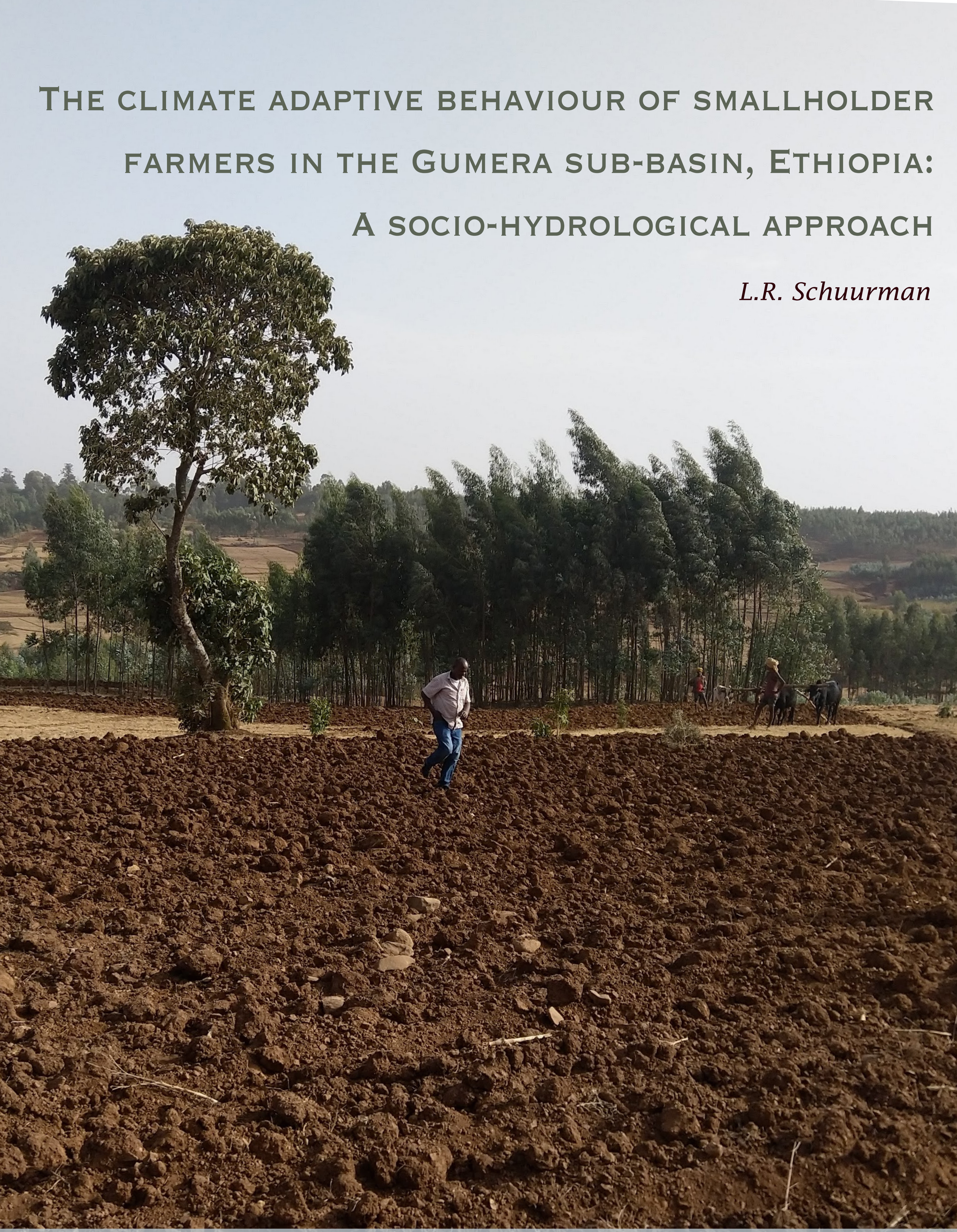
The climate adaptive behaviour of smallholder farmers in the Gumera sub-basin, Ethiopia: A socio-hydrological approach

L.R. Schuurman



TU Delft Delft University of Technology

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by

L. R. Schuurman

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L. R. Schuurman
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Executive summary

In Ethiopia, rainfall variability and changes in rainfall patterns, induced by climate change, could increase the frequency and occurrence of floods and droughts. Due to smallholder farmers in the Gumera sub-basin, Ethiopia, mostly relying on rainfed agriculture, climatic changes highly influence the agricultural production with corresponding negative effects on food security and their economic well-being. To reduce their vulnerability to climate variability, the majority of smallholder farmers take up adaptation strategies, whereas a small group of farmers does not have the capacity to adapt. The climate adaptive capacity of a farmer is thought to be influenced by his or her assets and climate perception. However, the understanding of how these factors combined influence the climate adaptive capacity of farmers and how climate adaptive behaviour influences a farmer's economic well-being is limited.

Therefore, via a bottom-up approach, this study aims to determine what factors drive the climate adaptive capacity of smallholder farmers in the Gumera sub-basin and how they adapt to climate variability. Focus Group Discussions are conducted prior to an individual household survey to obtain local-level knowledge and data on the characteristics of smallholder farmers. Subsequently, this data is used to develop a methodology to incorporate the climate adaptive behaviour of smallholder farmers in socio-hydrological modelling. By implementing a logit model, the (dynamic) adaptive capacity of smallholder farmers is implemented such that the system dynamics of smallholder farmers with respect to climate variability can be analysed. This provides the opportunity to create a better understanding of why farmers adapt to climate variability and its impact on their economic well-being.

From the Focus Group Discussions and the individual household survey it is observed that the majority of farmers adapt to climate variability by changing to a short cycle crop, mostly potato, and adjusting the planting and harvesting dates. They especially do so whenever a bad year occurs, which is defined by farmers as a drought when the onset of rains also occur late. The drivers that are found to mainly influence the uptake of these adaptation strategies are farm size, altitude, level of education, the number of livestock owned, capital, experience, access to a weather forecast, and labour availability. A small group of farmers does not take up adaptation strategies instead. First of all, their adaptive capacity is constrained by a lack of land, labour, and a weather forecast. Hereby, especially the access to a weather forecast is assumed to significantly increase the adaptive capacity, since all farmers with access to a weather forecast claim to adapt to climate variability. Secondly, the rather optimistic perception of non-adapting farmers towards climate change seems to limit their adaptive capacity. Thirdly, especially the limited use of the onset of rains by non-adapting farmers was observed to negatively influence their climate adaptive capacity.

Incorporating the climate adaptive behaviour of smallholder farmers in socio-hydrological modelling by enabling a logit model showed to be a successful approach. Based on the main drivers for the climate adaptive capacity, the model is able to simulate the agricultural practices with respect to climate variability, hereby distinguishing between adapting and non-adapting farmers. As such, the model has shown to be able to simulate agricultural practices that better coincide with what is observed during both the Focus Group Discussions and the household survey. In addition, the methodology used to evaluate the long-term effect of climate adaptation on the economic well-being of a farmer has the potential to help in creating a better understanding of why farmers adapt to climate variability. However, due to the model lacking the ability to accurately calculate crop yield estimates, the model cannot yet be used to answer the question why smallholder farmers adapt to climate variability and how climate adaptive behaviour influences their economic well-being.

Additional research is needed to obtain a more comprehensive understanding of the climate adaptive behaviour of smallholder farmers. Discussions with local farmers, especially in the higher altitude areas, can add relevant knowledge on farmers' climate behavioural aspects to this research. Furthermore, for one to be able to rely on the outcomes of this model, crop yield calculations should be improved in order to obtain good estimates. In addition, implementing the aspect of 'environmental awareness' is likely to improve the way in which the model describes the climate adaptive behaviour of smallholder farmers.

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Introduction

1.1. The World Food Problem

Eradicating hunger and malnutrition is one of the great challenges of the last decades. Worldwide there were 821 million people who did not get enough to eat in 2019 (see Figure 1.1). Although the trend in world hunger remains unchanged at a level just below 11% since 2015 after decades of steady decline, the number of people who suffer from hunger has slowly increased (FAO et al., 2019). The vast majority of the world's hungry people live in rural areas in developing countries and mostly depend on agricultural production for their subsistence (FAO, 2018b). With 133 million people in 2018 (30% of the population) (FAO et al., 2019), Eastern Africa encounters the highest prevalence of undernourishment (PoU). The Food and Agriculture Organization (FAO) defines PoU as the condition in which an individual's habitual food consumption is insufficient to provide the amount of dietary energy required to maintain a normal, active, healthy life (FAO, 2018b). In order to improve people's lives, the global community adopted 17 Sustainable Development Goals (SDG). "Zero Hunger" is one of these goals and is the priority of the World Food Programme (WFP) (see Figure 1.2). It pledges to end hunger, achieve food security, improve nutrition and promote sustainable agriculture (United Nations, 2015).

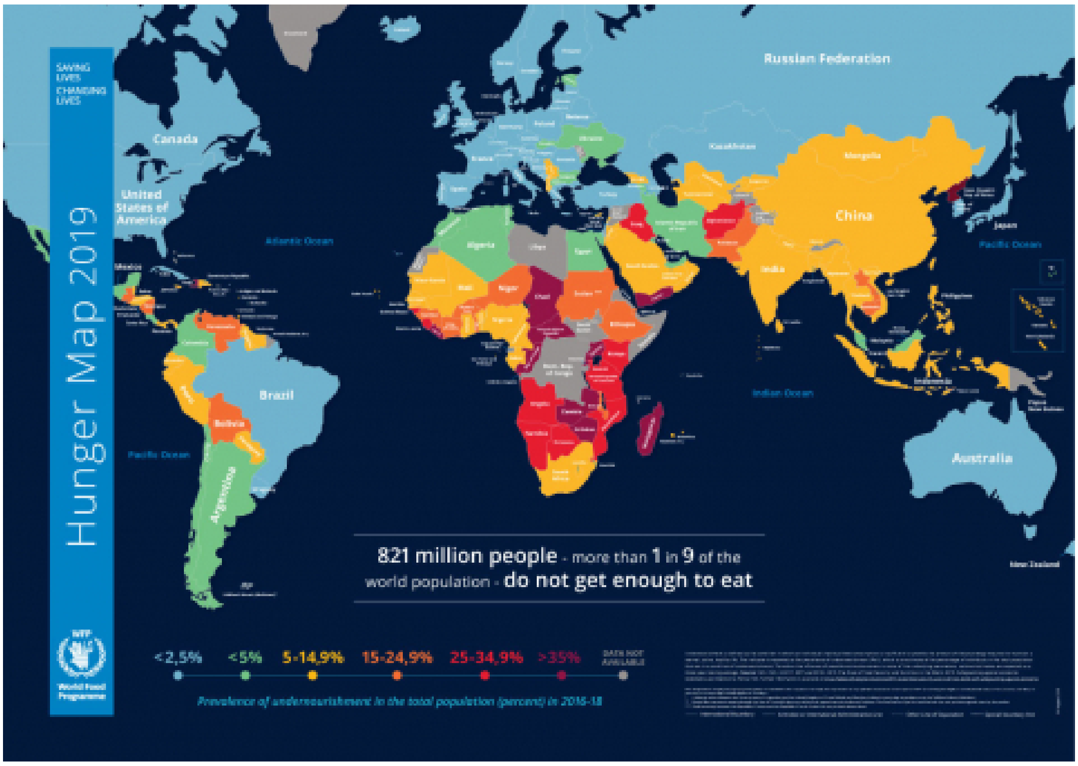


Figure 1.1: World Food Program (WFP): Hunger map of 2019 (FAO et al., 2019).

The rural poor who are dependent on their agricultural production for their subsistence are commonly known as smallholder farmers. Most often they are poor and food insecure, which is mostly caused by limited access to land and water, poor quality soils and their high vulnerability to land degradation and climatic uncertainty. This leaves them in a poverty trap with little or no scope to improve their livelihoods (Dile et al., 2013). A limited access to markets and services often intensifies this situation (Karfakis et al., 2017).

Figure 1.2: WFP: SDG 2 - Zero Hunger

Despite the critical situation smallholder farmers are in, they are highly important in the world food production. They own 90% of the 570 million farms worldwide and produce over 80% of the food consumed by the developing world (Karfakis et al., 2017). Smallholder farming is therefore key in achieving SDG 2 - Zero Hunger - by 2030. The United Nations (2015) state SDG 2 can be achieved by focusing on smallholder farmers. Doubling their agricultural productivity and incomes should help to end hunger, achieve food security and improved nutrition and promote sustainable agriculture. The FAO (2018b) even states that agricultural growth in smallholder farming and low-income economies is at least twice as effective as growth in other sectors at reducing hunger and poverty.

1.2. The Case of Ethiopia

With a population exceeding 115 million people, Ethiopia is the second largest country of Africa, and the fastest growing economy in the region. Over the past two decades, Ethiopia has gained notable progress, especially in the period 2008 to 2019 when economic growth reached 10% per year (World Bank, 2020). Despite the population having doubled in the last 25 years, and predicted to exceed 200 million by the year 2050, the rapid economic growth has resulted in reduction in extreme poverty and hunger rates (Worldometer, nd). Based on the national poverty line from 1996 to 2016, poverty in Ethiopia decreased from 46% to 24%. The national poverty line is based on the required food basket to achieve the minimum required daily calory intake of 2200 kilocalories per adult in Ethiopia (World Bank, 2020).

Despite these positive trends in economy and poverty reduction, Ethiopia still is one of the poorest countries in the world, ranking 173 out of 189 in the 2019 Human Development Index and 91 out of 113 in the 2019 Food Security Index (Global Food Security Index, 2019). Inequality is one of the reasons for this pattern. All over Ethiopia, urban areas have experienced a much faster decline of poverty (from 25.7% in 2011 to 14.8% in 2016) compared to rural areas that have only experienced limited progress (from 30.4% in 2011 to 25.6% in 2016). Since roughly 80% of the population of Ethiopia lives in rural areas and depends on agriculture, a large part of the Ethiopians does not profit from the economic growth and poverty reduction. Hence, inequality increased, which is likely to prevent poverty reduction in the future (World Bank, 2020).

The agricultural sector plays a significant role in the economic development of Ethiopia. This sector is dominated by smallholder farmers living in rural areas, who only marginally reap benefits of the economic growth. The Ethiopian Central Statistical Agency (CSA) classifies this group of farmers as small (i.e. < 25.2 ha), fragmented farms, producing mostly for own consumption (Taffesse et al., 2012). According to the Ministry of Agriculture and Rural Development (MoARD), agriculture in Ethiopia contributes to about 47% of the GDP, 90% of exports, and provides 85% of employment (Erkossa et al., 2009). Although Ethiopia has seen a decrease in the PoU from almost 40% in 2004-2006 to around 20% in 2016-2018, it still is one of the most food-insecure and famine affected countries as a large share of the country's population has been affected by chronic and transitory food insecurity (Sani and Kemaw, 2019). The decrease in PoU is mainly due to a more than doubling of Ethiopia's agricultural output in the period between 2005 and 2015. To a certain extent, this has been due to crop area expansion, the increased use of fertiliser, and the introduction of improved crop varieties. This has increased agricultural productivity, albeit not to the desired level yet. One of the objectives of Ethiopia's Growth and Transformation Plan 2015-2020 (GTP II) (Fiedler et al., 2018) was therefore to bring about a significant shift in agricultural productivity.

Climatic changes make it more challenging to reach this objective. Ethiopia's National Adaptation Program of Action (NAPA) says climate change in Ethiopia will cause changes in rainfall patterns, rainfall variability, and temperature, which could increase the frequency and occurrence of floods and droughts (The World Bank Group, 2011). As more than 90% of smallholder farmers in Ethiopia depend on rainfed agriculture, they are highly vulnerable to climatic variability. The climatic changes indicated by the NAPA could therefore highly influence the agricultural production with corresponding negative effects on food security (The World Bank Group, 2011). Hereby, climate variability is about deviations of weather patterns from year-to-year, whereas climate change is about a climatic change that persists for a decade or longer.

1.3. Scope of the Research

The Gumera sub-basin is one of the areas in Ethiopia in which many smallholder farmers live who depend on rainfed agriculture. It is part of the Amhara National Regional State (ANRS) and located in the Ethiopian highlands in the north west of Ethiopia, inducing large elevation differences. Although the Eastern Nile Technical Regional Office (ENTRO) states the Gumera sub-basin having a medium to high agricultural potential (ENTRO, 2007), often low crop production is obtained that also varies substantially from year-to-year due to this region being highly vulnerable to climate variability. This largely affects the economic well-being of farmers within this region. The high agricultural potential in combination with the high vulnerability of farmers to climate variability make that the Gumera sub-basin is chosen as the study area of this research.

The vulnerability of smallholder farmers in the Gumera sub-basin to climate variability is partly induced by the combination of rainfed agriculture on small and degraded plots on which only one crop a year is cultivated. This makes their crop production, and therefore their economic well-being, highly vulnerable to climatic changes that often induce short rainy seasons, droughts and floods, but also crop pests, weeds, and diseases. According to Asrat and Simane (2017), vulnerability is not a static concept. It not only depends on the rate of climate change, it is also determined by the extend to which a system is exposed, its sensitivity and adaptive capacity.

This thesis will mainly focus on the aspect of adaptive capacity, which is the ability of smallholder farmers to adapt to climatic changes, in order to increase their resilience towards, for example, floods and droughts. Hereby, the adaptive capacity might be limited due to the lack of certain assets, such as land, labour, credit, and information on climate (Gezie, 2019). According to Bryan et al. (2009), the adaptive behaviour of smallholder farmers is mostly related to recent climate events or trends as opposed to long-term changes in average conditions (i.e. climate change). As such, the way in which most smallholder farmers try to reduce their vulnerability to climate variability consists of adjusting their farming practices by taking up different (short-term) adaptation strategies, such as changing the crop type, sowing seeds later in case the rainy season starts late, or changing to off-farm non-agricultural labour. To a certain extent this is thought to be influenced by the smallholder farmer's perception of climate variability (Deressa et al., 2011), which, according to Gezie (2019), is significantly influenced by having access to information on climate. The access to weather information is therefore hypothesised to influence the climate adaptive behaviour of smallholder farmers (Wood et al., 2014).

However, the understanding of how these factors combined influence the climate adaptive capacity of smallholder farmers, and the related choices for certain adaptation strategies is limited (Wood et al., 2014). How, for example, does weather information influence the climate adaptive behaviour of a smallholder farmer and what drives the climate adaptive capacity? The understanding of how smallholder farmers perceive and adapt to climate variability gets even more urgent when taking into account the possible increase in the occurrence of floods and droughts (Deressa et al., 2011). This understanding will help to increase the adaptive capacity of smallholder farmers and to guide future adaptation strategies with respect to climate variability.

This research will therefore focus on the adaptive behaviour of smallholder farmers in order to cope with climate variability and how this influences their economic well-being. Hereby, adaptive behaviour induced by climate change (i.e. long term strategies), conflicts, pests and diseases, and land degradation are not taken into account as this is beyond the scope of this research. Within the scope of this research, the interactions between human and water systems are very important. The adaptation of smallholder farmers to cope with climate variability is an example of such interactions. Socio-hydrology, first introduced by Sivapalan et al. (2012), accounts for such dynamic coupled human-water interactions. It is a relatively new approach that provides the opportunity to explore the dynamics of smallholder farmers with respect to climate variability, and to investigate what drives their climate adaptive capacity. As such, it can be analysed whether farmers taking up climate adaptation strategies are indeed less vulnerable to climate variability. However, to date, only few studies (Di Baldassarre et al., 2015, Kuil et al., 2016, 2019, O'Keeffe et al., 2018) have incorporated the climate adaptive behaviour of farmers within a socio-hydrological model. This study aims to create a better understanding of the impact of climate variability on the system dynamics of smallholder farmers in the Gumera sub-basin by incorporating their climate adaptive behaviour. Hereby the socio-hydrological modelling framework of Pande and Savenije (2016) is used.

1.4. Objective and Research Questions

The objective of this research is to obtain a better understanding of the climate perception and the drivers of the climate adaptive capacity of smallholder farmers in the Gumera sub-basin, Ethiopia. Hereby the focus is on short-term adaptive behaviour with respect to climate variability. It composes a comprehensive bottom-up approach to analyse the characteristics and farming practices of smallholder farmers in the Gumera sub-basin in order to explain the mechanisms that influence their climate adaptive capacity. In addition, this research aims to establish a methodology to incorporate the climate adaptive behaviour of smallholder farmers in socio-hydrological modelling. Hereby, the socio-hydrological modelling framework of Pande and Savenije (2016) will be used. Enabling this model provides the opportunity to holistically simulate the system dynamics of smallholder farmers and to analyse the smallholder farmer dynamics induced by their climate adaptive behaviour.

To reach the objective of this thesis, the general research question to answer is formulated as follows:

What are the drivers of the climate adaptive capacity of smallholder farmers in the Gumera sub-basin and how can a socio-hydrological model be used to simulate their behaviour with respect to climate variability?

In order to answer the main research question, this thesis is subdivided into two major sub-questions:

1. **What drives the climate adaptive capacity of a smallholder farmer in the Gumera sub-basin?**
   - 1.1. What factors influence the crop production obtained by a smallholder farmer?
   - 1.2. What is the smallholder farmer's perception of climate change and variability?
   - 1.3. What agricultural decisions (i.e. adaptation strategies) do smallholder farmers make to adapt to climate variability?
   - 1.4. What are the major barriers smallholder farmer's face in order to adapt to climate variability?
   - 1.5. How is the climate adaptive behaviour of smallholder farmers influenced by weather information?
2. **How can a socio-hydrological model be used to simulate the climate adaptive behaviour and its impact on the economic well-being of smallholder farmers in the Gumera sub-basin?**
   - 2.1. In what way can the climate adaptive behaviour of smallholder farmers be incorporated in a socio-hydrological model?
   - 2.2. How are smallholder farmer dynamics influenced by the farmer's adaptive behaviour with respect to climate variability?

1.5. Reader's Guide

This section provides the structure of this thesis. In Chapter 2 an overview of the theoretical background is provided, in which the current scientific literature, relevant definitions, and key concepts are discussed. The characteristics of the Gumera sub-basin, such as the agro-climatic zones and climatic trends, will be described in Chapter 3. In addition, the agricultural practices of smallholder farmers within the Gumera sub-basin will be explained in this chapter. Subsequently, each of the two research sub-questions, formulated in Section 1.4, will be answered in a separate chapter. Both chapters contain an introduction, a description of the methodology used to answer the sub-question, a section in which the results are presented and discussed, and main conclusions. The first sub-question is answered in Chapter 4. It will explain and discuss the characteristics of smallholder farmers, their perception towards climate variability, and how each of these aspects influences their climate adaptive capacity and behaviour. Chapter 5 will explain the socio-hydrological model and answers the second sub-question. The way in which the climate adaptive behaviour of smallholder farmers in the Gumera sub-basin can be incorporated in a socio-hydrological model, and how this influences their farming practices within the model will be discussed. In Chapter 6 the results presented in Chapters 4 and 5 are discussed. The last chapter, Chapter 7, contains a comprehensive overview of the conclusions of this thesis and answers the research questions proposed in Section 1.4. In addition, it provides recommendations for further research.

2
Theoretical Background

This chapter describes the theoretical background that contains the concepts and main topics of this research. In Section 2.1, the term 'smallholder farmer' is described, as wells as other key terms that are used throughout this research. Subsequently, a literature study on the main general perceptions of Ethiopian smallholder farmers towards climate variability, and their climate adaptive behaviour is provided. Section 2.2 explains the aspects of socio-hydrology and how socio-hydrological modelling is used in other studies to describe the system dynamics of smallholder farmers. In addition, it will explain why socio-hydrology is suitable for analysing the climate adaptive behaviour of smallholder farmers.

2.1. Climate Adaptive Behaviour of Ethiopian Smallholder Farmers

In this section the key terms that play a central role throughout this research will be defined in Subsection 2.1.1. In addition, a better understanding of the climate perception and the climate adaptive behaviour of smallholder farmers in Ethiopia is created based on previous studies (see Subsection 2.1.2).

2.1.1. Key Terms Used Throughout the Research

The term '**smallholder farmer**' does not know an unambiguous definition. To clearly be able to distinguish smallholder farmers from other farmers, the definition of the Ethiopian Central Statistical Agency (CSA) is followed. The CSA classifies Ethiopian farms into two major groups: large commercial farms cultivating more than 25.2 hectares and smallholder farms cultivating less than 25.2 hectares (Taffesse et al., 2012). The latter is the group within which the large majority of smallholder farmers in Ethiopia belong. These farms, though small, are often fragmented, produce mostly for own consumption and generate only a small-marketed surplus (ADSWE, 2015a). For the remaining of this report, a smallholder farmer will be referred to as "farmer".

As more than 90% of these farmers in Ethiopia are dependent on rainfed agriculture, they are highly vulnerable to changes in climate. Although recent climate models say long term trends in rainfall are difficult to determine for Ethiopia (The World Bank Group, 2011), the country's National Adaptation Program of Action, says climate change in Ethiopia will cause changes in rainfall patterns, rainfall variability, and temperature, which could increase the frequency and occurrence of floods and droughts. A '**drought**' can be characterized as agricultural, hydrological, and meteorological (Van Loon, 2015). Hence, it is important to distinguish droughts. An agricultural drought is defined as a deficit of soil moisture, causing less water to be available to vegetation. Hence, it is strongly linked to crop failure. A hydrological drought occurs whenever there is a lack of water in the hydrological system, for example, causing low river discharge, and low water levels in lakes, reservoirs, and/or groundwater. At last, a meteorological drought occurs if precipitation reaches below the long-term mean. The latter definition is used within this research.

Variability in climate, induced by climate change, will highly influence the agricultural production with corresponding negative effects on food security (The World Bank Group, 2011). Among the heavy reliance on rainfall for agriculture, also unsustainable land use practices, and lack of necessary capital to invest in adaptation options exacerbate the vulnerability of Ethiopia to climate change and variability (World Bank, 2010). Note, 'climate change' and 'climate variability' are two distinct terms but often used interchangeably. In this research, for both terms, the definition stated by the Intergovernmental Panel on Climate Change (IPCC) is followed (IPCC, 2018):

*"**Climate change** is a change in the state of the climate that can be identified (e.g. by using statistical tests) by changes in the mean and/or the variability of its properties and that persists for an extended period, typically decades or longer. Climate change may be due to natural internal processes or external forcings such as modulations of the solar cycles, volcanic eruptions and persistent anthropogenic changes in the composition of the atmosphere or in land use."*

*"**Climate variability** are deviations of some climate variables from a given mean state (including the occurrence of extremes, etc.) at all spatial and temporal scales beyond that of individual weather events. Variability may be intrinsic, due to fluctuations of processes internal to the climate system (internal variability), or to variations in natural or anthropogenic external forcing (forced variability)."*

The ability of a farmer to adapt to climate variability depends, to a certain extent, on his or her '**adaptive capacity**'. This is defined by the IPCC as "The ability of systems, institutions, humans, and other organisms to adjust to potential damage, to take advantage of opportunities, or to respond to consequences" (IPCC, 2014). In this research, this is translated to the ability of a farmer to adjust to climate variability in order to reduce or moderate the potential negative effects, and is in the remaining of this research referred to as the climate adaptive capacity.

2.1.2. Farmer's Climate Adaptive Behaviour and Climate Perception

All over the world farmers face climate change and adapt by taking up adaptation strategies. This is assumed to not only be beneficial on the short-term, in terms of increasing yields during a bad year, but is also assumed to reap benefits on the long-term, such as reducing crop production and income variability and making production and livelihoods more resilient to climate change and variability (FAO, 2015). The way in which farmers behave with respect to climate variability is thought to be strongly influenced by the way in which they perceive climate change and variability (Deressa et al., 2011, Makate et al., 2017). Grunblatt and Alessa (2017) suggest a predictive relationship between the perception of environmental change and attitudes. Perceiving changes in climate and its related risks would therefore be an important first step in the process of adapting agriculture to climate variability (Deressa et al., 2011). The nature of farmer behavioural response to this perception will to a certain extent determine the adaptation strategy a farmer takes up and its outcome. Therefore, to understand the farmer's adaptive capacity to cope with climate variability it is important to know the farmer's perception of climate, the drivers and barriers to adaptation strategies and the actual methods with which these farmers adapt (Ado et al., 2019). All around the world several studies have researched the climate perceptions of farmers and their climate adaptive behaviour. Harmer and Rahman (2014) reviewed 18 studies that analysed the adaptation of farmers to climate change and variability. In total, 45 separate adaptation strategies were observed, in which strategies taken up by farmers had both spatial and temporal dimensions, and were influenced by a set of socio-economic factors, such as resources, gender, or cultural identities. In addition, Karki et al. (2020) reviewed 208 articles regarding the climate perception of farmers across the world, from which 39 were focussed on smallholder farmers. Several studies (Deressa et al., 2011, Kahsay et al., 2019) hypothesise that differing climatic conditions influence a farmer's perception of climate change and variability and their decisions to adapt, and are therefore often site specific. Farmers living in different agro-ecological zones, which are distinguished by different climatic conditions, would therefore use different adaptation strategies (Deressa et al., 2011). Therefore, this subsection will focus on the climate adaptive behaviour of smallholder farmers in Ethiopia and more closely in the Gumera sub-basin.

Farmer's climate perception

Several studies conducted in Ethiopia indicate that the perception of climate change is likely to affect how farmers will respond and adapt to climate change and variability (Bewket et al., 2011, Deressa et al., 2011, Gezie, 2019). Farmers are very likely to assess rainfall in relation to the needs of particular crops at particular times. As such, small changes in the amount of rainfall or the timing of the onset of rains can largely influence the farmer's climate perception. This is the reason there often exists a mismatch between the climate experienced by farmers and what is observed from meteorological station data (Ayal and Leal Filho, 2017, Regassa et al., 2010). Different from perceived rainfall, farmer's perceptions of changes in temperature are observed to be rather similar with meteorological station data (Kahsay et al., 2019). However, Kahsay et al. (2019) observed the farmers' perceptions of climate change and variability, that demonstrate decreasing mean annual rainfall and increasing temperature, to coincide with actual meteorological data. Hence, farmers have the ability to perceive the actual climatic changes. However, despite farmers being aware of changes in temperature and rainfall, they often fail to recognise these actual trends of climate change and variability (Kahsay et al., 2019). Adaptation to climate change requires the recognition of the need to adapt and the ability to adapt, and thus requires the awareness of climate change (Skambraks, 2014). There are multiple factors influencing the way farmers perceive climatic changes. This perception is highly personal, site specific, and likely to be influenced by past personal experience and cultural differences (Kahsay et al., 2019). In a study of Deressa et al. (2011), it was observed that experienced farmers are more likely to perceive climate change. In addition, the degree of education of the head of the household was hypothesized to also be positively related to awareness of climate change. This coincides with a study conducted by Maddison (2007), who analysed the farmers' perception of climate change and their adaptation in 10 African countries, amongst which Ethiopia. It was found that farmers with the greatest experience of farming were more likely to notice climate change, but educated farmers were more likely to take up adaptation strategies. It was therefore concluded that it is especially the availability and access to means that will increase an individuals' adaptive capacity. On the other hand, the lack of these can cause barriers to a farmer's adaptive capacity. In addition, Gezie (2019), who conducted a review study in Ethiopia, observed that higher incomes from both on-farm and off-farm activities were found to positively influence farmer's perception of climate change and variability (Gezie, 2019). At last, it was observed that access to information on climate change significantly influences the farmer's perception of climate change and variability and therefore creates higher environmental awareness. This was observed to result in more favourable conditions for taking up adaptation strategies in order to cope with climate change and variability. The access to weather information is therefore associated to influence the climate adaptive behaviour of farmers (Wood et al., 2014).

To provide an overview of how farmers, surrounding the Gumera sub-basin, perceive climatic changes the main results of a study conducted by Bewket et al. (2011) are described here. Bewket et al. (2011) conducted a study in the Ethiopian portion of the Nile river basin in which 500 randomly selected households were interviewed to assess the farmers' perceptions of climate change. The results indicated that the majority of these farmers perceived climatic changes, mainly in form of changes in rainfall and temperature, over the past two to three decades. About 82% of farmers perceived an increase in temperature, whereas 96% perceived overall shortage of rainfall. A similar share of farmers perceived that the onset of rains had become later over the years, but the cessation of rains to come early, resulting in an overall perception that the length of the crop growing period had decreased. About 77% of the respondents had observed considerable reduction in crop production.

Adaptation strategies

In order to cope with climatic changes, farmers adopt a variety of context-specific adaptation strategies. From surveys undertaken by multiple studies undertaken throughout Ethiopia (mainly in the regions Amhara, Oromiya, and Tigray) (Bryan et al., 2009, Gezie, 2019, Kahsay et al., 2019, Regassa et al., 2010) it can be concluded that the most common adaptation strategies include: use of changing crop varieties, soil conservation practices, adjusting planting and harvesting dates, and planting trees. According to Bryan et al. (2009) the adaptive behaviour of these farmers is more related to recent climate events or trends as opposed to long-term changes in average conditions. Moreover, their decision to adopt one of these farming practices depends on their personal experience of extreme events, rainfall frequency, timing and intensity.

Despite the perception of changes in climate, a large percentage of smallholder farmers (roughly 40%) did not make any adjustments to their farming practices (Bryan et al., 2009, Deressa et al., 2011). On-farm adaptation strategies, such as varying planting dates, use of drought tolerant crop varieties, soil conservation strategies, are based on farmers indigenous knowledge passed down from generations (Aniah et al., 2019). Wood et al. (2014) suggest, upon multiple literature studies, that assets and household wealth are necessary to allow adoption of adaptation strategies that may require access to capital. Adaptation to climate that requires these investments is, therefore, less likely to be carried out by the poor, who are often budget constrained. This coincides with what is observed by Gezie (2019), who observed that a lack of access to land, information, credit and labour were mentioned by smallholder farmers across Ethiopia to be the main barriers that keep them from adapting to climate variability.

2.2. Socio-Hydrology

This section explains what socio-hydrology is, its relevance, and how it differs from other modelling approaches (see Subsection 2.2.1). In addition, Subsection 2.2.2 describes how the climate adaptive behavioural aspects of farmers are incorporated in socio-hydrological models by previous studies, and explains the term 'environmental awareness'.

2.2.1. Relevance of socio-hydrological modelling

It is evident that societal actions influence the hydrology in many countries at a tremendous and increasing rate. In some cases this induces a significant stress on water systems, causing water to become a major limiting factor to the sustainable development of the society. The decreasing length of the rainy season perceived by smallholder farmers in the Gumera sub-basin is an example of this. This requires societies, such as these smallholder farmers, to adapt. There thus exists a strong interaction between societal and hydrological systems that co-evolve over time (Montanari et al., 2013). One way to analyse the interaction between these two systems is by the use of a mathematical hydrological model. However, to date, hydrological analyses focusing on the interaction between these two connected systems have mainly been conducted by considering each system separately. Therefore, hydrological models are particularly suited to simulate and predict processes for pristine catchments, whereby the interaction with society is often taken into account via independently developed models of societal behaviour. Hereby, the feedback between these models is often introduced by boundary conditions. As such, it may account for hydrological changes induced by shifts in external forcings or internal dynamics, but cannot account for more complex changes due to co-evolving model structures or parameters (Montanari et al., 2013)

An example is Integrated Water Resources Management (IWRM). The process of IWRM has been shown to be successful in accounting for these complex interactions between water and humans, and is widely adopted by political decision makers in many countries (Savenije and Van der Zaag, 2008). By acknowledging the entire water cycle, and taking into account the interests of water users in different sectors of a society, it addresses both the natural and human dimensions of water. It explores the interaction using a 'scenario-based' approach, hereby controlling the water system to reach desired outcomes for society and the environment (Sivapalan et al., 2012). However, by enabling this approach only limited attention is given to the co-evolutionary human-water interactions, as well as feedbacks and dynamics in system behaviour (Montanari et al., 2013). Due to the increasing impact of humans on the hydrological system, it is becoming more important to incorporate the co-evolution of human-water systems in such models, in order to reach a better interpretation of the interaction between water and humans. This has led the International Association of Hydrological Sciences (IAHS) to focus, from 2013-2022, on hydrology for society and related changes, including environmental feedbacks and humans as an essential part of hydrological systems (Montanari et al., 2013).

In case of this research, we want to explore the interaction between climate variability, which is part of the hydrological system, and the climate adaptive behaviour of smallholder farmers, which is the societal system, since these interactions are known to play a vital role in smallholder farmer dynamics. This concept of human-water interactions is incorporated in socio-hydrology, first introduced by Sivapalan et al. (2012). It is a relatively new holistic approach that provides the opportunity to couple human-water interactions. It focusses on the co-evolution of coupled human-water systems and thus explores the dynamics of people with respect to water variability (Sivapalan et al., 2012). As such, it is possible to link human behaviour, which might be influenced by several factors, such as economical and demographical factors, to the hydrology part of the model. In this way a socio-hydrological model provides the opportunity to holistically model the system dynamics of smallholder farmers by taking into account all of these factors. Socio-hydrological modelling can therefore help to better understand the system dynamics of smallholder farmers, which is defined as the dynamics of smallholder farmers, in terms of, for example, their economic well-being, farming practices taken up, and their level of food security, within the human-water system. Within a socio-hydrological model these system dynamics are modelled using stocks (calculated by differential equations), flows, and internal feedback loops.

2.2.2. Incorporating Climate Adaptive Behaviour in Socio-Hydrological Modelling

It is shown that the outcomes of Socio-hydrological models can improve the assessments of policy-makers for identifying the proper management strategies to cope with water resources challenges, especially water scarcity (Montanari et al., 2013). However, the challenging point in water resources management is that people try to adapt themselves to cope with environmental problems in order to satisfy their needs (Pouladi et al., 2019). In recent years, several socio-hydrological models have been developed to investigate the complex co-evolutionary interactions between hydrological systems and dynamic behaviours of farmers (Kuil et al., 2016, Pande and Savenije, 2016, Van Emmerik et al., 2014). Most of these models were developed through top-down approaches which make it possible to create an overview of a system. However, the fundamental background process are hereby overlooked (O'Keeffe et al., 2018). Bottom-up approaches, which focus more on the underlying linkages of sub-systems, could deliver more accurate results of socio-hydrological processes, especially when dynamic elements, such as the climate adaptive behaviour of smallholder farmers, are taken into account (Pouladi et al., 2019).

As is described by Subsection 2.1.2, Grunblatt and Alessa (2017) suggests a predictive relationship between the perception of environmental change and attitudes. Perceiving changes in climate and its related risks would therefore be an important first step in the process of adapting agriculture to climate variability (Deressa et al., 2011). One way of incorporating the human-water interactions is therefore by including the aspect of 'environmental awareness'. However, to date, only few studies have incorporated human adaptive behaviour with respect to climate variability in socio-hydrological models by enabling the 'environmental awareness' of farmers (Di Baldassarre et al., 2015, Dile et al., 2013, Kuil et al., 2016). The perception of changes in climate is captured in the aspect of 'environmental awareness', in which it is seen as a sort of memory bank, in which it could be a function of, for example, the number of days with water shortage, or the soil moisture content. The details and accuracy of people's memory of climate variability change based on personal perceptions (Singh et al., 2018), which, for example, are influenced by their farming experience. As such, people may exaggerate certain drought events and forget others based on how they were affected. Each of the frameworks proposed by these studies (Di Baldassarre et al., 2015, Dile et al., 2013, Kuil et al., 2016) uses socio-hydrological modelling as an explorative tool to support the understanding of human-water interactions. Although these models have been compared with empirical data, the approach of incorporating human-water interactions based on the 'environmental awareness' is not without critics from the social sciences. One critique is that strong and robust social theories are needed to underlie any mathematically based socio-hydrological model (Di Baldassarre et al., 2015). However, these current social theories are often underdeveloped or contested. In addition, there exist large gaps in our understanding of how human-physical systems function. Building socio-hydrological models would therefore be particularly valuable for exploring how variables effect system functioning and could therefore aid in the development of theories.

3

Study area

This chapter provides an overview of the study area of this research, the Gumera sub-basin. First, the geographic characteristics are described, after which Section 3.1 elaborates on the agro-climatic zones (ACZ) which largely separates the Gumera sub-basin into two parts. The main climate of the Gumera sub-basin is discussed in Section 3.2, together with climatic trends and variability and how this is related to El Niño weather events. Lastly, Section 3.3 gives an overview of the main agricultural practices of farmers in the Gumera sub-basin.

The study area for this research is the Gumera sub-basin. It is located in South Gondar zone that is part of the Amhara National Regional State (ANRS) in the north west of Ethiopia (see Figure 3.1). The area is separated by four Woredas (the third-level administrative division of local government in Ethiopia), namely Dera in the South West, Fogera in the North West, Farta in the North East, and East Este in the South East. Each of these Woredas is further subdivided into Kebeles, the smallest level of local government in Ethiopia. With more than 20 million people (making up 22.4% of the Ethiopian population), the ANRS is the second most populous region in Ethiopia (Dile et al., 2018). The Gumera sub-basin is part of the larger Lake Tana sub-basin, which has an average population density of 200 persons per km^2 (Abera, 2017).

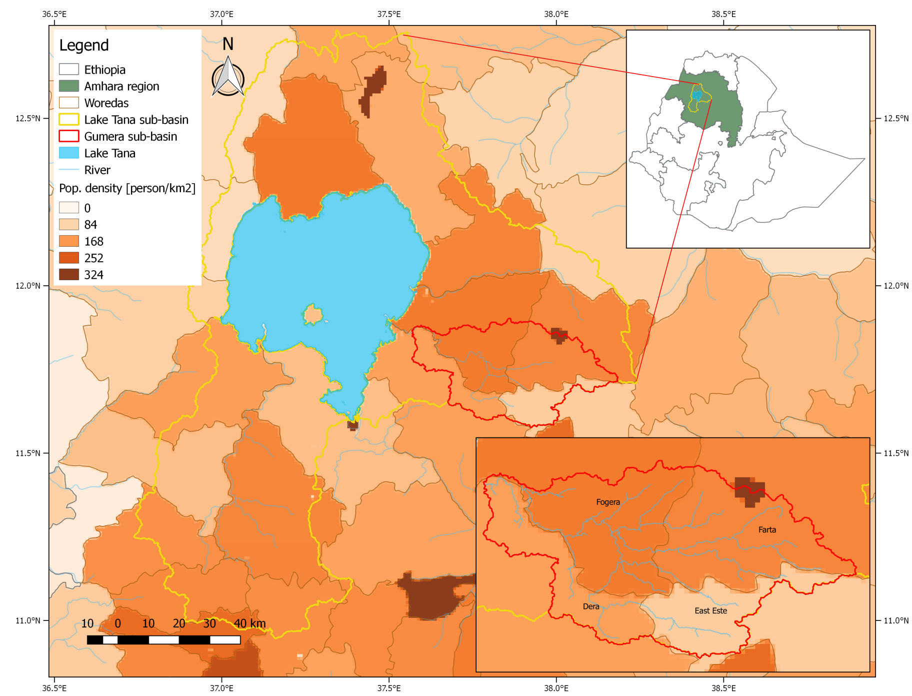


Figure 3.1: Spatial overview of the Gumera sub-basin in Ethiopia, indicating the population density per Woreda in person per km^2. The figure on the top right shows the location of the Lake Tana sub-basin in Ethiopia. The figure on the bottom right zooms in on the Gumera sub-basin, and indicates the four Woredas by which it is separated. Made by author.

