test for observable differences between households (farm, non-farm, and combined) using the one-way analysis of variance and chi-square tests for quantitative and qualitative variables, respectively. Table 4.1 shows that on the average, households are significantly different from each other. Non-farm households consume more food whilst farm households earn higher farm income, travel longer distance to access drinking water, and produce on

higher quality soils. Non-farm income is higher for households that earn both farm and non-farm income.

Table 4.1: Descriptive statistics of the variables

Quantitative variables (Mean)	Non-farm income	Farm income	Combined farm and non-farm income	Total	F	Prob>F
Food consumption per adult equivalence, PAE (US$ per day)	3.64	2.55	3.17	2.92	63.34	0.000
	5.30	*3.41*	*4.62*	*4.17*		
Non-farm income PAE (US$ per day)	2.65	0	3.16	1.17	1380.91	0.000
	4.27	*0*	*4.23*	*3.07*		
Farm income PAE (US$ per day)	0	2.48	2.06	1.82	678.96	0.000
	0	*3.25*	*3.25*	*3.01*		
Temperature (ºC)	26.48	26.58	26.51	26.55	23.51	0.000
	0.64	*0.68*	*0.66*	*0.67*		
Distance to drinking water (minutes)	2.54	9.24	6.85	0.12	311.47	0.000
	4.80	*13.18*	*10.26*	*0.19*		
Price index	93.16	111.44	105.51	106.04	13.92	0.000
	124.81	*152.58*	*142.59*	*144.86*		
Qualitative variables (Frequencies)	**Non-farm income**	**Farm income**	**Combined farm and non-farm income**	**Total**	**Chi^2**	**$Prob>Chi^2$**
Education 1 (primary)	1,307	2,714	881	4,902	693.18	0.000
	26.66	*55.37*	*17.97*	*100*		
Education 2 (≥secondary)	789	854	326	1,969		
	40.07	*43.37*	*16.56*	*100*		
Soil 1 (high-quality)	1,412	3,203	841	5,456	383.31	0.000
	25.88	*58.71*	*15.41*	*100*		
Soil 2 (Intermediate)	889	1,514	432	2,835		
	31.36	*53.4*	*15.24*	*100*		
Observations	2,452	6,022	1,723	10,197		

Notes: Our response variables are non-farm income, farm income, and food consumption. No education and low-quality soil serve as the base category for their respective variables. Whereas education refers specifically to the household head, the other variables refer to the entire

household. Temperature is the prevailing weather conditions recorded over a period of 38 years (1973-2011). Figure in italics are standard deviations for quantitative variables and percentage for qualitative variables.

4.4.2 The empirical model

Appendix 4.7 and 4.8 present results of the Heckman selection models (Equations 4.2a-b and 4.3a-b) that we apply to fit the farm and non-farm income utilised subsequently in the main model. Note that our selection instrument, population density, significantly impacts on farm participation negatively and non-farm participation positively as anticipated. Table 4.2 presents the population-averaged marginal effects of our 3SLS model (Equations 4.1a-c).

Table 4.2 suggests that farm income and non-farm income are substitutes rather than complements. That is, households appear to be facing a trade-off between farm and non-farm operation. Doubling of non-farm income leads to a 3.8% decline in farm income whilst doubling of farm income results in a 1% reduction in non-farm income. The inverse relationship between farm and non-farm income could be attributable to the resource constraints that households face (e.g. labour). In addition, households that adopt income diversification as a risk mitigation strategy will likely divert attention from (or may not even need) their secondary source of income once the primary source is sufficient.

In Burkina Faso, Ghana's immediate neighbour to the north, farm households allocate more resources to their farming activities when the climate is favourable and vice versa for non-farm operations (D'haen et al., 2014). A similar trade-off was observed for Nigeria but not Niger where favourable climatic conditions increase the probability of households undertaking non-farm activities (Nagler and Naudé, 2017).

Table 4.2 shows that the elasticity of consumption of farm income and non-farm income is 0.44 and 0.33, respectively. This result confirms the necessity of food. Contrary to our *apriori* expectations, the 0.11 difference in the elasticities of consumption of farm and non-farm income is statistically insignificant.[128] A positive relationship between non-farm

[128] The lower and upper limit of the 95% confidence interval (for the difference in elasticity) is -0.15

participation and food consumption has been established in a couple of areas including northern Ghana (Zereyesus et al., 2017), Nigeria (Babatunde and Qaim, 2010), Cambodia (Seng, 2015), and India (Imai et al., 2015).

Distance to drinking water has a negative effect on non-farm income. Households that travel longer distances for their drinking water earn less from non-farm income since such households are more likely to be in relatively undeveloped areas with limited access to non-farm opportunities. Households who stay an hour away from their source of drinking water earn 40% less non-farm income. As anticipated, we find that soil type influences farm income. High-quality soils improve annual farm income by about 40%.

Education is statistically significant across equations. For all our response variables, the differences in impact between the three levels of education (i.e. secondary vs primary, secondary vs no education, and primary vs no education) is also statistically significant at conventional levels. Non-farm income is impacted positively by education. This result is expected since accumulation of human capital has been established to be a key determinant of productivity.[129]

Apart from non-farm income, secondary or higher education also impacts positively on real food consumption. Compared to uneducated individuals, individuals with primary and higher education spend 22% and 66% more on food. Individuals are likely to become more restrictive or selective with foods as they acquire additional education. A couple of studies also find a positive relationship between education and consumption.[130] However, a few studies find an insignificant effect of education on food consumption (e.g. Skoufias and Vinha, 2013; Zhou and Turvey, 2015).

