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Modeling Crop Yield and Farmer Adaptation to Rainfall Variability
The case of Southern Ethiopia

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I hereby declare that this doctoral thesis is a result of my personal work and that no other than the indicated aids have been used for its completion. All quotations and statements that have been inferred literally or in a general manner from published or unpublished sources are marked as such. Furthermore, I assure that the work has not been used, neither completely nor in part, for achieving any other academic degree.

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Executive summary

Improving the livelihood of poor households in developing countries by increasing agricultural productivity and production becomes the priority agenda for development actors. However, variability in rainfall has confronted success in achieving this goal. There is pressing interest in analyzing the effects of rainfall variability on household welfare and identifying policy interventions to mitigate its adverse effects. Ethiopian economy primarily depends on rain-fed agriculture. Agriculture is the backbone of the country's economy; it contributes the lion's share of GDP, employment, export earnings, and livelihood. Fluctuations in rainfall distribution and intensity have severely affected the economy in general and the livelihood of smallholder households in particular; the agricultural sector is more prone to changes in climatic condition, which increases the risk of poverty and hunger for poor farm households.

Few studies have attempted to analyze the direct effects of rainfall variability on crop yield and its indirect effect on household welfare. Therefore, this thesis aimed at filling the knowledge gap on the impacts of rainfall variability on crop yield and welfare. Moreover, the study explores the role of adaptation strategies in mimicking the negative effects of rainfall variability accounting for household performance decision under resource constraint for Ethiopian farmers.

The study employed Mathematical Programming Based Multi-Agent System (MP-MAS) computer simulation techniques to analyze the effects of rainfall variability on crop yield, household welfare and the role of adaptation strategies in mitigating the adverse effects of rainfall variability. Prior to application to the study, the MP-MAS simulation model is parametrized, calibrated, and validated using data from the Ethiopian Rural Household Survey (ERHS), primary data collected from the research area and thirty year rainfall time series data obtained from meteorological stations located near to the study area.

To address the mentioned research question a wide range of rainfall and adaptation strategy scenarios were designed. The agent - based model enables us to incorporate different bioeconomic systems in the decision-making process by smallholder farmers, which is otherwise difficult under a real world situation where farm households face inseparable decision-making process. Moreover,

the model accounts for the heterogeneity in resource endowment, investment, production, consumption, agro-ecology, input constraints, and demographic distribution among households. Livestock, consumption, crop growth and irrigation water distribution models were combined in this study. The household food consumption decision is estimated by using three stages advanced consumption module and crop water requirement and irrigation water distribution modeled using inbuilt FAO CropWat and EDIC modules, and finally an empirical analysis was done by using STATA version 12.

The simulation result suggested that: (i) Both current and future rainfall variability would have negative effects on crop yield and household welfare. (ii) The yield of cereals crops and vegetables are negatively affected by rainfall variability: some perennial crops such as enset gains yield under rainfall variability. (iii) Household welfare deteriorated with rainfall variability; resource poor households are severely affected by rainfall variability. (iv) Adaptation strategies such as non-farm activities, irrigation, and soil and water conservation activities mitigate the negative effects of rainfall variability. (v) Improving the financial or non-farm constraints alone leads to increased income inequality.

Therefore, the recommended solution to reduce adverse effects of rainfall variability includes: (i) Implementing integrated policy interventions than a single strategy. (ii) Improving access to credit and access to non-farm activities. (iii) Designing a pro-poor intervention (such as improving the asset base of the poor households). (iv) Improving access and use of improved agricultural technologies, and (v) Increasing access and use of irrigation to enhance agricultural productivity

Zusammenfassung

Die Verbesserung der Lebensgrundlage der armen Haushalte in Entwicklungsländern durch die Erhöhung der landwirtschaftlichen Produktivität und Produktion wird zu einer Priorität für die Entwicklungsakteure. Allerdings beeinträchtigen Niederschlagsschwankungen das Erreichen des Ziels einer Welt ohne Hunger. Daher ist es von großer Bedeutung, die Auswirkungen der Niederschlagsvariabilität auf die Wohlfahrt der Haushalte zu untersuchen und mögliche Strategien zu identifizieren, um seine nachteiligen Auswirkungen zu reduzieren. Die äthiopische Landwirtschaft basiert hauptsächlich auf Regenfeldbau. Die Landwirtschaft ist das Rückgrat der Wirtschaft des Landes, denn sie trägt zum Hauptanteil des BIP, zur Beschäftigung und zum Export und Lebensunterhalt bei. Schwankungen der Niederschlagsverteilung und Intensität des Niederschlags haben ernste Folgen für die Gesamtwirtschaft und die Lebensgrundlage der Kleinbauern. Außerdem ist der landwirtschaftliche Sektor anfälliger für die Folgen des Klimawandels, der die Armut und das Hungerrisiko bei armen bäuerlichen Haushalten erhöht. Nur wenige Studien haben versucht, die direkten Auswirkungen von Niederschlagsvariabilität auf Erträge und ihre indirekte Wirkung auf die Wohlfahrt der Haushalte zu analysieren. Ziel dieser Arbeit ist es, einerseits die Wissenslücke zwischen Niederschlagsschwankungen, Feldfruchterträgen und Wohlfahrt zu schließen und anderseits die Rolle der Anpassungsstrategien zur Minderung der negativen Auswirkungen der Niederschlagsvariabilität mit Berücksichtigung der Haushalteigenschaft unter Ressourceneinschränkungen bei äthiopischen Landwirten zu untersuchen .

Die Studie nutzte das agentenbasierte Modellsystem MP-MAS (Mathematical programming-based multi agent system) zur Analyse der Auswirkungen von Niederschlagsvariabilität auf den Feldfruchtertrag und auf die Wohlfahrt der Haushalte und der Rolle von Anpassungsstrategien bei der Milderung der negativen Auswirkungen der Niederschlagsvariabilität. Um die genannte Forschungsfrage anzugehen, wurde eine breite Palette von Niederschlags- und Anpassungsstrategienszenarien entwickelt. Agentenbasierte Modellierung ermöglicht es verschiedene bio-ökonomische Systeme in den Entscheidungsprozess von Kleinbauern zu integrieren. Zudem wird in dem Model die Heterogenität in der Ressourcenausstattung berücksichtigt. Viehzucht, Anbau, Konsum, Pflanzenwachstum und Bewässerungswasser-

Verteilungsmodelle wurden in dieser Studie kombiniert. Die Entscheidung über den Lebensmittelkonsum der Haushalte wurde geschätzt durch die Nutzung des Three-stage consumption modules des MPMAS-Modells. Pflanzenwasserbedarf und Bewässerungswasserverteilung wurden mit FAO CropWat und EDIC Modulen modelliert. Auswirkungen von Niederschlagsschwankungen auf Feldfruchterträge und die Wohlfahrt der Haushalte wurden mit MP-MAS Software durchgeführt und schließlich die empirische Analyse mittels STATA gemacht.

Das Simulationsergebnis legte nahe, dass (i) sowohl die gegenwärtige als auch die zukünftige Regenvariabilität negative Auswirkungen auf die Ernte und das Auskommen der Haushalte haben würde (ii) die Getreide- und Gemüseernten von der Regenvariabilität negativ betroffen wären: einige mehrjährige Ernten wie etwa *Ensete* haben unter Regenvariabilität höhere Erträge (iii) das Auskommen von Haushalten sich mit Regenvariabilität verschlechtert; arme Haushalte ohne Ressourcen sind besonders stark betroffen (iv) Anpassungsstrategien wie andwirtschaftsfremde Aktivitäten, Bewässerung, boden- und wasserschonende Maßnahmen die negativen Auswirkungen von Regenvariabilität mildern (v) lediglich die Verbesserung der finanziellen, nicht das Feld betreffenden Zwänge nur zu höherer Einkommensungleichheit führt

Daher schließt die empfohlene Lösung zur Minimierung negativer Auswirkungen von Regenvariabilität Folgendes ein: (i) die Umsetzung integrierter Lösungsansätze statt einer einzigen Strategie (ii) verbesserter Zugang zu Krediten sowie Einkommensmöglichkeiten, die nichts mit der Landwirtschaft zu tun haben (iii) der Entwurf einer Intervention zum Vorteil der Armen (wie etwa die Verbesserung der Vermögensgrundlage armer Haushalte) (iv) verbesserter Zugang und Nutzung besserer landwirtschaftlicher Technik und verbesserter Zugang und Nutzung von Bewässerung, um die landwirtschaftliche Produktivität zu erhöhen

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List of Abbreviations

ADLI	Agricultural Development Lead Industrialization
AEZ	Agro-Ecological Zone
AIDS	Almost Ideal Demand System
ATJK	Adami-Tulu Jedo-Kombolica
CGE	Computable General Equilibrium
CSA	Central Statistical Agency
CWR	Crop Water Requirement
Diff.	Different
EDIC	Sector Irrigation Model
ENMA	Ethiopian National Meteorological Agency
ERHS	Ethiopian Rural Household Survey
ETB	Ethiopian Birr
FAO	Food and Agricultural Organization
FGT	Foster-Greer-Thornback
FML	Full Maximum Likelihood
GA	Gedebe-Asassa
GCM	Global Circulation Model
GDP	Gross Domestic Product
GE	General Entropy
GTP	Growth and Transformation Plan
IBM	International Business Machine
IFPRI	International Food Policy Research Institute
IMF	International Monetary Found
IPCC	Intergovernmental Panel on Climate Change
IWMI	International Water Management Institute
LA/AIDS	Linear Approximation of Almost Ideal Demand System
MAE	Mean Absolute Error

MILP	Mixed Integer Linear Programming
MoARD	Ministry of Agriculture and Rural Development
MoFED	Ministry of Finance and Economic Development
MP-MAS	Mathematical Programming-Based Multi-Agent System
NGO	Non-Governmental Organization
NSE	Nash-Sutcliffe Efficiency
OLS	Ordinary Least Square
PA	Peasant Association
PASDEP	Plan for Accelerated and Sustained Development to End Poverty
PCI	Precipitation Concentration Index
SAE	Standard Absolute Error
SNNPR	Southern Nations Nationalities and People Regional
SQL	Standard Query Language
SSA	Sub-Sahara Africa
TLU	Tropical Livestock Unit
WB	World Bank
WG	Wondo-Genet
WUA	Water Users Associations

Chapter 1: Introduction and background of Ethiopian Economy

1.1.Introduction

It has now become increasingly evident that climate variability has a far-reaching consequence on the livelihood of farm households in many developing countries. According to the IPCC (2014), high level of greenhouse gas concentration in the atmosphere is the main cause of climate variability and global warming. As the intensification of economic activities has resulted in the increased carbon dioxide release, human activity has significantly contributed to global warming (Skinner & Majorowicz 1999; Seo & Mendelsohn 2007; Kurukulasuriya & Mendelsohn 2008; Smith et al. 2009; Woldeamlak 2009). Furthermore, the existing vulnerabilities to climate variability are also expected to be exacerbated in the future (Müller et al 2011). Studies on global warming indicate that in the coming decades, the temperature is expected to increase between 2 and 5 degree Celsius (IPCC 2014). This increase in temperature would cause melting of ice in the polar areas and potentially induce flooding in different part of the world. In addition, global warming is likely to increase the intensity of hydrological cycles, which in turn increases the frequency of extreme events such as drought and flooding (IPCC 2007). In terms of rainfall, a study by Purkey et al. (2008) indicated that in the coming century, the world will experience 40% to 100% more dry years compared to the past century. Consequently, crop water demand is expected to increase by about 5 to 50% (Purkey et al. 2008), which affects crop yield since the sensitivity of crop yield depends on changes in greenhouse gas emission, water consumption and demand, which is further determined by the seasonal distributions and availability of water at different growing stages.

In particular, rainfall variability is expected to have a significant adverse effect on countries where agriculture is the main economic activity (IPCC 2014). As a result of climate variability, a significant shift in the pattern of rainfall distribution is expected to occur in the coming decades (Conway et al 2005; IPCC 2007; Bewket 2009). These shifts in the amount and intensity of rainfall are also projected to affect agricultural productivity, land suitability and welfare levels of households which derive their livelihood from agriculture (Fowler and Hennessy 1995; Fauchereau et al 2003; IPCC 2007). It mainly affects rain-fed, traditional, marginal, low-input using agriculture in developing countries and, thus, the loss in crop productivity further worsens already difficult food security situations (Lim Li Ching 2011; Knox et al 2012). Thereby, rainfall variability further widens income inequality, food insecurity, and malnutrition among the world population. Its impact on agriculture and hence food production is complex. Thus, rainfall variability directly affects food security by altering agro-ecological conditions and indirectly by retarding growth and altering the distribution of income (Parry et al 1999; Droogers 2004; Tao et al 2009; Hanjra and Qureshi 2010).

An increase in temperature and a decrease in rainfall will stress the crop production. Consequently, the demand for water will rise. Moreover, rainfall variability affects agriculture through reduced precipitation and increased evapotranspiration as an indirect result of a change in climatic variables other than the direct impacts on temperature and rainfall. As crop production and productivity are a function of climatic and environmental variables, this state of affairs is particularly worrying since agriculture in most developing countries is highly exposed to climate shocks and the over reliance of production activities on climate-sensitive sectors. Moreover, most farm households in many parts of the developing world have limited capacity to cope with the adverse effects of rainfall variability as they lack sufficient income to cover expenses related to adaptation. Africa often cited as one of the most vulnerable continents to the adverse effects of climate change as rain-fed agriculture is the main source of livelihood. Studies revealed that in Africa, agriculture constitutes approximately 30% of GDP, 50% of total export earnings and 70% of rural employment (Parry et al 2005; Devèze 2011). Under the climate change scenario, the continent experienced considerable reductions in agricultural yields and decrease crop production as a result about 65% additional number of people risk of hunger is expected to come from Africa (Parry et al 2005). Moreover, the continent accounts for 20% of the world's poor (Kang et al 2009), which further underscores how significantly livelihoods could vulnerable to the effects of rainfall variability. In addition, by increasing the cost of production, rainfall variability is also expected to slow down the progress made towards poverty reduction efforts in many parts of Africa (Benhin 2008; Kang et al 2009; Müller et al 2011; Field et al 2014).

Rainfall variability is already putting a significant negative effect on the overall economic performance of many African countries in general (Corobov 2002; Moriondo et al. 2011; Sultan et al. 2013) and Sub-Saharan Africa (SSA) in particular. SSA is characterized by subsistence agriculture, rampant food insecurity, and poverty, low rate of irrigation use and low productivity (Müller et al. 2011; Downing et al. 1997; Benhin 2008; Knox et al. 2012). Rainfall variability will, therefore,, aggravate the poverty and food insecurity situation of many smallholder farmers in SSA countries (Downing et al 1997; ENMA 2007; Müller et al 2011; Sultan 2012). Rainfall variability further increases the economic burden for African governments in terms of investments in adaptation mechanisms such as the expansion of irrigation infrastructures for the poor (Parry et al 2005). It reduces the welfare level of poor farm households and increases the risk of hunger and vulnerability in many parts of Africa. As a result, in most of these countries, achieving economic progress and improving the livelihood of African poor will be a significant challenge (Parry et al 2005).

Like other African countries; in Ethiopia, rain-fed agriculture is the hub of the economy. Agriculture contributes about 43% to GDP, 85% of employment, and 80% of foreign exchange earnings (MoFED 2010). Traditional and backward farming systems associated with low levels of improved agricultural technology use, low infrastructure, weak social and economic development, high poverty incidence and scant adaptive capacity make the country more vulnerable to the adverse effects of rainfall variability (Zegeye 2001, Tafere et al. 2010; Alem & Söderbom 2012). Weather in Ethiopia is characterized by significant regional variations in the distribution of rainfall and temperature. For instance, the mean annual temperature fluctuates between 10^0C to 35^0C in the highland and lowland areas of the country, respectively. Similarly, the mean annual rainfall ranges from 2000 mm in the southwest to less than 250 mm in the lowland area of Ogden (ENMA 2007; Bewket 2009). Moreover, rainfall is erratic and unpredictable, particularly during growing periods (Deressa et al. 2009). The unpredictable distribution of rainfall at critical months such as during the planting or harvesting stage of crops is also a prominent feature of rainfall in Ethiopia (Seleshi and Zanke 2004; ENMA 2007; Bewket 2009).

Ethiopian agriculture is mainly managed and operated by smallholder subsistence farmers. For instance, about 97% of crop production and 98% of the total area under crop cultivation is operated by private peasant holders, with average landholding size of 1.16 ha (CSA 2009; Matouš et al 2013). Moreover, limited financial, human and physical resource capacity of the country hinders progress in the agricultural sector and the intended economic growth (Deressa 2007; Gebremedhin et al. 2009; Mideksa 2010). In spite of considerable attention given by the Ethiopian government to the agricultural sector as the driving force to improve the overall economy, the sector is growing by far less than the growth rates of population and associated food demand (Gebremedhin et al. 2009). The slow pace of agricultural growth is reflected in the stagnant economic development of the country. Lack of appropriate policy interventions and technology options in response to changes in climatic conditions such as rainfall variability and other shocks have limited the ability of farmers to adapt to adverse climate conditions. These further aggravate food insecurity and poverty in the country (Degefe, 2002; Awulachew et al., 2005; Kedir, 2005; Lencha, 2008).

The country is endowed with key resources such as land, labor, and water to be used to combat the adverse effects of climate variability through improvements in production and productivity. For instance, in terms of land area, Ethiopia is the 10th largest country in Africa, with a total of 1.13 million km^2 and about 51.3 million hectares of arable land (MoAD 2010). However, only about 11.7 million (20% of the potentially arable land) area is currently being cultivated (MoAD 2010). It is also the second most populous country in Africa, with a population size of 85 million (CSA 2012; World Bank 2013). The population is predominately young, with those below 15 years of age accounting for about 45% of the total population, and the proportion of productive working age (15-64 years) population at about 52% (CSA 2007). The country is also considered the 'water tower' of Africa with annual water potential of 122 billion cubic meters. It possesses more than 40 large rivers, including the Blue Nile, Baro, Tekaze and Omo, with an irrigation potential of more than 3.5 million hectares of land per year (Abdurahman 2009; Hagos et al 2009).

Moreover, the country has different agro-ecological zones that are suitable for the production of different crops. Coffee, chat, enset, eucalyptus, avocado, and mango are the major perennial crops grown in the country. Ethiopia, the place of origin of coffee Arabica, is the world's 3rd largest coffee producer and the largest producer and exporter of coffee in Africa (Petit 2007; Chesley and Tefera 2012). As such, coffee is one of Ethiopia's main export agricultural commodities, followed by chat. About one million Ethiopian smallholder farmers produce coffee and more than 25% of Ethiopians directly or indirectly depend on coffee for their livelihood. Coffee also accounts for about 34% of export earnings (Petit 2007; Petty et al 2004).

Despite such a huge potential, only 3.5% of the water is used for irrigation purpose (Awulachew et al. 2005; Abdurahman 2009; Tilahun et al. 2011). This indicates the kind of potential that the country possesses to combat the adverse effects of rainfall variability through irrigation. In spite of this potential, agriculture remains mainly rain-fed which is highly sensitive to rainfall variability across time (Seleshi and Zanke 2004). According to a study by Conway et al. (2005), in the second half of the 20th-century negative rainfall irregularity has become the prominent feature of Ethiopia. Similarly, using precipitation concentration index (PCI) for northern Ethiopia Bewket (2009) indicates that about 60% of the years between 1975 and 2002 experienced rainfall below the long-term average. Moreover, studies on different regions of the country revealed that there is no uniform trend in temperature and rainfall pattern which affects crop yield (Alexandrov and Hoogenboom 2000).

1.2.Crop area cover and distribution

The land use and cover from production in 2009 in Ethiopia overall and the two study regions (Oromia and SNNPR) in particular are presented in Table 1.1. In Ethiopia, the total crop area under cereals, pulses, and oilseeds is about 70% (8.8 million hectares), 13% (1.6 million hectares), and 7% (0.9 million hectares), respectively. The Oromia region shows roughly similar land cover pattern to the national figures. However, in the SNNPR region, the distribution of crop area tends to be more diverse: cereals, pulses, and coffee and enset production accounts for about 55%, 12%, 7%, and 14% of the total crop area, respectively.

Table 1. 1 Distribution of area over crop categories for Ethiopia and the two study regions

	National		Oromia region		SNNPR region	
Crop type	Area (in ha)	Share [a]		Share [b]	Total area (in ha)	Share [c]
Total crop area	12,493,989		5,724,657		1,439,947	
Cereals	8,770,118	70.19%	4,064,069	70.99%	785,304	54.54%
Pulse	1,585,236	12.69%	616,035	10.76%	171,584	11.92%
Oilseed	855,147	6.84%	393,167	6.87%	7,491	0.52%
Vegetables	162,125	1.30%	61,839	1.08%	50,637	3.52%
Root crops	145,742	1.17%	66,175	1.16%	42,016	2.92%
Fruit crops	47,990	0.38%	18,321	0.32%	24,898	1.73%
Coffee	391,296	3.13%	284,630	4.97%	97,185	6.75%
Enset	278,668	2.23%	82,216	1.44%	196,066	13.62%
Chat	138,145	1.11%	96,326	1.68%	25,900	1.80%

Source: Compiled from CSA agricultural survey report (CSA 2009); a, is the share of each crop category in total crop area for Ethiopia, b and c are the shares of each crop category in Oromia and SNNPR regions respectively.

In the Ethiopian setup, the total area under crop production can be classified into eight main categories: cereals, pulses, oilseeds, vegetables, root crops, fruit crops, stimulant crops, and sugar cane. Stimulant crops consist of chat, coffee, and hops. Areas for sugarcane and hops were not presented in the table, as their share of the total crop area is insignificant (CSA 2009).

Table 1.2 National and study area modern agricultural input use trends for year 2008/9*.

Input type	National		Oromia		SNNPR	
	Area (ha)	Percentage [a]	Area (ha)	Percentage [a]	Area (ha)	Percentage [a]
Mineral fertilizer	5,418,761	43.37	2,589,787	45.24	730,493	50.73
Improved seed	465,809	3.73	216,908	3.79	70,070	4.87
Pesticides	1,884,009	15.08	1,409,905	24.63	172,232	11.96
Irrigation	164,370	1.32	72,977	1.27	24,125	1.68
Extension	1,496,003	11.97	427,121	7.46	70,127	4.87

Source: Compiled from CSA agricultural survey report (CSA 2009)*; a: percentages are computed by dividing the area under particular input service to total crop areas. *: For years (2008/2009), production year abstracted from the survey report of CSA, 2009.*

Table 1.2 shows the rate of improved agricultural input use, for example, mineral fertilizer, improved seed varieties, pesticides, irrigation, and extension services. Overall, improved input use is very low in the country. According to the Central Statistical Authority (CSA) survey report, the rate of using fertilizer as a productivity enhancing input is about 43% at the national level. In the SNNPR region, about 50%, 5% and 12% of the cultivated crop area is under mineral fertilizer, improved seed and pesticide use, respectively (CSA 2009). Crop area under irrigation is insignificant, accounting for less than 2% of the total crop area. Extension service packages and pesticides are important inputs for enhancement of agricultural productivity. In spite of two or three extension service workers in each peasant association (PA)[1] throughout the country, the percentage of area under this service is low. According to the same report, about 12% of the total crop area is under extension service and about 15% of the crop area is under pesticide use. Moreover, cross-sectional studies show that less than 2% of the total cultivable land is irrigated, and on average the crop yield fluctuates between 1.2 and 1.3 tons per hectare per year (Awulachew et al 2005; Hagos et al 2009; Tilahun et al 2011). Traditional, low yielding seed varieties dominate Ethiopian agriculture: the percentage of crop area under improved seeds is below 4% (Stepanek 1999; Awulachew et al 2005; Hagos et al 2009). The low level of input use, exacerbated by traditional and animal power driven farming and high rainfall variability, has perpetuated poverty and food insecurity in the country (Stepanek 1999; Yesuf and Bluffstone 2009).

1.3.Statement of the problem and objectives of the study

Increasing agricultural productivity via intensification of agricultural technology use is a policy agenda designed to improve the livelihood of farm households in developing countries. Ethiopia is a country with huge potential due to its fertile land, a favorable climate for diverse crop production and rearing livestock, and access to water. However, the effort to increase productivity is challenged by the weak capacity of poor farm households to adopt the technology, the lack of financial capacity to buy inputs, and weather shocks, putting the realization of development objectives under question. As a result, many Ethiopians face a severe drought, famine, and associated problems. Figures suggest that a high population growth rate (2.78% per annum), high poverty incidence (one-third of the population lives below one dollar a day and

[1] PA is the lowest administrative level in Ethiopia that is composed of villages

two-thirds live on less than two dollars a day (CSA 2012)), a high and increasing unemployment rate (IMF 2013), and severe environmental degradation (Matouš et al 2013) are the main threats that the country faces. According to the World Food Program, Ethiopia is one of the most food insecure countries in Sub-Saharan Africa. In 2009, there were about 12 million people in need of direct food aid (WFP 2009a). Moreover, the profound dependency of the economy on rain-fed agriculture and a limited capacity to adapt to climate change make the country vulnerable to climate shocks (Di Falco et al 2012).

The country has low capacity to respond to rainfall variability effects and has already suffered from both natural and man-made disasters, such as civil war, epidemic diseases, HIV/AIDS and drought. Famine and drought are common concerns of the country, and in the past 30 years, the country has faced a number of severe disasters in this regard. Between the years 1980 to 2010, about 86 disaster events were registered in the country. Among recorded disaster events, drought takes the lion's share: 96%, out of total disasters (Preventionweb 2010). As a result of Ethiopia’s frequent disaster events from 1980-2010, roughly 313,400 people were killed and properties valuing a total of $31,700,000 were destroyed (Preventionweb 2010).

On top of this, Ethiopian agriculture is predicted to face a serious challenge in the coming decades. Increased demand for farmland, fuel, transport infrastructure, and housing put tremendous pressure on the natural resources of the country. The forest cover of the country is deteriorating at an alarming rate: between the years 1972 and 2000, 40,000 ha (80%) of the forest was lost. Therefore, it is important to obtain alternative means of livelihood and adaptation strategies against rainfall variability, reduce poverty, increase household income, and decrease income inequality. To alleviate poverty and the associated socioeconomic problems, the Ethiopian government has implemented different poverty reduction and development strategies. Despite, these efforts, the number of people below the poverty line continues to increase (Gebremedhin et al 2004; Abebaw et al 2010; Matouš et al 2013). Poor land management systems and lack of sound environmental policy have worsened the poverty situation of the country (Gebremedhin et al 2004). Studies on the relationship between rainfall variability and household welfare in general and agricultural productivity, in particular, are scarce in developing countries such as Ethiopia (Deressa 2007; Mideksa 2010). Though Ethiopia has already experienced erratic weather that has significantly affected the economy, little is known about how rainfall variability and crop yield are related and occurring within the country. Accordingly, there is no clear policy designed to predict expected rainfall variability effects and adaptation measures. The variability in the amount and temporal distribution of rainfall is one of the most important factors that determines the fluctuation in crop yield (Bewket 2009).

Therefore, studying the impact of rainfall variability on agriculture, particularly on crop yield, household welfare and the role that adaptation strategies play in reducing the adverse effects of rainfall variability is crucial. Quantifying the potential effect of rainfall variability and providing direction for policy makers on how to abate the adverse effects can provide a scientific underpinning for sustainable resource utilization among different competitors and can improve the livelihood of farm households (Wang 2010).

1.4. Objective of the research

The general objective of this thesis is to examine the impacts of rainfall variability on agricultural production and on the livelihood of farm households in Ethiopia. More specifically, the objectives are:

i. Investigating and quantifying the relationship between rainfall variability and the yield of different crops in the study area.
ii. Examining the effects of rainfall variability on the household welfare; particularly on income, poverty, food security, and income inequality.
iii. Building a dynamic simulation model that integrates environment, biophysical and socioeconomic factors in the household decision-making process among alternative activities in the face of rainfall variability.
iv. The study particularly had the following objectives: (a) quantifying the effects of rainfall variability and its dynamics on household welfare; (b) identifying the roles that adaptation strategies such as irrigation, non-farm activities and soil and water conservation play in lessening the adverse effects of rainfall variability; (c) examining

income inequality and its dynamics with and without rainfall variability; and (d) to analyze the effects of future rainfall variability on household welfare as compared to current rainfall variability.

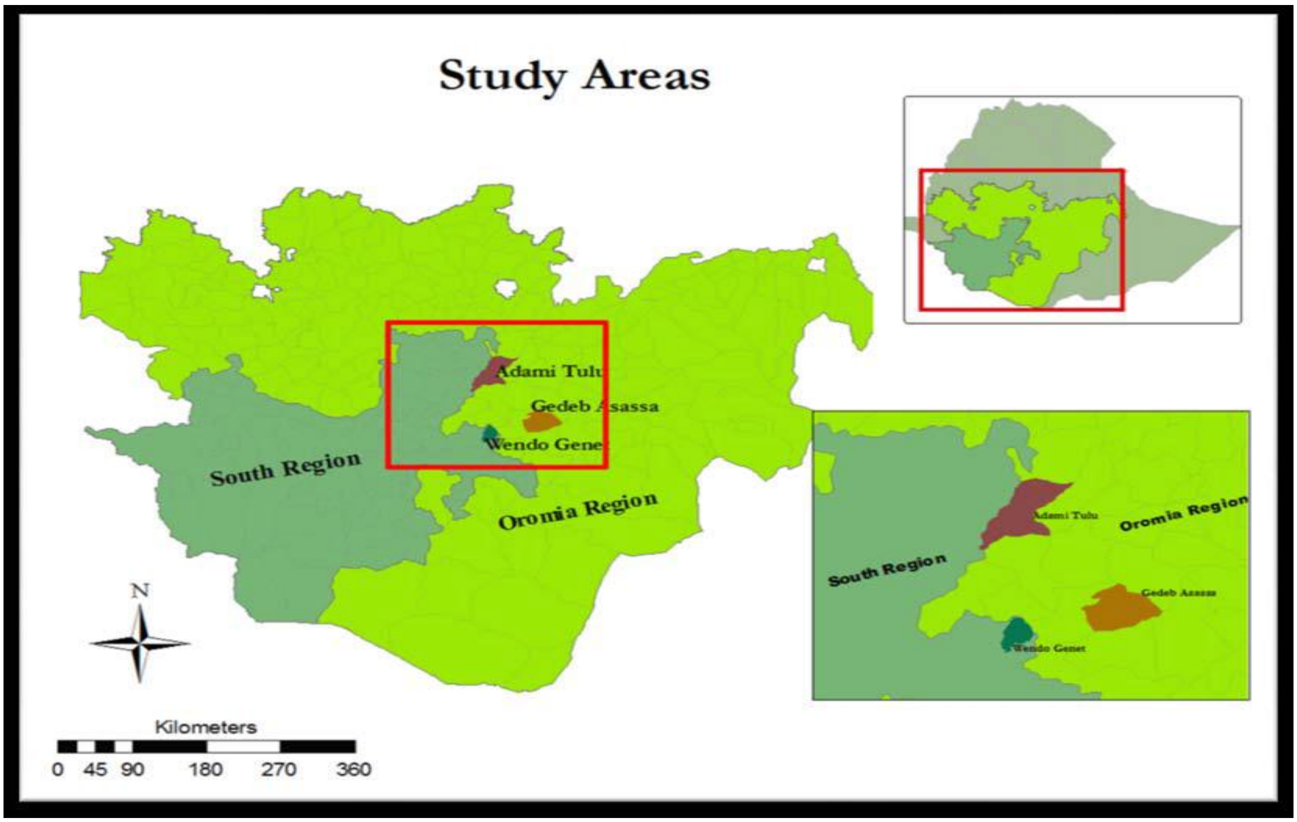
1.5.Description of the study area

Geographically, the study area is located in the southern part of Ethiopia. The three selected districts are located in the SNNPR and Oromia administrative regions of the country (see Fig.1.1). The area is characterized by an intensive crop-livestock mixed farming system. Production of cash crops such as coffee, banana, pineapple and other permanent crops is among the main agricultural activities in the area. Maize, wheat, and sorghum are produced for both market and home consumption. Particularly, in SNNPR enset (*Enset ventricosum*) and maize are the two dominant crops in terms of production area and coffee is an important source of income (Feleke et al 2005).

This study mainly focuses on three districts: Wondo Genet district from the Southern Nations, Nationality and People Region (SNNPR); and Adami-Tulu Jedo-Kombolcha and Dodola districts of the Oromia region. The districts were selected to represent diverse agro-ecological and farming practices and were considered as three different sectors in the Mathematical Programming-Based Multi-Agent System (MP-MAS) modeling process. In addition to diverse agroecology and farming systems, the districts have varied infrastructure, cropping, and socioeconomic characteristics. A detailed discussion of the characteristics of the three districts is presented in the following sections.

Wondo Genet (WG) is located in SNNPR, between $6^{0}45'$ N to $7^{0}15'$ N latitude and $38^{0}15'$ E to $38^{0}45'$ E longitudes, 280km from the Ethiopian capital Addis Ababa (Dessie and Kleman 2007). The district has an abundant natural resource endowment and a number of tourist attraction sites. It is one of the most densely populated districts of the region as a result of high population growth (Tsegaye et al 2013). The associated increased demand for natural resources such as land, water, and the forest is the main challenge facing the district. Furthermore, the district is known for its cash crops production, such as coffee, chat, sugarcane, avocado, and banana. However, in the past few years, it has been confronted with severe environmental threats to the the productivity of area. This is mainly due to a lack of good land management policies, unbalanced population growth and increased demand for fuel and house construction (Dessie and Kleman 2007). The forest cover of the district is one of the biggest in the country, although early and extensive deforestation in the country has led to severe depletion of natural forests, loss of biodiversity, impoverishment of ecosystems and land degradation. Deforestation is one of the most livelihood treating factor, further, trim down the crop yield and resulted in high poverty incidence and loss of agricultural productivity (Yirdaw and Luukkanen 2003; Tittonell and Giller 2013; Gebretsadik 2014).

Fig. 1. 1 Map of Ethiopia highlighting and expanding the study areas



Source: -Map of the study area adopted from (Hardilo 2012)

The second district included in this study is Adami Tulu Jedo Kombolicha (ATJK), located 200 km from Addis Ababa on a highway to Awassa in Oromia Regional State. The district has a population of 142,861 (CSA 2007). It is part of the Central Rift Valley system of the country and is the main trade route to the eastern part of the country. As the district is located between Lake Ziwaye and Lake Shalla, small-scale traditional irrigation is part of the farming system (Lencha 2008). The livelihood of the district mainly depends on mixed livestock and crop farming. The Agroecology of the district is classified as semi-arid, with an annual rainfall of about 700 mm and the main growing season (rainy season) is from June to September. The minimum, mean and maximum temperature of the district are 10, 20, and 28 degrees Celsius, respectively (Mitiku 2011).

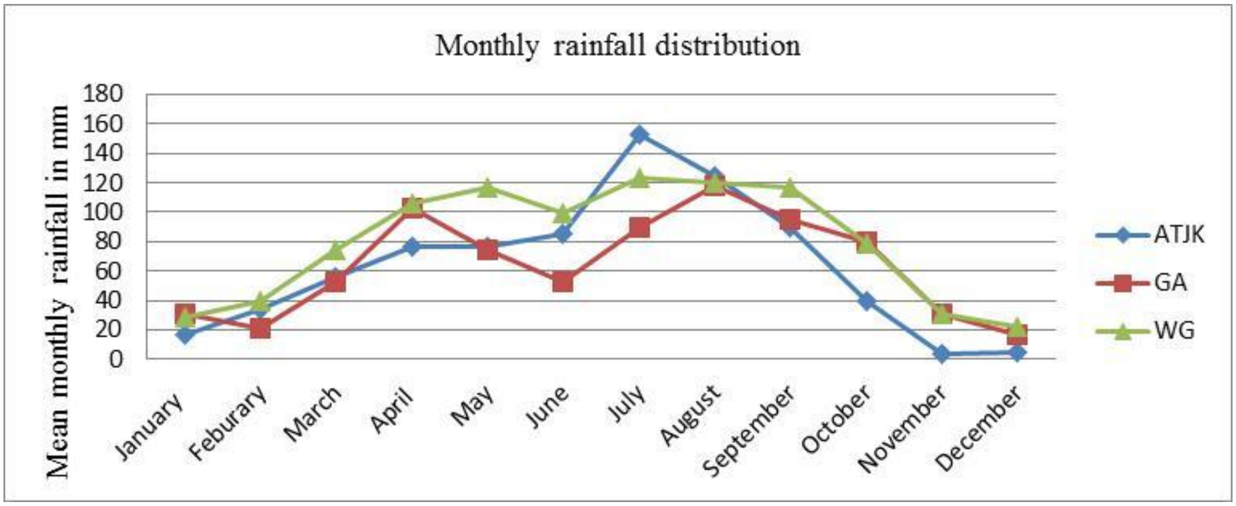
Crops grown in the area include maize, haricot bean, teff, wheat, and sorghum; with maize and haricot bean accounting for the largest share of the crop area. The main livestock types are cattle, sheep, goats, equines, and chickens. Lack of sufficient resources, such as land and oxen power, associated with erratic rainfall pattern, make agriculture the most difficult sector in the district. Farmers have attempted to reduce the adverse effects of rainfall that draw early and severe drought by using small-scale irrigation and participating in non-farm activities (Lencha 2008). Water availability, good infrastructure, and easily accessible input/output markets offer important potentials for the area (Lencha 2008; Mitiku 2011). However, the share of the irrigated area in the district remains small: there are about 31 small-scale irrigation schemes with a capacity of 2250 farm households, mainly practicing irrigated agriculture for horticulture crops. Farmers with access to irrigation grow vegetable crops such as onion, tomatoes, papaya, banana, and citrus fruits on small-scale using water pumped from the river. These crops give higher yields and returns on a small plot, improving farmers' livelihoods (Assefa 2008; Haylamicheal & Moges 2012; Lencha 2008; Mitiku 2011).

Gedeb Asassa (GA) is the third district included in this study; it is one of the districts of Arsi-Zone of Oromia Regional State and has a population of 194,817. It is located in the southern part of the country about 423 km away from Addis Ababa. The climatic condition of the district is uni-modal rainfall with a mean annual rainfall of 852 mm. The mean annual maximum and minimum temperature are 24.0^0c and 3.8^0c respectively (CSA 2007; ENMA 2007). Similar to the rest of the country, in this district too agriculture is the main livelihood activity. The major crops grown in this district are wheat, barley, and teff, with the crop area share of cereal crops about 93%.

1.5.1. Rainfall distribution of the study area

The distribution of 30-year time series rainfall data obtained from meteorological stations located near to the selected study districts (Awassa station for WG district, Ziway station for ATJK district and Bokoji for GA district), is presented in Fig. 1.2 and Table 1.3. The result presented in Table 1.3 shows the monthly rainfall distribution in the study area. According to the descriptive analysis of the rainfall data, the monthly average rainfall of the study area is 68 mm. The average monthly rainfall of Adami-Tulu Jedo Kombolicha (ATJK), Gedebe-Asasa (GA) and Wondo-Genet (WG) district is 62, 64 and 79 mm, with standard deviations of 13.91, 14.42 and 12.24 mm, respectively. The main rainy also growing season ranges from May to September; during this period, monthly rainfall is above the average. In ATJK district, the highest monthly average rainfall is registered in July. GA district receives its highest monthly rainfall in August. WG district, on the other hand, has more or less steady rainfall between the months of April and September. Fig. 1.2 presents the pattern of rainfall distribution over the months of the year for the three districts. The peak in rainfall distribution is found in the summer season, particularly between the months of June and August.

Fig. 1. 2 Monthly rainfall distribution of study area by districts 1974-2003



Source: Authors estimation from Ethiopian National Meteorology Agency database (ENMA, 2010)

1.5.2. Rainfall distribution and variability in study area

The results in Table 1.3 indicate the distribution of average annual rainfall over 30-years, presenting rainfall variability for the three districts. It is clear that WG, followed by GA, has the highest average annual rainfall. Furthermore, the analysis indicates that about 27% of the years registered a rainfall below the 25th percentile value. The mean annual rainfall is about 740, 760, and 950 mm in ATJK, GA and WG districts, respectively. More than 50% of the years have rainfall below the average value. The coefficient of variation in annual rainfall distribution is 15%, 22% and 23% for WG, GA and ATJK district, respectively. This indicates the difference in rainfall variability (variance) for the three districts. Accordingly, higher rainfall variability is observed in ATJK district, while the lowest variability is observed in WG. The minimum annual rainfall ranges from as low as 180 mm in GA to as high as 666 mm in WG. In general, the WG has shown more consistent, higher, and uniform rainfall distribution compared with the other two districts. One of the objectives of this study is to see how the rainfall variability affects the crop yield over time; it is likewise interesting to examine how crop yield is affected by the rainfall variability.

Table 1.3 Annual rainfall distribution in three districts 1974-2003

District	Mean	Std.	Min	Max	Median	75th	25th	CV (%)
ATJK	742	167	437	1096	756	864	613	23
GA	764	166	189	1012	765	876	722	22
WG	953	143	666	1228	953	1028	858	15

Source: Authors estimation from Ethiopian National Meteorology Agency (ENMA, 2010)

1.5.3. Household characteristics, asset endowments and plot-level information

A household's farm experience has a significant role in the probability of adopting new agricultural technology and on the productivity of the household. Families with younger heads-of-the-household are more likely to be educated and ready to adopt new agricultural technologies, but they are less likely to have better landholdings (Gebremedhin et al 2009). On the other hand, households with older heads are more likely to have better farming experience and know-how with regards to adjusting their farming techniques in response to rainfall variability. Characteristics of households in the study area are presented in Table 1.4. The average farming experience for all surveyed households is about 21 years. The average farm experience of surveyed households in GA district is 18 while the average farm experience of WG district is 23. The average age of household head in the study area is 43 years. All of the three districts have similar head-of-household ages.

The education level of the household head is an important component for the farm household's technology adoption and for diversification of income sources (Gebremedhin et al 2009; Raymond and Robinson 2013). The average year of schooling is about 4 years; demonstrating that most of the farmers attend only primary school. Female-headed households account for 10% of the total households. In ATJK district, about 15% of households are female-headed. The average landholding size is about 1.80 hectares, which is above to the national average of 1 hectare (CSA 2009; Gebremedhin et al 2009). Furthermore, the descriptive analysis shows that about 10%, 20% and 90% of households in ATJK, GA and WG districts, respectively, have access to irrigation water near to plots. Despite this irrigation potential, the share of irrigated plot is quite small: the proportion of farmers who use irrigation on their plots is about 3%, 1%, and 54%, in ATJK, GA and WG districts, respectively. The Wondo-Genet district has proportionally larger irrigation potential and irrigated areas compared with the other two districts. More than 50% of households in WG reported that they are practicing irrigation, mainly to grow crops such as maize, coffee, chat, enset, and sugarcane.