The Gumera sub-basin is located in the Ethiopian highlands between 11.5°N and 12°N latitude, and 37.5°E and 38.2°E longitude. The elevation ranges from 1786 meter above mean sea level (AMSL) in the west to 3709 meter AMSL in the east (see Figure 3.3). This means rather flat areas in the west, whereas it gets more hilly moving towards the east (see Figure 3.2). Here, the landscapes are separated by deep river valleys, which makes conducting agricultural practices more difficult. The Gumera river is the main river and drains into Lake Tana in the west. This is the largest lake in Ethiopia and is the origin of the Upper Blue Nile, contributing to 60% of the Nile River flow (Dile et al., 2018).

(a) West

(b) South

(c) East

Figure 3.2: Impressions of farming landscapes in the a) western part, b) southern part, and c) eastern part of the Gumera sub-basin in the beginning of March, 2020. Made by author.

3.1. Agro-Climatic Zones

This section describes the ACZs that divide Ethiopia into three major parts. In addition, the ACZs apparent in the Gumera sub-basin are described.

Although the entire Gumera sub-basin lies within one regional administration zone (i.e. ANRS), it consists of multiple agro-climatic zones (ACZs). An ACZ is defined by the FAO as "a land unit represented accurately or precisely in terms of major climate and growing period, which is climatically suitable for a certain range of crops and cultivars" (FAO, 2016). The purpose of ACZs is to separate areas with differing sets of potentials and constraints. This not only helps to improve the planning of agricultural development on a regional or national scale, but also to analyse impacts of climate variability and climate change on agriculture.

Taking into account the water balance and the growing period, Ethiopia can be divided into three major ACZs. The first one can mainly be found in the lowland areas in the East of Ethiopia, which receive little or no rainfall and thus have no significant growing period. In the western half of the country, the second major ACZ can be found. This region only knows one rainy season that extends from February/March to October/November, with decreasing duration of the rainy season from south to north. This part of the country therefore has only one growing period. The third major ACZ has two rainy seasons, the shorter rainy season from February to April, locally called the "Belg" rainy season, and a longer rainy season from June to September, locally called the "Meher" rainy season. This results in two growing periods. The areas receiving two rainy seasons are mostly located in the southern and the south eastern lowlands (FAO, 2016). The Gumera sub-basin is located in the second major ACZ as it only knows a single growing period, with a relatively short rainy season extending from June to September. However, the rainy season often is inconsistent of length and can extend from May to October (Wassie, 2017). This results in a largely varying length of the growing period, with a range of 131 to 180 days (Abebe et al., 2017). The length of growing period (LGP) for a given location is defined as the continuous period of the year in which precipitation exceeds half of evapotranspiration plus a certain period to evapotranspire an assumed volume of soil moisture storage. In addition, the mean daily temperature needs to exceed 6.5 °C during this period (FAO, 1996).

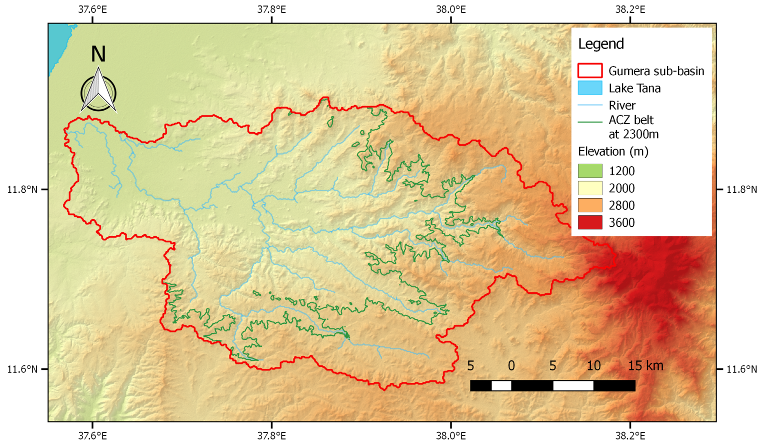


Figure 3.3: The two major agro-climatic zones covering the Gumera sub-basin separated by the ACZ belt at 2300 m AMSL (green line). The western part is located in the lower ACZ, called "Wet Weyna Dega". The eastern part is located in the upper ACZ, and is called "Wet Dega". Made by author.

Each of the major ACZs can be spatially differentiated by altitude and annual rainfall and their combined effects on the characteristics of agricultural production. This classification consists of six altitudinal levels that vary between dry, moist or wet conditions, and divides Ethiopia into 12 ACZs. With annual rainfall averaging to 1410 mm in the period 2000-2019, the Gumera sub-basin can be classified as "wet". When taking into account altitude, the Gumera sub-basin can be divided into four ACZs, namely 'Wet Weyna Dega' (1500-2300m AMSL), 'Wet Dega' (2300-3200m AMSL), 'Wet Wurch' (3200-3700m AMSL), and 'High Wurch' (above 3700m AMSL). However, as the latter two cover only 1% of the total area of the sub-basin and have very steep slopes, resulting in low agricultural practices, they are not taken into account in this research. Therefore, Figure 3.3 only shows the Wet Weyna Dega (in the west), and Wet Dega (in the east), which are separated by the ACZ belt at 2300m AMSL.

3.2. Climate

In this section the climate of Ethiopia, and more specifically of the Gumera sub-basin, will be described. First, the yearly cycle of rainfall and temperature will be shown, after which climate change and variability, and its effect on the Gumera sub-basin, will be explained. In addition, the effect of El Niño on the variability in weather patterns is described.

3.2.1. Seasonal Cycle

Ethiopia has a clear seasonal cycle that varies regionally and is dominated by the meridional migration of the Inter-Tropical Convergence Zone (ITCZ) (Gleixner et al., 2017). This causes the rainfall pattern in the Gumera sub-basin to be characterised by an almost unimodal wet season, meaning only one rainfall peak is apparent without alternation of humid and dry months (Herrmann and Mohr, 2011). The Gumera sub-basin thus has a clear seasonal cycle, with the rainy season (known as the 'Meher' season), typically occurring from May/June till September. May, therefore, is the month representing the most normal onset of rain (Legesse, 2017). Figure 3.4 shows the mean monthly

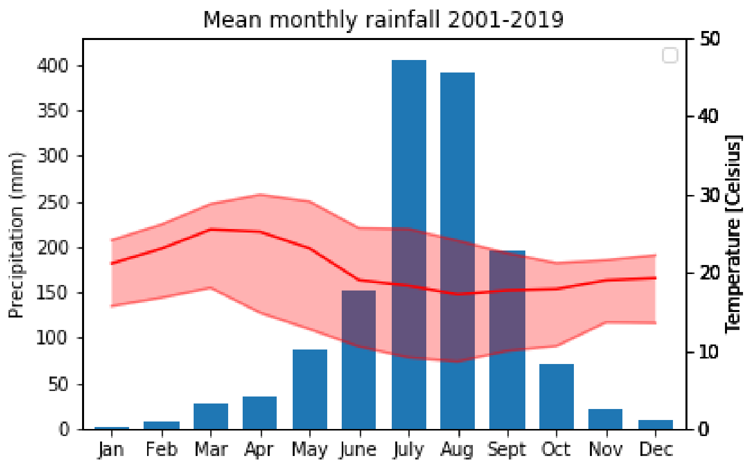


Figure 3.4: Mean monthly rainfall and temperature of the Gumera sub-basin from 2001-2019. Made by author. Data obtained from Funk et al. (2014).

rainfall and temperature for the Gumera sub-basin over the period 2001-2019. The average monthly temperature ranges from 27 °C in the months prior to the rainy season (i.e. March and April) to around 20 °C from June to December, the latter of which is the extend of the cropping season. The 'Meher' season is known for its 'kiremt' rains that account for approximately 80% of the annual rainfall. Over the last 15 years the amount of annual rainfall amounted to 1410 mm on average (Funk et al., 2014). Due to this relatively high amount of rainfall the Gumera sub-basin is known for having a relatively high rate of volumetric soil moisture compared to the rest of the country. The Eastern Nile Technical Regional Office (ENTRO) therefore states that the Gumera sub-basin has a low to very low risk to moisture stress, and can be classified as having medium to high agricultural potential (ENTRO, 2007).

3.2.2. Climate change and variability and the impact of El Niño

Due to Ethiopia's distinct seasonal cycle, and rainfall being highly erratic with large year-to-year variability, smallholder farmers face a very high risk of intra-seasonal dry spells and annual droughts (FAO, 2016). Every three to five years significant drought and flood events are occurring, impacting the livelihoods of farmers (Alemu and Mengistu, 2019). Due to climate change these phenomena are expected to become more severe in the future as rainfall variability will increase, possibly causing larger drought and flood disasters in Ethiopia (Alemu and Mengistu, 2019). Over the last 20 years, Ethiopia has seen droughts in the years 2000, 2002/2003, 2006, 2011, and 2015/2016. The latter one in 2015-2016, can be considered as the worst drought in the last 30 years, leaving 10 million people food insecure (Alemu and Mengistu, 2019, FAO, 2016).
Some of these droughts, such as the 2015-2016 drought, are related to El Niño weather events (see Figure 3.5). An El Niño event causes the northern part of Ethiopia to become much drier, whereas the southern part becomes much wetter resulting in floods. It is observed that with climate change, El Niño years could become more frequent, causing the Northern part of Ethiopia to experience more droughts (Gleixner et al., 2017). Although, not every drought is induced by El Niño, for example the drought years of 2000 and 2011 (Gro Intelligence, 2015b), it is estimated that 50 to 90% of crop failure is caused by El Niño. It can thus be seen as one of the most important factors having impact on the well-being of smallholder farmers in Ethiopia (Berhane and Tesfay, 2020).

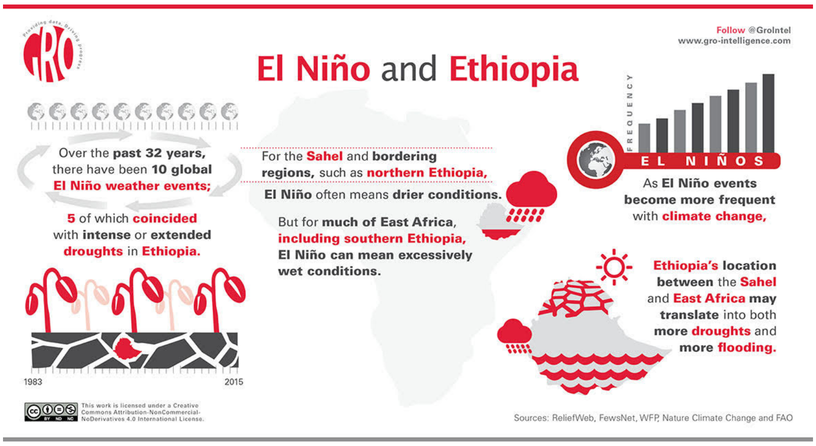


Figure 3.5: The impact of El Niño on Ethiopia (Gro Intelligence, 2015a).

Focussing on the Gumera sub-basin specifically, droughts and rainfall variability are the main climatic hazards. In Subsection 2.1.1, it was explained that the term 'drought' has multiple definitions. In this research, the drought is defined as a meteorological drought. In a study of Legesse (2017), conducted in the Lake Tana sub-basin, 30 years of rainfall data (from 1984 to 2014) has been analysed with respect to climate change trends, and droughts. Legesse (2017) found the Lake Tana sub-basin to have experienced moderate to mild drought years in 1992, 1994, 2003, 2004. More sever droughts occurred in 1995, 2002, 2009 and 2012. This not only suggests that occurrences of droughts have been rather frequent over the last 30 years, but also the drought severity has increased, especially after the year 2000. On top of this, Legesse (2017) concluded that the inter-annual rainfall variability has increased. On the long term a general decreasing trend of annual rainfall has been observed, together with a general increasing trend of the maximum and minimum temperature.

3.3. Agricultural practices

In this section a general picture will be sketched of the agricultural practices noticed in the Gumera sub-basin. This is done based on literature regarding the Lake Tana sub-basin. Hereby it is assumed that the Gumera sub-basin is a typical representation of a basin in the Lake Tana sub-basin in terms of land cover and geographic characteristics. This first analysis of agricultural practices will function as an initial perspective from which certain (supposedly valid) assumptions will be made. In Chapter 4 a more detailed description of the agricultural practices observed in the Gumera sub-basin will be given based on the results obtained from the FGDs and an individual household survey. When different patterns are observed this will be noted and discussed.

3.3.1. Landcover

In Figure 3.6 a GIS map of different land cover types in the Gumera sub-basin is shown. It can be seen that the major land cover is cropland at 65%. As slopes are more gentle in the western part of the sub-basin, cropland prevails in this area. The average household landholding size is 1.3 hectares (ADSWE, 2015a). From the total cropland, 83% is used for growing cereal crops, such as teff, maize, barley, finger millet, wheat, rice, and sorghum. This accounts for 87% of the total crop production in quintals (see Table 3.1). Root crops make up for 2.91% of the total cropland, in which potato took the largest share in terms of both the area it is planted (95.1%) and volume of crop production (in quintals) obtained. Since potato is the major food crop in the sub-basin particularly in highland areas, it is produced in larger volumes compared with other root crops, such as onion that covers only 1.3% of the area at which root crops are grown (ADSWE, 2015a). Table 3.1 shows an overview of the share of crop area used for each crop type, and the corresponding share of crop production in quintals.

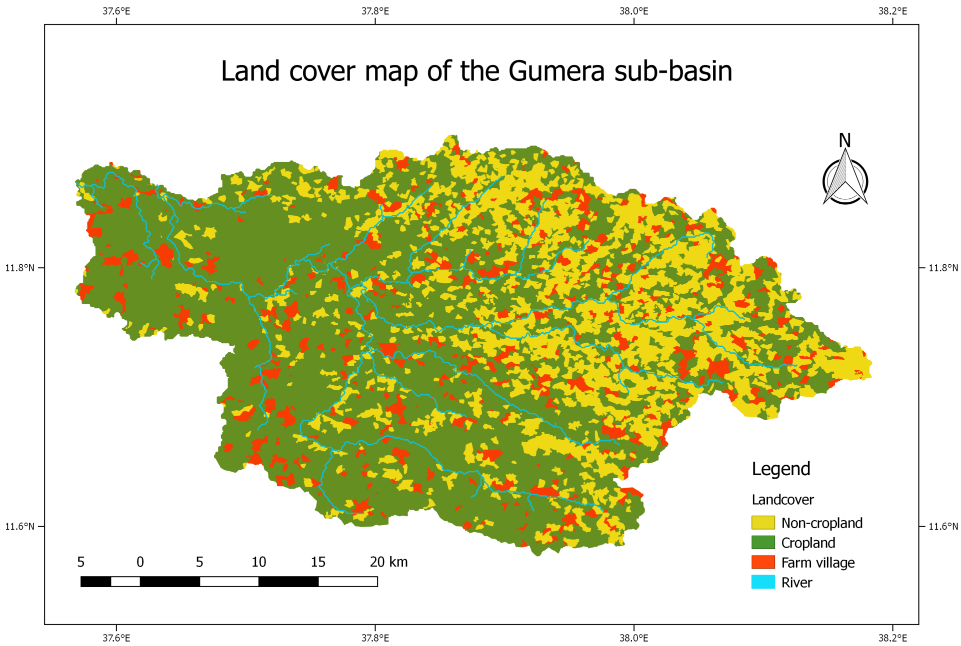


Figure 3.6: Land cover map of the Gumera sub-basin. Made by author. Data obtained from ADSWE (2015a)

3.3.2. Cropping pattern

The cropping pattern describes the system by which farmer's grow crops in a particular sequence. The most dominant cropping pattern in the Gumera sub-basin is rainfed crop rotation with possibly supplementary irrigation. Other cropping patterns used in the Gumera sub-basin are mixture, intercropping, and double cropping by using residual moisture. Due to the unimodal rainfall pattern, the most dominant cropping season is the Meher season. Most of the agricultural production is produced in this season.

Although ENTRO states the Gumera sub-basin having a medium to high agricultural potential (ENTRO, 2007), often low crop production is obtained that also varies substantially from year-to-year. This vulnera-bility is partly induced by the combination of rainfed agriculture on small and degraded plots with only one crop a year. This makes the production highly vulnerable to natural hazards such as droughts or erratic rainfall patterns, crop pests, weeds, and diseases. However, also low usage of purchased inputs, such as seeds, fertilizer and chemicals, and crop losses both in the field and during harvesting and storage, cause the crop production to be low and variable. Studies by FAO and others (ADSWE, 2015b, FAO, 2018c), suggest that losses of stored grains due to poor storage can be as high as 15-20% . As these smallholder farmers mainly produce for their own consumption, only a small fraction of the production is marketed. This often is needed to meet urgent cash needs or to buy staples later in the year (Stave et al., 2017).

Complementary livestock farming

Rearing livestock also plays an important role for farmers to deal with crop failures and therefore food security. It constitutes a major part of the farming system next to crop production. Most farmers do not have their own grazing land but make use of communal grazing areas (Tahir et al., 2018). In the Gumera-Ribb watershed the livestock density is 9.4 TLU/ha (Amsalu and Addisu, 2014). Besides livestock providing draft power and the production of milk and meat, it plays an important role for smallholder farmers to deal with crop failures (ADSWE, 2015a). Selling livestock forms a critical source of income in times of food insecurity (Brief, 2004). Cattle are the most important species kept by farmers in the Lake Tana sub-basin. Other livestock species reared are donkeys and mules, which are mainly used for transport, and goats, sheep, and chicken, which provide an important source of protein for smallholder farmers. The price of livestock animals varies significantly from time to time due to several factors (Abera, 2017).

	Share of crop area [%]	**Share of crop production in qt [%]**
Cereal crops		
Teff	25.8%	15.2%
Maize	19.3%	31.2%
Barley	10%	7.4%
Millet	8.3%	7.7%
Wheat	7.5%	7.2%
Rice	6.7%	2.5%
Sorghum	3%	2.7%
Triticale	*2.5%*	*13.3%*
Total	*83.1%*	*87.2%*
Root crops		
Potato	2.8%	7.25%
Onion	0,04%	0,08%
Other crops	14.1%	5.5%
Total	100%	100%

Table 3.1: Major crops grown in the Gumera sub-basin in terms of crop area, and production in quintals (qt) (ADSWE, 2015a). 1 quintal = 100 kg.

Rainfed agriculture

Within the Gumera sub-basin two main farming systems can be identified. The most dominant one is mixed crop-livestock rainfed farming, and accounts for the bulk of food production in the area. More than 80% of the cultivated land is rainfed (Abera, 2017). It is characterized by subsistence farming with low input - low output productivity. Cultivation of crops mainly takes place during the Meher season and is predominantly cereal based. Livestock production is undertaken complementary to producing crops. The most dominant cropping system used is crop rotation in which the type of crop grown is changed each year. This not only improves the soil structure and fertility, it also helps to control weeds, pests and diseases. As cereals are the staple food in this area, the cereal-cereal-cereal approach is most dominant and used by almost all farmers. The major rainfed crops grown in the Lake Tana sub-basin are teff, sorghum, barley, wheat, maize, and finger millet (ADSWE, 2015a). Pulses like beans, and chickpeas are also grown. Rice is grown only in the wetlands, especially in the Fogera and Dera Woredas. In these areas, rice is grown for two to three years without rotation (Abera, 2017).

Traditional irrigation systems

The second main farming system consists of irrigation and residual moisture. This farming system occupies the remaining land that is not used by the rainfed farming system (Abera, 2017). One of the reasons for the use of supplementary irrigation and residual soil moisture is that the rainy season in northern Ethiopia often does not exceed 65 days. As most of the crops require more than 80 days, the rainy season is shorter than the crop growing period (Berhane and Tesfay, 2020). Almost all irrigation systems are traditional small-scale irrigation systems (less than 200ha) and are found all over the region Hagos et al. (2009). In 2007, about 21% of the households in the Lake Tana sub-basin are engaged in small-scale irrigation activities (ADSWE, 2015a). However, the total irrigated area accounts for only 3.8% of the total cultivated land. About 35% of the small-scale irrigation systems consist of traditional river diversions. Modern small-scale irrigation technologies, such as motorized pumps, also have been developed and account for 33% of the irrigation activities. Irrigation is mostly used for vegetables such as potato and onion. In some areas, cereal crops, like maize and barley, and pulse crops are also grown using irrigation systems (ADSWE, 2015a).

Some farmers in the Lake Tana sub-basin also practice double cropping on black vertisol soil areas by using residual moisture (ADSWE, 2015a). Farmers near Lake Tana grow crops like chickpea, grass pea, and barley using the residual moisture that is always available and use the land that is freed as the water recedes during the dry season. Farmers in high altitude land areas particularly around Farta practice double cropping. This means they grow barley just after potato or vice versa. Closer to Lake Tana, rice or teff is planted during the Meher season, after which chickpea or grass pea is grown with residual moisture. The most common double cropping system in these areas is: rice - chickpea/grass pea/maize, teff - chick pea/grass pea/maize/fenugreek, and millet - chickpea/grass pea.

4

Characteristics of Smallholder Farmers in the Gumera sub-basin

In this chapter the characteristics of smallholder farmers in the Gumera sub-basin are discussed based on the outcomes of Focus Group Discussions and an individual household survey. General demographic, and socio-economic results will be shown, as well as the main farming practices conducted by farmers in the Gumera sub-basin. Subsequently, a more thorough analysis will be presented regarding the climate adaptive behaviour of these smallholder farmers. The farmer characteristics and their climate perception are linked with their climate adaptive capacity and behaviour. In addition, the barriers that keep farmers from adapting to climate variability are exposed.

4.1. Introduction

Sections 3.2 and 3.3 explored the agricultural practices of farmers in the Gumera sub-basin, and how they are influenced by changes in climate. It was observed that most farmers practice a mixed crop-livestock rainfed farming system, which makes them highly vulnerable to variability in climate, often induced by El Niño. In Subsection 2.1.2, an overview of the behaviour of farmers throughout Ethiopia with respect to climate variability is created based on previous studies conducted in the regions Amhara, Oromiya, and Tigray by Bewket et al. (2011), Bryan et al. (2009), Kahsay et al. (2019), Regassa et al. (2010). It was observed that the majority of farmers adapt to climate variability. By doing so, they take up adaptation strategies such as changing the crop type, soil conservation, shifting planting and harvesting dates, and planting trees. The choice of a farmer to adapt with a certain adaptation strategy was suggested to be influenced by their climate perception. In addition, some farmers did not take up adaptation strategies, claiming to be constraint by a lack of land, labour, weather information, and credit. However, it is not quite known how each of these farmer characteristics exactly drive the climate adaptive capacity and their choices for certain adaptation strategies.

This chapter explores, via a bottom-up approach, the differences between different groups of farmers within the Gumera sub-basin, and aims to create a better understanding of the drivers behind their agricultural decisions with respect to climate variability. In order to reach this objective Focus Group Discussions and a individual household survey are conducted to gather data from local farmers in the Gumera sub-basin. By gathering data on demographics, socio-economic parameters, climate perceptions and climate adaptive behaviour, a more in depth analysis will be conducted. Section 4.2 describes the methods used to answer the first sub-question proposed in Section 1.4. The results obtained from the Focus Group Discussions and the individual household survey are presented and discussed in Sections 4.3 and 4.4, respectively. At last, a conclusion is provided in Section 4.5.

4.2. Methodology

An effective and efficient approach to obtain good quality data is to conduct a field survey by combining several different methods (Freudenberger, 2008). The most appropriate combination of methods for this research is determined by considering the objectives as well as constraints such as time, money and expertise (Marsland et al., 2000). The objective of data gathering in this research is twofold. First, socio-economic data is required to both obtain knowledge on the livelihood of the farmers and to parameterise the socio-hydrological model with site specific data. Second, more qualitative data is needed on the farming practices of these farmers and their agricultural decisions to obtain a better understanding of the behavioural aspects. The latter type of data will be used to analyse what factors influence the choices farmers make regarding their agricultural practices and how they cope with climate variability.

In general, survey methodologies can be distinguished into two types, formal and informal surveys. Formal surveys are better to gather quantitative data, whereas informal surveys are better to gather qualitative data (Kleih and Wilson, 2001). To obtain high quality data it is often recommended that prior to a quantitative study a qualitative phase is conducted. This provides the opportunity to understand the vocabulary used by the smallholder farmers as well as understanding their motivations and attitudes towards, in this case, their agricultural behaviour (Marsland et al., 2000). Hence Focus Group Discussions(FGDs) were conducted prior to a formal survey, in order to improve the survey's design and questioning. The formal survey was in the form of an individual household survey.

This section describes the methods used to answer the first sub-question (see Section 1.4). The methodology consist of a field survey that composes two phases. In Subsection 4.2.1 the design of the FGDs, which composes the first phase of the field survey, is described. The main goal of these FGDs is to obtain insightful information from and about local farmers with respect to their farming practices, climate perceptions, and climate adaptive behaviour. This knowledge is then used to improve the individual household survey's design and questioning. The individual household survey composes the second phase of the field survey, and is described in Subsection 4.2.2. The design of this survey is explained, as well as which statistical tests are used for the data analyses.

4.2.1. Focus Group Discussions

The first phase of the field survey composes FGDs. A FGD is a Participatory Rural Appraisal (PRA) technique to gather qualitative information. It is frequently used to gain an in-depth understanding of social issues by learning about rural life and conditions from, with, and by rural people (Chambers, 1992). Bewket et al. (2011) and Regassa et al. (2010), for example, used FGDs in order to study the climate variability perceived by farmers in the Amhara region (amongst other regions in Ethiopia) and its agricultural impacts. In the same way, FGDs are conducted for this research in the Gumera sub-basin in order to investigate how local farmers perceive climate change and variability, how they behave upon this, and how this compares to what is found in similar studies conducted in Ethiopia (see Figure 4.1). In total three FGDs have been conducted, each in a different Kebele (i.e. the smallest level of local government in Ethiopia). The FGDs have been conducted in (from west to east) Jigena, Geregera, and Shime (see Figure 4.3).

Figure 4.1: An impression of the Focus Group Discussion conducted in Geregera. Made by author.

During a FGD, several diagrammatic techniques are frequently used to simulate debate and record the results. Participatory mapping, timeline, structured direct observation, and seasonal calendar, are some of these techniques, and are shortly discussed (Cavestro, 2003).

Participatory mapping can be used to depict infrastructures, natural resources, land ownership, soil types or cropping patterns. Local people create a map by drawing or modelling current or historical conditions. This allows to collect local people's perceptions and to recognize spatial relationships.

The approach of a timeline can be used to discuss the most important events in the community's past. Local histories will give a more detailed account of how things have changed or are changing, and can, for example, be developed for crops or population changes.

The methodology of "structured direct observations" allows a cross-check of findings of what people tell. Sometimes people idealise a situation and tell things which are more a description of how things should be than how things are. Direct observations also provide the opportunity to generate on-the-spot questions in direct interaction with the local people.

Although each of these techniques can (partly) provide the information desired, the use of a seasonal calendar was thought to be most suitable for this research. The use of a seasonal calendar is a more complementary approach compared to the other diagrammatic techniques. It provides the opportunity to obtain data regarding what decisions the smallholder farmers make, when and why, and is therefore used as the central discussion tool during the FGDs. During such a discussion local people were encouraged to fill in the matrix of the calendar. In this way the main objective, which is to learn about changes in farming practices over the year and to show the seasonality of agricultural and non-agricultural activities, is reached (Cavestro, 2003). Variables such as rainfall distribution, labour, income and expenditure, food availability, agricultural production, and planting and harvesting dates were drawn to show month-to-month variations and seasonal constraints. By enabling this method information is obtained on how smallholder farmers allocate their time as well as their labour in various activities. In addition, knowledge is gained on the frequency of occurrence of certain weather patterns, such as dry and wet years, and whether, in the perception of the smallholder farmers, this has changed over the last decades. Figure 4.2 shows a seasonal calendar created during one of the FGDs.

The target group for these FGDs were smallholder farmers in the Gumera sub-basin that grow crops by using either rainfed agriculture or irrigation or both. Ideally, contributions from both male and female, and younger and older household heads are gained to capture a representative view of the population. This provides a complete picture of community activities and the opportunity to highlight differences between each group. At the start of each FGD, general questions, such as household size, crop area, the crop types grown, the yield obtained, and the purpose of farming, were asked to get a basic overview of the group of farmers attending the FGD. Subsequently, the seasonal calendar was created, by first asking the farmer's definition of a bad year and how frequently they experience such a year. Based on this definition, for both an average and a bad year, the weather characteristics, such as rainfall, temperature, and wind, were indicated for each month. In addition, for both type of years, the farming practices, off-farm activities, as well as their level of food insecurity throughout the year were indicated. Furthermore, the farmers were asked what adaptation strategies they take up to cope with changes in, for example, the start and length of the growth season, and what drives them in their decision to alter their farming practices. Do they rely upon their own observations or do they decide upon a received weather forecast? If they, on the other hand do not adapt, what then are the constraints or barriers that prevent them from changing their farming practices? A full overview of the outcomes of each FGD can be found in Appendix A.

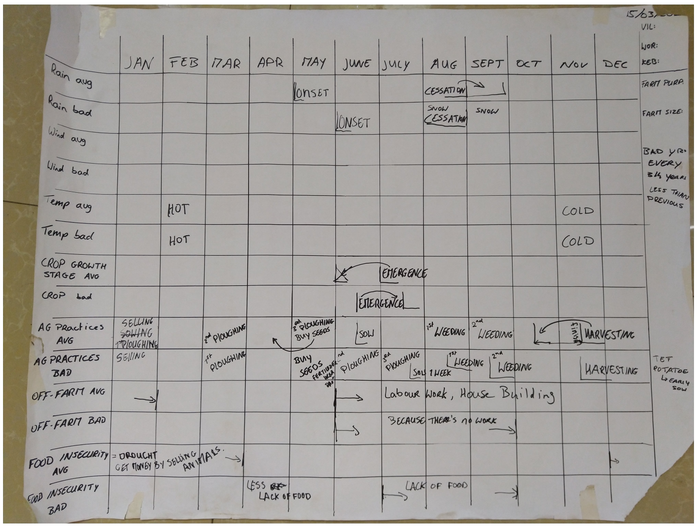


Figure 4.2: A seasonal calendar created during the FGD conducted in Shime. Made by author.

4.2.2. Design of the Individual Household Survey

The second phase of the field survey composes an individual household survey. This subsection describes the design of the individual household survey by indicating what type of questions are asked, and where the individual household survey is used for. Furthermore, it is explained how the required sample size is determined, as well as in what way the survey is conducted. In addition, the statistical methods used to analyse the data obtained are explained.

The aim of the individual household survey is twofold. First, detailed information on the socio-economic characteristics of smallholder farmers in the Gumera sub-basin is gathered to obtain knowledge on the livelihood of the farmers and to parameterise the socio-hydrological model with site specific data. Secondly, more qualitative data is needed on the farming practices of these farmers and their decision making to obtain a better understanding of the behavioural aspects with respect to climate variability. As such, the hypothesis that farmers adapting to climate variability are economically better off compared to non-adapting farmers can be analysed. The more qualitative data will be used to analyse what factors influence the choices farmers make regarding their agricultural practices and how they cope with climate variability. Reaching this objective can either be done through a sample survey or that of a census. Due to time and money constraints a sample survey is conducted in this research whereby each household is visited once. The most widely used method for collecting quantitative data is by conducting a questionnaire survey (Mukherjee, 1997). It provides a systematic, ordered way of obtaining information from respondents and enables precise and statistically analysable data (Norman, 1995). The FGDs, described in Subsection 4.2.1, were used to improve the questionnaire and to better incorporate the smallholder farmer perspectives within the questionnaire.

The first part of the questionnaire included questions regarding general demographic variables, such as gender, age, experience, household size, income and expenditure, and level of education. In addition, questions regarding their on- and off-farm activities, the crops they grow and the livestock they rear are asked. This provides the opportunity to distinguish between groups during the analysis, and observe possible differences in their decision-making. The largest part of the questionnaire is ascribed to questions that give information on the smallholder farmer's perception of climate change and their behaviour with respect to climate variability. The exact questions asked and how they are formulated were based on the theoretical background (see Subsection 2.1.2) and the outcomes of the FGDs, but were such that it remained within the scope of the research and that it could still be used as input for the socio-hydrological model. In order to minimise errors introduced by response fatigue, the time needed to conduct the survey should not be too long. Therefore, it is decided to categorise some variables such that it makes it easier and quicker to fill in the survey. Farmer experience is an example of a categorical variable, in which farmers could choose between six categories: 0-5 years, 6-10 years, 11-15 years, 16-25 years, 25-35 years, and more than 35 years. On average, the survey took 15-20 minutes. A full overview of the individual household survey can be found in Appendix B.

Required sample size

To make sure the results can be generalised over the larger population and to be able to appropriately perform statistical analyses the respondents need to be representative for the larger population (Kelley et al., 2003). Therefore, the farmers targeted for the household survey were selected by random sampling. To fall within the target group the participant should be cultivating land within the Gumera sub-basin, and (s)he is the head of a smallholder farmer household.

In addition, the study should contain sufficient statistical power in order to obtain unambiguous results. The power of a study roughly refers to the chances of finding an effect in a study given that it exists in reality (at the population level) (Brysbaert, 2019). The power of a study is increased by reducing the overlap of the distributions of two samples. This is achieved by following two strategies.

The first strategy, and the one a researcher can most easily control, is to increase the sample size (Cohen, 1992a,b). A larger sample size results in increased power. In this research, the sample size was calculated by the equation from Krejcie and Morgan (1970):

$$s = \frac{X^2 NP(1-P)}{E^2(N-1) + X^2 P(1-P)} \tag{4.1}$$

with:

s = required sample size
X^2 = the table value of chi-square for 1 degree of freedom at the desired confidence level
N = the population size
P = the population proportion
E = the degree of accuracy expressed as a proportion (i.e. margin of error)

An important indicator for calculating the required sample size, is the population size N, which for this research translates to the number of households in the Gumera sub-basin. The number of smallholder households in the Lake Tana sub-basin in 2015 was estimated at 661.423 households by ADSWE (2015a). With the

QGIS software it was determined that the Gumera sub-basin covers 12.5% of the entire Lake Tana sub-basin. Assuming the population density to be equally divided over the entire Lake Tana sub-basin, the number of households in the Gumera sub-basin is approximated at 74.567 (i.e. 12.5% of 661.423 households). For a 95% confidence level, the required sample size was calculated for varying population proportions and a margin of error ranging from 5% to 15% (see Table 4.1). By minimizing the margin of error (i.e. E = 0.05), the smallest required sample size, in order for the study to have sufficient power, was estimated at 382 households.

However, some researchers mention that looking at the significance level alone is not adequate for determining the required sample size (Brysbaert, 2019, Sullivan and Feinn, 2012). Cohen (1992a), for example, defined the statistical power of a significance test as the long-term probability of rejecting the null hypothesis, given the effect size in the population, the chosen significance level, and the number of participants tested. In research, the significance level and power are often fixed at 0.05 and 0.80 respectively (Beck, 2013), which makes the effect size the only factor that can affect sample size. Hence, the second strategy to increase power is to increase the effect size. The effect size allows you to communicate the practical significance of these results rather than only examining whether the results are likely to be due to chance as is done by the statistical significance (Sullivan and Feinn, 2012). The selection of an appropriate effect size is therefore essential. However, estimating the effect size is rather difficult. Cohen (1992a) made a distinction between three types of effect sizes (i.e. Cohen's d, hereafter referred to as 'd'): small effect sizes with d = 0.2, medium effect sizes with d = 0.5, and large effect sizes with d = 0.8. In recent years, it has become clear that most effect sizes in psychology are smaller than 0.5. Two large-scale replication studies of published findings pointed to an average effect size of 0.4 (Brysbaert, 2019). In a study of Stewart et al. (2016), comprising a total of 4.493 participants, the effect of training, innovation and new technology on African smallholder farmers' economic outcomes and food security is researched. In this research, effect sizes were found for the farmers' levels of food security, ranging from 0.71 - 0.86, and for farmers' income, ranging from 0.12 - 0.26. However, Stewart et al. (2016) advised to be cautious with using these effect sizes given the small sample and its risk of bias. Hence, it is rather difficult to obtain an accurate value for the effect size from literature.

Pop. proportion	**E = 0.05**	**E = 0.1**	**E = 0.15**
0,9	138	35	15
0,8	245	61	27
0,7	321	81	36
0,6	367	92	41
0,5	382	96	43

Table 4.1: Required sample size for varying population proportions and margin of error E (significance level (α) = 0.05). Calculated with equation 4.1.

In behavioural sciences, statistical power is often neglected due to power analyses being too complex to perform (Mayr et al., 2007). This causes the interpretation of insignificant results to be very difficult. Therefore, in this research, the software package GPower was used to determine the required sample size by taking into account the statistical power. GPower is a freeware program that allows high-precision power and sample size analyses (Cunningham and McCrum-Gardner, 2007). With an a priori power analysis, the sample size is computed as a function of the required power level (1 - β), the significance level (α) and the population effect size (d). The effect size in this study is related to the increase in crop yield due to a farmer adapting to climate variability. Hereby, the sample size is dependent on the statistical test used. In this study, the independent t-test was used frequently in order to check for significant differences between different groups of farmers. Enabling GPower, the sample size N is therefore calculated for a two-tailed t-test for two independent groups and equal numbers in each group, with a 95% significance level, and power ranging from 80 to 95%. Since from literature (Stewart et al., 2016) it was not clear what effect size would be suitable for this study, the sample size has been calculated for varying effect sizes (see Table 4.2. Considering a small effect size would be favourable as a priori the true effect size is not known. However, the sample size increases rapidly with decreasing effect size, ranging from 580 to 5200 for an effect size of 0.3 or lower. Collecting data from such a large sample was not feasible for this study taking into account time and cost constraints. Therefore, since an accurate estimation of the effect size is rather difficult, guidelines from literature were followed and the average effect size of 0.4, indicated by Brysbaert (2019), is used in this study.

Power	**Effect size**				
	d = 0.1	d = 0.2	d= 0.3	d = 0.4	d = 0.5
0.80	3142	788	352	200	128
0.90	4206	1054	470	266	172
0.95	5200	1302	580	328	210

Table 4.2: Required sample size for varying power and effect size, calculated with GPower (significance level (α) = 0.05) (Cunningham and McCrum-Gardner, 2007).

Looking at the sample sizes shown in Tables 4.1 and 4.2, a sample size between 328 - 382 smallholder farmer households is considered, with both the significance level and power at 95%, a margin of error of 0.05, and effect size of 0.4. This is assumed to be adequate for performing a well powered study and to obtain practically significant results. However, to account for missing respondents or badly conducted questionnaires, a higher number was used, namely 400 respondents.

Conducting the Individual Household Survey

In order to obtain a representative dataset and to capture the heterogeneity between farmers within the study area, the household surveys are divided amongst 11 Kebeles. Instead of selecting the Kebeles randomly, they are purposively selected in order to get a representative sample of the entire population. Spatial geography, and degree of cultivated land are taken into account when selecting appropriate Kebeles. This meant Kebeles with, for example, only a small percentage of cultivated land were not selected as this does not generalize to the region. The most eastern part of the area therefore is not represented as slopes are steep, population density is low and cropland only covers a small percentage. In addition, the Kebeles were selected such that both ACZs (i.e. Wet Weyna Dega, and Wet Dega) were equally represented in proportion to their area and number of households. However, due to COVID-19 induced logistical implications, the free choice of Kebeles was restricted and resulted in choosing the most feasible ones. This is the reason no Kebeles in the north western part of the study area were included. In addition, due to uncertainties whether or not some Kebeles could be reached without further restrictions in time (due to COVID-19 restrictions), the number of household surveys per Kebele was set to 40 in order to ensure the dataset would be large enough in case some Kebeles could not be reached. Despite these restrictions, a relatively good representation of both ACZs (with respect to their area and number of households) is obtained, in which the majority of respondents lives in the Wet Weyna Dega (see Table 4.3).

Kebele	**Respondents**	**Woreda**
1. Aribayitu	28	Dera
2. Genamechawecha	41	Farta
3. Geregera	30	Dera
4. Jigena	38	Dera
5. Licha Arida	39	East Este
6. Mahirderamariyam	40	Farta
7. Shimagile Giorgis	39	East Este
8. Shime	40	Dera
9. Tebabarina	29	Dera
10. Wegedame	30	Dera
11. Werken	40	Farta
Wet Weyna Dega ACZ (west)	218	
Wet Dega ACZ (east)	176	
Total	394	

Table 4.3: Number of household surveys conducted in each Kebele and ACZ for this research. Made by author.

The individual household survey has been conducted via ODK Collect (Hartung et al., 2010), and took approximately 20 minutes per survey. ODK Collect is an open source Android application that makes it possible to program a questionnaire and conduct it without network connectivity. Due to COVID-19 induced logistical implications it was not possible to conduct the household survey myself. Therefore, the household survey is conducted by the help of several Agricultural Experts located in the Gumera sub-basin. These local Agricultural Experts are experienced in conducting such a survey, and are in close contact with the local farmers. The Agricultural Experts were instructed to interview households by random sampling, interviewing a couple of randomly chosen farmers distributed over multiple villages within one Kebele. As such, it is assumed an unbiased representation of the total population would be obtained. Following this approach, a dataset of 394 respondents is obtained (after excluding inadequate household surveys). The number of households interviewed per Kebele and ACZ is shown in Table 4.3. The geographical spreading of household surveys conducted is shown in Figure 4.3.

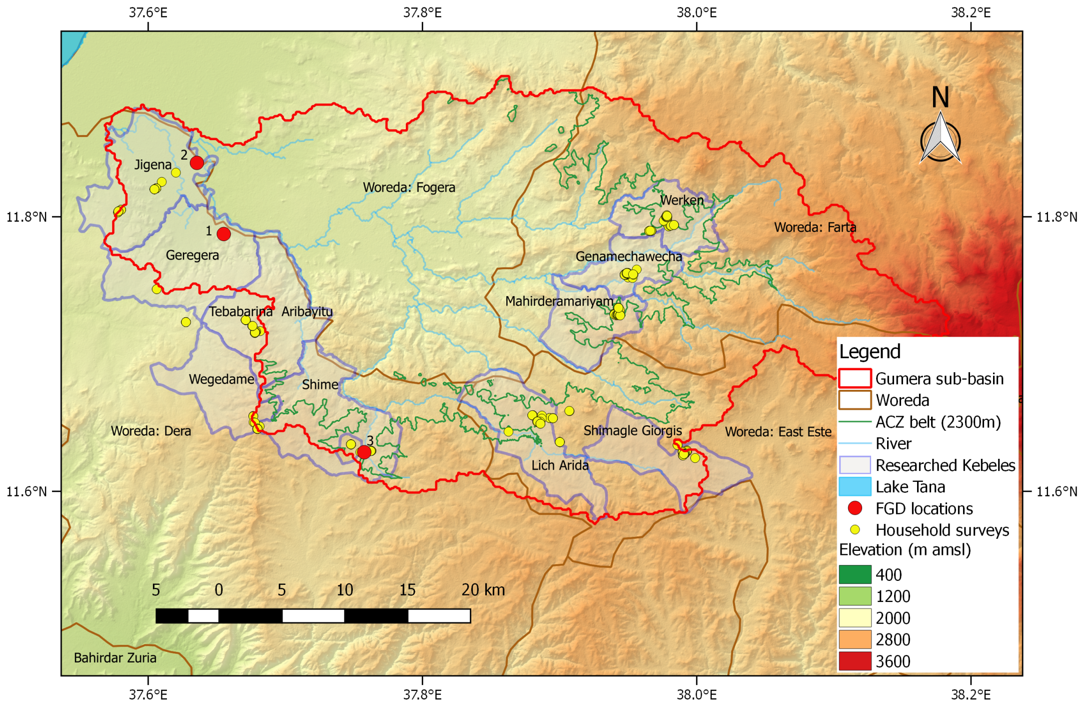


Figure 4.3: Spatial overview of the location of the FGDs and of the respondents of this study's individual household survey, both conducted in the Gumera sub-basin. Made by author.