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and 0.36, respectively.

[129] See Syverson (2011) for a survey of the literature.

[130] For example, Asiimwe and Mpuga, 2007; Bandyopadhyay and Skoufias, 2012; FAO, 2016; Safir et al., 2013; Skoufias et al., 2012.

We find a positive relationship between the price index and farm income but estimate a negative correlation between non-farm income and the price index. The negative correlation between the price index and non-farm income reaffirms our earlier observation that households tend to treat farm income and non-farm income as substitutes. Our price index estimate suggests that non-farm workers are more likely to switch to agriculture as prices of food-crops and livestock (or earnings from agricultural production) increase and vice versa.[131] The net effect of an increase in price is a reduction in real food consumption. A 1% increase in prices results in a 1% reduction in real food consumption. The high responsiveness of food consumption to price could be due to the possibility of households switching between food types (e.g. switching from maize and sheep consumption to millet and goat consumption) or because food constitutes a large share of household expenditure hence subsistence households may be constrained to reduce food consumption as price increases.

Temperature impacts negatively on all our response variables. Temperature is also significant across equations. It is already known that warming reduces the productivity of both farm and non-farm workers (Hsiang and Deryugina, 2014). Furthermore, we established in Chapters 2 and 3 that warming affects aggregate Ghanaian farm income negatively by favouring the production of low-value drought-tolerant commodities over high-value drought-susceptible commodities. As expected, Table 4.2 shows that warming impacts farm income more than non-farm income. The impact of warming on farm income is almost triple that of non-farm income. Whereas a 1°C increase in temperature reduces non-farm income of an average adult by 6%, farm income of an average adult declines by 16%. The difference in impact is statistical significant at the 1% level. This result support earlier observations that global

[131] Recall that our price index variable is a weighted average of food-crop and livestock prices and therefore relates directly to farm income. See Section 4.3.2.

warming affects the agricultural sector more than other sectors of the economy (Amisigo, et al., 2015; Jones and Olken, 2010; Thomas and Rosegrant, 2015; World Bank, 2010). In the United States of America for instance, an extra warm day reduces total income per capita by $14.78 with the non-farm component amounting to $3.03 (Hsiang and Deryugina, 2014).

Warming has a negative effect on real food consumption. A 1°C increase in temperature results in a 4% decrease in the real food consumption of an average adult. The quadratic specification of temperature in our model allows for its effects to be non-monotonic. Appendix 4.1 shows that the marginal effect of temperature on real food consumption is negative (positive) for observations below (above) 26.8^{o}C. As shown earlier in the conceptual framework (see Section 4.3.1), warming can impact negatively on average real food consumption by reducing productivity (e.g. agricultural yields or the number of hours worked) and food intake. In the absence of planned adaptation, controlled experiments have also shown that the human body autonomously adapts to warming by decelerating metabolism, energy expenditure and energy intake (Lichtenbelt et al., 2001; Westerterp-Plantenga et al., 2002). A computable general equilibrium modelling by Arndt et al., (2014) predict up to a 4% decline in average real food consumption in Ghana by 2050.

Although our results are not directly comparable to the larger literature because of the differences in agro-ecologies and choice of climate variable, it is worth highlighting some previous findings. Foltz et al., (2013) report a positive relationship between warming and food consumption in Ethiopia that could be resulting from the thriving of heat loving crops especially in the cool highlands of the country. Relying on data from rural Mexico, Skoufias and Vinha (2013) observe that warmer than average wet seasons result in higher expenditure per capita. The increase in consumption is supported by the sale of assets and assistance from safety networks. Zhou and Turvey (2015) also find that warming increases the intake of carbohydrates and fats but decreases the intake of protein in rural China. Hirvonen (2016)

and Lazzaroni and Bedi (2014) both report a negative relationship between food consumption and temperature variability. In the case of Uganda, Asfaw et al., (2015) report that temperature variability does not generally affect food consumption.

Robustness check

We subject our model to a few robustness checks. We replace our household price index with a less precise (and maybe a more exogenous) district-level price index[132] and present the results as Appendix 4.2. We apply two alternate regression techniques (2SLS and OLS) to our model and present the results as Appendix 4.3. Although this study focusses on temperature, rainfall is another climate variable that is frequently studied. Therefore, we include rainfall, $(\text{rainfall})^2$ and (temperature*rainfall) interaction as additional covariates in Appendix 4.4. In Appendix 4.5, we apply our model to three different subsamples derived on the basis of household size (that is households with up to three members, four to six members, and more than six members). In our final robustness check, we estimate a simple linear function (instead of a quadratic function) and present the results as Appendix 4.6.

Appendix 4.2 shows that our estimation result is fairly robust to a change in how we measure the price index. Appendix 4.3 shows that the 2SLS estimates are similar to the 3SLS estimates. The OLS estimates for the farm and non-farm income equations are also comparable to the 3SLS estimates. However, the OLS estimates for the food consumption equation are generally larger than the 3SLS estimates with non-farm income impacting negatively on real food consumption contrary to expectation. The temperature and other effects do not change much when we control for rainfall (Appendix 4.4). Our rainfall estimates are practically insignificant as rainfall will have to change by at least 10,000mm in

[132] That is, all farm and non-farm households within a district are assigned the same price index in which case there is likely to be a distortion between producer price and consumer price because of a possible difference between farm-gate price and district market price.

order to have any practical effect. Therefore, our emphasis on temperature is justifiable. We get results that are generally comparable to our preferred estimates when we apply our model to three subsamples (Appendix 4.5) and when we estimate a simple linear function (Appendix 4.6). The only notable exception is that the temperature effect on real food consumption varies by subsample (Appendix 4.5).