Table 1.4 Average household and plot characteristics of the study area

Districts	ATJK (N=60)	GA (N=60)	WG (N=60)	Total (N=180)
Household -level data				
Farm experience (years)	21.76	17.59	23.05	20.81
Age head (years)	42.14	42.18	44.07	42.80
Education head (years)	3.83	4.88	3.70	4.11
Sex head (male=1, female=0)	0.85	0.93	0.93	0.91
Farm size (hectare)	2.86	2.49	0.96	1.80
House size (person)	7.03	7.82	8.18	7.68
Income from largest source (Birr/yr)	3745	4927	5251	4646
Plot-level data				
Total number of plots	152	184	112	448
Access to irrigation (yes=1, no= 0)	0.08	0.21	0.86	0.32
The plot is irrigated (yes=1, no= 0)	0.03	0.01	0.54	0.15
Manure (yes=1, no= 0)	0.82	0.61	0.75	0.73
Perennial tress (ha)	0.00	0.04	0.84	0.29
The plot is certified (yes=1, no= 0)	0.98	0.82	0.00	0.61

Source: - *Author's computation from a survey conducted by Master Students in Institute 490A, 2010;* 19.01 Birr = 1 USD.

Manure is the main agricultural input for smallholder farmers: it is applied vastly, especially on farmyard plots to improve soil fertility and hence crop yield. More than 70% of the households in the study area replied that they use manure as an input on their plots. Land certification is a new government policy designed to guarantee land ownership for farmers, secure tenure rights, and to improve land management and use (Holden et al 2007). Labor is one of the main inputs in the production process, particularly during land preparation, planting, and postharvest processing. Furthermore, labor determines productivity levels and the production capacity of households (Di Falco et al 2011). The average family size of the study area is 7.68. Gedebe-Asassa district has a largest family size (8.18) compared with the other two districts. The national average family size in Ethiopia is about 5.6 people per household (CSA 2007). Average income from the largest income source is 4646 Ethiopian Birr (ETB). The average income for ATJK, GA, WG district was found to be 3,745, 4,927, and 5,251 Birr per year per household, respectively. Households in WG generate, on average, 40% more income from their primary income source compared to households in ATJK district.

Table 1.5 Plot level water availability of surveyed households

Water availability *	ATJK (n=60)	GA (n=60)	WG (n=60)
If the plot has very good water available (yes=1, no=0)	0.03	0.03	0.31
If the plot has good water availability (yes=1, no=0)	0.07	0.09	0.35
If the plot has fair water available (yes=1, no=0)	0.11	0.30	0.27
If the plot has poor insufficient water (yes=1, no=0)	0.77	0.51	0.04
If the plot is waterlogged (yes=1, no=0)	0.02	0.08	0.04

*Source: Author's computation from a survey conducted by Master Students in Institute 490A, 2010 *. In the survey question regarding the water availability near to plots is administered in qualitative form.*

Table 1.5 provides information on water availability around the plots. As can be seen, more than 75% of households in ATJK district replied that they experience water scarcity problems, and about 20% indicated that they have at least fair water availability near to their plots. Similarly, about 60% of the plots in GA are located in water-deficient areas. Households in WG, on the other hand, reported that about 90% of their plots are in a water available area, and more than 30% even indicated they were in very good water available area. The water availability for plots may influence the household decision of whether to use irrigated farming or not.

Table 1.6 Technology adoption and access to institutions in the study area

Adaptation –Innovation	ATJK (N=60)	GA (N=60)	WG (N=60)	Total (N=180)
Used chemical fertilizer (yes=1, no=0)	0.21	0.71	0.53	0.49
Practiced soil conservation (yes=1, no=0)	0.24	0.07	0.12	0.14
Practiced water conservation (yes=1, no=0)	0.49	0.41	0.40	0.44
Practiced counter plough (yes=1, no=0)	0.55	0.52	0.23	0.46
Practiced build stone bunds (yes=1, no=0)	0.03	0.11	0.03	0.06
Has access to credit (yes=1, no=0)	0.53	0.34	0.00	0.23
Has access to extension services (yes=1, no=0)	0.73	0.82	0.65	0.73
Number extension visits (days)	8.00	5.00	4.00	6.00
Has a cell phone (yes=1, no=0)	0.38	0.52	0.45	0.45

Source: Author's computation from a survey conducted by Master Students at Institute 490A, 2010. N is the number of households in each district.

Use of chemical fertilizer on the plots is considered to be an important means of increasing agricultural productivity by smaller farm households. The use of modern agricultural inputs such as mineral fertilizer improved seed varieties, pesticides and other improved farming technologies are found to increase crop yield and hence improve the livelihood of farmers in many developing countries (Stepanek 1999). The diffusion of fertilizer in Ethiopia is one of the lowest in Sub-Sahara Africa. As can be seen from Table 1.6, the share of farmers in the study area applying mineral fertilizer is below 50%. About 20%, 70% and 50% of households in ATJK, GA, and WG, respectively, apply fertilizer on their plots. Soil conservation is a crucial soil management strategy, as it prevents soil and water from being washed away by wind or flooding (Kato et al 2011). As such, soil conservation helps to increase soil fertility and improve crop yield (Mbaga-Semgalawe and Folmer 2000; Amsalu and de Graaff 2007; Kato et al 2011; Jara-Rojas et al 2013). About 25% of households in ATJK practice soil conservation activities on their plots to protect soil from erosion and runoff. Conversely, only 7% of households in GA practice soil conservation activities.

Farmers must have information on agricultural technology, innovations, adaptation strategies, and market prices before they decide whether to adopt or use them. Lack of information is indicated in many studies to be a predominant problem of households in need of technological improvements (Bryan et al 2009; Deressa et al 2009; Di Falco et al 2011). Availability of a means of communication will improve access to information about the market price and assist farmers in getting a reasonable price for their products. Telephone is a new technology for farm households in the study area. In fact, in the study area, less than 50% of households have reported that they have private cell phones. Training, farmer's schools, and provision of technology-related advice and follow up with the agricultural extension service could help farmers adopt new technologies and encourage them to produce marketable goods. Addressing farmers' problems and providing the necessary advice is one of the policy directions set by the Ethiopian government to increase the productivity of smallholders. Extension service workers have visited about three-quarter of the farmers in the study area at least once. The survey indicates that households receive extension services for specific topics, such as livestock breeding, crop production and marketing, improved varieties, and farming technologies.

Table 1.7 The share of major crops grown in the study area in cultivated area

	Shares (%) in total crop area			
Crops	ATJK (N=60)	GA (N=60)	WG (N=60)	All (N=180)
White teff	7.90	0.30	0.00	2.80
Black teff	6.20	2.70	1.00	3.30
Barley area	2.80	20.30	0.00	7.60
Wheat area	13.20	69.90	0.00	27.40
Maize area	60.70	0.30	18.90	27.00
Sorghum area	5.10	0.00	0.00	1.70
Coffee area	0.00	0.20	6.40	2.20
Chat area	0.00	0.00	40.60	13.50
Enset area	0.00	0.00	11.40	3.80
Avocado area	0.00	0.00	16.80	5.60
Total crop area (ha)	143.00	204.00	55.00	402.00

*Source: -Author's computation from a survey conducted by Master Students at Institute 490A, 2010. * Sum of percentages might not add up to 100% as only main crop area is presented in the table. Area is in hectares*

The study area contains diverse agro-ecological conditions and farming activities. ATJK district has a climate suitable for cereal crop production, and as such, maize and wheat are the major crops grown in the area. In this district white teff, black teff, barley, wheat, sorghum, and maize account for about 8%, 6%, 3%, 13%, 5%, and 61% of the total crop area, respectively. Perennial crops such as chat, coffee, enset, and avocado, cover 80% of the land in WG, with the remaining, 20%, mainly covered by maize. Similarly, GA district has a cereal-based farming system, with wheat and barley accounting for the lion's share of the total cultivated area. In GA, the share of crop area under wheat and barley is about 70% and 20%, respectively. A closer look at the distribution of crop area among different crops reveals diverse agroecology and the research area represents well the regional land use. Taking all the districts together, wheat and maize, followed by barley, are the main crops grown in the study area.

Table 1.8 Demographic, livestock and perennial asset endowment of the districts

Asset name	ATJK (N=60)	GA (N=60)	WG (N=60)	All (N=180)
Male-children (age <5 years)	1.78	2.28	2.18	2.08
Female-children (age <5 years)	1.35	1.62	1.85	1.61
Young-females (age between 6 and 14)	0.30	0.13	0.22	0.22
Young-males (age between 6 and 14)	0.22	0.33	0.32	0.29
Adult-females (age above 14 years)	1.77	2.08	1.77	1.87
Adult-males (age above 14 years)	1.62	1.37	1.85	1.61
Cattle (number)	2.48	2.12	*1.80*	*2.13*
Goat (number)	2.95	0.52	*0.90*	*1.46*
Sheep (number)	1.42	3.48	*1.20*	*2.03*
Coffee tress area (ha)	0.00	0.02	0.06	0.03
Chat trees area (ha)	0.00	0.00	0.45	0.15
Enset area (ha)	0.00	0.00	0.15	0.05
Banana area (ha)	0.00	0.00	0.03	0.01
Eucalyptus area (ha)	0.00	0.02	0.02	0.00
Avocado area (ha)	0.00	0.00	0.16	0.05

Source: Author's computation from a survey conducted by Master Students at Institute 490A, 2010

The first six rows of the above table show the distribution of demographic assets of the households. Household members classified into six age-sex categories. On average, households in the study area have 2.08 male children, 1.61 female children, 1.87 female adults and 1.61 male adults. Livestock and land devoted to perennial crops indicate the difference in resource distribution among the three districts. The major livestock is cattle, which comprises cows, heifers, bulls, and oxen. Households in WG district have smaller number of livestock compared with other districts. GA has a larger sheep population: 3.5 sheep per household on average. The goat population is higher in ATJK. The average number of cattle, goats, and sheep in the study area is 2.13, 1.46, and 2.03 per household, respectively. Livestock is considered to be an indicator of wealth and social status. Moreover, livestock serves as an informal insurance against crop failure or other shocks: when a household faces a consumption shock or a shortage of food for the family, livestock can be sold to help smooth consumption.

In the study area, cash crops are grown for market. Income from the sale of cash crops improves household welfare. Perennial crops provide products with better prices, higher yields, and year-to-year growing possibilities. Table 1.8 indicates that households in ATJK have no area allocated for perennial crops. This is because the soil and climatic conditions of the district are not favorable for perennial crop cultivation. There is only a small amount of land allocated for perennial crops in GA district. On average, households in GA allocated 0.04 hectares of land for coffee and eucalyptus trees. The suitability of soil and agro-climatic conditions of WG enable households to allocate a proportionally larger area for perennial crop plantations. The descriptive analysis shows that on average households in WG have 0.15, 0.05, 0.05, and 0.03 hectares of chat, avocado, enset, and coffee plantations, respectively. Chat and coffee are the major cash crops grown in farmyard plots. In WG district, despite the small landholdings per household, a larger share of the crop area is allocated for perennial trees.

1.6.Methodology and Data

1.6.1. General overview of rainfall variability models

The relationship between crop yield and rainfall variability is mainly studied by employing Agro-ecological Zone (AEZ) models, Agro-economic (AE) models or a Hedonic Price (Ricardian) approach (Eid et al 2007; Kabubo-Mariara and Karanja 2007; Seo and Mendelsohn 2007; Lang 2007; Lippert et al 2009). AEZ models use simulated crop yield for different agro-ecological zones and compare the result with the maximum yield at the different agro-ecological zone. However, they fail to predict all components of rainfall variability effect. The AE model uses experimentally produced yield effects of rainfall variability in a laboratory under controlled situation; they fail to incorporate possible changes in farming systems, farmers' adaptation to rainfall variability and future technological progress in agriculture to curtail the effect of rainfall variability (Mendelsohn et al 1996). Apart from its weakness in assuming constant price over time, hedonic price modeling better captures the adaptation of farmers to rainfall variability (Seo and Mendelsohn 2007). Crop simulation and Ricardian models are the two primarily used a measure of economic impacts of climate change on African agriculture (Kurukulasuriya and Mendelsohn 2008). However, due to the complexity of climate-environment and human interactions, most models only capture a fraction of such real world conditions. Accordingly, these models either underestimate or overestimate the effects of rainfall variability on agriculture and social welfare in general and as such fail to recommend plausible policy responses (Seo and Mendelsohn 2007; Tao et al 2009).

To recommend policy directions that help to minimize the adverse effect of rainfall variability on Ethiopian agriculture, particularly on crop yield and household welfare, this study used agent-based simulation modeling to examine farmers' adaptation strategies and their role in reducing the adverse effect of rainfall variability. The study analyzes the effects of rainfall variability on different crop yields and its implication for household welfare. The relationship between rainfall variability, adaptation strategies, and their consequence on crop yield is widely studied at the national and global level. However, little is known about how rainfall variability, agricultural yield, and farmers' adaptation strategies are related at the household level, especially in developing countries such as Ethiopia (Deressa et al 2009; Kato et al 2011). Furthermore, there is a dearth of studies on the links between adaptation strategies and crop yield, factors determining the farmers' decision to adopt, the role of adaptation on reducing the effects of rainfall variability, reducing poverty, and improving household food security (Deressa et al 2009; Di Falco et al 2011).

Therefore, this study has double importance: First, it narrows the knowledge gap on rainfall variability impacts and farmers' adaptation strategies at the household level. As such, it contributes to the existing knowledge of rainfall variability and adaptation strategies. Second, it helps policy makers in Ethiopia and other developing countries to design policies that can significantly abate negative effects on crop yield and the livelihood of farm households from rainfall variability. A difference of this study to other studies is the use of a model that encompasses both biophysical and economic models. This study uses Mathematical Programming-Based Multi-Agent System (MP-MAS) model developed by a research team lead by Professor Thomas Berger at the University of Hohenheim. The model has been applied in different case studies on countries such as Ghana, Uganda, Ethiopia, Thailand, Chile, Peru, Vietnam, and South Germany. The model is found to be robust and captures real world interactions, simulating the effects of these interactions at the household level see (Berger 2001; Berger & Schreinemachers 2006; Schreinemachers et al. 2007; Schreinemachers et al. 2009).

Moreover, this simulation model enables one to see the dynamic aspect of household characteristics and the interactions between human beings and the environment. Using an agent-based modeling approach considerably overcomes the limitations of other bio-economic models: MP-MAS is able to capture the complex real-world interaction of climate, environment and human beings (Berger et al 2006; Berger and Schreinemachers 2009; Schreinemachers and Berger 2011). According to Berger & Schreinemachers, (2006), representing the physical landscape of a study area through layers of grid cells, with farm households as individual agents and interactions based on pre-defined heuristics, can efficiently capture heterogeneity among different actors. The potential of MP-MAS to account for heterogeneity and interdependency among agents and their environment at a disaggregated level is one of the primary strengths of the model (Berger 2001; Schreinemachers 2005; Berger and Schreinemachers 2006; Schreinemachers et al 2007; Schreinemachers and Berger 2011; Troost 2013).

1.6.2. Explanation of data used in the study

The study used data from both primary and secondary sources. Climate data is obtained from the Ethiopian National Meteorological Agency (ENMA), and crop production data from the Central Statistical Agency (CSA). Price data is obtained from the Ethiopian Rural Household Survey (ERHS) data conducted by the International Food Policy Research Institute (IFPR) and the Central Statistical Authority of Ethiopia. Primary data is obtained from a survey conducted by Master Students in 2010 from the study area districts and is used for additional information on household characteristics. Farm experience, sex, and age of the household members, education, household size, landholding size, income from the major crop sale, access to irrigation water and soil type, data is obtained from data collected by the Master Students. Moreover, the author has conducted key informant interviews on household rainfall vulnerability, adaptation strategies (soil and water conservation activities and irrigation, and associated acquisition costs), and constraints in the study area. Secondary data on climate variables such as temperature, relative humidity and precipitation (rainfall) were obtained from ENMA; crop production, land use, yield per hectare, fertilizer and improved seed use was obtained from the CSA and ERHS data sets.

Chapter 2: Assessment of climate variability models and empirical literature review

2.1.Introduction

There is a vast set of emerging studies on the effects, perception and adaptation strategies to climate change. In literature, it has been understood that farmers' perceptions and adaptation efforts can significantly reduce the adverse effects of climate change, including rainfall variability (Klein et al 2007; Kurukulasuriya and Mendelsohn 2008). Adaptation to climate change is defined as adjustments in ecological, social or economic systems in response to actual or expected climatic stimuli and their impacts and effects (Smit et al 1999; IPCC 2007). Based on their perception and adaptation practice, farmers are categorized into three groups. The first group are farmers who perceive climate change but do not adapt to it. The second group, farmers who change their farming practice and adopt different adaptation strategies for other purposes not solely related to climate change; and a third group, are those who perceive and adapt to climate change (CR et al 2000; Adger et al 2005). Perception of and an adaptation to climate change are the most important factors in terms of reducing its adverse effect.

2.2. Farmers' perception and adaptation strategies to climate change in Ethiopia

Studies on farmers' climate change perception and adaptation strategies in Ethiopia revealed that even though more than 90% of farmers perceive climatic changes, only 58% have practiced some kind of adaptation strategies while about 40% did not take any kind action against climate change (Di Falco et al 2012). The same study indicated that about 68% and 62% of farmers perceived an increase in mean temperature and decline in mean annual rainfall, respectively, in the past twenty years. Both social and economic factors have significantly contributed to the low level of adaptation: studies showed that information on climate change and limited financial capacities are the two factors most hindering adaptation to climate change (Bryan et al 2009; Deressa et al 2009; Di Falco et al 2011).

Farmers to curtail the adverse effects of climate change have practiced different strategies. The most prominent adaptation strategies during climatic shocks are selling of livestock, changing crop varieties, shifting planting dates, practicing soil and water conservation activities, borrowing money from relatives and friends, using improved agricultural inputs, and irrigation (Deressa et al 2009). However, these adaptation strategies are not free of cost or easily available (Robinson et al 2013). A study by Deressa et al. (2009) in the Nile Basin of Ethiopia showed that the major constraints for climate change adaptation are lack of financial capacity, lack of information on climate change, shortage of labor and land, and poor irrigation structure and access. Lack of information on climate change is a good indicator for the absence of research in the area. Thus, it is crucial to study the rainfall variability impacts on agriculture and provide advice to policymakers and other economic agents who are working on climate-related adaptation and mitigation strategies (Deressa et al 2009).

Impacts of climate variability on agriculture have been assessed mainly using two approaches: The first is a partial equilibrium approach, which assesses the impact of climate variability by considering only part of the economy, with the assumption that different sectors of the economy are independent of one another and do not affect each other. This approach includes crop simulation modeling, Agro-Economic Zone (AEZ) models and Ricardian models (Mendelsohn and Dinar 1999; Deressa 2007; Lang 2007; Sultan 2012). The second approach is a general equilibrium approach, which evaluates the impact of climate variability on the whole economy as a complete set, assuming different sectors in the economy are interdependent (Deressa 2007). This approach includes models such as Computable General Equilibrium (CGE) and Integrated General Equilibrium (IGE) models. Thus, compared with other approaches, the general equilibrium approach best captures the economy-wide effects of climate variability and gives a clear picture of its impacts on both agriculture and non-agriculture sectors simultaneously (Berrittella et al 2006; Deressa 2007; Tubiello and Fischer 2007; Bigano and Tol 2008; Zhai et al 2009; Palatnik et al 2010).

2.3. Agro-Economic Zone Models

Agro-economic zone (AEZ) models, also called “production function approach,” was first used in the study of global climate change’s impact on agriculture by Adams (1989). This model uses production functions and varies the relevant environmental inputs, such as temperature, precipitation, and CO_2 levels, to estimate impacts on agricultural production of input variation

(Mendelsohn, et al., 1994). Because of its experimental design, the model gives unbiased estimates of the effect of climate change on the yield of specific crops. The disadvantage of the agro-economic modeling approach is that the estimates of the model do not account for the possible compensatory responses, such as adaptation and mitigation strategies made by farmers to abate the adverse effects (Schlenker et al 2005). For instance, farmers may change the intensity and variety of inputs such as fertilizer and improved seed used in response to changes in climatic conditions (Deschenes and Greenstone 2007). Moreover, the model focuses on the agricultural sector and ignores interrelationships with other sectors of the economy, which may determine input prices and allocation (Schlenker et al 2005).

2.4.Ricardian Model

By using cross-sectional data on climate, farmland prices, and other geographic and economic data on agriculture in the United States, Mendelsohn, et al. (1994) used a Ricardian approach. This approach corrects for the bias in AEZ: Instead of studying the effect of climate change in the yield of a specific crop, the authors examined how climate in different places affects the net value of farmland by considering all possible adaptation strategies (Mendelsohn et al 1994). As such, this approach accounts for both direct yield effects and indirect (substitution) effects of climate change (Mendelsohn et al 1994). Similarly, in an analysis of the impact of climate change on German agriculture, Lang (2007) used this approach with agricultural survey data from 800 representative farmers in Western Germany and weather data from 75 weather stations in Germany. This study measures the land value as rent for a hectare of land per year, considering the difference in land quality and specialization. The author combined the estimation result with a global warming scenario and estimated that German agricultural would gain from climate change in the short run, with the maximum gain attained at a temperature increase of 0.6^0c (Lang, 2007). Beyond this, the value of agriculture will be negatively affected (Lang, 2007). Furthermore, Lippert, et al. (2009) used a Ricardian approach with cross-sectional data from a 1999 German agricultural survey and climate data from a network of German weather observation stations in their study of climate change impacts on agriculture in Germany. The authors come up with similar conclusions as Lang (2007). Specifically, the study revealed that in the short run, German agriculture will benefit from climate change; land rental value, which depicts land productivity, is expected to increase along with rising temperature and declining spring precipitation (Lippert, et al 2009).

Additionally, using cross-sectional data from Latin America Seo & Mendelsohn (2007) examined the effect of climate, soil and other control variables on both land rent value and net revenue. They concluded that both land value and net revenue are sensitive to temperature and precipitation. Other similar studies that made use of a Ricardian approach include a study by Eid, et al. (2007) on agriculture in Egypt; Kabubo-Mariara & Karanja (2007) using cross-sectional data from Kenyan agriculture; Lambi & Forbang (2009) employing cross-sectional data from farm household in Cameron; Benhin (2008) on Agriculture from South African; and Mano & Nhemachena (2007) with cross-sectional data from Zimbabwe. All of the studies concluded that an increase in temperature and a decrease in precipitation would negatively affect agriculture.

The clear advantages of the Ricardian approach are that if land markets are operating properly land purchase prices reflect the present discounted value of land rents into an infinite future and that the approach accounts for possible adaptation strategies that farmers may practice against climate change (Holden et al 2007; Seo and Mendelsohn 2007; Deschenes and Greenstone 2007). However, the approach has been severely criticized by Deschenes & Greenstone (2007). Their argument is that the validity of the Ricardian approach depends on the consistent estimation of the effect of climate change on farmland value (Deschenes and Greenstone 2007). However, there is a set of unmeasured characteristics. Soil quality and optional values of land (converted to a new use) are important determinants of output and land value in agricultural settings: These factors were ignored in the estimation process under Ricardian approach. Accordingly, the estimates of climate change effects of this approach may be confounded with other factors that will affect land productivity and profitability (Mundlak 1961; Mendelsohn et al 1994; Hoch 1996; Kabubo-Mariara and Karanja 2007; Deschenes and Greenstone 2007).

2.5.Computable General Equilibrium Models (CGE)

Climate variability affects different sectors and actors of the economy, such as agriculture, trade, tourism, markets, environment, and human beings. It is vital, therefore, to study the interaction between different economic sectors and the direct and indirect effects of climate variability on related sectors. Computable General Equilibrium (CGE) models are a class of economic models that use actual data to estimate how an economic system might respond to changes in policy, technology, preference, climate shocks, or other external factors. General equilibrium models first came to use in the work of Harberger (1962) and Johansen (1963). Using two production sectors (one corporate and one non-corporate), Arnold Harberger used 1950 U.S data and examined the incidence of a corporate income tax with the model. Leif Johnson extended the model to nineteen production sectors and applied it to 1950's data to identify the source of Norwegian economic growth between the years 1948 and 1953.

These models provide consistent estimates on the response of the whole economy to changes in other parts of the economy while considering inter-linkages among industries, markets, trade, and regions. Accordingly, the models were intensively used in the study of markets, trade, tourism, industry, and climate variability. For instance, a study by Berrittella et al., (2006) used a CGE model to investigate the impact of climate variability on the global tourism economy. They concluded that at the global level, the effect of climate variability on tourism is neither negative nor positive. This is mainly because of the fact that the climate shock resulted in a redistribution of tourism income both within regions and across regions (Berrittella et al 2006). However, in the short run, the model expected that the European Union would be positively affected by climate variability (Berrittella et al 2006). Moreover, the study indicated that by the year 2050, climate variability would affect world GDP in a range of -0.3% to 0.5% (Berrittella et al 2006). Similarly, Bigano, et al., (2008) used CGE models for analysis of climate variability on sea level rise and tourism flow, concluding that climate variability will cause a loss of GDP within the range of 0.1% in South East Asia to 0.0004% in Canada (Bigano et al 2008). This study also revealed that the flow of tourism will favor Western Europe, Japan, Korea, and Canada at the expense of all other regions of the world (Bigano et al 2008).

Recent studies by Wei, et al. (2009) and Zhai, et al. (2009) on the impact of climate variability on agriculture in the People's Republic of China used CGE modeling. These studies simulated scenarios of climate variability to induce global agricultural productivity changes and showed that the impact of climate variability on Chinese agriculture will be moderate (Wei et al 2009, Zhai, et al., 2009). Similarly, a study on the impact of climate variability in Egypt by Onyeji & Fischer (1994) indicated that climate variability will have both direct and indirect effects on agriculture (Onyeji and Fischer 1994). The same study concluded that by the year 2060, Egyptian GDP would decline by 6%, and as a result, food and crop prices are expected to increase up to 30% and 90%, respectively (Onyeji and Fischer, 1994). Palatnik et al. (2010) used Integrated Computable General Equilibrium (ICGE) modeling to examine the economic impact of climate variability on the Israeli economy and concluded that even under the carbon dioxide tax compensation, GDP will decline in real terms by 0.45% and welfare will diminish by 0.34% (Palatnik et al 2010). Despite the substantial application of CGE models in the studies of climate variability effects, the modeling approach has its own limitations. Specifically, CGE models are too complicated to develop, understand, and involve a substantial number of parameters and substructures. Moreover, they do not predict the real world situation so much as they indicate the future tendency of how the economy will fluctuate (Ackerman 2002).

2.6.Mathematical Programming-Based Multi-Agent System (MP-MAS)

The Mathematical Programming-Based Multi-Agent System (MP-MAS) model first came into use by Balmann (1997), followed by Berger (2001). The MP-MAS model is part of a family of multi-agent system models and consists of coupled models of population, demography, crop growth, market, perennial, livestock, irrigation, and soil. The model captures well the complex interactions of different economic agents (Berger 2001; Berger and Schreinemachers 2006; Schreinemachers et al 2007; Schreinemachers and Berger 2011). This model combines biophysical and economic models. In particular, the effect of rainfall variability on crop production effectively captured using an internally coupled CropWat model. In this simulation model, a household faces investment, production, and consumption decisions under resource constraints. Investment decision-making depends on future expected yields and prices of crops, which are considered to be uncertain for the farmers. Consumption decisions involve a three-stage decision-making process and are estimated using a Linear Approximation of Almost Ideal Demand System (LA/AIDS).

Using Mathematical Programming (MP) to simulate the household decision-making under such uncertainty and integrating socioeconomic models with biophysical models will give a better understanding of climate change induced rainfall variability effects on agriculture. Moreover, the model is at present being used in a number of different country case studies. Based on Balmann (1997), Berger (2001) has developed a simulation model for water allocation and technology diffusion in Chilean households. Schreinemachers et al. (2007) applied MP-MAS to simulate food security and soil fertility dynamics in Uganda. In addition, the model is being applied in country studies of Peru, Uganda, Ghana, Ethiopia, Germany, Thailand, and Vietnam.

2.7.Review of climate change studies in Ethiopia

As there are limited studies on the impact of climate change, and hence rainfall variability, for Ethiopia, few methodological approaches have been used for rainfall variability impact assessments in the Ethiopian context. In the past few decades, Ethiopia has experienced severe climatic events, such as drought, flooding, and associated chronic famine. However, there have been few studies on the impact of rainfall variability and the potential roles that adaptation strategies play in reducing the adverse effects (Deressa et al 2009; Mideksa 2010; Di Falco et al 2011). Moreover, these studies mainly used partial equilibrium or general equilibrium analysis, which examine the climate variability impact on the national or regional level using highly aggregated data sets. As such, they fail to give consistent estimates of the effect of rainfall variability at the household level. Accordingly, there is no sound policy designed to ameliorate the potential impacts of rainfall variability on Ethiopian economy in general and on the Ethiopian agricultural sector in particular (Deressa et al 2009; Mideksa 2010; Di Falco et al 2011).

Deressa (2007) applied a Ricardian approach on cross-sectional data from thousand households in Nile basin of Ethiopia to analyze the economic impact of climate variability on Ethiopian agriculture. In this study, the author examined the economic impacts by regressing net revenue per hectare on different climatic, economic, and social variables. Moreover, linear and quadratic terms for the temperature and precipitation during two cropping seasons, soil type, asset ownership, and demographic characteristics of households were included in the model. The study concluded that all variables have significant impacts on net revenue per hectare. Specifically, it concluded that increased temperature significantly reduced the net revenue per hectare by US$998 and US$1277 during winter and summer seasons, respectively. Increased precipitation during the spring season enhanced net revenue per hectare by US$225. The effects of climate change varied from one agro-ecological zone to another, and the impact depended on the existing climatic conditions of the agro-ecological zones. For example, increased temperature severely affects the hot and very warm arid lowland areas. However, the increase in temperature benefited the cool regions. The study analyzed the expected impact of climate variability using predictions from three climate change models, namely CGM2, HaDCM3 and PCM Special Report on Emission Scenario (SRES), all of the predictions forecasted increases in temperatures in the years 2050 and 2100. The HaDCM3 and PCM models predicted an increase in precipitation. CGM2 predicted a decrease in precipitation in the years 2050 and 2100. Moreover, all SRES predictions showed decreases in net revenue per hectare in the years 2050 and 2100.

A similar conclusion was drawn by Mideksa (2010) using an economy-wide disaggregated general equilibrium model for the Ethiopian economy using nationally aggregated data for production, consumption and trade. The author disaggregated the production sector into agriculture, manufacturing, and service. The study further disaggregates agricultural products into food crops, traditional exportable, nontraditional agricultural exportable and other agricultural products. The study concluded that climate variability makes the economic perspective of the country harder in at least in two ways: First, climate variability reduces agricultural production and output. Since agriculture is highly interlinked with other sectors, climate change impacts would reduce GDP by 10%. Second, climate variability affects the economy by increasing the income disparity between the poor and rich. Accordingly, the GINI coefficient is expected to increase by 20%, further aggravating poverty in the country (Mideksa 2010). Thus, rainfall variability would pose a significant negative threat to the Ethiopian economy.

In contrary to the above results, You & Ringler (2010) used multi-market, multi-regional, multi-sector general equilibrium models to examine the potential impact of climate variability on the Ethiopian economy. The authors considered three major factors changing under global warming: water constraints, flood losses, and CO_2 fertilization for eleven administrative regions of the country. The study revealed that in the coming decades leading to 2050; both temperature-induced evapotranspiration (ETO) and precipitation would increase. Precipitation is expected to be more fluctuating and inconsistent. The increase in precipitation increases the effective water supply for crop production and, thereby, the incidence of flooding events. Simultaneously, the increase in the ETO raises water demand. However, the change in climatic condition does not appear to alter the GDP growth rate. This is because the increase in precipitation and ETO will not be significant and will have opposite effects. Therefore, climate variability is estimated to not have a prominent effect on Ethiopian agriculture (You and Ringler 2010). However, You & Ringler, (2010) remains an outlier. All other studies agreed that, at least in the long run, climate variability will have a negative effect on the Ethiopian economy.

The degree of benefit or losses for a country from climate change depends mainly on its adaptive capacity and geographic locations (Kurukulasuriya and Mendelsohn 2008). Low latitude countries are predicted to be negatively affected by erratic climate change (IPCC 2007). Ethiopia is one among the many world countries that are more susceptible to a negative climate variability impact (Di Falco et al 2012). Therefore, it is of significant importance to study the adverse impact of rainfall variability and identify adaptation strategies and their importance in reducing the effects of rainfall variability at the household level. This study uses MP-MAS model to analyze the effects of rainfall variability on crop yield and household welfare, such as income, poverty, food consumption, and income inequalities.

Chapter 3: Model structure and estimation of parameters

3.1. Introduction

This chapter discusses research methodology and parameter estimations used in the process of model development. In this thesis, Mathematical Programming-Based Multi-Agent System (MP-MAS) is constructed for Ethiopia by using the standard query method (MySql) approach. The model consists of 2,969 activities, 289 constraints, and 1800 agents. Data from three main sources have been used to develop the model. : The first source is the Ethiopian Rural Household Survey (ERHS). This is a longitudinal data started in 1987 in Ethiopia and conducted at five-year intervals; the most recent data was conducted in 2009. This study used the recent 2009 dataset for the estimation of advanced consumption coefficients, crop production, and input uses. Second, data obtained from Masters Students from the Institute of Rural Development Theory and Policy (490A) in University of Hohenheim is used to estimate cropping activities, resource availability of households in the study area such as land, labor, and livestock, and irrigation information. Third, data on crop yield, the input response of yield, livestock production, perennial yields, adaptation strategies, and related information were obtained from literature and expert interviews during fieldwork in the research area between January and February 2013.

Rural households perform different farming and non-farming activities in Ethiopia. Accordingly, different annual and perennial cropping, livestock production, and labor activities were included in the model. Moreover, a simple EDIC hydrology module, CropWat module, and a three-stage advanced consumption module were developed to identify irrigation water use by crops, the impact of water deficit on crop yield, and consumption pattern of households, respectively. The chapter is organized into eight main sections: section one introduces the data sources; section two discusses the methodology (MP-MAS; section three presents a discussion on the climate change adaptation strategies and how it is implemented in MP-MAS; section four presents the production function and parameter estimation; section five discusses the three stage advanced consumption module; section six explains the future rainfall variability and household welfare and section seven conclude the chapter by discussing empirical analysis of the consumption function.

3.2. MP-MAS model structure and implementation

The MP-MAS modeling approach uses the IBM Library (OSL) to solve complex optimization problems under a pre-specified set of constraints. This kind of optimization represents the real world situation in which all households allocate their resources in order to maximize expected income or some other objective by means of their available resources. Since it allows individual agents to maximize the specific objective under consideration, MP-MAS differs from the traditional aggregate based approaches of maximization. In the MP-MAS, the decision problem that individual faces can be represented by a set of optimization and constraint equations. Households allocate their limited resources in a way that can maximize their objective function while satisfying the input requirements and resourceconstraints. The simplified numerical specification of the model is presented below.

The general optimization problem can be presented as:

$$max\, Z = \sum_{j=1}^{n} c_j x_j \qquad 3.1$$

Subject to constraints:

$$\sum a_{ij} x_{ij} \leq b_i \qquad \text{all } i = 1 \;\; to\, m \qquad 3.2$$

$$x_j \geq 0 \qquad \text{all } j = 1\; to\; n \qquad 3.3$$

Where Z represents the farm household’s objective, which is a linear function of alternative farm activities x_j $(j = 1\; to\; n)$, such as growing crops (with different input-output combinations), raising livestock (different livestock type with varying ages), hiring in and out of labor, consumption (from own produced or market), adopting new agricultural technology, participating in non-farm activities, taking credit, making deposits in the bank and expected per unit rate on the deposit, c_j. In the MP-MAS the optimization problem can be net farm income, net household income, or utility (income and consumption) (Schreinemachers & Berger, 2011), a_{ij} are the quantities of resource, b_i , required to produce one unit of activity x_j, for instance the amount of labor required to cultivate one hectare of maize. The optimization algorithm in MP-MAS finds values of x_j that yield the highest possible value of Z, satisfying the resources constraints b_i and a non-negativity condition for x_j. The technical coefficients (quantity required) a_{ij} can be obtained from empirical estimations, survey data, field experimentation, advanced literature, or expert opinion. The input requirement a_{ij} for a particular activity x_j can be presented at specific time interval (monthly, yearly, quarterly, or seasonally). For instance, labor requirements to grow a crop on a hectare of land can be classified further into different growing stages, such as land preparation, planting, weeding, and harvesting.

The objective function to be maximized is the difference between the sums of all revenue that can be generated from all activities and the sum of all costs associated with the generation of the revenue. For instance, households can generate revenue by selling goods (x_g^s), such as crops (x_c^s), livestock and livestock products (milk, meat) (x_l^s), hiring out labor (L_{ho}), receiving an interest rate on deposits (D), and take credit (C_r). Households incur costs of purchasing goods (e.g. food) (x_f^p) and inputs (livestock feed, fertilizer, seed) (x_i^p), pay wages (w_{hi}) for hired in labor (L_{hi}), and pay interest (i_c) on credit (C_r). Therefore, equation 3.1 can be extended into different sub-functions representing revenue and the associated cost of different activities.

$$\max \quad \pi = \sum_{g=1}^{n} P_g^o x_g^s - \sum_{g=1}^{n} P_g^I C_g^b \qquad 3.4$$

$$= \sum_{c=1}^{c} P_c^s x_c^s + \sum_{l=1}^{l} P_l^s x_l^s + w_{ho} L_{ho} + i_d D + C_r$$

$$- \sum_{k=1}^{f} P_k^f x_f^p - \sum_{i=1}^{r} P_i^i x_i^p - w_{hi} L_{hi} - i_c C_r \qquad 3.5$$

Where π is gross margin to be maximized, P_g^o and P_g^I are per unit selling prices for goods produced and per unit costs of inputs used to produce goods, respectively. C_g^b is the vector of the amount of input b used to produce particular good g; P_c^s and P_l^s are the selling prices for crops and livestock, respectively; w_{ho} and w_{hi} are wage rates on hired out and hired in labor; i_d and i_c are the interest rates received from deposit and paid for credit, respectively. P_k^f and P_i^i are prices of food category k and input i, respectively. Agents can either sell or buy goods and services to satisfy their investment, production, and consumption needs. Their selling and buying decision is determined by their capacity and resource availability (i.e. they cannot use or sell more than what they produce). Not all goods are marketable, although some goods, such as mineral fertilizer, must be purchased from the market. Agents cannot use more labor than their available family labor and hired in labor. Similarly, land used for cultivation cannot exceed the available land endowment.

3.2.1. Balancing labor constraints

MP-MAS implements, household labor by dividing members into different sex-age categories and estimating their respective labor provision (labor contribution), which enables agents to get different amounts of labor provision from each age-sex category. Similarly, other household assets such as livestock and perennial allocated for the households based on the cumulative distribution of each asset or directly on the amounts owned by the household.

Agent's labor capacity (L) is a function of family members working on the farm (l^{fam}) and the amount of labor hired from the market (l^{hi}). Available labor (L) can be used for crop production (l^{crp}), keeping livestock (l^{liv}) and non-farm activity (l^{off}), as well as being hired out (l^{ho}). Thus, L can be presented as:

$$L = l^{fam} + l^{hi} = l^{crp} + l^{liv} + l^{off} + l^{ho} \qquad 3.6$$

Agents cannot use more than their available labor, therefore, equation 3.6 is rewritten as:

$$l^{crp} + l^{liv} + l^{off} + l^{ho} - l^{fam} - l^{hi} \leq 0 \qquad 3.7$$

The amount labor from family members is the product of the number of family members x_{fam}^{fam} and their labor contribution, which depends on the sex and age of household members. Hired in labor is a product of the number of hired people, and the corresponding number of hours worked. Similarly, labor requirements for a particular activity are the sum of the person-days required per unit of each activity. Thus, the above equation can be written as:

$$\sum_{c} x_c^{crp} l_c^{crp} + \sum_{l} x_l^{liv} l_l^{liv} + \sum_{f} x_f^{off} l_f^{off} + \sum_{o} x_{ho}^{ho} l_{ho}^{ho}$$

$$- \sum_{m} x_{fam}^{fam} l_{fam}^{fam} - \sum_{i} x_{hi}^{hi} l_{hi}^{hi} \leq 0 \qquad 3.8$$

Where, x_c^{crp} is the amount of land in hectare crop grown and l_c^{crp} is the amount of labor used per hectare. x_l^{liv} is the amount of livestock kept and l_l^{liv} is labor requirement for livestock; x_f^{off} is the number of family members who worked in off-farm activities and l_l^{liv} is the number of hours worked by family members off-farm. x_{ho}^{ho}/x_{hi}^{hi} is the number of family members who hired out/in labor and l_{ho}^{ho}/l_{hi}^{hi} is the number of hours worked on other households field by family members and the number of hours worked by hired labor on farmer land. Land balancing follows a similar procedure as the labor, except that land marketing is not implemented in this model. Available land can be used for crop production or livestock, if the land is not used for either of the two it left as fallow land.

3.2.2. Balancing financial activity and liquidity

The available cash (C) at the start of the production cycle can either be deposited (D) to earn interest (i_d) or used for the purchase of agricultural inputs (I). If the available cash is not enough to cover production costs (input costs), agents can supplement their cash requirement by taking short-term credit (C_r). Moreover, agents cannot use more cash than what they have or they borrow.