Methods of Statistical Data Analysis

The data obtained from the individual household survey is analysed using IBM SPSS Statistics 25 software (IBM Corp., 2017). Prior to the actual analysis, the dataset is checked for errors, such as outliers, and are either corrected or deleted as they can highly influence the outcome of the statistical analysis. Outliers are defined as data points that differ significantly from other observations. They can be introduced by wrongly interpreting the question, it can be a typo, or it can be a right answer but from a very atypical or unique farmer that is not representing the rest of the population. In general farmers who do not grow crops are excluded from the dataset. Farmers who do not rear livestock are kept in. Appendix B.3 gives an overview of typical outliers that are dealt with to prevent them from influencing the outcomes of the statistical analysis.

Like other studies that focus on adaptation strategies of smallholder farmers (Ado et al., 2019, Motbainor et al., 2016), descriptive statistics like the mean, standard deviation, frequencies and percentages, are used to summarize the data collected and to provide a general picture of the farmer characteristics. Independent-samples t-test (two-tailed) and chi-square test (in case of categorical variables) (Pallant and Manual, 2010) were employed to test the null hypothesis (H_o) stating there not being a significant difference in, for example the mean experience, education, capital, and time spend on agricultural activities, between two groups of farmers, such as between male and female farmers, or between farmers in the lower and upper ACZ. Hereby, the mean, standard deviation (SD), t statistic, p-value and the 95% confidence interval (CI) are consistently provided. In the case of a comparison between multiple groups an analysis of variance (one-way ANOVA) is conducted, whereby differences between the group means, for example the crop yield obtained by farmers in different Kebeles, are analysed (Pallant and Manual, 2010). Again, by testing the null hypothesis it is analysed whether H_o can be accepted, meaning there not being a significantly difference between the groups of farmers. Hence the alternative hypothesis (H_1) states the group means are significant different. In case the p-value is smaller than 0.05, H_o gets rejected, and the group means are assumed to be significant different. Whenever a p-value is shown in this study, these are the hypotheses tested, unless stated otherwise.

$$H_o : \mu_1 = \mu_2 \tag{4.2}$$

$$H_1 : \mu_1 \neq \mu_2 \tag{4.3}$$

Subsequently, statistical tests are conducted in order to find linkages between certain variables in order to be able to explain the differences observed and to investigate what variables could explain the behaviour of farmers. As such, the farmer characteristics, their perceptions, and uses of information sources are linked with their climate adaptive behaviour. Multiple (stepwise) linear regression and binary logistic regression are conducted in order to analyse which variables significantly influence the climate adaptive behaviour of a farmer, and are explained in more detail below.

Multiple Linear Regression Analysis

Linear regression is a frequently used model in statistics to determine the relationship between a dependent and independent variable. Multiple linear regression is an extension of this model, in such that it is used to analyse the relationship between a dependent variable and multiple independent variables (Pallant and Manual, 2010). As such, it can help to assess how much of the variance in a continuous dependent variable can be explained by a set of independent variables. In this research, (stepwise) multiple linear regression is used to assess which farmer characteristics (i.e. the independent variables) explain the variance in crop yield (i.e. the dependent variable) obtained by farmers in the Gumera sub-basin. Since there is no single variable in the individual household survey capturing "crop yield" in its entirety, a MRA is conducted for the major crop types separately. The independent variables, from which is suggested to possibly influence crop yield, that are taken into in the MRA are: altitude, crop area, education, inputs (i.e. chemical, fertiliser, and seed use), livestock, access to a weather forecast, climate adaptation, labour availability, irrigation, experience, capital and borrowing money, and the distance to the closest market. Those independent variables that classify as significant predictor for at least two different crops are assumed to be the main predictors for crop yield. When presenting the results of the MRAs, three statistical variables are displayed. The unstandardised coefficient (B) of each independent variable is presented, which indicates the change in the dependent variable for every unit increase in the independent variable. The probability level (p) is provided, which tells whether or not an individual independent variable significantly predicts the dependent variable. At last the R-square (R^2) value is shown, which indicates how much of the variance in the dependent variable is explained by the set of independent variables. Prior to each multiple linear regression analysis, preliminary analyses were conducted to ensure no violation of the assumptions of normality, linearity, multicollinearity, and homoscedasticity. Each of these assumptions are explained in Appendix C.1. In addition, an explanation of the statistical variables, as well as the full output of each MRA is included in Appendix C.1.

Binary Logistic Regression Analysis

Binary logistic regression was used to assess how well a set of predictor variables (which can be both categorical and continuous variables) predict a categorical dependent variable (Pallant and Manual, 2010). In this research, binary logistic regression is used three times. First, it is used to determine which farmer characteristics (i.e. the predictor variables) predict the climate adaptive capacity of a farmer and to what extent (see Subsection 4.4.8). Hereby, farmer characteristics that during the analysis are found to be possibly influencing the climate adaptive capacity of a farmer are included. Repetitively, each farmer characteristic showing the highest level of significance is removed from the analysis, until only significant predictor variables within the model. The second time binary logistic regression is conducted, only those farmers that claim to adapt to climate variability are taken into account. As such, it can be determined which farmer characteristics predict the adaptation strategy a farmer takes up (see Subsection 4.4.9). Hereby, for each binary logistic regression, it was consistently checked whether the sample data fits the normal distribution of the population, and thus represents the data you would expect to find in the actual population. Prior to conducting each binary logistic regression the data was checked for multicollinearity, since logistic regression is sensitive to high correlations among the predictor variables. The full output of each binary logistic regression analysis discussed in this section, as well as an explanation of the statistical variables, is presented in Appendix C.2.

4.3. Results and Discussion of FGDs

In this section, the results of the FGDs will be discussed. Each separate subsection describes the major observations from one FGD. Subsection 4.3.4 provides an overview of the overall conclusions from the FGDs. A full overview of the observations of each FGD is provided in Appendix A.

4.3.1. FGD 1: Geregera

Geregera is a Kebele located in the Wet Weyna Dega ACZ (i.e. the lower ACZ) in the Southwest of the Gumera sub-basin at 1786m AMSL. This makes it being located close to the wetlands of Lake Tana. This has allowed farmers to grow rice, although the main crop grown is maize. The major farming practice consist of a mixed crop-livestock farming system. In an average year, the farmers sow maize at the start of the rainy season at the beginning, and harvest in the beginning of October just after the cessation of rains has occurred. In addition, they work on off-farm activities whole year round. The farmers mention a bad year, which they define as a drought with a short rainy season from the end of June till halfway September, to occur every 10 years. To deal with a bad year farmers use irrigation from the Gumera river. However, in case the Gumera river is dry, the farmers decide to grow a short cycle crop, such as teff, and simultaneously change the planting (to the end of June) and harvesting date. Off-farm work is taken up if rains do not come at all. Decisions regarding the farming practices are based on their own observations of weather patterns, such as clouds and wind, since no weather forecast is available to them.

4.3.2. FGD: Jigena

Jigena is a Kebele located in the Wet Weyna Dega ACZ (i.e. the lower ACZ) in the Southwest of the Gumera sub-basin at 1790m AMSL, just west of Geregera and therefore closer to the wetlands of Lake Tana. Hence, the main crop is rice in a mixed crop-livestock farming system. In addition, farmers work on off-farm activities whole year through. Other crops like teff, onion and maize are grown under irrigation on a different plot. The farmers claimed not to experience rain shortage and to not have been food insecure for the last 30 years. Instead of droughts, the major challenge is floodings. Extreme floodings are experienced by these farmers once every 4 to 5 years. At times of such extreme floodings, farmers will get a flood warning and start building dikes to prevent their plot from flooding. If the dikes do not hold, the farmer demolishes its crops, ploughs the land again after the flooding has disappeared and starts growing short cycle crops like teff, vetch, or chickpeas.

4.3.3. FGD:Shime

Shime is a Kebele located in the Wet Weyna Dega ACZ (i.e. the lower ACZ) in the south of the Gumera sub-basin at 2210m AMSL. Just like farmers in Jigena and Geregera, the main farming system practised by farmers in Shime is that of mixed crop-livestock. The main crop grown by the farmers is teff, besides maize, potato and barley, due to higher altitudes. Throughout the rainy season farmers are provided with a weather forecast, upon which they determine what crop to grow and when to sow. During an average year the rains start at the beginning of May and last until the end of September. In comparison with farmers in Jigena and Geregera, farmers in Shime seem to have more difficulties to become food secure. Food insecurity is experienced by these farmers from December till March. Whenever a bad year happens, defined by the farmers as a drought with a short rainy season, farmers will switch to a short cycle crop, such as potato or teff. In such a year, these farmers claimed to face food insecurity all year round, reaching its peak during the rainy season from July till September. On top of that, during a bad year, no off-farm labour is available for farmers in Shime, which makes it impossible for them to adapt to a bad year by conducting off-farm activities, as is done by farmers in Geregera.

4.3.4. Conclusion and Assumptions from the FGDs

By conducting the FGDs more local information is obtained regarding the farming practices, climate perceptions, and climate adaptive behaviour of farmers in the Gumera sub-basin. It is observed there being similarities between farmers in different Kebeles, but also quite some heterogeneities have been discovered.

Although Geregera, Jigena, and Shime are located relatively close to each other, large heterogeneity between farmers in these three Kebeles is observed during the FGDs. Not only do farmers in each Kebele grow a different main crop, they also rely upon different information sources (i.e. own observations of weather patterns or access to a weather forecast), which could induce different behaviour with respect to climate variability. In addition, farmers in, especially, Jigena face different climatic challenges. On top of that, whereas farmers in Jigena and Geregera mention to be food secure throughout the entire year, and use irrigation as a coping mechanism, farmers in Shime mention to be food insecure from December till March instead. In a drought year they even mention to be food insecure whole year through, in which food insecurity is highest in the months July till September. At first sight, altitude and geographic location seem to play an important role in all of these facets, as the location of farmers in Jigena and Geregera close to Lake Tana allow them to grow rice. This makes them vulnerable to floodings, unlike farmers in Shime who experience droughts as the main climatic challenge instead. Taking into account all of these differences observed in farmer characteristics between farmers in the three different Kebeles, the assumption is made that there are largely two types of farmers. Farmers growing rice living in the most western part of the Gumera sub-basin close to Lake Tana and for whom floodings compose the major climatic challenge, and farmers not growing rice living at higher altitudes and defining a bad year as a drought. However, since only three FGDs have been conducted in the western and southern regions of the Gumera sub-basin, little is known about farmers in the northern and eastern regions, which are just like farmers in Shime living at higher altitudes away from Lake Tana. Suggesting that the type of climatic challenge (i.e. floodings or droughts) is induced by location and altitude, and that this highly characterises a farmer and his or her agricultural behaviour, it is assumed that farmers in Shime are the most representative farmers for farmers in the rest of the Gumera sub-basin in which no FGD has been conducted.

Despite the differences between farmers in different Kebeles, similarities are also observed. As such, the adaptation strategies taken up by farmers in each Kebele to cope with climate variability are rather similar. Changing crop type (albeit with different crop types) and shifting planting and harvesting dates are amongst the major adaptation strategies. In addition, supplementary irrigation and changing to off-farm non-agricultural activities are also adopted, but mainly by farmers in Jigena and Geregera.

4.4. Results and Discussion of Individual Household Survey

From the FGDs discussed in Section 4.3, heterogeneity between farmers in different Kebeles is observed with respect to the types of crops grown, the climatic challenges faced, and the level of food security. This resulted in the assumption that their are largely two groups of farmers within the Gumera sub-basin, namely rice growing farmers located close to Lake Tana facing floodings as the major climatic challenge, and non-rice growing farmers in the rest of the Gumera sub-basin facing droughts. On the other hand, similarities were observed with respect to the type of adaptation strategies taken up in order to cope with climate variability, which mainly consisted of changing the crop type and the planting and harvesting dates. However, since the FGDs have only been conducted in the western part of the Gumera sub-basin, this is a largely fragmented picture of farmers throughout the Gumera sub-basin.

In this section the results of the individual household survey will be presented and discussed in order to obtain a better understanding of the climate adaptive behaviour of farmers throughout the Gumera sub-basin. The design of this survey and how it is conducted is described in Subsection 4.2.2. In addition, it includes an explanation of the statistical tests that are used to analyse the individual household survey.

In this section, first an overview of the demographics, socio-economic status, and farming practices of the farmers will be presented in Subsections 4.4.1 and 4.4.2. Differences between farmers will be shown by clustering upon Kebele and ACZ in order to analyse the spatial heterogeneity in the Gumera sub-basin observed during the FGDs (see Subsection 4.4.3). Hereby, the focus is on mainly crop yield, as it is seen as the main indicator for agricultural productivity, which is stated by the United Nations (2015) to be key to end hunger, achieve food security and promote sustainable agriculture. Subsequently, a more thorough analysis on climate perceptions and related behavioural aspects will be discussed, as well as the information farmers use to make their decisions (see Subsections 4.4.5 - 4.4.9).

4.4.1. Demographics, Socio-Economic Status, and Labour

This subsection provides an overview of the general characteristics of farmers in the Gumera sub-basin with respect to demographics, experience, education, economic status, and labour.

In total 394 farmers have been interviewed. Clustering on ACZs (discussed in Section 3.1), the slight majority of these farmers (55.3%) live in the lower Weyna Dega ACZ, and 46.7% live in the upper Dega ACZ. With reference to Woredas (see Chapter 3, Figure 3.1), half of the farmers live in Dera (49.5%), one third lives in Farta (31%), and 19.5% lives in East Este. Fogera is not represented in this study. The large majority of farmers are male household heads, with only 48 being female headed (12.2%) (see Table 4.4). This corresponds to the

	Male [μ, σ]	**Female** [μ, σ]	**Total** [μ, σ]
Nr of farmers	346 (87.8%)	48 (12.2%)	394
Experience			
<15 years	16.2% [10.1, 3.51]	33.3% [10.2, 3.0]	18% [10.1, 3.4]
15-35 years	44.9% [24.8, 5.22]	27.1% [27.8, 5.4]	43% [25, 5.3]
>35 years	38.8%	39.6%	39%
Education			
Illiterate	55.7%	79.2%	58%
Literate	33.6%	16.7%	32%
Educated	10.7%	4.2%	10%

Table 4.4: Differences between female and male farmers in the Gumera sub-basin with respect to population size, farming experience, and education. Experience is a categorical variable as explained in Subsection 4.2.2, therefore the mean (μ), and standard deviation (σ) come from narrower bins.

13% of female headed households found in the Tana sub-basin Land Use Planning and Environmental Study Project (ADSWE, 2015a).

The average farmer in the Gumera sub-basin is 48 years old (SD = 9.8), has 28 years of experience (SD = 11.5), and has had no education. Experience, in this research, is defined as the number of years a farmer is farming as the head of the household. In terms of education, only 10% followed at least one year of education. The majority (58%) was illiterate, whereas 32% was able to read and write. Here a difference is seen in gender, in which almost 80% of female farmers was illiterate compared to 55.7% of male farmers. In terms of experience, female farmers are slightly less experienced than male farmers, albeit insignificant. Overall, almost 40% of all farmers have more than 35 years of experience (hereafter referred to as "experienced farmers"), whereas only 18% has less than 15 years of experience (hereafter referred to as "slightly experienced farmers"). Farmers that have 15 to 35 years of experience are referred to as "moderately experienced farmers". Almost 40% of all educated farmers are slightly experienced. This suggests that less experienced farmers are more likely to have followed at least one year of education.

The household size ranges from 2 to 10 family members, with 5.45 family members on average, from which 2.7 members are dependents. Dependents are defined as family members outside the range of 15-65 years and are therefore considered to be outside the workforce. Male farmers have significantly larger households than females, with 5.59 and 4.52 family members respectively. From all respondents, only two mentioned not to grow crops but to only rear livestock, and are thus removed from the dataset. Five farmers say to only grow crops. Hence, the large majority (98.7%) of farmers practices a mixed crop-livestock farming system. This agrees with what is found in literature (see Section 3.3).

Per household there are, on average, 3.8 family members working on the farm, including the household head. Since on average 2.75 family members are within the workforce, this suggests that on an average farm one dependent helps with on-farm agricultural activities. The total on-farm workload of a family is 15 persondays per week on average, which means that each family member works approximately 4 days per week on the farm. Most labour is spend on growing crops with 89% of the farmers spending 7-10 hours per day on their crops. The time spend on livestock is a bit less, with 75% of the farmers spending 1-3 hours per day. Domestic labour, such as household activities, and collecting water and firewood, also accounts for 1-3 hours per day for 83.5% of all farmers. A clear difference on time spend per activity is seen between gender. Female farmers spend significantly more time on domestic labour compared to male farmers, with 5.2 and 2.2 hours per day respectively. They also spend significantly less time on cropping activities, with 6.8 hours/day and 8.4 hours/day, respectively.

Less than 2% of the households have employees working on the farm, and only 3 farmers mentioned working for another farm. Since, this is such a small percentage of the sample, employees and off-farm agricultural activities will be neglected in the remaining of this study. Off-farm non-agricultural activities are more favourable instead. Roughly 30% of all farmers say to be working on such activities for one day a week, from which 81.5% of these farmers live in the South West of the Gumera sub-basin in the Kebeles Tebabarina, Aribayitu, Wegedame, and Shime. On average they earn 46 Birr/day. Thus, a clear distinction between farmers in different Kebeles is observed with respect to whether or not off-farm non-agricultural activities are conducted. This distinction between farmers in different Kebeles was also observed during the FGDs, albeit that the composition of Kebeles is somewhat different. During the FGDs it were mainly farmers in Jigena and

Geregera that mentioned to work on off-farm non-agricultural activities the whole year through, whereas farmers in Jigena and Geregera interviewed via the individual household survey barely mention to work on such activities. This could be due to farmers attending at the FGDs living closer to a larger village or market where more off-farm non-agricultural activities could be available.

In terms of capital, an average farmer in the Gumera sub-basin has 18.121 Birr. One fifth of all farmers borrows money, which is 10.850 Birr/year on average. With 21.9%, male farmers show significantly higher capital than female farmers. In addition, farmers in the lower ACZ are observed to have significantly higher capital (21.674 Birr/household) than farmers in the upper ACZ (13.721 Birr/household), a difference of 60%. In addition, farmers in the lower ACZ are more likely to borrow money. It can thus be suggested that farmers in the lower ACZ are economically better off than farmers in the upper ACZ. This is partly induced by rice growing farmers, which are all located in the lower ACZ, as they show significant higher capital (22.300 Birr/household) than non-rice growing farmers (17.300 Birr/household). Furthermore, a positive correlation is observed between capital and the level of education. The relationship between farmer experience and capital shows a different trend, in which moderately experienced farmers show highest capital. The amount of farmers borrowing money shows a negative correlation with experience, which suggests that farmers with less experience are more likely to borrow money.

4.4.2. Farming Practices

The average farm size of a household is 1.40 hectares, with a range of 0.25 to 6.5ha. Although male farmers have a slightly larger farm size (1.41 ha) compared to female farmers (1.31 ha) no significant difference is observed. In addition, no difference in average farm size is observed between farmers in the lower and upper ACZ. On average 1.16 hectares is assigned to crops, with a range of 0.125 to 4 hectares. Hereby, positive correlations are observed with experience and education. As such, farmers with less than 15 years of experience are observed to have significantly smaller crop area (0.83 ha) compared to farmers with more than 15 years of experience (1.24 ha). This correlation is probably related to land reform laws introduced in the 1990s (Headey et al., 2014). In addition, illiterate farmers show significant smaller crop area (0.95 ha) compared to farmers that are either literate, or have had some form of education (1.45 ha). With respect to grazing land, the average farmer has 0.26 ha assigned to grass land for livestock. However, 88 farmers (21%) rearing livestock mention not to have a distinct grazing area. From this it can be suggested these farmers have their livestock grazing on communal areas as described in Subsection 3.3.2. The average livestock density for farmers claiming to have private grazing area is 16.46 TLU/ha. This is rather high compared with the observed livestock density of 9.4 TLU/ha by Amsalu and Addisu (2014) in the Gumera-Ribb watershed. Therefore, it is assumed that all farmers with a private grazing area also make use of communal grazing areas.

ACZ	Kebele	Farmers	Maize	Teff	Barley	Wheat	Millet	Potato	Onion	Rice
1	**Jigena**	38	97%	31%	0%	0%	0%	0%	100%	100%
	Geregera	30	100%	50%	0%	0%	83%	0%	33%	76%
	Tebabarina	29	100%	100%	93%	6%	17%	13%	3%	0%
	Aribayitu	28	100%	82%	32%	0%	57%	10%	0%	0%
	Shime	40	100%	100%	32%	7%	72%	100%	0%	0%
2	**Wegedame**	30	100%	96%	26%	33%	6%	46%	0%	0%
	Licha arida	39	100%	100%	0%	100%	0%	46%	15%	0%
	Shimagle giorgis	39	92%	100%	74%	100%	0%	100%	7%	0%
	Mahirderamariyam	40	100%	100%	92%	47%	15%	87%	10%	0%
	Genamechawecha	41	100%	100%	68%	0%	58%	97%	36%	0%
	Werken	40	97%	92%	92%	25%	0%	60%	0%	0%

Table 4.5: Crops grown by the respondents of the household survey conducted in the Gumera sub-basin, indicated per Kebele. The percentages represent the share of farmers within the specific Kebele claiming to grow the specific crop type. The left column indicates in which ACZ the Kebele is located, whereby ACZ 1 indicates the lower ACZ called "Wet Weyna Dega", and ACZ 2 indicates the upper ACZ called "Wet Dega".

Based on literature (see Section 3.3) and the FGDs (see Section 4.3) the major crop types mentioned by farmers are included in the household survey. This resulted in two crop types: cereal crops, including maize, teff, barley, wheat, millet, sorghum and rice, and root crops, including potato and onion. Table 4.5 provides an overview of the crops grown by farmers per Kebele and ordered by ACZ.

This shows that maize and teff are the major crops grown by almost all farmers. However, respectively 31% and 50% of farmers in Jigena and Geregera do not grow teff. Instead rice is grown by almost all of these farmers, due to them being close to the wetlands of Lake Tana, which was also observed during the FGDs. Furthermore, barley is grown by almost 50% of all farmers, in which farmers in the upper ACZ are significantly more likely to grow barley, X^2 (1, N=394) = 9.915, p = 0.002. Wheat and millet are grown by less than 30% of all farmers, whereas sorghum (not included in Table 4.5) is not grown by any of the surveyed farmers.

With respect to root crops, potato is the dominant crop and grown by a slight majority of all farmers (54%). Similar to barley a clear distinction is seen between farmers in the different ACZs, in which farmers in the upper ACZ are significantly more likely to grow potato, X^2 (1, N=394) = 17.128, p = < 0.001. Onion is less prevalent, and only grown by 19% of the farmers. For simplicity, it is decided to only keep in the most prevailing crops for the remaining of this research. Wheat, millet, sorghum and onion are therefore not taken into account in the further analysis. Rice, although not one of the prevailing crops, is left in as it is the main crop for especially farmers in Jigena and Geregera as was observed in the FGD (see Subsection 4.3.2). Hence, the crops taken into account during this research, in order of the number of farmers growing the crop, are maize, teff, potato, barley, and rice.

Supplementary irrigation is used by 43% of all farmers, in which quite a distinct division is observed between Kebeles and crop types. Except for maize, irrigation is barely used to grow cereals. Also rice is not irrigated as it is grown in the wetlands. Potato is the major irrigated crop. Furthermore it is observed that almost all farmers in Jigena use irrigation for all crop types, whereas also the majority of farmers in the eastern part of the Gumera sub-basin (i.e. the Kebeles Licha Arida, Mahirderamariyam, Genamechawecha, and Werken) use irrigation.

With respect to livestock, cattle is the most dominant type and owned by almost every farmer (98%). The slight majority of farmers own sheep, and one third owns donkeys. Goats and mules are owned by 11 and 5% of all farmers respectively. No distinct differences are found between male and female farmers. However, when converting livestock to TLU (Tropical Livestock Unit) it is observed that male farmers (M = 3.59, SD = 1.89) own significantly more TLU compared to female farmers (M = 2.81, SD = 1.80; t (393)= 2.685, p = 0.008, two-tailed). A large difference can be noticed when comparing livestock per Kebele. A minimum of 2 TLU per farmer is seen in the Kebeles located in Farta Woreda, in the north east of the Gumera sub-basin, whereas farmers in Geregera own almost 6 TLU on average. This also results in a significant difference between farmers in the upper ACZ (M = 3.27, SD = 1.72) and lower ACZ (M = 3.67, SD = 2.00; t (394)= 2.098, p = 0.037, two-tailed), in which farmers in the lower ACZ own more livestock on average. The income and expenditure are rather equal for each type of livestock and is 1500 and 1000 Birr per unit per year, respectively. A large share of farmers, 84%, sells livestock in times of food insecurity to be able to have enough liquidities to buy food.

4.4.3. Observed Crop Yield Obtained by Smallholder Farmers

This subsection provides an overview of the observed crop yields of the surveyed farmers in the Gumera sub-basin. The heterogeneity observed between farmers in different Kebeles is explored.

Crop yield is one of the most important output parameters for a farmer, and has great influence on the households food security and economic well-being. For each crop type taken into account in this research, Table 4.6 gives the average, minimum and maximum crop yields obtained by farmers in the Gumera sub-basin, as well as the standard deviation. This is checked with observed average crop yields for the Amhara region in 2015 during a sample survey conducted by the CSA of Ethiopia (Central Statistical Agency, 2015). It can be concluded that for most crops the observed average yield is comparable with what is found by the CSA. However, the observed production of rice is relatively high in the Gumera sub-basin. This could be due to the fact that rice is only grown in Jigena and Geregera, which are supposedly high performing Kebeles.

	Mean	SD	Min	Max	Census 2015
Barley	23.8	7.6	7	39	17.3
Maize	30.7	7.7	9	60	35.8
Potato	151	48.3	30	320	154.4
Rice	40.2	1.9	30	44	29.4
Teff	13.8	4.7	3	26	15.8

Table 4.6: Average, minimum, and maximum crop yield obtained by respondents of the household survey conducted in the Gumera sub-basin, checked with average crop yields observed in the Amhara region in the census conducted by Central Statistical Agency (2015). All crop yields presented are in Qt/ha. SD = standard deviation. 1 Qt (quintal) = 100 kg.

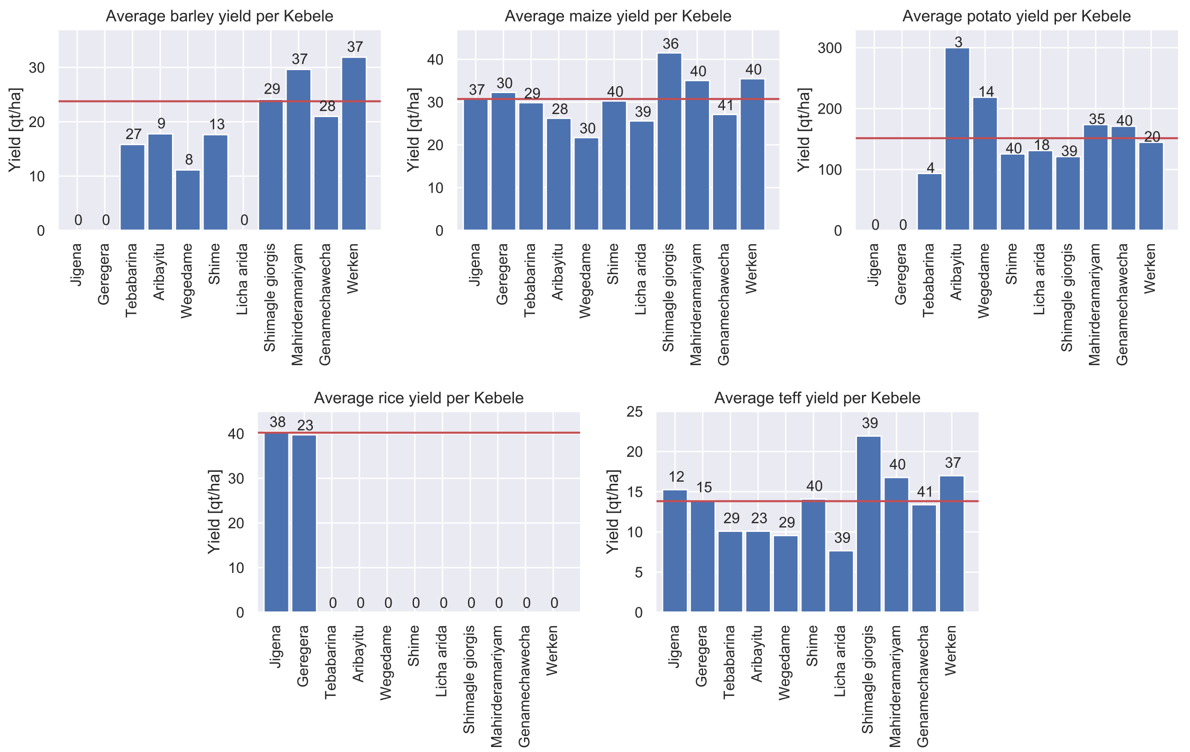


Figure 4.4: Average crop yields obtained by farmers in each Kebele per crop type. The horizontal red line represents the observed average crop yield over all respondents of the household survey conducted in the Gumera sub-basin. On top of each bar the number of farmers within the Kebele growing the certain crop are indicated. All crop yields presented are in Qt/ha. 1 Qt (quintal) = 100 kg. Made by author.

Although the average yields show normal values, a large range of minimum and maximum crop yields is observed. This would suggest there existing large heterogeneity in terms of crop yield obtained by farmers throughout the Gumera sub-basin. This could be due to climate variability since most farmers fully rely upon rainfed agriculture. A second explanation could be the large altitude differences between Kebeles in the Gumera sub-basin, which can have large effects on crop growth. Potato and barley, for example, perform better at higher altitudes, which could lead to large differences between farmers in the higher and lower ACZ. For each crop type the average crop yield obtained per Kebele is indicated in a bar plot shown in Figure 4.4. It can be observed there being large differences between farmers in different Kebeles within the Gumera sub-basin. As mentioned, this could be due to the altitude differences between the Kebeles. As such, it can be observed that it are especially farmers in the eastern Kebeles (i.e. Shimagle Giorgis, Mahirderamariyam, Genamechawecha, and Werken) that perform above average, with respect to barley, maize, and teff. In the case of potato, farmers in Aribayitu (located in the lower ACZ) show exceptional high yields. However, due to the very small sample size, the high yields are not very reliable. Hence, it are especially farmers in the upper ACZ, living in the Kebeles Wegedame, Mahirderamariyam, and Genamechawecha that obtain high potato yields.

However, there are multiple other factors that could induce these differences. Labour availability and the number of livestock owned by a farmer could be important factors. In addition, input variables such as seed usage, whether or not fertiliser and chemicals are used and in what proportions, but also crop area, irrigation and soil fertility could have major influence on the crop yield obtained by a farmer. However, soil fertility is out of scope of this research and therefore not taken into account.

4.4.4. Main Predictors for Crop Yield

This subsection presents and discusses the results of the (stepwise) multiple regression analyses conducted (see Subsection 4.2.2) in order to discover which factors influence the crop yield of a farmer most. Table 4.7 shows the significant predictors for the yield of each crop type. A full overview of the output of each of the MRAs is included in Appendix C.1.

It can be observed that 6 variables are suggested to be significant predictors for at least two different crops, namely access to a weather forecast, fertiliser use, adaptation to climate variability, crop area, chemical use, and farmer experience. Hence, these variables are assumed to be the main predictors for crop yield. Fertiliser use is the only main predictor showing a negative correlation with crop yield (for barley and teff), whereas adaptation to climate variability (for barley and maize) and crop area (for maize and teff) show a clear positive correlation on crop yield. Farmer experience and access to a weather forecast have positive effects on maize and teff yields, but show a negative correlation with yield of potato. The reason for farmer experience and the access to a weather forecast showing opposite correlations for potato in comparison with the other crop types is not completely clear. However, a possible explanation could be that potato is a relatively new crop in the Gumera sub-basin. Hence, experienced farmers could be less familiar with growing this type of crop compared to other crops, and the value of having a lot of experience would therefore diminish. However, the negative correlation of potato yield with access to a weather forecast is hereby not explained.

	Predictors	**B**	**p**	**R^2**
Barley	Constant	18.168	0.000	
	Climate adaptation	6.753	0.000	
	Fertilizer use	-0.023	0.000	
	Labour availability	1.018	0.010	0.452
Maize	Constant	25.025	0.000	
	Weather forecast	5.449	0.000	
	Crop area	2.782	0.004	
	Market distance	-0.404	0.002	
	Climate adaptation	3.279	0.042	0.268
Potato	Constant	178.159	0.000	
	Weather forecast	-48.944	0.000	
	Irrigation	-35.002	0.001	
	Chemical use	29.810	0.025	
	Experience	-1.334	0.004	
	Seed use	0.013	0.010	0.445
Teff	Constant	11.480	0.000	
	Weather forecast	5.304	0.000	
	Fertilizer use	-0.016	0.000	
	Chemical use	2.282	0.000	
	Crop area	1.620	0.002	
	Experience	0.068	0.007	
	Capital	-6.3E-05	0.031	0.651

Table 4.7: The main predictors for yield per crop type obtained from the multiple regression analyses, in which all farmers are included (n=394). Checked for all criteria. Per crop type the predictors are ranked on R^2 change from top to bottom. An explanation of the statistical variables (i.e. B, p, and R^2) are explained at the end of Subsection 4.2.2. The output of each MRA is included in Appendix C.1.

In Subsection 2.1.2 it was explored that the farmer experience and access to weather information are related to the farmer's climate perception, which was suggested to influence the climate adaptive behaviour of farmers. Since the focus of this research is on the climate adaptive behaviour of smallholder farmers, the main predictors, namely access to a weather forecast, adaptation to climate variability and farmer experience, are the most relevant predictors to look at. For each of these predictors the influence on crop yield will be further analysed.

Access to a Weather Forecast

During the individual household survey the farmers are asked if they receive or have access to a weather forecast and whether or not they use it during their decision making. Almost 30% of all surveyed farmers claimed to have access to a weather forecast. Often this weather forecast is obtained via the Agricultural Experts on Kebele level, which on their turn receive the information from meteorological stations or agricultural agencies on Woreda level. Only in Geregera (66.7%), Jigena (68.4%) and Shimagle Giorgis (100%), the majority of farmers receives a weather forecast (see Figure 4.5). In other Kebeles, either none, or up to 29% of all farmers receive a weather forecast. The weather forecast mostly comprises information regarding the amount of rainfall, and the timing of the onset and cessation of the Meher season. In Jigena also a flood warning is part of the weather forecast. Furthermore, some farmers obtain information regarding the length of the Meher season and what crop to grow. Almost two third of these farmers receive a weekly weather forecast all year

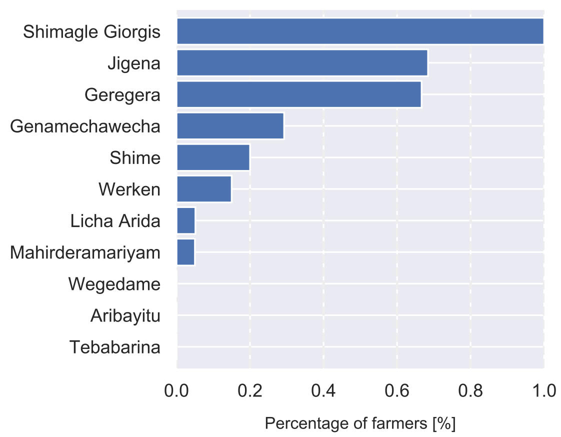


Figure 4.5: A horizontal bar chart showing the percentage of surveyed farmers per Kebele that have access to a weather forecast. Made by author.

round, whereas other farmers receive a weekly weather forecast only during the extend of the rainy season, which ranges from April till September.

Two third of the farmers receiving a weather forecast fully or partly base their agricultural decisions upon this information. Interestingly, it were especially farmers living in the upper ACZ that use the weather forecast information (85.5%) for their agricultural decisions. In comparison, 92% of farmers not using weather forecast information during their decision making live in the lower ACZ, from which the majority (73%) lives in Jigena and Geregera. This could possibly be due to the fact that in these lower altitude regions the weather forecast is more likely to be used as a flood warning during the growth season when agricultural decisions prior to the growth the season are already made. This is also what was observed during the FGD conducted in Jigena (see Subsection 4.3.2). It can thus be suggested that the large majority of non-rice growing farmers receiving a weather forecast use the forecast information for agricultural decisions.

Adapting to Climate Variability

In total, 12.4% (i.e. 49 farmers) of all surveyed farmers claimed not to have made any adjustments to their farming practices in the last 10 years in order to cope with the year-to-year variability of the rainy season. Hence, it is assumed these farmers do not adapt to climate variability. This same group of farmers (plus 7 other farmers, 14% in total) claim not to have made any adjustments to long term changes in the rainy season over the last 30 years. All of these farmers are located in the western part of the Gumera sub-basin in the Kebeles Aribayitu, Geregera, Shime, Tebabarina, and Wegedame, from which only the latter is located in the upper ACZ (see Figure 4.6). In addition, the majority of farmers who do not reconsider their farming practices every year again, also do not take up adaptation strategies. Comparing Figure 4.6 with Figure 4.5 it can be observed that the Kebeles showing a relatively low share of adapting farmers coincide with Kebeles in which barely any farmer has access to a weather forecast. Furthermore, none of the non-adapting farmers mention to have access to a weather forecast. This means that all farmers receiving a weather forecast are actually adapting to climate variability.

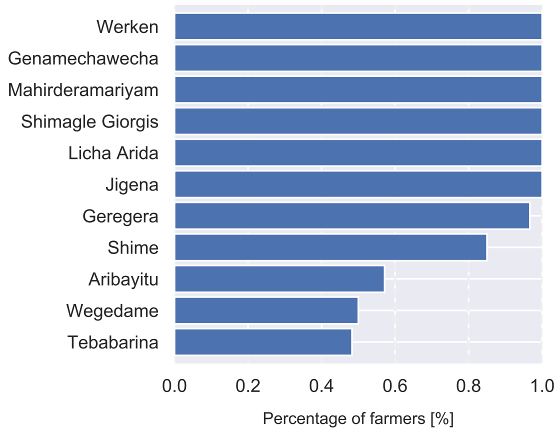


Figure 4.6: A horizontal bar chart showing the percentage of surveyed farmers per Kebele that claim adapt to climate variability. Made by author.

Farmer Experience

The average experience of a farmer in the Gumera sub-basin is 28 years. However, as is shown in Figure 4.7, quite some variation in experience can be observed between farmers in different Kebeles. A clear division is seen by comparing farmers clustered by the ACZ. In general, farmers in the Dera Woreda (i.e. the lower more western part of the Gumera sub-basin), especially rice-growing farmers in Jigena and Geregera, have less experience compared to non-rice growing farmers located at higher altitudes in Farta and East Este Woreda. As an example, farmers in Werken (37 years on average) have almost twice as much experience compared to farmers in Jigena (17.5 years on average). No clear explanation is found for this distribution, but it again suggests that rice-growing farmers in Jigena and Geregera are a different type of farmer compared to the rest of the Gumera sub-basin. Comparing Figure 4.7 with Figure 4.6 it is observed that it are mostly those Kebeles with low experience who are non-adapting. This is also what is observed when conducting an independent-samples t-test, from which can be suggested that farmers adapting to climate variability (M = 28.81, SD = 11.79) are more experienced than non-adapting farmers

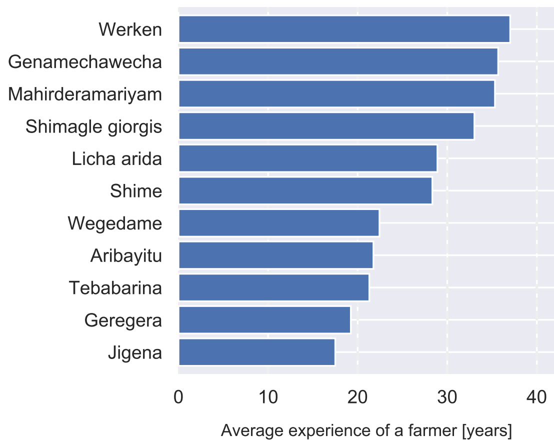
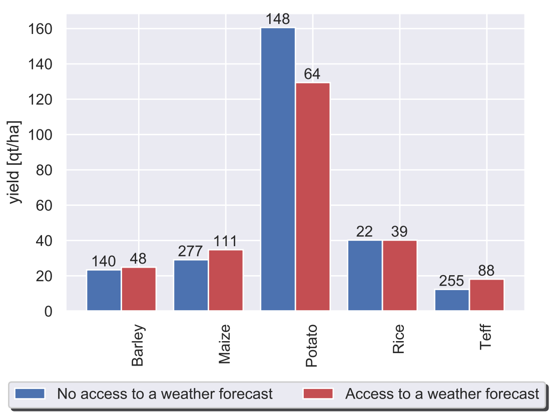


Figure 4.7: A bar chart showing the average years of experience of a farmer per Kebele. Made by author.

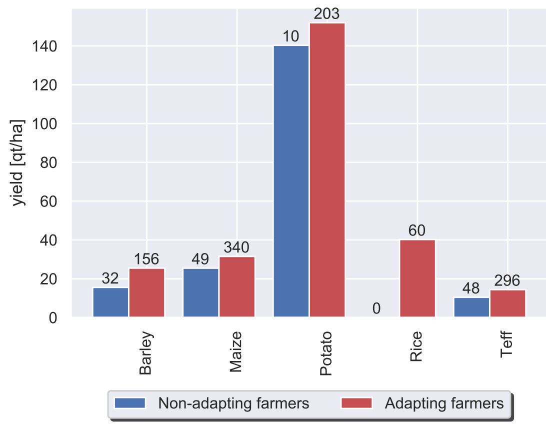
(M = 22.98, SD = 7.89; t (394)= -4.507, $p < 0.001$, two-tailed). This difference gets even bigger if you do not take into account non-rice growing farmers, which all claim to adapt to climate variability. No correlation was found between farmer experience and having access to a weather forecast.

The effect of the main predictors on crop yield

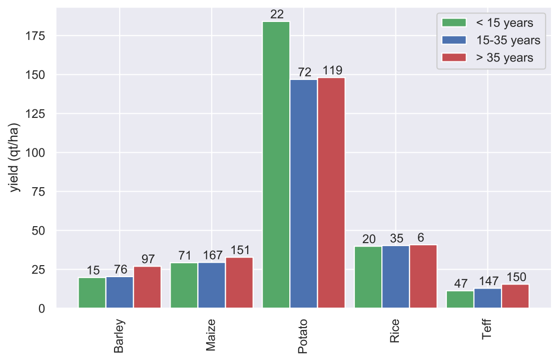
Figure 4.8 presents the differences in crop yield between farmers grouped by the three main predictors for crop yield on which is the focus in this research: access to a weather forecast, adaptation to climate variability and farmer experience. In Figure 4.8a, it can be observed that for almost all cereal crops, except for rice, farmers with access to a weather forecast show higher yields compared to farmers without access to a weather forecast (see Figure 4.8a). An independent-samples t-test showed the difference for maize (mean difference = -7.45, 95% CI: -9.40 to -5.51) and teff (mean difference = -6.41, 95% CI: -7.47 to -5.36) to be significant ($p < 0.001$), whereas the difference observed for barley yield (mean difference = -1.50, 95% CI: -3.44 to 0.44) was insignificant. The opposite relationship between crop yield and access to a weather forecast was observed for potato, the major root crop grown in the Gumera sub-basin, for which farmers without access to a weather forecast show significantly higher yields (mean difference = 31.16, 95% CI: 19.69 to 42.63) compared to farmers with access to a weather forecast ($p < 0.001$).