Overall, our results show that temperature impacts negatively on food consumption. We find evidence in support of the claim that warming impacts the agricultural sector more than other sectors of the economy since we estimate a larger negative effect of temperature on farm income than non-farm income.

Table 4.2: Population-averaged marginal effects of warming on income and food consumption (3SLS)

Variable	Log(non-farm income)	Log(farm income)	Log(real food consumption)
Temperature (^{o}C)	-0.060***	-0.159***	-0.039**
	0.0007	*0.0011*	*0.020*
Log(non-farm income)		-0.038***	0.330**
		0.0078	*0.1143*
Log(farm income)	-0.012***		0.437***
	0.0023		*0.0599*
Soil 1 (high-quality)		0.403***	
		0.0017	
Soil 2 (Intermediate)		0.385***	
		0.0018	
Distance to drinking water (hours)	-0.402***		
	0.0018		
Education 1 (primary)	0.056***	0.074***	0.224***
	0.0008	*0.0015*	*0.0232*
Education 2 (≥secondary)	0.128***	-0.032***	0.655***
	0.0010	*0.0022*	*0.0323*
Price index	-0.001	0.142	-1.043***
	0.0004	*0.0004*	*0.0095*

Notes: The endogenous variables are non-farm income, farm income, and food consumption. Figures in italics are the standard errors and those in normal type are the marginal effects. ** and *** signify significance levels at 5% and 1%, respectively. No education and low-quality soil serve as the base category for their respective variables. Whereas education refers specifically to the household head, the other variables refer to the entire household. Temperature is the prevailing weather conditions recorded over a period of 38 years (1973-2011).

4.5 Summary and Conclusions

Relying on a large micro-level dataset (10,200) from Ghana, we apply the Heckman selection model to fit farm and non-farm income and then use the 3SLS to simultaneously estimate the impact of temperature on farm income, non-farm income, and food consumption. Our data shows that an average Ghanaian adult spends about US$2.90 daily on food. In addition to transitory or fixed income, an average adult earns about US$3.00 daily from both farm and non-farm sources. The average long-term temperature is about 27°C. An average household travels 7 minutes to access drinking water and is headed by a person with some form of formal education.

We find that farm income and non-farm income both impact positively on real food consumption but estimate an inverse relationship between the two types of income. All things being equal, this finding implies that individuals are better off specialising in either farm or non-farm operations as opposed to combining the two. Specialisation affords individuals the opportunity to focus investment, accumulate knowledge, minimise errors, and increase productivity. We also find that soil quality has a positive effect on farm income whilst distance to drinking water, an indicator for level of development, has an inverse relationship with non-farm income. As expected, we observe an inverse relationship between real food consumption and general price level.

Our main variable of interest, temperature, has a negative effect on real food consumption. Similarly, warming impacts negatively on farm income and non-farm income with the former being more affected. All things being equal, our results imply that warming will likely reduce food security and possibly general welfare. Therefore, any intervention aimed at improving climate resilience or food security would be beneficial.

We conclude the study with a caveat. Note that our results may not be a very good approximation of the impact of temperature on food consumption if households' consumption in the survey year was unrepresentative of their consumption pattern in the last 3 decades, however, we suspect household food consumption behaviour has been relatively stable over the period because of the likelihood of constancy in taste (especially for rural dwellers) as well as the cultural and social ties that tend to bind a group of people to their staple foods. Lastly, this study provides evidence on the effects of temperature on food consumption, the focus of a future research would be to compare the impact of warming on food and non-food consumption with more emphasis on the effects of warming on non-food consumption.

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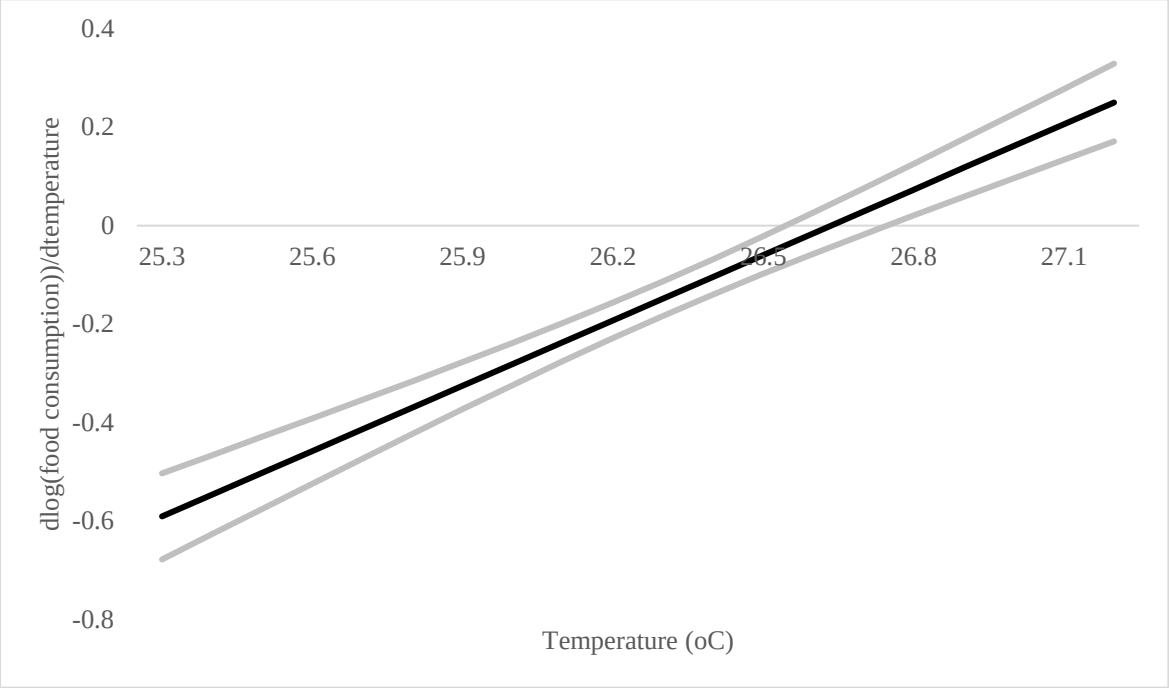
Appendices 4