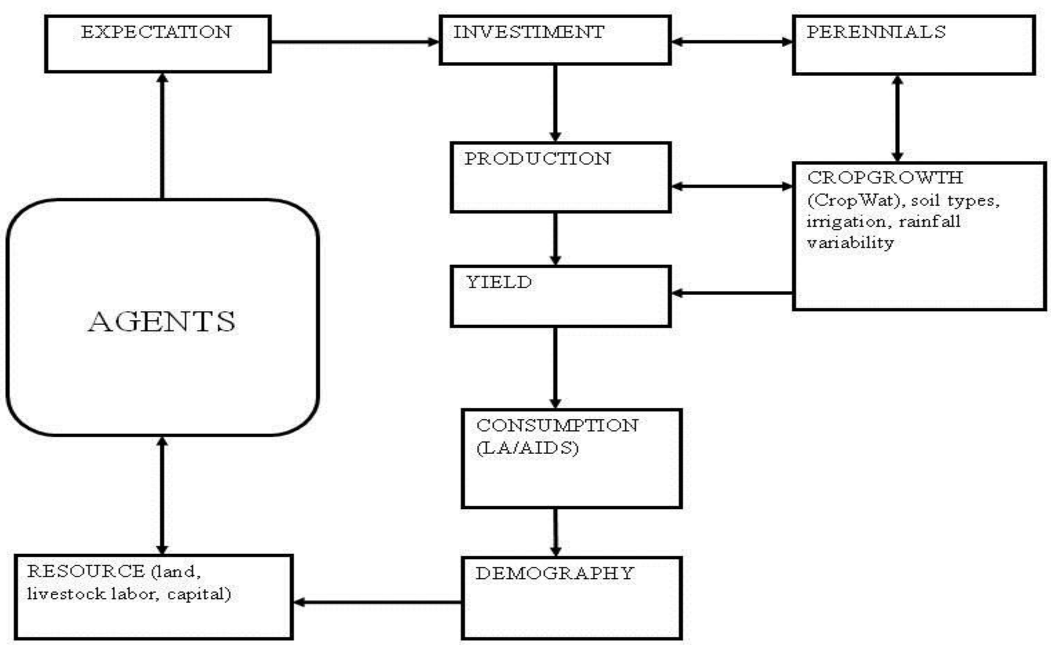
$$D + I - C - Cr \leq 0 \qquad 3.9$$

In MP-MAS specially in MP-MASQL credit is implemented by introducing special class called MASSTANDARD that account for all activities and constraints related to agents liquidity endowment; financial requirements; taking short-term credit and paying interest rate; depositing the excess cash in the bank and earning interest; maximum credit value and maximum amount of credit that can be defaulted. The interest rates on short-term credit and short-term deposit provided in a separate parameter named called "interest_short_term_credit" and "interest_short_term_deposit" Scenarios for different credit access (no credit, current credit, and full credit) access implemented in this study, by defining each of the three different credit scenarios using a special field called SCENDEF (for scenario definition). This class needs different table values or functions for each of the scenario types, with column names "scenario" for the name of a scenario; "variable" for the name of the variable that changes with the scenario and the "value" the value of the variable for a particular scenario. Similarly, scenarios for access to irrigation water (irrigated area), soil and water conservation activities, non-farm activities implemented in MP-MAS by defining the scenarios with and without access to these activities; under access, households have a chance to practice the corresponding activities (non-farm, soil and water conservation, and irrigation). If a household has reported they used soil and water conservation activities, access and availability of the SWC presented for a corresponding segment of the population of the MP-MAS and implemented as innovation activity. For detailed technics on the implementation of credit, scenario development, and innovation; refer MP-MASQL manual (Troost 2013).

The irrigation component in the MP-MAS is activated by using CropWat, which is an internal implementation of FAO56 crop growth under water deficit in MP-MAS and the corresponding EDIC hydrology module. Implementation of CropWat needs detailed information on expected precipitation and evapotranspiration for each month of the year and the actual time series precipitation and evapotranspiration for each month over water flow years for each sector. The monthly evapotranspiration values are reference values, which transformed into plant specific evapotranspiration by multiplying with the plant-specific coefficient in a particular month and entered for each cropping activity that involves crop under consideration. In addition, the effective rainfall that can be used by the crop is specified by assuming 80% of the actual rainfall.

Similarly, EDIC which is a simple sector-based node-link hydrology model used to simulate irrigation water requirement under deficit water, and interacts with CropWat module, implemented by providing the detailed specification of input data requirements. In addition to the actual and expected water flow, EDIC needs information on the type of irrigation method, the share of each agent in the sector, and the share of the sector from the available water flows. For this study, rainfall data used for CropWat is extracted from thirty-year time series rainfall data obtained from the meteorological stations located near to the study area. The water inflow data for the irrigation scheme is obtained from the inflow data from the Bulbula River (see appendix B) and the agent water right is based on the availability of irrigable land for each household.

Fig. 3. 1 Agent decision making and biophysical module flow chart



Source: Author's design based on the literature on MP-MAS

Fig.3.1 shows the flow of decision-making process by agents as implemented in MP-MAS. It combines two components (agent decision and biophysical modules). The component that results from agent decision-making includes investment, production, and consumption. The biophysical module involves the crop growth module, CropWat, which estimates the expected crop yield; this study uses a module of CropWat built-in to the MP-MAS model. Every time a decision is made, it involves the three phases of investment, production, and consumption.

Agents make investment and production decisions depending on the expected long-term yield, prices, resource availability, and policy changes. Investment decisions include whether to acquire assets, such as land and livestock; whether to practice soil and water conservation; and whether to begin a perennial plantation. After the investment decision, resource endowments of each agent are updated. The biophysical conditions, in turn, influence production and consumption decisions. Yield is estimated by the crop growth model (CropWat), accounting for land availability, soil suitability, climatic variables (rainfall variability), irrigation water, and other management practices. The effect of rainfall variability in MP-MAS is implemented by changing the expected crop yield under different rainfall distribution. Potential yield for the crop is obtained from CSA. The yield corresponding to each of the random rainfall distribution is generated internally by using MPMAS built in CropWat module. This module estimates the yield considering the crop water requirement, effective water used by crop, evapotranspiration and irrigation water availability.

After getting information on the level of crop yield, the agents decide on the consumption level. Consumption decisions involve whether to sell their produce or to purchase from markets to meet household members' food requirements, which depend on the demographic composition of the household members. Depending on the simulated yield, MP-MAS calculates agent revenues, part of which is consumed or used for repaying of debt on short-term credit, with the remaining included in savings to be used for investment or production in the subsequent production periods. This finalizes the decision process in the first period and requires second round decision making for the next period.

3.3.Climate change adaptation strategies and their implementation in MP-MAS

In this study, adaptation strategies used as buffers against rainfall variability have been identified through econometric estimation and consultation with experts in the study area. The econometric estimation considers factors determining agricultural input use and participation in non-farm activities. Studies on rainfall variability (see Bryan et al 2009; Deressa et al 2009) have documented that a set of different adaptation strategies has been implemented by farm households to adapt to adverse rainfall variability impacts (Bryan et al 2009; Deressa et al 2009). These strategies range from changing cropping time to improved crop varieties. Ability to adapt by farm households, however, is limited by social, economic, physical, and individual factors. A study of water and soil conservation technologies used as a buffer against rainfall variability risk in Ethiopia by Kato et al. (2011) reveals that 30% of the studied farmers were practicing soil and water conservation activities in response to perceived increases in the long-term temperature and its impact on crop yield. In addition, the study showed that the country should consider different soil and water conservation activities to mitigate the negative impact of rainfall variability on crop yield (Kato et al 2011; Di Falco et al 2011).

Similarly, studies by Di Falco et al. (2011) and Di Falco and Bulte (2013) on climate variability and adaptation strategies used in Ethiopia have shown that different soil and water conservation activities, including the use of fertilizer and improved crop and livestock varieties, are highly practiced. For instance, a study by Di Falco et al. (2011) indicated that about 35% of households practice soil and water conservation in response to long-term perceived change in rainfall. On the other hand, 42% and 57% of households did nothing in response to a long-term change in temperature and rainfall, respectively (Di Falco et al 2011). The use of improved drought and disease tolerant crop varieties, improving information on rainfall variability and decision making, promoting crop diversification, and investment in agricultural infrastructure can likewise increase households' resilience to rainfall variability (Noltze et al 2013).

In addition, farmers have developed their own way of mitigating rainfall variability impacts through personal experience. Rainfall variability in the long-run result in reduced soil fertility, thus farmers try to reduce the loss in soil fertility and crop yield by practicing different activities. Accordingly, they practice soil and water conservation, fertilizer, planting trees, taking part in non-farm activities, selling assets such as livestock and other area specific modern and traditional ways to abate the negative impacts of rainfall variability (Deressa et al 2009). Thus, in the study area, three major adaptation strategies (soil, and water conservation, participating in non-farm activities and irrigation) and improving access to credit are found to be the most important solutions against rainfall variability.

3.3.1. Fertilizer and non-farm activities

It has been documented that access to assets, credit and information on adaptation strategies encourages household to adopt strategies against rainfall variability (Deressa et al 2009). Due to liquidity constraints, application of fertilizer in the study area is very low. By increasing productivity, fertilizer consequently increases food security and reduces the poverty level of households (Liverpool and Winter-Nelson 2010; Birner et al 2011; Druilhe and Barreiro-hurlé 2012). A number of factors determine the farmer's decision to apply fertilizer. The marginal effect analysis of the determinants of fertilizer use; using a probit model computed based on ERHS 2009 data is presented in Table 3.1. This analysis shows that male-headed households are about 5% more likely to use fertilizer than their female counterparts. The analysis further indicated that access to credit, extension services and markets play statistically significant positive roles in determining the decision whether to adopt fertilizer or not. Farmers with access to credit are 17% more likely to apply fertilizer than those without credit access. Households with better access to input and output market are 43% more likely to use fertilizer than those without market access. Accesses to extension services increase the probability of using fertilizer: Farmers with access to extension service are 26% more likely to apply fertilizer than those without access to extension. The household's total livestock unit, a proxy for the wealth status of households, is positively related to the probability of using fertilizer. One additional livestock unit (TLU) from the mean value of 2.2 will increase the probability adopting fertilizer by about 6%.

Table 3. 1 Marginal effect probit estimation on adoption of fertilizer and non-farm activities

Variables	Mfx Fertilizer	Mfx Non- farm
Sex (male=1, female=0)	0.05(0.062)	0.008(0.023)
Age (years)	-0.002(0.002)	-0.002(0.002)
Education head (years)	0.003(0.006)	0.005(0.005)
Household size (person)	-0.007(0.012)	0.006(0.028)
Farm size (ha)	0.004(0.029)	-0.006(0.030)
Access to credit (yes=1, no=0)	0.170***(0.06)	0.115***(0.05)
Access to extension (yes=1, no=0)	0.261***(0.051)	0.079(0.051)
Access to market (yes=1, no=0)	0.425***(0.045)	0.09***(0.054)
Tropical livestock unit (TLU)	0.063***(0.014)	0.007(0.128)
Crop income (Birr/year/household)	-0.000(0.001)	-0.001***(0.000)
Livestock income (Birr/year/household)	0.000(0.002)	0.000(0.000)
Non-farm income (Birr/year/household)	-0.000(0.000)	

Sources: Author's estimation from ERHS survey data, 2009; $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$; *Mfx: marginal effects the coefficients are interpreted as the change from the mean value of continues variables and changing from 0 to 1 for dummy variables. Standard errors are in the parenthesis. The probability of adopting fertilizer and non-farm activities are the dependent variables for fertilizer and non-farm activity equations.*

Non-farm activities are an alternative source of household income, and important source for income diversification, minimize the risk associated with low agricultural productivity. The marginal effect of probit regression analysis using ERHS, 2009, in table 3.1 reveals that crop income is negatively associated with the probability of participating in non-farm activities. This implies that farmers who have a larger income from crop production tend to work on their own farm rather than participating in the non-farm activity. Furthermore, higher income from farm activity means a higher opportunity cost of participating in non-farm activities. The probit model further depicts that access to credit and markets are found to have a significant and positive impact on the probability of participating in non-farm activities. Access to credit increases the likelihood of participating in non-farm activities by about 12%. Similarly, access to the market is found to increase the probability of participating in non-farm activities by 9%. This result highlights the importance of improving financial capacity and access to markets for smallholder farmers to increase their participation in non-farm activities and f fertilizer use

3.3.2. Soil and water conservation (SWC)

The study has implemented soil and water conservation (SWC hereafter) activity in the model as an alternative farm management technique. Households have alternative ways of producing crops under different management schemes, including growing crops with and without fertilizer, and using SWC or without SWC. If they chose to grow with fertilizer, they can choose between different intensity levels of mineral fertilizer and farm labor (five fertilizer intensity and ten labor intensity levels were included in the activity list). Similarly, they have two soil management possibilities, such that, agents can grow either with or without SWC activities. Growing crops with SWC requires additional investment costs and increased labor input. This involves adjustments in production cost and labor use. Thus, if households decide to grow crops with SWC, the variable cost is increased by the amount of the cost required to implement the SWC. A yield premium is estimated from the survey data to see the return from the adoption of SWC. Thus, the expected yield is increased by this yield premium if the household decides to grow with SWC. As different crops give varying returns from the application of SWC, estimating the yield premium for different soil and input combinations gives different yield premium. However, households can grow various crops on one plot with SWC practices, therefore, in the model, we used the average yield premium factor of 0.15[2] for SWC.

[2] This figure is obtained by using the Endogenous Regime Switching (ERS) regression discussed below. Yield is found to increase by 15% with SWC

3.3.3. The role of soil and water conservation on rainfall variability

This section explains the steps used to estimate coefficients for the role of soil and water conservation activities on crop yield. Adaptation to rainfall variability and its impact on crop yield can be modeled in two stages. The first stage is to model the selection function for the household decision to choose SWC, which depends on household characteristics and other socioeconomic behavior of the agents. The most important driving force behind the decision to practice SWC is the net benefit that can be obtained from the adoption of SWC. If A_i^* denotes the net benefit from practicing SWC, A_i^* can be expressed in terms of explanatory variables assumed to affect the net benefit.

$$A_i^* = Z_i\alpha + \mu_i \ with \ A_i^* = \begin{cases} 1 \ if \ A_i^* > 0 \\ 0 \ otherwise \end{cases} \qquad 3.10$$

$$Regime\ 1: \ Y_{1i} = X_{1i}\beta_1 + \varepsilon_{1i} \ if \ A_i = 1 \qquad 3.11$$

$$Regime\ 2: \ Y_{2i} = X_{2i}\beta_2 + \varepsilon_{2i} \ if \ A_i = 0 \qquad 3.12$$

Where, Z is a vector of variables assumed to determine the decision whether to adopt or not, α is a parameter to be estimated and μ is the error term in the selection equation, Y_{1i} and Y_{2i} are the expected crop yield value per hectare when the latent variable A_i occurs and does not occur, respectively. X_{ij} is a vector of explanatory variables assumed to affect the expected crop yield value per hectare, which includes climate variables (rainfall, temperature, drought, flood), inputs (fertilizer, seed, manure, labor), household characteristics (sex, age, education, family size), assets (land, livestock, machinery), and institutional factors (credit, extension service, trainings). Y_{1i} and Y_{2i} will not be observed simultaneously: the covariance of the error terms ε_{1i} and ε_{2i} is undefined. However, ε_{1i} and ε_{2i} are internally correlated via the first selection equations. Therefore, ε_{1i} , ε_{2i} and μ_i have a trivariate normal distribution with the expected mean of zero and covariance of Ω defined as:

$$\Omega = \begin{bmatrix} \delta_\mu^2 & \delta_{1\mu} & \delta_{2\mu} \\ \delta_{1\mu} & \delta_1^2 & . \\ \delta_{2\mu} & . & \delta_2^2 \end{bmatrix} \qquad 3.13$$

Where δ_μ^2, δ_1^2 and δ_2^2 are the variance of selection (3.10), error terms in (3.11) and (3.12), respectively; $\delta_{1\mu}$ and $\delta_{2\mu}$are the covariance of the error term in the selection equation and the continues equations, i.e (ε_{1i} and μ_i) and (ε_{2i} and μ_i), respectively. The variance of the error term in selection equation δ_μ^2 can be assumed to be unit as the estimation done up to the scale (Maddala 1986). The structure of the variance-covariance relationship indicates that conditional expected values of the error terms ε_{1i} and ε_{2i} are different from zero. Therefore, the decision to adopt or not (selection equation) depends on the covariance between μ_i and ε_{ij}. If the covariance $\delta_{i\mu}$ is statistically significant (stronger), then the crop yield value per hectare and the decision to adopt are correlated. If such correlation exists, it is an indicator for the presence of heterogeneity between the groups rather than simple sample selection bias in deciding to adopt. According to (Maddala 1986) this type of model is known as "Endogenous regime switching regression model". An efficient approach to estimate endogenous switching regression models is the use full maximum likelihood (FML) estimation (Lee 1997; Di Falco et al 2011).

3.3.4. Conditional expectation and effect of heterogeneity

According to Di Falco et al. (2011), crop yield value per hectare can be used to measure the role that SWC activities play in crop productivity. This study adopted methodology used in the study of Di Falco et al. (2011), which measures the role of climate change adaptation strategies on crop productivity at the plot level. Endogenous regime switching regression model is used to estimate the actual and counterfactual effects of SWC on crop yield value per hectare for households that adapted and for those who did not adapt. Thus, it is possible to compare the role of SWC on expected crop yield value per hectare for the adaptor and non-adaptor farm households in actual and counterfactual cases. Accordingly, the role of SWC on the expected crop yield value per hectare can be estimated in different setups, as indicated in Table 3.2.

Table 3.2 Conditional actual and counterfactual expected crop yield value per hectare

Sub-samples	Decision level	
	Adopt	Not adopt
Adopters	$(a)\ E\left(Y_{1i}/A_i = 1\right) = X_{1i}\beta_1 + \sigma_{1\mu}\lambda_{1i}$	$(b)\ E\left(Y_{1i}/A_i = 0\right) = X_{2i}\beta_1 + \sigma_{1\mu}\lambda_{2i}$
Non-adopters	$(c)\ E\left(Y_{2i}/A_i = 1\right) = X_{1i}\beta_2 + \sigma_{2\mu}\lambda_{1i}$	$(d)\ E\left(Y_{2i}/A_i = 0\right) = X_{2i}\beta_2 + \sigma_{2\mu}\lambda_{2i}$

This approach enables us to estimate the role of SWC on crop yield value per hectare accounting for heterogeneity of farm households. The row difference measures the role SWC plays when a heterogeneity effect is controlled while the column differences measure the role of SWC for households that adopted and did not adopt under actual and counterfactual situations. The diagonal elements (a) and (d) present the expected crop yield value in the sample data set for adopters and non-adopters farm households, respectively. Similarly, cells (b) and (c) represent the counterfactual expected crop yield value for adopters and non-adopters, respectively.

3.3.5. Results and discussion of endogenous switching regression analysis

The data for this analysis is obtained from the survey conducted by master's students in 2010 in the study area (Wondo-Genet, Gedeb-Asasa, and Adami-tulu). The data covers the household socio-economic characteristics, crops grown, yield in the two growing seasons (Meher and Belg), input uses, and the status of SWC activities at the plot level. The dependent variable considered in this analysis is the aggregated values of different crops yield value per hectare in Ethiopian Birr (ETB). This helps us to create a single analysis unit despite different yield values for different crops. The crop yield values were obtained by multiplying the yield with the corresponding market prices of the crop. Crops grown using the SWC activities are maize, wheat, barley, teff, and sorghum.

The following table presents the estimated results of yield premiums from using SWC considering the heterogeneity effects and soliciting only the role of SWC on crop yield value per hectare at the plot level.

Table 3.3 Estimated conditional actual and counterfactual expected yield value (ETB/ha) [3]

Sub-sample	Decision level		SWC effects
	To Adapt (A)	Not to adapt(B)	(A-B)
Adopters	(a) 4,166	(b) 1,055	(f) 3,111***(523)
Non-adopters	(c) 7,455	(d) 3,341	(g) 4,114***(365)
Heterogeneity	(a)-(c)=-3,289***(328	(b)-(d)=-2,286***(89)	(f)-(g) =1,003(957)

Sources: Author's computation from survey conducted by Masters Student at Institute 490A, 2010, using a movestay command of STATA addins; * *$p < 0.05$,* ** *$p < 0.01$,* *** *$p < 0.001$, standard errors are in the parenthesis*

Table 3.3 shows the estimated result of endogenous regime switching regression on the role of SWC on expected crop yield value for adaptor and non-adaptor farm households. Figures in cells (a) and (d) represent the observed crop yield value per hectare under actual conditions for sampled households. Accordingly, farm households who adopt SWC obtained on average 4,166 ETB per hectare, while farm households who didn't adapt obtained 1,055 ETB per hectare. This indicates that the crop yield value per hectare for adopter households is about 25% (825 ETB/ha) higher than that of non-adopter. However, the result does not account for the heterogeneity effects emanating from the farm household characteristics, and thus, the results might be overestimated. In reality adaptation and the behavior of household can be influenced by multiple factors and thus the adaptation decision can potentially be exogenously determined. Therefore, a consistent estimation on the role of SWC must consider the heterogeneity aspects of farm households charcterstics that affects the decision to adopt. Figures in cells (c) and (b) present the counterfactual expected yield value per hectare for non-adaptor and adaptor farm households, respectively. If farm households who actually practiced SWC decided to change their regime to not practice (cell (b)) the expected crop yield value per hectare would be 1,055 ETB/ha (3,111 ETB/ha less than the actually observed value). Therefore, considering the counterfactual conditions of farm households,

[3] Crop yield value per hectare considered at plot level. Household related variables such as age, education, access to credit, training, household size did not vary across plots. The scale analysis is at plot level, figures presented in the table are the average yield value per plot. For detailed discussion on endogenous regression model see Di Falco et al. (2011).

the productivity effect of SWC for those who actually adopted is about a 75% increase. This means that SWC increases the expected crop yield value per hectare by 75% for adopters. Similarly, cell (c), indicates the counterfactual case for farm households who did not adopt. If farm households who did not adopt SWC switched, they could have obtained 3,289 ETB/ha. According to the estimation result, SWC activities have a positive effect on those who fail to adopt if they were to change their regime to adapt. Thus, adaptation to rainfall variability (SWC) can significantly increase farm productivity and the overall livelihood of farm households. However, SWC might have a vital positive impact for those who did not actually adopt if they change their regime to adapt. From the results in Table 3.3 and the discussion following it, SWC activities increase crop yield value per hectare for the current non-adaptors by about 4,114 ETB, if they could have adopted SWC (under counterfactual case).

Figures in the third column of Table 3.3 show the counterfactual case for adaptors and the actual case for non-adaptors. Comparing cells (b) and (d), farm households who have actually adapted could have obtained a significantly lower value than farmers who did not adapt if they had decided not to adapt. This further suggests that the productivity difference is not only due to the adoption of SWC, rather it depends on household characteristics. Therefore, it is necessary for the government and other institutions to consider factors that have driven the difference in adaptation decision in order to maximize the benefits from adaptation strategies and safeguard farmers from adverse rainfall variability impacts. In fact, the difference between cells (a) and (c) subordinates the importance of rainfall variability adaptation for the farm households who did not adapt. As can be seen from the results, farm households who did not adapt would have obtained a higher per hectare value by far than those who actually adapted if they could have adopted. Finally, the adaptation effect analysis has revealed the importance of adaptation to non-adopters who actually adopted. The increase in yield value is converted to the corresponding changes in yield, by dividing the yield values with the price.

Table 3.4 Description of variables for adopter and non-adopter farm households (N=180) in the study area

Variables	Total sample	Adopters	Non-adopters
Adaptation (yes=1, no=0)	0.12	1.00	0.00
Productivity (ETB/ha)	3,063	4,070	2,930
TLU (Tropical Livestock Unit)	3.09	4.19	2.95
Crop income (ETB/year/household)	11,920	15,870	11,402
Household size (person)	8.00	7.56	8.05
Education head (year)	4.57	2.49	4.84
Age head (year)	42.82	46.36	42.36
Number extension visit (number)	5.37	6.00	5.29
Credit access (yes=1, no=0)	0.42	0.49	0.41
Sex head (male=1, female=0)	0.91	0.84	0.92
The plot is certified (yes=1, no=0)	0.87	0.92	0.87
Plot size (ha)	0.79	0.81	0.79
Training received (yes=1, no=0)	0.78	0.82	0.78
The soil is infertile (yes=1, no=0)	0.14	0.10	0.14
The soil is medium (yes=1, no=0)	0.59	0.74	0.57
The soil is fertile (yes=1, no=0)	0.27	0.15	0.29

Sources: Author's computation from a survey conducted by Master Students at Institute 490A, 2010; Number of observations is 326. The analysis is done at plot level for the major crops (maize, wheat, barley, sorghum and teff) grown using SWC in the study area.

The descriptive analysis of resource endowment differences between SWC adaptor and non-adaptor farm households shows the divergence between the two groups. It is clear that the adaptive behavior of the households can be elucidated from the resource bases and availability. According to the results in

Table 3.4, about 12% of farm households in the study area have implemented SWC activities on their plots. Average yield value per hectare (productivity) for adopter households is 4,070 ETB and that of non-adopters is 2,930 ETB. Livestock assets are an important indicator of the household wealth status of subsistence smallholder farmers; adopter households keep a little over one livestock unit more than non-adopters do. Similarly, adopter households are found to have 30% more income from crop sale than non-adaptor households. The average year of schooling for adopter households is 2.5 years while that of non-adopters is 4.8 years. Moreover, adopters received farm management training 10% more than that of non-adopters. On average about 30% of the plots owned by non-adopters, have fertile soil compared with 15% for adopters, which indicates adopter households were challenged by soil infertility and thus chose to practice SWC on their plots.

Results of an endogenous regime switching regression model are reported in **Error! Reference source not found.**. The model estimates the coefficients of selection equations (3.11) using a probit model on the decision to practice SWC, the results indicated in Column (a) are the marginal effects. Column (b) and (c) present results for functions (3.12) and (3.13) measuring the effects of household and plot level variables on expected crop yield value per hectare for adopters and non-adopters, respectively. The coefficients from the probit model on the determinants of SWC adaptation decision (column (a)) of **Error! Reference source not found.** show that both household and plot characteristics determine the decision to practice SWC. The role of SWC on yield value per hectare is analyzed by classifying households into adopters and non-adopters. The difference between the coefficients for the variables in columns (b) and (c) of **Error! Reference source not found.** illustrates the presence of heterogeneity among farm households in the sample regarding resource endowment and returns from different input factors. Fertilizer use and TLU are significantly associated with an increase in the crop yield value per hectare for adopters, which is consistent with predictions of the economic theory that fertilizer increases productivity and TLUs capture the effects of reduced capital constraints required to adopt SWC. The estimation results of equation 3.5 suggest that the main driving factors in a farm household's decision to adopt SWC against rainfall variability are age, farming experience, household size (labor endowment), fertilizer use training, and access to credit. The capital required for SWC construction comes either from asset sale or from short-term credits

Table 3.5 Endogenous regression on decision to adopt and role of SWC on yield value (ETB/ha)

			Endogenous switching regression			
	A		B		C	
Dependent variable	Adoption[a]		Adoptor (ETB/hectare)		Non-adoptor (ETB/hectare)	
	Mfx.	Stdv.	Coff.	Stdv.	Coff.	Stdv.
Sex (male=1, female=0)	-0.50	(0.32)	4006*	(2184.59)	274	(585.41)
Education (year)	-0.03	(0.04)	2801	(182.31)	30	(31.23)
Age (year)	-0.09***	(0.02)	-367	(220.73)	184***	(39.04)
Age square (year)	0.00***	(0.00)	0.00	(1.69)	-2***	(0.34)
House size (person)	-0.04*	(0.02)	-740***	(251.29)	52	(56.63)
Logarithmic Income (ETB)	0.22	(0.15)	-3111***	(965.23)	-292**	(133.86)
TLU (units)	0.02	(0.01)	571***	(149.72)	-21	(33.38)
Fertilizer use (yes=1, no=0)	-0.42***	(0.15)	5573***	(1768.60)	1129***	(364.83)
Experience (year)	0.02**	(0.01)	206***	(65.99)	-46**	(22.02)
GA district (yes=1, no=0)	-0.00	(0.17)	-6675***	(1817.17)	65	(374.85)
Extension visit (days)	0.02	(0.02)				
Training (yes=1, no=0)	-0.13**	(0.06)				
Land is certified (yes=1, no=0)	0.05	(0.26)				
Credit access (yes=1, no=0)	0.13***	(0.02)				
Constant	0.54	(0.42)	28171***	(8553.11)	-7556	(0.00)

*Standard errors in parentheses * p<0.10, ** p<0.05, *** p<0.010; [a] Results of model (A) are the marginal effects from the probit model of adoption (= 1, if adopt, 0 otherwise), model (B) and (C) present the coefficients from endogenous regression. Sources: Author's computation from a survey conducted by Master Students in Institute 490A, 2010; Estimation is done by using full information maximum likelihood approach, using movestay commands in STATA 12. The coefficients for adaptation (model a) are the results of the first selection equation presents the marginal effects on yield value.*

Access to credit is positively and significantly associated with the probability of adopting SWC activities. Adopting soil and water conservation activities requires acquisition costs, such as wages to hire additional labor as SWC increases labor demand for maintenance and construction, and thus the positive relationship between access to credit and adoption of SWC is expected. Households with access to credit are 13% more likely to adopt SWC, compared to those without. This highlights the importance of financial intervention in order to increase the probability of adopting SWC by farm households. Age of the household is positively related to the probability of adopting SWC. Household size, fertilizer use, and training had an expected negative relationship with the pattern of SWC adoption. As one would expect household size (source of labor) might have positive linkage with the probability of SWC adoption since SWC requires more labor for construction and maintenance. Moreover, SWC increases the productivity of other inputs such as fertilizer; therefore, those who use fertilizer are more likely to practice SWC. However, SWC improves the return from fertilizer application in model b and c. Furthermore, the result indicated that farmers applying fertilizer on their plots are less likely to practice SWC. The SWC affects land productivity by reducing the inputs requirement; as it increase per hectare yield through improved soil depth and water retention capacity, increased organic matter and consequently reduces input requirements such as fertilizer; therefore, those households using fertilizer are less likely to adopt SWC. Furthermore, an interesting difference in unit return between adopter and non-adopter households is that of fertilizer: per hectare productivity by those who simultaneously adopt fertilizer and SWC is about 5,600 ETB higher than those who used neither fertilizer nor SWC. However, the productivity difference for those who use fertilizer but not SWC is about 1,130 ETB higher than those who use neither fertilizer nor adopt SWC. The age of the head of the household is positively associated with the likelihood of adopting SWC. Increasing the livestock endowment from the mean value by one unit increases the per hectare productivity by 570 ETB for adopters and has no significant impact on the productivity of non-adopters. Increasing years of farm experience by one year; increase (decreases) productivity by about 200 and 50 ETB, respectively,of adopters and non-adopters.

3.3.6. The role SWC on crop yield value per hectare

In addition to inputs farm management activities such as soil and water conservation, planting trees, the use of irrigation, and the household's non-farm income source determine the level and productivity. This section of the study examines the magnitude and the directions of different adaptation strategies on land productivity per hectare by regressing different socio-economic and environmental variables on the crop yield value. Land productivity is measured by considering the crop yield value per hectare, which is the aggregate of the yield values of different crops. This is because it is difficult to compute the yield response of each crop used in the study for the SWC separately. Moreover, the response of different crops to SWC cannot be viewed separately, since farmers can cultivate different crops on the same plots simultaneously and quantities of different crops cannot be aggregated. This suggests working with the crop yield value per hectare than quantity produced per hectare. The first step in the household's choice of the decision whether to adopt a particular adaptation strategy is to see whether adopting a strategy is beneficial or not compared with not adopting. The profitability of an adaptation strategy is an endogenous phenomenon rather than exogenously determined. Therefore, household characteristics and other institutional variables determine the net benefit of a given rainfall variability adaptation strategy. Table 3.6 presents the results of the OLS regression analysis on the determinants of the crop yield value per hectare considering adaptation as a dummy variable (1 if farm households adapt SWC and 0 otherwise). The magnitude and directions of the estimated coefficients for the crop yield value per hectare functions are consistent with the economic theory: SWC, sex, age, education and good water availability on the plot show positive and statistically significant relationships with productivity. Soil and water conservation activities are found to have a statistically significant positive effect on productivity at the 1 % level of error probability. Farm households that have adopted SWC produced about 2,000 ETB per hectare higher than non-adopter. Male-headed households are more productive than their female-headed counterparts with about 1,000 ETB more per hectare yield value. Education and age of household head are positively associated with productivity at lower levels.

Table 3.6 OLS estimation of determinants of crop yield value (ETB/ha) in the study area

Dependent variable yield value (ETB/ha)	Coefficient	P>t
Adaptation (yes=1, no=0)	2035***	(0.000)
Sex (male=1, female=0)	1016*	(0.061)
Education (years)	263***	(0.010)
Education square (years)	-15**	(0.014)
Head age (years)	178***	(0.001)
Head age square (years)	-2***	(0.001)
Fertilizer used (yes=1, no=0)	593	(0.179)
Very good water (yes=1, no=0)	-960	(0.209)
Good water (yes=1, no=0)	1344**	(0.028)
lnIncome[a] (ETB/hh)	-198	(0.287)
Fertile soil (yes=1, no=0)	-250	(0.456)
Number of extension visit (days)	15	(0.630)
Family size (person)	2	(0.974)
Use manure (yes=1, no=0)	330	(0.331)
Tropical livestock unit (TLU)	-79	(0.397)
Squared TLU	8	(0.133)
Credit Access (yes=1, no=0)	-476	(0.324)
Credit access and fertilizer (yes=1, no=0)	-74	(0.910)
Lnplot size [b](ha)	-2048***	(0.000)
Constant	-2860	(0.115)
N	270	

*Sources: Author's computation from a survey conducted by Master Students at Institute 490A, 2010; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. [a] is the natural logarithm of household income per household. [b]is logarithm of plot size in a hectare. The scale of analysis is at the plot level, considering yield value on the plot. Yield value of Maize, teff, wheat, barley and sorghum used in the analysis.*

Households with heads having basic education and a young age are more likely to adopt new agricultural technology and apply inputs efficiently and are more productive than those households with highly educated and older heads. This is mainly because better-educated heads have a higher chance of participating in non-agricultural activities and as such might not be allocating all their resources in agriculture. The optimal levels of education and age of household head, which will lead to a positive impact on productivity are 8.8 and 44.5 years. Water availability near the plot might have a decisive impact on adopting irrigation and other inputs. Accordingly, the results above indicated that farm households with good water availability drive higher crop yield value per hectare compared with those households that have poor water access. Good water access near the plot is associated with about 1,300 ETB more per hectare value compared with the plots with poor water access. The negative coefficient on very good water availability depicts high water on a plot area translating to a higher risk of flooding and reduced soil fertility causing lower productivity. Plot size is negatively associated with the productivity level, the larger the plot size the less likely the farmers invest in yields enhancing technology and the lower the yield and hence lower productivity.

3.3.7. The role irrigation on rainfall variability

Irrigation is one of the priority areas to improve the world food production in order to reduce food insecurity in many parts of the world. Moreover, irrigation is a valuable asset to improve production, productivity, and food security of households and to boost the overall economy. Currently, world agriculture is under irrigation from different water sources, such as rivers, canals and groundwater (Allen 1998; Hussain & Hanjra 2004). The Ethiopian government has put a significant effort in modernizing agriculture and fostering the economic growth of the country by using its huge water potentials. For instance, the 2005/6-2009/10 Plan for Accelerated and Sustained Development to End Poverty (PASDEP) emphasizes the expansion of existing irrigation schemes and new investments in irrigation infrastructure to end poverty and improve the livelihood of smallholder farmers (MoFED 2006). The currently utilized portion is just below 3% of the potential and only a fraction of the total cultivated area is under irrigation (Abdurahman 2009; Hagos et al 2009; Tilahun et al 2011). This confirms that the existence of a window to increase agricultural productivity via irrigation. Irrigation has direct and indirect positive impacts on the livelihood of farm households. Irrigation increases yield, production, and crop pattern diversification, and, therefore, increases income and food security, reduces poverty and the risk of crop failure, and improves year round off-farm participation of households. Different studies in small-scale, medium-scale and large-scale irrigation schemes come up with different per hectare gross margin figures. The net benefit per hectare of irrigated agriculture is estimated by deducting operating costs from the gross revenue (income) for irrigated and non-irrigated plots (Hagos et al 2009), the gross margin depends on the scale and management level of the irrigation. A study by a team from the International Water Management Institute (IWMI) in Ethiopia reported that after adjusting for annual replacement cost the annual gross margin from irrigation is about 220% higher than the gross margin from rain-fed agriculture (Hagos et al 2009).

In this study, the impact of irrigation on the effects of rainfall variability and its role in improving the livelihood of farm households is analyzed using the EDIC (Spanish acronym of Civil Engineering Consortiums in Chile) simulation model (see section 3.2.2). The model has been used to simulate the water distribution for each agent at plot level by considering the subsample of the households with access to irrigation, actual and expected water flows, actual and expected precipitation, the proportion of inflow used for irrigation purpose, and agents' water requirements on a monthly basis. However, the data required to develop fully privileged EDIC was missing in the survey. Therefore, information collected from a qualitative questionnaire, consultation with experts and literature has been used to fill the gaps in the data. The only question that farmers were asked during the survey regarding irrigation is "Do you have access to irrigation." However, implementation of irrigation in EDIC for MP-MAS requires a detailed dataset of the water availability (supply), the water share for each farmer, the inflow and outflow information on the river, crop water requirements, and evapotranspiration. Information related to CropWat can be estimated using the CROPWAT 8 tool and feed into the model. Similarly, the water requirements for each crop can be obtained from an FAO drainage paper and other literature. However, agent water rights should be obtained from the actual data. In one of the study sites, there is an irrigation scheme called the Halenku Irrigation Project. The Water User Association (WUA), a body responsible for water distribution and planning, manages the irrigation scheme. The WUA plans annual growing activities and periods, maintain the channels, and collects electricity fees from members for the pumping usage (the cost of water use). There are 36 hectares of land under the irrigation command area distributed to 72 farmers. One farmer cannot have more than 0.5 hectares of land in the project. The main cost for the water use is electricity bills. The water distribution depends on the land availability (0.5 ha) and each plot can be irritated about six hours in a week. Water from the Bulbula River is extracted into the main canal using an electric pump with a capacity of 98 l/s. From the main canal, secondary and tertiary canals extend to the farmers' plots. The exact amount of irrigation water that the farmer receives was not recorded, but the amount of water is agreed to be proportional to the plot size (rule for water distribution). Therefore, EDIC is parameterized based on the plot size, assuming the maximum irrigable land per agent cannot exceed 0.5 ha. The discharge rate of the water from the Bulbula River is obtained from the Meteorological station and WUA. The annual average discharge of the Bulbula River (the sources of irrigation water) at Adami-Tulu is 168.07 million cubic meters or 5.32m^3/s (Assefa 2008) (see appendix B).

3.3.8. Access to credit and non-farm activities

Lack of sufficient financial capacity is one of the main problems indicated as the cause for low levels of climate change adaptation, and thus indirectly for the vulnerability of farm households to rainfall variability. In this model, access to credit was implemented in three approaches: The first is to let the households continue to the existing credit access, the second is to increase credit access to its full potential and the third is completely removing access to credit. In each credit scenario, the corresponding household welfare indicators were analyzed to see the effects of credit access in reducing the adverse effects of rainfall variability. The results are compared to current rainfall variability and hypothetical constant rainfall distributions. Similarly, households are provided with additional non-farm activities such that they can allocate their labor endowments between farm and non-farm activities based on the unit return from each source (see section 3.2.2 for discussion on implementation of credit and non-farm activities in MP-MAS).

3.4. Production functions

Input responses for each crop yield were estimated by a Cobb-Douglas production functions. The average crop yield is estimated from all possible input (labor, fertilizer, SWC) and environmental (soil and season) combinations. The final estimates were cross-checked with the regional average figures from the literature. The Cobb-Douglas production function is estimated from the 2009 Ethiopian Rural Household Survey (ERHS) dataset for each crop by considering fertilizer, labor, seed, and soil types as determinants of crop yield. White teff, black teff, barley, wheat, maize, sorghum, green beans, horse beans, haricot beans, potato, onion, and tomato are included in cropping activities. Teff is a major cereal crop in Ethiopia, accounting for the lion’s share in area and production of cereal crops (CSA 2012). Moreover, it is used to prepare the widely eaten traditional bread ‘‘Injera’’ and has nutritional value for human and livestock. Mineral fertilizer used per hectare is classified into six levels with amounts of 0, 21.71, 45.99, 85.57, 139.14, and 182.91 kg per hectare. The yield response for each crop at each fertilizer level is estimated by plugging in fertilizer quantity into the production function. Similarly, labor used (person-day per hectare) is classified into ten levels 10, 19.25, 26.07, 34.16, 46.63, 64.01, 74.89, 96.53, 152.23 and 219.69. These values were estimated from ERHS data by generating Quintiles for fertilizer and labor. After estimating the input levels, the yield is computed by inserting each fertilizer-labor combination in Cobb-Douglas production function equations of 3.14.to 3.18. The coefficients of the soil types vary from one soil to another because different soil types have different fertility levels and productivity. Black soil is presented here as an example. However, in the model, all three types of soils were included by changing the coefficients associated with each soil.

$$lnY_{wteff} = 4.76 + 0.29 * \ln(Fert) + 0.07 * \ln(Lab) + 0.62 * BlackSoil \qquad 3.14$$

$$lnY_{bteff} = 5.43 + 0.02 * \ln(Fert) + 0.21 * \ln(Lab) + 0.81 * BlackSoil \qquad 3.15$$

$$lnY_{barley} = 4.79 + 0.31 * \ln(Fert) + 0.20 * \ln(Lab) + 0.49 * BlackSoil \qquad 3.16$$

$$lnY_{wheat} = 4.99 + 0.34 * \ln(Fert) + 0.14 * \ln(Lab) + 0.53 * BlackSoil \qquad 3.17$$

$$lnY_{maizeRainfed} = 5.55 + 0.21 * \ln(Fert) + 0.17 * \ln(Lab) + 0.62 * BlackSoil \qquad 3.18$$

Where lnY_i the natural logarithm of the yield of i^{th} is crop; $Fert$ is the amount fertilizer used; Lab is the amount of labor. Unlike other crops, maize yield is regressed on labor, fertilizer, seed, and the interaction terms, this is due to the fact maize is grown using improved seed varieties but for other crops the use of improved seed varieties is minimal. The changes in maize yield for a unit change in fertilizer (seed) is a function of the amount of seed (fertilizer), respectively (Stepanek, 1999). The coefficients in equations 3.19 to 3.22 confirm that the yield response to fertilizer and improved seed depends on the level of input use and the varieties. The coefficients are adopted from the work of Stepanek (1999) who studied the impacts of different inputs on maize yield in agro-ecologically similar areas as the study sites.

$$\frac{dYield_{maize}}{dSeedRate} = -192 + 1.51 * Fert_{amout}(ImprovedSeed) \quad 3.19$$

$$\frac{dYield_{maize}}{dSeedRate} = -185 + 1.51 * Fert_{amout}(TraditionalSeed) \quad 3.20$$

$$\frac{dYield_{maize}}{dFert} = -3.25 + 1.51 * Seed_{amout}(Traditional) \quad 3.21$$

$$\frac{dYield_{maize}}{dFert} = 26 + 1.51 * Seed_{amout}(Improved) \quad 3.22$$

Growing activities in MP-MAS were generated by considering six fertilizer levels, ten labor levels, two growing seasons (Mehr and Belg), three soil types, two seed types (improved and traditional) and two soil and water conservation activities (SWC). The yields estimated from ERHS using the production function were compared with figures in national statistics and the constant terms were adjusted to obtain closely related yield values. The coefficient of the constant term of the production function was adjusted to get a close match between the estimated yield used in the model development and the yield from the census. This ensures that the yield used in the model is plausible and within an acceptable range of surveyed data. It is clear from Table 3.7 that estimated crop yields are in a close match with census average values. Similarly, the maximum and minimum values are also within a comparable range. This is a technique used to ensure consistency between the estimated yield used in the model and the yield from the surveys. After generating different cropping activities based on the levels and varieties of inputs, the expected yield estimated using the above equations were imputed into the CropWat model to be used in MP-MAS simulation. Households have a wider range of possible choices among different activity compositions while satisfying the constraints and achieving their objectives. Finally, in the matrix of the MP-MAS model, the CropWat module of MP-MAS provided the actual and expected yield, adjusted for rainfall variability and other climate variables.