(a) Access to a weather forecast



(b) Adaptation to climate variability



(c) Farmer experience

Figure 4.8: Differences in crop yield between farmers grouped by a) access to a weather forecast, b) climate adaptation, and c) experience. The number of farmers is shown at the top of each bar. All crop yields presented are in Qt/ha. 1 Qt (quintal) = 100 kg. Made by author.

Clustering farmers by climate adaptation (see Figure 4.8b), the group of non-adapting farmers shows significant lower yields for all cereal crops ($p < 0.001$) compared to adapting farmers. In addition, adapting farmers show higher yields for potato compared to non-adapting farmers, albeit it a insignificant difference. This is most likely due to the small number of non-adapting farmers growing rice (n=10), causing the reliability of crop yield to be rather low. Since only 10 potato growing farmers (4.7%) claim to be non-adapting, which is 21% of the non-adapting farmers, potato could be assumed to be and adaptive crop amongst non-rice growing farmers, from which 71% grows rice, a significant difference, X^2 (1, N=333) = 43.103, $p < 0.001$. In the same way, it could be suggested that growing rice might be an adaptation strategy on itself, since all rice growing farmers are adapting as well.

Farmer experience shows a positive correlation with crop yield for all cereal crops but rice (see Figure 4.8c). In which farmers with more than 35 years of experience show significantly higher yields for barley, maize, and teff, compared to farmers with less than 35 years of experience ($p < 0.001$). In the case of potato, the opposite pattern is observed, as the group of farmers with less than 15 years of experience show significantly higher yields ($p < 0.01$), compared to farmers with more than 15 years of experience. However, the reliability of the potato yield obtained by slightly experienced farmers is doubtful due to the small sample size (n=22). Therefore, the observed negative correlation between experience and potato yield is not very strong.
Figures 4.5 - 4.8 have resulted in a few interesting observations:

- Non-rice growing farmers living in the lower ACZ are most likely not to have access to weather forecast, least likely to adapt to climate variability, and are less experienced.
- All farmers with a weather forecast adapt to climate variability.
- Potato can be suggested to be the main adaptive crop, since, in contrast with adapting farmers, it is barely grown by non-adapting farmers.
- Climate adaptation, access to a weather forecast and farmer experience all show a positive correlation with yield of cereal crops.
- Yield of potato shows a negative correlation with access to a weather forecast. A weak negative correlation is found with farmer experience, whereas a weak positive correlation is found with climate adaptation.

The observation that all farmers with access to a weather forecast are adapting to climate variability provides the opportunity to analyse the effect of having access to a weather forecast on the crop yield of adapting farmers. Hence the farmer experience is left out of this analysis. The farmers are hereby clustered into the following three groups:

- Group 1: Non-adapting farmers without access to a weather forecast (N = 49)
- Group 2: Adapting farmers without access to a weather forecast (N = 229)
- Group 3: Adapting farmers with access to a weather forecast (N = 115)

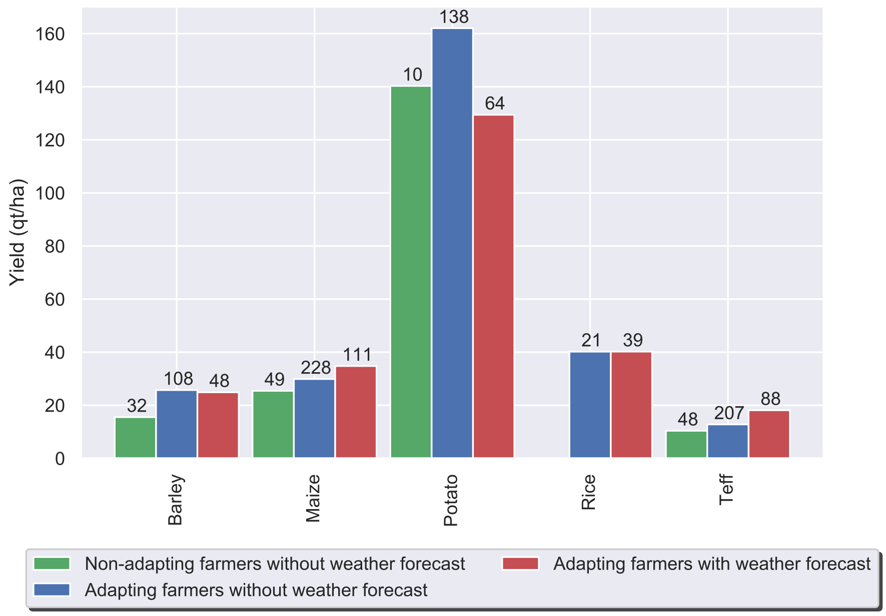


Figure 4.9: Difference in yield for each crop type between farmers grouped by both access to a weather forecast and climate adaptation. The number of farmers is shown at the top of each bar. All crop yields presented are in Qt/ha. 1 Qt (quintal) = 100 kg. Made by author.

Figure 4.9 shows the differences in crop yield after clustering the farmers accordingly. An independent-samples t-test shows that adapting farmers with access to a weather forecast show significantly higher yields for both maize (M = 34.78, SD = 7.59) and teff (M = 18.11, SD = 4.43), compared to adapting farmers without access to a weather forecast (maize: M = 29.88, SD = 6.94; t (339)= -5.915, $p < 0.001$, two-tailed, teff: M = 12.78, SD = 4.01; t (294)= -10.129, $p < 0.001$, two-tailed). In the case of barley and rice no significant differences are observed between the two groups of adapting farmers. With respect to barley yield, non-adapting farmers obtain significantly lower yields compared to adapting farmers, a difference of roughly 60%. Yields obtained for potato show contradictory results, in which adapting farmers not having access to a weather forecast show much higher yields compared to adapting farmers with access to a weather forecast. Even non-adapting farmers show higher yields for potato than adapting farmers with access to a weather forecast, albeit insignificant due to the small number of non-adapting farmers (n = 10) growing potato. According to W.B. Abebe (a local agricultural ministry expert) (personal communication, October 2020), this could be due to the location in which potato is grown and the quality of the soil. From the group of adapting farmers without a weather forecast, over 55% lives in Aribayitu, Wegedame, Mahirderamariyam and Genamechawecha. These are all Kebeles performing above average in terms of potato yield (see Figure 4.4). Compared with adapting farmers with access to a weather forecast, only 21.9% lives in one of these high performing Kebeles. It could thus be that potato is very sensitive to the location it is grown and the soil fertility, diminishing the effect of having access to a weather forecast. However, since soil fertility is not taken into account in this research, this relationship cannot be analysed.

To conclude this subsection, it can be suggested that having access to a weather forecast, adapting to climate variability and farmer experience all play a positive role for most of the major crops in the Gumera sub-basin. Hence, non-adapting farmers without having access to weather forecast perform significantly less than adapting farmers, which is very likely to make them even more vulnerable to climate variability. The question therefore is what keeps non-adapting farmers from taking up adaptation strategies. Is it only due to them not having access to a weather forecast or are there other factors in play that affect the capacity to adjust their farming practices in order to cope with climate variability? And what is the role of experience in this situation? Are farmers with more experience better able to, for example, assess climate variability and to act and adjust their agricultural practices accordingly? In order to get a better insight into these knowledge gaps, the following subsections will comprise a more thorough analysis regarding the behavioural aspects of a farmer in the Gumera sub-basin.

4.4.5. Barriers to climate adaptation

In Subsection 4.4.4 it is discovered there being a small group of farmers that does not adapt to climate variability. In this subsection, the survey question asking these farmers what the reason is to decide not to adapt to year-to-year variability of the Meher season is analysed. Subsequently, each of the main barriers is quantified and discussed.

Figure 4.10 shows the barriers mentioned by the non-adapting farmers in this study's individual household survey, by which none of the farmers did not provide an answer. Similar to what was found in literature, a lack of land, labour, and access to a weather forecast turn out to be the major barriers that keep farmers from adapting to climate variability. However, a lack of credit, supposedly also one of the main barriers, is only mentioned by one respondent in the individual household survey of this research. The same yields for the availability of seeds. In addition, cultural purposes prevent some farmers from taking up adaptation strategies. Interestingly enough, none of the farmers mentioned there not to be a need to adjust. This suggests that all farmers feel the urge to adapt to climate variability but lack the capacity to do so.

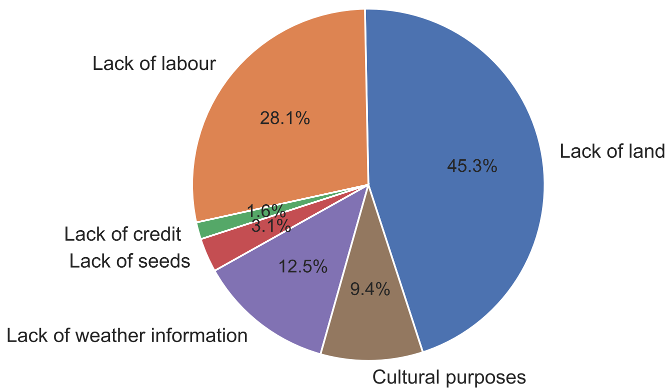


Figure 4.10: Barriers to adaptation mentioned by non-adapting farmers (N = 49) in the household survey in this research. Made by author.

In Table 4.8, for each barrier mentioned, the average results of relating questions included in the individual household survey are presented for both adapting and non-adapting farmers, in order to check the hypothesis (which is accepted if $p < 0.05$) that non-adapting farmers have less access to the three main barriers: land, labour and a weather forecast. In the paragraphs below it is discussed, for each barrier, whether this hypothesis can be justified and if these barriers can validly be assumed to be real constraints to climate adaptation.

		Adapting		**Non-adapting**		**p-value**	**CI 95%**	
		Mean	SD	Mean	SD		Lower	Upper
Farm area	Grass area (ha)	0.22	0.18	0.08	0.12	<0.001	-0.20	-0.09
	Crop area (ha)	1.19	0.70	0.96	0.61	0.021	-0.41	-0.04
	Total area (ha)	1.44	0.90	1.09	0.82	0.011	-0.62	-0.08
Labour	HH farmers (persons)	4.41	1.50	3.60	1.20	<0.001	-1.25	-0.37
	Crops (hr/day)	8.38	1.20	7.12	1.97	<0.001	-1.86	-0.66
	Livestock (hr/day)	3.84	2.89	2.96	1.26	<0.001	-1.35	-0.41
Weather forecast	Yes	33.4%	-	0.0%	-	<0.001	-	-
Seed use	Barley (kg/ha)	237.2	85.98	156.4	44.47	<0.001	-101.6	-60
	Maize (kg/ha)	24.4	7.32	29.0	7.12	<0.001	2.45	6.83
	Potato (kg/ha)	2429	1148	1398	584	<0.001	-1467	-595
	Teff (kg/ha)	60.4	38.10	39.6	7.57	<0.001	-25.7	-15.9
Capital	Capital (Birr)	18.341	12.782	16.582	9335	0.354	-5484	1966
	Borrowing money	22.6%	-	10.2%	-	0.014	-	-

Table 4.8: The results on an independent-samples t-test to check for differences between all adapting (N = 345) and non-adapting farmers (N = 49), with respect to the main barriers. The average, standard deviation (SD), p-values, and the 95% confidence interval are provided. If $p < 0.05$ then a significant difference between both groups of farmers is assumed.

1. Lack of land

A lack of land is mentioned most often to form a barrier for non-adapting farmers to take up adaptation strategies in order to cope with climate variability. Land in this case can be the total farm size, or it can be the crop or grazing area owned by a farmer. Comparing the land area owned by adapting and non-adapting farmers (see Table 4.8) a significant difference is observed, in which adapting farmers, on average, have a total farm size that is 0.35ha larger than that of non-adapting farmers, a significant difference. In addition, non-adapting farmers have a significantly smaller area available for crops. The largest difference is observed for grass area available for livestock. Two third of non-adapting farmers do not own grassland at all, compared to only 14.2% of the adapting farmers, a significant difference ($p < 0.001$). It can thus be concluded that non-adapting farmers have significantly less land available, hence it is assumed that a lack of land indeed can be a constraint to climate adaptation.

2. Lack of labour

A lack of labour is mentioned by 28.1% of the non-adapting farmers (see Table 4.8). Labour is hereby defined as the total available labour, which consists of family members that help on the farm and employees. However, since barely any farmer has employees working on the farm, total available labour is assumed to be solely consisting of family labour. Comparing the number of family members that work on the farm (i.e. household farmers) between adapting and non-adapting farmers (see Table 4.8), it is observed that non-adapting farmers have, on average, almost one family member less helping with agricultural activities. In addition, non-adapting farmers spend significantly less time per day on growing crops and rearing livestock. Based on these results, the hypothesis that non-adapting farmers have less labour available can be accepted.

3. Lack of access to a weather worecast

The access to a weather forecast shows a clear distinction between adapting and non-adapting farmers (see Table 4.8). In total, just above one third of the adapting farmers receives a weather forecast, whereas none of the non-adapting farmers have access to weather forecast information. This was also discovered in Subsection 4.4.4. From this it can be suggested that the farmers adaptive capacity is much larger when having access to a weather forecast. Not having access to a weather forecast could thus be a real constraint. This is in line with what was mentioned by farmers attending the FGD in Geregera (see Subsection 4.3.1). These farmers without access to a weather forecast mentioned that it would be very helpful to receive a weather forecast. In their opinion, this would not only help them in making better agricultural decisions, they could also better plan their food consumption as they would not have to save their crop storage in case a bad year is coming. Instead they could either consume if food is scarce or sell if food is abundant. Based on their opinion, it could be suggested they would rely less on uncertainties of the coming rainy season when having access to a weather forecast.

4. Cultural purposes, lack of seeds and credit
For 9.4% of non-adapting farmers, cultural purposes causes them to stick with their regular farming practices instead of adjusting to the variability of the Meher season (see Table 4.8). Although it not being a large share of farmers, other studies have found similar results stating that cultural characteristics affect farmer's choices of certain strategies (Adimassu and Kessler, 2016). However, investigating in what way cultural characteristics prevent farmers from taking up adaptation strategies falls outside the scope of this research and will not be taken into account during the remaining of this research. The lack of seeds and credit is only mentioned by 3.1 and 1.6% of the non-adapting farmers, respectively. This suggests that both parameters do not have much influence on whether a farmer will adapt to climate variability or not. However, when comparing both groups of farmers significant differences arise with respect to seed use, and borrowing money (see Table 4.8). Except for maize, adapting farmers use a significantly higher seed rate for each crop type. Notice, that rice is not shown here as rice is not cultivated by non-adapting farmers. In addition, capital is also in favour of the adapting farmer, albeit an insignificant difference. In terms of borrowing money, a significant larger share of adapting farmers borrows money compared to non-adapting farmers. This suggests that adapting farmers not only have slightly higher capital, but are also more likely to be in the position to borrow money. Despite having lower capital and being less likely to borrow money, non-adapting farmers do not perceive capital to be a barrier to climate adaptation.

It can thus be concluded that a lack of land, labour and a weather forecast are the major barriers that keep farmers from taking up adaptation strategies. However, it is not yet clear whether these parameters can individually prevent farmers from taking up adaptation strategies or that it is a combination of the three. In addition, it is unknown at what point, for example, the labour availability reaches a critical threshold that makes farmers unable to adapt to climate variability. On top of that, other factors could be in play as well. As indicated in Subsection 2.1.2 the farmer perception of changes in climate and the information sources used during the decision making is suggested to influence his or her attitude towards climate adaptation (Deressa et al., 2011, Grunblatt and Alessa, 2017). Besides the barriers discussed, these could therefore be an additional factor influencing the adaptive capacity of a farmer.

4.4.6. Farmer's Perception of Climate Variability

This subsection discusses the perceptions of the surveyed farmers in the Gumera sub-basin regarding climate variability. In the individual household survey, farmers were asked how they have perceived both climate change and variability. Unfortunately, the answers on the perception of climate variability turned out to be of bad quality (except for temperature), due to a supposedly misunderstanding of the question. Therefore, these questions are excluded from the analysis, and only the perceptions of climatic changes on the long term (i.e. over the last 30 years), except for temperature, will be discussed. The results are presented in Figure 4.11, whereby farmers are clustered on climate adaptation and the access to a weather forecast.

Except for the almost unanimous perception of farmers that the mean temperature has increased over the last 30 years, and that the onset of rains has become later in the season, which both correspond to observations explored in Subsection 2.1.2 by Bewket et al. (2011), quite some significant differences in climate perception between the three groups of farmers are observed. On the short term, temperature variability is perceived to increase by almost all farmers having access to a weather forecast, whereas only half of the farmers without access to a weather forecast perceived an increase. For the group of farmers without access to a weather forecast, no significant difference is observed between adapting and non-adapting farmers. The same yields for the amount of dry spells occurring during the rainy season, in which a large share of adapting farmers with a weather forecast perceived an increase in the number of dry spells compared to only 14% of adapting and non-adapting farmers without a weather forecast. The timing of the cessation of Kiremt rains shows the opposite. Almost 90% of farmers without a weather forecast perceive the cessation to have become later over the last 30 years, compared to only 33% of farmers with access to a weather forecast. In terms of rainfall and

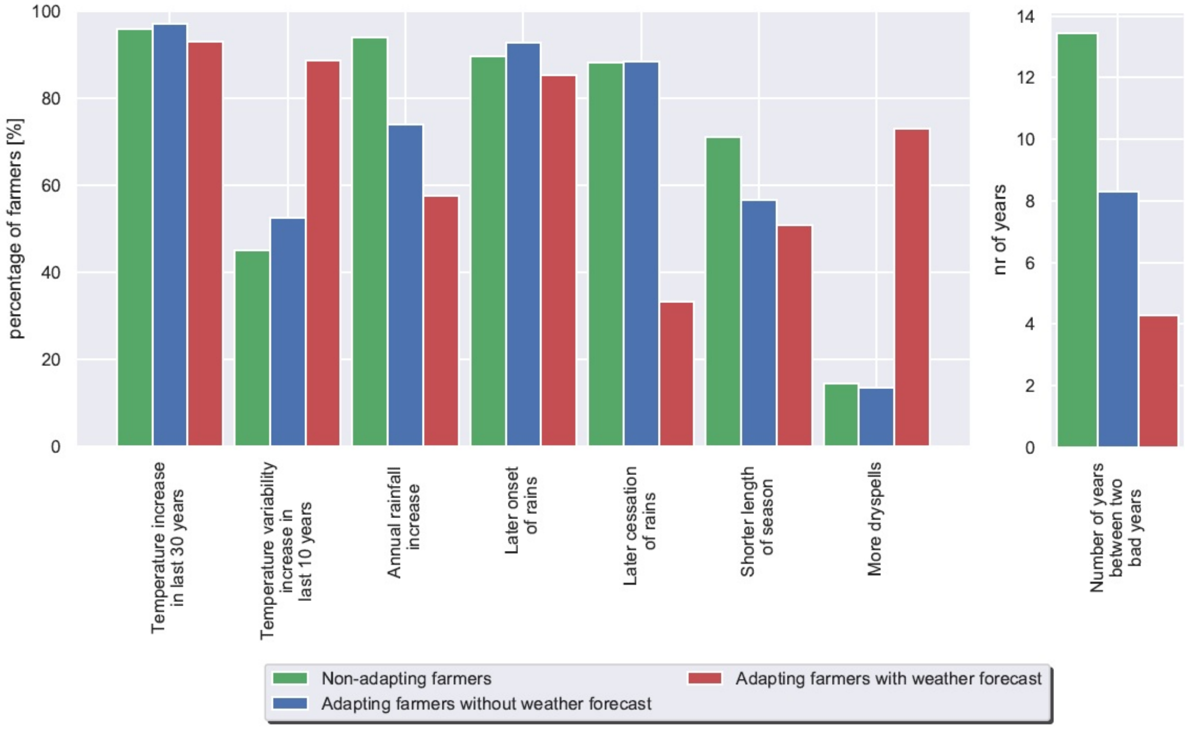


Figure 4.11: The farmer's perception of changes in weather patterns over the last 30 years, and the frequency with which a bad year is experienced, for non-adapting farmers (N = 49), adapting farmers without access to a weather forecast (N = 229), and adapting farmers with access to a weather forecast (N = 115). Made by author.

length of the Meher season significant differences are observed between adapting and non-adapting farmers. Almost all non-adapting farmers have perceived an increase in annual rainfall, while 71% has perceived the Meher season to have become shorter over time. A smaller share of adapting farmers, on the other hand, have perceived these same trends. Therefore, with respect to trend of annual rainfall, the group of adapting farmers is in more agreement with what is found in climate studies in the Amhara region, who discovered a general decreasing trend of annual rainfall over the last 30 years (Skambraks, 2014, Tadesa, 2020).

On the right side of Figure 4.11 the perceived frequency with which the three groups of farmers experience a bad year is presented. A bad year, in this context, is defined as either a drought or a flood. Here, large differences are observed between the three groups, in which adapting farmers with access to a weather forecast claim to experience a bad year most frequently. This group of farmers says to experience a bad year once every four years on average, which is roughly three and two times as often than, respectively, non-adapting and adapting farmers without access to a weather forecast. However, within the group of adapting farmers with access to a weather forecast, a clear split is observed between farmers in Shimagle Giorgis and all other farmers. All farmers in Shimagle Giorgis having access to a weather forecast, who on average have 32 years of experience, claim to never have experienced a bad year. The remaining share of adapting farmers in other Kebeles who have access to a weather forecast claim to experience a bad year once every 3.5 years on average, with 75% experiencing a bad year once every 2 years. For farmers growing rice, the majority experiences a bad year once every 2-5 years. In addition, experienced farmers (i.e. > 35 years of experience) say to experience a bad year once every 5 years, on average, which is twice as often compared to farmers with less than 35 years of experience.

Overall, it can thus be concluded that there are large differences in the perception between these three groups of farmers, whereby it seems like non-adapting farmers without a weather forecast have a slightly more positive view on the long term climatic changes. They have perceived less variability in temperature, more rainfall, and less dry spells. All supposedly positive trends for productive agriculture, although they are also more likely to perceive the Meher season to have become shorter. In addition, it is interesting to notice the deflecting perceptions of farmers with access to a weather forecast. They are much more likely to perceive increasing variability in temperature, a decrease in annual rainfall, an earlier cessation of rains, more dry spells during the Meher season and more bad years. This suggests that having access to a weather forecast could make farmers more aware of changes in the climatic pattern, giving them the urge to adapt to changes in climate. Although there deviating perceptions of climate change do not tell whether their perception on climate variability is different as well, it could be a possible explanation why all farmers having access to a weather forecast are actually taking up adaptation strategies to cope with climate variability. The difference observed in occurrences of a bad year would suggest there being a correlation between how often a farmer experiences a bad year and how likely (s)he therefore is to adapt. It thus could be that a farmer not experiencing a bad year for a long time may not be sufficiently triggered to take up adaptation strategies when bad year predictors are observed. On the other hand, it could be that farmers with a weather forecast are more likely to classify a rainy season as a bad year, compared to farmers without access to a weather forecast. From the results discussed it can therefore be suggested that the perception of changes in climate can indeed influence the adaptive capacity of a farmer as was indicated by Deressa et al. (2011), Grunblatt and Alessa (2017).

4.4.7. Information sources used to make agricultural decisions

In addition to a lack of land, labour, and a weather forecast, and the climate perception of a farmer, the information on which a farmer bases his or her agricultural decisions could possibly influence the adaptive capacity of a smallholder farmer. This subsection describes the information sources used by the surveyed farmers in the Gumera sub-basin in order to decide what agricultural practices to take up.

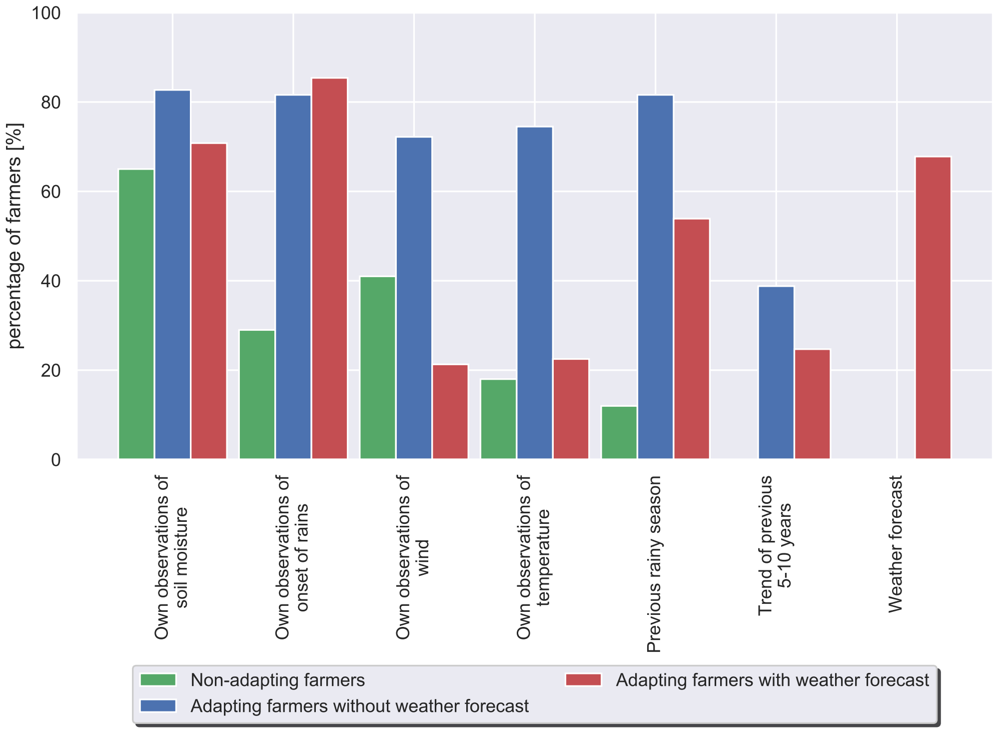


Figure 4.12: Information sources for agricultural decision making by non-adapting farmers (N = 49), adapting farmers without access to a weather forecast (N = 229), and adapting farmers with access to a weather forecast (N = 115) in the Gumera sub-basin. Made by author.

Figure 4.12 shows the information sources used by each of the three groups of farmers. Overall, the most used sources of information are own observations of soil moisture, onset, and the previous rainy season. The own observations of wind and temperature, and the climatic trend over the last 5 to 10 years are less prevailed. However, between the three groups significant differences are apparent. Whereas soil moisture is used by a large share of farmers in each group, the onset of rains and the previous rainy season show large differences between especially adapting and non-adapting farmers. Compared to adapting farmers, from which 83% bases their agricultural decisions on the onset of rains, a much smaller share of the group with non-adapting farmers (29%) is using the onset of rains, a significant difference, X^2 (1, N=394) = 65.549, $p < 0.001$. Similarly, adapting farmers (74.5%) are much more likely to use the onset the previous rainy season to decide upon their agricultural decisions, compared to non-adapting farmers (12.2%), X^2 (1, N=394) = 72.130, $p < 0.001$. Comparing the group of adapting farmers with and without access to a weather forecast, especially large differences are seen for the use of own observations of wind and temperature. In addition, the use of both the previous rainy season and previous 5-10 rainy seasons is less for farmers with access to a weather forecast compared to adapting farmers without a weather forecast. On the one hand, this could suggest that having access to a weather forecast makes farmers less dependent on their own observations of such weather characteristics, causing them to fully rely upon the weather forecast. On the other hand, it could be that this group of farmers, due to them relying upon the weather forecast, has not developed the ability to perceive the importance of weather characteristics such as wind and temperature.

4.4.8. Predictors for the Climate Adaptive Capacity

This subsection describes which farmer characteristics are suggested to significantly influence the climate adaptive capacity of a farmer, by the use of a binary logistic regression. From the analysis so far, it is observed there are three factors that could possibly explain the capacity of a farmer to adapt to climate variability: 1) the main barriers (i.e. lack of land, labour, and a weather forecast), 2) the farmers' perception on climatic changes, and 3) the information upon which a farmer bases his or her agricultural decisions. In Subsection 4.4.4, it was assumed that all farmers having access to a weather forecast have the capacity to adapt to climate variability. Hence, only for those farmers not having access to a weather forecast, a binary logistic regression analysis is conducted, as is explained at the end of Subsection 4.2.2. A full overview of the output of the binary logistic regression is provided in Appendix C.2.2.

Figure 4.13 shows the result of the binary logistic regression analysis. An explanation of each of the statistical variables is provided in Appendix C.2.1. In total, three variables (i.e. farm size, household labour availability, and the use of onset of rains during the agricultural decision making) come out as significant predictors for the climate adaptive capacity of a farmer in the Gumera sub-basin. Other variables that were considered in the analysis but found to be insignificant were capital, farmers' climate perception with respect to onset, cessation, annual rainfall, dry spells, and temperature, and the information sources, except for the onset of rains, discussed in Subsection 4.4.7. The full model was statistically significant with a Chi-square value of 60.54 and $p < 0.001$, which indicates that the model is able to distinguish between farmers who do and do not have the capacity to adapt to climate variability. Together, the three predictors explain between 19.6% and 32.3% of the variance in the climate adaptive capacity of farmers in the Gumera sub-basin, and correctly predict the climate adaptive capacity of 82.4% of all farmers. In total, 30 farmers are predicted not to have the capacity to adapt to climate variability, compared to 49 farmers that mentioned in the household survey not to adapt to climate variability. From the predictors, the use of onset is the strongest predictor. If a farmer bases his or her agricultural decisions upon the onset of rains this farmer is 8.339 times more likely to have the capacity to adapt to climate variability compared to a farmer who does not use the onset of rains. Also, farm size and household labour availability show positive correlations with climate adaptive capacity. Since both variables are continuous variables, this means that if farm size and household labour availability increase by one unit, and all other independent variables remain constant, the probability of a farmer to adapt to climate variability increases with, respectively, 1.733 and 1.035.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Step 1[a]	Farm size	.550	.261	4.425	1	.035	1.733	1.038	2.893
	Household labour	.034	.013	6.663	1	.010	1.035	1.008	1.062
	Use of onset of rains	2.121	.375	31.949	1	.000	8.339	3.997	17.400
	Constant	-1.355	.543	6.231	1	.013	.258		

a. Variable(s) entered on step 1: Farm size, Household labour, Use of onset of rains.

Figure 4.13: A binary logistic regression analysis showing the main predictors for the climate adaptive capacity of surveyed farmers in the Gumera sub-basin (N = 278). Surveyed farmers with access to a weather forecast are excluded from this analysis.

4.4.9. Adaptation Strategies to Climate Variability

This subsection explains and discusses the adaptation strategies taken up by the surveyed farmers in the Gumera sub-basin. Differences between the three groups of farmers, clustered on climate adaptation and access to a weather forecast, are explored, as well as the differences between Kebeles. In addition, the main predictors for adaptation by changing the crop type, and changing the planting and harvesting dates are explored by conducting a binary logistic regression. For a full overview of the output of each binary logistic regression see Appendix C.2.

From the FGDs, discussed in Section 4.3, it is known that farmers adapt to climate variability by changing the crop type, and the date at which they sow their seeds (i.e. the planting date), and harvest their crops (i.e. harvesting date). Furthermore, farmers in Jigena and Geregera mentioned to also take up off-farm labour in case a bad year occurred and the crops had failed. In the household survey, adapting farmers were asked with what adaptation strategies they adapt to climate variability. The results are shown in Figure 4.14. Note that non-adapting farmers are excluded from this analysis, hence 345 adapting farmers are included in this analysis.

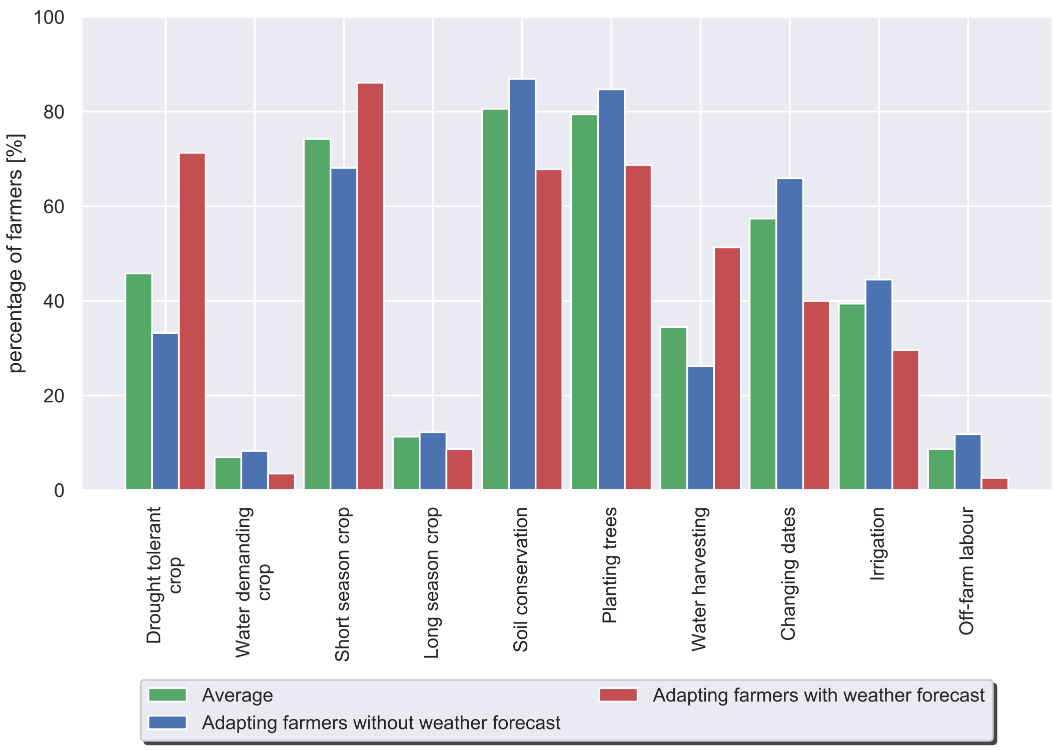


Figure 4.14: The share of adapting farmers (N = 344) in the Gumera sub-basin adapting by each adaptation strategy. Adapting farmers without access to a weather forecast (N = 229) are compared with adapting farmers with access to a weather forecast (N = 115). Made by author.

From Figure 4.14, it can be observed there being four adaptation strategies taken up by more than half of all adapting farmers in the Gumera sub-basin, namely soil conservation (80.6%), planting trees (79.4%), changing to a short season crop (74.2%), and changing planting and harvesting dates (57.4%). This corresponds very well with what was explored from literature in Subsection 2.1.2. Changing to a drought tolerant crop (46%), water harvesting (34%) and irrigation (39%) are also relatively frequently used adaptation strategies. Changing to a long season, or water demanding crop is not preferred at all and only taken up by as much as 11.3% and 7% respectively. This also corresponds with the overall perception of farmers, observed in Subsection 4.4.6, that the rainy season has become shorter over the last 30 years. Taking up off-farm labour is also not a very preferred strategy to cope with climate variability, and only taken up by 8.7% of all adapting farmers. This might be due to there not being off-farm labour available during years in which adaptation strategies are required (i.e. in a bad year), as was mentioned by farmers in Shime during the FGD, which is discussed in Subsection 4.3.3.

Since the focus in this research is on the adaptation of farmers to year-to-year climate variability, the focus is on adaptation strategies regarding the yearly recurring (short-term) agricultural choices a farmer has to make. Adaptation strategies such as soil conservation, planting trees, water harvesting and irrigation are therefore not further investigated since they are seen as long term solutions for which serious investments are needed. Hence, the focus in this research is on changing crop type, changing planting and harvesting dates, and switching to off-farm labour. Herein, significant differences can be observed between adapting farmers with and without access to a weather forecast. Having a weather forecast seems to make farmers significantly more likely to adapt by changing to a drought tolerant (X^2 (1, N=344) = 43.265, $p < 0.001$) and short season crop (X^2 (1, N=344) = 11.963, $p = 0.001$). On the other hand, adapting farmers without access to a weather forecast are significantly more likely to adapt by changing the planting and harvesting dates, X^2 (1, N=344) = 20.001, $p < 0.001$. From the small number of farmers switching to off-farm labour (N=31), 90% does not receive a weather forecast, a significant difference with X^2 (1, N=344) = 6.995, $p = 0.008$. This could suggest that farmers without a weather forecast find themselves more often in the situation in which crop production has failed, at which point the only option to earn money is off-farm labour. However, since this is only a very small sample size the reliability of this correlation is not very strong.

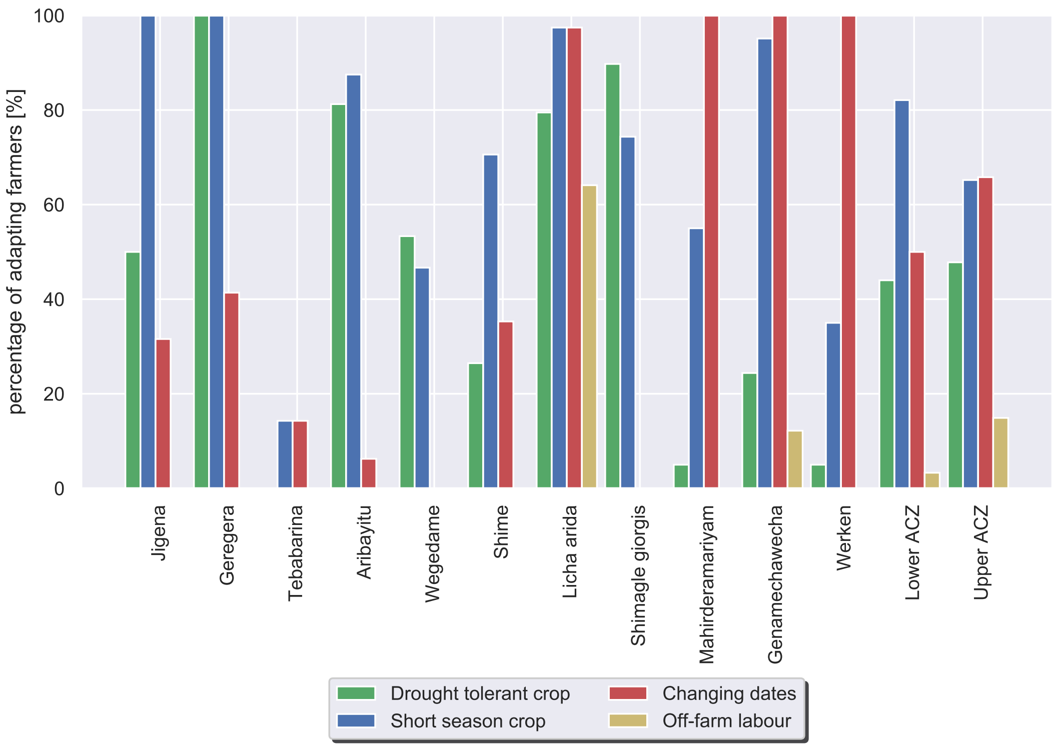


Figure 4.15: The share of adapting farmers (N = 344) in the Gumera sub-basin, grouped by Kebele, and ACZ, that claims to adapt by changing to a drought tolerant crop (N = 159), changing to a short season crop (N = 255), changing the planting and harvesting dates (N = 197), and changing to off-farm labour (N = 31). Made by author.

In addition, clear differences are seen when comparing adaptation strategies taken up by farmers in different Kebeles. Figure 4.15 shows the differences for the four adaptation strategies we focus on. From this we can conclude that it are mostly farmers in the eastern more elevated part of the Gumera sub-basin (i.e. Licha Arida, Mahirderamariyam, Genamechawecha) who are adapting by changing the planting and harvesting dates, whereas changing to a drought tolerant crop is much less preferred. This is also shown by clustering the farmers upon the ACZ they are in. In the lower ACZ (i.e. Wet Weyna Dega) farmers are more likely to adapt by changing to a short season crop (X^2 (1, N=345) = 11.868, $p = 0.001$), whereas farmers in the upper ACZ (i.e. Wet Dega) are more likely to adapt by changing planting and harvesting dates (X^2 (1, N=345) = 8.173, $p = 0.004$). This would suggest that altitude is an important factor influencing the type of adaptation strategies a farmer adapts with. Off-farm labour is basically only taken up by farmers in Licha Arida located in the upper ACZ. The pattern observed during the FGD in Shime, where no off-farm labour is said to be available during bad years, can thus be justified for most Kebeles. However, this does not agree with what is observed during the FGDs in Jigena and Geregera, in which farmers mentioned to take up off-farm labour, in case crop production failed. It could thus be that either surveyed farmers do not see off-farm labour as an adaptation strategy, or the farmers joining the FGD in Jigena and Geregera were not representative for the population in Jigena and Geregera.

Overall, it can thus be concluded that quite some heterogeneity exists between farmers with respect to the type of adaptation strategies taken up. The access to a weather forecast seems to play an important role but also farmers at different altitudes show deviating behaviour. However, it is likely there being more factors influencing the type of adaptation strategy a farmer takes up. In order to determine which factors can be assumed to be major predictors for the type of adaptation strategy taken up by a farmer, binary logistic regression analyses have been conducted for each adaptation strategy separately, as explained at the end of Subsection 4.2.2. Hereby it is chosen to only focus on adaptation by changing to a short season crop and by changing the planting and harvesting dates, since these are the two major adaptation strategies taken up by farmers in the Gumera sub-basin. Furthermore, farmers that say not to adapt to climate variability are left out of the analyses. Also rice growing farmers are not taken into account since, based on the FGDs and the results discussed, this group of farmers experiences very different climatic challenges, which might induce significant different climate adaptive behaviour compared to farmers in the rest of the Gumera sub-basin. It would therefore affect the analyses. Hence, in total 285 adapting non-rice growing farmers are included in the analyses.

Adapting with a short cycle crop

Figure 4.16 shows the results of the binary logistic regression analysis in order to determine the likelihood of a farmer to adapt by changing to a short cycle crop. An explanation of each of the statistical variables is provided in Appendix C.2.1.

In total, five variables (i.e. elevation, education, farm size, number of livestock (in TLU), and capital) come out as significant predictors for this type of adaptation strategy. Other variables that were considered in the analysis but found to be insignificant were gender, farmer experience, household labour availability, market distance, weather forecast, information sources discussed in Subsection 4.4.7, and farmers' climate perceptions discussed in Subsection 4.4.6. The full model was statistically significant with a Chi-square value of 37.77 and $p < 0.001$, which indicates that the model is able to distinguish between farmers who do and do not change to a short cycle crop in order to cope with climate variability. Together, the five predictors explain between 12.4% and 17.5% of the variance in this type of adaptation strategy, and correctly classified 69.1% of farmers. As such, 240 farmers where predicted to adapt by changing to a short cycle crop, whereas 196 surveyed farmers claimed to take up this adaptation strategy.