Appendix 4.1: Marginal effects of temperature on food consumption (disaggregated by temperature). In grey is the 95% confidence band.



Appendix 4.2: Sensitivity of our model to a different measure of price (3SLS)

Level of measure of price index	Household (preferred model)			District		
Variable	Log(non-farm income)	Log(farm income)	Log(food consumption)	Log(non-farm income)	Log(farm income)	Log(food consumption)
Temperature (ºC)	-0.060***	-0.159***	-0.039**	-0.057***	-0.132***	-0.043**
	0.001	0.001	0.02	0.001	0.001	0.02
Log(non-farm income)		-0.038***	0.330***		-0.028***	0.314***
		0.008	0.114		0.004	0.114
Log(farm income)	-0.012***		0.437***	-0.011***		0.504***
	0.002		0.06	0.003		0.073
Soil 1 (high-quality)		0.403***			0.334***	
		0.002			0.001	
Soil 2 (Intermediate)		0.385***			0.328***	
		0.002			0.001	
Distance to drinking water (hours)	-0.402***			-0.402***		
	0.002			0.002		
Education 1 (primary)	0.056***	0.074***	0.224***	0.056***	0.044***	0.232***
	0.001	0.002	0.023	0.001	0.001	0.023
Education 2 (≥secondary)	0.128***	-0.032***	0.655***	0.129***	-0.040***	0.657***
	0.001	0.002	0.032	0.001	0.001	0.032
Log(price index)	-0.001***	0.142***	-1.043***	-0.070***	0.660***	-1.577***
	0.0004	0.0004	0.0095	0.0073	0.0056	0.1908

Notes: We construct a different price variable for each 3SLS model. For the first model, we construct a household level price index for farm households and assign to non-farm households the price index of the farm household that is closest to them. In the other model, all households (both farm and non-farm) are assigned a district level price index. Our endogenous variables are non-farm income, farm income, and food consumption. Figures in italics are the standard errors and those in normal type are the marginal effects. ** and *** signify significance levels at 5% and 1%, respectively. No education and low-quality soil serve as the base category for their respective variables. Whereas education refers specifically to the household head, the other variables refer to the entire household. Temperature is the prevailing weather conditions recorded over a period of 38 years (1973-2011).

Appendix 4.3: Sensitivity of our preferred model to different estimation methods (household price index)

Estimation method	3SLS (preferred model)			2SLS			OLS		
Variable	Log(non-farm income)	Log(farm income)	Log(food consumption)	Log(non-farm income)	Log(farm income)	Log(food consumption)	Log(non-farm income)	Log(farm income)	Log(food consumption)
Temperature (ºC)	-0.060***	-0.159***	-0.039**	-0.060***	-0.159***	-0.039**	-0.059***	-0.158***	-0.140***
	0.001	0.001	0.02	0.001	0.001	0.02	0.001	0.001	0.019
Log(non-farm income)		-0.038***	0.330***		-0.038***	0.329***		-0.030***	-0.565***
		0.008	0.114		0.008	0.114		0.007	0.104
Log(farm income)	-0.012***		0.437***	-0.012***		0.437***	-0.010***		0.254***
	0.002		0.06	0.002		0.06	0.002		0.055
Soil 1 (high-quality)		0.403***			0.403***			0.403***	
		0.002			0.002			0.002	
Soil 2 (Intermediate)		0.385***			0.385***			0.385***	
		0.002			0.002			0.002	
Distance to drinking water (hours)	-0.402***			-0.402***			-0.402***		
	0.002			0.002			0.002		
Education 1 (primary)	0.056***	0.074***	0.224***	0.056***	0.074***	0.224***	0.056***	0.073***	0.324***
	0.001	0.002	0.023	0.001	0.002	0.023	0.001	0.001	0.023
Education 2 (≥secondary)	0.128***	-0.032***	0.655***	0.128***	-0.032***	0.655***	0.128***	-0.033***	0.821***
	0.001	0.002	0.032	0.001	0.002	0.032	0.001	0.002	0.031
Log(price index)	-0.001***	0.142***	-1.043***	-0.001***	0.142***	-1.043***	-0.001***	0.142***	-1.024***
	0.0004	0.0004	0.0095	0.0004	0.0004	0.0095	0.0004	0.0004	0.0091

Refer to the notes of Appendix 4.1.