Table 3.7 Yield distribution of model input and regional values (kg/ha) used in MP-MAS

Crop name	Mean	Minimum	Maximum	Regional average[4]	Variable cost (ETB/ha)
White teff	1,115	433	1,904	1,118	532
Black teff	1,117	213	1,690	1,118	415
Barley	1,731	812	3,142	1,774	491
Wheat	1,880	961	3,117	1,865	136
Maize	2,345	1,328	3,773	2,345	229
Sorghum	1,626	396	3,176	1,626	231
Onion	3,199	2,597	3,635	3,198	188
Tomato	3,000	2,000	4,000	3,117	188
Irrigated Maize	7,500	6,000	8,000	NA	300
Irrigated Green beans	6,000	4,000	8,000	NA	188
Irrigated Haricot beans	1,831	180	3.651	NA	687
Irrigated Horse beans	745	292	1,530	NA	1,289
Potato	9,391	2,371	2,9141	NA	313

Source: Author's estimation from ERHS database, 2009, Note: - NA data not available.

3.4.1. Perennial (permanent) crops

Perennial crops are crops with a gestation period of greater than one year. Once they are planted, they occupy land for a certain number of years and begin producing after one year or later. Thus, farmers incur negative cash flows, especially in the first years of perennial plantation during which perennial crops do not give any yield. Coffee, chat, enset, eucalyptus, avocado, and mango are the major perennial crops grown in the study area.

Input uses, yield and production costs for perennials vary with the age of the plantation. Perennials are implemented as investment decisions. The input data specifies input requirements (cash, labor, water) and the quantity of output produced per hectare at specified life times of the perennial plantation (Schreinemachers and Berger, 2011; Troost 2013). Perennial yield, pre-harvest and harvest cost are compulsory inputs in the model implementations (Troost 2013). Potential yield,

[4] Regional crop yield is estimated from Central Statistical data (CSA,2009)

life span, average labor requirements per year, pre-harvest and harvest cost of different perennials included in the model are presented in **Error! Not a valid bookmark self-reference.**.

The perennial crops included in MP-MAS model are coffee, chat, enset, eucalyptus, banana, and mango. The input data required for perennial crop implementation are the average life span of the crop, the proportional yield from the potential yield at different age of the plantation, labor requirement at different age, crop water requirement, yield reduction factor, and cost associated with plantation. Moreover, harvesting the crop and the cumulative distribution of the plantation area of the perennials for different segments of the surveyed area are required. Perennial crops are crops, which once planted, occupy land for a certain lifespan, longer than a year. Yields, production costs, and input requirements may change with age. As perennial crops are along-term investment, planting perennial crops need a decision on investment and production. In MP-MAS perennial crops are implemented in several stages, which need decision making on investment and production by farm households. First as investment object, they need asset endowment (land, labor and capital) and corresponding constraints, and an investment activity. Second, as perennial requires a production process; there are growing activities, which include labor requirement, harvest and pre-harvest costs, and different management strategies. As the yield and input requirement for perennial plantation changes with the age, age-specific input and potential yield need to present in MP-MAS. There is information on production and investment decision that is not changing with the age of the perennial such as the yield balance, the coefficients of production and investment coefficients. However, inputs changes with the age such as perennial yield, per-harvest costs, and harvest costs are provided with their respective tables in the MP-MAS. Moreover, future yield and selling values need to be specified in the model as perennial need a future yield constraint and future selling activities. Therefore, in addition to current selling and yield, information is provided for future selling and yield functions. Perennial crops have a longer gestation period, during which they will not yet give full yield as concurrently; households may face negative cash flows due to cash requirement and forgone revenue from the previously grown plantations. In MP-MAS, cash surplus from the previous year will be used to minimize the probability of becoming bankrupt.

Table 3.8 Yield, life span, labor and pre-harvest and harvest cost of crops used in the model

Crop	Yield (kg/ha)	Lifespan (yr)	Labor [b]	Pre-harvest cost [c]	Harvest cost [c]
Coffee	672	25	6	484	5,318
Chat	838	6	26	1,065	1,875
Enset	2,000	4	31	1,238	1,250
Eucalyptus [a]	10,000*	5	27	1,103	325
Avocado	6,613	15	10	350	3,886
Banana	7,093	3	25	883	800
Mango	7,604	30	6	338	3,530

Source: Author's estimation from (CSA 2009; IFPRI 2011) and expert consultation in the study area; yr: Year; [a] Trees per hectare; [b] Man Days per hectare per year; [c] ETB per hectare per year.

3.4.2. Livestock module

Livestock contributes tremendously to poverty alleviation in developing countries. The sale of livestock products (such as milk, meat, manure and draft power) increase income, food security and productivity of poor households (Alary et al 2011).. Livestock is kept as a means of wealth accumulation, income diversification and a source of inputs (such as draft power, transportation, and manure) for crop production.

Implementing a livestock module in MP-MAS requires data on livestock input requirements (labor, pastureland, and cash) and output quantities (milk, meat, and offspring) per head for each species and age. The livestock module in this study used data from the literature. Three major livestock types (cattle, goats, and sheep) are modeled in the study. The livestock module provides a detailed representation of livestock production and investment (herd size can be increased by using own farm offspring or purchasing from the market), including rearing and aging. Livestock is used as a liquidity reserve (farmers can generate income required to cover household expenditure) and a source of household food. As with perennial crops, livestock requires investment, maintenance and inputs to sustain (Troost 2013). The model requires detailed input information on age-specific input requirements and livestock products for both male and female animals. This is a true representation of smallholders in developing countries, who strive to make decisions that satisfy their family food demand under strict resource constraints (Troost 2013). Cattle, sheep, and goat provide two major marketable products (meat and live weights).

The livestock model implemented in MP-MAS is based on detailed individual representation including simulation of offspring, aging, and the possibility of using livestock as liquidity in the case of financial shortage. In MP-MAS model livestock implemented by assigning values for sell at start period, selling at the end period, investment activities, maintenance activities and their corresponding asset endowments and constraints for each age and sex of the livestock type (cattle, goat, and sheep). In a way, that female should produce offspring and male should not. In the model, detailed information is provided on the name, life span, acquisition cost, and sales activities for the livestock product (milk and meat), sales activities for live weight at the start of the period and end of the period. Activities and input requirements that changes with age of the livestock (live weight, liquidity, labor, and land) are presented in a dynamic way that changes according to the age of the livestock. For the more detailed implementation of livestock in MP-MAS refer to MP-MASQL manual (Troost 2013).

3.4.3. CropWat module

An increase in temperature and a decrease in rainfall stress crop production. Consequently, the demand for water will rise. Rainfall variability can affect agriculture through reduced precipitation and increased evapotranspiration as a result of changes in climatic variables. Crop production and productivity are a function of climatic and environmental variables. Rainfall variability influences water availability, variability, and demand. As temperature rises, evapotranspiration escalates, thereby increasing the crop water requirement. In recent years, important advancements have taken place in methodological approaches in measuring the impact of rainfall variability, adaptation, mitigation, vulnerability, and risk on both human and natural systems (Moonen et al 2002; Estrada et al 2012). These innovations have improved scientific decision-making and preparedness of farm households. Thus, the vulnerability of human and natural systems to rainfall variability can now be assessed in different ways (Antle 1996; Raes et al 2006; Doria and Madramootoo 2009; Araya et al 2011; Nkomozepi and Chung 2012).

The effect of rainfall variability on agriculture in general and on main crop (maize, wheat, teff, barley, sorghum and perennial crops) production, which accounts for more than 90% of the total crop production and the main staple food in the study area (MoFED 2011), is analyzed using the built in CropWat component of MP-MAS. This module is used to simulate crop yield under different rainfall distributions and corresponding water deficits. In this study, thirty-year time series rainfall data is obtained from three meteorological stations (Zeway, Awassa, and Bokoji), which are located near to the study sites. This time series data were used to generate thirty random rainfall distributions using Monte Carlo simulation. Crop yield is simulated for each of the random rainfall distributions along with the resulting water deficit using MP-MAS built in CropWat. The simulate yield value of each crop was provided in MP-MAS to be used in agent decision-making. CropWat simulates the expected yield by considering crop water requirements and the corresponding yield reduction factor if the water requirement is not satisfied. Crop Water Requirement (CWR) is the amount of water required for crops to grow. The crop water requirement can be achieved by either rainfall or irrigation. According to the FAO (1998), the water requirement (CWR) for crop c in month, m, is a function of the crop coefficient (K_c), potential evapotranspiration ETO and the crop planted area (Area) and given as follows:

$$CWR = K_c * ETO * Area \qquad 3.23$$

ETO is location specific and function of climatic variables. The ETO either can be derived from FAO CROPWAT 8 or from specialized literature. The Crop Water Requirement (CWR) satisfied either by irrigation (IRR) or the effective rain (which is the amount of rain directly used by crop (ERR)). Thus, following Schreinemachers (2005) the water requirement of crop c in month m is given as follows:

$$CWR = ERR + IRR \qquad 3.24$$

The climatic inputs required to calculate crop water requirements are monthly maximum and minimum temperature, wind speed, humidity, sun hours, radiation, and potential evapotranspiration. Radiation and potential evapotranspiration are computed internally. Precipitation and effective rainfall are computed using the CropWat model. There are a number of ways to estimate the effective rain from time series data. This study uses the USDA S.C. Method, which takes 80% of rainfall as effective rain. Crop-related variables include the planting and harvesting dates, crop specific evapotranspiration coefficient K_c, and the yield reduction factor at different growing stages and root depth obtained from FAO drainage paper 56. Part of the crop water requirement that is not satisfied by the rainfall or irrigation is called deficit irrigation ($DIRR$), thus, the deficit irrigation of crop, $c,$ in month,m is given by the following relational function:

$$DIRR_{cm} = CWR_{cm} - ERR_{cm} - IRR_{cm} \qquad 3.25$$

The magnitude of yield reduction is expressed as the ratio of deficit irrigation ($DIRR$) and crop water requirement (CWR) that shows the percentage of crop water requirement that is not satisfied either by rainfall or irrigation. These values have different effects on crop yield depending on which grown stage the crop faces water deficit. If a crop is under deficit irrigation, the yield will be reduced by a factor of yield reduction coefficient K_r. In MP-MAS setup, the yield reduction factor, Kr, is computed by taking the average of the non-water deficit growing months of the crops as the representative reduction factor and the value is imputed for CropWat module.

3.5. Parameterization of three stage advanced consumption model

The main objective of this section is to analyze income, own price and cross price elasticity of demand for different food categories using the 2009 Ethiopian Rural Household Survey (ERHS) dataset. The Linear Approximation of the Almost Ideal Demand System (LA/AIDS) is used to achieve the aforementioned objective. Moreover, the section will shed light on the determinants of household consumption and saving, and the difference in expenditure pattern in different food classes.

3.5.1. Linear Approximation of Almost Ideal Demand System (LA/AIDS)

In the MP-MAS, the agents decide how much and what to consume to satisfy the minimum food requirements of their household members (Schreinemachers and Berger 2006; Schreinemachers et al 2007). Household nutrient requirements can be met either from own produce or by purchasing food the market (Schreinemachers and Berger 2006; Schreinemachers et al 2007). The food requirement can be derived from a combination of different food items that must satisfy resource, production, and consumption constraints.

3.5.2. The theory behind the three-stage advanced consumption model

A three-stage consumption model has been implemented in the MP-MAS in a such a way that agents first allocate income into saving and expenditure and then allocate expenditure into food and non-food expenditures before finally deciding how much to spend on specific food categories (Schreinemachers and Berger 2006). The proportion of saving from total income depends on socioeconomic and environmental characteristics. Saving is determined by income, which in turn is a function of the different income generating activities. This study considers farm and non-farm income sources. Farm income includes the sale of crop grain and crop residues, livestock and livestock products, perennials (coffee and chat), land rent and related activities. Non-farm income includes remittances, daily wages, petty trade, female activities (homemade crafts), the sale of assets and safety net programs. Different food categories and their respective shares in food expenditure are presented in Table 3.12. The estimated coefficient of income elasticities, cross-price elasticities, and own price elasticities are feed into MP-MAS for the simulation household income allocation.

3.5.3. An econometric estimation of the LA/AIDS coefficients

Demand for commodities at the household level depends on economic, environmental, and household characteristics, the relative price of the commodities, and the real income earned. Moreover, the age-sex composition, educational status of household members, occupation, asset availability, and geographic environment in which the household located are factors that determine the demand level of commodities (Nyankori 1996). The first step in income allocation is to allocate the disposable income into saving and consumption. Let disposable income be denoted by INC, consumption (expenditure) by EXP, and saving by $SAVE$; disposable income is either consumed or saved for future consumption (Schreinemachers 2005): Thus income can be expressed as:

$$\mathrm{INC} = \mathrm{EXP} + \mathrm{SAVE} \tag{3.26}$$

After allocating income into saving and expenditure, the second step is to assign expenditure into food and non-food expenditure. If FEX denotes food expenditure and NFX non-food expenditure total expenditure can be written as:

$$EXP = FEX + NFX \tag{3.27}$$

The third step is to distribute the total food expenditure into different food categories, if FEX_{ci} denotes the expenditure on i^th food category; total food expenditure written as:

$$FEX = \sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{FEX}_{\mathrm{Ci}} \tag{3.28}$$

The household's consumption level also depends on the size of household and other environmental variables. The larger the family size, the larger will be the food consumption of the household and the more funds must be allocated for expenditure, and the higher the food expenditure will be in proportion. Therefore, expenditure is a function of total expenditure and household characteristics:

$$EXP = \beta_0 + \beta_1 lnINC + \beta_2 HS + \sum_i \gamma_i X_i \tag{3.29}$$

Where, EXP is household expenditure, $lnINC$ is the natural logarithm of income from farm and non-farm activities, HS is household size, and X is set of village and other variables that affect the consumption level of households. This study subsequently uses MP-MAS simulated consumption expenditure to examine the levels of poverty in the research area.

3.5.4. Almost Ideal Demand System (AIDS)

Almost Ideals Demand System (AIDS) is a two-stage budget demand procedures in which utility maximizing consumers make a consumption decision in two separate steps. The first step is to allocate expenditure into broad groups of goods. The second step is to allocate expenditure into different categories in each group of goods. The share in the expenditure of food is further assigned to different food categories. The share of i^{th} good category in j^{th} group is a function of price and income. Based on Deaton and Muellbauer (1980) this share is written as:

$$w_i = \alpha_i + \sum_{k=1}^{n} \gamma_{ij} \ln P_j + \beta_i \ln(X/P) + u_i \qquad 3.30$$

Where w_i is the budget share of good i, u_i is a random disturbance term, p_j is the price of the j^{th} category of food, X is income and P is a price index defined by:

$$\log P = \alpha_0 + \sum_k \alpha_k \log P_k + 1/2 \sum_j \sum_k \gamma_{kj} \log P_K \log P_j \qquad 3.31$$

P_k is the price of k^{th} food category and P_j is the price of j^{th} food category. The model meets the constraints of adding up, homogeneity, and symmetry condition:

i. $\sum_{i=1}^{n} \alpha_i = 1, \sum_{i=1}^{n} \gamma_{ij} = 0, \sum_{i=1}^{n} \beta_i = 0$ (adding up)
ii. $\sum_j \gamma_{ij} = 0$ (homogeneity)
iii. $\gamma_{ij} = \gamma_{ji}$ (symmetry)

The constraints imply that an Almost Ideal Demand System (AIDS) representation of demand function is one in which the sum of expenditure shares in each group is added up to the total expenditure ($\sum w_i$=1), and that functions are homogeneous of degree zero in prices and total expenditure is taken together. Each γ_{ij} represents the effect on i^{th} budget share of one percent increase in the j^{th} price with a constant income to price index ratio (Deaton and Muellbauer 1980), β_i measures the real expenditure (income to price ratio) effect on budget share of i^{th} good category. Accordingly, data on the price of each item in the food category and their budget shares, household income and the price index for each category was analyzed. Own price, cross price and income elasticities were computed for each food category. Own price, cross price and compensated income elasticity are given as follows:

Own price elasticity $\epsilon_{ii} = -1 + \frac{\gamma_{ii}}{w_i} + w_i$ 3.32

Cross price elasticity $\epsilon_{ij} = \frac{\gamma_{ij}}{w_i} + w_i$ 3.33

Income elasticity $\eta_i = 1 + \frac{\beta_i}{w_i}$ 3.34

3.5.5. Measuring poverty incidence, gap, and severity

Poverty can be measured using different approaches. Income, welfare, and expenditure are among the widely used approaches for poverty measures. This study adopted the food expenditure method by employing the Foster-Greer-Thornback (FGT) approach to measure household headcount poverty, poverty gap, and severity of poverty. The estimation of the poverty line is based on the requirement of 2,200 kcal per day per adult food consumption, which is the national poverty line in Ethiopia (CSA 2012). This can be converted into 3.36 giga joule (GJ) energy consumption equivalent per year per adult. Therefore, the GJ of the household was estimated from the MP-MAS simulation result by dividing the energy consumption of households by adult equivalent. The estimated values are compared against the poverty line of 3.36 GJ per year per adult to compute incidence, gap, and severity of poverty in the households. The FGT can be presented as:

$$\mathrm{FGT}_\alpha = \frac{1}{N}\sum_{i=1}^{H}\left(\frac{z - y_i}{z}\right)^{\propto} \qquad 3.35$$

Where, N is population size in the economy (total number of agents in the model in our case), H the number of poor agents, y_i is the giga joule food consumption of the i^{th} household, z the poverty line and $\propto$ is a sensitivity parameter. If $\propto$ is zero, it measures the headcount poverty (ratio or the fraction) of population living below the poverty line. If $\propto$=1, FGT measures the average poverty gap, or the amount of income required to lift up individual to the poverty line. Finally, if $\propto$=2, FGT measures the severity of poverty by combining information on both income and poverty inequality among people below poverty line (Foster et al 1984).

3.6.Future rainfall variability and analyzing its effects on household welfare

The effects of future rainfall variability on household welfare are examined by generating trends of sequential rainfall distribution. This is done by generating random rainfall distribution using Monte Carlo simulation for thirty years rainfall data obtained from meteorological stations located near to the study area (rainfall from Bokoji station is used for Gedebe-Assa; Rainfall from Awassa station is used to generate rainfall distribution for Wondo-Genet and rainfall from Zeway meteorological station used to represent Adami-Tulu). After identifying the rainfall distribution for each study area, anomalies are constructed using the time series rainfall distribution. Each rainfall year is assigned to its corresponding anomaly (e.g. if the annual rainfall of a particular year is below/above two times the standard deviation from the long-term average rainfall, the year is classified as very dry/ very wet year. Similarly, if rainfall is within 0.5 standard deviations from the long-term average rainfall it is classified as a normal year). Finally, scenarios were designed by increasing the number of drier (wetter) years and computing the average simulated estimation values for each of the future rainfall scenarios; the result is compared with the current variability and hypothetical constant rainfall values. The probability of anomaly incidences is first computed from the time series rainfall data using a Standardized Anomaly Index (SAI formula 3.36). Subsequently, each simulation run is divided into five sequences of anomaly, namely very dry, dry, normal, wet, and very wet. This approach provides an area average index of relative rainfall based on standardized rainfall totals. Following (Bordi et al 2001), SAI can be computed as:

$$SAI_i = \frac{x_i - \bar{x}}{\sigma} \qquad 3.36$$

Where SAI and x are the Standardized Anomaly Index and the rainfall total of a particular year, respectively, and $\bar{x}$ and σ are the long-term average rainfall and standard deviation of the entire rainfall series of the area, respectively. Based on these statistics, years are classified as dry (below 0.5 standard deviation from the mean), normal (within 0.5 standard deviation from average rainfall), and wet (above 0.5 standard deviation from average rainfall) in the sequence of time series rainfall.

Table 3. 9 SAI ranges used for the classification of years into dry and wet anomaly

SAI values	Anomaly
SAI <-2	Very dry
-1.99<= SAI <-0.5	Dry
-0.5 <= SAI<=0. 5	Normal
0.5< SAI<=1. 99	Wet
SAI >2	Very wet

Source: (Bordi et al 2001). *For this study, two anomalies were designed the dry anomaly and the wet anomaly compared to the current average rainfall distribution and the results are presented for two additional scenarios*.

3.7.Empirical analysis on determinants of household saving and expenditures

Saving (expenditure) functions are estimated by unrestricted ordinary least square regression using robust regression; the results are presented in table 3.10. The sum of income coefficients in saving and expenditure functions add-up to a unity. The sign of the coefficients is in line with the economic theory of saving. Household savings increase at an increasing rate with income and the consumption increases at a declining rate. The share of saving in income increases with the level of income. The coefficients of income and income squared are interpreted from the mean change. The figures show that households tend to save about 31% of their income, which is not realistic under real world situations, where a majority of households has negative savings. Household size (represented by the energy equivalent of Giga joule, computed by converting household members to their adult equivalent energy requirements) is found to have a statistically significant negative relationship with saving and a positive relationship with the expenditure: Households with larger families allocate a proportionally larger share of their income to expenditure. Regional dummies reveal statistically significant differences regarding saving and expenditure behavior. Southern is the geographic dummy used to capture the distribution of saving and expenditure function in the joint area of SNNPR and Oromia regional states, with the variable taking value of one if household falls in the southern part of the country. Tigray, Oromia, Amhara, and SNNPR are the regional dummies representing the four major regions, with Amhara region is used as a reference. Except the Oromia regional state dummy, other regions were found to save more than the base regional state of Amhara. Regional dummies are included in the regression to account for the composite constant term in the saving function and the estimates are based on the national database.

Table 3.10 Regression estimates of saving and expenditure

Variables	Saving	Expenditure
Income	0.31***(0.07)	0.69***((0.07)
Income square	7.99E-06*** (0.00)	-7.99E-06*** (0.00)
Giga joule	-156.99***(-7.73)	156.99***(-7.73)
Dummy Southern	1844.56 **(1024.71)	-1844.56** (1024.71)
Dummy Tigray	4612.29***(836.07)	-4612.29***(836.07)
Dummy Oromia	-3491.85***(983.74)	3491.85**(983.74)
Dummy SNNPR	2569.74***(1203.83)	-2569.74***(1203.83)
Constant	-6065.93**(719.63)	6065.93**(719.63)
Observations	1136	1136

*Sources: Author's estimation from Ethiopian Rural Household Survey data, 2009; ***, **, *, are significant at 1%, 5% and 10% level of error respectively.*

3.7.1. Food and non-food expenditure function

Table 3.11 reports estimates of food and non-food expenditure functions. According to the estimation results, other than the Oromia regional state dummy, all variables are strongly associated with the expenditure function. The log of per capita expenditure is found to be negatively associated with food expenditure. A larger family size (billion joules) is positively related to the food expenditure function. Compared with Amhara regional state, all other regions except Tigray have a higher share of food expenditure in total expenditure. These coefficients have been used in the parameterization the consumption module of MP-MAS.

Table 3.11 Regression estimates of food and non-food expenditures using ERHS 2009

Variables	Food expenditure	Non-food Expenditure
Ln(pcExpend)	-0.040***(0.006)	0.040***(0.006)
Bjoule	0.002***(0.000)	-0.002***(0.000)
Southern	0.018***(0.004)	-0.018***(0.004)
Tigray	-0.013***(0.003)	0.013***(0.003)
Oromia	0.004(0.003)	-0.004(0.003)
SNNPR	0.007***(0.003)	-0.007**(0.003)
Constant	1.052**(0.033)	0.052**(0.033)
Number of observations	1342	1342

Sources: Author's estimation uing the Ethiopian Rural Household Survey data, 2009; Standard errors in parentheses, Ln (pcExpend) is the natural logarithm of per capita expenditure in ETB; * *$p < 0.05$,* ** *$p < 0.01$,* *** *$p < 0.001$.*

Table 3.12 Food categories, items, average budget shares, and unit values in the sample[a]

No	Name of category	List of items	Budget share (%)[b]	UV [c]
1	Cereals	Teff, wheat, maize, barley, sorghum, millet	45.44	3.65
2	Legumes	Lintels, horse beans, cow peas, chick peas	9.00	7.90
3	Root crops & enset	Potatoes, sweet potatoes, and enset	8.88	4.00
4	Fruits & Vegetables	Orange, banana, avocado, carrot	2.86	7.25
5	Animal products	Milk, beef, mutton, butter, chicken	6.93	34.50
6	Purchased necessities	Salt, coffee, oil, leaf, green pepper, bread	22.50	19.11
7	Others	All other food items	4.34	7.10
	Total		100	

Sources: -Author's estimation from Ethiopian Rural Household Survey data, 2009; [a] Number of observation=1342; [b] computed based on weekly expenditure; .[c] Unit value.

Table 3.12 reports the name of the food category, a list of food items included, in a particular category, average budget shares, and unit values for each of the seven food categories included in the MP-MAS parameterization. The estimation of budget shares of food categories reveals that cereals and purchased necessities represent, about 45% and 23% of the food expenditure, respectively. Legumes, root crops, and animal products account for about 9%, 9%, and 7% of the total food expenditures, respectively. This indicates that households in rural Ethiopia spend a higher proportion (about 70%) of their food budget on cereals and purchased necessities (salt, oil, coffee, honey, species, green paper, and bread). Fruit and vegetable consumption in the country is low: the share of vegetables and fruits in food expenditure is below 3%. Similar results were registered in a study by Tafere et al., (2010), who found that the share of oil and fats in total food expenditure is 10%, and that of species is 9%; totaling to 19% for purchased necessities. Furthermore, studies by Tafere et al., (2010) and Alem & Söderbom, (2012) on food demand elasticity estimation from a household income, consumption and expenditure survey indicated that in rural Ethiopia about 5% of food expenditure is spent on coffee and related food items (Tafere et al 2010; Alem & Söderbom 2012). A unit value for each food category was estimated by taking the price of each food category in total expenditures and averaging it with the food item's price. Animal products are the most expensive in terms of average unit values, followed by purchased necessities. In general, cereals, legumes, root crops, fruits and vegetables, animal products and purchased necessities have unit values of 3.7, 7.9, 4.0, 7.3, 34.5, and 19.1, respectively. The difference in expenditure shares most likely reflects the difference in quantity and quality of purchased food items in the food category (Alfonzo and Peterson 2006).

3.7.2. Income, own and cross price elasticity

Income, own and cross price elasticity are estimated by applying Heckman two-stage logit model, followed by Zellner's seemingly unrelated regression model (see Appendix A) on food expenditure. Food categories were obtained by grouping different food items from the Ethiopian Rural Household Survey database, by adopting IFPR's food classification. The description of items included in each food category is explained in Table 3.12. The coefficients presented in Table 3.13 were estimated by constraint regression in which adding up, symmetry and homogeneity constraints are set prior to the estimation. The adding up restriction was satisfied by omitting one demand equation in the regression and was estimated by omitting one of the coefficients and calculating this coefficient by imposing restrictions on the adding up constraint (*i.e.*, the sum of constant terms, price coefficients and income coefficients across all equations is respectively, add up to unity, zero and zero). Estimated income elasticity is found to be positive and near to one for all food categories. A commodity group is classified as a necessity if the income elasticity is between zero and one, and a luxury if it is greater than one (Nyankori 1996).

Table 3. 13 Expenditure and cross price elasticity for food categories using LA/AIDS

No	Category	Income elasticity [b]	Cross and own price elasticity [a]						
			1	2	3	4	5	6	7
1	Cereals	1.13	-0.56	0.46	0.49	0.45	0.47	0.44	0.44
2	Legumes	0.87	0.12	-1.30	0.31	0.15	0.13	0.04	0.18
3	Root crops & enset	0.93	0.28	0.31	-1.06	0.08	0.02	0.03	0.24
4	Fruits& vegetables	0.92	-0.07	0.21	-0.01	-1.13	-0.04	-0.05	0.28
5	Animal products	1.00	0.15	0.12	0.01	0.04	-1.14	0.01	0.09
6	Necessities	0.85	0.20	0.21	0.21	0.22	0.21	-0.68	0.23
7	Others	0.91	-0.14	0.23	0.35	0.21	0.08	0.07	-1.50

Sources: Author's estimation from Ethiopian Rural Household Survey data, 2009; the coefficients are estimated by employing Heckman two-stage probit followed by Zellner's seemingly unrelated regression; [a] Compensated (Hicksian) price elasticities; [b] Income elasticity at an average level of income.

Own price elasticity estimates of all food categories are found to be negative. Demand for many of the food categories is quite elastic with respect to own price. According to the estimation results, five out of seven food categories have own elasticities greater than one in absolute value. Larger figures of elasticity in absolute terms indicate a higher variability in the quality of the food categories, and thus for smaller changes in the price of the food category households adjust, not only the quantity consumed but also the composition of commodities consumed. The food category with the highest own price elastic demand (in absolute values) is the "other" food category (1.5), followed by legumes (1.3). However, their unit values are among the lowest. It is likely that there will be a wider discrepancy in the quality of the items included in these categories and, therefore, there will be an elastic response in demand for price changes. Moreover, the estimation results indicate that the income elasticities for most of the food categories are close to one or greater, suggesting that many of the food categories are luxury goods in terms of expenditure. However, it is noted that the expenditure elasticity measures the change in demand in terms of quantity and quality of a particular food category, and thus the coefficients of elasticities might be overestimated since the estimates are based on the multi-stage budgeting process. According to results in Table 3.13, all food categories show negative own price elasticity. Uncompensated price elasticity (in absolute values) for cereals, legumes, root crops, fruits and vegetables, animal products and purchased necessities are found to be 0.56, 1.3, 1.06, 1.13, 1.14, and 0.68, respectively. For the most, food categories reveal positive cross price elasticities with the “other” category. The own price elasticity for cereals, -0.56, indicates that a 10% increase in cereals price is associated with a 5.6% decrease in demand for cereals, indicating cereals are a price inelastic commodity. Households compensate the loss in consumption from increased cereal prices by consuming more of other food products. In particular, they compensate the loss of consumption from a 10% increase in cereal price by increasing consumption of the “other” food category or a mix of different food categories by at least 44%. Moreover, there is strong substitutability of products as a response to changes in the price of other product groups. Tafere et al., (2010) found similar results in their study: they found a cross price elasticity for cereal crops that ranges from -0.84 to -0.98. Furthermore, income elasticity analysis indicates that, except for cereals and animal products, demand for all food categories will increase below 10% for a 10% increase in income. A study by Tafere et al., (2010) on the food demand elasticity for rural and urban Ethiopia found that the income elasticity for cereal crops (teff, wheat, barley, maize, sorghum), is within the range of 0.66 and 1.07. Furthermore, they concluded that the income elasticity of teff, the most eaten crops, is 1.08 in rural Ethiopia, substantiating the result from this study. When household income increases by 10%, demand for cereals is expected to increase by 11.3%. This might be mainly influenced by demand for teff, which can be both a necessity and luxury good, depending on the quality of the teff: When income increases, households choose to consume high quality (white) teff rather than consuming black teff or mixing teff with other cereals.

Household nutrient requirements depend on compositions and the requirements of each household member. This demand can be satisfied either from own produce or food purchased from the market. Different food categories give different level of nutrients (energy and protein). If the nutrient supply from own sources is not enough to satisfy the family nutrient requirement, food categories with better nutrient contents can be bought from the market. In this study, household size is converted into million-joule equivalence by assigning the corresponding energy requirements of household age-sex compositions.

The elasticity estimates are required to parameterize three-stage consumption module in MP-MAS. The elasticity table containing the food category pairs and corresponding elasticities is presented in table format in MP-MASQl to be used for simulation. Similarly, information on energy contents, and coefficients of income, expenditure share, and household size, in food budget share (equation 3.30) of each food category, is provided to be used in the simulation of household consumption.

The effect of rainfall variability on household food consumption and poverty is computed by considering different adaptation strategies using the MP-MAS simulation result. Moreover, poverty dynamics and food consumption changes as a result of changes in external factors such as rainfall, price, wage and input prices estimated for different income class of households. The analysis result is presented in chapter five of this study.

Chapter 4: Model validation and calibration

4.1.Introduction

Model validation and calibration is the most important step in developing empirical models in that it assures the reliability of the model. In addition, validation of the model shows how the model fits the data and whether it is sufficiently accurate in replicating the real world observations. A validated model suggests that the result is robust and trustworthy. Validation of agent-based models can be done at both the micro and macro levels (Berger and Schreinemachers 2006). So far, MP-MAS users have applied different methods to validate their models. These include land use patterns, average and median crop yields, the share of the inter-cropped area, adoption of different technologies, liquidity and income, and resource endowment differences between model agents and survey households (Berger 2001; Schreinemachers and Berger 2006; Schreinemachers et al 2007; Schreinemachers and Berger 2011). In this study micro level validation was performed using the crop level area allocation per year from the survey and model. Macro level validation was done at aggregate levels of total crop sale values for model agents and survey households.

4.2.Importance of validating and calibrating a model

In recent years, the use of simulation models has been dramatically increasing for predicting or describing the reaction of agents or systems to external or internal changes by government agencies, policy makers and planners (Oreskes et al 1994). Simulation models are used mainly with the goal of prescription (to improve or design decision making) and to consider the effects of a policy change (Oreskes et al 1994; Sargent 1998). Thus, model validation represents an important step in any empirical model analysis. The model cannot be used confidently to analyze the unknown nature of a system from the available data unless its validity is established (Sargent 1998). Furthermore, validation of a model must be adequate for the objective of the modeler, in this case, to be accepted and used to support the policy decision-making process and solve real world problems. Thus, the question of, “does the model correctly reproduce the behavior of the real world system” is an important concern for the model developers and users, in particular, decision-makers who use model results and for the public that would be affected by the decision (Henriksen et al 2003; Pontius Jr et al 2004; Kirk Nordstrom 2012).

The term validation increasingly used interchangeably with the term verification (the assertion of established truth), which is misleading: unless in a closed system, any proposition cannot be verified. According to Schlesinger et al. (1979), as cited in Sargent (1998), model validation is usually defined as “substantiation that a computerized model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of the model” (Sargent 1998). The inverse problem is one of the main challenges that model developers face. A modeler is most knowledgeable about the distribution of the dependent variable to be modeled; however, the distribution of the independent (explanatory) variables is exogenously determined and is least known to the modeler. Therefore, there must be a tuning process to get as close a match as possible between the observed dependent variables and simulated dependent variables, which involves manipulation of independent variables within allowable ranges of values. This process is known as model calibration (Oreskes et al 1994).

4.3.Methodologies for model validation and calibration

The argument by Oreskes et al. (1994) emphasized that a thorough assessment of the accuracy of numerical models is most important when using the model in public policy design or decision making. However, demonstrating the truth of the model (verification) is impossible in open systems. A model is developed for the specific purpose of solving a problem at hand and its validity is determined with respect to the ability of the model in replicating the intended purpose and achieving the required goal. There are two basic approaches to decide whether a model is valid or not: The first approach is a subjective judgment by the model developer based on the outcomes from different model validity test run results. This involves the inclusion of the model users during the model development and validation stages, and hence, it increases the acceptance and credibility of the simulation models. The second approach is making a decision whether the model is valid or not by appealing to an independent body with a better understanding of the model’s purpose and the real system (Sargent 1998).

4.4.Validation techniques and their pros and cons

The validation technique applied for a particular model depends on the questions that the model tends to answer, knowledge of the system and data availability. Validation can be either subjective or objective. Subjective model validation requires the modeler's decision in judging the validity of the model, while objective validation involves mathematical or statistical test procedures, such as graphical presentation, hypothesis tests, and confidence intervals. In the literature different model, validation and verification techniques were identified. Main validation techniques include:

- Comparing the outcomes from valid model (model under consideration) with the outcomes of other validated models;
- Event validity: comparing the occurrence of events in the simulated model with the real world system;
- Extreme condition test: comparing the occurrence of extreme events in the model with a real situation;
- Face validity: asking individuals with the knowledge of the system, e.g., whether the simulated outcomes or input-output relationship is logically correct, reasonable and acceptable,
- Internal validity: several runs of the simulated model are made and the stochastic behavior to the robustness and consistency of the model outcomes are examined, larger deviations in outcomes from different runs indicating less consistency and higher variability in the model making the model invalid), and
- Parameter variability-sensitivity testing: looking the response of the model outcomes for changes in input variables (Davis et al 1991; Oreskes et al 1994; Sargent 1998).

Model outputs can be compared with the actual system or the outputs of other model results to see performance behavior. Graphs, confidence intervals, or hypothesis tests can be used to compare the model validity. Empirical validation techniques used in this study are discussed and their mathematical formulas are presented below:

i. Coefficient of determination (R-squared), a numerical measure that indicates how well the data fits the model;

ii. Slope coefficient of regression: This is obtained by regressing the survey results on the model values, showing how close the model values to the survey values.

iii. Nash–Sutcliffe model efficiency coefficient: is a coefficient that assesses the predictive power of the model; and

iv. Standardized Absolute Error (SAE): is the simplest descriptive statistics of deviation of the simulated values from the observed values (Voas & Williamson, 2001).

The validation techniques explained in the above section can be presented as follows:

i. Coefficient of determination (R^2)

$$R^2 = \frac{SS_{reg}}{SS_{tot}} \qquad 4.1$$

Where R^2 is the coefficient of determination; SS_{tot} is total sum of squares of the deviations of the observations from the mean value; SS_{reg} is regression sum of square (explained sum of square), is a measure of the proportion of variance in the data that can be explained by the regression. The coefficient of determination, R^2, is used to measure how well the simulated data fits the survey data. It measures the proportion of variance in the survey data explained by the simulated data. The closer the value of R^2 to 1 among the best linear unbiased estimates (BLUE), the better the model is. The coefficient of determination for the model result is obtained by regressing the survey data on the simulated data.

ii. The slope of regression coefficient can be presented as follows:

$$O_i = \beta_i S_i \qquad 4.2$$

Where O is observed values from the survey; β is the regression coefficient, is a measure of the change in the observed values to a unit change in simulated values, the closer the regression coefficient, β, to 1 the better the model in explaining observed dataset.

iii. The Nash–Sutcliffe model efficiency coefficient is another measure used to assess the predictive power of simulation models in explaining the observed dataset. It is defined as:

$$E = 1 - \frac{\sum_{i=1}^{N}(O_i - S_i)^2}{\sum_{i=1}^{N}(O_i - \bar{O})^2} \qquad 4.3$$

Where O_i is the observed value; S_i is the simulated or model value; and $\bar{O}$ is the mean of the observed values. An efficiency of 1, i.e., E = 1, corresponds to the case where model perfectly fits (matches) to the observed data. If an efficiency is zero, i.e., E = 0, the model is as accurate as the mean of observed values in predicting the data, whereas an efficiency less than zero ($E < 0$) occurs when the observed mean is a better predictor than the model. The closer the model efficiency is to one, the more accurate the model is.

iv. Standardized Absolute Error (SAE) presented as:

$$SAE = \frac{\sum_i |O_i - S_i|}{T} \qquad 4.4$$

Where O_i is the observed value SAE is a measure of absolute error normalized by the count of the individual entities, T ; the lower bound of SAE is zero indicating prefect fit of the model. The average SAE can be computed from different simulation, so, it is possible to compare the values across different simulations. Voas and Williamson, 2001, suggested using $1 - SAE$ coefficient of the model as a measure of efficiency; if the value of $1 - SAE$ is less than zero, the model is worst fit than the random allocation and the closer $1 - SAE$ is to one the more reliable the model is in explaining the real data.

4.5.Application to MP-MAS Ethiopia

In this study, the inadequacy and limited accuracy of the survey data are the main challenges in identifying appropriate parameters to achieve model validation. As the objective of the model is to simulate the effects of rainfall variability by accounting for interactions between environment, climate, and human beings, soliciting the right validation variable that accommodates heterogeneity among agents is of the foremost importance. Landholding is found to be highly associated with household production, investment, and consumption behavior. Moreover, the land is highly correlated with other household characteristics and assets, such as livestock, labor availability, input use, productivity, and the overall performance of the farm enterprise. Therefore, if the model is valid with respect to actual and simulated landholding size, it is evident that the model is good enough in explaining and simulating the real world at least for the purpose of the study. The average of simulation results for the first three years of simulation period was used to compute the model values. This is mainly the model results can be influenced by the availability of resources and the current characteristics of the households. Therefore, it is apparent to compare the survey results with the average of at least three simulation period figures.