From the predictors, farm size turns out to be the strongest predictor. For every additional hectare of available land a farmer is 1.72 times more likely to switch to a short cycle crop in order to cope with climate variability. Also, education and the number of livestock owned show positive correlations with adapting with a short cycle crop. Different from the other variables, education is a categorical variable instead of a continuous variable. In Table 4.9 the categories by which farmers could answer are presented. The odds ratio EXP(B) of education thus means that the probability of a literate farmer to adapt by changing the crop type is 1.467 higher than an illiterate farmer. For the continuous variables the odds ratio represents the increase in probability with every unit increase in the continuous variable. Elevation and capital are the only predictors showing a negative correlation, which suggests that farmers at higher altitudes or with more capital available are less likely to adjust with a short cycle crop. This is somewhat counter-intuitive as potato was assumed to be the major adaptive crop (see Subsection 4.4.4) and is mainly grown in the upper regions of the Gumera sub-basin. Therefore, one would expect farmers at higher altitudes to be more likely to change crop type in order to cope with climate variability.

	Educational status
Level 1	Illiterate
Level 2	Able to read and write
Level 3	1-4 grades completed
Level 4	5-8 grades completed
Level 5	9-10 grades completed
Level 6	11-12 grades completed
Level 7	Technical and vocational college diploma
Level 8	Degree and above

Table 4.9: Levels of education

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Step 1[a]	Farm size (ha)	.543	.255	4.527	1	.033	1.722	1.044	2.840
	Elevation (m)	-.005	.001	15.751	1	.000	.995	.993	.998
	Education	.383	.185	4.284	1	.038	1.467	1.021	2.110
	Livestock (TLU)	.231	.111	4.373	1	.037	1.260	1.015	1.565
	Capital (Birr)	-.000045	.000	10.006	1	.002	1.000	1.000	1.000
	Constant	10.289	2.696	14.563	1	.000	29416.066		

a. Variable(s) entered on step 1: Farm size (ha), Elevation, Education, Livestock, Capital.

Figure 4.16: A binary logistic regression analysis showing the variables significantly influencing the choice of a farmer to adapt by changing to a short cycle crop. Surveyed non-adapting farmers and rice growing farmers are excluded from this analysis, hence the analysis is conducted for 285 farmers in the Gumera sub-basin. A full output of the binary logistic regression and explanation of the statistic variables can be found in Appendix C.2.3.

Adapting by changing planting and harvesting dates

The results of the binary logistic regression, conducted to assess the factors having significant influence on the farmer's choice of changing the planting and harvesting dates due to climate variability, are shown in Figure 4.17. An explanation of each of the statistical variables is provided in Appendix C.2.1.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Step 1[a]	Elevation	-.006	.001	17.948	1	.000	.994	.992	.997
	Livestock (TLU)	-.736	.129	32.628	1	.000	.479	.372	.617
	Education	1.011	.227	19.886	1	.000	2.747	1.762	4.283
	Experience	.064	.017	13.792	1	.000	1.066	1.031	1.103
	Weather forecast	-1.389	.440	9.984	1	.002	.249	.105	.590
	Household labour	.105	.016	44.875	1	.000	1.111	1.077	1.146
	Constant	9.680	2.842	11.597	1	.001	15991.262		

a. Variable(s) entered on step 1: Elevation, Livestock (TLU), Education, Experience, Weather forecast, Household labour.

Figure 4.17: A binary logistic regression analysis showing the variables significantly influencing the choice of a farmer to adapt by changing the planting and harvesting dates. Surveyed non-adapting farmers and rice growing farmers are excluded from this analysis, hence the analysis is conducted for 285 farmers in the Gumera sub-basin. A full output of the binary logistic regression and explanation of the statistic variables can be found in Appendix C.2.4.

Similar to what is observed for the change to a short cycle crop, elevation, education, and the number of livestock are significant predictors. In addition, farmer experience, access to a weather forecast, and labour availability turn out to have significant influence on the farmer's choice whether or not to change his or her planting and harvesting dates in times of climate variability. Other variables that were considered in the analysis but found to be insignificant were gender, farm size, capital, market distance, information sources discussed in Subsection 4.4.7, and farmers' climate perceptions discussed in Subsection 4.4.6. The full model is statistically significant with a Chi-square value of 161.32 and $p < 0.001$. The model, thus, has the ability to distinguish between farmers who do and do not shift the planting and harvesting dates in order to cope with climate variability. Together, the six predictors explain between 43.3% and 59.1% of the variance in this type of adaptation strategy, and correctly classified 81.3% of farmers. As such, 177 farmers where predicted to adapt by changing the planting and harvesting dates, whereas 178 surveyed farmers claimed to take up this adaptation strategy. From the predictors, education shows the strongest influence on whether or not a farmer changes its planting and harvesting dates. With every extra level of education (see Table 4.9) a farmer is 2.75 times more likely to adapt to climate variability by changing his or her planting and harvesting dates. In addition, the access to a weather forecast has quite some influence, such that a farmer having access to a weather forecast is 0.25 times less likely to adapt by this strategy than farmers without access to a weather forecast. Elevation, and the number of livestock (in TLU) show a negative correlation as well, whereas farmer experience and labour availability show a positive relationship with changing planting and harvesting dates in order to cope with climate variability.

4.5. Conclusion

This section provides an overview of the main conclusions drawn from the results from the FGDs and the individual household survey discussed in Sections 4.3 and 4.4, respectively.

Basically all farmers in the Gumera sub-basin (98.4%) practice a mixed crop-livestock farming system. The major crops grown are maize, teff, potato, barley and rice. However, from the FGDs it was discovered there being quite some heterogeneity between farmers in different Kebeles with respect to the type of crop grown, climatic challenges faced, and the level of food insecurity. Based on these differences, it is assumed there being largely two groups of farmers within the Gumera sub-basin. The first and somewhat smaller group exists of rice growing farmers who live in the lower altitude western part of the Gumera sub-basin for which floodings compose the major climatic challenge, but never face food insecurity. All of these farmers are observed to adapt to climate variability. The second, much larger group exists of non-rice growing farmers living at a higher altitude throughout the rest of the Gumera sub-basin for which droughts compose the major climatic challenge. These farmers claim to face food insecurity during the months December till March, each year again.

Heterogeneity is especially observed in the crop yield obtained by farmers in different Kebeles, with some Kebeles showing yields twice as high as others. The access to a weather forecast, fertiliser and chemical use, adaptation to climate variability, crop area, and farmer experience are found to be main predictors for the variance in crop yield. For all cereal crops, except for rice, adaptation to climate variability, farmer experience, and the access to a weather forecast are suggested to positively influence crop yield. In the case of potato, the only root crop taken into account in this research, only a positive correlation is found between yield and adaptation to climate variability. Farmers without access to a weather forecast, and those who are slightly experienced show significantly higher yields for potato.

Although adaptation to climate variability shows large positive results on crop production for each type of crop, 12.4% of the surveyed farmers say not to have adopted strategies to cope with climate variability in the last 10 years. Neither have they adopted strategies to cope with climate change in the last 30 years. Each of the non-adapting farmers live in Kebeles located in the western part of the Gumera sub-basin (i.e. in the lower ACZ) and experience droughts as the major climatic challenge. Droughts are defined by these farmers as a bad year with a short rainy season and a late onset. These farmers feel the urge to take up adaptation strategies but are constrained by especially a lack of land, labour and not having access to a weather forecast. Especially, having access to a weather forecast seems to have a major influence on the adaptive capacity of a farmer since all farmers receiving a weather forecast are taking up adaptation strategies. Furthermore, those farmers that adapt to climate variability have, on average, 0.35 hectares of land and one family member working on the farm more compared to non-adapting farmers. It is therefore suggested that the availability of land, labour and a weather forecast positively influence the climate adaptive capacity of a farmer in the Gumera sub-basin.

In addition, large differences are observed with respect to both the long term climate perception and the sources of information farmers use to determine what agricultural practices to take up. Over the last 30 years, almost all surveyed farmers have perceived a temperature increase, and the onset of rains to have become later. However, in general, farmers with access to a weather forecast seem to be better aware of the actual changes in climate as their perception is in more agreement with what is concluded by several climate studies. Non-adapting farmers seem to have a more optimistic perception of changes in climate instead. They perceived less variability in temperature, more rainfall, later cessation of rains and less dry spells. All of which are opposite perceptions from what is perceived by adapting farmers with access to a weather forecast. The group of adapting farmers without access to a weather forecast find themselves more or less in the middle of both groups. The same trend is seen for the frequency with which a bad year occurs, in which adapting farmers having access to a weather forecast mention a bad year to occur roughly three times as often (once every 4 years) compared to what is mentioned by non-adapting farmers (almost once every 14 years). Also the farmer experience showed a positive correlation with the frequency with which a bad year occurs. It can therefore be suggested that adapting farmers, especially those with access to a weather forecast, are better aware of climate variability, which seems to increase their climate adaptive capacity.

With respect to the information sources used by farmers to make agricultural decisions large differences are observed between adapting farmers and non-adapting farmers. Whereas all farmers take soil moisture into account, adapting farmers are much more likely to base their agricultural decisions upon the onset of rains and the previous rainy season compared to non-adapting farmers. It is therefore suggested that not using such sources of information limits the climate adaptive capacity of non-adapting farmers. Within the group of adapting farmers, farmers with access to a weather forecast seem to rely upon this information. They make less use of own observations of certain weather characteristics, such as wind and temperature, compared to adapting farmers without access to a weather forecast.

It can thus be concluded that the barriers to climate adaptation, the farmer's climate perception, and the type of weather information used by a farmer are all suggested to influence the climate adaptive capacity of a farmer. Together, the farm size, labour availability within the household, and the use of own observations of the onset of rains positively influence the climate adaptive capacity of farmers in the Gumera sub-basin. The most preferred adaptation strategies of surveyed farmers that claim to adapt to climate variability are changing to a short cycle crop, and changing the planting and harvesting dates. These are the same adaptation strategies that were mentioned by farmers during the FGDs. The likelihood of a farmer to adapt by changing to a short cycle crop is found to be positively influenced by the farm size, level of education, and the number of livestock owned, whereas altitude and capital show a negatively correlation. Hereby, potato is assumed to be the main crop with which farmers adapt, since (differently from other crops) a much larger share of adapting farmers (60%) grows potato compared to non-adapting farmers (20%). In addition, potato is a short cycle crop. The likelihood of a farmer to adjust the planting and harvesting dates in order to cope with climate variability is also positively influenced by the level of education, and negatively by the altitude. Furthermore, it is found that farmer experience, and labour availability positively influence the likelihood of a farmer to change planting and harvesting dates, whereas the number of livestock owned, and access to a weather forecast show a negative correlation.

5

Incorporating Climate Adaptive Behaviour in a Socio-Hydrological Model

In this chapter a socio-hydrological model is presented which can be used to simulate the system dynamics of smallholder farmers in the Gumera sub-basin with respect to climate variability. The methodology presented shows how our knowledge on the climate adaptive behaviour of farmers, obtained from Focus Group Discussions and the individual household survey, is used to incorporate these behavioural aspects into the socio-hydrological model. Examples of how this influences the agricultural practices of farmers are shown, as well as an illustration of what the impact of climate adaptation could be on the farmer economic well-being.

5.1. Introduction

In Chapter 4 it was discovered that there exists large differences between farmers in terms of crop yield obtained. Climate adaptation, having access to a weather forecast, and experience were amongst the main predictors that were able to explain the variance in crop yield (see Subsection 4.4.4). The vulnerability of farmers to climate variability causes a large share of farmers to adjust their farming practices in order to cope with these variabilities. However, the way in which farmers adapt can vary and is influenced by multiple factors, such as experience, education, and capital, as well as their perception of climate change and the weather information available to them. This results in farmers taking up different adaptation strategies, such as changing the crop type and/or changing the planting and harvesting dates, which creates a heterogeneous environment. On the other hand, there is a relatively small group of farmers for which the adaptive capacity is constrained by certain barriers, such as land and labour availability. This withholds them from taking up adaptation strategies. All of these factors influence the system dynamics of a farmer, causing each farmer to perform differently in terms of crop yield obtained and their economic well-being.

In Section 2.2 it was explained how socio-hydrology can be used to simulate the system dynamics of smallholder farmers by taking into account the 'environmental awareness'. Although the experience of a farmer, which can be linked to the environmental awareness, was observed to significantly influence the climate adaptive behaviour of farmers in the Gumera sub-basin (see Section 4.4), the aspect of environmental awareness is not taken into account in this research. This is due to current social theories being underdeveloped or contested and might therefore not be capable of underlying mathematically based socio-hydrological models (see Subsection 2.2.2). Hence, there exists a lack of understanding of how the environmental awareness exactly influences the climate adaptive behaviour of a farmer. This chapter therefore presents a novel methodology to incorporate the climate adaptive behaviour of smallholder farmers within a socio-hydrological model. Hereby, the climate adaptive behaviour of farmers in the Gumera sub-basin is incorporated based on observations from the FGDs and the individual household survey, and is accounted for by the use of a logit model. In this way the co-evolutionary dynamics of coupled human-water systems are taken into account via a bottom-up approach. The framework of Pande and Savenije (2016) is hereby used as a starting point (see Figure 5.1). In this framework six main assets of a typical smallholder farmer are coupled: water storage capacity, capital, livestock, soil fertility, grazing access, and labour availability. Hydro-climatic variability is hereby incorporated as a main driver and source of uncertainty for the smallholder system, such that the sensitivity of a smallholder's well-being and his or her resilience can be studied. This research aims to improve the socio-hydrological modelling framework of Pande and Savenije (2016) by incorporating the climate adaptive behaviour of smallholder farmers in the Gumera sub-basin. Hence, the model is applied to a different study area compared to Pande and Savenije (2016), which focussed on smallholder farmers in Maharashtra, India. Since it is likely that Ethiopian farmers act differently from Indian farmers, as they might face different challenges and have different cultures, some of the assumptions made by Pande and Savenije (2016) are adjusted.

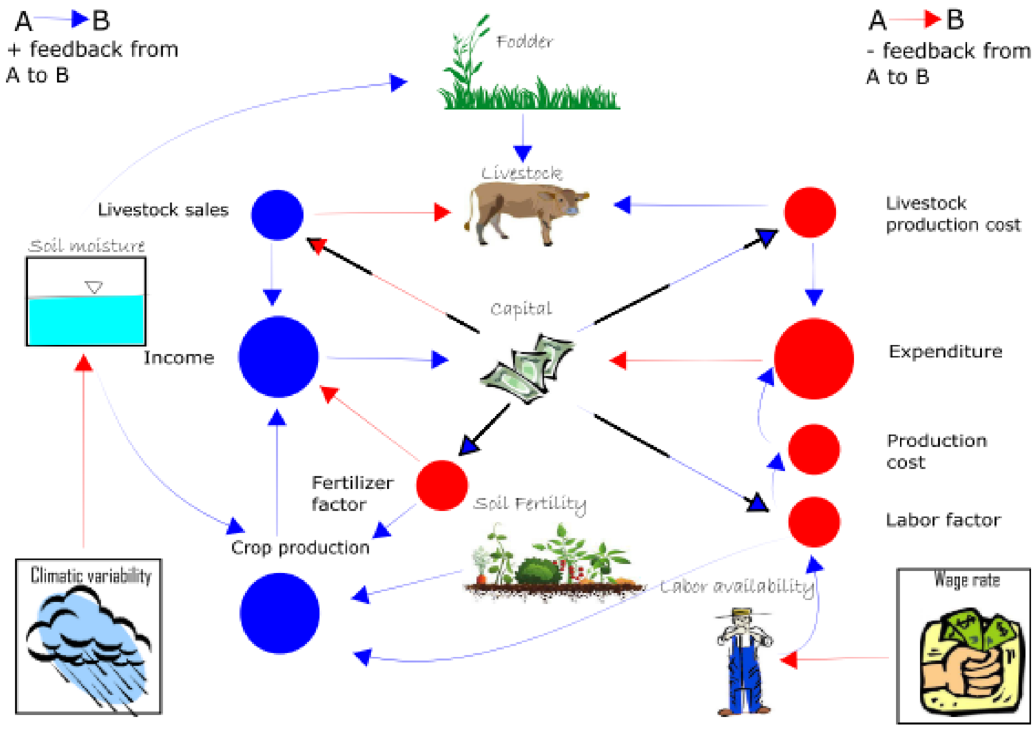


Figure 5.1: The socio-hydrological modelling framework of Pande and Savenije (2016). "An illustration of feedbacks between dominant socio-hydrological state variables and fluxes. The dashed feedbacks (in black) are activated when the capital stock falls below or close to 0. Two examples are shown of factors that are external to the dynamic system; climatic variability and off-farm wage rate. Six socio-hydrological state variables are shown: water storage, soil fertility, capital, livestock, fodder, and labour availability. Socio-hydrologic flux variables are crop production, livestock sales, expenditure, livestock production costs, crop production costs, labour factor, and fertiliser factor that influence the co-evolution of socio-hydrological state variables."

In Sections 5.2 and 5.3 the set up and use of the socio-hydrological model is explained. Section 5.2 describes the main aspects of the socio-hydrological modelling framework of Pande and Savenije (2016). It includes a brief description of the major mechanisms apparent, the input data used for the model, assumptions and adjustments made. For the remaining of this research, the model described in Section 5.2 will be referred to as the "reference model". Section 5.3 describes what we call the "behavioural model". This model differs from the reference model since it also incorporates the climate adaptive behavioural aspects of smallholder farmers in the Gumera sub-basin. This section presents a methodology that can be used to incorporate the climate adaptive behaviour of smallholder farmers in the Gumera sub-basin in a socio-hydrological model. In Section 5.4, examples of how the climate adaptive behaviour of farmers incorporated in the behavioural model influences their agricultural practices are presented and discussed. In addition, the corresponding results with respect to the crop yield obtained and the economic well-being of farmers is presented in comparison with the reference model and with what was observed in the household survey. A conclusion of the performance of, especially, the behavioural model is included in Section 5.5.

5.2. Methodology - Reference Model

In this section the reference model will be described according to the six state variables that are also taken into account by Pande and Savenije (2016). The first two subsections describe the farming practices that are assumed to be taken up by the farmers in the reference model, and the model input parameters. Subsection 5.2.3 describes the state variables, which are water storage, capital, livestock, grazing area, soil fertility and labour availability. All but labour availability are influenced by external factors, such as climatic variability, and socio-hydrological flux variables, such as crop production, income from crop and livestock sales and expenditure due to crop and livestock costs, and therefore co-evolve over time. Hence, the labour availability is, other than is assumed by Pande and Savenije (2016), assumed to be at steady state throughout the simulation period. This assumption is based on two observations in this research's individual household survey. First of all, it was observed that barely any farmer hires employees (see Subsection 4.4.1), hence the available labour solely comes from household members. Second, it is observed that during a bad year farmers barely switch to off-farm non-agricultural activities instead of growing crops and rearing livestock. From this it is concluded that labour availability of farmers in the Gumera sub-basin is not influenced by external factors, such as climatic variability. The simulation period for which this model is ran is from 2000-2018.

5.2.1. Farming practices

In the reference model, a distinction is made between two groups of farmers. The first group consists of what we call rice-growing farmers. These are farmers living in the western part of the Gumera sub-basin who cultivate rice. All other farmers belong to the second group of farmers and are referred to as non-rice growing farmers. The reason for this split are the substantial differences observed between these two groups during both the FGDs (see Section 4.3) and the individual household survey (see Section 4.4). Each group of farmers were observed to take up different farming practices, face different climatic challenges and experienced a different level of food insecurity. For a large part, these differences are induced by the location rice growing farmers are in, as they live close to the wetlands of Lake Tana, making them able to grow rice. Hence, for the reference model, it is assumed the farming practices taken up by farmers cultivating rice deviate at some points from all other farmers in the Gumera sub-basin. Furthermore, since it has not been able to conduct a FGD in the eastern part of the Gumera sub-basin, the farming practices of non-rice growing farmers are based on what is observed during the FGD conducted in Shime, as was assumed that farmers in Shime best represent farmers in the rest of the Gumera sub-basin (see Subsection 4.3.4).

In the reference model, all farmers follow the exact same farming practices year after year throughout the length of the simulation period. The farming practices farmers conduct are based on observations during the FGDs (see Section 4.3), the individual household survey (see Subsection 4.4.2), and a study from ADSWE (2015a) conducted in the Lake Tana basin (see Section 3.3). Hereby, the farming practices of the two groups of farmers are different in terms of the crops grown and the cropping sequence. An overview of the farming practices, comprising the farming system, cropping pattern followed, and planting and harvesting dates, is provided in Table 5.1. Behavioural aspects regarding adaptation to climate variability are not yet incorporated in the reference model. Furthermore, note that other than the framework of Pande and Savenije (2016), the reference model incorporates multiple crops. As is explained in Subsection 4.4.9, irrigation is not taken into account in this research, and is therefore left out of the model.

Table 5.1 presents the farming practices per group of farmers. For the reference model, it is assumed that all farmers in the Gumera sub-basin follow a crop-livestock rainfed farming system, in which they use rotational cropping. This means they grow one crop a year, whereby non-rice growing farmers change the crop type every year in order to enhance soil fertility. The hereby followed cropping sequence is maize - teff - barley. Farmers growing rice do not switch crop type every year, but grow rice three years in a row, after which they grow teff. Hence, these farmers do not grow barley, and maize. The planting and harvesting dates are set for each crop based on observations during the FGDs and in agreement with W. B. Abebe (personal communication, October 20, 2020), and do not differ per year.

5.2.2. Model inputs

In order to simulate the system dynamics of farmers in the Gumera sub-basin, area specific data is very valuable for the accuracy of outcomes of the socio-hydrological model. Therefore, a large part of the individual household survey constitutes of parameters that yield as input for the model. The majority of these parameters are of socio-economic nature such as family size, crop area, and initial capital, which can differ per farmer and can directly be used as input for the model. For other parameters assumptions are required before they

	Non-rice growing farmers	**Rice growing farmers**
Farming system	Crop-livestock rainfed farming	Crop-livestock rainfed farming
Crops grown	Barley, Maize, Teff	Rice, Teff
Cropping pattern	Rotational cropping	Rotational cropping
Repeating cropping order	Maize, Teff, Barley	Rice, Rice, Rice, Teff
Planting date	Barley = May 1	Rice = June 1
	Maize = May 1	Teff = June 15
	Teff = June 15	
Harvesting date	Barley = Aug 31	Rice = Nov 1
	Maize = Oct 1	Teff = Oct 15
	Teff = Oct 15	

Table 5.1: The standard farming practices that are assumed to be taken up by farmers in the Gumera sub-basin in the reference model, distinguished between the two groups of farmers. The assumptions are based on the FGDs, the individual household survey, the study of ADSWE (2015a) conducted in the Lake Tana basin, and discussions with W. B. Abebe (personal communication, October 20, 2020).

can be used. Examples of such parameters are the minimum and maximum crop yield a farmer can obtain, which are assumed to be same for each farmer. The minimum yield is assumed to be 0, as it is associated with the crop having failed due to pests, diseases, and/or extreme flooding or a drought, leaving no yield left for farmers to consume, sell, or store. The maximum (or potential) yield, is set equal to the maximum of the maximum yield obtained amongst the respondents of this research's household survey. It is assumed to be the maximum or potential yield a farmer can obtain under the most ideal circumstances within the Gumera sub-basin. The maximum value observed for each type of crop is verified with literature in order to make sure these are valid values to use (see Table 4.6 in Subsection 4.4.3). All data obtained from this research's individual household survey and used as input for the model is described in the following subsections.

In addition, remote sensing data for geographical and hydrological data specifically for the Gumera sub-basin is obtained and used as input for the socio-hydrological model. These are important characteristics for determining the water balance that indirectly affects the system dynamics of a farmer. Datasets of daily precipitation and potential evapotranspiration for the length of the simulation period, and geographical data, such as soil depth and type, are used to determine the soil moisture content over time. In addition, crop specific input parameters are obtained in order to be able to calculate crop yield. The source and type of each of these data types will be discussed below separately.

Precipitation

Beck et al. (2017) evaluated the performance of 22 satellite rainfall products globally by comparing satellite estimate against gauge measurement. Results from this study showed that CHIRPS Version 2 outperformed other satellite rainfall products in the case of Ethiopia. In addition, Alemu and Wimberly (2020) concluded that Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) rainfall data showed the least bias and error, and the best agreement with station rainfall data. Therefore, daily rainfall from the CHIRPS product is used in this research as input for the socio-hydrological model. The CHIRPS data archive is a quasi-global (50S-50N) time series that expands from 1981 to near-real time precipitation with a gridded resolution of 0.05 degree and units of mm/day (Funk et al., 2014). Figure 5.2 shows the spatial distribution of average annual rainfall in the Gumera sub-basin for the period from 2000 to 2018. The average annual rainfall in the Gumera sub-basin ranges from 1308 and 1588 mm, and averages to 1420 mm.

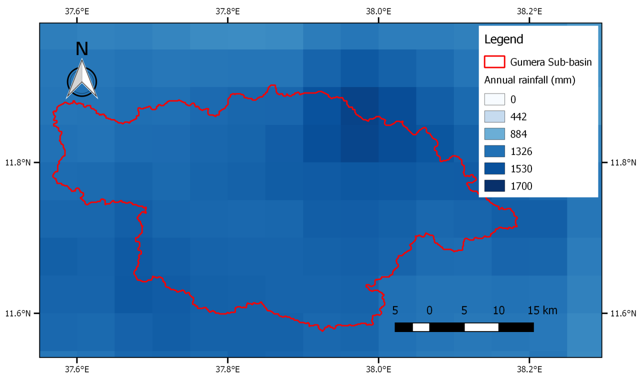


Figure 5.2: Average annual precipitation (in mm) in the Gumera sub-basin with 500m spatial resolution obtained from CHIRPS precipitation dataset for the period 2000-2018 (Funk et al., 2014). Made by author.

Potential evapotranspiration

The MOD16A2 Version 6 Evapotranspiration/Latent Heat Flux product is used in this research as potential evapotranspiration input for the socio-hydrological model (Running et al., 2017). This is the only global readily-available open-source evapotranspiration product providing real-time evapotranspiration estimates. It is an 8-day composite dataset with a 500 meter pixel resolution, and is based on the Penman-Monteith equation. For the socio-hydrological model the Potential Evapotranspiration (PET) layer, with unit 0.1 $kg/m^2/8day$ (which is equal to mm/8day), is used for the period from 2001 to 2018. Hereby, each pixel value represents the cumulative PET over the eight days within the composite period. Before this dataset can be used as input for the socio-hydrological model it needs some pre-processing. First, the pixel values are transformed from 8day to daily values, in which leap years are taken into account. In addition, the Moderate Resolution Imaging Spectroradiometer (MODIS) product does not calculate PET for non-vegetated pixels, such as water bodies, and urban or barren areas. Instead, these pixels are given a value ranging from 32761 to 32767. To deal with these large values, the monthly average of the Gumera sub-basin is assigned to non-vegetated pixels. The average annual potential evapotranspiration for the Gumera sub-basin is 2423 mm.

Soil characteristics

Soil depth is an important input parameter for the socio-hydrological model, as it largely determines the soil moisture storage capacity and therefore the water availability for the vegetation. The soil depth dataset of the African Soil Information Service (AfSIS) is used in this research (Hengl et al., 2015). Enabling new types of soil analysis and statistical methods AfSIS develops continent-wide digital soil maps for sub-Saharan Africa at 250 meter spatial resolution. By developing these maps both remote sensing imagery and ground observations are used. The soil depth in the Gumera sub-basin ranges from 57 to 175 cm, and is on average 153 cm.

In addition, the AfSIS dataset on soil type fractions is used in this research (Hengl et al., 2015). This dataset provides the fractions of clay, sand, silt and coarse fragments at six standard soil depths at a 250 meter spatial resolution. This dataset is used in order to determine the soil type of the study area, which is done by following the method of the soil texture triangle (USDA, 2017). This is a widely-used tool developed by the United States Department of Agriculture (USDA), with which soil types can be identified according to the fractions of sand, silt, and clay particles. From the AfSIS dataset on soil type fractions the average fractions of clay, sand, and silt over both the area and depth are found to be 54%, 21% and 25% respectively for the Gumera sub-basin. Utilising the soil texture triangle the soil type in the Gumera sub-basin can be classified as clay. This corresponds with what is found in literature (Mamo and Jain, 2013, Van Landtschoote, 2017).

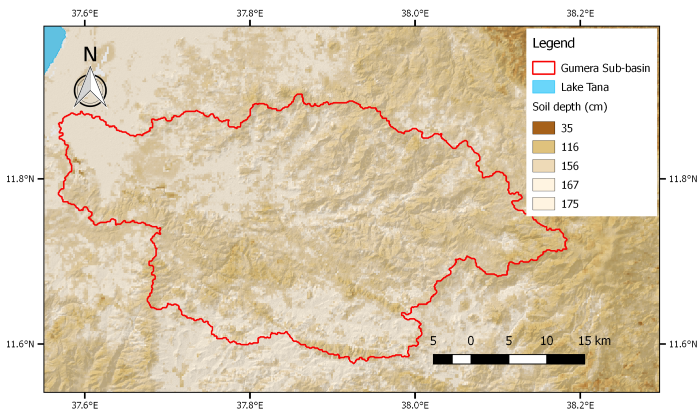


Figure 5.3: The soil depth (in cm) in the Gumera sub-basin with 250m spatial resolution obtained from AfSIS (Hengl et al., 2015). Made by author.

Crop specific parameters

For each crop the yield is calculated following the framework of AquaCrop (Raes et al., 2012). This approach requires a set of crop specific parameters in order to calculate the crop yield. The majority of crop specific parameters are obtained from the FAO, unless more area specific data is available from studies conducted in the Amhara region. For all crops but teff (i.e. barley, maize, potato, and rice) basal crop coefficients (K_{cb}) and length of growth stages (i.e. t_ini, t_dev, t_mid, t_end) are obtained from Allen et al. (1998). Since no data is available on K_{cb} values for teff, it is approximated from crop coefficient (K_c) values by lowering the K_c values in proportion to what is seen for comparable crops such as barley and wheat (Araya et al., 2011, Yihun, 2015). In the case of potato, area specific values are obtained from studies conducted by Demelash (2013), Steduto et al. (2012). The total crop cycle length (t_grow) and the number of days after which 90% of the crops has emerged (t_CCo) are obtained via multiple studies conducted in Ethiopia and the FGDs. For maize, the duration of senescence (in days) is obtained from Gebreselassie et al. (2015). For all other crops, the duration of senescence is approximated to be 10 days shorter than the final growth stage (i.e. t_end). Other crop parameters, required to calculate crop yield, such as crop water productivity (CWP), the canopy growth coefficient (CGC), the canopy decline coefficient (CDC), maximum canopy cover (CCx), harvest index (HI_o), minimum and maximum effective rooting depth (Z_n, and Z_max), root zone shape factor (n), soil water stresses (P_lower and P_upper), and base temperature (T_base), are obtained from FAO Aquacrop manuals (Raes et al., 2012, Steduto et al., 2012). However, since the reference model does not yet accept growing degree days as input, the CGC and CDC values of the FAO Aquacrop manual cannot be used. Therefore, the generic values of c3 and c4 crops, as indicated by Steduto et al. (2012), are assigned to each crop according (accordingly) to whether it is a c3 or c4 crop. In general, c4 crops have higher water use efficiency, or in other words crop water productivity (CWP). In case of this research, the only c4 crop taken into account is maize. An overview of all crop specific parameters is presented in Table 5.2.

	Units	**Barley**	**Maize**	**Potato**	**Rice**	**Teff**
#plants	*plants/ha*	2250000 (1)	31250 (3)	60000 (2)	900000 (1)	19000000 (4)
CC_o	*%*	3.38 (1)	0.097 (3)	1.20 (1)	4.95 (1)	2.85 (4)
CCx	*%*	75 (1)	90 (3)	95 (1)	90 (1)	80 (4)
CGC	*%*	12.4 (2)	14.6 (3)	10.5 (2)	10.5 (2)	9.9 (4)
CDC	*%*	7.7 (2)	11.4 (3)	2.0 (2)	5.0 (2)	16.2 (4)
CWP	*gram/m2*	15 (1)	32 (3)	20 (6)	19 (1)	20 (4)
HI_o	*%*	47.5 (2)	50 (2)	85 (2)	37.5 (2)	25 (4)
f_hi	-	1	1	1	1	1
Z_max	*cm*	1250 (7)	1800 (3)	600 (2)	750 (2)	450 (2)
Z_n	*cm*	300 (1)	300 (1)	300 (1)	300 (1)	300 (1)
n	-	1.5 (1)	1.3 (1)	1.5 (1)	2.5 (1)	1.5 (1)
P_upper	-	0.65 (1)	0.72 (3)	0.6 (1)	0.4 (1)	0.79 (4)
P_lower	-	0.2 (1)	0.14 (3)	0.2 (1)	0 (1)	0.5 (4)
T_base	°C	2 (1)	8 (1)	2 (1)	8 (1)	10 (1)
Kcb_ini	-	0.15 (7)	0.15 (7)	0.15 (7)	1 (7)	0.15 (5)
Kcb_mid	-	1.1 (7)	1.15 (7)	1.1 (7)	1.15 (7)	1 (5)
Kcb_end	-	0.15 (7)	0.15 (7)	0.65 (7)	0.58 (7)	0.7 (5)
t_ini	*days*	15 (7)	30 (7)	15 (7)	30 (7)	15 (5)
t_dev	*days*	30 (7)	40 (7)	30 (7)	30 (7)	25 (5)
t_mid	*days*	65 (7)	50 (7)	35 (7)	60 (7)	50 (5)
t_end	*days*	40 (7)	30 (7)	30 (7)	30 (7)	30 (5)
t_CCo	*days*	15 (7)	7 (3)	15 (6)	30	6 (4)
t_Ss	*days*	30	37 (3)	20	20	20
t_grow	*days*	150 (7)	150 (3)	110 (6)	150 (7)	120 (4)
t_x	*days*	105	93	75 (6)	90	97
Max yield	*qt/ha*	48	80	350	48	40

Table 5.2: Crop specific parameters used as input for the socio-hydrological model. Sources: [1] Raes et al. (2012), [2] Steduto et al. (2012), [3] Gebreselassie et al. (2015), [4] Araya et al. (2011), [5] Yihun (2015), [6] Haverkort et al. (2012), [7] Allen et al. (1998). Maximum yields are obtained from the household survey.

5.2.3. The State Variables

In this subsection the way each state variable is calculated in the reference model will be discussed. It will be explained by which parameters it is influenced, and how the state variables are interacting with each other. All variables are based on the outcomes of the individual household survey conducted in this research (see Section 4.4), and are verified upon discussions with a local agricultural ministry expert (W.B. Abebe, personal communication, June-December, 2020).

Water storage

The hydrological part of the socio-hydrological reference model is in the form of a single layer bucket model. All water in excess of the water storage capacity (S_{max}) is assumed to be removed from the smallholder system as excess runoff. Furthermore, percolation from the root zone storage is neglected, which is according to Kuil et al. (2019) a valid assumption as areas with sloping terrains and clayey soils are not conducive to deep percolation. Interception is neglected as well, causing all precipitation to infiltrate into the soil.

In this research a brief overview is provided of the main mechanisms of the methodology with which the attainable crop biomass and harvestable yield are calculated. For a full overview of the methodology used I would like to refer to the master thesis of D. Djohan (Djohan, 2021). The methodology is based on the Aquacrop framework, whereby is accounted for variation in soil moisture in the root zone (Raes et al., 2012). Due to the lack of local daily minimum and maximum temperature data, stresses due to temperature are neglected. The stresses that affect the growth of the canopy cover and the biomass respectively are therefore solely represented by water shortage in the root zone. The total available water (TAW) for a crop changes over time and is influenced by the root zone development throughout the growing period. The TAW is defined as the total amount of water that can be stored in the soil and is available to plants. In other words, it is the difference between the amount of water that is in the soil at field capacity (FC), and the amount of water that is in the soil at wilting point (WP). According to the FAO, typical values for FC and WP for clayey soils are 0.36, and 0.22 respectively (Allen et al., 1998). The soil moisture is calculated on a daily basis using Eq. 5.1. The other state variables are calculated at a yearly basis.

$$SM_{t+1} = max(0, min(SM_t + P - E_m, SM_{fc,max})) \tag{5.1}$$

Here, SM_t is the soil moisture at time t in mm, P is the precipitation in mm/day, E_m is the evaporation met in mm/day, and $SM_{fc,max}$ is the maximum soil moisture defined as field capacity in mm. In addition to the soil moisture calculation, each time step the daily biomass increase (m) per unit area per mm of water transpired (g/m^2/day) is calculated using Eq. 5.2.

$$m_t = K_T * CWP * \frac{Ta_t}{ET_{c,t}} \tag{5.2}$$

Here, K_T is the temperature stress coefficient [-], which is a value between 0 and 1 depending on the air temperature with respect to the upper and lower air temperature threshold. Due to the temperature stress being neglected in this research, K_T is always 1, and therefore does not affect the biomass production. Furthermore, CWP is the normalized crop water productivity in g/m^2, T_a is the actual transpiration in mm, and ET_c is the reference evapotranspiration in mm. The total biomass B (g/m^2/year) is the sum of m over the entire crop growth period (i.e. from planting until harvesting).

Once the water balance is solved, and the total biomass is calculated, the crop yield Y [kg/ha/year] is obtained from the total biomass at harvest by multiplying the total biomass B with the harvest index HI [-] (see Eq. 5.3). Following this procedure gives the crop yield obtained at the end of the cropping season at a yearly basis.

$$Y = (HI_o * B)/10 \tag{5.3}$$

Capital

The farmer's capital C(T) in Birr is given by a differential equation, which is a function of yearly income (m(T) [Birr/year]), expenditure (z(T) [Birr/year]) and loans of the farmer from off-farm non-agricultural activities (w(T) [Birr/year]), and a depreciation rate δ (see Eq. 5.4).

$$\frac{dC}{dT}(T) = -\delta \frac{C(T)}{\Delta T} + m(T) - z(T) + w(T) \tag{5.4}$$

The income generated by a farmer consist of incomes from livestock, crop and labour sales, as well as sales of non-agricultural products. Labour sales are hereby defined as the income earned by working on off-farm agricultural and non-agricultural activities. However, based on the results of the individual household survey conducted in this research, from which less then 1% of the respondents mentioned to work on off-farm agricultural activities (see Subsection 4.4.1), it is assumed none of the farmers is working on off-farm agricultural activities. Off-farm non-agricultural activities are apparent though, with the average wage earned by a farmer being 46 Birr/day. Livestock sales exist of income generated by selling livestock and annual incomes from selling livestock products (e.g. milk). The annual income from selling livestock products, which is a constant throughout the simulation period, is based on the average income from cattle mentioned by farmers in the individual household survey, since cattle are the dominant livestock species in the Gumera sub-basin, and is verified with W. B. Abebe (personal communication, December 17, 2020). The price of livestock is determined the same way and based on the minimum and maximum price of cattle, and is each year adjusted with the rate of inflation.

Crop sales consist purely out of the income generated from selling own grown crops. It is assumed a farmer only sells his or her crops if the crop production (after subtracting post harvest losses of 15% (ADSWE, 2015a)) is larger than the required crop consumption by the household. If this is the case, the farmer will sell all of the remaining crops produced. The required consumption per person per day is based on the required food basket set by the World Bank (2020). According to the World Bank the threshold for minimum required daily calorie intake to meet energy requirements is 2200 calories per person per day (World Bank, 2020).

The expenditures of a farmer consist of expenses on food bought for the household, labour costs, the interest on loan, taxes on crop and livestock sales, and other expenses, as well as the costs of purchased non-food items. The costs of non-food items exists of costs for crop production inputs, such as seeds, fertiliser and chemicals, and livestock costs, such as regular annual costs (e.g. veterinary costs and fodder) and costs of buying additional livestock. Note, additional livestock is only bought if capital is above zero. Expenses on investments and school fees are neglected in this research. Since it is assumed farmers not having employees, labour costs are 0. The expenditure on food for consumption depends on the farmer's crop production. As such, the farmer will only buy food in case his or her crop production is insufficient to provide each family member of 2200 kilocalories per day. In addition, the farmer's capital needs to be larger than 0.

Livestock

In this research, multiple livestock types are taken into account. As such, it differes from the framework of Pande and Savenije (2016), in which only cattle is taken into account. The livestock types accounted for are cattle, sheep, goats, donkeys, and mules, and are converted to Tropical Livestock Units (TLU). This is a common unit frequently used by the FAO. The TLU conversion factors used by the FAO (FAO, 2018a) are used in this research: cattle = 0.7, goat = 0.1, sheep = 0.1, donkey = 0.5, and mule = 0.7. Since cattle is the dominant livestock type in the Gumera sub-basin, it is used as the reference livestock type. This means that all variables and rates that are linked to livestock are based on cattle, and therefore converted with a factor 0.7 in order to account for the conversion of cattle to TLU.

Besides livestock providing nutritional sources, manure and power for ploughing, it can also function as a source of capital in times of crop failure. In Subsection 4.4.2 it was discovered that a large share of farmers (84%) sells livestock in times of food insecurity to be able to have enough liquidities to buy food. For simplicity, in the reference model it is assumed that all farmers will use this kind of coping strategy when capital falls below zero.

The amount of livestock owned by a farmer L(T) in TLU varies according to the net birth rate, purchases and selling of livestock, and the carrying capacity, which is influenced by the available grass biomass (G(T)) (see Eq. 5.6). The number of livestock owned by a farmer is hereby limited to the maximum number of livestock observed in the household survey, being 9.1 TLU. Ethiopian farmers often do not have their own grazing land but make use of communal grazing areas (Tahir et al., 2018). The grazing area of a farmer therefore is a summation of the share from communal grazing land and own grazing area. The share of communal grazing land assigned to a farmer is a function of livestock density and the amount of TLU owned (see Eq. 5.5).

$$A_g = A_{g,private} + \left(\frac{L - (A_{g,private} * L_d)}{L_d}\right) \tag{5.5}$$

Where A_g is total grass area of a farmer (ha), and is the sum of private and communal grass area. $A_{g,\text{ private}}$ is the grass area owned by a farmer (ha), and L is the number of livestock in TLU. The livestock density (L_d

[TLU/ha]) is assumed to be equal to 9.4 TLU/ha and is based on a study by Amsalu and Addisu (2014) conducted in the Gumera-Ribb watershed.

In this research, the carrying capacity, which is the maximum number of TLU that a given area of grass land can support on a sustainable basis, does not play a major role since Ethiopian households often keep livestock beyond the carrying capacity of the land (Amsalu and Addisu, 2014). Therefore, to prevent the carrying capacity from affecting the number of livestock owned by a farmer, it is assumed that the available grass biomass is not limited by water stress and assumed to be met the whole year through. Such, the carrying capacity barely functions as a limitation to livestock growth. The total number of livestock owned by a farmer (in TLU) is calculated by Eq. 5.6.

$$\frac{dL}{dT}(T)\Delta T = max(L(T) + (r_L * L(T) * (1 - \frac{L(T)}{K_L}) + I_b(T) + I_s(T))\Delta T, 0) - L(T) \quad (5.6)$$

Here, r_L is the biological rate of growth, which includes the birth and death rates, as well as the growth in livestock size due to weight gain. The variable K_L is the carrying capacity [-], I_b is the amount of livestock purchased, which is 0 if the farmer's capital is below or equal to 0. The amount of livestock sold is represented by I_s and is only larger than 0 if the farmer's capital is equal or below 0.