Appendix 4.4: Sensitivity of our preferred model to inclusion of rainfall (3SLS)

Level of measure of price index	Household (temperature only /preferred model)			Household			District		
Variable	Log(non-farm income)	Log(farm income)	Log(food consumption)	Log(non-farm income)	Log(farm income)	Log(food consumption)	Log(non-farm income)	Log(farm income)	Log(food consumption)
Temperature (ºC)	-0.060***	-0.159***	-0.039**	-0.070***	-0.063***	-0.069***	-0.068***	-0.026***	-0.088***
	0.001	0.001	0.02	0.001	0.003	0.021	0.001	0.001	0.02
Rainfall (mm)				-5.7×10^{-5}***	-7.7×10^{-5}***	-2.5×10^{-4}***	-5.8×10^{-5}***	1.0×10^{-4}***	-3.4×10^{-4}***
				1.4×10^{-6}	8.4×10^{-6}	4.5×10^{-5}	1.5×10^{-6}	1.8×10^{-6}	4.7×10^{-5}
Log(non-farm income)		-0.038***	0.330***		-0.095***	0.385***		-0.047***	0.345***
		0.008	0.114		0.021	0.129		0.004	0.129
Log(farm income)	-0.012***		0.437***	-0.006***		0.577***	-0.004		0.699***
	0.002		0.06	0.002		0.069	0.003		0.087
Soil 1 (high-quality)		0.403***			0.379***			0.301***	
		0.002			0.004			0.001	
Soil 2 (Intermediate)		0.385***			0.330***			0.259***	
		0.002			0.005			0.001	
Distance to drinking water (hours)	-0.402***			-0.359***			-0.356***		
	0.002			0.001			0.001		
Education 1 (primary)	0.056***	0.074***	0.224***	0.049***	0.056***	0.210***	0.048***	0.045***	0.207***
	0.001	0.002	0.023	0.001	0.004	0.023	0.001	0.001	0.023
Education 2 (≥secondary)	0.128***	-0.032***	0.655***	0.125***	-0.034***	0.661***	0.126***	-0.032***	0.659***
	0.001	0.002	0.032	0.001	0.006	0.033	0.001	0.001	0.033
Log(price index)	-0.001***	0.142***	-1.043***	-0.001***	0.161***	-1.069***	0.011	0.206***	-1.352***
	0.0004	0.0004	0.0095	0.0004	0.001	0.0119	0.006	0.006	0.182

Rainfall is the prevailing weather conditions recorded over a period of 38 years (1973-2011). Refer to the notes of Appendix 4.1.

Appendix 4.5: Estimates of our preferred model disaggregated by household size (3SLS)

Household size	1-3			4-6			>6		
Variable	Log(non-farm income)	Log(farm income)	Log(food consumption)	Log(non-farm income)	Log(farm income)	Log(food consumption)	Log(non-farm income)	Log(farm income)	Log(food consumption)
Temperature (°C)	-0.069***	-0.181***	-0.003	-0.034***	-0.168***	0.115***	-0.095***	-0.155***	0.045
	0.001	0.002	0.03	0.002	0.005	0.042	0.002	0.002	0.045
Log(non-farm income)		-0.054***	0.936***		-0.350***	3.991***		-0.015**	0.081
		0.009	0.123		0.108	0.835		0.007	0.157
Log(farm income)	-0.013***		0.494***	-0.010		0.715***	-0.028***		0.461***
	0.004		0.079	0.006		0.086	0.006		0.123
Soil 1 (high-quality)		0.508***			0.428***			0.394***	
		0.003			0.005			0.002	
Soil 2 (Intermediate)		0.342***			0.438***			0.335***	
		0.003			0.005			0.002	
Distance to drinking water (hours)	-0.801***			-0.088***			-0.473***		
	0.005			0.005			0.004		
Education 1 (primary)	0.003	0.097***	0.307***	0.078***	0.130***	-0.078	0.131***	0.078***	0.178***
	0.002	0.002	0.033	0.002	0.01	0.079	0.002	0.002	0.051
Education 2 (≥secondary)	0.107***	0.089***	0.647***	0.145***	-0.072***	0.300**	0.118***	-0.003	0.649***
	0.002	0.003	0.043	0.003	0.018	0.138	0.003	0.003	0.073
Log(price index)	0.013***	0.131***	-1.085***	-0.017***	0.122***	-1.008***	-0.002**	0.103***	-1.027***
	0.0006	0.0006	0.0125	0.0009	0.0024	0.0198	0.0009	0.0007	0.0175

Refer to the notes of Appendix 4.1.

Appendix 4.6: Sensitivity of our preferred model to different functional forms (3SLS).

Specification of temperature	Preferred model (Quadratic specification of temperature in all equations)			Linear specification of temperature in all equations			Quadratic specification of temperature in only the farm income equation		
Variable	Log(non-farm income)	Log(farm income)	Log(food consumption)	Log(non-farm income)	Log(farm income)	Log(food consumption)	Log(non-farm income)	Log(farm income)	Log(food consumption)
Temperature (°C)	-0.060***	-0.159***	-0.039**	-0.048***	-0.140***	-0.070***	-0.048***	-0.158***	-0.121***
	0.001	0.001	0.02	0.001	0.001	0.019	0.001	0.001	0.019
Log(non-farm income)		-0.038***	0.330***		-0.028***	0.331***		-0.038***	0.331***
		0.008	0.114		0.006	0.116		0.008	0.116
Log(farm income)	-0.012***		0.437***	-0.008***		0.428***	-0.007***		0.166***
	0.002		0.06	0.002		0.062	0.002		0.054
Soil 1 (high-quality)		0.403***			0.369***			0.404***	
		0.002			0.001			0.002	
Soil 2 (Intermediate)		0.385***			0.398***			0.385***	
		0.002			0.001			0.002	
Distance to drinking water (hours)	-0.402***			-0.398***			-0.398***		
	0.002			0.002			0.002		
Education 1 (primary)	0.056***	0.074***	0.224***	0.053***	0.080***	0.226***	0.053***	0.074***	0.260***
	0.001	0.002	0.023	0.001	0.001	0.023	0.001	0.002	0.023
Education 2 (≥secondary)	0.128***	-0.032***	0.655***	0.126***	-0.031***	0.648***	0.126***	-0.032***	0.654***
	0.001	0.002	0.032	0.001	0.002	0.032	0.001	0.002	0.032
Log(price index)	-0.001***	0.142***	-1.043***	-0.004***	0.135***	-1.032***	-0.004***	0.142***	-1.001***
	0.0004	0.0004	0.0095	0.0004	0.0003	0.0095	0.0003	0.0004	0.0088

Refer to the notes of Appendix 4.1.