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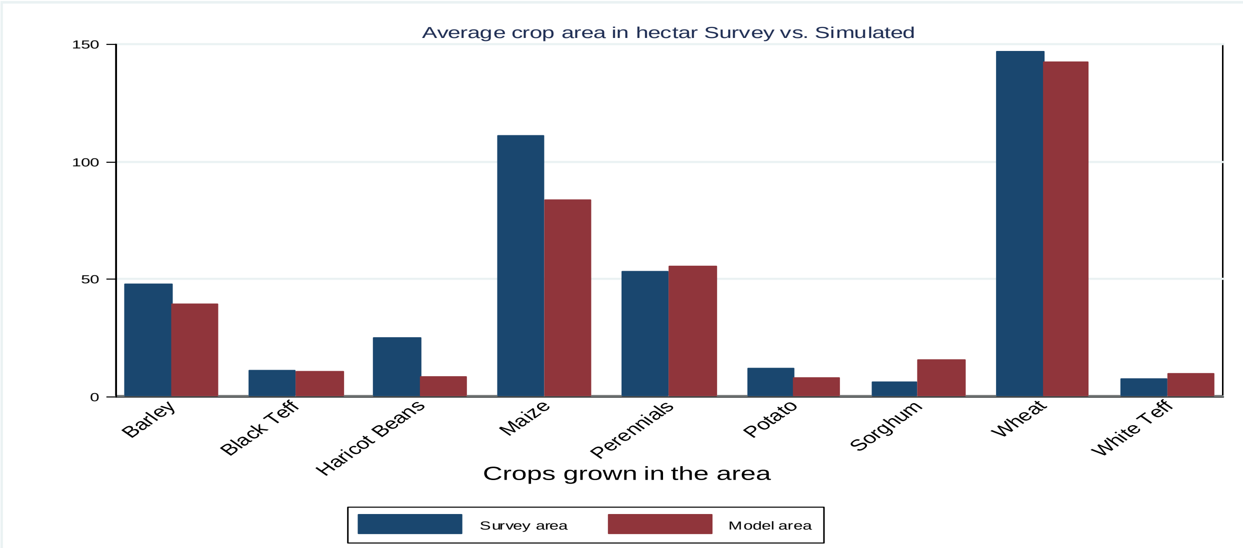
Both graphical and hypothesis tests were employed to assess the sufficiency of the model in replicating the real world observations. Graphic validation techniques can be used to make a subjective judgment, face validity, and visual inspection of the model. Fig. 4. 1 presents the distribution of total land area among different crops for the model and survey areas. The research area is predominantly a cereal-producing area, followed by perennials. The blue bars in the figure represent the total land area in the survey, allocated for the corresponding crop while the red bars show simulated area allocated for each crop. Maize and wheat are the main cereals grown in the study area; followed by perennial crops. The perennial area is the sum of the area allocated for coffee, chat, enset, eucalyptus, banana, avocado, and mango. Perennial crops are grown particularly in the Wondo-Genet district, mainly for the purpose of cash generation. The figures suggest a close match regarding land allocation between model agents and survey households. It is also clear that the landholding and distribution over crops are fragmented and very small. In general, a total landholding is below one hectare per crop per household.

Fig. 4. 1 Simulated and survey areas for the major crops* grown in the study area



Source: Author's computation from a survey conducted by Master Students at Institute 490A, 2010 and simulation results from MP-MAS. Crop area used for the model validations includes areas in hectare allocated to crops such as wheat, maize, barley, perennial (total of enset, chat, eucalyptus, banana, mango, and avocado area), haricot beans, potato, sorghum, and teff.

4.5.1. Land availability, confidence interval and hypothesis test

Comparison of one of the model parameters, land distribution, for model agents and survey population is presented in Table 4. 1. The table indicates that the average landholding for survey household is 2.51 hectares and that of modeled agents is 2.48 hectares. The difference is emanated from rounding of the area to the nearest integer plot level in the model, as the model uses fixed size plots (a quarter of a hectare) as a measure of land area. The estimation results show that about 75% of the households have three or fewer hectares of land. It is also clear that, except for the median landholdings, all other estimates are similar to the surveyed and modeled population. This suggests the existence of a close match between the survey and model values regarding area distribution.

Table 4. 1 Descriptive analysis of land area in hectare for model agents and survey households

Population	Mean	Sdv.	Min	Max	p25	p50	p75	p90
Survey	2.51	3.01	0.14	23.50	0.76	1.75	3.00	5.00
Model	2.48	2.98	0.25	23.50	0.75	1.50	3.00	4.99

Source: Author's computation from a survey conducted by Master Students in Institute 490A, 2010 and simulation results from MP-MAS. The results are based on 180 households in the survey and 180 for agents in the model and the model results are the average of three simulation periods for the same number of households. Sdv: Standard deviation; min: minimum; Max: maximum; p25, p50, p75, and p90, are, respectively, 25th, 50th, 75th, and 90th percentiles of the land distribution.

In addition to descriptive analysis of landholding size between survey households and model agents, the author computed measures of variability in detail including confidence intervals. Table 4.2 presents the estimation results for mean, standard deviation, and confidence interval regarding land size for survey and simulated values.

Table 4.2 Confidence interval validation of the area in hectare between the model and survey households.

Group	Observation	Mean	Std. Err.	Std. Dev.	[95% conf.	interval]
Survey	180	2.51	0.23	3.01	2.06	2.96
Model	180	2.48	0.22	2.99	2.04	2.92
Combined	360	2.50	0.16	3.00	2.18	2.81
Difference		0.03	0.32		-0.59	0.65
P-value		0.93				
T-statistics		0.09				
Hypothesis test		Ha: diff != 0				

Source: Author's computation from a survey conducted by Master Students at Institute 490A, 2010 and simulation results from MP-MAS. The results are based on the average area of three simulation period for the model values and the survey area is the observed values from 180 households in the study area. Std. hy: standard error; Std. dev.: standard deviation; 95% conf.: 95% confidence intervals.

Two sample t-tests with unequal variance for mean comparison between the survey and simulated area confirmed non-rejection of the null hypothesis. Therefore, there is no significant difference in land distribution, comparing survey households and the agent population. This result is in line with the graphic validity test mentioned above. Moreover, it is clear from the confidence intervals that the simulated values are within the acceptable range of the survey values. The range of simulated land values lay completely within the survey area confidence interval.

4.5.2. Measures of Goodness of fit and model efficiency

To check the predictive accuracy of the model, model goodness-of-fit was measured by running simulations for twenty random seed values, resulting in twenty random populations, and comparing the land allocation in these generations with the land allocation observed in the survey. Each random population outcome is compared with the survey data result and the surveyed land is regressed on the simulated land. The result in Table 4.3 confirms that irrespective of the random population chosen, the model is at least 91% fit to the survey data. On average about 95% of the variability in the distribution of the survey area is explained by the model area, with the worst- and best-fit values of 91% and 98%, respectively. Moreover, the R-squared coefficients are close to unity, indicating that the survey is well replicated by the model result.

According to the regression coefficients of the survey area on the model area using equation 4.2; the average error that cannot be captured by the model is 3% and the worst error value is 12%, meaning that on average the model results are 3% overestimated. The estimated coefficients from the regression of the survey area on model area found to be around unity, confirming a close match between simulated and survey areas.

Nash-Sutcliffe model efficiency coefficient (NSE) value, using equation 4.3, show the model is efficient enough in replicating the survey population. The closer the NSE value is to one, the more efficient the model is. If the NSE values are less than zero, the average values are more powerful than the model in explaining variation in the data. According to the estimates of NSE coefficients, MP-MAS simulation is least 91% more efficient than the average values, whilst the best and the worst fits are, 97 and 95%, respectively.

Moreover, additional validation, using Standard Absolute Error (SAE), estimated by equation 4.4, supported the validity of the model in predicting the real data. The results indicate that model simulation is good enough in replicating the true values. Generally, the estimation result of the analysis of model fit indicated that model values are almost perfect matches to observed values.

Table 4.3 Measures of model goodness of fit averaged over three simulation periods.

Model population	R-square	Coefficient	NSE	1-SAE
1	0.97	1.08	0.96	0.80
2	0.96	1.02	0.96	0.77
3	0.91	0.95	0.91	0.70
4	0.96	1.04	0.96	0.80
5	0.94	1.04	0.93	0.76
6	0.97	1.02	0.97	0.81
7	0.95	1.00	0.95	0.76
8	0.97	1.08	0.96	0.80
9	0.96	1.12	0.95	0.74
10	0.94	0.98	0.94	0.77
11	0.92	1.04	0.92	0.74
12	0.94	0.94	0.93	0.71
13	0.95	1.01	0.95	0.78
14	0.96	1.03	0.96	0.77
15	0.96	1.08	0.95	0.75
16	0.98	1.07	0.97	0.81
17	0.97	1.09	0.95	0.75
18	0.96	0.97	0.96	0.79
19	0.95	1.00	0.95	0.75
20	0.94	1.05	0.94	0.73
Average	0.95	1.03	0.95	0.77
Worst fit	0.91	1.12	0.91	0.70
Best fit	0.98	1.00	0.97	0.81

Source: Author's computation from a survey conducted by Master Students at Institute 490A, 2010 and simulation results from MP-MAS. Each model population runs for three simulation periods using MP-MAS model, the figures are the average of the three simulations periods. NSE and SAE are Nash–Sutcliffe model efficiency coefficient and standard absolute error. R-square and coefficient are from the regression of survey crop area on the corresponding model area.

4.5.3. Model robustness

Internal validity is one of the techniques used to measure the model sufficiency and accuracy in simulating the system under consideration. Area allocation for each crop in different runs (seed values) is presented in Table 4.4. The larger the deviation in outputs from different simulation runs, the higher the model variability and the less robust the model is. Simulation from twenty random seed values shows that the maximum and minimum variability measured by standard deviation is about 13 and 3 hectares, which is observed in barley and teff areas, respectively. Moreover, the coefficient of variation, which measures the consistency of the model over simulation runs, indicates that the percentage deviation for the main crops is below 7%. The overall coefficient of variation is about 3%, meaning that 97% of the variance in the survey area is captured in the model area.

Simulation considers the average of three simulation periods. This is because the current decision of the household production, investment, and consumption depend on liquidity endowment from the previous period, therefore, the average of recent three years values can represent the true decision and can be compared with the observed values. The simulated values are the average of three-period simulations for each random population. Table 4.4 reports total land allocated for each of the major crops from twenty different simulation runs. Maize and wheat followed by barley and perennials account for the major land area cover. The average survey area covered with wheat, maize, barley, and perennials is about 150, 100, 48, and 60 hectares, respectively. While the average simulated area for these crops is about 144, 91, 44, and 61 hectares, respectively. This shows a non-significant variation in total land-cover distribution for the model and survey households regarding different crops. Moreover, the percentage error between the model and survey area resulted in ranges from -4% to 10%, with the total percentage error of about 4%. Additionally, the x-y distribution of area under different crops for survey and model agents reveals that except for haricot beans and perennials, the area of most crops is located around the 45' line. Furthermore, it is clear from *Source: Author's computation from a survey conducted by Master Students in Institute 490A, 2010 and simulation results from MP-MAS;* [a] *Perennial area includes area allocated for coffee, chat, enset and eucalyptus production;* [b] *Model mean area is the average area of the 20 random populations;* [c] *is the* *standard deviation of the area over 20 populations and [d] is obtained by dividing [b] to .[c] The simulation results are the average of three simulation periods for 180 agents using MP-MAS simulation model.*

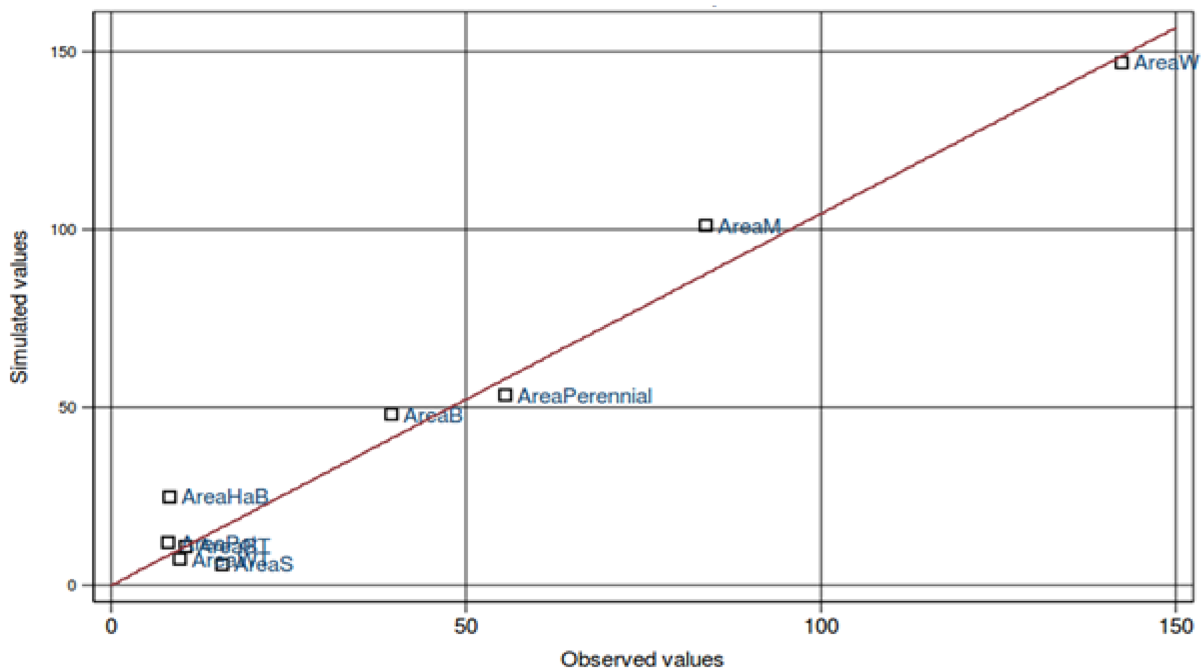
Fig. 4. 2 that, areas of sorghum, black teff, and barley were concentrated around the lower left corner of the figure. The close match between the survey and the simulated model areas for different crops has shown a strong tie between the survey and simulated area. This further supports the validity of the simulation model even at lower aggregation level. Agents allocate a higher proportion of land for maize and wheat cultivation in the area.

Table 4.4 Area allocated in ha for the major crops over 20 random population and survey.

Population	Seed	Area of major crops in hectare for different runs					
		Barley	Teff	Maize	[a] Perennial	Wheat	All
Survey area		48.00	11.08	101.00	59.00	147.00	366.08
pop1	1	51.59	8.75	93.04	60.99	133.72	348.09
pop2	2	36.71	10.41	91.17	62.16	147.73	348.19
pop3	3	28.70	8.67	86.74	63.31	161.88	349.30
pop4	4	55.28	6.23	92.56	68.20	138.12	360.38
pop5	5	44.60	6.97	93.92	68.10	130.79	344.39
pop6	6	52.50	6.24	97.43	53.87	134.04	344.07
pop7	7	34.44	9.24	91.16	58.98	135.05	328.88
pop8	8	42.55	15.05	90.51	58.43	156.80	363.33
pop9	9	30.83	13.72	87.59	61.21	152.80	346.16
pop10	10	70.98	14.04	92.34	58.83	131.56	367.74
pop11	11	28.70	8.67	86.74	63.31	161.88	349.30
pop12	12	28.70	8.67	86.74	63.31	161.88	349.30
pop13	13	42.10	11.32	81.41	60.54	151.73	347.10
pop14	14	55.28	6.23	92.56	68.20	138.12	360.38
pop15	15	44.60	6.97	93.92	68.10	130.79	344.39
pop16	16	52.50	6.24	97.43	53.87	134.04	344.07
pop17	17	34.44	9.24	91.16	58.98	135.05	328.88
pop18	18	42.55	15.05	90.51	58.43	156.80	363.33
pop19	19	30.83	13.72	87.59	61.21	152.80	346.16
pop20	20	70.98	14.04	92.34	58.83	131.56	367.74
[b] Model mean area		43.94	9.97	90.84	61.44	143.86	350.06
[c.] Standard deviation:		12.99	3.22	3.85	4.30	11.94	10.94
[d.]Coefficient		29.56%	32.24%	4.24%	6.99%	8.30%	3.12%
Percentage		8.46%	9.98%	10.06%	-4.14%	2.14%	4.38%

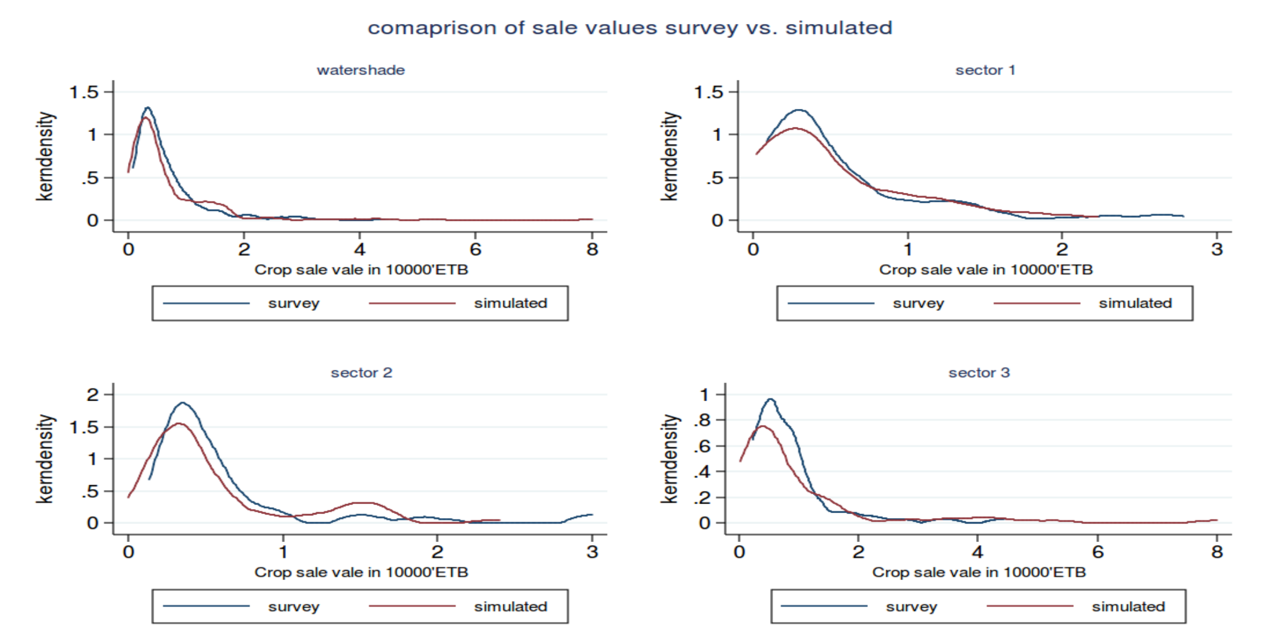
Source: Author's computation from a survey conducted by Master Students in Institute 490A, 2010 and simulation results from MP-MAS; [a] Perennial area includes area allocated for coffee, chat, enset and eucalyptus production; [b] Model mean area is the average area of the 20 random populations; [c] is the standard deviation of the area over 20 populations and [d] is obtained by dividing [b] to .[c] The simulation results are the average of three simulation periods for 180 agents using MP-MAS simulation model.

Fig. 4. 2 Scatter diagram of simulated crop area on Y-axis and observed crop area on X-axis



Source: Author's computation from a survey conducted by Master Students in Institute 490A, 2010 and simulation results from MP-MAS. Values on the x-axis are the area in a hectare of crops in the survey and the values on the y-axis are their corresponding simulated values using MP-MAS simulation model. The simulated area is the average of three simulation periods using MP-MAS simulation model on 180 households land distribution. The red line is a 45' line, the closer the crop area to the diagonal line the closer are the simulation and survey results.

Fig. 4. 3 Validation of crop sale values at sector level



Source: Author's estimation from MPMAS simulation experiment and survey data 2010

Note: *The figures are the survey and simulated crop sale values for households and their corresponding simulated areas in the simulation. Values at watershed (the entire sample) of the study area and the values at sectors are the simulation results at each study sites.*

4.5.4. Disaggregated validation of total sale by sector

Fig. 4. 3 compares the distribution of household total sales values computed for the survey and model at sector and watershed levels. Crop sales values in the model are computed by multiplying the quantity of each crop sold with a corresponding market price. Similarly, the crop sales value of the survey is estimated by comparing the share of each crop in the total household income and the revenue from the sale of crops accordingly, as households were asked to give the share of each crop in total income. The model sales values are the average of ten random population and seed runs over three periods. The sales value distribution supports the idea that the model is valid in representing the reality on the ground, as established with the validation coefficients and graphical presentations. As shown in Fig. 4. 3, there is a close match between the survey and model sales values even at the sector level. Moreover, it is clear that there is a higher disparity between the

model and survey sales values at the sector level compared to the watershed (aggregated population) level. This is mainly attributed to the small sample size in each sector compared with the watershed, which arise due to the difference in the distribution variances at the sector level and the lack of consistent crop sales reports in the survey, the latter being caused by recalling problems and underestimation of the sale values by surveyed households.

Chapter 5: Simulation and Scenario Analysis

5.1. Introduction

This chapter presents an in-depth analysis of the simulation results from the MP-MAS model. The model structure, estimations of model parameters and validity testing were discussed in Chapters 3 and 4 of this thesis. Since the objective of this study is to explore the expected effects of rainfall variability on crop yield and farmers' adaptation strategies to mitigate the adverse effects of rainfall variability, scenarios have been developed and analyzed to address different research questions. An analysis of simulation results is presented in seven sections. Section 2 discusses the business as usual (baseline) scenario. Section 3 discusses the effects of rainfall variability on crop yield. Section 4 analyzes the effects of rainfall variability on household welfare. Section 5 elaborates the importance of adaptation strategies to reduce the negative effects of rainfall variability. Section 6 summarizes the sensitivity of the model results to external shocks. Section 7 concludes the chapter by discussing the analysis of the effects of future rainfall variability. The simulation was run for eighteen periods to see how rainfall variability affects crop yield, income, poverty, food consumption, and income inequality among farm households in the study area.

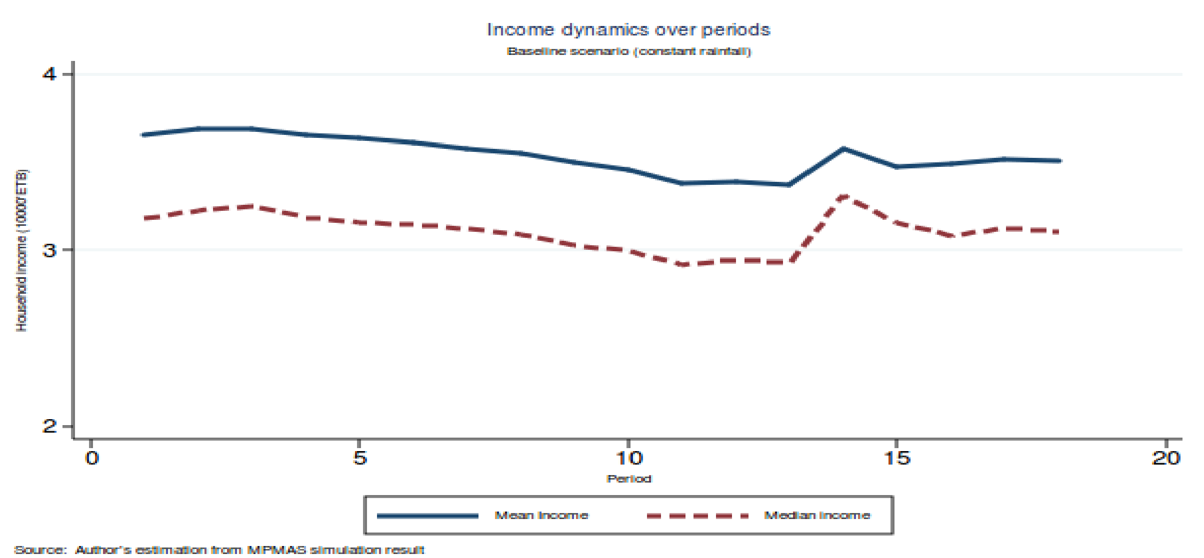
5.2. Analysis of baseline scenarios

This study considers two rainfall scenarios in investigating the effects of rainfall variability on crop yield and household welfare (income, poverty, and food consumption). The baseline scenario assumes the hypothetical constant (average rainfall of past thirty years, 1974-2003) rainfall. The second rainfall scenario assumes variable rainfall (random rainfall distribution for the past thirty years). Thirty random rainfall distributions are generated from the time series rainfall data using Monte Carlo simulation. The rainfall data used for the study comes from three meteorological stations (Bokoji, Zeway, and Awassa), which are located near to three study districts, Gedeb-Assasa, Adami-Tulu, and Wondo-Genet, respectively. For each of the rainfall distributions crop yield, income, poverty, and food security distributions were simulated by using the MP-MAS simulation model; the average of the simulation results from thirty runs and eighteen simulation periods for each run is used as the value of variable rainfall. Similarly, for the baseline scenario, a simulation is run for eighteen simulation periods of constant (average of thirty random) rainfall distribution. The results from the two rainfall distributions, hypothetical constant and variable (random) rainfall distribution, are compared to make an analysis of the impact of rainfall variability on crop yield and household welfare. Analysis of simulation results and discussion are presented in subsequent sections.

5.2.1. Dynamics of simulated income over periods of constant rainfall

Fig. 5. 1 illustrates the general overview of the trajectory of household income over the simulation periods assuming hypothetical constant rainfall. The distribution of the average simulated household income points out that household income has slightly declined until the 13th period and rises by about 6%, from 33,700 to 35,800 ETB (Ethiopian ETB), in the 14th period, before declining back by 3% to 34,750 ETB in the 15th period and continue with the previous trend thereafter. Fluctuation in household income takes place because perennial crops realize varying yields that increase over simulation periods until it reaches full potential and declines afterward over the life span. Particularly, coffee and avocado give potential yields after 15 years, which increases income for the households and thus the rise in income in the fifteenth period is expected. The slight decline over the course of the first thirteen periods is mainly attributed to depletion in household liquidity. Indeed, the increase in income is accounted by the achievement of full coffee yield at the 14th period, which subsequently increases household's income. The income of all agents is not increased rather the subsample of the agents of those who start growing perennial of age one at the start of the simulation. The full potential yield achieved by the subsample of farmers increases the average income in the fourteenth period. Not only the income from the sale of perennials product increases but also negative cash flows due to the investment on perennials is reduced. Agents are allocated with perennial area based on a survey perennial area by generating perennial area segment; moreover, the model is set to assign random age distribution for the perennial crops for each agent. Generally, household incomes decline steadily over the simulation period.

Fig. 5. 1 Dynamics of average simulated income, assuming constant rainfall over periods[a]



[a] *The figures are the average of eighty simulation periods considering hypothetically long term constant yearly average rainfall distribution.*

Moreover, Fig. 5. 1 indicates that the mean income always lays above the median income value, further demonstrating that the income distribution is right-skewed, which in turn suggests that a few wealthier households own a larger portion of income; which increases income inequality. Average per household simulated income under the baseline scenario (Hypothetical constant rainfall) is 35,400 ETB with a coefficient of variation 63%, indicating higher disparity regarding income distribution among the households.

5.2.2. Distribution and dynamics of poverty

Estimated poverty rates and distribution over five-period intervals of simulation for the baseline scenario are reported in Table 5. 1. The result suggests that headcount poverty is 33.82% with respect to food poverty, which is close to the national poverty line of 33.62% in 2010/11 (CSA 2012). Similarly, the poverty gap and severity were 10.5% and 4.4%, respectively, which are also similar to the national estimates of 10.5% and 4.6%, respectively (CSA 2012). However, the figures are slightly above the regional poverty rates. This is mainly due to missing information on household consumption in the ERHS 2009 data and the corresponding assumption made on the representativeness of consumption function coefficients from the national dataset for the study area. Moreover, the national poverty estimates are based on the survey data of 2010/11 collected by CSA and the model values are based the older 2009 dataset, which might have contributed to the slight difference, as poverty rates are declining over time in the country. The distribution of the average of five-year-interval simulated poverty indicators in Table 5. 1 shows decreasing poverty after the tenth period. This is due to full potential yield achieved from the perennial crops onwards from the tenth period, and hence an improved income.

Table 5. 1 Simulated total and five years average poverty distribution for model agents

		Periods [b]		
Parameters	Average [a]	0-4	5-10	11-15
Headcount index (%)	33.82	34.56	34.85	33.05
Poverty gap index (%)	10.54	10.22	11.14	10.31
Poverty severity index (%)	4.37	3.90	4.63	4.36

Source: Author's estimation from MP-MAS simulation experiment, 2013; [a] is the average values over simulation periods; [b] are average poverty measures over distinct intervals of five periods.

5.3. The effect of rainfall variability on crop yield

Rainfall variability has a negative direct effect on crop yield. It has negative indirect welfare effects through declined production and productivity of agriculture. The decline in yield translated into reduced household income leading to increased poverty, and food insecurity. Table 5.2 reports results for simulated yields under variable and constant rainfall for the major crops. Moreover, the table reports percentage changes in simulated mean crop yield for the major crops between hypothetical constant (constant hereafter) and current variable (variable hereafter) rainfalls. The results suggest that the effect of rainfall variability on the mean crop yield is crop specific. Rainfall variability has a distinctive effect on crop yield depending on the crop's response to changes in climatic variables. Thus, the findings suggest that on average some crops are negatively affected by rainfall variability while others are positively affected by rainfall variability. It is clear from the simulated results in Table 5.2 that, except for a few crops (onion and enset); most crops were negatively affected by rainfall variability. For instance, compared to constant rainfall the yield of horse beans is decreased by about 16% under rainfall variability. This is because of the fact that horse beans have higher sensitivity to rainfall variability than other crops (Allen 1998). Similarly, under variable rainfall, the mean yield of major crops, such as wheat, maize, and barley is declined by about 7%, 9%, and 5%, respectively. However, the mean simulated yield of enset under rainfall variability is slightly greater than the yield under hypothetically constant rainfall. This is because enset is known to have relatively better resistance to weather shock compared with other crops grown in the study area; accordingly, the mean enset yield has increased on average by about 7% under rainfall variability. Even if the yield of some crops is found to be greater with variable rainfall, the positive changes in yield between variable and constant rainfalls are not statistically significant, which substantiate that negative yield effect of rainfall variability outweighs potential positive effects. The average yield effect of rainfall variability on all crops is presented in the last column of Table 5.2. From the last column, it is indicated that the effect of rainfall variability on the mean yield, considering all crops and computing the mean yield difference between constant and variable rainfall conditions, is statistically significantly negative. On average about 8% crop yield [5] reduction is expected under rainfall variability. Therefore, one can conclude that rainfall variability imposes a significant negative impact (t=-29.75) on the mean yield of crops in the study area. The results further suggest that fluctuations in climatic variables, particularly in rainfall are expected to increase the loss in crop yield. The graphic presentation of the simulation results in Fig. 5.2 confirms the results in Table 5.2 and discussions that follows.

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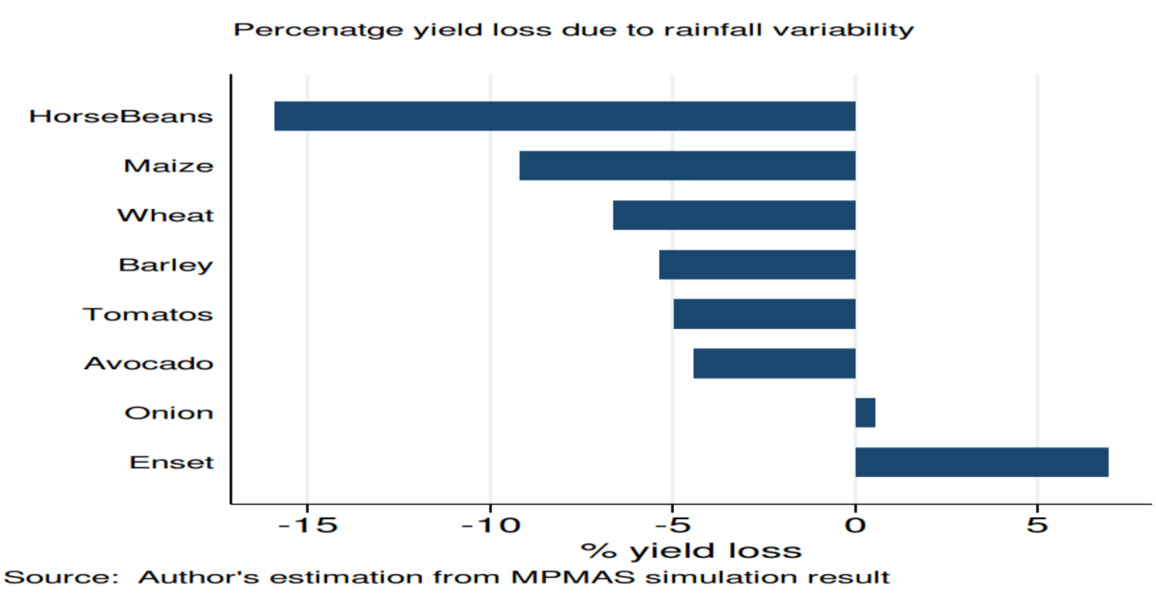
[5] *Considering all crops included in the model (some crops gains yield under rainfall variability while others lose yield, rainfall variability results sometimes in better rainfall and the other time bad rainfall distribution)*

Table 5.2 Estimation result of the effect of rainfall variability on mean yield

Crop name	Yield (kg/ha) Variable	Yield (kg/ha) Constant	% change [a]	t-test [b]
Wheat	1893.76	2028.54	-6.64	-4.57***
Maize	3838.34	4216.97	-8.98	-5.89***
Barley	1074.79	1133.19	-5.09	-4.06***
Tomato	4924.58	5165.01	-4.66	-0.25
Onion	5590.86	5576.97	0.25	0.58
Horse beans	1243.47	1477.71	-15.85	-7.64***
Enset	617.79	576.74	7.19	0.09
Avocado	1602.47	1676.03	-4.39	-0.02
All	2332.84	2547.81	-8.44	-29.75***

*Source: Author's estimation from MP-MAS simulation experiment, 2013; [a] Percentage yield difference is a difference in yield under variable and constant rainfalls; [b] t-test is computed by using two-tailed mean difference significance test using STATA 12 04 version. ***, **, *, are significant at 1%, 5% and 10% level of error respectively.*

Fig. 5.2 Percentage change in crop yield between variable and constant rainfalls



Note: Values are averaged over the eighteen simulation periods; yield under variable rainfall is the average of thirty simulation runs.

5.4. The effects of rainfall variability on household welfare

The effect of rainfall variability on household welfare, particularly on income, food consumption, and poverty is found to be moderate. Welfare loss is estimated by comparing the agent's well-being under constant rainfall and corresponding simulation results with variable rainfall. Analysis of the effect of rainfall variability was achieved by running simulations for thirty randomly generated rainfall samples and computing average income, poverty and food consumption over eighteen simulation periods. Finally, the estimated values under variable rainfall are compared with the values from constant rainfall.

5.4.1. The effect of rainfall variability on household income

Fig. 5.3 presents the kernel density distribution of simulated income under variable and constant rainfalls. The mean effect of rainfall variability on simulated income is the distance between the red line (income with constant rainfall) and the blue line (income with variable rainfall). Estimation results indicated that on average, simulated household income under rainfall variability is about 3% lower than the income without rainfall variability. In the previous section, it was indicated that rainfall variability negatively affects crop yield. Moreover, it has been shown that rainfall variability reduces crop yields by about 8%. The negative effect of rainfall variability on crop yield has resulted in decreased simulated income. The dynamic of simulated income under variable and constant rainfall distributions is shown in Fig. 5.4. From the figure, it is apparent that in 16 out of 18 simulation periods household income under constant rainfall is greater than the income with variable rainfall. The trajectory of income over the simulation periods showed slightly declining trend of income both under variable and constant rainfall. Moreover, income with rainfall variability has more fluctuations over the simulation periods than income with constant rainfall. However, income under constant rainfall shows a uniform and slightly declining trend.

Fig. 5.3 Distribution of household income (10,000'ETB) with and without rainfall variability

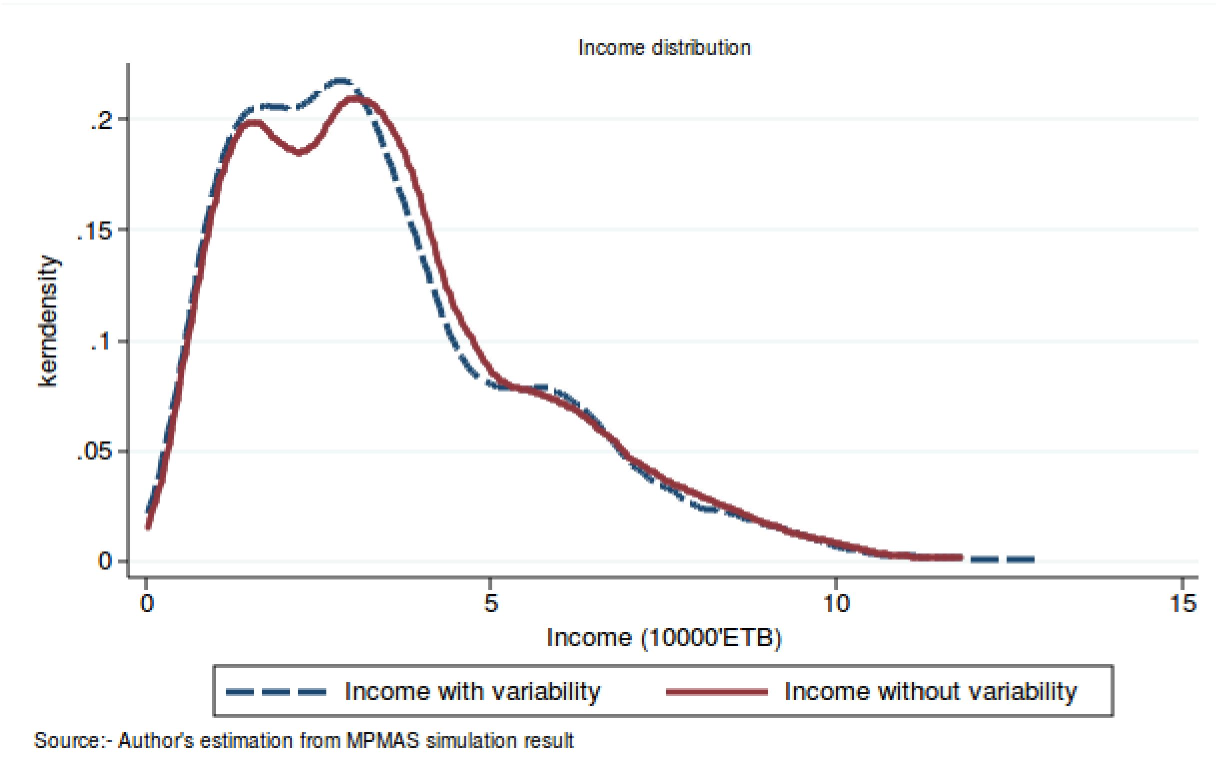


Fig. 5.4 Dynamics of household income (10,000'ETB) with and without rainfall variability

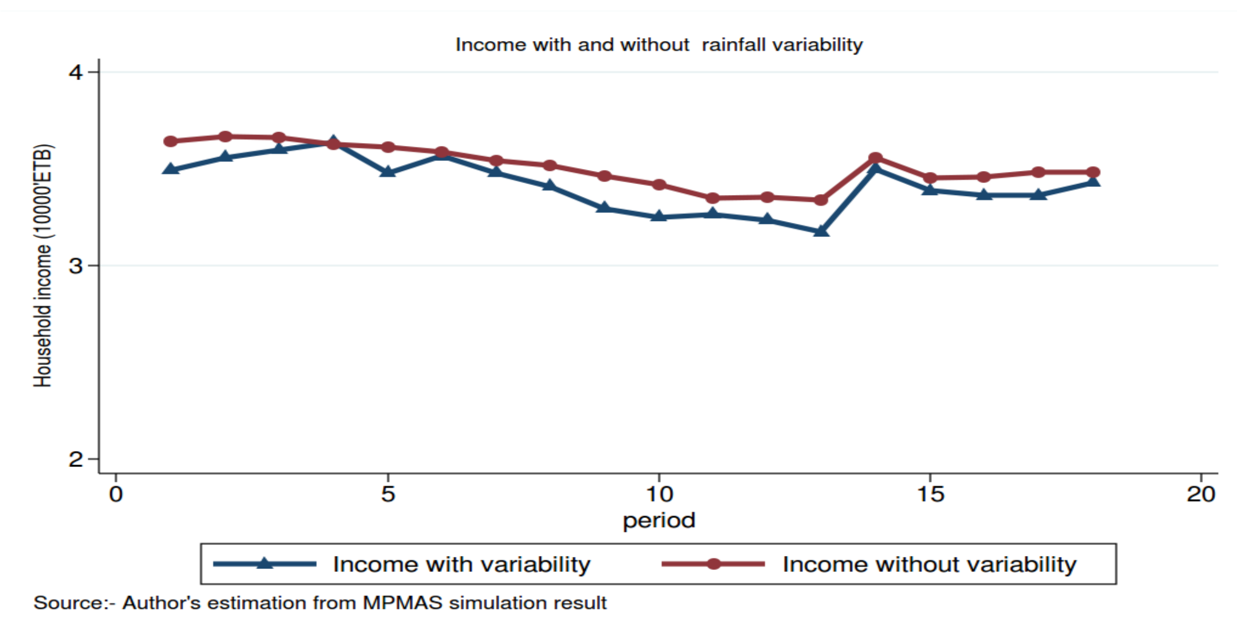
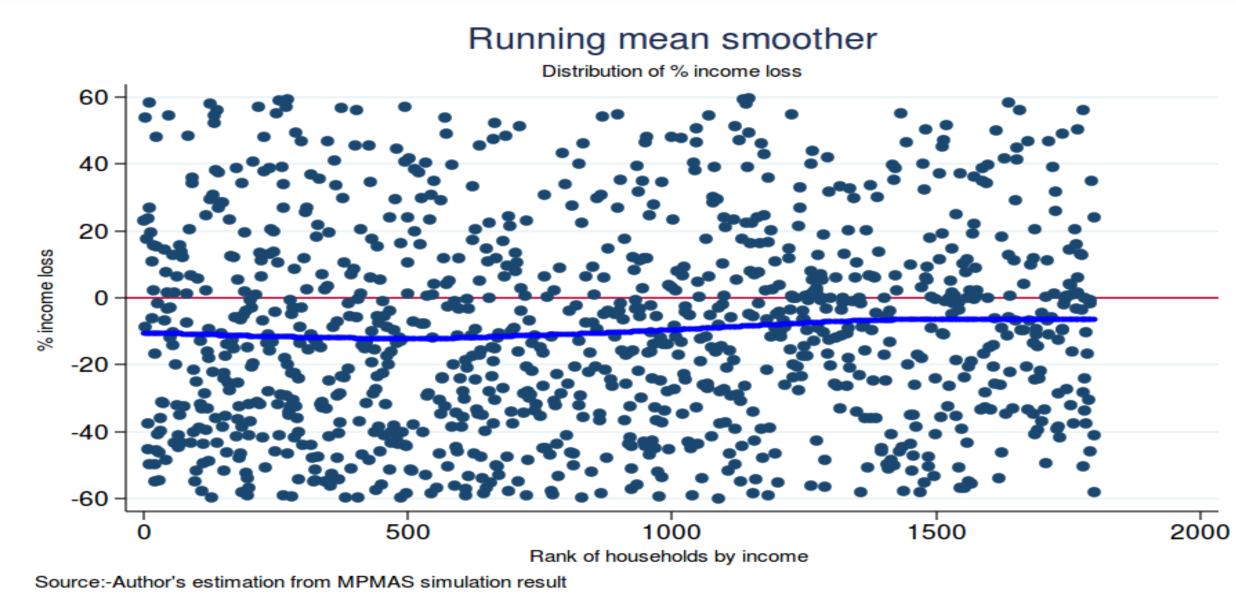


Fig. 5.5 Distribution of percentage income loss by agents due to rainfall variability



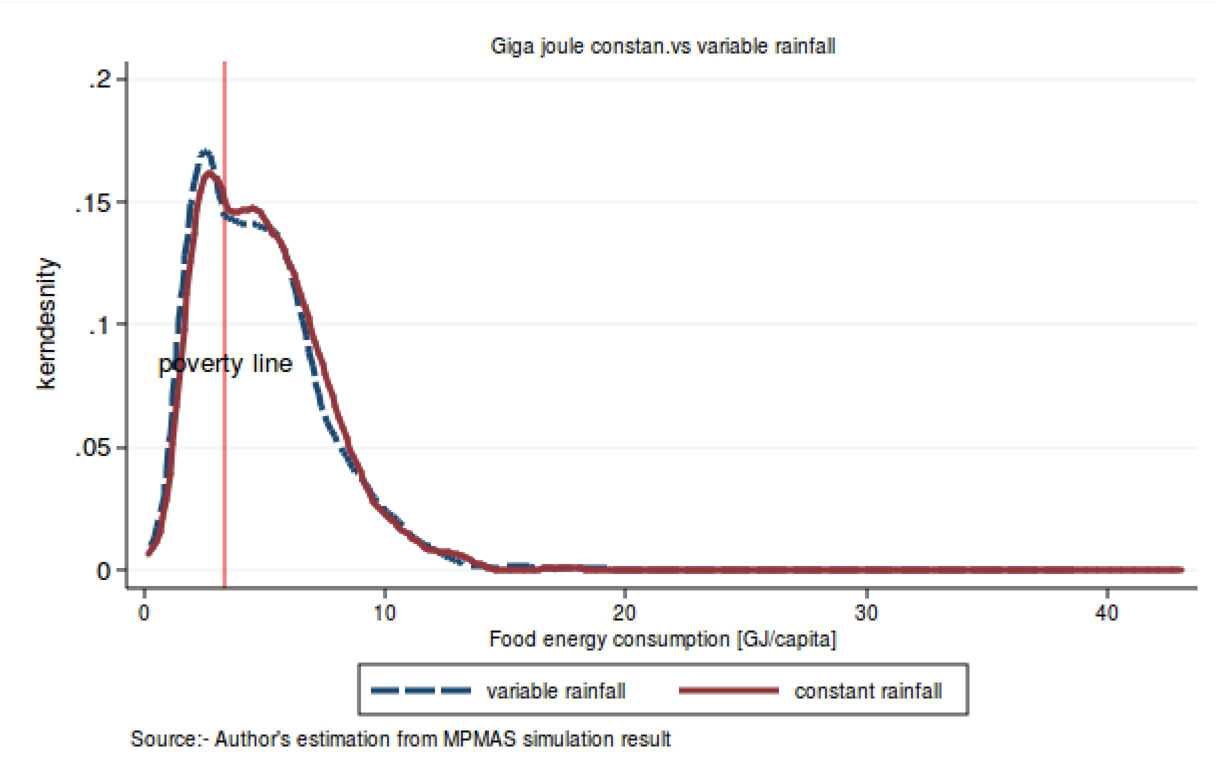
Note: percentage income change is computed by subtracting income with variable rainfall from that of constant rainfall and dividing the result for income under constant rainfall.