Grass biomass

The grass biomass is given by equation 5.7. It is assumed that grass growth is not constrained by water shortage and grows the whole year through. The grazing land drives the fodder availability, in which it is assumed that the farmer does not buy additional fodder from other sources. Hence, the grass biomass stock (G [kg]) of a farmer is a function of grass yield, grass area, and consumption of grass by livestock (see Eq. 5.7).

$$\frac{dG}{dT}(T)\Delta T = min(G(T) + (A_g * Y_g - c_L(T))\Delta T, A_g * Y_{g,max}\Delta T) - G(T) \quad (5.7)$$

Here, A_g is the grass area in ha, $Y_{g,max}$ is the maximum grass yield possible in kg/ha/year, Y_g is the actual grass yield in kg/ha/year in year T, which is calculated under the assumption that the water demand is always met (see Eq. 5.9). Furthermore, $c_L(T)$ is the consumed grass by livestock and is given by Eq. 5.8).

$$c_L(T) = min(G(T), L(T) * n_{L,f} * (1 - n_{L,r})) \quad (5.8)$$

Here, L(T) is the amount of livestock in TLU owned by a farmer in year T. In addition, $n_{L,f}$ is the feed requirement rate in kg/TLU/year and $n_{L,r}$ is the feed residue rate [-].

The actual grass yield (Y_g) is a function of the yield water response rate (Ky_g [-]) and the water demand of grass ($WD_g(T)$ [mm]), which is a function of the K_c of grass and the potential evapotranspiration.

$$Y_g(T) = max(0, min(1, 1 - Ky_g * (1 - WD_g(T)))) * Y_{g,max} \quad (5.9)$$

Soil fertility

The soil fertility is a function of the amount of nitrogen in the soil and affects the crop yield obtained (see Eq. 5.11). The nitrogen amount is influenced by the use of commercial fertiliser and manure applied by the farmer, nitrogen fixation, and the removal of nitrogen due to the nitrogen uptake by crops and grass. Subsequently, it is converted to a fertiliser factor , which has a value between 0 and 1, and directly affects the crop yield obtained. The fertiliser factor is calculated by Eq. 5.10. The way in which it influences the crop yield is given by equation 5.12.

$$f_{fert} = \frac{Y_{min}}{Y_{max}} + min(\frac{f_{app} + manure_{app}}{A_c * F_{max}}, 1) * (1 - \frac{Y_{min}}{Y_{max}}) \quad (5.10)$$

Here, f_{fert} is the fertiliser factor [-]. Y_{min} is the minimum yield in kg/ha and for each crop equal to 0, whereas Y_{max} is the maximum yield in kg/ha. An overview of maximum crop values is presented in Table 5.2. Furthermore, f_{app} and $manure_{app}$ are the amount of fertiliser and manure applied by the farmer in kg nitrogen respectively, A_c is the crop area in ha, and F_{max} is the maximum nitrogen application rate in kg nitrogen per ha. Since Y_{min} is equal to 0, the fertiliser factor is solely influenced by the amount of fertiliser and manure applied per unit area relative to the maximum nitrogen application rate. As such, it is negatively correlated with crop yield.

$$\frac{dF}{dT}(T) = max(f(T) - u(T) * A_c, 0) \tag{5.11}$$

Here, f(T) is the fertilisation in kg/year due to the sum of fertiliser and manure application by the farmer and nitrogen fixation through for example rain. In addition, u(T) is the nitrogen uptake by crops in kg/year. In this research, nitrogen loss due to soil erosion losses is not taken into account.

Labour availability

In this research, the amount of labour available to a farmer is constant over time. Hence, a farmer does not make a trade-off between on-farm and off-farm work, as is done in the framework of Pande and Savenije (2016). The labour availability is equal to the amount of family members that help on the farm plus the household head multiplied by the amount of days in a year the household head works on the farm. Hereby it is assumed that all other family members working on the farm, work the same amount of days on the farm as the household head. The maximum amount of days a person can work in a year has been set to 260 (i.e. all days in a year except weekend days).

In addition to the soil fertility, the labour availability also affects the crop yield obtained. The labour factor affecting crop yield is the ratio between labour availability and maximum labour for crop production. Just like the fertiliser factor, the labour factor has a value between 0 and 1, and negatively correlates with crop yield. The final crop yield obtained by a farmer is calculated by Eq. 5.12.

$$Y_{final} = f_{fert} * f_{labour} * Y \tag{5.12}$$

5.2.4. Adaptation strategies

Within the socio-hydrological modelling framework of Pande and Savenije (2016) two adaptation strategies are incorporated that change the dynamics of the smallholder farmer system once certain thresholds are exceeded. The two thresholds incorporated are related to the capital of a farmer and the marginal value of on- and off-farm labour.

Capital deficit

The first threshold is activated whenever the farmer's capital reaches below zero. In this case, it is assumed the farmer will save money by cutting down on expenses. However, prior to reducing expenses the farmer will try to get the capital deficit back to 0 by selling livestock. If this is not sufficient, (s)he will cut down on expenses in the following order: investments, school fees, interest payments on loans, tax on agricultural income, livestock costs, and crop costs. The farmer will stop this sequence once the capital deficit is brought back to zero. If the capital deficit cannot be brought back to 0 by these expenditure cuts the farmer is considered to be unsustainable.

Labour trade-off

The second adaptation strategy is based on the choice for the most profitable occupation. Every year the farmer makes a trade-off between on-farm crop production and off-farm non-agricultural activities. However, during the FGDs it was discovered that this trade-off is not always as straightforward for farmers in the Gumera sub-basin (see Section 4.3) unlike for farmers in Maharahstra, India Pande and Savenije (2016). In case crops fail during a bad year, farmers in the Gumera sub-basin mentioned there often not being off-farm work available, in case this trade-off does not exist. In addition, only 11% of the respondents of the individual household survey mentioned to adapt to climate variability by shifting towards off-farm non-agricultural activities (see Subsection 4.4.9, Figure 4.15), from which 83% were all located in the same Kebele (i.e. Licha Arida). Hence, it is assumed that a farmer in the Gumera sub-basin does not consider this trade-off, and thus does not choose for off-farm activities in favour of crop production.

5.2.5. Assumptions

In building the reference model, multiple assumptions are made whenever data is not available. These are backed by the results of the FDGs or the individual household survey, or expert consultations. Table 5.3 shows the most important assumptions made in the reference model. All of these assumptions are also incorporated in the behavioural model described in Section 5.3.

#	Assumptions
1	Seepage at the bottom of the reservoir is neglected
2	Interception is neglected, all precipitation infiltrates into the soil
3	Moisture in excess of maximum storage is removed from the smallholder system as runoff
4	Soil degradation is neglected
5	Grass growth is not constrained by water shortage and grows the whole year through
6	Temperature stress on crop growth is neglected
7	Farmers do not have employees
8	Farmers do not work on off-farm agricultural activities
9	Each family member that works on the farm works the same amount of hours per week on the farm as the household head
10	Farmers do not use irrigation
11	Minimum yield is equal to zero
12	Maximum yield is equal to the maximum yield observed in the household survey
13	Farmers grow only one crop a year

Table 5.3: An overview of the main assumptions made in the socio-hydrological model.

5.3. Methodology - Behavioural model

In this section the so called "behavioural model" will be discussed. This model is an extension of the reference model that also models the climate adaptive behaviour of smallholder farmers in the Gumera sub-basin. Hence, although the main farming practices (see Table 5.1) remain the same, in the behavioural model farmers have the opportunity to take up adaptation strategies in order to cope with climate variability. Hence, each individual farmer makes his or her own choices based on his or her adaptive capacity, which is determined by enabling a logit model. Both, the farmer adaptive capacity and the related decisions are influenced by factors that were found to significantly affect the climate adaptive behaviour of smallholder farmers in the Gumera sub-basin in Section 4.4. The agricultural decisions farmers make in order to cope with climate variability are solely linked to the agricultural practices reconsidered by a farmer every year again (i.e. what crop type to grow and when to plant and harvest). Hence, only one time in the year (i.e. prior to the start of the rainy season) the farmer decides whether to adapt to climate variability and in what manner. In case the farmer does not have the capacity to adapt, (s)he will stick with the main farming practices presented in Table 5.1.

By incorporating the climate adaptive behaviour of a farmer in the behavioural model, it allows us to analyse the influence of climate adaptive behaviour on the agricultural performance and economic well-being of a farmer compared to non-adaptive patterns simulated by the reference model. In the following subsections, the behavioural aspects of a farmer in the Gumera sub-basin in terms of adaptation strategies incorporated in the behavioural model will be explained step by step following the flowchart indicated in Figure 5.4. Subsection 5.3.1 describes the adjustments to the farming practices with respect to the reference model. The way in which the climate adaptive capacity of a farmer is determined by the model is explained in Subsection 5.3.2. In Subsection 5.3.3 the adaptation strategies taken up by farmers, and how this is incorporated in the behavioural model is explained. At last, Subsection 5.3.4 presents a methodology used to evaluate the long-term effect of climate adaptation on the economic well-being of farmers in the behavioural model.

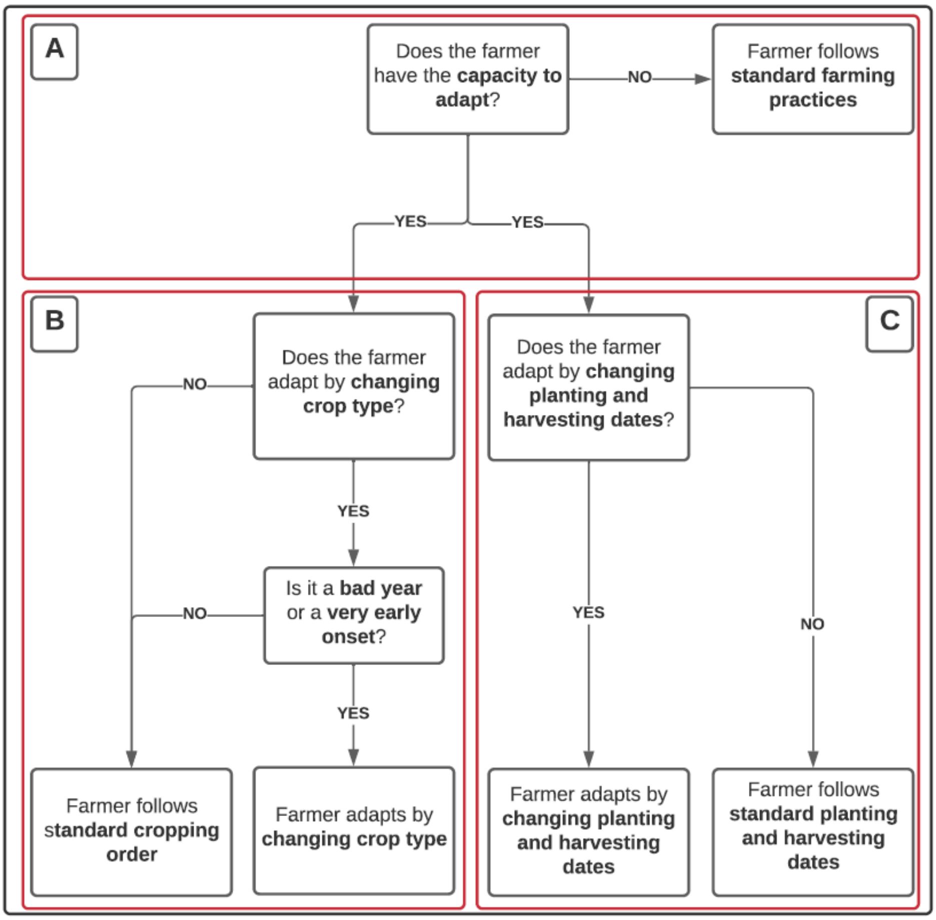


Figure 5.4: A flow chart describing the climate adaptive behavioural aspects of non-rice growing farmers in the Gumera sub-basin incorporated in the behavioural model. In part A, it is determined whether or not a farmer has the capacity to adapt. Part B and C describe the behaviour of adapting farmers with respect to changing the crop type and the planting and harvesting dates respectively.

5.3.1. Adjustments to the Farming Practices

In Subsection 5.2.1 the standard farming practices taken up by farmers in the Gumera sub-basin are explained. For a large part these farming practices remain the same for the behavioural model compared to the reference model. Also the distinction between rice growing farmers and non-rice growing is the same in both models. However, there are two adjustments to these standard farming practices in the behavioural model.

First of all, farmers that have the capacity to adapt to climate variability have the choice to do so by taking up two adaptation strategies. They can either adapt by changing the crop type, and/or by changing the planting and harvesting dates. Whenever a farmer does not have the capacity to adapt, (s)he will follow the standard farming practices as indicated in Subsection 5.2.1. In this case, there is no difference between a farmer in the reference model and a non-adapting farmer in the behavioural model.

Secondly, besides the crops incorporated in the reference model (i.e. barley, maize, rice, and teff), one additional crop is taken into account in the behavioural model. This is potato, which, in Subsection 4.4.9, was assumed to be the major adaptive crop. Teff is assumed to be the second adaptive crop, based on observations during the FGDs (see Section 4.3) and it being a short cycle crop. Hence, in case a non-rice growing farmer adapts to climate variability two years in a row by changing the crop type, teff will be used as the adaptive crop in the second year. As such, the rotational cropping pattern, in which a different crop is grown each year, is still followed. Since none of the rice growing farmers grows potato, the only adaptive crop for this group of farmers is teff. This assumption is based on what was mentioned during the FGDs conducted in Jigena and Geregera.

In Subsections 5.3.2 and 5.3.3 the way in which these climate adaptive behavioural aspects are incorporated in the behavioural model are further explained. Hereby, the focus is mainly on non-rice growing farmers, since all rice growing farmers were, in Subsection 4.4.8, assumed to have the capacity to adapt. Hence, the implementation of their climate adaptive behaviour in the behavioural model is rather simple. Whenever this group of farmers experiences a bad year they grow teff and shift the planting and harvesting date by 45 days. This assumption is based on the FGD conducted in Jigena (see Subsection 4.3). The climate adaptive behaviour of non-rice growing farmers is presented by the flowchart shown in Figure 5.4. This shows a simplified overview of all climate behavioural aspects of non-rice growing farmers incorporated in the behavioural model, and is followed step by step in the following subsections.

5.3.2. Determining the Climate Adaptive Capacity

The first step in the behavioural model regarding the climate adaptive behavioural aspects of non-rice growing farmers is indicated by part A of the flowchart presented in Figure 5.4. Here it is determined whether or not a farmer has the capacity to adapt. In Subsection 4.4.8 it was assumed farmers having access to a weather forecast have the capacity to adapt to climate variability. For all other farmers, three variables turned out to significantly influence the climate adaptive capacity. It was discovered that farmers having a larger farm size, more labour available, and who base their agricultural decisions upon their own observations of the onset of rains, were more likely to adapt to climate variability. Hence, in the behavioural model, the climate adaptive capacity of non-rice growing farmers without access to a weather forecast depend on these three factors, and is calculated with a logistic model function given by equation 5.13.

	Variable	**Coefficient (B)**
	β_0	-1.355
$\mathbf{X_1}$	Farm size [ha]	0.550
$\mathbf{X_2}$	Use of onset of rains	2.121
$\mathbf{X_3}$	Household labour [days/year]	0.034

Table 5.4: Variables and coefficients included in the logistic model to determine the probability of a farmer to adapt to climate variability

$$P = \frac{1}{1 + e^{-(\beta_0 + \sum_{n=1}^{n} \beta_i * X_i)}} \tag{5.13}$$

Here, P is the probability of a farmer to adapt, n is the number of variables included in the model, and X_i are the predictors for the climate adaptive capacity of a farmer: farm size, labour available, and usage of own observations of onset of rains. The latter in this case is either 0 if a farmer does not make use of the onset of rains, or 1 if (s)he does use the onset of rains for agricultural decisions. The variables farm size and labour available are continuous variables, and constant for each farmer throughout the simulation period. The values for β_i are the coefficients related to each predictor and are obtained from the binary logistic regression analysis conducted in Subsection 4.4.8.
The exact values are presented in Table 5.4. The value of β represents the increase or decrease in the probability that a farmer adapts by a one unit increase of the predictor. In this case, all of the β coefficients are positive, except for β_0, meaning an increase in any of the three predictors will have a positive effect on the probability of a farmer to adapt. It is assumed that whenever P is larger than 0.5 a farmer has the capacity to adapt to climate variability. A probability smaller than or equal to 0.5, indicates the farmer does not have the capacity to adapt and will follow the standard farming practices. Since all three predictors do not change over time and are therefore constant throughout the entire simulation period, a non-adapting farmer cannot become an adapting farmer over time. The calculated probability to adaptation for each farmer is shown in Figure 5.5 by the logistic regression curve.

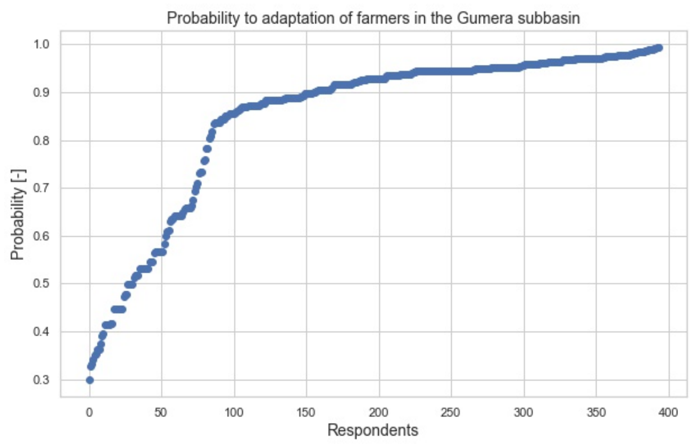


Figure 5.5: A logistic regression curve showing the probability of adaptation to climate variability of each farmer in the Gumera sub-basin that took part of the individual household survey. Made by author.

5.3.3. Adaptation Strategies

The second step in the behavioural model is to determine what adaptation strategy a farmer takes up once (s)he has the capacity to adapt to climate variability. This is shown by part B and C of the flowchart presented in Figure 5.4. In Subsection 4.4.9 it was discovered there are two major adaptation strategies that farmers in the Gumera sub-basin take up to cope with climate variability:

1. Adaptation by changing the crop type
2. Adaptation by changing the planting and harvesting dates

Hereby, a farmer can adapt by just one or both adaptation strategies. For each adaptation strategy the probability of a farmer to adapt by taking up this strategy is determined via the corresponding logistic model described in Subsection 4.4.9. Hereby, the choice of a farmer for a certain adaptation strategy is independent from other farmers. The behavioural aspects that correspond to each of the adaptation strategies is explained in the following two subsections.

Changing the crop type

In the behavioural model, the first adaptation strategy with which a farmer can adapt to climate variability is changing the crop type. Part B of the flowchart shows in which case a farmer that has the capacity to adapt to climate variability will actually adapt by changing the crop type.

The first step is to determine the likelihood of a farmer to adapt by changing the crop type. In Subsection 4.4.9, it was discovered that there are five variables that seem to significantly influence the probability of a farmer to adapt to climate variability by changing the crop type: the altitude, the farmer's level of education, the farm size, the number of livestock owned, and the farmer's capital (see Table 5.5). The first three variables are constants, whereas the number of livestock and capital will change over time as described in Subsection 5.2.3. Therefore, the probability of a farmer to adapt by changing the crop type can change throughout the simulation period. Hence, the adaptive behaviour of a farmer is dynamic. Looking at the negative coefficient for capital, shown in Table 5.5, this, for example, means that a farmer that is becoming more rich (in terms of capital) over time, will become less likely to adapt by changing the crop type, and vice versa. The probability of a farmer to change the crop type is determined by equation 5.13, in which the threshold for adaptation is 0.5. The values for β for each variable are given in Table 5.5 and correspond to the values of B obtained in the binary logistic regression conducted in 4.4.9. Hence, if the probability of a farmer is lower than or equal to 0.5, the farmer will not adapt by changing the crop type and will grow the next crop in the repeating cropping order given in Table 5.1. On the other hand, if P is higher than 0.5, the farmer will change the crop type to adapt to climate variability. However, (s)he will only do so whenever a bad year occurs, or when the onset of rains is exceptionally early. Hence, the second step to determine if a farmer adapts by changing the crop type is to determine whether or not an exceptional year is occurring.

	Variable	**Coefficient (B)**
	β_0	10.153
$\mathbf{X_1}$	Altitude [m]	-0.005
$\mathbf{X_2}$	Education	0.383
$\mathbf{X_3}$	Farm size [ha]	0.543
$\mathbf{X_4}$	Livestock [TLU]	0.231
$\mathbf{X_5}$	Capital [Birr]	-0.000044

Table 5.5: Variables and coefficients included in the logistic model to determine the probability of a farmer to adapt by changing the crop type. The values are obtained from the binary logistic regression conducted in Subsection 4.4.9.

During the FGDs farmers in Geregera and Shime defined a bad year as a drought year when the rains also start late. This definition is used in this research and translated in the model by stating that a bad year occurs whenever the onset of rains occurs later than one standard deviation of the mean. Hence, to be able to classify a year as a bad year, we first need to determine the onset of rains. Hereby, the methodology used in studies of Mellander et al. (2013), Segele and Lamb (2005) is followed, which both showed good performance for determining the onset and cessation of kiremt rains in Ethiopia, and the Upper Blue Nile basin, respectively. The first step is to characterise the region as 'wet' or 'dry', since this influences the definition of onset and cessation. A wet region is defined as a region receiving at least 30 rainy days (i.e. a day with > 0.1 mm of rainfall) during the months July and August. From CHIRPS rainfall data it is determined that the Gumera sub-basin receives 30 rainy days or more in 97% of the time, hence the definition of onset and cessation for a wet region is followed.

Subsequently, the onset and cessation are determined based on a set of criteria. However, by trial and error it is found that the criteria provided by the FAO (2019) give better estimates for both the onset and cessation of rains. Hence, in this research, the following criteria for determining the onset of rains are followed. The onset starts at the first day of a 7-day period, in which at least 25 mm of precipitation occurs and 4 rainy days are included. Furthermore, it should not be followed by and 8 day (or more) dry spell in the next 30 days. A dry spell is hereby defined as a contiguous series of non-rainy days. In order to prevent these criteria to give a very early or late onset, the onset is restricted to occur two months before or after the climatological onset. For the Gumera sub-basin the climatological onset is estimated on findings of Segele and Lamb (2005) and set on June 10 (see Figure 5.6).

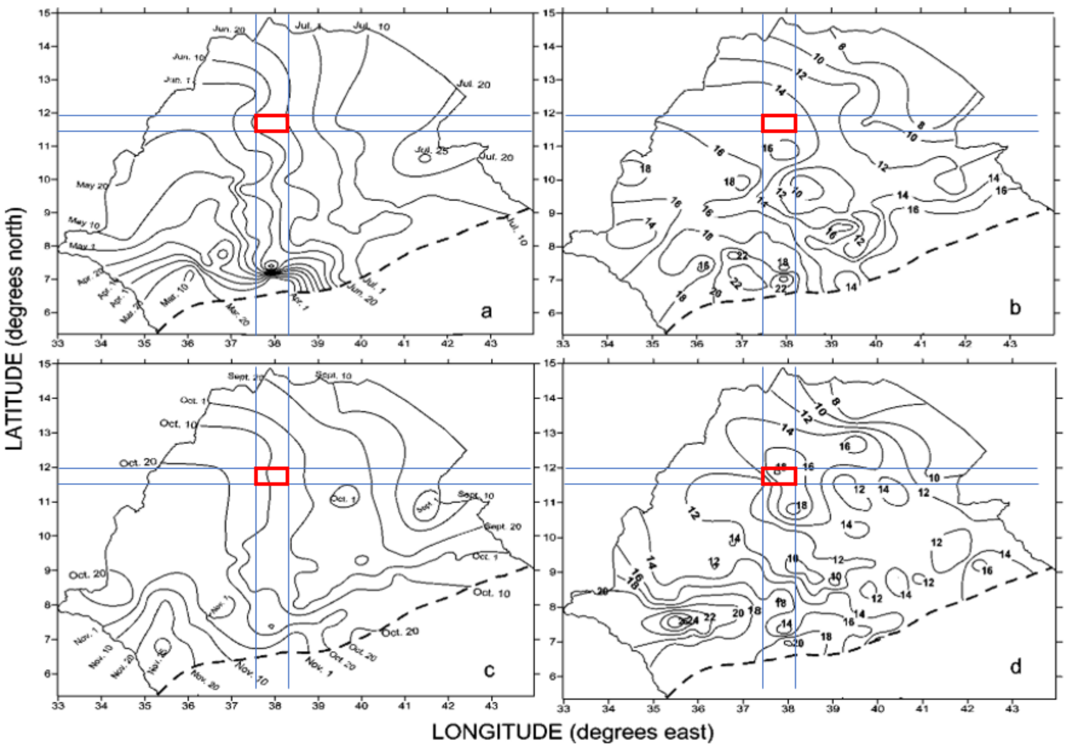


Figure 5.6: Long-term Kiremt onset and cessation patterns. (a) Mean onset date, and (b) its standard deviation (days). (c) Mean cessation date, and (d) its standard deviation (days). The red rectangles indicate the Gumera sub-basin, and are added to the original figure created by Segele and Lamb (2005).

In the case of cessation, the following criteria are followed. The cessation starts at the first day of the first 15 day dry spell occurring after the onset. Hereafter no persistent rains should occur. Just like the climatological onset, the climatological cessation is estimated based on findings of Segele and Lamb (2005) and is set at October 10 for the Gumera sub-basin (see Figure 5.6). To prevent the occurrence of a very early or late cessation, the cessation of Kiremt rains is assumed to occur within 2 months before or after the climatological cessation. For the Gumera sub-basin this means the cessation occurs within the period of August 10 until December 10.

By incorporating the criteria for determining the onset and cessation of rains, it can be determined whether or not a bad year occurs. Hence, in the behavioural model, for each farmer each year it is checked whether the onset of rains occurs one standard deviation later than the mean. If this is the case, a bad year occurs, and the farmer will adapt by growing potato, or teff in case potato is already grown in the previous year. In case the onset of rains is exceptionally early instead (i.e. more than one standard deviation prior to the mean), it is assumed the farmer will expect a long rainy season, and decides to grow a long cycle crop. The farmer will therefore decide to grow maize, or barley in case maize is already grown in the previous year. In case the onset of rains falls within one standard deviation of the mean, the farmer will not adapt by changing the crop type, and will follow the standard farming practices by growing the next crop in the cropping order as indicated in Table 5.1.

Changing the planting and harvesting dates
Besides changing the crop type, farmers can also choose to cope with climate variability by changing the planting and harvesting dates (see part C of Figure 5.4).

The first step is to determine the likelihood of a farmer to adapt by changing the planting and harvesting dates. In Subsection 4.4.9, it was discovered that there are six variables that seem to significantly influence the probability of a farmer to adapt to climate variability by changing the planting and harvesting dates. As was the case for the choice of changing the crop type, the choice of changing the dates seems to be significantly influenced by the altitude, the farmer's level of education, and the number of livestock owned. However, where livestock showed a positive correlation with changing the crop type, it shows a negative correlation with changing the planting and harvesting dates. In addition, the choice for a farmer to adapt by changing these dates depends on the farmer experience, the labour availability and whether or not the farmer has access to a weather forecast. The choice of a farmer to adapt by changing the planting and harvesting dates being influenced by the number of livestock owned, which is a dynamic variable, induces the adaptive behaviour of a farmer to be dynamic. Looking at the negative coefficient for livestock, shown in Table 5.6, this, for example, means that a farmer experiencing an increase in the number of livestock owned will become less likely to adapt by changing the planting and harvesting dates, and vice versa. The probability of a farmer to adapt by changing the planting and harvesting dates is calculated with equation 5.13, whereby a farmer will only adapt if the probability P is larger than 0.5. If P is lower than or equal to 0.5, the farmer will stick with the standard planting and harvesting dates as indicated in Table 5.1. The corresponding values for β are given in Table 5.6.

	Variable	**Coefficient (B)**
	β_0	9.680
X1	Altitude [m]	-0.006
X2	Education [-]	1.011
X3	Experience [years]	0.064
X4	Livestock [TLU]	-0.736
X5	Weather forecast [-]	-1.389
X6	Household labour [days/year]	0.105

Table 5.6: Variables and coefficients included in the logistic model to determine the probability of a farmer to adapt by changing the planting and harvesting dates.

In the behavioural model, a farmer adapting to climate variability by changing the planting and harvesting dates will do so based on the timing of the onset and cessation of rains. The date at which each crop is planted and harvested with respect to, respectively, the onset and cessation of rains, is determined from observations during the FGDs, and upon discussions with W. B. Abebe (personal communication, October 20, 2020). An overview of these planting and harvesting dates are shown in Table 5.7. Note that, different from adapting by changing the crop type, a farmer can change the planting and harvesting dates each year regardless of it being a bad year.

	Planting date	**Harvesting date**
Barley	Onset	Cessation - 30 days
Maize	Onset	Cessation + 30 days
Potato	Onset	Cessation - 30 days
Teff	Onset + 45 days	Cessation + 45 days

Table 5.7: For each crop the planting and harvesting dates based on, respectively, the onset and cessation of rains. These dates are followed by a farmer that adapts to climate variability by changing the planting and harvesting dates. These assumptions are based observations during the FGDs, and upon discussions with W. B. Abebe (personal communication, October 20, 2020).

5.3.4. Methodology to Evaluate the Long-term Effect of Climate Adaptation

In this subsection, a methodology to show the effect of climate adaptation on the long run is presented. Besides the assumed short-term benefits of adapting to climate variability, in terms of increasing yields during a bad year, climate adaptation is also assumed to generate long-term benefits such as reducing the variability in both crop yield and income, and making production and livelihoods more resilient to climate change and variability (FAO, 2015). Due to the reduction in crop yield variability, the average crop production, and therefore crop income, might be lower compared to a non-adapting farmer, but more stable. The expected effect of climate adaptation therefore is that a farmer will find him or herself, in the long run, in an economically more stable situation. In order to show this effect of climate adaptation on the long run, the socio-hydrological model is simulated multiple times, with each simulation based on a different time series of both precipitation and potential evapotranspiration. As such, not only the long-term effect of climate adaptation can be evaluated, also the impact of randomness on the outcomes of the socio-hydrological model can be reduced.

A modified SIMGEN, based on the method developed by Greene et al. (2012), is used in order to generate multiple time series of precipitation and PET. The algorithm is a multivariate stochastic weather generator and has been successfully applied in the Western Cape province of South Africa and in the south-eastern region of South America. The algorithm generates stochastic synthetic projections of the variable conditions based on daily precipitation, and minimum and maximum temperature data. Whereas Greene et al. (2012) distinguishes between three process classes, being the anthropogenic trend component, an annual-to-decadal component, and a sub-annual component, this study only takes into account the latter two. The sub-annual component accounts for both the seasonal cycle and daily variations, whereas the annual-to-decadal component incorporates the variability on annual to decadal time scales by utilizing a vector autoregressive model. Since the precipitation and PET time series, used in this research, only cover 18 years, long-term climatic trends (i.e. over multiple decades) are neglected.

Before the time series are stochastically generated, the daily CHIRPS precipitation dataset and minimum and maximum temperature datasets are processed into the right format such that it fulfils the requirements of the SIMGEN package. However, due to a lack of accurate local daily minimum and maximum temperature data from the Gumera sub-basin extending the simulation period, the daily MOD16A2 PET time series is used to derive daily temperature data for the entire simulation period. The conversion is realised by utilising the Hamon equation for calculation of potential evapotranspiration, given by equation 5.14 (Allen et al., 1998, Lu et al., 2005). The obtained temperature time series is used as the maximum temperature. In order to create a time series for the minimum temperature, the minimum temperature of one historical year is stacked 18 times in order to create a time series equal to the length of the simulation period. Hence, each year in this time series of minimum temperature is the same.

$$PET = k * 0.165 * 216.7 * N * (\frac{e_s}{T + 273.3}) \tag{5.14}$$

Here, PET is the potential evapotranspiration in mm/day, k is a proportionality coefficient equal to 1 [-], N is the daytime length [x/12hours] and calculated by N = (24 / π) * ω, where ω is the sunset hour angle in radians. Furthermore, T is the daily temperature [°C], and e_s is the saturation vapour pressure [mb], which is defined by equation 5.15.

$$e_s = 6.108 e^{(\frac{17.27T}{T+237.3})} \tag{5.15}$$

The sunset hour angle ω depends on the latitude and declination (both in radians) and is given by equation 5.16.

$$\omega = cos^{-1}[-tan(\delta) tan(\phi)] \tag{5.16}$$

The declination is determined by equation 5.17, where J is the Julian Day of the year.

$$d = 1 + 0.033 cos(\frac{2\pi}{365} J) \tag{5.17}$$

Once the daily temperature dataset has been obtained, both the precipitation and temperature datasets are used as input for the SIMGEN algorithm in order to stochastically generate multiple time series (Greene et al., 2012). Subsequently, the stochastically generated temperature time series are converted to PET in order to be able to use it as input for the socio-hydrological model. This conversion is again done with the Hamon equation (see equations 5.14 - 5.17).

With the set of stochastically generated time series for both precipitation and PET the required number of simulations, in order to characterise the sensitivity of the model outputs to uncertainty in weather data, is determined. The required number of simulations is determined based on the number of simulations after which the mean of the farmers' average capital at the end of the simulation period (i.e. in the year 2018) gets stable. Figure

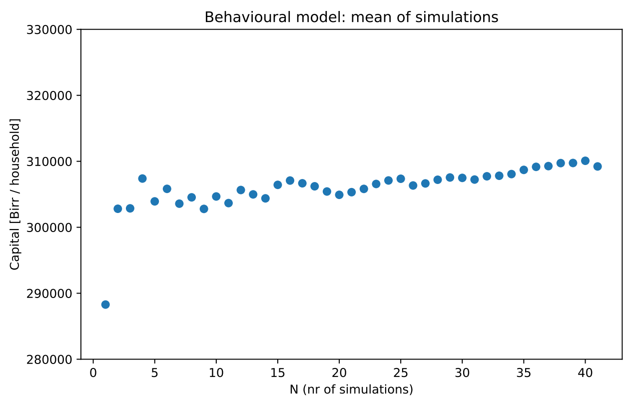


Figure 5.7: The mean of the farmers' capital at the end of the simulation period for multiple simulations of the behavioural model. Made by author.

5.7 shows mean after every additional simulation, from which can be concluded that after 25 simulations the mean remains rather stable. Hence, the required number of simulations in order to characterise the randomness in the model is 25.

In order to observe the effect of climate adaptation on the long-term, the mean and standard deviation of a farmer's capital at the end of the simulation period in the behavioural model, averaged over 25 simulations, is compared with the reference model. As such, it can be evaluated whether climate adaptive behaviour has the expected effect on the long-term economic situation of a farmer, which is a lower (on average) but more stable economic situation.

5.4. Results and Discussion of the Socio-Hydrological Model

In this section the influence of the climate adaptive behaviour, incorporated in the behavioural model, on the farming practices of farmers in the Gumera sub-basin is presented and discussed by means of a few examples. In addition, the performance of farmers with respect to the crop yield obtained and their economic well-being is presented and discussed in comparison with the reference model. Hereby, the values presented represent the average value over 25 simulations. In addition, this is compared with what was observed in the household survey in Sections 4.3 and 4.4. The four groups identified in these sections, which were observed to perform different with respect to the crop yield obtained and behave different with respect to climate variability, are repeatedly compared with each other:

1. Group 1: Rice growing farmers, which are all adapting to climate variability
2. Group 2: Non-rice growing farmers who do not adapt to climate variability, and do not have access to a weather forecast
3. Group 3: Non-rice growing farmers who adapt to climate variability, but do not have access to a weather forecast
4. Group 4: Non-rice growing farmers who adapt to climate variability, and have access to a weather forecast

Table 5.8 shows the number of farmers that were observed to belong to each group of farmers in the household survey, and compares this with the size of each group in the behavioural model. This shows deviating group sizes for both non-adapting farmers, and adapting farmers without access to a weather forecast, which is the result of determining the climate adaptive capacity of a farmer via a logit model. This causes 18 farmers to be classified as an adapting farmer in the behavioural model, while, in the household survey, these farmers claimed not to be adapting to climate variability. Despite these deviations, the size of each group remains in the same order of magnitude.

Group of farmers		**Nr of farmers**	
		Behavioural model	**Household survey**
Rice growing farmers		61	61
Non-rice growing farmers	Non-adapting farmers	30	48
	Adapting farmers without a weather forecast	227	209
	Adapting farmers with a weather forecast	76	76

Table 5.8: The number of farmers per group in the behavioural model, compared with what was observed in the household survey.

5.4.1. Crop Yield Obtained by Farmers

This subsection analyses the simulated crop yield obtained by farmers in the Gumera sub-basin by both the reference and behavioural model. Comparing both models with each other gives an indication of the influence of the climate adaptive behaviour incorporated in the behavioural model. In addition, the crop yield obtained by farmers in the model is compared with the results from the household survey.

Table 5.9 shows the simulated crop yield in both the reference and behavioural model. The average, minimum, and maximum crop yields are presented for each crop, and compared with the results from the household survey conducted in the Gumera sub-basin. For clarity, the crop yield shown is the harvestable yield, hence it is the calculated crop yield after correction for labour and fertiliser factors (see equation 5.12). Both the reference and behavioural model show rather similar results, in which farmers in the reference model obtain slightly higher yields for barley and teff, but lower yields for maize. Note that potato is not grown in the reference model and therefore does not show better any results. Compared with what is observed in the household survey, for all cereal crops (i.e. barley, maize, rice, and teff) both models overestimate the average and maximum crop yield obtained by farmers. Especially, the average yield of maize includes a large error, overestimating the average yield by a factor 2.5, compared to the average maize yield observed in the household survey. On the other hand, the yield of potato is underestimated instead. The average potato yield, obtained by farmers in the behavioural model, is 5 times lower compared to the observed average potato yield in the household survey. However, it is not unlikely that crop yields observed in the household survey contain some error. It could be that farmers are unwilling to reveal total crop yield, which is likely to lead to underestimates of crop yield (Dorward and Chirwa, 2010). This would mean the actual crop yield to be closer to the results of the model, except for potato.

		Avg	**Min**	**Max**	**Household survey**		
					Avg	Min	Max
Barley	Reference	3350	170	4600			
	Behaviour	3100	35	4600	2380	700	3900
Maize	Reference	7630	260	9350			
	Behaviour	7700	230	9350	3070	900	6000
Potato	Reference						
	Behaviour	3010	0,5	6590	15.100	3000	32.000
Rice	Reference	5060	4150	5070			
	Behaviour	5060	4150	5070	4021	3000	4400
Teff	Reference	2380	140	2720			
	Behaviour	2210	30	2720	1380	300	2600

Table 5.9: Simulated crop yield in kg/ha by both the reference and behavioural model, and compared with the average observed crop yield in kg/ha in the household survey conducted in the Gumera sub-basin.

Due to the crop yield not being predicted well by both the reference and behavioural model, the relationship between the three groups of non-rice growing farmers, with respect to crop yield obtained, is different compared to what was observed in the household survey. In Subsection 4.4.4, it was discovered that non-adapting farmers obtained significantly lower yields for all cereal crops compared to adapting farmers. In addition, adapting farmers with a weather forecast obtained significantly higher yields compared to adapting farmers without a weather forecast for the two major crops grown in the Gumera sub-basin, maize and teff, and performed similar with respect to barley. In the case of potato, adapting farmers without a weather forecast showed significantly lower yields compared to adapting farmers with access to a weather forecast.

If we compare this with the results of the model, a rather different pattern arises. Figure 5.8 shows the average crop yield obtained by each group of farmers per crop type, for both the reference and behavioural model. Opposite from what was observed in the household survey, the non-adapting farmers in both the reference and behavioural model show similar or even higher average yields for each crop type compared to both groups of non-rice growing adapting farmers. In addition, where non-rice adapting farmers with a weather forecast showed significantly higher crop yields for maize and teff in the household survey, in the model they show the lowest yields of all groups. From this it can be concluded that the crop yield predicted by the model is not mimicking the pattern observed in the household survey. The model highly underestimates potato yield and overestimates yield of cereal crops, which, to a certain extent, causes the model to show an almost opposite relationship between the three groups of non-rice growing farmers. This makes that we cannot rely on the system dynamics in the behavioural model induced by incorporating the climate adaptive behaviour. Therefore, in the following subsection the system dynamics will not be analysed, but examples are shown of how incorporating the climate adaptive behaviour influences the agricultural practices of farmers in the behavioural model.

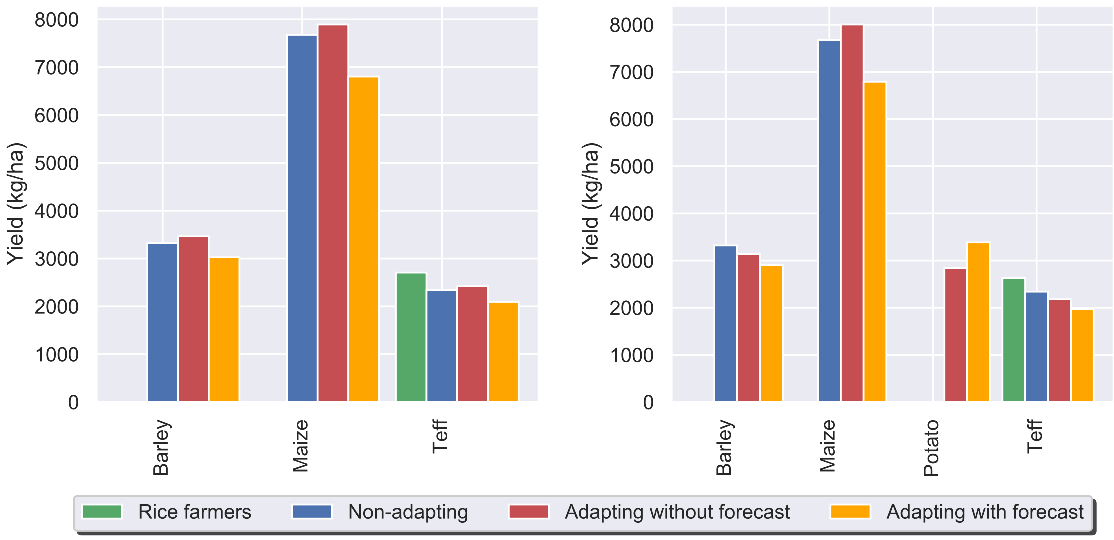


Figure 5.8: The average harvestable crop yield obtained by each group of farmers per crop type for both the reference (left figure) and behavioural model (right figure). Made by author.

5.4.2. The Influence of Climate Adaptation on the Farming Practices

Farmers in the behavioural model can adapt to climate variability depending on whether they have the capacity to adapt. If they do, they can adapt by changing the planting and harvesting dates and/or changing the crop type. As such, farmers can adapt by changing the crop type to a short cycle crop (i.e. potato or teff) in case of a bad year, which was defined as a drought year in which rains also start late, or to a long cycle crop (i.e. maize or barley) in case of an exceptionally early onset of rains. In addition, farmers can change the planting and harvesting dates based on, respectively, the onset and cessation of rains. In this subsection, four examples will be presented of a year in which an adapting farmer, in the behavioural model, adjusts his or her farming practices to cope with climate variability. The first example will show how an adapting farmer responds to an exceptionally early onset, whereas the other three examples will show how an adapting farmer responding to a bad year. Hereby, one example of each adaptation strategy or combination of strategies is presented. These examples are consistently compared with the same farmer in the reference model, in which each farmer follows the pre-defined standard farming practices indicated in Table 5.1.

	Mean	**Std**	**Range** (μ +/- σ)
Onset	June 9	24 days	May 16 - July 3
Cessation	October 8	22 days	Sept 16 - Oct 30
Season length	121 days	34 days	87 - 155 days

Table 5.10: The mean, and standard deviation of the main characteristics of the rainy season in the Gumera sub-basin: onset, cessation, and season length. The range indicates the period within which a farmer expects a "normal" year to occur.