Appendix 4.7: Different estimates of the farm income Heckman selection model

Variable	Preferred model	Household size = 1-3	Household size = 4-6	Household size > 6	Linear specification of temperature	District level price	Controlled for rainfall
Temperature (ºC)	-140.0***	-126.4***	-152.5***	-182.4***	-142.5***	-127.2***	-70.3**
	20.2	27.6	32.3	51.2	20.3	20.5	30.2
Rainfall (mm)							-0.031
							0.072
Non-farm income	-0.018	-0.016	-0.070***	-0.012	-0.017	-0.023	-0.018
	0.016	0.028	0.025	0.034	0.016	0.016	0.016
Soil 1 (high-quality)	359.3***	332.4***	365.4***	464.3***	322.2***	294.7***	305.8***
	36.9	53.7	57.1	84.4	35.8	37.2	37.4
Soil 2 (Intermediate)	337.3***	204.3***	374.0***	384.2***	347.8***	287.4***	265.0***
	42.7	65.5	68.6	87	43.1	43.7	48.6
Education 1 (primary)	75.8**	72.0	124.0***	96.5	79.9***	46.8	60.5**
	30	41.8	47.4	68.7	30.1	30.2	30.3
Education 2 (≥secondary)	-28.2	59	-84.5	-8.4	-27.1	-44	-22.1
	58.9	84.9	88.7	131.9	59.4	58.6	58.4
Log(price index)	127.0***	89.1***	113.9***	124.3***	121.9***	624.5**	136.2***
	9.4	12.4	15.1	25.4	9.3	287.3	9.6
Selection equation							
Temperature (ºC)	-0.013**	-0.01	-0.028***	-0.014	-0.009	-0.011	-0.007
	0.006	0.01	0.01	0.009	0.007	0.006	0.008
Rainfall (mm)							$-1.1\text{x}10^{-4}$***
							$2.6\ \text{x}10^{-5}$
Non-farm income	$-2.8\ \text{x}10^{-5}$***	$-4.0\ \text{x}10^{-5}$***	$-4.1\ \text{x}10^{-5}$***	$-2.6\ \text{x}10^{-5}$***	$-2.9\ \text{x}10^{-5}$***	$-2.9\ \text{x}10^{-5}$***	$-2.8\ \text{x}10^{-5}$***
	$4.4\ \text{x}10^{-6}$	$7.7\ \text{x}10^{-6}$	$6.2\ \text{x}10^{-6}$	$5.7\ \text{x}10^{-6}$	$4.4\ \text{x}10^{-6}$	$4.3\ \text{x}10^{-6}$	$4.4\ \text{x}10^{-6}$
Soil 1 (high-quality)	-0.224***	-0.230***	-0.201***	-0.126***	-0.213***	-0.219***	-0.222***
	0.011	0.019	0.017	0.017	0.011	0.012	0.012
Soil 2 (Intermediate)	-0.220***	-0.235***	-0.228***	-0.108***	-0.234***	-0.209***	-0.183***
	0.013	0.022	0.02	0.019	0.013	0.013	0.015
Education 1 (primary)	-0.148***	-0.135***	-0.144***	-0.062***	-0.150***	-0.147***	-0.149***
	0.01	0.016	0.015	0.016	0.01	0.01	0.01
Education 2 (≥secondary)	-0.416***	-0.392***	-0.378***	-0.191***	-0.420***	-0.415***	-0.413***

Variable	Preferred model	Household size = 1-3	Household size = 4-6	Household size > 6	Linear specification of temperature	District level price	Controlled for rainfall
	0.013	0.018	0.023	0.035	0.013	0.013	0.013
Log(price index)	-5.5×10^{-5}	-0.016***	0.002	0.001	0.002	-0.230***	0.001
	0.003	0.004	0.004	0.005	0.003	0.084	0.003
Population density (per km^2)	-5.7×10^{-5}***	-5.5×10^{-5}***	-4.8×10^{-5}***	-4.4×10^{-5}***	-5.6×10^{-5}***	-5.7×10^{-5}***	-5.8×10^{-5}***
	2.1×10^{-6}	3.1×10^{-6}	3.1×10^{-6}	3.8×10^{-6}	2.1×10^{-6}	2.1×10^{-6}	2.1×10^{-6}
Observations	10,197	4,910	3,656	1,631	10,197	10,197	10,197

Refer to the notes of Appendix 4.1.