Fig. 5.5 presents the distribution of percentage income loss for the entire sample. Each point on the graph represents an income loss due to rainfall variability for each household. More points lie below the red line, indicating that the negative effect of rainfall variability on income outweighs its positive effects. Although, both richer and poorer households affected negatively by rainfall variability, the proportion of poor who lose income under rainfall variability is higher than that of their richer counterparts.

5.4.2. Effect of rainfall variability on food consumption and poverty

Fig. 5.6 presents the kernel density distribution of household food consumption under constant and variable rainfall distribution. Rainfall variability disproportionately affects poor households. As can be seen from the figure, more people will fall below the poverty line with rainfall variability compared with constant rainfall.

Fig. 5.6 Distribution of food consumption (giga joule per capita) over rainfall scenarios



Source: -Author's estimation from MP-MAS simulation experiment, 2013; Note: Vertical red line is the national poverty line, placed at, 3.36 giga joules per capita on the x-axis.

Table 5.3 Effects of rainfall variability on simulated income across four income quartiles [a]

Income quartile	% change [b]	TLU [c]	Household size [d]	Labor (MD)	Land size (ha)
Quartile 1	-24.83	0.42	8.42	1490	2.72
Quartile 2	-12.32	1.03	8.78	1496	2.52
Quartile 3	-6.61	1.99	9.03	2291	2.75
Quartile 4	5.78	8.41	10.57	4790	2.32
Total	-9.51	3.03	9.22	2557	2.58

Source: -Author's estimation from MP-MAS simulation experiment, 2013; [a] Model agents are categorized into four income quartiles based on simulated income; [b] percentage changes are from income with constant rainfall; [c] is Tropical Livestock Unit.; [d] in person.

Assessment of asset endowment differences and the percentage mean income effect of rainfall variability on different income class of households are presented in Table 5.3. The second column of the table clarifies that rainfall variability reduces the income for the majority of households. Except for the fourth income quartile, all income groups of households affected negatively by rainfall variability. The severity of the effects of rainfall variability declines with income level and becomes positive at the fourth income quartile. The first income quartile of households faces about 25% income loss due to rainfall variability; similarly, the second and the third income quartiles give up about 12% and 7% of the income under rainfall variability, respectively. However, the income of households in the fourth quartile increased under variable rainfall scenario. This might be explained by the fact that richer households have the capacity to adjust their farming techniques and the possibility to engage in non-agricultural sectors and generate more income from non-farm activities. As can be seen from Table 5.3, richer households have better resource endowments compared with poorer ones. Households in the highest income quartile were found to have larger asset endowments, including livestock, labor, and land, than households in the lower income quartile. For instance, households in the fourth income quartile have four and eight times more tropical livestock unit (TLU) than households in the third and the second income quartiles, respectively. Similarly, family labor in the fourth quartile is more than triple than that of households in the first quartile. There is no significant difference among different income quartiles regarding the number of family members and land size. In general a larger household size is observed in the study area, as the demographic nature of the area is characterized by high population density and fertility rates, resulting in increased demand for food, which must be mostly derived from the agricultural sector.

The difference in asset endowments might explain the difference in response to rainfall variability among income quartiles. Better off households are in a position to increase their herd size by purchasing livestock, with lower price from poorer households during variable rainfall and selling back at a higher price when the rainfall is good. Moreover, households with higher income increase propensity to save as caution and invest in non-agricultural sector, thus increase their income (Van de Steeg, J. et. al, 2013). These generate net positive income for the better off households from rainfall variability.

Table 5.4 Estimation of the effects of rainfall variability on household welfare

Parameters	Constant rainfall	Variable rainfall	% difference
Income (10,000'ETB/year)	3.54	3.44	2.82***
Giga joule per capita	5.05	4.87	3.41***
Poverty incidence (%)	33.82	36.99	-9.37***
Poverty gap (%)	10.53	12.38	-17.52***
Severity of poverty (%)	4.36	5.47	-25.20***

*Source: Author's estimation from MP-MAS simulation experiment, 2013, Note: - Mean percentage difference significance is computed by using paired t-test using STATA 12.04. ***, **, *, are significant at 1%, 5% and 10% level of error respectively.*

Table 5.4 reports the estimated coefficients from the simulation model of the effects of rainfall variability on household income, food consumption (Giga joule per capita), and poverty. The results suggest that rainfall variability significantly reduces household income and worsen the poverty situation. Moreover, annual household incomes decline by about 3% with rainfall variability. Similarly, rainfall variability resulted in about a 3% decline in food consumption. The decrease in income and food consumption has a primarily negative effect on the household poverty level. All aspects of poverty are found to increase with variable rainfall in comparison with constant rainfall, which means that rainfall variability increases the proportion of people falling below the poverty line. For instance, poverty incidence, the poverty gap, and poverty severity increased by about 9%, 18%, and 25%, respectively. Thus, rainfall variability not only affects headcount poverty, but also the distribution of poverty among the poor.

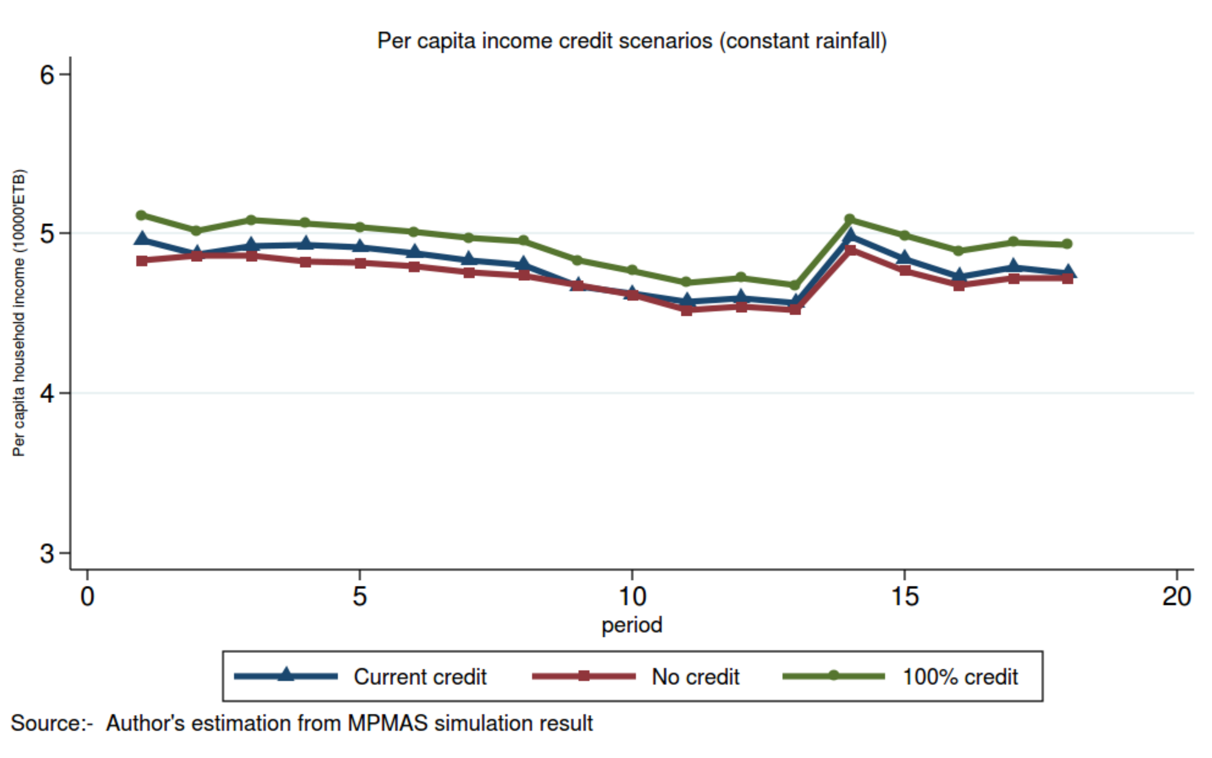
5.5. The role of rainfall variability adaptation strategies and access to credit

In this study, three major adaptation strategies (non-farm, irrigation, and SWC (soil and water conservation)) and access to credit have been identified, as a solution to mitigate rainfall variability effects (for a detailed explanation of the adaptation strategies and their implementation in MP-MAS see Chapter 3 of this thesis). The following section discusses the role of different adaptation strategies and access to credit on household income, poverty, and consumption under constant and variable rainfall. On the other hand, these are the policy interventions that have to be implemented by local governments to mitigate rainfall variability effects. The policy interventions include easing the financial constraint that farmers face by facilitating credit access and availability, improving access to non-farm activities, improving irrigation infrastructure and agriculture for smallholder farmers, and increasing awareness of water and soil conservation activities.

5.5.1. The role of access to credit on welfare baseline scenario

In this simulation analysis, three credit scenarios have been constructed. Namely, the current credit scenario, which assumes current credit access continue in the future too; the no credit scenario, where all households denied access to credit; and the full credit access scenario, where all households have access to credit whether they choose to take credit or not. The dynamics of household per capita income over the simulation period for the three credit scenarios are presented in Fig. 5.7. The figure shows that the dynamics of per capita income does not vary from period to period based on the credit scenarios. The simulation results further showed that in fifteen out of eighteen simulation periods, simulated per capita income under the current credit scenario (the blue line in Fig. 5.7) is above the per capita income without access to credit (the red line in the figure). However, if all households obtain access to credit, per capita income (the green line in the figure) will be, by far, greater than the per capita income under the current or no credit scenario. A closer look at the gap between the lines over the simulation periods suggests that if the current credit scenario prevails in the future, it will not bring any significant additional change in per capita income than if there were no access to credit. Nevertheless, improving credit access to the full potential will bring a significant change in per capita income under constant rainfall.

Fig. 5.7 Dynamics of per capita income over credit scenarios



Note: Income with current credit assumes base credit; income with no (100%) credit is average income, assuming no (full), respectively, credit access for households. All income is based on constant rainfall state.

5.5.2. The role of access to credit on food consumption constant rainfall

In this section, the percentage change in food consumption for different credit scenarios is computed assuming constant rainfall. Analysis of the simulated food consumption over the three credit scenarios considering constant rainfall indicated that per capita food consumption under the full credit access scenario is 3.80% and 5.61% higher than that under the current credit and no credit scenarios[6], respectively. On the other hand, food consumption with current credit is 1.89% higher and 3.95% lower than that of no credit and full credit scenarios, respectively. The distribution of food consumption in Fig.5.8 substantiates the argument that credit has a positive effect on the food consumption of households under constant rainfall. Furthermore, the graph

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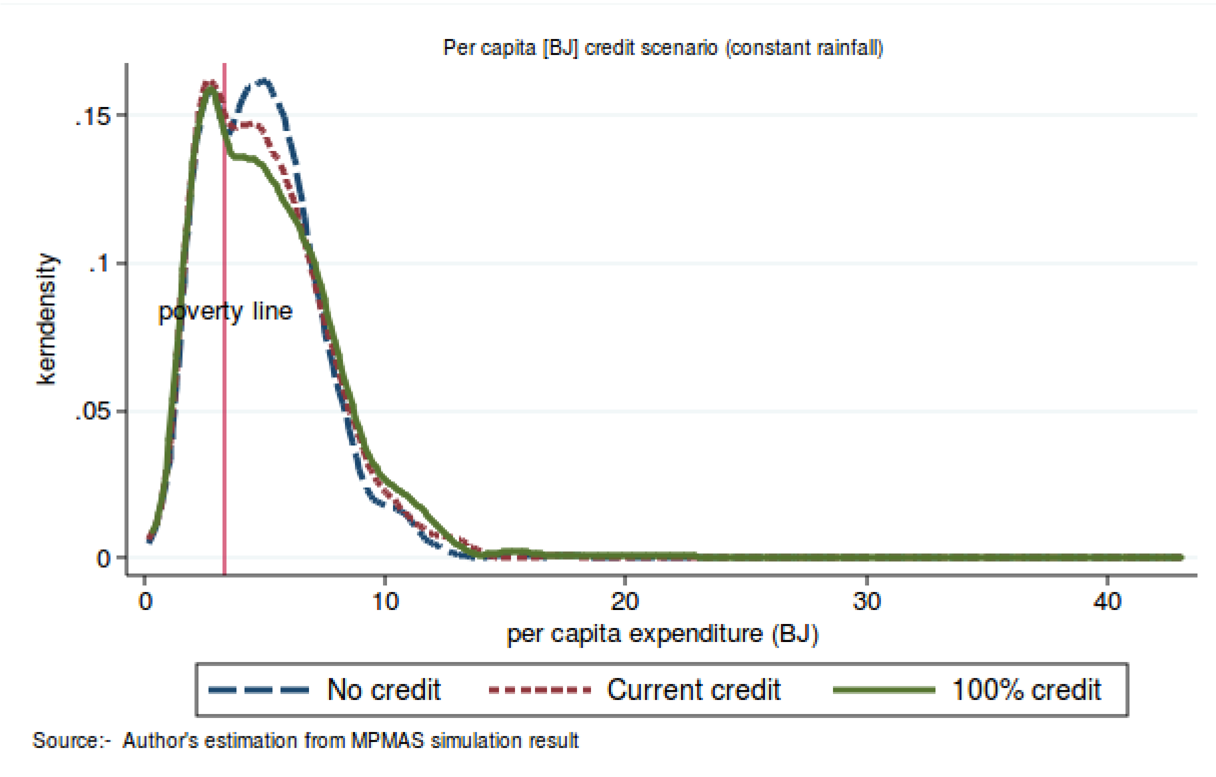
[6] The result table is not shown here.

depicts that the poorest households might not benefit from the credit.

Fig. 5.8 Distribution of food consumption over three credit scenarios



Note: Vertical red line is the national poverty line, placed at 3.36 giga joule per capita on the x-axis.

5.5.3. The role of access to credit on welfare under variable rainfall

The previous section discussed the role of credit on household income and food consumption under constant rainfall. However, the role of credit might be constrained by rainfall variability. Improving financial constraints by providing better credit access to rural households increase the adaptation capacity of households against rainfall variability and improve their livelihood. Simulation results from a combination of the rainfall variability and credit scenarios are presented in Table 5.5. Scenarios 1-3 (SCC, SCC0, and SCC100) are constructed by changing credit access from zero to full credit while keeping rainfall at a constant level in the simulation model. Similarly, scenarios 4-6 (SVC, SVC0, and SVC100) are constructed by taking average values of thirty variable rainfall simulation runs with changing credit access. Both groups of scenarios were based on the average of eighteen simulation periods. The percentage change in income is computed by taking the "current credit and constant rainfall (SCC)" as a baseline credit scenario and calculating the deviation of each scenario from this value. Except for the "full credit access with constant rainfall scenario (SCC100)", all other scenarios have lower income compared to the baseline scenario. Assuming credit access and other variables at current levels, rainfall variability was found to reduce simulated household income by 2.54%.

Table 5.5 Income estimates under credit and rainfall scenarios

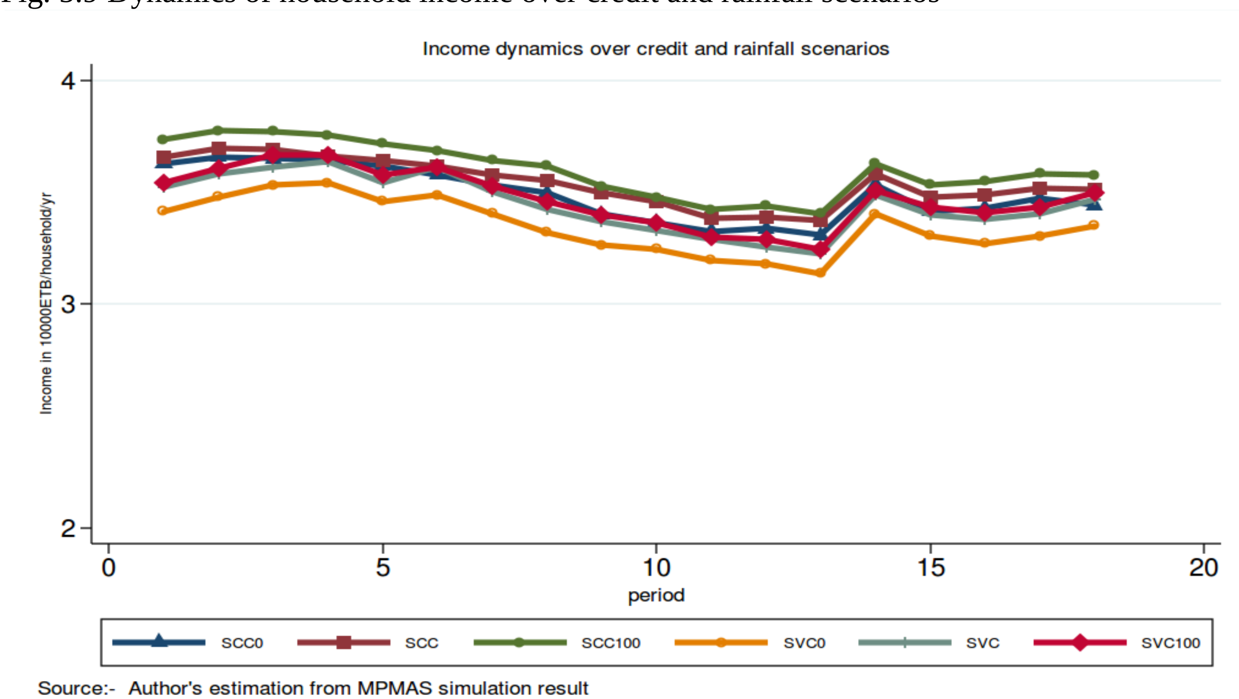
No	Scenario name	Rainfall	Credit	Income	% change [a]
1	SCC	Constant	current	3.54	0.00
2	SCC0	Constant	no	3.49	-1.41
3	SCC100	constant	all	3.61	1.69
4	SVC	variable	current	3.45	-2.54
5	SVC0	Variable	no	3.35	-5.37
6	SVC100	Variable	all	3.47	-1.98

Source: Author's estimation from MP-MAS simulation experiment, 2013; [a] percentage changes are from the base (SCC) scenario; Note: SCC (constant rainfall and current credit); SCC0 (constant rainfall without credit); SCC100 (constant rainfall with full credit); SVC (variable rainfall and current credit); SVC0 (variable rainfall without credit); SVC100 (variable rainfall with full credit; income is in 10,000 Ethiopian ETB.

The highest income loss, due to rainfall variability is registered, when rainfall variability is associated with no credit access, i.e. the "no credit and variable rainfall (SVC0)" scenario. Income in SVC0 scenario is 5.37% lower than that of the baseline scenario. When compared with the constant rainfall scenario, rainfall variability resulted in reduced income even under full access to credit. However, when comparing income under the variable rainfall scenarios based on credit levels, credit improves household income. Household income in the SVC0 scenario is 2.89% lower than the income in SVC scenario. However, full access to credit does not significantly improve income under variable rainfall. Income under the SVC100 scenario is only 0.58% higher than the income under SVC scenario. This implies that under variable rainfall, credit will not significantly improve the adaptation capacity of households. It is clear from this simulation results that household income is considerably threatened by rainfall variability. The negative effects of rainfall variability dramatically increase under no credit scenario. Moreover, credit has a more significant positive effect on income under constant rainfall than under variable rainfall. The dynamic distribution of income for scenarios of different rainfall and credit combination is presented in Fig.

5.9. The figure depicts that income under full credit and constant rainfall, line SCC100, lay above all other income lines throughout the simulation periods. Furthermore, the graph indicated that the income line with no credit and variable rainfall, line SVC0, lays far below all other income lines. This is because rainfall variability affects household income unless some coping mechanisms, such as investment in the non-agricultural sector or additional income generating activities are implemented, which need the financial support provided through credit. Moreover, there is no clear difference in income dynamics between "current credit and variable rainfall" and "full credit and variable rainfall" scenarios. As evident from the gaps between the lines, credit has a momentous role in improving household welfare in the first five simulation periods.

Fig. 5.9 Dynamics of household income over credit and rainfall scenarios

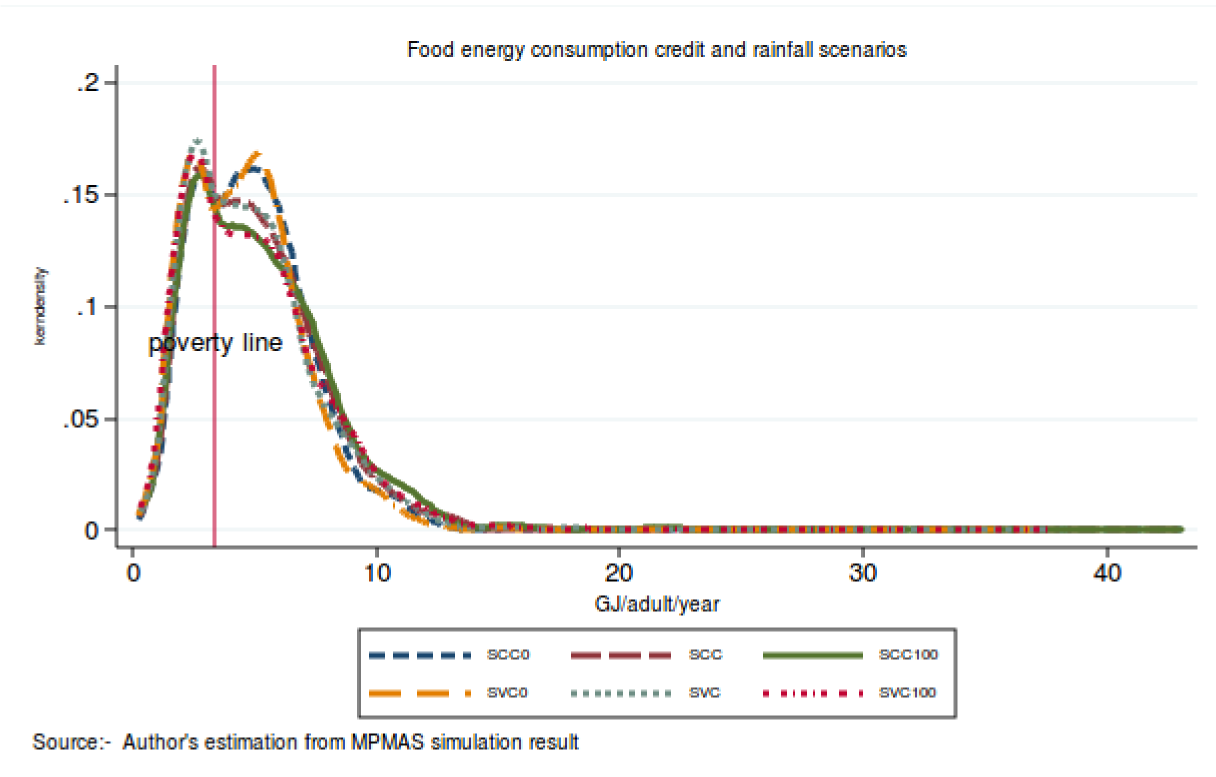


Note: SCC (constant rainfall and current credit); SCC0 (constant rainfall without credit); SCC100 (constant rainfall with full credit); SVC (variable rainfall and current credit); SVC0 (variable rainfall without credit); SVC100 (variable rainfall with full credit)

5.5.4. Rainfall variability, food consumption and access to credit

Reducing food consumption in quality and quantity, purchasing additional food, and consuming different food items are among the many coping strategies that households pursue against rainfall variability. However, a lack of financial capacity is the main limiting factor in times of climate shocks. Thus, it is not surprising that by easing the financial constraints, access to credit improves the food consumption of households. Therefore, access to credit is the most important factor in terms of increasing the coping ability of farm households in the face of rainfall variability. Fig. 5.10 indicates that increasing access to credit to its fullest potential increases food consumption.

Fig. 5.10 Distribution of food consumption over credit and rainfall scenarios



Note: SCC (constant rainfall and current credit); SCC0 (constant rainfall without credit); SCC100 (constant rainfall with full credit); SVC (variable rainfall and current credit); SVC0 (variable rainfall without credit); SVC100 (variable rainfall with full credit.

Fig. 5.10 indicates that under no access to credit scenario, the proportion of people living below the poverty line increases confound by rainfall variability. Moreover, rainfall variability triggers welfare losses by increasing the risk of poverty and widening income inequality. The simulation analysis found that rainfall variability generally increases household welfare losses. Accordingly, headcount poverty, the poverty gap, and poverty severity increase from current levels[7] of 33.82%, 10.53% and 4.36% to 36.99%, 12.38 % and 5.47%, respectively, with under rainfall variability and current credit. The poverty effects of rainfall variability are strongest under the no credit access scenario.

5.5.5. The role of non-farm activity in mitigating rainfall variability

One of policy interventions for mitigating the adverse effects of rainfall variability is increasing access to non-farm activities and improving the marketing system for the produce. Non-farm activities, such as carpentry, shopping, petty trade, and working on handcrafts, generate additional income for households (see appendices C). Moreover, these activities are less likely to be affected by rainfall variability. Thus, they improve the resilience of farm households in the face of rainfall variability. In the MP-MAS simulation model, the role of non-farm activities was estimated by providing agents with an option to work on non-farm activities parallel to farming activities. This involves re-allocation of family labor between farm and non-farm activities within the model. Households only allocate labor for non-farm activities if the labor return of non-farm is greater than that of farming activities.

[7] See column 2 of table 5.4

Table 5.6 The role of non-farm activities on welfare under constant and variable rainfall

Variables	List of credit and rainfall combination scenarios					
	SCC	SCCN	SCC100N	SVC	SVCN	SVC100N
Average Income (10,000'ETB/year)	3.54	3.56	3.61	3.45	3.43	3.60
Food consumption (GJ/capita)	5.05	5.06	5.13	4.88	4.81	4.86
Headcount poverty (%)	33.82	33.53	33.34	36.99	36.71	36.47
Poverty gap (%)	10.54	10.47	10.25	12.32	11.97	11.71
Squared poverty gap (%)	4.37	4.36	4.28	5.43	5.35	5.30

Source: Author's estimation from MP-MAS simulation experiment, 2013; Note: The figures are averaged over eighteen simulation periods and runs; SCC (constant rainfall and current credit); SCCN (constant rainfall with the current credit and non-farm); SCC100N (constant rainfall with full credit and non-farm); SVC (variable rainfall and current credit); SVCN (variable rainfall with the current credit and non-farm); SVC100N (variable rainfall with full credit and non-farm).

Table 5.6 reports the simulated income, food consumption, and poverty for a combination of rainfall, credit, and non-farm scenarios. Noticeable variation in household income is found under different combinations of rainfall and policy interventions. The results suggest that providing a combination of policy options for farm households increases their resilience against rainfall variability and hence improves welfare. In the previous section, it was noted that credit has a limited role in compensating the income loss due to rainfall variability unless it is accompanied by additional income generating activities. Providing access to non-farm activities and the required finance through credit access encourages households to invest in non-farm, and climate proof enterprises, hence diversify their income sources and subsequently increase adaptive capacity against rainfall variability. The results in Table 5.6 indicate that compared to the baseline scenario, SCC, providing households with access to additional income generating (non-farm) activity increases income. Furthermore, the results show that under constant rainfall, providing access to non-farm increases household income by 1% and 2%, for current and full credit access, respectively. Improving access to non-farm activities with credit increases income and improve poverty. For instance, under variable rainfall, access to non-farm activity with credit increases income by 5%, from 3.45 to 3.60 (ten thousands of ETB). This further highlights that access to non-farm activity mitigates the adverse effects of rainfall variability if accompanied by full access to credit. Thus, even under the variable rainfall scenario, when accompanied by a full credit access to non-farm activity reduces headcount poverty by 1%, from 36.99% to 36.47%. This might happen concurrently with the improved financial capacity to take on non-farm activity in the presence of rainfall shock, which buffers farmers against the expected income loss due to crop failure. Moreover, rainfall variability induces losses of income and productivity, which challenges the effectiveness of credit and non-farm activities, by forcing households to use the credit for basic consumption rather than investing in non-farm productive assets. The weak contribution of non-farm activity towards poverty reduction might be explained by the fact that, access to non-farm activity fuels up income inequality. Due to the existence of entry barriers (land, labor, finance) to non-farm activities; access to non-farm activity may have a disproportionate impact on poor households, favoring those households who are already better off (Barrett et al 2001; Escobal 2001). Thus, access to non-farm activities alone might not significantly improve the poverty situation under variable rainfall. From the estimates of poverty gap and its square, it is further evident that access to non-farm activities slightly improves poverty.

5.5.6. Rainfall variability, adaptation strategies and income inequality

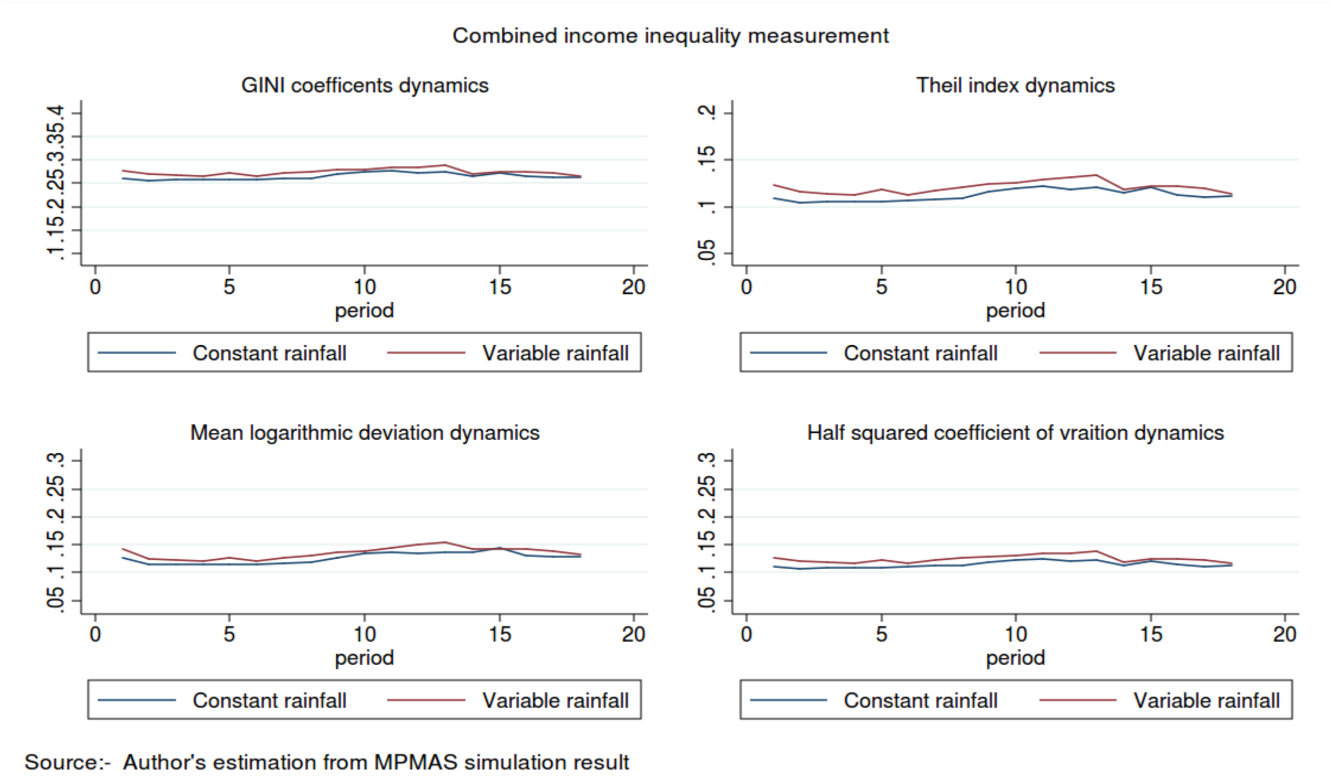
This study makes use of four measures of income inequality between variable and constant rainfall scenarios; namely a general entropy index, half mean logarithmic deviation, Theil index, and Gini coefficients. The estimation results of these measures are presented in Table 5.7. To investigate income disparity between households for the two rainfall scenarios (constant and variable) a general entropy index (GE) was employed. This index measures the degree of redundancy in income data which can be viewed as how income is distributed among households and whether the distribution is diversified, non-random, and compressible or segregate (Schutz 1951; Atkinson 1970; Jenkins 1995). GE measures the sensitivity of income inequality in different tails of the income. The more positive (negative) the value of $\propto$ is, the more sensitive the GE ($\propto$), where $\propto$ equals -1, 0, 1, 2, is to the income differences at the top (bottom) of the distribution (Atkinson 1970). Irrespective of the method used to assess income inequality among the households with and without rainfall variability, it is indicated that rainfall variability increases income disparity. Considering the mean logarithmic deviation of income GE (0) as a measure of income inequality, income disparity increases by 7%, from 12.7% without rainfall variability to 13.6% with rainfall variability. Moreover, the Theil's entropy index, GE (1), indicates that income disparity increases from, 11.27%, without rainfall variability to 12.12%, with rainfall variability (about an 8%) increase in income inequality. Similarly, the GE (2) measure shows that income with rainfall variability is about 9% more diversified than income without rainfall variability. The most popular and widely used measure of income inequality in literature (Atkinson 1970), the Gini coefficient, shows that income inequality increases from 26.54% without rainfall variability to 27.49% with rainfall variability.

Table 5.7 Income inequality with and without rainfall variability general entropy estimation

	1000 (GE ()) [a]			
	Aggregate	Constant	Variable	% Difference
	General entropy indices GE(∝)			
GE(0)	131.65	126.79	136.18	7.41
GE(1)	117.06	112.74	121.19	7.50
GE(2)	119.99	114.94	125.00	8.75
GINI	270.36	265.38	274.94	3.60
	Atkinson indices A(∝)			
A(0.5)	105.21	98.55	105.44	6.99
A(1)	223.57	212.04	223.95	5.62
A(2)	997.11	997.58	997.09	-0.05

Source: Author's estimation from MP-MAS simulation experiment, 2013; GE (0), mean logarithmic deviation (MLD); GE (1), Theil index; GE (2), half square coefficient of variation; GINI, Gini coefficient. The, indices were computed with ineqdeco command in STATA 12; [a] GE (∝)'s are multiplied by 1000 to increase decimal place and improved comparisons.

Fig. 5.11 Combined graphs of income inequality over different inequality measures



Source: Author's estimation from MP-MAS simulation experiment, 2013; GE (0); Each graph is based on the measures of the income inequality dynamics over simulation periods compared between hypothetically constant and current variable rainfall scenario for each measure of income inequality.

The Atkinson measure of inequality shows closely comparable inequality estimates with the previously used approaches. In this measure too, rainfall variability appeared to be an important determinant of income inequality. Rainfall variability is associated with higher income disparity compared with constant rainfall. The higher values of A (2) compared with A (0.5) or A (1), is an indicator of the sensitivity to income inequality at the bottom of the income distribution, in the other words the lowest income group. Atkinson inequality estimates show that income divergence increases by about 7% and 8% with rainfall variability, for the sensitivity parameters of 0.5 and 1, respectively. Estimates in the second column of the second panel of Table 5.7 show the income that is required to achieve equitable social welfare at present. For instance, a 0.11 for the sensitivity of A (0.5) suggests that the same level of social welfare could have been achieved by 89% of current income. Likewise, income inequality is more sensitive to lower income group and there is no significant difference in income due to rainfall variability at the bottom income classes. Furthermore, the dynamics of income inequality over simulation periods has shown a slight increase in income inequality. Fig. 5.11.reveals that in all measures of income inequality, income is more disperses with rainfall variability than without. Income inequality increases over simulation periods for Theil's entropy index and the mean logarithmic deviation measures of income inequality. The income disparity difference between with and without rainfall variability diminishes to zero in two scenarios in the fourteenth period. Generally, rainfall variability increases the loss of social welfare and increases income disparity among the households.

5.5.7. Income inequality under different rainfall variability adaptation strategies

To investigate the possible impacts of adaptation strategies on income inequality, the author has computed income inequality while considering different adaptation strategies. Achieving equitable income, while also minimizing the effects of rainfall variability is a primary goal of policy designers. Addressing income inequality is foremost important when rainfall variability is under consideration and its mitigation strategies were designed. In the previous section, it was indicated that rainfall variability increases income inequality compared with constant rainfall. Moreover, policy interventions that are meant to reduce the adverse effects of rainfall variability bring income inequality. The figures presented in Table 5.8 show the Gini coefficients and the Theil index of measure of income inequality estimates associated with different adaptation strategies. Estimation results show that six out of ten scenarios have higher Gini coefficients compared to the baseline scenario; this shows that any policy intervention to mitigate rainfall variability should be addressed in such a way that it will not aggravate income inequality. Introducing credit to all households under variable rainfall increases income inequality to 34.18% from 33.08% with current credit levels. However, if credit access is provided along with non-farm activities, income inequality is reduced to 32.64%. This is due to the fact that access to credit and non-farm activities encourage households to invest in non-farm enterprises and generate additional income, which further reduces income inequality among households. In MP-MAS access to non-farm activities are implemented as innovation, in a way that first access to non-farm activities generated from the survey data and access, probability presented for each of the household segments based on the survey data. Household decision to participate in a non - farm activity is determined by labor availability; the maximum number of person-days that can be allocated to non-farm activities are three. The return from working in non-farm activities is given as daily wage. Income derived from non-farm activities can be used to purchase agricultural inputs, food requirements and improve labor productivity for landless households and increase labor wages (Barrett et al 2001; Démurger et al 2010).

Table 5.8. Income inequality over adaptation scenarios

Code of scenario	Definition	Gini	Theil index
SCC	Current credit with constant rainfall (Base)	33.08	17.39
SVC	Current credit with variable rainfall	33.18	17.55
SCC0	No credit with constant rainfall	32.23	16.54
SVC0	No credit with variable rainfall	33.49	17.91
SCC100	100% credit with constant rainfall	33.02	17.34
SVC100	100% credit with variable rainfall	34.18	18.59
SCCN	Current credit, constant rainfall, and non-farm	32.77	17.03
SVCN	Current credit, variable rainfall, and non-farm	33.96	18.33
SCC100N	100% credit, constant rainfall and non-farm	32.64	16.91
SVC100N	100% credit, variable rainfall and non-farm	33.84	18.20

Source: -Author's estimation from MP-MAS simulation experiment, 2013. ; Note: SCC (constant rainfall and current credit). SVC (variable rainfall and current credit).SCC0 (constant rainfall without credit). SVC0 (variable rainfall without credit); SCC100 (constant rainfall with full credit); SVC100 (variable rainfall with full credit). SCCN (constant rainfall with current credit and non-farm). SVCN (variable rainfall with current credit and non-farm); SCC100N (constant rainfall with full credit and non-farm); SVC100N (variable rainfall with full and non-farm), SVC (variable rainfall with full credit and non-farm).