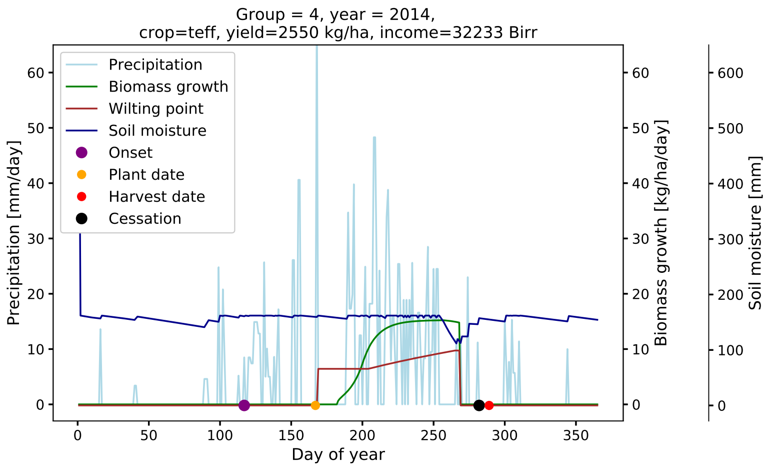
In the behavioural model, the timing of planting and harvesting crops of adapting farmers fully depends on the onset and cessation of rains. In addition, whether or not a farmer adapts by changing the crop type depends on the timing of the onset of rains with respect to the mean onset and cessation of rains experienced in the Gumera sub-basin throughout the simulation period. Table 5.10 presents the average characteristics of the rainy season in the Gumera sub-basin from 2001 to 2018 (i.e. throughout the simulation period), as well as the standard deviation. The range presented is especially important for the onset of rains, since this forms the boundaries outside which a farmer expects an exceptional year to occur. If, for example, the onset of rains occurs later than July 3, a farmer classifies this year as a bad year, expects a short rainy season to occur, and takes up one or two adaptation strategies, but only if (s)he has the capacity to do so.

Changing to a long cycle crop

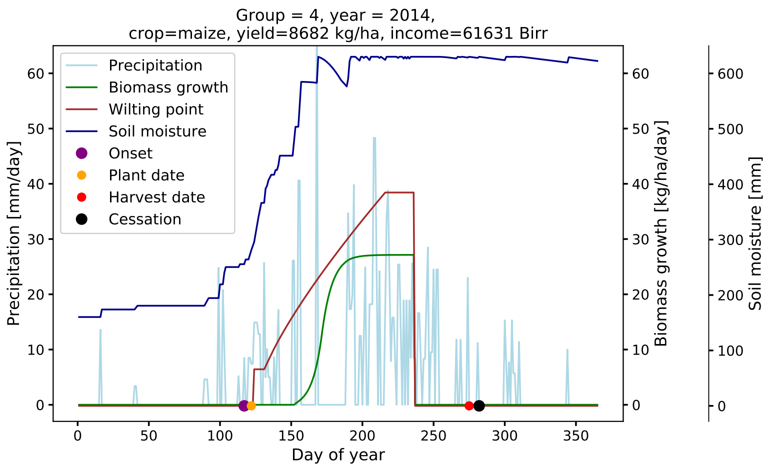
Figure 5.9 shows an example of the farming practices of an adapting farmer with access to a weather forecast in the year 2014. This year has a very early onset of rains, occurring at April 26, which is roughly one and a half month prior to the average onset of rains. Hence, the rainy season starts exceptionally early. On the other hand, the cessation, occurring at October 8, coincides with the average cessation of rains (see Table 5.7). Due to the very early onset of rains, the length of the rainy season is very long with 165 days.

In Figure 5.9a the farming practices taken up in the reference model are shown. It can be observed that the farmer grows teff, and sows seeds at the corresponding pre-defined planting and harvesting dates, which are June 15, and October 15. Although, the farmer obtains rather high crop yield an income he only makes use of roughly two third of the rainy season. Since teff is a short cycle crop, requiring only 120 days to fully mature, it would be more profitable for a farmer to grow a long cycle crop with higher yields in case of such a long rainy season.

This is exactly what happens in the behavioural model (see Figure 5.9b). The farmer expects a long rainy season due to the very early onset of rains, and decides to adapt by changing to the long cycle crop maize. Since maize requires 150 days to fully mature, the farmer makes full profit of the long rainy season, obtaining high crop yield and income. Although the highly overestimated maize yield might give a distorted picture looking at crop yield and income, the behaviour of the farmer in the behavioural model with respect to climate variability, in which (s)he changes the crop type based on the expected type of rainy season, seems to be in more agreement with what is observed in the FGDs and the household survey.



(a) Reference model



(b) Behavioural model

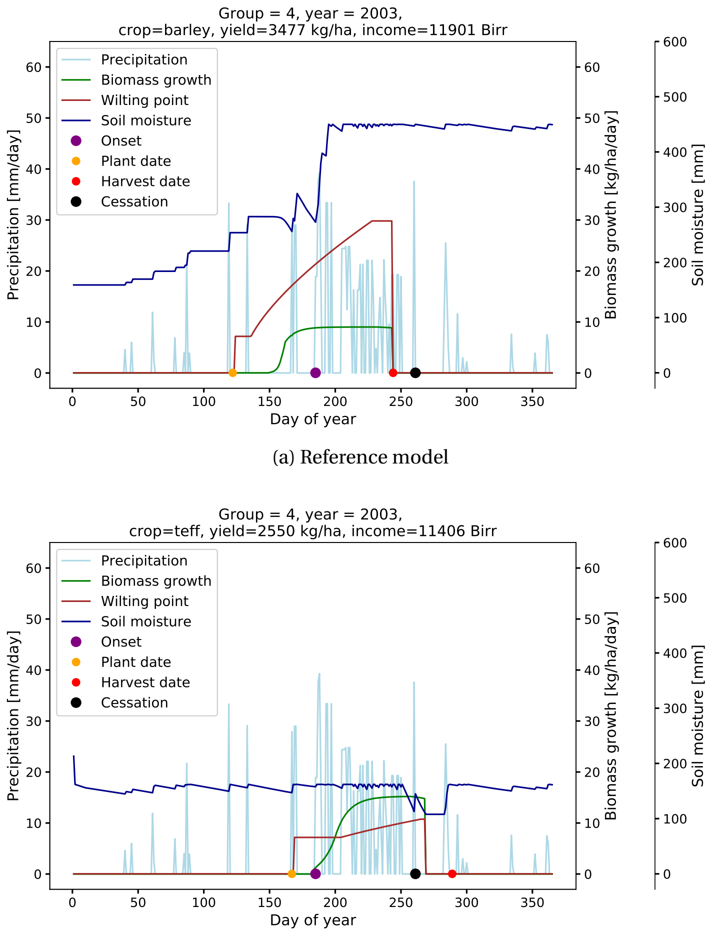
Figure 5.9: An example of the farming practices of a farmer in a year with a long rainy season, for both a) the reference model and b) the behavioural model. In the behavioural model the farmer is adapting to climate variability by changing to the long cycle crop, maize. Wilting point is related to the axis of soil moisture. Made by author.

Changing to a short cycle crop

Figure 5.10 shows an example of the farming practices of an adapting farmer with access to a weather forecast in the year 2003. This year the onset of rains is late, occurring at July 3, and is therefore classified as a bad year. On the other hand, the cessation of rains occurs quite early in the year, at September 17 with respect ot the average cessation (see Table 5.7). This causes the length of the rainy season to be only 76 days.

In Figure 5.10a shows the situation in the reference model. It can be observed that the farmer grows barley, which is a long cycle crop requiring 150 days to fully mature. This is twice as long as the length of the rainy season in this year, hence it is unlikely for a farmer to grow barley in such a short rainy season. In addition, the pre-defined planting date of barley does not match the start of the rainy season, as it is approximately 60 days prior to the onset of rains, at which point only few rain events have occurred. The farmer would therefore be very likely to obtain low yields. However, due to the model overestimating the yield of barley, the farmer still obtains a very high yield, and high income.

In the behavioural model (see Figure 5.10b), the farmer acknowledges the late onset of rains, expects a short rainy season to occur, and adapts by changing to a short cycle crop, which in this case is teff. Since teff only requires 120 days to fully mature it better corresponds to the length of the rainy season. On top of that, the pre-defined planting and harvesting dates better match the onset and cessation of rains respectively, since teff is regularly sown and harvested after the onset and cessation. As such, the farmer makes better use of the short rainy season, and obtains the maximum yield for teff (see Table 5.9).



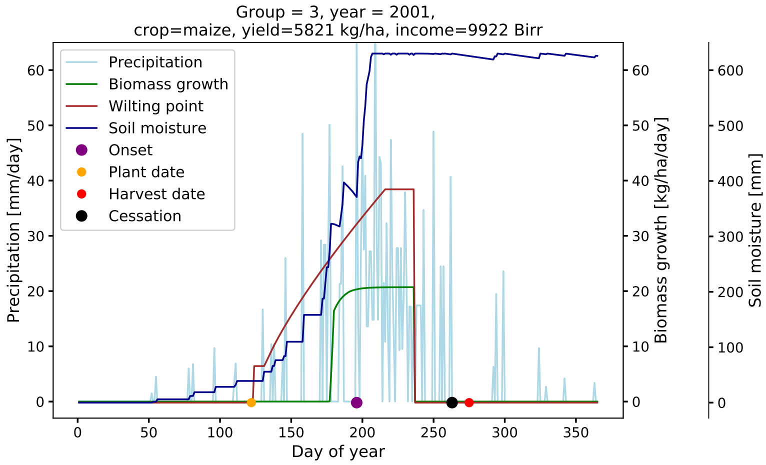
(a) Reference model

(b) Behavioural model

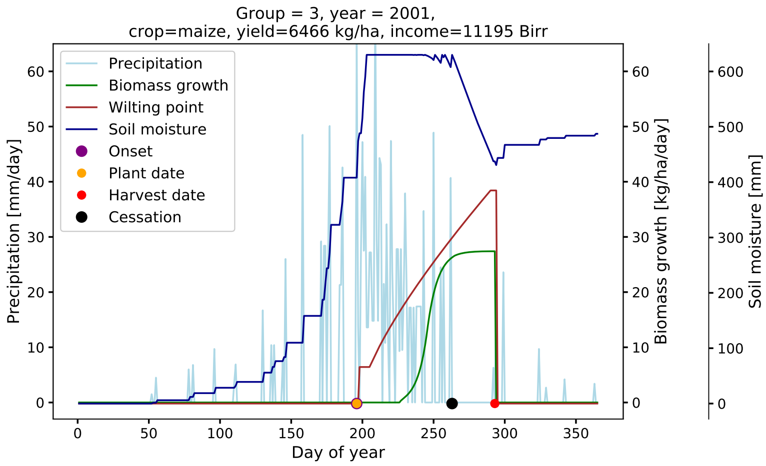
Figure 5.10: An example of the farming practices of a farmer in a bad year, for both a) the reference model and b) the behavioural model. In the behavioural model the farmer is adapting to climate variability by changing to the short cycle crop, teff. Wilting point is related to the axis of soil moisture. Made by author.

Shifting planting and harvesting dates

Figure 5.11 shows an example of the farming practices of an adapting farmer without access to a weather forecast in the year 2001, which is the first year of the simulation period. This year has a late onset of rains, occurring at July 14, and therefore is classified as a bad year. On the other hand, the cessation of rains occurs quite early in the year, at September 19 (see Table 5.7). This causes the length of the growing season to be only 67 days.



(a) Reference model



(b) Behavioural model

Figure 5.11: An example of the farming practices of a farmer in a bad year, for both a) the reference model and b) the behavioural model. In the behavioural model the farmer is adapting to climate variability by changing the planting and harvesting dates. Wilting point is related to the axis of soil moisture. Made by author.

In Figure 5.11a shows the situation in the reference model. It can be observed that the farmer grows maize, and sows seeds at the corresponding pre-defined planting date (i.e. the first of May). However, due to the onset of rains being very late in the year (i.e. at July 14), the farmer sows seeds 74 days prior to the onset of rains, whereas it is observed from the FGDs that farmers normally sow maize seeds simultaneously with the onset. This causes the farmer to sow seeds at the time only few small rain events have occurred and soil moisture is still below wilting point, hence there is no water available to the plant. A very unlikely timing for a farmer to sow seeds. It is roughly 50 days later that soil moisture exceeds the wilting point, and their being water available to the plant in order to gain biomass. In addition, although the farmer is harvesting the crop after cessation, (s)he does so at a time soil moisture is almost at its maximum, and therefore does not make use of the residual moisture that is still available in the soil. It can thus be concluded that this farmer, by following the standard farming practices, does not make good use of the type of rainy season that is occurring.

In the behavioural model (see Figure 5.11b), the adapting farmer classifies this year as a bad year due to the late onset of rains, hence (s)he is expecting a short rainy season to occur. To cope with this variability in climate, the farmer adapts by solely changing the planting and harvesting dates. Note, the farmer still grows maize. The farmer therefore shifts the planting date such that it coincides with the onset of rains, whereas (s)he waits with harvesting until 30 days after the cessation has occurred (as was assumed in Subsection 5.3.3, see Table 5.7). It can be observed that, opposite from what was the case in the reference model, the soil moisture is much higher than wilting point at the time of sowing seeds. In addition, the farmer harvests the crop at the time soil moisture is just above wilting point. As such, it makes full use of the residual moisture that is left in the soil after cessation. In comparison with the reference model, the farmer in the behavioural model makes better use of the very short rainy season by shifting the planting and harvesting dates. As such, the farmer obtains higher crop yield and higher income compared to the situation in the reference model. From this example it can thus be concluded that the behavioural model is able to capture the farming practices with respect to climate variability which were observed during the FGDs and in the household survey.

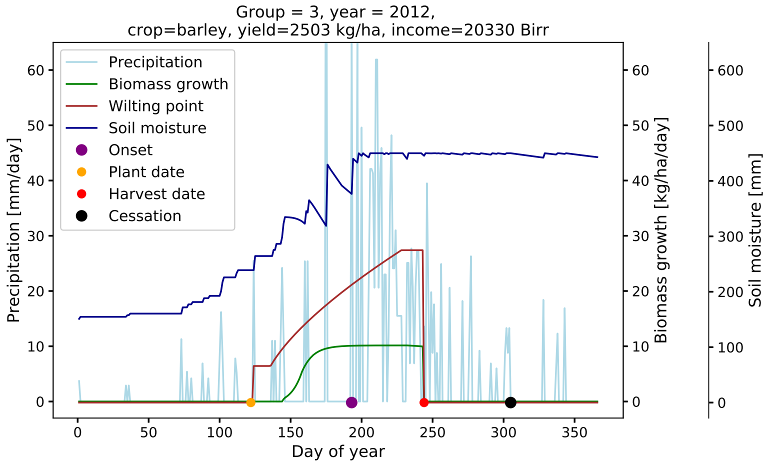
Changing to a short cycle crop and shifting planting and harvesting dates

Figure 5.12 shows an example of the farming practices of an adapting farmer without access to a weather forecast in the year 2012. This year has a very late onset, occurring at July 10, and is therefore classified as a bad year. Similarly, the cessation occurs rather late in the year, at October 31, causing the season length to be 112 days. Hence the rainy season is not only rather short, but also has shifted by roughly one month with respect to the average timing of the rainy season.

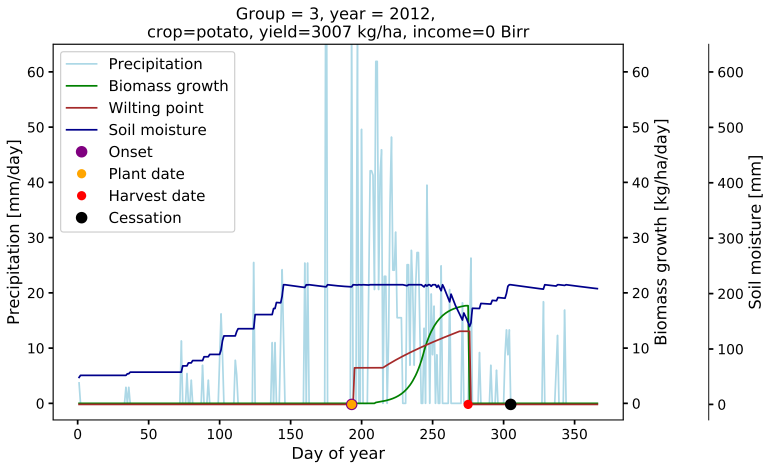
In Figure 5.12a the farming practices taken up by the farmer in the reference model are shown. It can be observed that the farmer grows barley, which requires 150 days to fully mature, and therefore does not really suit the rather short rainy season. In addition, the farmer sows at the pre-defined dates for barley, which are May 1 and August 31, respectively. This causes the farmer to sow seeds 70 days prior to the onset, and harvests 60 days prior to the cessation, whereas barley is regularly sown at the onset and harvested 30 days prior to the cessation. By not adapting to the climate variability this farmer does not make full profit of the rainy season.

Comparing this with the farming practices of the same farmer in the behavioural model (see Figure 5.12b), it can be observed that the farmer adapts to climate variability by both changing to a short cycle crop, in this case potato, and shifts the planting and harvesting dates. As such, the farmer takes up farming practices that better fit the rainy season. However, due to the model overestimating yield of barley, and highly underestimating potato yield, in the reference model the farmer still obtains a high yield and high income, whereas in the behavioural model this farmer is left without any income.

Based on the examples discussed in this subsection, it can be concluded that, despite the model not being able to give good estimates for crop yield, incorporating the climate adaptive behaviour of farmers successfully account for the climate adaptive behaviour of farmers in the Gumera sub-basin. The agricultural practices taken up by farmers in the behavioural model better coincide with what is observed during the FGDs and the household survey, compared to the reference model. In comparison with reference model, adapting farmers in the behavioural model show to choose the crop type that better fits the rainy season, and the more appropriate dates to plant and harvest with respect to the type of rainy season that is occurring.



(a) Reference model



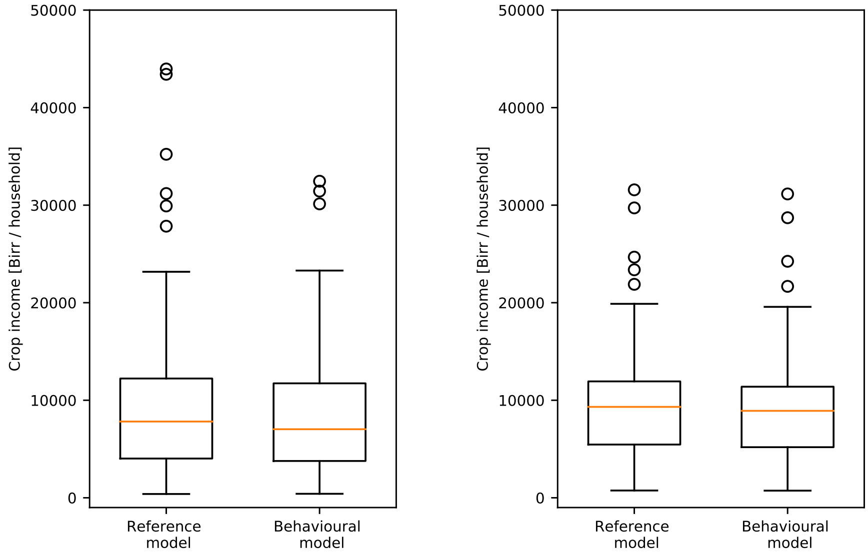
(b) Behavioural model

Figure 5.12: An example of the farming practices of a farmer in a bad year, for both a) the reference model and b) the behavioural model. In the behavioural model the farmer is adapting to climate variability by both changing to the short cycle crop, potato, and changing the planting and harvesting dates. The biomass growth is in kg/ha/day. Made by author.

5.4.3. The Effect of Adaptation

This subsection illustrates that making use of multiple stochastic simulations, as described in Subsection 5.3.4, provides the opportunity to analyse the effect of climate adaptation on the economic well-being of smallholder farmers in the Gumera sub-basin. The effect of climate adaptation was suggested to work on the long run, in which the average income from crops of adapting farmers would be lower but more stable compared to that of non-adapting farmers. Hence, by adapting to climate variability, the economic situation of a farmer would become more resilient with respect to climate variability.

Figure 5.13 is only used for illustration purposes. It illustrates the effect of adaptation, induced by incorporating the climate adaptive behaviour of smallholder farmers in the Gumera sub-basin, captured by the behavioural model. It shows a boxplot of both the mean (see Figure 5.13a) and standard deviation (see Figure 5.13b) of the income from crops for 30 non-rice growing adapting farmers over 25 simulations of 18 years for both the reference and behavioural model. As such, it is accounted for the long-term effect of climate adaptation. Each of these farmers shows a lower mean and standard deviation in the behavioural model compared to the reference model. Hence, the overall average mean and standard deviation of crop income for these 30 farmers is, respectively, 7.2% and 24.2% lower in the behavioural model compared to the reference model. This would suggest that these farmers show the desired effect of adaptation to climate variability, in which they obtain a more stable income from crops. However, due to the crop yields not being predicted well in this model, this suggestion cannot be relied upon. Hence, Figure 5.13 only functions as an illustration that shows what the effect of climate adaptation would look like and how it can be evaluated. Therefore, if one would



(a) Standard deviation of crop income

(b) Mean of crop income

Figure 5.13: An illustration of the effect of climate adaptation on a) the mean and b) the standard deviation of crop income for 30 non-rice growing adapting farmers. Each of these farmers shows a lower mean and standard deviation with respect to crop income after 25 simulations of 18 years in the behavioural model compared to the reference model. Reference model: mean = 12.524 Birr, SD = 11.378 Birr. Behavioural model: mean = 9497 Birr, SD = 10.565 Birr. Made by author.

implement this model with the right yields, following this methodology would provide the opportunity to assess the simulated impact of climate adaptation on the farmers economic well-being. From this, it is then possible to conclude why farmers are adapting.

5.5. Conclusion

This section provides conclusions on the methodology and corresponding results described and discussed in Sections 5.2, 5.3 and 5.4. It has been observed that the socio-hydrological model highly underestimates yield of potato, which is the adaptive crop, and overestimates yield of cereal crops. Therefore the system dynamics of farmers, induced by incorporating the climate adaptive behaviour of a farmer, cannot be relied on. Despite the socio-hydrological model not being able to give good estimates of crop yield, it has the ability to better describe the agricultural practices of farmers with respect to climate variability. As such, it is shown that the climate adaptive behaviour of a farmer can be successfully incorporated in a socio-hydrological model by the use of a logit model. Based on the main drivers of climate adaptive capacity, obtained via a bottom-up approach, the socio-hydrological model can distinguish between adapting and non-adapting farmers. Hereby, based on the onset of rains and farmer characteristics, adapting farmers adapt to climate variability by either changing to a long or short cycle crop, or shifting the planting and harvesting dates. By doing so, the agricultural practices with respect to climate variability simulated by the model better coincide with what is observed during the FGDs and the household survey. Unlike the reference model, the behavioural model shows adapting farmers to choose the crop type that better fits the rainy season, and the more appropriate dates to plant and harvest with respect to the type of rainy season that is occurring. In addition, since the climate adaptive behaviour is influenced by continuous variables that change over time, the model is able to account for the dynamic adaptive capacity of a farmer with respect to climate variability. In addition, the methodology to evaluate the real effect of climate adaptation on the economic well-being of a farmer is shown to be feasible. By stochastically creating multiple time series of precipitation and potential evapotranspiration, and simulating the model multiple times for each time series, it can be evaluated what the long-term effect of climate adaptation is on the economic well-being of a farmer, by just focusing on the mean and standard deviation of the income from crops.

6 Discussion

The results presented in Sections 4.3, 4.4 and 5.4, which provide an answer to the research questions stated in Section 1.4, come with several uncertainties and/or limitations. These uncertainties could be introduced by the methodologies used and assumptions that are made throughout the process. This chapter discusses the main uncertainties and limitations of each methodology used (i.e. FGDs, household survey, and socio-hydrological model) and how this might have influenced the answers on the research questions. For some of these limitations future recommendations are provided in Chapter 7.

6.1. Focus Group Discussions

The first methodology used in this study in order to gain local-level knowledge from smallholder farmers in the Gumera sub-basin was in the from of FGDs, discussed in Subsection 4.2.1. By conducting these FGDs in different regions of the Gumera sub-basin, a good indication of the farmers' perceptions, characteristics and behaviours with respect to climate variability, representative for the entire population, would have been obtained. However, due to COVID-19 related restrictions, constraints were introduced on time and movement. Hence, it was only possible to conduct three FGDs, all in the lower ACZ in the western part of the Gumera sub-basin. Furthermore, the participating farmers were all male farmers, and predominantly quite intelligent and experienced farmers claiming to adapt to climate variability. Although it was observed from the household survey the majority of farmers in the Gumera sub-basin to be adapting to climate variability, experienced, and male farmers, the farmer perspective obtained from the FGDs might have been biased and not representative for the entire population of the Gumera sub-basin. Therefore, deviating perceptions, characteristics, and behaviours of, for example, farmers in the upper ACZ, female farmers or farmers with less experience, might have been missed out on.

Since the FGDs form the basis of both the household survey and the socio-hydrological model, it is likely that the perspective of experienced male farmers in the lower ACZ is dominant in this research. As such, agricultural practices of farmers in especially the upper ACZ could be underexposed in this research. An example of this is that farmers in the Gumera sub-basin in high altitude lands, particularly in Farta (located in the North East of the Gumera sub-basin), practice double cropping. They, for example, grow barley just after potato or vice versa (ADSWE, 2015a). However, based on the FGDs it was assumed all farmers in the Gumera sub-basin to practice rotational cropping, in which farmers grow one crop a year. Therefore, double cropping, which is suggested to make farmers less vulnerable to climate variability (Meza et al., 2008), has not been taken into account in both the household survey and the socio-hydrological model.

6.2. Household survey

With respect to the household survey, there are a few aspects that might introduce some error or uncertainties in the data. This largely consists of two aspects. First, there is uncertainty whether the respondents of the household survey are a good representation of the entire population in the Gumera sub-basin, which is related to limitations of the FGDs discussed in Section 6.1. Second, assumptions to determine the sample size might have introduced some uncertainties in the results. Each of these aspects is discussed below in further detail.

First of all, one of the known disadvantages of a household survey is that it basically reflects the 'world view' or perceptions from the researchers on the topic to be examined by means of the household survey. The respondents, hereby, merely answer the questions thought to be important and relevant by those designing and canvassing the household survey (Mukherjee, 1997). As such, the real perspectives of local farmers might be missed out on. In this study, this effect is tried to be minimised by adjusting the household survey based on the observations during the FGDs. As such, the farmer perspective is tried to be incorporated as much as possible. However, as is discussed in Section 6.1, the farmers attending the FGDs might not have been a good representation of the entire population. Therefore, the perspective of farmers incorporated in the household survey might be biased towards experienced male farmers in the lower ACZ. Furthermore, the farmers attending the FGDs were rather intelligent, answering questions including rates such as kg/ha, with ease. It was therefore assumed to be possible to incorporate such questions in the household survey. However, when analysing the data, a large share of surveyed farmers was observed to be illiterate, suggesting they have a lower level of intelligence compared to farmers attending the FGDs. Some questions in the household survey, including rates, could therefore have been too complicated for some farmers to give an accurate answer, which could have introduced some error in the data.

Another uncertainty affecting the reliability of the data obtained by the household survey, is that it cannot be assured that the household survey is conducted by random sampling. The household survey was conducted by several local Agricultural Experts who are experienced in conducting such a survey, and are in close contact with the local farmers. However, due to the abrupt ending of the field campaign, induced by COVID-19 related restrictions, it was not possible to check whether the Agricultural Experts indeed conducted the household surveys by random sampling. However, acknowledging their experience in conducting surveys it is assumed a good representation of the population is obtained. This is also partly validated by the average age of the household head, family size, and the share of adapting and female farmers in the household survey, which are all very similar to what is found in studies conducted within or close to the Gumera sub-basin (ADSWE, 2015a, Bryan et al., 2009).

Second, for determining the required sample size of the household survey an average effect size (d) of 0.4, based on two large-scale behavioural studies (Brysbaert, 2019), was used. This average effect size was used due to it being rather difficult to give a better estimate for the effect size of climate adaptive behaviour of smallholder farmers a priori, and collecting data from a very large sample was not feasible within the scope of this study. Knowing that behavioural effects are often small, the effect size of 0.4 used in this study might not have been sufficient to pick up certain effects of behavioural aspects of farmers with respect to climate variability. A smaller effect size, and therefore a bigger sample size, would therefore improve the analysis on farmers and the reliability, especially for the smaller groups of non-adapting and female farmers. An example of an effect that might have been missed out on due to the average effect size of 0.4, is the effect of capital on climate adaptation. From literature it is known that a lack of capital can be a real constraint to climate adaptation (Gezie, 2019), indicating that non-adapting farmers experience a lack of capital. Although a rather large difference in capital (10%) was observed in the household survey between adapting and non-adapting farmers, no significant effect was found in this research. With a larger sample size this difference might have been significant, resulting in a possible different outcome of the barriers to climate adaptation.

An additional comment must be made on the scope of this research. Certain factors that might be of significance for the climate adaptive behaviour of a farmer are, due to the scope, not included in this research. Hence, this research does not provide a complete picture of all factors possible influencing the climate adaptive behaviour of smallholder farmers in the Gumera sub-basin. For example, soil degradation, which is known to be a big issue in the Gumera sub-basin, the interaction between farmers, as well as the influence of pests and diseases, such as the most recent threat in the from of COVID-19, are assumed to influence the climate adaptive behaviour of a farmer, but are not included in this research. To create an overarching view of the influence of all of these aspects on the climate adaptive behaviour further research that links these different aspects is needed.

Overall, it can be concluded that the combination of limitations might have introduced some uncertainties in the data obtained from the household survey. This is likely to have influenced the results obtained in this research, especially with respect to the groups of farmers representing a small proportion of the population (i.e. non-adapting and female farmers). The conclusions drawn on the climate perception of non-adapting farmers and the information used to make agricultural decisions (both assumed to be important drivers for the climate adaptive behaviour of a farmer), are based on small samples and therefore prone to uncertainties in the data. On the other hand, the results obtained regarding adapting farmers and the influence of, for example, having access to a weather forecast are rather strong. However, one has to be very careful with drawing conclusions on what is observed from the household survey. Concluding on causations, for example, is not possible, hence each significant influence found in this research can only suggest a correlation (and its direction) between variables.

6.3. Socio-Hydrological model

In Chapter 5 a methodology is presented to incorporate the climate adaptive behaviour of smallholder farmers in a socio-hydrological model. Enabling this methodology has been shown to improve the simulation of agricultural practices of farmers with respect to climate variability. However, the question why farmers adapt to climate variability and how it impacts their economic well-being could not be answered due to the model not being capable of giving good estimates of crop yield. This section describes limitations of the model that influence the crop yield calculation. In addition, the methodology with which the climate adaptive behaviour of farmers in the Gumera sub-basin is incorporated, and its shortcomings are discussed.

6.3.1. Crop yield calculations

In Section 5.4 it was observed that the calculated yield of cereal crops was highly overestimated by the model, whereas the yield of potato, which is the major adaptive crop, was highly underestimated. As a consequence, the system dynamics of smallholder farmers represented by the model, which are highly influenced by crop yield, cannot be relied upon. The reason for the socio-hydrological model not being capable of calculating crop yield estimates that are comparable with what is found in literature and observed in the household survey, is due to some limitations in the model, as described below.

First of all, the soil moisture is described by a one bucket model, without seepage at the bottom of the reservoir. In addition, all precipitation is assumed to fully infiltrate into the ground, whereby moisture in excess of the maximum storage is removed from the smallholder system as runoff. Interception is hereby neglected, even though interception is found to be an important process in the water balance (De Groen and Savenije, 2006, Love et al., 2010). The combination of neglecting both seepage and interception causes moisture in the ground to be only removed from the system by soil evaporation and water uptake from plants, and gets replenished rather quickly by small rain events. This causes the soil moisture content to remain high even after the long dry season. Figure 6.1 and 6.2 show examples in which, prior and after the rainy season, soil moisture remains at the maximum storage capacity despite the occurrence of only few small rain events. As a consequence, there is always water available for the plants even if a farmer sows seeds two months prior to the onset of rains, as was observed in Subsection 5.4.2. As a result, the model overestimates crop yields even in the case of a bad year or in the case of bad timing of planting and harvesting dates. To make the model more realistic, and to prevent very high yields even in the case of a mismatch between planting date and onset, a better approach of modelling the soil moisture content might be to start each year with an 'empty bucket' (i.e. zero soil moisture in the ground). Figure 6.1 shows an example of how this would look like. As such, planting seeds too early would coincide with very low soil moisture content and the crop suffering from water stress.

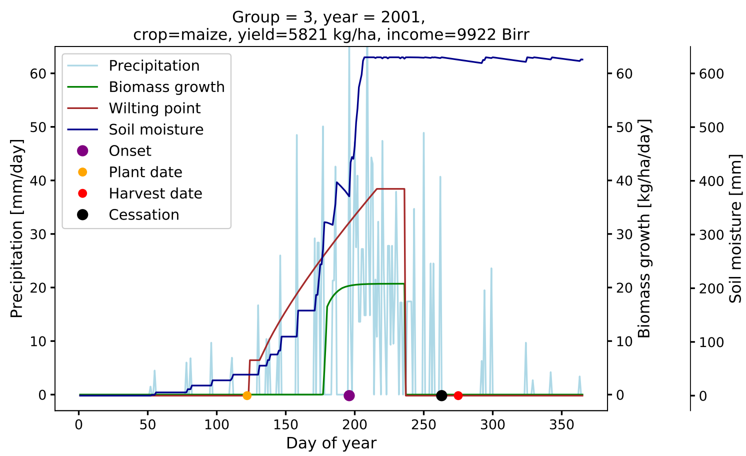


Figure 6.1: An example of the farming practices of a farmer in a bad year, for the reference model, showing that the soil moisture content remains high after the cessation of rains has occurred. Wilting point is related to the axis of soil moisture. Made by author.

A third aspect that might contribute to the overestimation of crop yield is temperature. In this model temperature stresses are not taken into account, due to a lack of accurate daily temperature data from local meteorological stations. Although it is uncertain to what extent temperature stresses affect crop yield calculations by the model, with the observed increasing trend of temperature in Ethiopia (Legesse, 2017) it becomes more and more important to take into account temperature in such models. Not only due to it influencing crop yield, but also due to it being an important source of information for farmers, as is suggested from the household survey. Almost 80% of adapting farmers without access to a weather forecast claim to use their own observations of temperature to determine what agricultural practices to conduct.

Another factor that is likely to introduce some error in the crop yield calculation is the fertiliser factor. This is a factor between 0 and 1, and is defined as the amount of fertiliser applied by a farmer (in terms of Nitrogen) divided by the maximum Nitrogen application rate, and influences crop yield directly. As such, a fertiliser overuse does not affect crop yield, but using a fertiliser rate lower than the maximum application rate (causing the fertiliser factor to be smaller than 1) negatively affects the crop yield obtained by a farmer. As such, the model predicts higher crop yields for farmers using higher rates of fertiliser. This is the exact opposite from what is observed in the household survey, in which fertiliser was found to be a significant predictor for crop yield, showing a negative correlation. Due to the large influence of the fertiliser factor on crop yield in the model, and it introducing a correlation in the opposite direction from what was observed in the household survey, an error in the crop yield calculation might be introduced. Hence, to reduce the error in crop yield calculations within this model, the influence of fertiliser use should be critically looked at. Related to this aspect of fertiliser use is soil fertility, which is not taken into account, although it being observed to compose a major limitation to crop production in the Lake Tana sub-basin (Abera, 2017).

At last, uncertainties in crop yield calculations could be introduced by the input data. In this research, the MOD16A2 potential evapotranspiration dataset (Running et al., 2017) is used as input for the model. Although MOD16A2 does not provide the best performance of PET estimates, it is used in this research due to it being the only global readily-available open-source evapotranspiration product providing real-time evapotranspiration estimates. For further studies, better performing higher spatial resolution products, such as Landsat (Vogels et al., 2020), or, if available, daily temperature data from local meteorological stations are recommended. Furthermore, in order for the model to calculate crop yield, crop specific parameters are required as input. For maize, and teff these are based on studies conducted in comparable regions in Ethiopia. However, due to a lack of local studies, parameter values for barley, potato and rice are based on more general values used by the FAO. This could introduce some error in the crop yield calculation as parameter values could differ between regions. The highly underestimated yield of potato could be introduced by this.

6.3.2. Limitations to Climate Adaptive Behaviour

The methodology presented in this research has been shown to successfully account for the climate adaptive behaviour of smallholder farmers in a socio-hydrological model. By enabling a logit model the socio-hydrological model can distinguish between adapting and non-adapting farmers based on their farmer characteristics that are suggested from the household survey to significantly influence the climate adaptive capacity of a farmer. As such, with respect to climate variability, the agricultural practices taken up by farmers in the behavioural model, better coincide with what is observed during the FGDs and in the household survey, compared to the reference model. However, a limitation to the current model is that the climate adaptive behaviour of farmers in the Gumera sub-basin is triggered solely by the onset of rains.

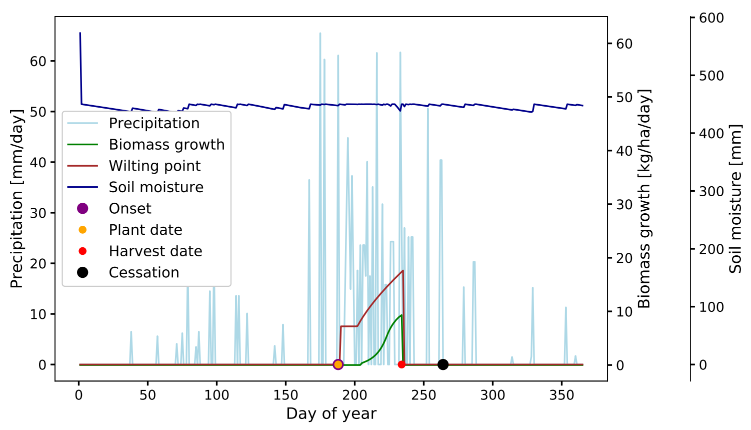


Figure 6.2: An example of the farming practices of an adapting farmer in a bad year, for the behavioural model, showing soil moisture to be very high prior to the onset of rains, and planting and harvesting dates to be very close to each other. Wilting point is related to the axis of soil moisture. Made by author.

Although this has been observed, both during the FGDs and in the household survey, to be a very important indicator influencing the choice of a farmer to adjust his or her agricultural practices, and such adapt to climate variability, there are several other factors influencing the behaviour of adapting farmers with respect to climate variability. Own observations of the previous rainy season, wind, and temperature have all been observed to be largely used information sources by adapting farmers without access to a weather forecast. Solely using the onset of rains is therefore a rather simplified way of triggering climate adaptive behaviour. However, it is a first step in the development of a methodology that enables to better simulate the climate adaptive behaviour of smallholder farmers in a socio-hydrological model. Another limitation to this approach is the way in which the planting and harvesting dates depend on the strict definitions of the onset and cessation of rains, which can introduce odd behaviour by adapting farmers. Figure 6.2 shows the agricultural practices of a farmer adapting by changing the planting and harvesting dates. Hereby, the timing of planting and harvesting are determined by the strict definitions of both events, causing the time between planting and harvesting to be only 43 days. It is very unlikely a farmer would harvest crops so soon after planting. Furthermore, by enabling a logit model an arbitrary threshold of 0.5 is used upon which is determined whether or not a farmer adapts and with what adaptation strategy. This influences the number of farmers that have the capacity to adapt to climate variability and, subsequently, the number of farmers taking up one of the two adaptation strategies. In this research, this threshold gave an adequate division of the number of farmers adapting to climate variability. However, using a somewhat lower or higher threshold would influence this division, and should carefully be chosen in further research.

Another limitation to the current model is that it can only simulate droughts. Instead of droughts, rice growing farmers are mostly affected by floodings as was observed during the FGDs. This causes this group of farmers to adapt to climate variability in different ways. However, due to the socio-hydrological model not being able to simulate floodings, the climate adaptive behaviour of rice-growing farmers cannot be represented by the model very well. The socio-hydrological model is therefore only capable of simulating the behaviour of the vast majority of farmers for whom droughts compose the major climatic challenge.

6.3.3. Long-term Effect of Climate Adaptation

In this research a methodology is presented to evaluate the long-term effect of climate adaptation on the economic well-being of a smallholder farmer. Hereby, the model is simulated multiple times, each time with a different time series of precipitation and potential evapotranspiration. To generate these time series a multivariate stochastic weather generator (SIMGEN) has been applied, based on daily time series of precipitation and minimum and maximum temperature. Due to the lack of temperature data from local meteorological stations, the temperature time series were obtained by converting the MOD16A2 Evapotranspiration into temperature via the Hamon equation, despite the MOD16A2 Evapotranspiration being based on the Penman Monteith equation. By mixing up two different approaches for calculating evaporation, an error might have been introduced, affecting crop yield calculations.

7

Conclusion and Recommendations

Smallholder farmers in the Gumera sub-basin mostly rely on rainfed agriculture, in which the majority of farmers grow one crop a year. The main crops grown are maize, teff, potato, barley, and rice. Rainfall variability and changes in rainfall patterns, induced by climate change, could increase the frequency and occurrence of floods and droughts. Due to farmers mostly relying on rainfed agriculture, this highly influences the agricultural production with corresponding negative effects on food security and their economic well-being, leaving farmers highly vulnerable to year-to-year climate variability. A large share of smallholder farmers claim to take up adaptation strategies in order to cope with these year-to-year variabilities in climate.

The main objective of this study was to determine how farmers behave with respect to climate variability and what factors drive the climate adaptive capacity of smallholder farmers in the Gumera sub-basin, Ethiopia. In addition, the aim was to establish a methodology to incorporate the climate adaptive behaviour of smallholder farmers in socio-hydrological modelling, which provides the opportunity to create a better understanding of why farmers adapt to climate variability and its impact on their economic well-being.

Which factors drive the climate adaptive capacity of a farmer was analysed by the use of Focus Group Discussions and an individual household survey. This revealed that the majority of farmers indeed adjust their agricultural practices in order to cope with climate variability. They especially do so whenever a bad year occurs, which is defined by farmers as a drought when the onset of rains also occur late, inducing a very short rainy season. The mostly applied (short-term) adaptation strategies with respect to climate variability are changing to a short cycle crop, such as potato and teff, and adjusting the planting and harvesting dates. However, there is also a small group of farmers that do not take up adaptation strategies, but rather stick with conventional agricultural practices.

The drivers that determine whether or not a farmer has the capacity to adapt to climate variability is found to be three fold. The assets of a farmer for a large part determine the climate adaptive capacity. As such, a lack of land, labour, and a weather forecast were observed to compose main barriers to climate adaptation. In addition, large differences between adapting and non-adapting farmers were observed with respect to their long-term climate perception. Non-adapting farmers seemed to have a more optimistic perception of the changes in climate compared to adapting farmers. They perceived less variability in temperature, more rainfall, later cessation of rains and less dry spells. In addition, they were observed to experience a bad year 3 times less often than adapting farmers. At last, the information sources used by farmers to decide upon their agricultural practices, seem to highly influence the capacity of a farmer to adapt to climate variability. Especially the use of the onset of rains is suggested to be an important driver for farmers to adapt. By each of these three aspects, the access to a weather forecast seems to play a central role. It seems to influence the climate perception of a farmer as well as the information sources used. On top of that, all farmers having access to a weather forecast adapt to climate variability, suggesting that a weather forecast highly influences the climate adaptive capacity and behaviour of a farmer.