Appendix 4.8: Different estimates of the non-farm income Heckman selection model

Variable	Preferred model	Household size = 1-3	Household size = 4-6	Household size > 6	Linear specification of temperature	District level price	Controlled for rainfall
Temperature (°C)	-108.9**	-131.6	-71.8	-145.3	-94.8**	-105.7**	-138.7**
	44.2	68	73.7	110.1	43.6	44.7	54.4
Rainfall (mm)							-0.128
							0.128
Farm income	-0.056	-0.047	-0.099	-0.031	-0.056	-0.056	-0.052
	0.035	0.082	0.062	0.065	0.035	0.035	0.035
Distance to drinking water (hours)	-509.0**	-1098.7***	-72.1	-538.1	-500.9**	-512.0**	-490.3**
	204.3	386.7	356.3	392.7	204.4	204.6	202.1
Education 1 (primary)	99.7	9.3	131.3	219.9	95.9	100.1	89.6
	77.4	137.6	124.8	157.4	77.4	77.2	75.1
Education 2 (≥secondary)	236.7***	232.3	232.1	198	233.5**	239.8***	241.0***
	91.2	146.5	144.6	236.4	91.3	91.1	91.5
Log(price index)	-2.3	21	-26.8	-8.1	-6.6	-133.9	-0.22
	19	29.4	29.2	53.5	18.9	569	19.6
Selection equation							
Temperature (°C)	-0.023***	-0.013	-0.054***	-0.028	-0.024***	-0.022***	-0.049***
	0.006	0.009	0.011	0.018	0.006	0.006	0.007
Rainfall (mm)							$-6.9\text{x}10^{-5}$***
							$2.3\ \text{x}10^{-5}$
Farm income	$-2.3\ \text{x}10^{-5}$***	$-3.7\ \text{x}10^{-5}$***	$-5.5\ \text{x}10^{-5}$***	$-2.5\ \text{x}10^{-5}$**	$-2.3\ \text{x}10^{-5}$***	$-2.3\ \text{x}10^{-5}$***	$-2.4\ \text{x}10^{-5}$***
	$5.0\ \text{x}10^{-6}$	$9.4\ \text{x}10^{-6}$	$8.5\ \text{x}10^{-6}$	$1.0\ \text{x}10^{-5}$	$5.0\ \text{x}10^{-6}$	$5.0\ \text{x}10^{-6}$	$5.0\ \text{x}10^{-6}$
Distance to drinking water (hours)	-0.127***	-0.132***	-0.175***	-0.185***	-0.126***	-0.128***	-0.114***
	0.028	0.046	0.052	0.053	0.028	0.028	0.027
Education 1 (primary)	0.082***	0.088***	0.109***	0.057**	0.082***	0.083***	0.071***
	0.01	0.014	0.017	0.024	0.01	0.01	0.01
Education 2 (≥secondary)	-0.011	-0.009	0.027	0.026	-0.012	-0.01	-0.019
	0.012	0.015	0.022	0.041	0.012	0.012	0.012
Log(price index)	$-2.5\ \text{x}10^{-4}$	-0.005	-0.003	0.004	$-1.0\ \text{x}10^{-6}$	-0.170**	0.003
	0.003	0.004	0.005	0.009	0.003	0.083	0.003

Variable	Preferred model	Household size = 1-3	Household size = 4-6	Household size > 6	Linear specification of temperature	District level price	Controlled for rainfall
Population density (per km^2)	8.2 x10^{-6}***	7.5 x10^{-6}***	1.0 x10^{-5}***	6.1 x10^{-6}	8.2 x10^{-6}***	8.6 x10^{-6}***	1.1 x10^{-5}***
	1.9 x10^{-6}	2.0 x10^{-6}	3.1 x10^{-6}	7.0 x10^{-6}	1.7 x10^{-6}	1.7 x10^{-6}	1.7 x10^{-6}

Refer to the notes of Appendix 4.1.

Chapter 5

Summary and Conclusions

Climate change is certain.[133] It is now clear that human activity influences the process. Global warming will continue for centuries even if current anthropogenic emissions were curtailed (Intergovernmental Panel on Climate Change, IPCC, 2014). Climate change is both an environmental problem and a developmental challenge (Ministry of Food and Agriculture, MoFA, 2010). Even though climate change will affect every sector of the economy, the agricultural sector will be the hardest hit since the sector depends directly on biodiversity and environmental conditions. Agricultural productivity is partly determined by temperature, rainfall, soil fertility, and the right balance between predators and pollinators (Clements et al., 2011). Warming tends to impact negatively on agricultural production (growth, yield, and quality) and can convert agricultural lands into drylands (Nardone et al., 2010).

Climate change is already impacting agriculture in Africa. The continent's agricultural sector is dominated by smallholder subsistent farmers.[134] Outputs are generally low as a result of a combination of biotic and abiotic factors such as low soil fertility, inadequate access to agro-inputs, poor infrastructure, and markets. Climate change adds to these burdens (Alliance for a Green Revolution in Africa, AGRA, 2014). Owing to the over reliance on the weather and limited opportunities for economic diversification coupled with multiple stresses, climate change has the potential to halt or even reverse gains made by Sub-Saharan Africa's agricultural yields, food security, and economic development (Di Falco, 2014).

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[133] In Ghana, a reduction in the number of rainy days, delay in the onset of the rainy season, and prolonged drought within the rainy season have been observed (Amikuzino and Donkoh, 2012; Lacombe et al., 2012). It is estimated that rainfall has been reducing at an average rate of 2.3mm per annum since the 1960s (World Bank, 2010).

[134] About 90% of farm holdings in Ghana are less than 2 hectares in size. Agricultural production in the country is mostly manual with little mechanisation (MoFA, 2014).

The economy of Ghana depends largely on agriculture. The importance of the agricultural sector to the country's economy cannot be overemphasised. About 52% of households in Ghana own or operate a farm (GSS, 2014). Agriculture is a major foreign exchange earner. The growth of the sector is necessary for the overall economic growth and development of the country (MoFA, 2010). Nevertheless, agricultural production in the country varies with the amount and distribution of rainfall (MoFA, 2014). Less than 1% of agricultural production in the country is under irrigation (MoFA, 2010; 2014; World Bank, 2010). Thus, Ghana's rain-fed agriculture is very vulnerable to climate change. Therefore, this thesis examines the economic impacts of climate change by analysing a large microlevel data.