Access to credit under variable rainfall induces escalated income inequality. If variable rainfall is considered income inequality rises from 33.18% with current credit to 34.18% with full credit access. The 1% point increase in income inequality is attributed to the effects of rainfall variability, which reduces productivity and production of households by varying degrees depending on current income levels. The highest income inequality is registered for the scenario with full credit access and variable rainfall. The Theil index of inequality measure moves in the same direction as the Gini coefficient. Both measures show that income inequality is aggravated by the introduction of rainfall variability adaptation strategies; unless corrective mechanisms are implemented or integrated strategies are practiced.

5.5.8. The role of soil and water conservation and irrigation

Irrigation and soil and water conservation activities are the main rainfall variability adaptation strategies practiced by farm households in the study area. These strategies involve changing of traditional farming techniques. As was discussed in previous chapters of this thesis, there were different soil and water conservation activities performed in response to rainfall variability in the study area. Furthermore, some farmers practice small-scale irrigation. The role that these strategies play in mitigating rainfall variability effects is computed by analyzing welfare for households with and without such strategies under constant and variable rainfall. To do so, agents were classified into two groups: those who have access to irrigation and practice soil and water conservation activities and those without access. Yield premium is computed for each adaptation strategy, including operational cost. Table 5.9 reports the analysis of simulation results regarding the role of irrigation in improving welfare under constant and variable rainfall conditions. Households with access to irrigation have 27% and 3.96%, respectively, more income than house those without access to irrigation under constant and variable rainfall. The low contribution of irrigation to income under the variable rainfall scenario might be explained by the difference in resources other than irrigation between the two groups. Moreover, the results are average values of the bad and good rainfall years; the gain from irrigation under variable rainfall is not strong enough to compensate the loss in welfare due to rainfall variability.

Table 5.9 The role of irrigation in mitigating rainfall variability

	Irrigated agriculture			
	Constant rainfall		Variable rainfall	
Accessibility	No access	Access	No access	Access
Income (10,000'ETB/year)	3.03	3.84 (27%)	3.47	3.61 (4%)
Food expenditure (GJ/capita)	5.37	5.01	5.79	4.98
Headcount poverty (%)	38.69	32.43	28.57	35.52

Source: -Author's estimation from MP-MAS simulation experiment, 2013; Note: values in the table are the averaged figures over simulation periods and runs computed from the simulation results for households with access to irrigation and those without irrigation access.

Rainfall variability brings unstable yield and benefits. When the rain is favorable farmers decides to invest more on agriculture and expect higher returns. However, if they face low rainfall, crop yield declines, and poverty incidence increases. The other problem that arises when rainfall is variable is a fluctuation in irrigation water flows. Thus, rainfall variability affects the effectiveness of irrigation in responding to challenges induced by variability. Soil and water conservation activities were found to increase agricultural productivity by improving water availability and soil fertility. According to econometric analysis, soil and water conservation activities were found to increase crop yield on average by 15% and the per capita food consumption by about 48%. Compared to those who did not use soil and water conservation activities, households who practice soil and water conservation were found to have greater food consumption and less likely to be poor. This progress is achieved as a result of increased productivity and production through the use of soil and water conservation activities. In general, adaptation strategies have a positive effect on the welfare of households and increase resilience capacity.

5.6. Sensitivity analysis of the model results

Sensitivity analysis is performed to examine the responses of the model results to expected changes in external factors such as output (crop and livestock) prices, wage rates, rainfall and inputs (fertilizer and seed) prices. The objective of sensitivity testing is to check how agents react to shocks in external factors. Accordingly, the sensitivity of major parameters, such as simulated household income, per capita food consumption and poverty, is analyzed for the percentage changes in prices, rainfall and wage rate. For this purpose, simulation experiments are carried out under the constant rainfall scenario for different levels of positive and negative changes in external factors. The sensitivity of each of the three parameters (income, poverty and food consumption) is estimated at different levels of changes.

5.6.1. Sensitivity of simulation results to changes in output prices.

The selling and consuming of own produce are an important component of household wealth and food security. Thus, a fall in crop prices will influence the simulated poverty incidence depending on the current economic profile of households. An increase in crop prices increases the poverty incidence of net-buyers but decreases the probability of falling below the poverty line for net-sellers. In developing countries like Ethiopia, a large proportion of households are dependent on the agriculture sector, either as subsistence farmers or engaged in day labor work for their livelihoods. While complete dependence on the market for food security is a greater risk in the case of adverse economic, political or climate shocks (Isik-dikmelik 2008). Many households depend on the own production of staple crops. In this simulation analysis, households are classified as net-buyer or net-sellers based on their livelihood profile. Correspondingly, households who sell more than they buy on the market are classified as net-sellers while those who buy more than they sell are classified as net-buyers. Those who sell the same amount of food as they buy are classified as self-sufficient households (WFP 2009; Ivanic & Martin 2008; Isik-dikmelik 2008). The classification of households into different livelihood profiles indicates that about 22% of households are net-sellers and 77% are net-buyers, and only 1% of the households are self-sufficient. Therefore, changes in output prices will have differential effects on household welfare, depending on whether the household is a net-seller or a net-buyer. Indeed, increased output prices are expected to improve the livelihood of net-seller households, but negatively affect net-buyers (Ivanic and Martin 2008). Simulated household headcount poverty estimates for percentage changes in output prices are presented in Table 5.10. The result suggests that increasing output prices are associated with increased poverty, and decreasing output prices resulted in a decrease in the poverty rate. For instance, a 50% decrease in output price from the base reduces the poverty incidence from 34% to 23%. Conversely, a 50% increase in output price from the base is associated with an eleven percentage point increase in headcount poverty. However, a 10% increase in output price does not alter the poverty incidence significantly, while, a 10% decrease resulted in 4-percentage point reduction in poverty. Similarly, per capita food consumption is inversely related to changes in output prices. In general, when output price increases (decreases) food consumption decreases (increases).

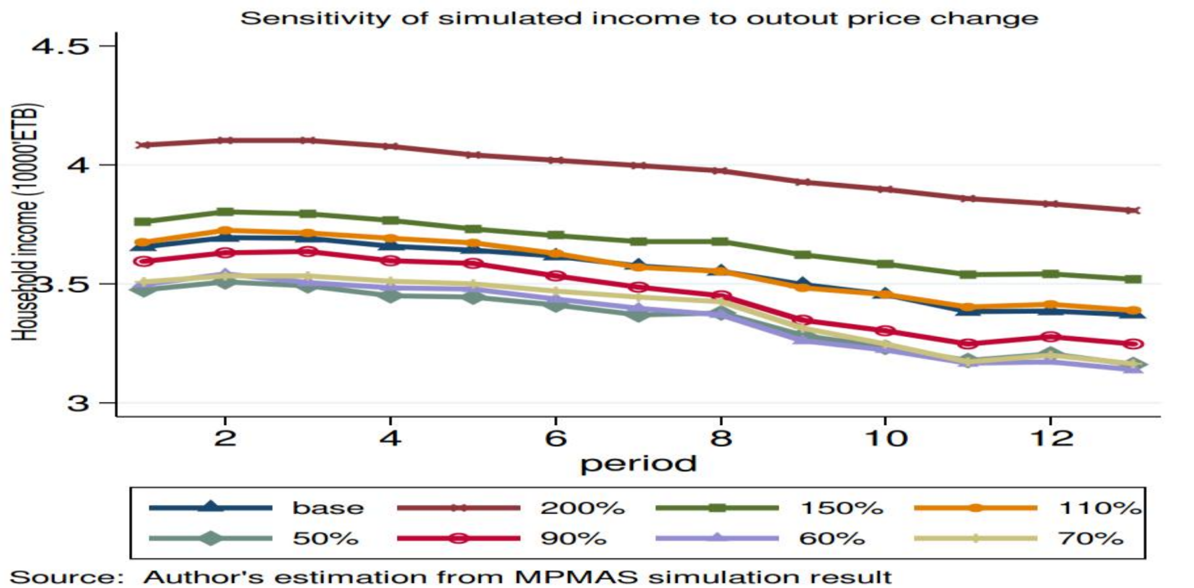
Table 5.10 Response of simulated poverty and food consumption to changes in output price

	Percentage changes in output prices							
Variables	Base	-50%	-30%	-10%	+10%	+30%	+50%	+100%
Poverty (%)	33.82	23.37	28.12	29.79	34.19	40.02	44.80	54.10
GJ/capita [a]	5.05	6.88	6.15	5.47	5.00	4.66	4.28	3.70

Source: Author's estimation from MP-MAS simulation experiment, 2013; Note: price changes are from the current price levels considering the constant level of rainfall. Here an output price represents the price of crops and livestock.
[a] GJ/capita is the Giga joule per capita food consumption of the households.

Fig. 5.12 presents the dynamics of simulated household income for percentage changes in output prices. It is indicated that increasing the output price by 100% from the current level resulted in higher income over the simulation periods compared with other price changes. A 10% increase in output prices does not bring significant changes in income compared with the base price. Similarly, 50% and 40% reductions in prices seem to have similar effects on simulated income.

Fig. 5.12 Income dynamics for changes in output prices over simulation periods



Note: Graph lines represent income dynamics simulated by changing the prices of outputs (crop and livestock) by a factor of 0.1, 0.3, 0.4, 0.5, and 1.

5.6.2. Sensitivity of simulation results to changes in rainfall

In the study area, rainfall shortage is one of the important factors that determines the crop production and, hence, household welfare. Household income changes as the rainfall changes, better rainfall resulted in better crop yields and increased income. After running the simulation experiments for the rainfall change scenarios, the study analyzed the sensitivity of household income, per capita food consumption, and poverty for ±5%, ±10%, ±15%, and ±20% changes in rainfall from the average value (baseline). Table 5.11 shows that the simulated income and per-capita food consumption generally increases (decreases) with increasing (decreasing) rainfall, respectively, while poverty goes in the opposite direction to changes in rainfall. This implies that the current level of average rainfall is below the average rainfall level required to achieve potential yield, and except for few crops, increasing rainfall increases crop yield and thereby improves household welfare. Specifically, the result indicates that simulated income and food consumption increase by about 3% and 10%, respectively, following a 20% increase in rainfall. On the other hand, poverty declines by six-percentage point, for a similar increase in rainfall from the mean rainfall.

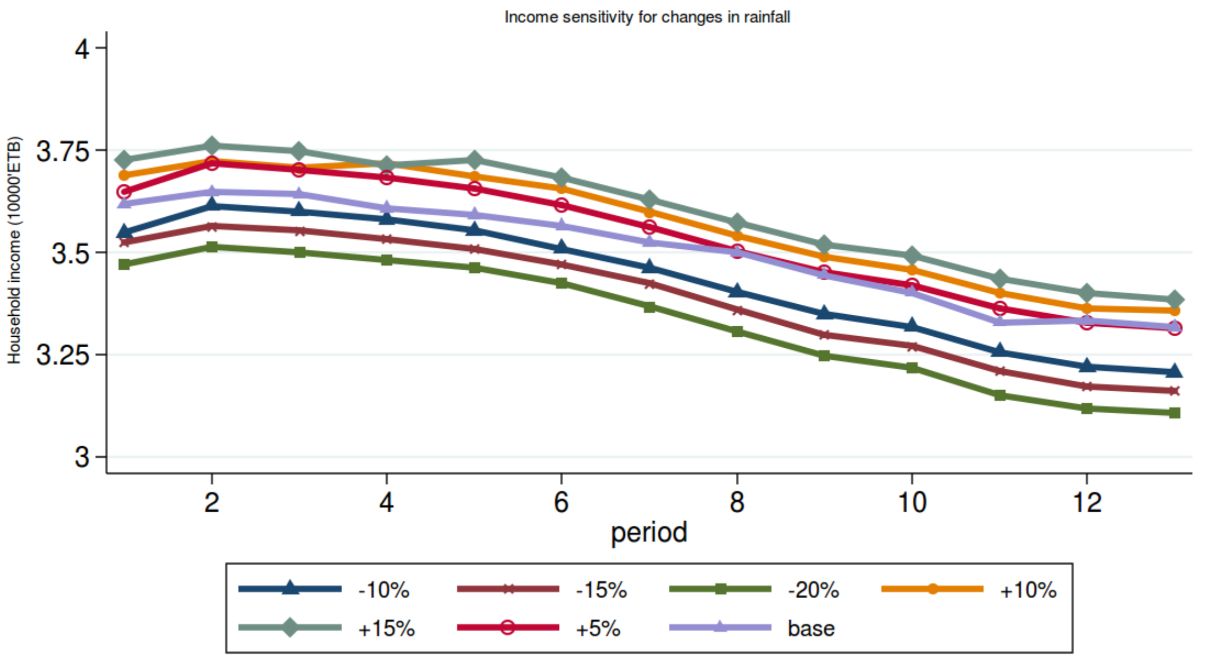
As evident from Table 5.11, a 20% reduction in rainfall from the mean value leads to about 15% and 5% decline in simulated household income and food consumption, respectively. On the other hand, 10% and 15% decrease in rainfall resulted in about 1% and 3% loss in per-capita food consumption, respectively; however, poverty increases by about two, and three percentage points for similar decreases in rainfall. All the aforementioned three parameters show significant shifts from the mean values for changes of 15% and above in rainfall. Nevertheless, income losses due to decreases in rainfall are greater than the gains from similar increases in rainfall. Furthermore, a 10% decrease in mean rainfall is associated with a 5% loss in simulated income and a 2-percentage point increase in headcount poverty. Dynamics of income sensitivity under different percentage changes in rainfall is presented in Fig. 5.13. Income under a 15% increase in rainfall always lay above incomes observed under other percentage increases in rainfall.

Table 5.11 Sensitivity of simulated results to percentage changes in rainfall

	% changes from the baseline		
Rainfall scenarios [d]	Income [a]	Expenditure [b]	Poverty [c]
Scenario-rainfal-20%	-15.35	-4.52	3.55
Scenario-rainfal-15%	-13.18	-2.59	2.70
Scenario-rainfal-10% [c]	-4.84	-1.41	1.8
Scenario-rainfal-5%	-0.18	-1.41	0.20
Scenario-rainfal+5% [c]	0.15	4.69	-1.35
Scenario-rainfal+10%	1.93	4.81	-2.27
Scenario-rainfal+15%	2.44	8.67	-5.04
Scenario-rainfal+20%	3.15	10.12	-5.97

Source: Author's estimation from MP-MAS simulation experiment, 2013; a: -percentage change from the baseline income; b: -percentage point change from the baseline; c: - an average of three simulation periods; [d] Simulation runs were done for each of the rainfall changes over eighteen periods.

Fig. 5.13 Dynamics of simulated income for percentage changes in rainfall over periods

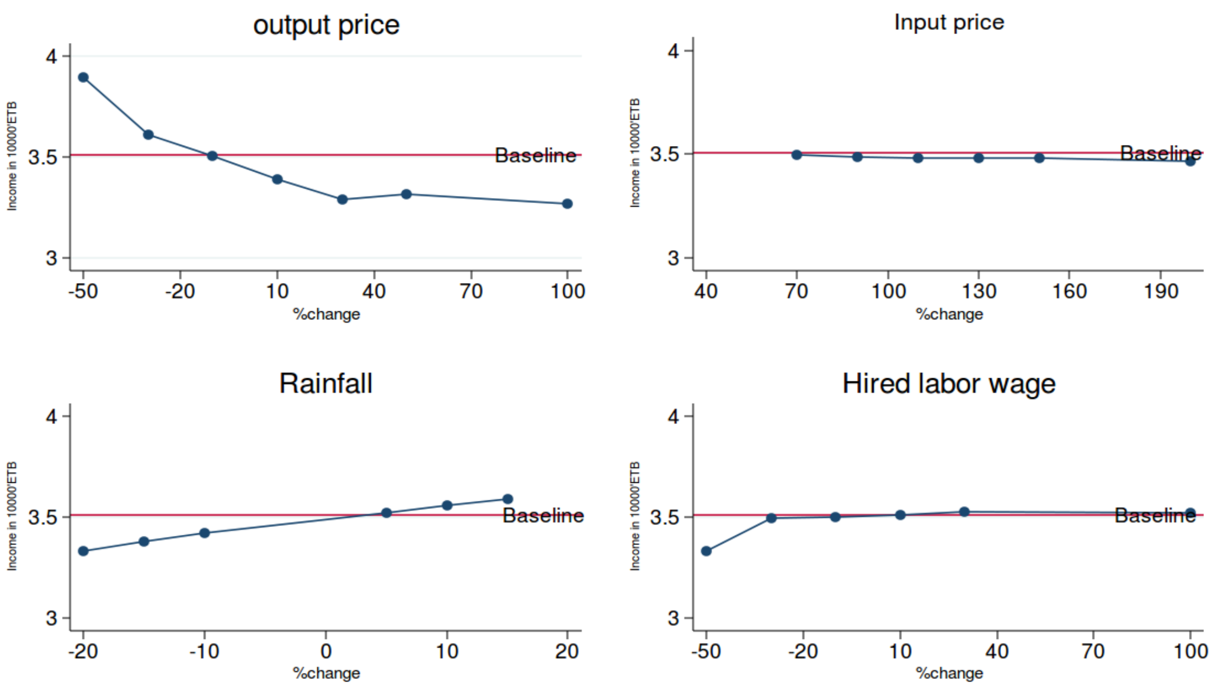


Source: Author's senstivity estimation from MPMAS simulation experiment

Note: The simulation results are averaged values for households for different runs based on the level of rainfall changes, changes are computed from the hypothetically constant rainfall values.

Fig. 5.14 presents a combined graph of simulated income sensitivity for changes in output prices, input prices, rainfall, and wage rates. Each portion of the figure shows the difference in income for each simulation scenario compared with the baseline scenario. Simulated income is directly related to changes in rainfall. As the current mean rainfall is not sufficient to achieve potential yield, increases in rainfall positively affect the yields of most crops, which in turn increases household income. Nevertheless, this is not a general truth for all levels of rainfall increases, at some point after the optimal rainfall, further increases in rainfall may reduce yield, and hence a quadratic relationship is expected between the two variables.

Fig. 5.14 Sensitivity of simulated income for changes in external factors



Source: Author's estimation from MPMAS sensitivity experiment

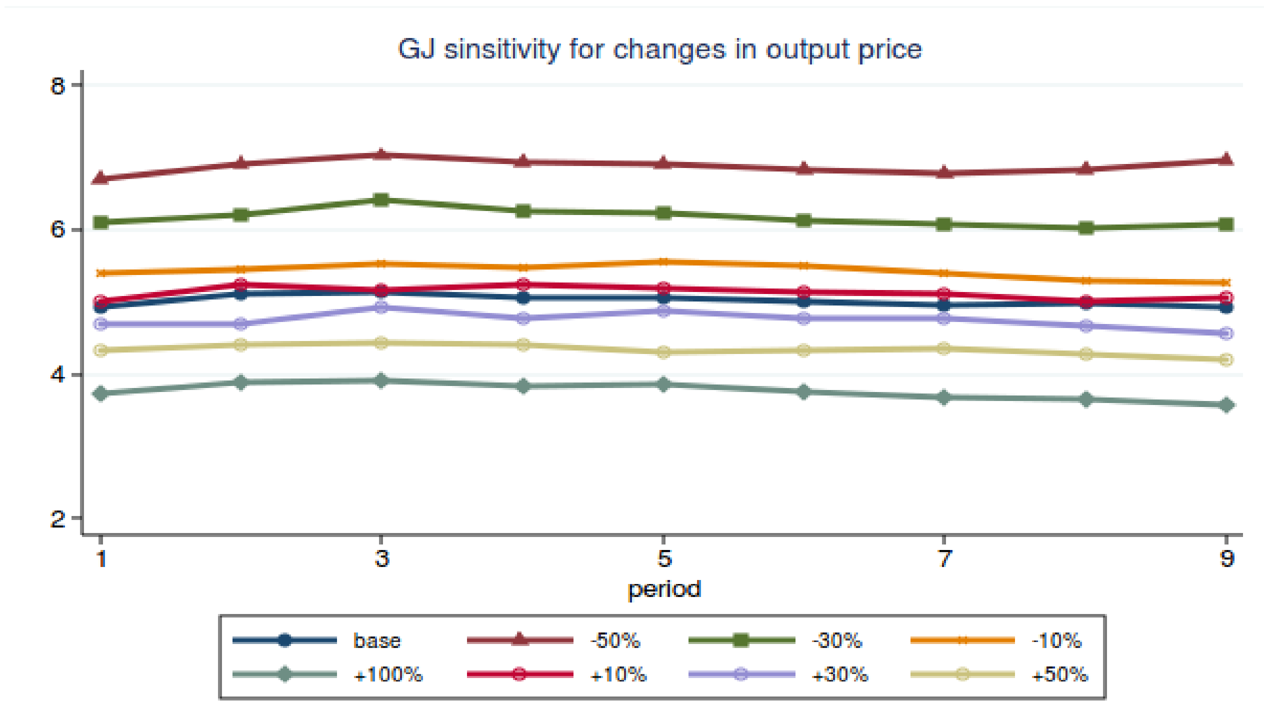
Note: The graph represents the income levels corresponding to changes in output price, input price, wage rate and rainfall.

On the other hand, simulated income is found to be insensitive to changes in input (fertilizer and seed) prices and the wage rates. The insensitivity of simulated income to changes in input prices is indirectly related to the insensitivity of crop yield for input uses. This is mainly explained by the low rate of input use by farm households in the study area and the possibility of growing crops without any improved technology. The other factor that might cause insensitivity of simulated income to increases in the wage rate is the availability of cheap family labor, which substitutes for hired labor when the wage rate goes up. Therefore, production and productivity of crop are only slightly influenced by input prices and wage rates, resulting in insensitivity in simulated household income.

5.6.2. Sensitivity of food consumption for changes in output price

The dynamics of the responses of food consumption to changes in output prices are presented in Fig. 5.15. Food consumption is one of the household welfare indicators that are likely to be affected by rainfall variability. When households face poor rainfall, respond by reducing food consumption, and when farmers face better rainfall, they increase their food consumption (Parry et al 1999). As can be seen from Table 5.11, food consumption moves in the same direction as rainfall change. Furthermore, Fig. 5.15 indicated that food consumption dynamics is consistent over simulation periods; a 50% reduction in output price resulted in higher food consumption while a 100% increase in the lowest food consumption level throughout the simulation periods. Compared with baseline a 10% increase in output price does not bring significant change in food consumption.

Fig. 5.15 Dynamics of per capita food consumption over simulation periods



Source: -Author estimation from MP-MAS simulation results, 2010;.Note: The simulation results are averaged values for households over different runs based on the level of rainfall changes, changes are computed from the hypothetically constant rainfall values.

Fig. 5.16 Sensitivity of food for changes in output price and rainfall

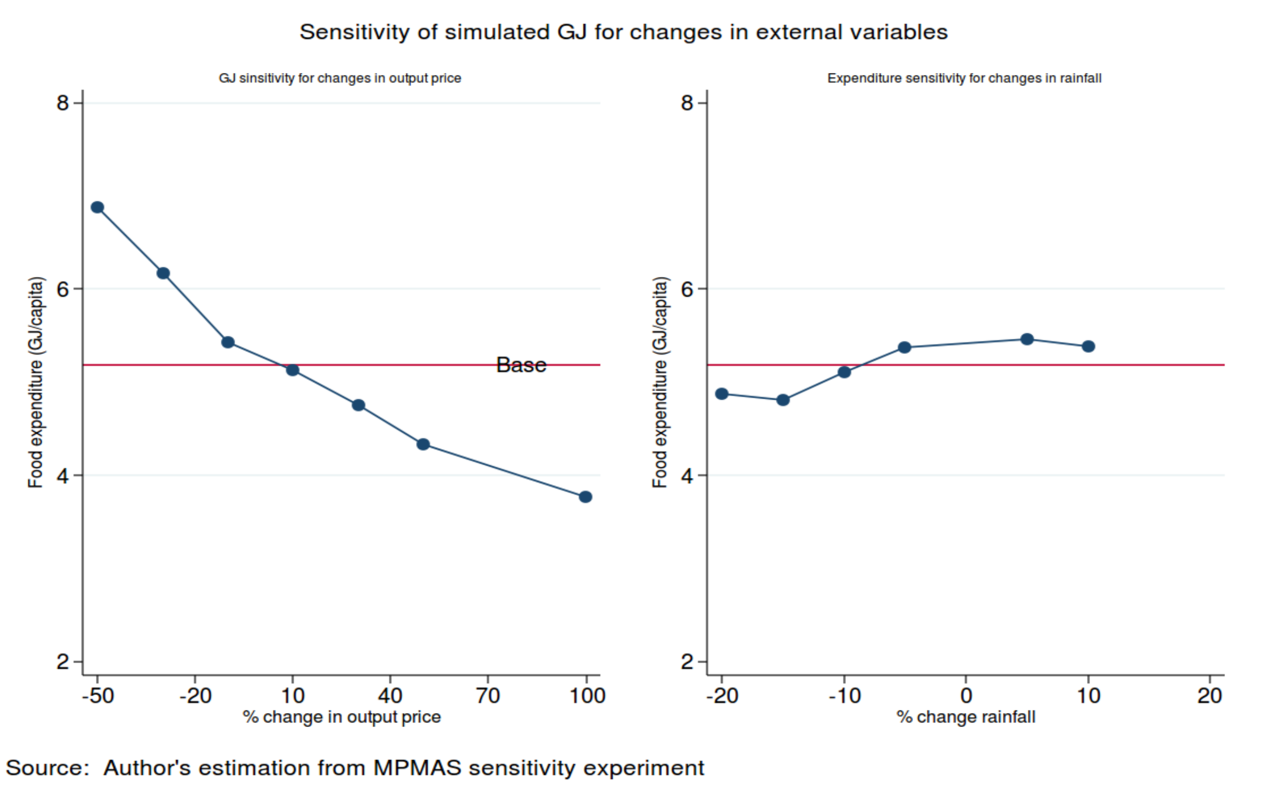


Fig. 5.16 shows a decline in household food consumption for changes in output prices. As stated in the previous section, the majority of households in the study area are net-food buyers; therefore, increasing output prices negatively affect food consumption. Thus, increased output prices are associated with a loss of household welfare. However, increases in rainfall amounts from mean values have steadily increasing effects on household food consumption. Generally, the sensitivity analysis of simulated model results (income, poverty, food consumption) confirmed that the results are in line with economic theory and replicates the real world situation. Simulated household income, poverty, and food consumption respond to changes in output prices, input prices, wage rates, and rainfall. Moreover, increases in output prices deteriorate the poverty situation of poor households. Increased amounts of rainfall from the average value are associated with increased income and reduced poverty incidence. Additionally, sensitivity analysis confirmed that income is insensitive to changes in wage rates and input prices, which sheds light on the importance of

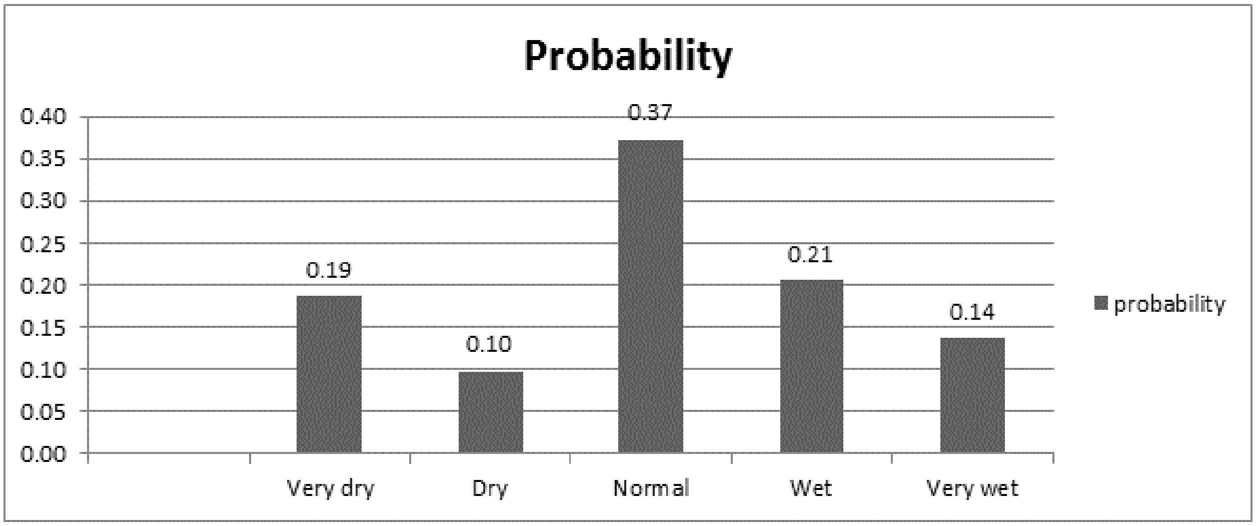
addressing the low level of agricultural input use in the study area to increase crop productivity and hence the welfare of households.

5.7. Analysis of the effects of future rainfall variability

Rainfall in Africa exhibits differing degrees of temporal variability (Hulme et al 2001). Unknown values of climate sensitivity, different predicted values from different climate projection models for future rainfall variability and the inherent unpredictability of climate make understanding and predicting future rainfall variability under climate change to be difficult for climate researchers in Africa (Hulme et al 2001). There has been relatively little work published on rainfall variability under future climate change in Africa. Some regions of Africa are expected to experience more severe extreme events while others may experience stable rainfall variability (Hulme et al 2001). Thus, the cause of decadal and multi-decadal rainfall variability remains uncertain. Considering B_1 low scenario in some equatorial east African countries, rainfall in December to February is expected to increase by 5 - 30%, while June to August rainfall is expected to decrease 5 - 10% (Hulme et al 2001). Moreover, with more rapid global warming scenarios (e.g. A_1 high), an increasing area of Africa would experience a significant change in rainfall variability. East Africa would experience a significant increase in December to February rainfall, up to 50 or 100%, while, the Horn of Africa and northwest Africa would experience a significant decrease in June to August rainfall. For Ethiopia, most of GCM generates the most extreme wetting scenarios (Hulme et al 2001). The reasons that make the prediction of future rainfall variability difficult are the exclusion of important determinants of future climate characteristics, such as changes in land cover, dust and biomass aerosol loading, the EL Ni‘no effects and the predication capability of most climate models (Hulme et al 2001). Therefore, simulating future rainfall variability under climate change is a challenging issue. Thus, it is recommended that focusing on the adaptation strategies for short-term climate change is most important in the African context. This study understands the importance of future rainfall variability on household welfare and attempts to gain insights by comparing the simulation results for current and future rainfall variability.

This section discusses the results of the analysis of future rainfall variability by considering different rainfall anomalies. Simulation results from MP-MAS are re-sampled to classify the simulation runs into five anomalies: namely very dry, dry, normal, wet, and very we: to examine the effects of future rainfall variability on the household welfare. The probability of anomaly is computed by using Standardized Anomaly Index (SAI) (equation 3.36). The probability distribution of rainfall anomalies is presented in the following figures.

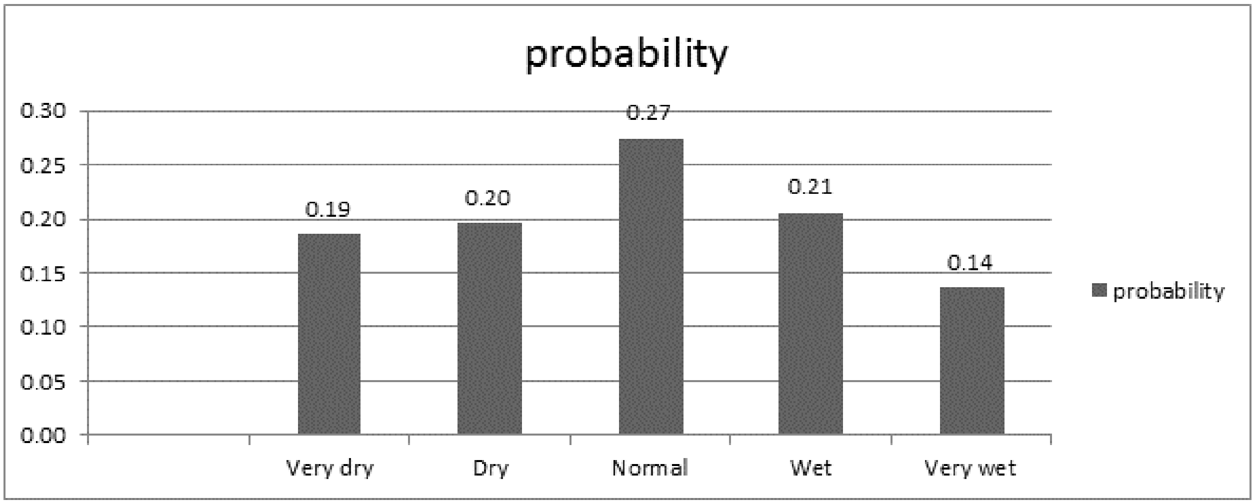
Fig. 5.17 Probability of anomaly current rainfall variability sequence for years 1974-2003



Source: Author's computation from the time series data of 1974-2003; Note: -Probabilities are computed by using equation 3.36 and classified based on SAI criterion.

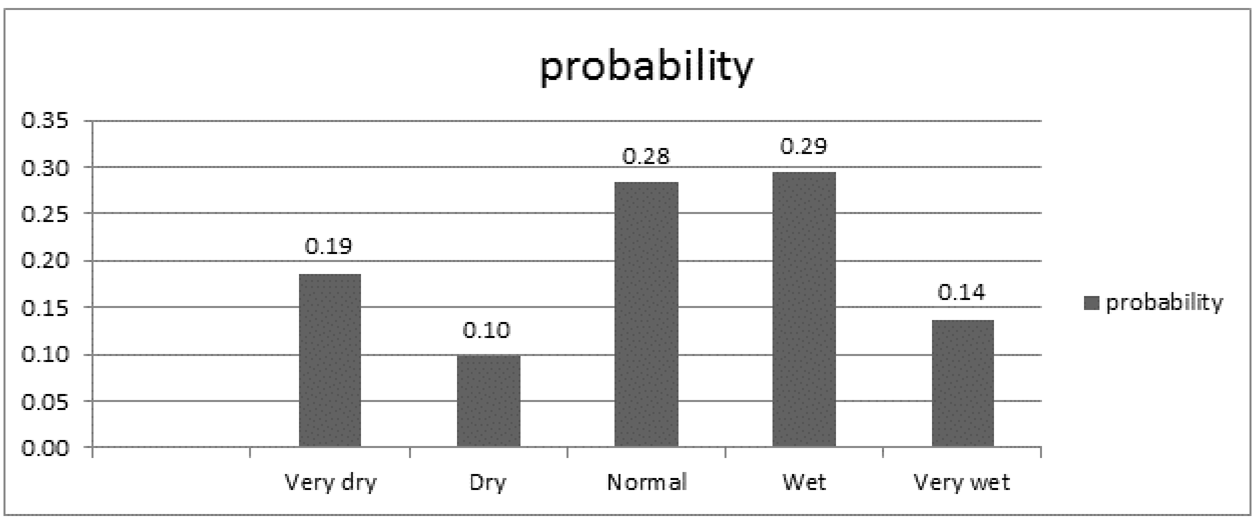
Classification of simulation runs based on SAI for the observed time series rainfall data indicates that rainfall anomalies tend to follow a nearly normal distribution. About 20%, 10%, 40%, 20%, and 10% of the simulation series are found to be very dry, dry, normal, wet, and very wet, respectively. However, it is uncertain which rainfall trend will be revealed in the future. Therefore, the study examined the effects of future rainfall variability by assuming different likelihoods. Most importantly, two main future rainfall distributions were assumed; one in which 50% more dry years of time series data are likely to occur and the second case considers the opposite; with 50% more wet years occurring.

Fig. 5.18 Probability of anomaly assuming 50% more dry years from observed values



Source: Author's computation from the time series data for 1974-2003; Note: -Probabilities are computed by using equation 3.36 and classified based on SAI criterion

Fig. 5.19 Probability of anomaly assuming 50% more wet years from observed rainfall



Source: Author's computation of the time series data for the years 1974-2003; Note: -Probabilities are computed by using equation 3.36 and classified based on SAI criterion.

Assuming 50% more dry years (Fig. 5.18) resulted in less normal years and the same level of other anomalies. Similarly, increasing the number of wet years by 50% (Fig. 5.19) resulted in a reduced number of normal years, keeping other anomalies at the current level. After generating the future rainfall anomalies from the time series rainfall data and classifying the simulation runs as wet, normal and dry runs: the effects of future rainfall variability on household welfare is estimated by re-sampling of the simulation results. Simulated results are analyzed by assuming future rainfall anomalies and the corresponding figures are compared against the results with the current variability. The simulation results presented in Table 5.12 indicate that if the future is drier than the baseline scenario (hypothetical constant rainfall); household income is expected to decline by 3.17%. Similarly, if more wet years are realized, income is expected to decrease by 2.52%. Therefore, compared with the baseline scenario, future anomalies are expected to adversely influence income and the livelihood of households in the study area. Except for the assumption of hypothetically constant rainfall, all instances of the rainfall variability deteriorate household welfare. Compared with current rainfall variability, an increased number of wet years scenario is associated with an increased simulated income and an increased number of dry years is associated with lower income.

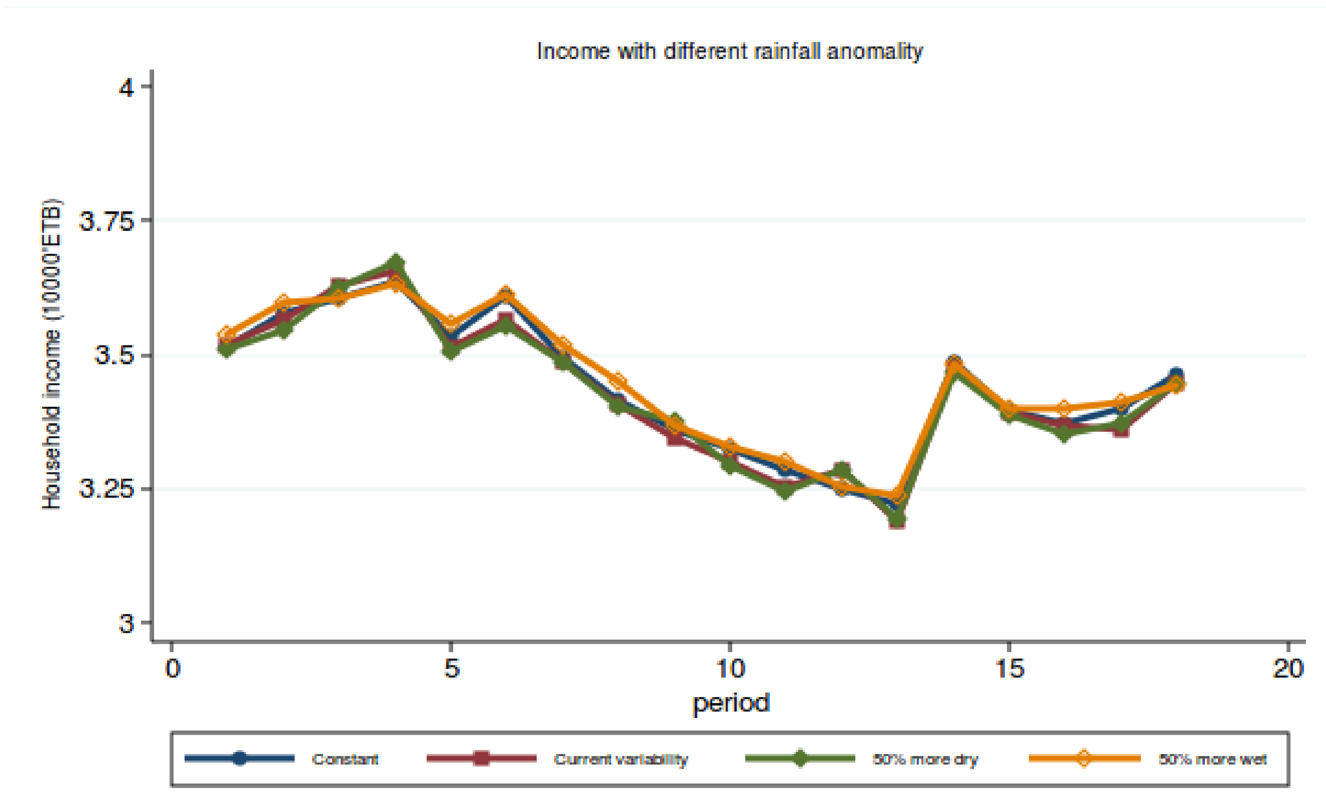
Fig. 5.20 presents the distribution of simulated income computed over four rainfall anomalies. It shows a clear difference in income across different anomalies. In most of the simulation period, except constant rainfall, income is greater under the rainfall sequences with 50% more wet years than under other rainfall anomalies. However, the comparison of average income over simulation periods revealed that income with hypothetically constant rainfall is greater than any other rainfall scenarios (Table 5.12). The lowest simulated income, about 34,300 ETB, is observed under 50% more dry year's scenario. Simulated income under the 50% more wet years assumption clearly sites above all other rainfall anomalies for the second five-year simulation period (6^{th} to 10^{th} in Fig. 5.20). Similarly, the kernel distribution of income for rainfall anomalies shows that income under hypothetical constant rainfall dominates the incomes with other rainfall sequences (Fig. 5.21). Fifty percent more dry years resulted in lower income and it has significantly reduced the income of the poorest group.