In Chapter 2, we model how climate variables influence households' choice of farming systems using a multinomial logit model. The majority of studies estimate the impact of climate change on either crop[135] or livestock choice,[136] with only a few studies examining how climate influences the choice of farm type. The few studies that examine farm type either employ aggregate data (e.g. Chatzopoulos and Lippert, 2015; Mu et al., 2013) or undertake macro-analysis (e.g. Seo, 2012; 2015), thereby masking local effects. In addition to estimating local effects, tree-crops form part of the mix of farm types considered in our study.

We find that the main farming systems in Ghana are specialised livestock, specialised food-crops, tree-based, and mixed (food-crop and livestock) farms. An increase in temperature or a decline in rainfall favours the selection of specialised livestock and mixed farms. Temperature impacts negatively on the selection of specialised food-crop and tree-based farms. There is a direct relationship between rainfall and the selection of specialised food-crop farms. A simulation of the effects of climate change that utilises the multinomial estimates and future climate projections show that farmers are likely to adapt to climate

[135] For example, Issahaku and Maharjan, 2014a, b; Kurukulasuriya and Mendelsohn, 2008.
[136] For example, Chapter 3 (of this thesis); Kabubo-Mariara, 2008; Seo and Mendelsohn, 2008.

change by replacing tree-based and specialised food-crop farms with specialised livestock and mixed farms. Our findings have important policy implications since tree-based farms (specifically cocoa farms) are the most profitable farm type.

In Chapter 3, we estimate the impact of climate change on crop selection and revenue using a flexible structural Ricardian model (SRM).[137] We find that the selection of cassava, plantain, rice, and yam decline with an increase in temperature and vice versa for groundnut. Temperature has a hill-shape (U-shape) relationship with maize (millet) selection. The probability of selecting cassava, plantain, rice, and yam increase with rainfall whilst the selection of groundnut, millet, and maize decline with rainfall.

We find that the effects of climate on crop revenue are generally consistent with the selection effects thus crops that are frequently selected with warming (or rainfall) also generate revenues that are impacted positively or are less negatively affected by temperature (or rainfall) and vice versa. The only notable exception that requires further research is plantain which is less frequently selected under warm conditions but generate revenue that are impacted positively by temperature. A simulation of the effects of climate change shows that crop farmers will likely adapt by switching from high-value but climate-susceptible crops such as yam to low-value but climate-resilient crops such as millet.

In Chapter 4, we explore the relationship between temperature and food consumption. We attempt to link the strand of literature that focusses on the impact of global warming on food consumption with the literature that focusses on the impact of climate on agriculture. We link these two strands of literature by simultaneously estimating the impact of temperature on farm income, non-farm income, and food consumption. Our 3SLS estimates show that

[137] The SRM is a simultaneous two-stage optimisation technique. In order to increase the flexibility of our SRM, we control for temperature-rainfall interaction in the first stage and then estimate the second stage semi-parametrically.

warming impacts negatively on farm income, non-farm income, and real food consumption. A 1°C increase in temperature results in a 4% decline in real food consumption. All things being equal, an average adult will likely reduce consumption to match income if warming were to reduce productivity (e.g. number of hours worked or agricultural yields).

Ghana's agricultural output (Figure 1.5) and welfare levels have improved over the last 50 years even though rainfall and temperature during the period declined and increased, respectively. The historical increase in output and welfare can be attributed to increment in area under prodution (Figure 1.4) but given that land is a finite resource, production will likely decrease if the strategy to dealing with a worsening climate (going forward) is to continue to put more land under cultivation as the historical trend has shown. The use of technology (assuming it continues to be relevant in future) is the other alternative that can be employed to ensure that production increases even if the climate worsens and the area under cultivation reaches its limit. Unfortunately, and as indicated earlier on, the cross-sectional models that we use have some limitations including an inability to capture technology and other factors that vary over time. Nonetheless, our results are consistent with earlier Ghanaian studies such as Issahaku and Maharjan (2014a) who find, *inter alia*, a 16% decline in the output of yam (a highly profitable and exportable crop) by 2025. Arndt et al., (2014) and the World Bank (2010) both observe an inverse relationship between household income or consumption and global warming. In the case of Arndt et al., (2014), they find a decline in real household consumption of up to 4% by 2050.

Overall, our thesis shows that climate change will likely have a net negative effect on Ghana's agriculture and real food consumption if the current status quo remains. This is mainly because farming systems and food-crops that are currently less susceptible to climate change also happen to be less profitable so climate-induced widespread adoption of such farm and crop types will be a source of concern (as aggregate farm value will fall under such

a scenario). Given such a bleak prospect, it is important for the government and its development partners to implement measures that can either improve the climate resilience of highly profitable but climate-susceptible farming systems and food-crops or alternatively improve the productivity of less profitable but climate-resilient food-crops and farm types.

We conclude the thesis with two caveats. Firstly, our data were all obtained from secondary sources. Thus, our estimates are subject to all the likely problems associated with the use of secondary data. Reliability of our estimates to a large extent depends on the reliability of the data. The Ghana Statistical Service and US National Oceanic and Atmospheric Administration (NOAA), however seem to be credible institutions whose data can be trusted. Furthermore, we recognise that in the absence of data limitations, a more biological measure of climate such as sunshine hours and soil moisture content could have been more revealing than temperature and rainfall.

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