Table 5.12 Simulated income (10,000'ETB) over future and current rainfall anomaly

Anomaly	Mean	Std. Dev.	Min	Max	Change from base
Hypothetical constant	3.54	0.11	3.37	3.69	0.00%
Current variability	3.44	0.13	3.22	3.64	-2.81%
50% more dry years	3.43	0.13	3.20	3.67	-3.17%
50% more wet years	3.45	0.13	3.24	3.63	-2.52%

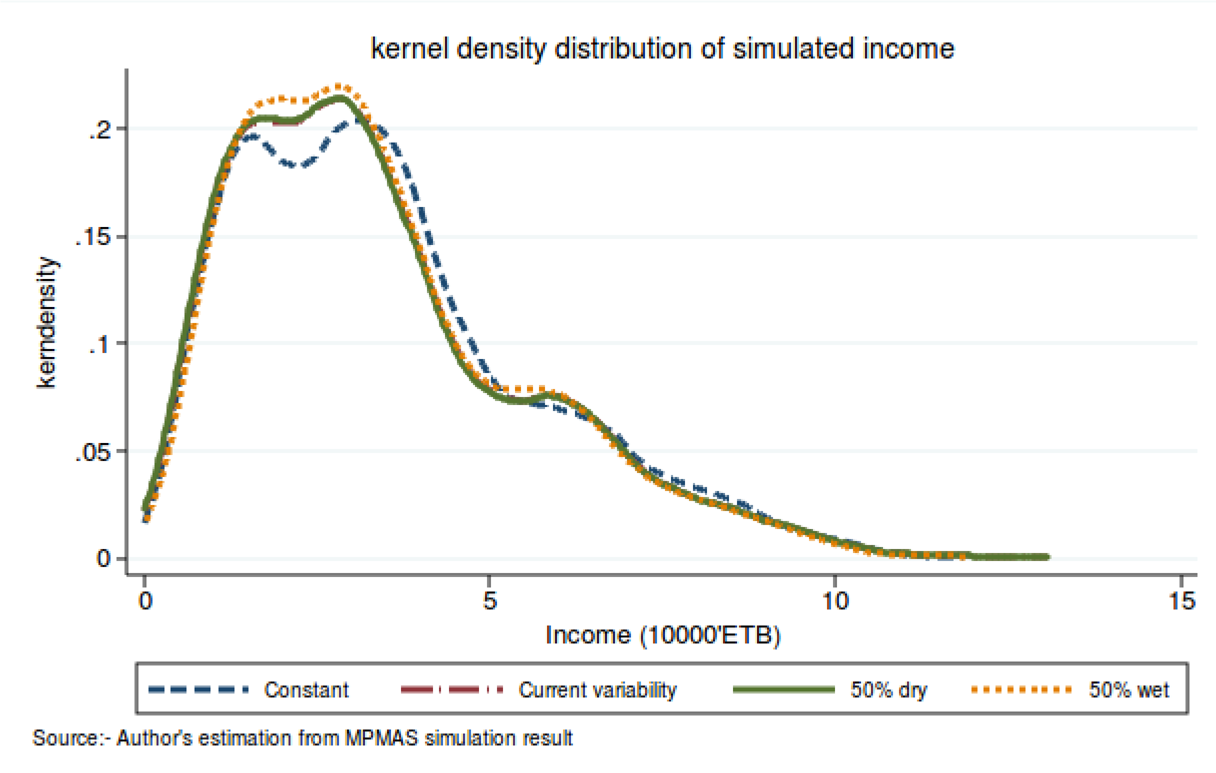
Source: Resampled and analyzed from MP-MAS simulation result, 2003; Note: The values are averaged over eighteen simulation periods. More dry and wet years sequences are classified based on the random rainfall distribution based on SAI values.

Fig. 5.20 Distribution of income (10,000'ETB) computed for different rainfall anomalies



Source: - Author's estimation from the resampled from MP-MAS simulation results, 2013; Note: The figures are in ten thousand of the Ethiopian Birr computed for hypothetical constant, current variability, 50% more dry years and 50% more wet years.

Fig. 5.21 Kernel density distribution of estimated income over rainfall anomalies



Note: The figures are in ten thousand of the Ethiopian Birr computed for hypothetical constant, current variability, 50% more dry years and 50% more wet years.

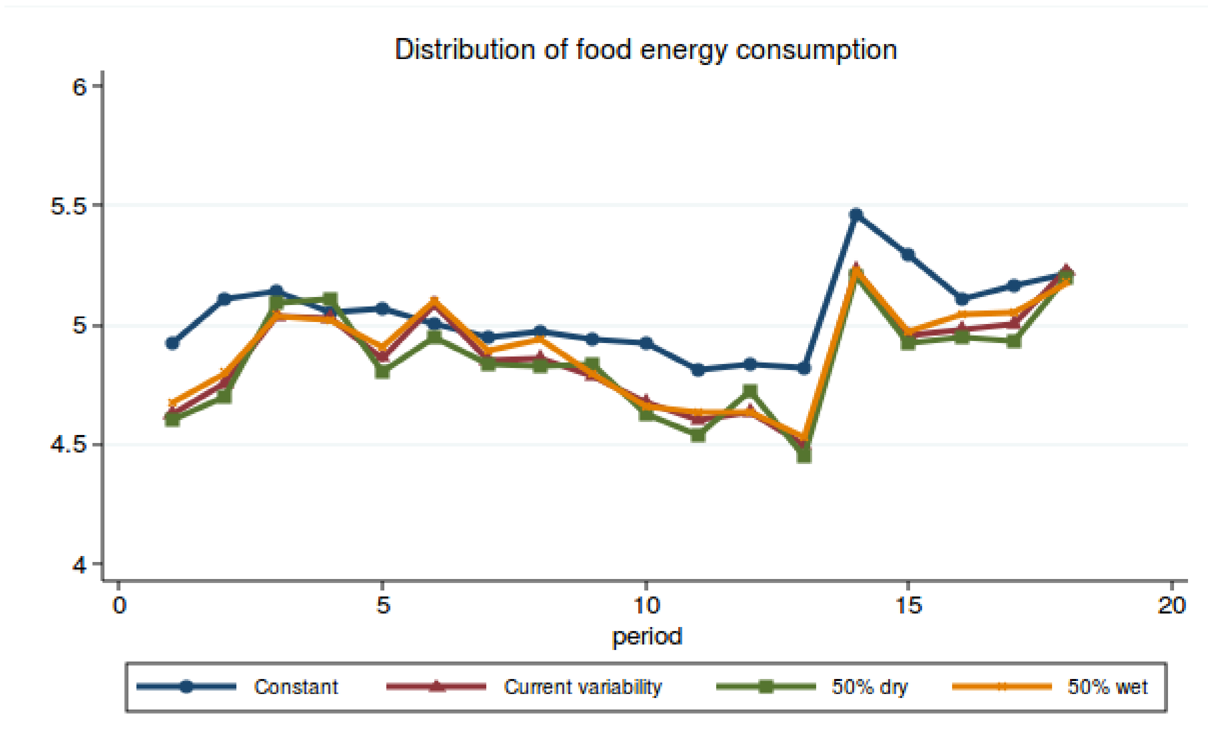
Table 5.13 Simulated food consumptions (GJ/capita) for rainfall anomalies

Anomaly	Mean	Std. Dev.	Min	Max	Changes	CV
Hypothetical constant	5.05	0.17	4.81	5.46	0.00%	3%
Current variability	4.87	0.21	4.50	5.23	-3.86%	4%
50% more dry years	4.85	0.22	4.45	5.21	-2.97%	5%
50% more wet years	4.90	0.21	4.53	5.23	-3.42%	4%

Note: Simulated food consumption (GJ/capita) assuming hypothetical constant, current variable, 50% more dry and 50% more wet sequences. Changes are from the base (Hypothetical constant case), CV: Coefficient of variation.

Table 5.13 reports the estimated effects of rainfall variability on food consumption for four rainfall anomalies. Namely, hypothetical constant, current variability, 50% more dry years, and 50% more wet years. It is indicated that rainfall anomalies have reducing effects on per capita food consumption. Comparing the estimated per capita food consumption between hypothetical constant and 50% more dry years suggests that, on average, households face about 3% of food consumption losses under 50% more dry years. Furthermore, rainfall variability increases the variability in food consumption, with the largest coefficient of variation, 5%, prevailing in 50% more dry years scenario and the smallest, 3%, under hypothetical constant rainfall (Table 5.13).

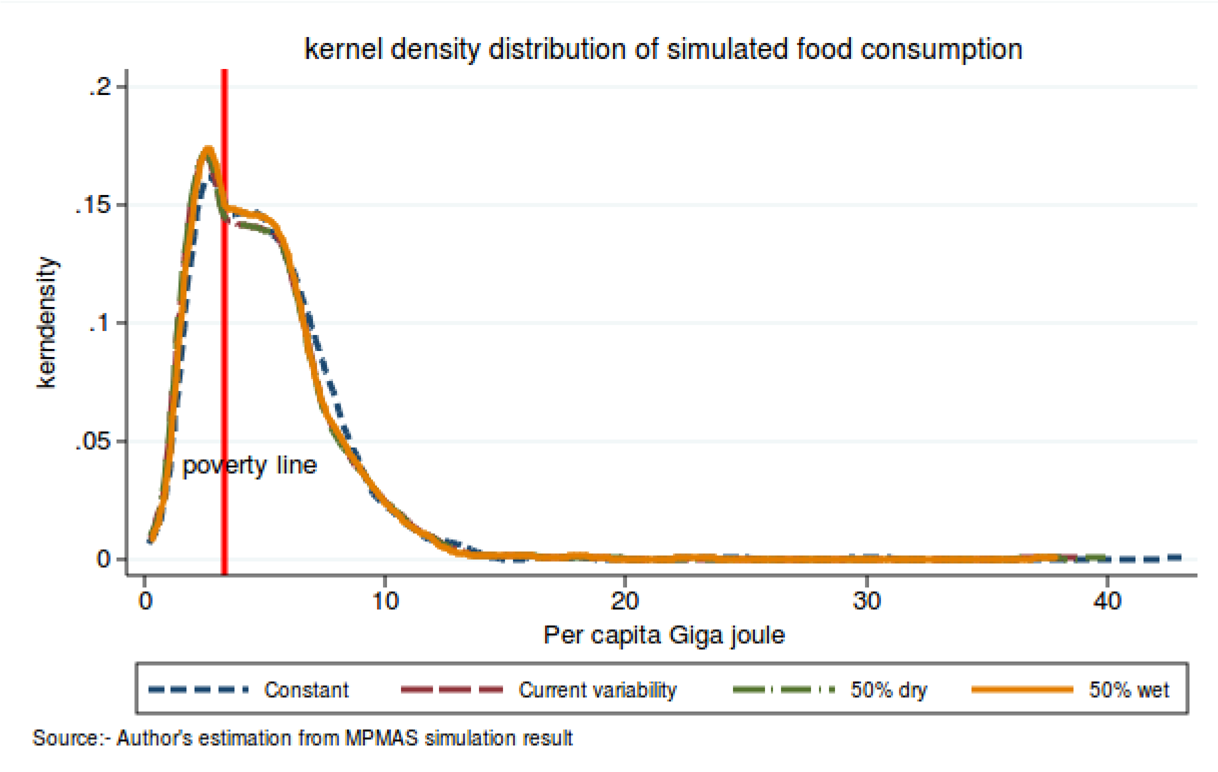
Fig. 5.22 Distribution of food (GJ/capita) consumption for different rainfall anomalies



Source: Author's estimation from the re-sampled from MP-MAS simulation results; Note: The figures are in Giga joule per capita computed for hypothetical constant, current variability, 50% more dry years and 50% more wet years.

Trajectories of simulated per capita food consumption shown in Fig. 5.22 indicate that food consumption under hypothetically constant rainfall followed by under 50% more wet rainfall scenario sits above other rainfall anomalies. The figure also shows that in most simulation periods, food consumption with 50% more wet years surpasses that off with current variability or a 50% increase in dry years. Moreover, compared with other rainfall anomalies the income distribution under hypothetically constant rainfall follows a relatively smoother trend. Fig. 5.23 shows that the distribution of estimated food consumption depends on the assumed rainfall anomalies. Food consumption under a hypothetically constant rainfall distribution is greater than that of under other rainfall anomalies.

Fig. 5.23 Kernel density distribution of food consumption for rainfall anomalies



Note: The figures are in Giga joule per capita computed for hypothetical constant, current variability, 50% more dry years and 50% more wet years.

Table 5.14 The effects of rainfall variability on poverty, assuming different anomalies

Anomaly	Headcount poverty	Poverty gap	Squared poverty gap
Hypothetical constant	33.82	10.53	4.36
Current variability	36.99	12.38	5.47
50% more dry years	37.32	12.56	5.57
50% more wet years	36.65	12.19	5.35

Source: Author's estimation from the re-sampled resulted of MP-MAS simulation, 2013; Note: The figures are averaged over simulation periods for each of the rainfall anomalies.

Table 5.14 reports the estimated effects of rainfall variability on poverty, assuming different rainfall anomalies. The result shows that, compared with hypothetically constant rainfall, all other rainfall scenarios have increasing impacts on the three measures (headcount poverty, poverty gap and squared poverty gap) of poverty. Compared to the hypnotically constant rainfall scenario, the more dry years anomaly resulted in increased in each of the three poverty measures. Estimates for the headcount poverty suggest that, compared to a hypothetical constant rainfall scenario, on average, assuming 50% more dry (wet) years in the future, resulted in about a three-percentage point increase in the share of people live below the poverty line. However, compared to the current variability 50% more wet years scenario resulted in about 1% less proportion of people live below poverty line. In conclusion, the results from analysis of the re-sampled rainfall distribution suggest that, compared to a hypothetical constant rainfall scenario, both current and future rainfall variability is associated with declines in household income and food consumption, and an increase in poverty. Moreover, rainfall variability is intensifying the existing vulnerability of the poor households who depend on agriculture as a means of livelihood.

Chapter 6: Conclusion and policy implications

6.1. Main findings of the study

The last chapter of this thesis discusses the methodological advancement of MP-MAS compared with other simulation models, summarizes the main findings of the study, and discusses the limitations of the study, and direction for further research on this topic. This study used data from both primary and secondary sources to examine the impacts of rainfall variability on crop yield and household welfare, considering different adaptation strategies. Descriptive, econometric, and simulation analysis were used to elucidate the distribution of household resource, to examine the role of adaptation strategies in curbing the effects of rainfall variability; identify factors that determine technology adoption; and estimate the coefficients of production and consumption function in rural Ethiopia. The estimated coefficients from econometric models were used to parameterize Mathematical Programming-Based Multi-Agent System (MP-MAS) model. MP-MAS is an optimization model that enables the integration of factors assumed to affect farmer decision-making by combining different sub-models such as perennials, livestock, crop growth, and consumption. The flexibility of the model helps to incorporate demographic, environmental, and socioeconomic characteristics into the decision-making process of the households. The model simulates the effects of rainfall variability and the outcomes at a household level. Moreover, the model is a biophysical model that systemically replicates the real world situation in which a heterogeneous population of farm households decide on resource allocation towards farming and non-farming activities. Households must make decision of allocating resources into different activities, such as growing crops, keeping livestock, consumption, and savings.

For this study, MP-MAS model was developed based on the prevailing socioeconomic characteristics of households. The effects of rainfall variability were addressed by considering crop water requirement and the response of crop yield to changes in climatic variables, mainly rainfall. Prior to implementing the model to the objectives of this study, its validity was tested and calibrated. Model sensitivity analysis is done by examining the response of model results to changes in external factors such as rainfall, output prices, input prices, and wage rates. The model is found to be consistent and robust; this increases the reliability of the results and, therefore, the simulation were expected to be a replication of the real world under the given information. The model is employed to simulate the impacts of rainfall variability on crop yield and household welfare; it allows us to simulate not only the current conditions of rainfall variability effects, but also the anticipated state and dynamics associated with alterations to the systems.

The study area is characterized by crop-livestock mixed farming, diverse agro-ecology and farming practices. Rain-fed small-scale agriculture is the main means of livelihood in the study area. Rainfall distribution of the study area is more variable and erratic. Analysis of rainfall variability in the study area reveals a high prevalence of inter- and intra-annual rainfall variability. Description of the household asset base and consumption behavior showed that households are different from one another considering the resource base depending on geographic location. Compared with resource-rich households, households with limited asset endowment are more vulnerable to rainfall variability and are more likely to face welfare loss under rainfall variability. Econometric analysis of the consumption function indicated that larger household size is associated with decreased probability of saving. Expenditure on food consumption is positively associated with the number of household members. Households compensate the loss in consumption of one food category due to a price increase, by consuming more of the substitute food categories. The cereal food category were more elastic to price change than any other food category.

The simulation results indicated that rainfall variability adversely affects crop yield and welfare; under rainfall variability, crop yield is declined by 8%. However, the yields of different crops showed varying responses to rainfall variability. Rainfall variability increases variability in crop yield, making agriculture risky economic sector unless corrective measures are implemented. As agriculture is strongly linked to other economic sectors, changes in agricultural sector due to rainfall variability affect different aspects of livelihood. Studies showed that the Ethiopian GDP would be reduced by 10% due to rainfall variability and income inequality is expected to increase by 20% (Mideksa, 2010). The negative effect of rainfall variability on crop yield translates to a decrease in income and food consumption, thereby, increases the share of people living below the poverty line and aggravating the income inequality. Different income segments of the population affected differently by rainfall variability. Compared with the richer income group, the poorest income class were affected severely by rainfall variability. The analysis of the effects of both current and future rainfall variability on income, food consumption, and poverty concluded that rainfall variability worsens the welfare of the household. It is indicated that current rainfall variability decreases household income, by 2.82%, and food consumption by 3.41%. It also increases headcount poverty and income inequality.

Integrated policy intervention such as financial intervention through credit, non-farm income generating activities, access to irrigation and soil and water conservation activities reduce the adverse effects of rainfall variability. For instance, non-farm activity with full credit access increases income by about 4%, which is strong enough to offset the income loss due to rainfall variability. However, households willing to adopt a given adaptation strategy might not have the capacity to do so due to their limited asset base (such as land, labor and capital), and lack of information or/and limited access to adaptation strategies. Compared to the baseline scenario, under variable rainfall scenario, removing access to credit resulted in about 3% income loss; on the other hand improving access to credit from current level to its full potential would not compensate the income loss. Under the baseline scenario, access to non-farm activity marginally increases income, but no change observed under variable rainfall scenario. Irrigation is found to be one of the most important determinants of crop yield and therefore household welfare. The study concludes that households with access to irrigation generated 27%, and 4% more income than those without access to irrigation under baseline and current rainfall variability scenarios, respectively. This indicates rainfall variability reduces the benefits of using irrigation. Similarly, practicing soil and water conservation activity increases per hectare crop yield value and hence improve the adaptive capacity of farm households.

Improving the asset base of households and access to credit, access to irrigation, access to non-farm activity and improving adoption of soil and water conservation activities increases the resilience against rainfall variability. Increasing access to financial sources alone might not bring the required changes in the livelihood of farm households unless and otherwise accompanied by other productive strategies such as access to non-farm activities. Therefore, integrated policy interventions are critically important in addressing the adverse effects of rainfall variability.

6.2. Limitations of the study

As other studies and models, there are limitations in this study too, that needs to be addressed and improved in future research. The first set of limitations arises from the assumption made about constant prices and policies in the future. Future price data are, however, notoriously difficult to obtain as there is no reliable forecasted data about future price trends. Thus, constant price is assumed for the future simulation periods. However, the assumption of constant price is the most unlikely situation in reality, as the world food price has soared in the past years and is expected to further increase in the future. Therefore, the effects of rainfall variability might be significantly larger than the figures found in this study. Secondly, government policies might change in the future as the Ethiopian government is planning to shift the economy from agriculture-led development towards an industry-based economy. This might reduce the dependence of households on the climate-sensitive agricultural sector, and hence rainfall variability might have smaller effects on the household welfare. Thirdly, the country is expected to implement agricultural policies that given higher priority to irrigation infrastructure, and soil and water conservation activities. This further reduces the effects of rainfall variability on crop yield by increasing productivity and production. On the other hand, expansion of urbanization and industrialization may reduce the cheap labor supply for the agricultural sector. This means that agricultural income may be sensitive to changes in the labor wage, which was not the case in this study. Therefore, this is a research gap that can be addressed in the future research interested on rainfall variability and its effects.

The second set of limitations of the study arises from the quality of the data from the 2009 ERHS, dataset, from where the estimations of input use such as fertilizer, soil characteristics, and the coefficients of three-stage consumption models were estimated. On the one hand, ERHS collect information from fifteen representative villages of the whole country, but data at plot level were missing or had errors. On the other hand, in ERHS, there were no data for the sites considered in this study. To improve the data quality the study has supplemented the results by considering secondary data sources and primary data (using key informant interviews) from the study area. Moreover, as data for the study site was not available; national data from ERHS was used to estimate the household food demand response to changes in prices. Therefore, it is recommended that household-level production and consumption data is used to further improve the precision of estimates used to parametrize MP-MAS. This would make the results representative and enable more enlightening conclusion. Additionally, due to lack of detailed water distribution data in the irrigation schemes of the research sites, proxy estimates were used in the computation of EDIC water requirements and distribution over agents. Thus, detailed analysis of crop yield responses to water stress, water distribution rules, the cost of irrigation and water flows can be improved further.

The third limitation is due to the complexity of issues to be bound within the scope this study: the role of institutional and local adaptation strategies such as local saving institutions, using local knowledge and forecasts, risk-sharing activities, farmer producer organization, social networking "idir[8]" and "equib[9]", and technology diffusion were not captured in this study. Yet, the simulation results are plausible and they could be further improved by using area specific and more detailed dataset for the model parameterization.

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[8]*Idir is the social group formed by villagers to share funeral and related expenses*

[9] *Equib is a group formed to save money and other important household requirements where each member receive the collected money at round base within specified time*.

6.3. Conclusion

In conclusion, rainfall variability poses a significant threat to agricultural production and productivity in Ethiopia. Agriculture is the most sensitive economic sector for rainfall variability due to its high dependency on climatic variables. The Ethiopian economy is mainly driven by rain-fed agriculture, and thus, is highly vulnerable to rainfall variability. The majority of the country's population directly or indirectly depend on this sector for their livelihood. Rainfall variability is expected to increase the risk of hunger, food insecurity, and poverty and income inequality; particularly of the poor households. Rainfall variability affects crop yield, and, hence, reduces household income, and increases poverty and food insecurity. Limited access to finance is found to be one of the most contributing factors to the low level of climate change adaptation. Improving access to credit besides increased access to non-farm activities was found to increase the adaptive capacity of households against rainfall variability. This is because, access to non-farm activities and credit, increases the opportunity to participate in non-agricultural and climate proof livelihood activities and generate additional income. Increasing agricultural technology adoption (fertilizer, and irrigation) is found to directly increase the crop yield, and indirectly, the income of the household. Access to irrigation is found to increase the production and productivity of the plots and thus improve household welfare. It is indicated that both yield-enhancing and income increasing interventions are found to reduce the adverse effects of rainfall variability, however, some of the adaptation strategies were found to increase the income disparity. Both credit and non-farm activities increase the income inequality under variable rainfall scenario. But, simultaneous intervention of credit and non-farm activities improves income inequality compared with the baseline scenario. By enabling cultivation of new crop varieties and encourage commercial farming; irrigation and soil and water conservation activities increased the crop yield and household welfare. Household income is found to be sensitive to changes in output prices, and move in the opposite direction with changes in output prices. This mainly attributed by the fact that more than seventy-five percent of households in the study area are net-food buyers. Therefore increasing output price increases the welfare loss, poverty incidence and decreases income. The sensitivity analysis showed that rainfall has a positive effect on household income and helps reduce poverty. In this study, income is found to be insensitive to changes in input prices such as fertilizer, seed, and labor. This is due to the low rate of improved agricultural input use and the possibility of growing crops without any improved agricultural technologies. Not only current and future rainfall variability, but also its adaptation strategies, such as non-farm activities and access to credit may also increase income inequality unless implemented in integrated way.

6.4.Recommendation for future research and policy direction

Given the importance of climate variability, research should focus on investigating the response of different crops yield to changes in climatic variables and identifying an appropriate strategy to reduce its adverse effects. Research should focus in particular, on the impact of rainfall variability on crop yield, and hence, household income, poverty, food consumption and income inequality. Further effort is required to examine the role that adaptation strategies play in mimicking adverse effects of rainfall variability on crop yield and household welfare. Moreover, it is important to understand the effect of adaptation strategies on income distribution. The distributional effects of rainfall variability and the corresponding adaptation strategies on income inequality received less attention from the researchers. Both rainfall variability and adaptation strategies against it increases the income inequality. Therefore, research should focus on both level and distributional effects of rainfall variability on crop yield and household income.

Policies designed to increase the resilience of households against rainfall variability and improve the livelihood must consider the provision of integrated strategies rather than targeting single strategy. This is most important to improve the adaptive capacity of households without worsening the income inequality. Thus, it is worth understanding the impacts of adaptation strategies in reducing the effects of rainfall variability and income distribution at the same time. There must be a crosscheck of whether the policies aiming at increasing adaptive capacity against rainfall variability are improving income disparity and increasing the overall welfare of the households. An integrated policy intervention is required to minimize the adverse effects of rainfall variability and increase the livelihood of farm households.

Therefore, attention must be given to expanding integrated polices such as improving access to finance and non-farm activities, expanding investment on irrigation infrastructure, improving access to agricultural inputs such as fertilizer and seeds, and the required finance.

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8. Appendices

8.1. Appendix A

A. 1: Heckman two stage estimation of AIDS for share of cereals in food expenditure

Dependent variable=share of food category 1 (Cereals) in food expenditure	Coef.	se
ln of Unit value of food Category 1	0.0728**	(0.0275)
ln of Unit value of food Category 2	-0.0284	(0.0231)
ln of Unit value of food Category 3	0.00710	(0.0109)
ln of Unit value of food Category 4	0.00469	(0.0154)
ln of Unit value of food Category 5	-0.00216	(0.00614)
ln of Unit value of food Category 6	0.0275	(0.0199)
ln of Unit value of food Category 7	-0.00527	(0.00320)
mc_stone	0.00133	(0.00404)
Bjoule	-0.000260	(0.000258)
Years of head Education	0.00000237	(0.000457)
Age head(yrs)	-0.0000337	(0.000197)
Sex	0.00174	(0.00607)
Southern	0.0111	(0.00884)
Constant	0.151***	(0.0434)
ln of Unit value of food Category 1	-0.313	(1.265)
ln of Unit value of food Category 2	0.568	(1.004)
ln of Unit value of food Category 3	-0.323	(0.609)
ln of Unit value of food Category 4	0.807*	(0.393)
ln of Unit value of food Category 5	-0.684*	(0.338)
ln of Unit value of food Category 6	0.355	(0.464)
ln of Unit value of food Category 7	-0.165	(0.151)
mc_stone	0.691***	(0.143)
Dummy region Tigray	-4.896	(0)
Dummy region Oromiya	-5.099***	(0.537)
Dummy region SNNPR	-5.176***	(0.524)
Mjoule	0.00000907	(0.0000122)
Constant	1.086	(1.318)
Mills		
Lambda	0.0854*	(0.0387)
N	845	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A. 2: Heckman two stage estimation of AIDS for share of legumes in food expenditure

Dependent variable=share of food category 2 (Legumes) in food expenditure	Coef.	se
ln of Unit value of food Category 1	0.0106	(0.00931)
ln of Unit value of food Category 2	-0.0107	(0.00755)
ln of Unit value of food Category 3	0.00208	(0.00369)
ln of Unit value of food Category 4	0.00690	(0.00495)
ln of Unit value of food Category 5	0.000569	(0.00199)
ln of Unit value of food Category 6	0.00840	(0.00704)
ln of Unit value of food Category 7	0.00282^{**}	(0.00107)
mc_stone	-0.00434^{***}	(0.00126)
Bjoule	-0.0000337	(0.0000874)
Years of head Education	0.0000536	(0.000155)
Age head(yrs)	-0.0000171	(0.0000672)
Sex	-0.00208	(0.00207)
Southern	0.0108^{***}	(0.00309)
Constant	0.165^{***}	(0.0136)
ln of Unit value of food Category 1	-1.943	(1.917)
ln of Unit value of food Category 2	0.00973	(1.385)
ln of Unit value of food Category 3	-1.572	(1.470)
ln of Unit value of food Category 4	-2.008	(1.082)
ln of Unit value of food Category 5	-0.947	(0.492)
ln of Unit value of food Category 6	0.803	(0.662)
ln of Unit value of food Category 7	-0.220	(0.212)
mc_stone	1.176^{***}	(0.292)
Dummy region Tigray	-4.271	(2.579)
Dummy region Oromiya	-5.535^{*}	(2.822)
Dummy region SNNPR	-6.163^{*}	(2.801)
Mjoule	0.0000804^{**}	(0.0000256)
Constant	-3.918	(0)
Mills		
Lambda	0.0122	(0.0135)
N	845	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Author's estimation from ERHS (2009) survey

A. 3: Heckman two stage estimation of AIDS for share of root crops in food expenditure

Dependent variable=share of food category 3 (Root crops and enset) in food expenditure	Coef.	se
ln of Unit value of food Category 1	-0.00348	(0.0117)
ln of Unit value of food Category 2	-0.00698	(0.00952)
ln of Unit value of food Category 3	-0.00547	(0.00451)
ln of Unit value of food Category 4	0.0112	(0.00599)
ln of Unit value of food Category 5	-0.0112***	(0.00252)
ln of Unit value of food Category 6	-0.00784	(0.00854)
ln of Unit value of food Category 7	0.000797	(0.00131)
mc_stone	0.000621	(0.00157)
Bjoule	-0.0000759	(0.000106)
Years of head Education	-0.000156	(0.000186)
Age head(yrs)	0.0000765	(0.0000802)
Sex	-0.00382	(0.00249)
Southern	-0.00523	(0.00373)
Constant	0.174***	(0.0170)
ln of Unit value of food Category 1	2.488	(1.276)
ln of Unit value of food Category 2	-1.875*	(0.952)
ln of Unit value of food Category 3	-1.197	(0.784)
ln of Unit value of food Category 4	-0.772	(0.624)
ln of Unit value of food Category 5	-1.950***	(0.363)
ln of Unit value of food Category 6	-0.102	(0.564)
ln of Unit value of food Category 7	-0.211	(0.152)
mc_stone	0.927***	(0.175)
Dummy region Tigray	-5.022***	(0.533)
Dummy region Oromiya	-5.134***	(0.474)
Dummy region SNNPR	-5.826	(0)
Mjoule	0.0000433**	(0.0000160)
Constant	-1.644	(1.726)
Mills		
Lambda	0.0345***	(0.00955)
N	845	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Author's estimation from ERHS (2009) survey

A. 4: Heckman two stage estimation of AIDS for share of fruits and vegetables in food expenditure

Dependent variable=share of food category 4 (Fruits and Vegetables) in food expenditure	Coef.	se
ln of Unit value of food Category 1	0.0305	(0.0253)
ln of Unit value of food Category 2	-0.00697	(0.0203)
ln of Unit value of food Category 3	0.00725	(0.00996)
ln of Unit value of food Category 4	0.0282*	(0.0126)
ln of Unit value of food Category 5	-0.00612	(0.00540)
ln of Unit value of food Category 6	0.0138	(0.0187)
ln of Unit value of food Category 7	0.00203	(0.00282)
mc_stone	-0.00323	(0.00321)
Bjoule	-0.000182	(0.000226)
Years of head Education	-0.000248	(0.000406)
Age head(yrs)	0.0000181	(0.000176)
Sex	-0.00239	(0.00543)
Southern	0.0137	(0.00820)
Constant	0.182***	(0.0347)
ln of Unit value of food Category 1	5.987**	(2.043)
ln of Unit value of food Category 2	1.560	(1.516)
ln of Unit value of food Category 3	0.382	(0.592)
ln of Unit value of food Category 4	1.743	(0.936)
ln of Unit value of food Category 5	-5.387***	(1.286)
ln of Unit value of food Category 6	0.438	(1.098)
ln of Unit value of food Category 7	-0.157	(0.223)
mc_stone	1.942***	(0.465)
Dummy region Tigray	-4.777	(3.288)
Dummy region Oromiya	-7.438	(3.836)
Dummy region SNNPR	-8.349*	(4.098)
Mjoule	0.0000937**	(0.0000292)
Constant	-7.657	(0)
Mills		
Lambda	0.0746***	(0.0216)
N	845	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Author's estimation from ERHS (2009) survey

A. 5: Heckman two stage estimation of AIDS for share of animal products in food expenditure

Dependent variable=share of food category 5 (Animal products) in food expenditure	Coef.	se
ln of Unit value of food Category 1	-0.0160	(128899.4)
ln of Unit value of food Category 2	-0.00677	(105606.4)
ln of Unit value of food Category 3	-0.000748	(50923.6)
ln of Unit value of food Category 4	0.0108	(68705.0)
ln of Unit value of food Category 5	0.0131	(26901.3)
ln of Unit value of food Category 6	-0.0276	(85997.5)
ln of Unit value of food Category 7	0.0000804	(15038.4)
mc_stone	-0.00144	(16704.8)
Bjoule	-0.0000520	(1202.1)
Years of head Education	-0.0000763	(2168.6)
Age head(yrs)	0.0000785	(942.0)
Sex	0.0000817	(28943.6)
Southern	-0.00550	(41553.0)
Constant	0.133	(180619.1)
ln of Unit value of food Category 1	23.31	.
ln of Unit value of food Category 2	3.229	(15896.9)
ln of Unit value of food Category 3	-4.091	(0)
ln of Unit value of food Category 4	-33.55	(15159.3)
ln of Unit value of food Category 5	14.96	(17100.9)
ln of Unit value of food Category 6	21.74	(8560.3)
ln of Unit value of food Category 7	-1.666	(3329.3)
mc_stone	32.42	(1754.3)
Dummy region Tigray	43.01	.
Dummy region Oromiya	-10.76	(0)
Dummy region SNNPR	-20.43	(0)
Mjoule	0.00145	(0.413)
Constant	-244.8	(0)
Mills		
Lambda	400667.6	(1.32945e+13)
N	845	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Author's estimation from ERHS (2009) survey

A. 6: Heckman two stage estimation of AIDS for share of purchased necessities in food expenditure

Dependent variable=share of food category 6 (Purchased necessities) in food expenditure	Coef.	se
ln of Unit value of food Category 1	0.000471	(318973.5)
ln of Unit value of food Category 2	-0.00989	(262693.8)
ln of Unit value of food Category 3	0.0189	(125876.7)
ln of Unit value of food Category 4	-0.0110	(169447.5)
ln of Unit value of food Category 5	0.0261	(66319.8)
ln of Unit value of food Category 6	-0.0871	(212277.8)
ln of Unit value of food Category 7	0.00184	(37080.7)
mc_stone	-0.0159	(41253.8)
Bjoule	-0.000326	(2946.8)
Years of head Education	-0.000332	(5355.9)
Age head(yrs)	-0.0000427	(2322.9)
Sex	-0.00424	(71529.3)
Southern	-0.00477	(103188.3)
Constant	0.387	(443215.5)
ln of Unit value of food Category 1	301.1	.
ln of Unit value of food Category 2	352.3	(14227.1)
ln of Unit value of food Category 3	-36.65	(9389.1)
ln of Unit value of food Category 4	-62.69	(135247.9)
ln of Unit value of food Category 5	67.98	(13418.7)
ln of Unit value of food Category 6	246.9	(20618.7)
ln of Unit value of food Category 7	26.77	(3863.3)
mc_stone	269.8	(2716.8)
Dummy region Tigray	191.0	.
Dummy region Oromiya	-159.8	(0)
Dummy region SNNPR	-197.2	(13867.3)
Mjoule	0.00454	(0.513)
Constant	-1778.1	(0)
Mills		
Lambda	-987934.4	(1.02862e+13)
N	845	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Author's estimation from ERHS (2009) survey

8.2. Appendix B

Water discharge of Bulbula River at Adami -Tulu Station (1980-2004)

Year	Jan	Feb	Mar	Apr	May	June	July	Aug	Sept	Oct	Nov	Dec	Annual
1980	10.47	5.49	2.41	1.6	1.5	0.46	0.5	2.25	5.24	5.4	3.1	1.01	39.43
1981	0.55	0.44	0.56	0.51	0.59	0.52	0.59	6.29	32.65	47.61	33.45	20.59	144.4
1982	8.48	4.25	2.67	1.6	1.43	0.78	0.69	5.55	17.52	21.1	9	6	79.07
1983	5.15	3.13	2.16	2.41	4.04	11.51	15.38	35.36	93.58	87.8	84.25	50.23	395
1984	29.09	15.33	8.38	3.66	1.81	1.44	1.78	7.77	14.29	11.74	5.59	2.47	103.4
1985	1.04	0.75	0.67	0.5	0.47	0.46	0.47	0.84	5.2	6.86	2.57	1.27	21.1
1986	0.67	0.57	0.57	0.55	0.58	0.49	0.61	3.38	7.93	10.84	5.54	3.23	34.96
1987	1.76	0.63	0.6	1.51	2.16	6.26	4.36	6.44	10.65	14.82	8.51	5.19	62.89
1988	3.19	2.16	1.74	1.75	1.69	1.71	1.76	3.92	13.21	37.55	27.52	16.15	112.4
1989	8.87	4.77	3.03	3.79	2.05	2.11	2.74	7.39	27.37	36.37	18.4	10.02	126.9
1990	9.08	1.12	3.73	8.63	7.35	2.12	3.25	9.83	38.15	39.09	21.73	19.86	163.9
1991	9.29	3.3	1.81	0.7	0.81	0.34	1.1	12.27	48.93	41.81	25.05	13.98	159.4
1992	5.95	2.02	0.66	0.29	0.04	0.01	0.11	12.23	58.94	67.18	50.12	30.88	228.4
1993	18.24	12.6	5.85	2.91	9.2	14.88	23.16	54.34	72.16	64.77	44.95	29.9	353
1994	21.28	12.12	8.88	4.79	0.13	0.1	0.08	10.55	38.85	48.58	36.3	27.42	209.1
1995	13.96	5.59	4.01	1.21	4.8	2.6	2.87	10.17	24.22	62.84	42.43	30.46	205.2
1996	4.93	1.48	0.76	0.84	2.31	7	19.26	55.86	92.77	77.1	48.55	33.49	344.4
1997	23.01	16.39	11.07	18.83	15.39	8.19	14.44	24.13	26.07	22.74	19.17	12.62	212.1
1998	7.22	3.58	3.18	0.92	1.63	1.47	2.03	24.48	63.33	85.41	72.03	55.54	320.8
1999	39.46	24.51	3.82	1.33	1.5	1.03	1.98	9.33	19	46.05	58.43	48.78	255.2
2000	28.78	14.52	4.45	1.73	1.37	0.6	1.68	4.57	16.07	37.58	39.13	42.01	192.5
2001	22.57	17.18	9.73	7.44	3.17	1.36	10.7	20.01	65.17	63.76	37.59	30.93	289.6
2002	25.8	8.93	6.49	4.96	2.11	1.12	5.71	4.98	7	3.84	2.85	32.59	106.4
2003	1.69	0.68	3.24	2.48	1.06	0.88	0.72	1.96	5	4.73	2.92	2.62	27.98
2004	0.36	0.01	0	0	0	0	0	0.82	5.08	4.82	1.83	1.59	14.51
Mean	12.04	6.462	3.619	2.998	2.688	2.698	4.639	13.39	32.34	38.02	28.04	21.15	168.1

Source WUA, MoWR (2012)

8.3.Appendix C

i. Data sources and estimation of expenditure functions

This study utilizes household survey data obtained from the Ethiopian Rural household survey in 2009, which is part of the longitudinal panel dataset from 1989 to 2009. This database contains detailed information from the same households over twenty years at five-year intervals (IFPRI 2011). For the purpose of simplicity and representation of current economic situation, the study used the latest 2009 data set. The data is collected and jointly managed by IFPRI (International Food Policy Research Institute), Addis Ababa University (AAU), University of Oxford and Central Statistical Agency of Ethiopia. Household food expenditure from purchase, own sources and gifts (from relatives, government or any other sources) was asked in quantity and also including in-kind expenditures. In-kind expenditure is transferred to monetary terms by multiplying the standard quantities with the district prices. In the Ethiopian Rural Household Panel Survey (ERHS) data, various expenditure sources are identified: expenditure is further divided into food and non-food expenditure.

ii. Food expenditure

Food expenditure is further classified in different food categories. Accordingly, food expenditure includes expenditures for; Cereals crops (teff, wheat, maize, barley, sorghum, milt); Legumes (lintels, horse beans cow peas, check peas); Root crops & enset (potatoes, sweet potatoes and enset); Fruits & vegetables (orange, banana, avocado, carrot); Animal products (milk, beef, mutton, cheese, butter, egg, chicken); Purchased necessities (salt, oil, coffee, honey, species, green paper, bread); Others (includes other items which are rarely consumed by household and not included in above list).

iii. Non-food expenditures

Non-food expenditure, include expenditures for: Clothing (clothes, shoes, fabric); Social contributions and ceremonial expenses (ceremonial expenses, idir i.e. social contribution for saving and risk sharing, church, and compensation and penalty, voluntary contribution and taxes);

Asset and purchase of durables (cooking pots, sheets, towels, blankets, furniture, lamp/torch, building materials, saving and credits, repair and maintenance, bicycle, bio-gas); Agricultural inputs purchase (fertilizer, land rent, pesticides, labor, and oxen); Others non-food (transport, school fees, cigarette, tobacco). The classification of food categories and the items included in each food category was based on the survey questionnaire from the data used. Unit values were estimated as weighted average prices for each food category in household food expenditure.

iv. Household income sources and the shares in total income

Table C.1 reports the household income sources and their shares of total income. The majority of the rural population in Ethiopia depends entirely on agriculture for their livelihood. According to the figures in the table, crop production contributes the lion's share to household total income: accounting for more than one-third of the total income. Other income sources include income from remittance, homemade handcrafts, asset sale, productive safetnet, and related activities. Moreover, most of the households are subsistence producers; meaning, they produce and consume their own produce. If own production falls short of to meet a household food demand, it sells what is in excess and buys what is in shortage. However, households decide to sell their livestock only when they do not have other means to sustain their family life..

Table C.1 Income sources and their shares of total income

Source	Mean Income (ETB/yr)	Share (%) in total income
Crop	2591	35
Livestock	798	11
Non-farm	618	8
Only women activity	1635	22
Other income	1789	24
Total	7430	100
Number of observations	1567	

Sources: Author's estimation from ERHS survey data, 2009; Women activities are activities solely performed by female family members such as weaving.

Women contribute a significant share to household income in addition to their role in managing family and directly participating in both farming and non-farming activities. They generate a substantial share of household income via female activities. In Ethiopia, there are activities particularly performed by female members of the household; these include making and selling of home produced food and drinks, charcoal making, collecting and selling firewood, the making and selling of handicrafts and pottery. As can be seen from the table, a women-only activity contributes about 20% to family income. When farmers have free time from farming, they choose to supplement their income by participating in non-farm activities, which includes petty trade, preparing and selling farm tools for other farmers; and carpenter. The weak labor market and shortage of non-farm activities mainly hinders families from participating and generating additional income. The average household income is about 7400 ETB (370 Euros) per year. Thus, policies targeting poverty reduction should focus on the multiple dimensions of farm household welfare, including empowering women and creating better markets for homemade products, improving access to non-farm activities, and strengthening other income generating activities.