With this knowledge on the climate adaptive behaviour of smallholder farmers in the Gumera sub-basin, obtained from Focus Group Discussions and an individual household survey, a methodology is developed to incorporate this behaviour into socio-hydrological modelling. By enabling a logit model it has been shown that a socio-hydrological model can successfully account for the climate adaptive behaviour of a farmer. Based on the main drivers of the climate adaptive capacity of a farmer it can distinguish between adapting and non-adapting farmers. Hereby, based on the onset of rains, adapting farmers adapt to climate variability by either changing to a long or short cycle crop, or shifting the planting and harvesting dates. By doing so, the agricultural practices with respect to climate variability simulated by the model better coincide with what is observed during the FGDs and the household survey. In addition, the methodology used to evaluate the long-term effect of climate adaptation on the economic well-being of a farmer has the potential to help in creating a better understanding of why farmers adapt to climate variability. However, due to the model lacking the ability to accurately calculate crop yield estimates, the model cannot yet be used to create a better understanding of how climate adaptive behaviour influences the system dynamics of smallholder farmers.

7.1. Recommendations

Based on the results from the FGDs, the individual household survey and the socio-hydrological model, some recommendations for further research are made.

During this research the data gathered from smallholder farmers in the Gumera sub-basin was influenced by COVID-19 restrictions. Although a large part of the Gumera sub-basin has been covered by the household survey, only in the western part FGDs have been conducted. Due to these restrictions certain behavioural aspects with respect to climate variability of farmers in, especially, the eastern and northern part of the Gumera sub-basin might have been missed out on. For further research, it is recommended to conduct FGDs in these parts of the Gumera sub-basin as well. This would result in a more comprehensive understanding of the climate adaptive behaviour of smallholder farmers.

The methodology presented in this study is a first step in incorporating the climate adaptive behaviour of smallholder farmers in socio-hydrological modelling. However, to really be able to use this model to create a better understanding of the system dynamics of smallholder farmers with respect to climate adaptation, one should critically look at the crop yield calculations in order to improve the reliability of the model. Local values for crop specific parameters are required, as well as how the soil moisture content is described especially during the dry season. Furthermore, daily temperature data from local weather stations and calculating evapotranspiration upon this might give better estimates for crop yield. At last, the way in which the fertiliser factor directly influences crop yield calculations is rather simplistic and introduces a supposedly wrong correlation. It is therefore recommended for further research to analyse the relationship between the fertiliser factor and crop yield in more detail, such that, for example, an overuse of fertiliser can also influence crop yield negatively.

At last, it is recommended to create a less rigid way of determining the planting and harvesting dates. One way of doing this, is to incorporate more factors, in addition to the onset of rains, that trigger the climate adaptive behaviour of a farmer. The 'environmental awareness' is such a factor which is already researched in several studies (see Subsection 2.2.2), and linked to the farmer experience, which, in this research, is observed to influence the climate adaptive behaviour. However, to date, the way in which the 'environmental awareness' exactly influences the agricultural choices of a farmer is unknown and rather complex, hence further research is required. Another factor that can be used is temperature, since this has been observed to be an important factor upon which adapting farmers without access to a weather forecast determine their choice for certain agricultural practices. Incorporating temperature in the model has as additional effect that it might improve both crop yield calculations, and stochastically generated time series of evapotranspiration that are used to evaluate the long-term effect of climate adaptation on the economic well-being of farmers.

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A

Focus Group Discussions

A.1. FGD 1: Geregera

The first FGD is conducted in Geregera, located in the southwest of the Gumera sub-basin. In total, six male farmers joined the FGD. Overall, there was a lot of consensus between the farmers, and no real discussion points or disagreements became apparent. Although, no females took part of the FGD, it is assumed the information obtained and the trend of the answers given during the FGD provide a good indication for the entire population in the kebele. This assumption is assumed to be valid as only 13% of the household heads (in 2007) in the Lake Tana sub-basin is female (ADSWE, 2015a).

The major crops grown in Geregera (1786m amsl) are sorghum, teff, millet, rice and maize. The reason rice is grown by these farmers is because of the location close to the wetlands of Lake Tana. The average smallholder farmer household size is 8-10 persons, and has a mixed crop-livestock farming system, which means farmers grow crops and rear livestock simultaneously. The farmsize ranges from 0.5 to 3 hectares with 1 hectare on average.

The farmers define an average year as a year in which the onset of the kiremt rains start at the beginning of May and end in the 3rd week of September. In such a year the main crop grown by these farmers is maize. Besides growing crops, they also undertake off-farm activities during the entire year. This mostly consist of buying products, such as sugar, oil etc., from a wholesaler and selling it as a retailer at village level.

In contrast to an average year, a bad year is defined as a drought. The kiremt rains start late at the end of June and stop before mid September. The rainy season thus becomes very short. However, according to the farmers, such a year only occurs once every 10 years. In order to deal with a bad year farmers make use of irrigation. The farmers use water from the Gumara river to water their crops. By doing this they prevent themselves from having to food insecurity. However, whenever the Gumara river runs out of water, irrigation is not possible anymore, and they switch to other coping mechanisms. One of the options is to start growing vetch and chickpeas which can grow from residual moisture. Another option is to grow teff instead of maize, as teff has a shorter growth cycle. Instead of sowing maize in the 1st week of May, they now sow teff at the end of June when the onset of rains occur. The farmers thus change the crop type and the planting date. If no irrigation is possible and rainfall stays out, the farmers go for labour downstream instead of growing crops. They dig up sand from the river bed and sell it for 2000 - 4000 BIRR/vehicle (=10MT).

The decision making on what crop to grow and when is based on the farmer's own weather observations, such as clouds and wind. For example, cold northerly winds mean rainfall is coming and they expect early sowing. The farmers do not receive a weather forecast from an external organisation. However, in their opinion it would be very valuable to obtain a weather forecast. It would help them to better plan on whether to store, consume or sell their yield. They do not have to save their storage in case a bad year is coming. They can thus consume or sell their full production instead of saving it.

A.2. FGD 2: Jigena

The second FGD is conducted in Jigena (1790m amsl), which is located west of Geregera and even closer to the wetlands of Lake Tana compared to Geregera. It therefore is no surprise, one of the main crops is rice. Other crops grown are vetch, millet, teff, onion, and maize, of which the latter three are irrgiated crops. Maize and onion are grown on a different plot which is only used for irrigation. This field is used twice a year, first onion is grown whereafter it is swapped with maize. Rice is grown on a separate plot because this needs to be flooded most of the time.

Farmers in this Kebele do not experience rain shortage, and mention not to have been food insecure for the last 30 years. The main problem farmers face in this area is flooding instead of drought. This is because of Jigena being located in a low lying area close to Lake Tana and its wetlands. Therefore it is the ideal conditions for growing rice. However, due to extensive rainfall floodings can occur causing huge damage to the crops. Whenever such a flood occurs, the farmers demolish their crops, prepare the land again by ploughing and sow other crops like vetch and chickpea. Sowing of these crops mainly starts in October, sometimes September. The floodings are occuring every year, which is the reason farmers grow rice. Once every 4 to 5 years these floodings are extreme and the rice production is likely to fail. To prevent the rice production from failing, the farmers start building dikes. However, if this is not sufficient, they will demolish the crops, plough the land again after flooding has dissapeared, and start sowing other crops like legumes (e.g. vetch and chickpeas). An early warning system from the agricultural office at woreda level or the meteorological station tells the farmers via phone when such a flooding is expected to occur. Upon this information farmers start acting accordingly.

Only sometimes this area faces long dryspells (i.e. no rain for a month) in september. If such periods happen to occur, the farmers use additional irrigation to prevent crops to fail and obtain a good yield.

Throughout the year, farmers also undertaking off-farm activities besideds growing crops and rearing livestock. These activities encompass trading, owning a shop, brokery works (i.e. selling and buying products for others), maintenance of pumps, and making furniture from wood.

A.3. FGD 3: Shime Kebele

In Shime (2210m amsl) the main crop grown is teff. Other crops grown are maize, potato, barley, and sorghum. The major difference in types of crops grown compared to Jigena and Geregera is due to the difference in altitude. The farmers obtain weather information from extension agents, who on their turn receive information from meteorologists. This weather information contains forecasts on the onset of rains, soil moisture content, what seed to use (improved seeds), and the duration of rains. This information is provided starting in April until the agricultural practices come to an end. Farmers buy their seeds from farm associations. However, for teff there often is not enough seeds, which makes the appliance of teff seeds lower than desired (roughly 12 kg/ha).

In an average year the rains start at the beginning of May, and end at the end of September. In such years farmers encounter food insecurity in the months outside the growing season (i.e. December till March). During a bad year, which is defined as a drought, rains come late (June) and end early (end of August). The farmers mainly grow teff and potato since these crops have a short growth cycle. During a bad year food insecurity is experienced all year round, but most intense from July till September.

During an average year off-farm activities, such as building houses, are mainly practiced from June till January. In a bad year, no off-farm activities are practiced as there is almost no work available.

B

Individual Household Survey

B.1. Quantitative part

Question	Units
Name of enumerator	/
Name of the head of the household who is being interviewed	/
Date	/
GPS location	/
Name of the village	/
Woreda	/
Kebele	/
What is your age?	/
What is your gender?	/
What is the highest level of education you completed?	/
How large is your household (including yourself)?	persons / household
How many household members are outside the range of 15-65 years (including yourself)?	persons / household
How many years have you worked as a farmer since you are the head of the household?	years
How many persons from your household help you farm?	persons / household
How many days per week do you and your household members work on the farm?	mandays / week / household
How many employees do you have?	employees / household
How many days per week do your employees work on the farm?	mandays / week / employee
Do you grow crops?	/
Are you rearing livestock?	/
How many hours per day do you spend on on-farm cropping activities?	hours / day / person
How many hours per day do you spend on on-farm livestock activities?	hours / day / person
Do you work for another farmer?	/
How many days per week do you spend on off-farm agricultural activities?	days / week / person
How much do you earn if you work for another farm?	Birr / day / person

Question	Units
How many days per week do you spend on off-farm non-agricultural activities?	days / week / person
How much do you earn for off-farm non-agricultural activities?	Birr / day / person
How many hours per day do you spend on domestic household activities?	hours / day / person
How large is your total farm area in hectares?	ha / household
How large is the area on which you cultivate your crops in hectares?	ha / household
How large is the area on which you hold your livestock (grass area) in hectares?	ha / household
What crops do you grow?	/
Do you use irrigation?	/
For which crops do you use irrigation?	/
How high is your average yield of maize in quintals/hectare?	Qt/ha
How high is your minimum yield of maize in quintals/hectare?	Qt/ha
How high is your maximum yield of maize in quintals/hectare?	Qt/ha
How high is your average yield of teff in quintals/hectare?	Qt/ha
How high is your minimum yield of teff in quintals/hectare?	Qt/ha
How high is your maximum yield of teff in quintals/hectare?	Qt/ha
How high is your average yield of barley in quintals/hectare?	Qt/ha
How high is your minimum yield of barley in quintals/hectare?	Qt/ha
How high is your maximum yield of barley in quintals/hectare?	Qt/ha
How high is your average yield of sorghum in quintals/hectare?	Qt/ha
How high is your minimum yield of sorghum in quintals/hectare?	Qt/ha
How high is your maximum yield of sorghum in quintals/hectare?	Qt/ha
How high is your average yield of wheat in quintals/hectare?	Qt/ha
How high is your minimum yield of wheat in quintals/hectare?	Qt/ha
How high is your maximum yield of wheat in quintals/hectare?	Qt/ha
How high is your average yield of rice in quintals/hectare?	Qt/ha
How high is your minimum yield of rice in quintals/hectare?	Qt/ha
How high is your maximum yield of rice in quintals/hectare?	Qt/ha
How high is your average yield of millet in quintals/hectare?	Qt/ha
How high is your minimum yield of millet in quintals/hectare?	Qt/ha
How high is your maximum yield of millet in quintals/hectare?	Qt/ha
How high is your average yield of potatoes in quintals/hectare?	Qt/ha
How high is your minimum yield of potatoes in quintals/hectare?	Qt/ha
How high is your maximum yield of potatoes in quintals/hectare?	Qt/ha
How high is your average yield of onion in quintals/hectare?	Qt/ha
How high is your minimum yield of onion in quintals/hectare?	Qt/ha
How high is your maximum yield of onion in quintals/hectare?	Qt/ha
How high is the average maize consumption of the household in quintals/year?	Qt / year / household
How high is the average teff consumption of the household in quintals/year?	Qt / year / household
How high is the average barley consumption of the household in quintals/year?	Qt / year / household
How high is the average sorghum consumption of the household in quintals/year?	Qt / year / household
How high is the average wheat consumption of the household in quintals/year?	Qt / year / household
How high is the average rice consumption of the household in quintals/year?	Qt / year / household
How high is the average millet consumption of the household in quintals/year?	Qt / year / household

Question	Units
How high is the average potatoe consumption of the household in quintals/year?	Qt / year / household
How high is the average onion consumption of the household in quintals/year?	Qt / year / household
Does your maize production meet your family's food requirement?	/
Does your teff production meet your family's food requirement?	/
Does your barley production meet your family's food requirement?	/
Does your sorghum production meet your family's food requirement?	/
Does your wheat production meet your family's food requirement?	/
Does your rice production meet your family's food requirement?	/
Does your millet production meet your family's food requirement?	/
Does your potatoe production meet your family's food requirement?	/
Does your onion production meet your family's food requirement?	/
For how many months does your maize production cover your household's consumption?	months / year
For how many months does your teff production cover your household's consumption?	months / year
For how many months does your barley production cover your household's consumption?	months / year
For how many months does your sorghum production cover your household's consumption?	months / year
For how many months does your wheat production cover your household's consumption?	months / year
For how many months does your rice production cover your household's consumption?	months / year
For how many months does your millet production cover your household's consumption?	months / year
For how many months does your potatoes production cover your household's consumption?	months / year
For how many months does your onion production cover your household's consumption?	months / year
What is the distance to the closest market?	km
For how much do you sell your maize at the market in birr/kilogram?	Birr/kg
For how much do you sell your teff at the market in birr/kilogram?	Birr/kg
For how much do you sell your barley at the market in birr/kilogram?	Birr/kg
For how much do you sell your sorghum at the market in birr/kilogram?	Birr/kg
For how much do you sell your wheat at the market in birr/kilogram?	Birr/kg
For how much do you sell your rice at the market in birr/kilogram?	Birr/kg
For how much do you sell your millet at the market in birr/kilogram?	Birr/kg

Question	Units
For how much do you sell your potatoes at the market in birr/kilogram?	Birr/kg
For how much do you sell your onion at the market in birr/kilogram?	Birr/kg
What types of livestock do you have?	/
How many cattles do you have?	cattle / household
How many sheep do you have?	sheep / household
How many goats do you have?	goats / household
How many donkeys do you have?	donkeys / household
How many mules do you have?	mules / household
How much do you expend on one cattle in Birr/one year?	Birr/ cattle / year
How much do you expend on one sheep in Birr/one year?	Birr / sheep / year
How much do you expend on one goat in Birr/one year?	Birr / goat / year
How much do you expend on one donkey in Birr/one year?	Birr / donkey / year
How much do you expend on one mule in Birr/one year?	Birr / mule / year
How much is your income from one cattle in Birr/one year? (excluding selling of cattle)	Birr/ cattle / year
How much is your income from one sheep in Birr/one year? (excluding selling of sheep)	Birr / sheep / year
How much is your income from one goat in Birr/one year? (excluding selling of goats)	Birr / goat / year
How much is your income from one donkey in Birr/one year? (excluding selling of donkeys)	Birr / donkey / year
How much is your income from one mule in Birr/one year? (excluding selling of mules)	Birr / mule / year
What is the minimum price of one cattle in Birr/cattle?	Birr / cattle
What is the maximum price of one cattle in Birr/cattle?	Birr / cattle
What is the minimum price of one sheep in Birr/cattle?	Birr / sheep
What is the maximum price of one sheep in Birr/cattle?	Birr / sheep
What is the minimum price of one goat in Birr/goat?	Birr / goat
What is the maximum price of one goat in Birr/goat?	Birr / goat
What is the minimum price of one donkey in Birr/donkey?	Birr / donkey
What is the maximum price of one donkey in Birr/donkey?	Birr / donkey
What is the minimum price of one mule in Birr/mule?	Birr / mule
What is the maximum price of one mule in Birr/mule?	Birr / mule
Do you use chemicals or pesticides?	/
What type of chemicals or pesticides do you use?	/
If you use liquid chemicals, how much do you use in liter/year?	L / year / household
If you use powder chemicals, how much do you use in kilogram/year?	kg / year / household
Do you use fertilizer?	/
What type of fertilizer do you use?	/
How much fertilizer do you use on average in kilogram/year?	kg / year / household
How much maize seeds do you use each year on average in kilogram/hectare?	kg/ha
How much teff seeds do you use each year on average in kilogram/hectare?	kg/ha
How much barley seeds do you use each year on average in kilogram/hectare?	kg/ha
How much sorghum seeds do you use each year on average in kilogram/hectare?	kg/ha

Question	Units
How much wheat seeds do you use each year on average in kilogram/hectare?	kg/ha
How much rice seeds do you use each year on average in kilogram/hectare?	kg/ha
How much millet seeds do you use each year on average in kilogram/hectare?	kg/ha
How much potatoes seeds do you use each year on average in kilogram/hectare?	kg/ha
How much onion seeds do you use each year on average in kilogram/hectare?	kg/ha
Do you have access to extension services?	/
What type of extension services do you make use of?	/
What is your initial capital?	Birr / household
Do you borrow money?	/
How much money do you borrow?	Birr / household
If you experience food insecurity, do you sell as much livestock as needed to be able to have enough money to buy food?	/
How much do you spend on food in an average year?	Birr / household / year
How much do you pay your employees in Birr/day?	Birr / day / employee

Table B.1: The quantitative part of the household survey that is conducted with smallholder farmers in the Gumera sub-basin

B.2. Qualitative part

Climate change perception
Have you noticed any long term changes in the mean temperature over the last 30 years?
Have you noticed changes in the mean temperature over the last 10 years?
Have you noticed any long term changes in the annual amount of rainfall over the last 30 years?
Have you noticed any long term changes in the onset of the rainy season over the last 30 years?
Have you noticed any long term changes in the cessation of the rainy season over the last 30 years?
Have you noticed any long term changes in the duration of the rainy season over the last 30 years?
Have you noticed any long term changes in the number of dryspells over the last 30 years?
Indicate your perception on the year-to-year variability of the onset of the rainy season in the last 10 years:
Indicate your perception on the year-to-year variability of the total amount of rainfall in the last 10 years:
Indicate your perception on the year-to-year variability of the cessation of the rainy season in the last 10 years:
Indicate your perception on the year-to-year variability of the duration of the rainy season in the last 10 years:
Indicate your perception on the year-to-year variability of the number of dryspells in the rainy season in the last 10 years:
How important is the timing of the onset of the rainy season for getting a good yield?
How important is the amount of rainfall for getting a good yield?
How important is the timing of the cessation of the rainy season for getting a good yield?
How important is the duration of the rainy season for getting a good yield?
How important is it that there are no dryspells in the rainy season for getting a good yield?
How often does a bad year occur?
Do you face food insecurity in a bad year?

Weather information
Do you receive a weather forecast?
In what month do you receive the weather forecast?

Climate change perception
How often do you receive the weather forecast?
What does the weather forecast include?
Does the weather forecast influence your crop-related decisions?
What farming-related decisions get influenced by the weather forecast?
What are the constraints that prevent you from adjusting your decisions?
What information would you need in a weather forecast in order to be able to make better farming practice related decisions?
What would you do different in your farming practices if you would receive this weather information?

Adaptation strategies
Have you made adjustments in your farming practices in the last 30 years in order to cope with the long term changes in the rainy season?
Have you made adjustments in your farming practices in the last 10 years in order to cope with the year-to-year variabilities of the rainy season?
What adjustments have you made in your farming practices in the last 30 years in order to cope with the long term changes in the rainy season?
What adjustments have you made in your farming practices in order to cope with the year-to-year variability of the rainy season?
In what month do you plant your seeds during a bad year?
What is the reason you did not adjust your farming practices in the last 30 years in order to cope with the long term changes in the rainy season?
What is the reason you did not adjust your farming practices in the last 10 years in order to adapt to the year-to-year variability in the rainy season?
Are you reconsidering your farming practices every year again in order to cope with the year-to-year variability of the rainy season?
Upon what information do you base your farming practice decisions?
What additional adjustments to your farming practices would you consider in the future in order to cope with the year-to-year variability of the rainy season?
If you would receive a detailed weather forecast on the onset and duration of the rainy season, would you then change your crop type?
If you would receive a detailed weather forecast on the onset and duration of the rainy season, would you then change your planting and harvesting dates?

Table B.2: Qualitative part of the household survey that is conducted with smallholder farmers in the Gumera sub-basin.

B.3. Processed outliers

Prior to the actual analysis of the household survey, the dataset is checked inadequate surveys and errors, such as outliers. Outliers are either corrected or deleted as they can highly influence the outcome of the statistical analysis. Outliers are defined as data points that differ significantly from other observations. They can be introduced by wrongly interpreting the question, it can be a type, or it can be a right answer but from a very atypical or unique farmer that is not representing the rest of the population. In general farmers who do not grow crops are excluded from the dataset.

In total 441 household surveys were conducted. Each survey is checked on the percentage of questions filled in, and the time of completion. A share of the respondents only filled in less than 30% of the questions, hence these are removed from the dataset. All other surveys, answered at least 90% of the questions and are kept in. Furthermore, surveys that were completed within 10 minutes were assumed to be inaccurate and were removed from the dataset as well. In addition, two respondents were found not growing crops, hence both respondents are removed from the dataset. This resulted in a dataset containing 394 household surveys. After deletion of inadequate household surveys, each survey is checked for outliers.

Conversion errors

For some questions it is assumed conversion errors were made, as the answers were a factor 10 or 100 higher than the average observed. These cases were assumed to be conversion errors and were divided by 10 or 100, respectively, to correct for this. These conversion errors were observed in questions for crop yield, livestock prices, fertiliser use, and seed usage.

Errors on working days

In the household survey farmers were asked how many family members help on the farm, as well as how many days per week they together work on the farm. In some cases these questions were filled in such that a family member would work more than 7 days per week on the farm. If this was the case, the number of days a family member was working on the farm was set back to 7, which is the maximum possible. Hereby it is assumed that the number of family members working on the farm was filled in correctly.

Double answers

In the second part of the questionnaire questions are asked regarding the farmer's long term perception of changes in onset, cessation and duration of the rainy season. An example of such a question was: "Have you noticed any long term changes in the onset of the rainy season over the last 30 years?". Hereby, the farmer could answer with: "1. Yes, earlier onset", "2. Yes, later onset", or "3. No". Some farmers filled in both answer 1 and 2, which are opposite from each other.

C
Statistical analysis

In this appendix the statistical tests conducted to analyse the individual household survey and relevant variables (see Chapter 4) are explained. Hereby, the textbook of Julie Pallant is followed (Pallant and Manual, 2010).

C.1. Multiple Regression Analysis

In this section the assumptions that are needed to be met in order to conduct a multiple regression analysis (MRA) are explained, as well as all variables incorporated. Subsequently, the output of each MRA is presented.

C.1.1. Assumptions of MRA

Prior to each multiple linear regression analysis, preliminary analyses were conducted to ensure no violation of the assumptions of normality, linearity, multicollinearity, and homoscedasticity. Each of these assumptions are explained below.

Outliers

Outliers are defined as data points that differ significantly from other observations. They can be detected from the a scatterplot of the standardised residuals. Each case that shows a standardised residual of more than 3.3 or less than -3.3 is considered to be an outlier. The "Casewise Diagnostics" table presents each of these outliers. In the sample is normally distributed, not more than 1% of the cases is expected to fall out fall outside of this range. The influence of the outlier on the results of the model can be checked by the value of Cook's Distance, which is shown in the bottom of the "Residuals Statistics" table. Each case with a value large than 1 can be assumed to be a potential problem, and is removed from the dataset.

Homoscedasticity

Homoscedasticity, or homogeneity of variances, refers to whether the residuals are equally distributed, or whether they tend to bunch together at some values, and at other values, spread far apart. The data is homoscedastic if the residuals are randomly distributed in the scatterplot of standardised residuals. The opposite of homoscedasticity is heteroscedasticity, which is the case if the scatterplot shows a cone or fan shape.

Linearity, and Normality

Linearity and normality are checked with the Normal Probability Plot of the Regression Standard Residual (P-P plot) and the Scatterplot. The residuals are simply the error terms, or the differences between the observed value of the dependent variable and the predicted value. If the residuals lie in a reasonable straight line from bottom left to top right, it can be assumed the residuals to be normally distributed. Only if there are drastic deviations this assumption is violated. Linearity means that the predictor variables in the regression have a linear relationship with the outcome variable. In most cases linearity can be assumed if the residuals are normally distributed and homoscedastic.

Multicollinearity

Multicollinearity exists when the independent variables are highly correlated (i.e. $r > 0.9$). This can be checked by the values of Tolerance and VIF. Tolerance is an indicator of how much of the variability of the specified independent variable is not explained by the other independent variables in the model is calculated using the formula 1 - R-squared for each variable. If this value is smaller than 0.10 it indicates that the multiple correlation with other variables is high, suggesting the possibility of multicollinearity. The other value given is the VIF (Variance inflation factor), which is the inverse of the Tolerance value. VIF values above 10 would be a concern here, indicating multicollinearity.

C.1.2. MRA: Barley Yield

For barley none of the assumptions are violated. The scatterplot of residuals (see Figure C.8) does not show any values outside the range of -3.3 and 3.3. Hence, it is assumed no outliers are present in the dataset that might violate the outcome of the model. In addition, homoscedasticity can be assumed since the residuals do not show a particular shape. Although the residuals show some deviation from the straight diagonal line in the P-P plot (see Figure C.7) no drastic deviations are present. Hence, normality is assumed. Therefore, since normality and homoscedasticity are assumed, also linearity can be assumed. At last, the coefficients table (see Table C.4) shows the tolerance and VIF values of each variable included in the model. The tolerance values are within 0.868 and 1, and thus remain above the minimum threshold of 0.1, whereas the VIF values range from 1 to 1.152, and thus remain below the maximum threshold of 10. Hence, multicollinearity is not present in the model.

Descriptive Statistics

	Mean	Std. Deviation	N
Barley yield	21.57471	6.949372	87
Elevation	2320.20	167.968	87
Education	1.47	.713	87
Experience	30.51	10.403	87
Household farmers	4.218	1.5621	87
Crop area	1.21575	.644663	87
Barley irrigation	.02	.151	87
Market distance	3.420	1.9483	87
Livestock (TLU)	3.554022989	1.816513694	87
Chemical use (liquid)	.8190	.50533	87
Chemical use (powder)	.3603	.42455	87
Fertiliser ues	277.8160920	100.1211509	87
Barley seeds	194.17	78.911	87
Capital	14798.85	7265.905	87
Borrowing money	.08	.274	87
Weather forecast	.43	.497	87
Climate adaptation	.80	.399	87

Figure C.1: "Descriptive statistics" table: the descriptive statistics, including the mean and standard deviation, for the dependent variable, barley yield, and all independent variables taken into account in the MRA.

Model Summary[d]

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.523[a]	.274	.265	5.955848	.274	32.085	1	85	.000
2	.638[b]	.406	.392	5.417450	.132	18.734	1	84	.000
3	.672[c]	.452	.432	5.237345	.045	6.877	1	83	.010

a. Predictors: (Constant), Climate adaptation

b. Predictors: (Constant), Climate adaptation, Fertiliser ues

c. Predictors: (Constant), Climate adaptation, Fertiliser ues, Household farmers

d. Dependent Variable: Barley yield

Figure C.2: "Model Summary" table: a summary of the model containing the significant predictors for barley yield, namely climate adaptation, fertiliser use, and labour availability, with R^2 = 0.45. Together, these three variables account for 45% of the variance in barley yield.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1138.134	1	1138.134	32.085	.000[b]
	Residual	3015.130	85	35.472		
	Total	4153.264	86			
2	Regression	1687.968	2	843.984	28.757	.000[c]
	Residual	2465.296	84	29.349		
	Total	4153.264	86			
3	Regression	1876.593	3	625.531	22.805	.000[d]
	Residual	2276.672	83	27.430		
	Total	4153.264	86			

a. Dependent Variable: Barley yield

b. Predictors: (Constant), Climate adaptation

c. Predictors: (Constant), Climate adaptation, Fertiliser ues

d. Predictors: (Constant), Climate adaptation, Fertiliser ues, Household farmers

Figure C.3: "ANOVA" table: the overall regression model was significant, $F(3, 83) = 22.81$, $p < 0.001$, $R^2 = 0.45$.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	14.235	1.445		9.855	.000	11.363	17.107					
	Climate adaptation	9.122	1.610	.523	5.664	.000	5.920	12.324	.523	.523	.523	1.000	1.000
2	(Constant)	22.418	2.302		9.737	.000	17.840	26.996					
	Climate adaptation	7.847	1.494	.450	5.252	.000	4.875	10.818	.523	.497	.441	.961	1.040
	Fertiliser ues	-.026	.006	-.371	-4.328	.000	-.038	-.014	-.460	-.427	-.364	.961	1.040
3	(Constant)	18.168	2.753		6.598	.000	12.691	23.644					
	Climate adaptation	6.753	1.504	.388	4.491	.000	3.762	9.743	.523	.442	.365	.887	1.127
	Fertiliser ues	-.023	.006	-.328	-3.876	.000	-.034	-.011	-.460	-.392	-.315	.924	1.082
	Household farmers	1.018	.388	.229	2.622	.010	.246	1.789	.430	.277	.213	.868	1.152

a. Dependent Variable: Barley yield

Figure C.4: "Coefficients" table showing the direction and value of the significant predictors for barley yield. In addition, the tolerance and VIF values are shown, and exceed the thresholds of 0.1 and 10, respectively. Hence, there is no violation of multicollinearity in the model.

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	9.10050	30.39740	22.36448	5.041817	187
Std. Predicted Value	-2.670	1.889	.169	1.079	187
Standard Error of Predicted Value	.635	3.990	1.129	.407	187
Adjusted Predicted Value	9.10050	30.39740	22.37054	5.033566	187
Residual	-14.123013	14.323798	1.324428	5.473995	187
Std. Residual	-2.697	2.735	.253	1.045	187
Stud. Residual	-2.657	2.714	.244	1.040	187
Deleted Residual	-14.123013	14.367772	1.318367	5.577400	187
Stud. Deleted Residual	-2.761	2.751	.245	1.047	187
Mahal. Distance	.270	30.959	3.283	3.377	187
Cook's Distance	.000	.174	.015	.025	187
Centered Leverage Value	.003	.356	.038	.039	187

a. Dependent Variable: Barley yield

Figure C.5: "Residuals Statistics" table

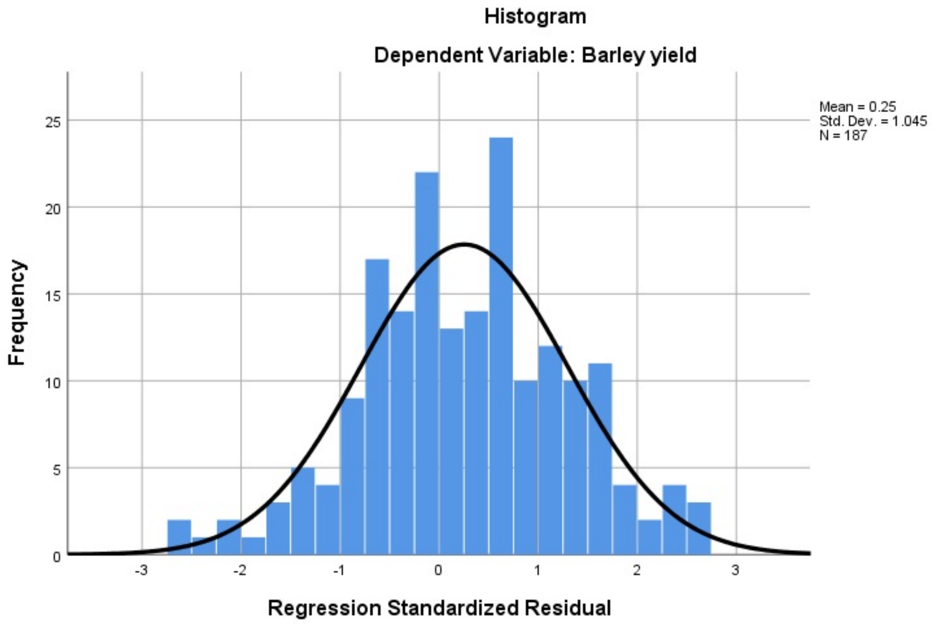

Figure C.6: A histogram showing a normal distribution of the standardised residuals for the dependent variable, barley yield, with sample size = 187, mean = 0.25 and standard deviation = 1.045.

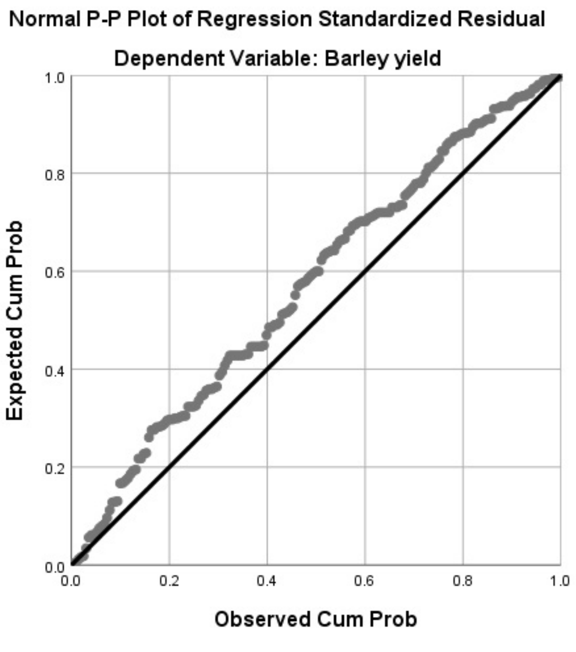

Figure C.7: A P-P plot showing the residuals for the dependent variable, barley yield. No major deviations are apparent, hence normality can be assumed.

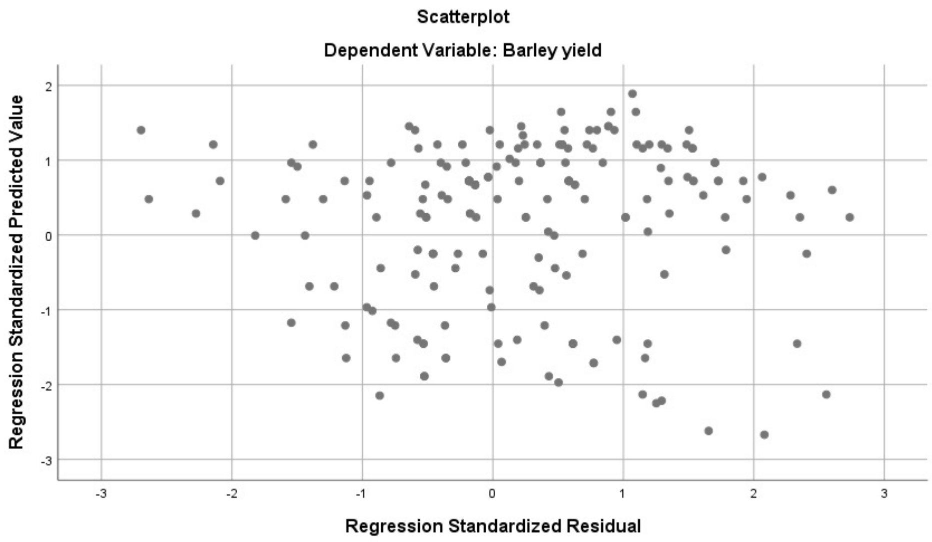

Figure C.8: A scatterplot of the standardised residuals. Since none of the standardised residuals are outside the range of -3.3 and 3.3, it can be assumed there are no outliers present.

C.1.3. MRA: Maize Yield

Below the output of the MRA conducted with maize yield as the dependent variables is shown. For maize none of the assumptions are violated. The scatterplot of residuals (see Figure C.15) shows a few values outside the range of -3.3 and 3.3, from which the statistics are shown in Table C.13. However, since the Cook's Distance indicated in Table C.14 is 0.131, and thus lower than 1, it is assumed the outliers are not causing any problems for the outcome of the model. Furthermore, homoscedasticity can be assumed since the residuals do not show a particular shape in the scatterplot (see Figure C.15). Also normality can be assumed, since the residuals barely show any deviation from the straight diagonal line in the P-P plot (see Figure C.17). Therefore, since normality and homoscedasticity are assumed, also linearity can be assumed. At last, the coefficients table (see Table C.12) shows the tolerance and VIF values of each variable included in the model. The tolerance values of the final model are within 0.781 and 0.915, and thus remain above the minimum threshold of 0.1, whereas the VIF values range from 1.093 to 1.280, and thus remain below the maximum threshold of 10. Hence, multicollinearity is not present in the model.

Descriptive Statistics

	Mean	Std. Deviation	N
Maize yield	30.89380531	8.661396174	226
Elevation	2202.38	253.373	226
Education	1.57	.842	226
Experience	26.08	11.830	226
Household farmers	4.467	1.6364	226
Crop area	1.12168	.582179	226
Irrigation	.23	.425	226
Market	5.686	4.0994	226
TLU	3.977433628	1.877888781	226
Chemical use (liquid)	1.3993	1.18114	226
Chemical use (powder)	1.3290	2.47284	226
Fertilizer use	370.3883136	181.9841924	226
Maize seeds	26.2221	7.94995	226
Capital	16659.29	9930.932	226
Borrowing money	.21	.410	226
Weather forecast	.40	.491	226
Climate adaptation	.88	.330	226

Figure C.9: "Descriptive statistics" table: the descriptive statistics, including the mean and standard deviation, for the dependent variable, maize yield, and all independent variables taken into account in the MRA.

Model Summary[e]

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.408[a]	.167	.163	7.923471524	.167	44.861	1	224	.000
2	.473[b]	.224	.217	7.666443327	.057	16.272	1	223	.000
3	.504[c]	.254	.244	7.533248507	.030	8.955	1	222	.003
4	.517[d]	.268	.254	7.479536605	.014	4.200	1	221	.042

a. Predictors: (Constant), Weather forecast

b. Predictors: (Constant), Weather forecast, Crop area

c. Predictors: (Constant), Weather forecast, Crop area, Market

d. Predictors: (Constant), Weather forecast, Croparea, Market, Climate adaptation

e. Dependent Variable: Maize yield

Figure C.10: "Model Summary" table: a summary of the model containing the significant predictors for maize yield, namely access to a weather forecast, crop area, market distance, and climate adaptation, with $R^2 = 0.27$. Together, these four variables account for 27% of the variance in maize yield.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2816.418	1	2816.418	44.861	.000[b]
	Residual	14063.034	224	62.781		
	Total	16879.451	225			
2	Regression	3772.771	2	1886.385	32.095	.000[c]
	Residual	13106.681	223	58.774		
	Total	16879.451	225			
3	Regression	4280.988	3	1426.996	25.145	.000[d]
	Residual	12598.463	222	56.750		
	Total	16879.451	225			
4	Regression	4515.945	4	1128.986	20.181	.000[e]
	Residual	12363.506	221	55.943		
	Total	16879.451	225			

a. Dependent Variable: Maize yield

b. Predictors: (Constant), Weather forecast

c. Predictors: (Constant), Weather forecast, Crop area

d. Predictors: (Constant), Weather forecast, Crop area, Market distance

e. Predictors: (Constant), Weather forecast, Crop area, Market distance, Climate adaptation

Figure C.11: "ANOVA" table: the overall regression model was significant, $F(4, 221) = 20.18$, $p < 0.001$, $R^2 = 0.27$.

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	28.022	.679		41.243	.000	26.683	29.361					
	Weather forecast	7.211	1.077	.408	6.698	.000	5.090	9.333	.408	.408	.408	1.000	1.000
2	(Constant)	24.414	1.110		21.995	.000	22.227	26.602					
	Weather forecast	5.505	1.124	.312	4.896	.000	3.289	7.721	.408	.312	.289	.858	1.165
	Crop area	3.822	.948	.257	4.034	.000	1.955	5.689	.374	.261	.238	.858	1.165
3	(Constant)	27.284	1.452		18.788	.000	24.422	30.146					
	Weather forecast	6.009	1.118	.340	5.377	.000	3.807	8.212	.408	.339	.312	.839	1.192
	Crop area	3.021	.969	.203	3.118	.002	1.112	4.930	.374	.205	.181	.793	1.261
	Market distance	-.382	.128	-.181	-2.993	.003	-.633	-.130	-.214	-.197	-.174	.922	1.085
4	(Constant)	25.025	1.815		13.789	.000	21.449	28.602					
	Weather forecast	5.449	1.143	.309	4.768	.000	3.197	7.701	.408	.305	.275	.791	1.264
	Crop area	2.782	.969	.187	2.871	.004	.873	4.692	.374	.190	.165	.781	1.280
	Market distance	-.404	.127	-.191	-3.174	.002	-.654	-.153	-.214	-.209	-.183	.915	1.093
	Climate adaptation	3.279	1.600	.125	2.049	.042	.126	6.432	.246	.137	.118	.891	1.122

a. Dependent Variable: Maize yield

Figure C.12: "Coefficients" table showing the direction and value of the significant predictors for maize yield. In addition, the tolerance and VIF values are shown, and exceed the thresholds of 0.1 and 10, respectively. Hence, there is no violation of multicollinearity in the model.

Casewise Diagnostics[a]

Case Number	Std. Residual	Maize yield	Predicted Value	Residual
9	3.459	52.00000000	26.13066681	25.86933319
151	3.547	58.00000000	31.46821105	26.53178895
222	3.272	60.00000000	35.52613055	24.47386945
223	3.179	60.00000000	36.22166115	23.77833885
246	-3.004	9.000000000	31.46821105	-22.4682110

a. Dependent Variable: Maize yield

Figure C.13: "Casewise Diagnostics" table showing all outliers in the model with the dependent variable maize yield.

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	23.08415222	43.87249756	30.68430670	4.209285222	388
Std. Predicted Value	-1.743	2.897	-.047	.940	388
Standard Error of Predicted Value	.754	3.498	1.086	.377	388
Adjusted Predicted Value	23.42707062	43.87249756	30.68735642	4.210259425	388
Residual	-22.4682102	26.53178978	.0397520188	7.209265655	388
Std. Residual	-3.004	3.547	.005	.964	388
Stud. Residual	-3.026	3.526	.007	.965	388
Deleted Residual	-22.8022518	26.88280296	.0367023016	7.300860705	388
Stud. Deleted Residual	-3.084	3.621	.007	.970	388
Mahal. Distance	1.279	39.557	4.211	4.352	388
Cook's Distance	.000	.097	.004	.010	388
Centered Leverage Value	.006	.175	.019	.019	388

a. Dependent Variable: Maize yield

Figure C.14: "Residual Statistics" table showing the statistics of the residuals. Cook's Distance is 0.097, from which it can be concluded that the outliers are no potential problem for the outcome of the MRA.

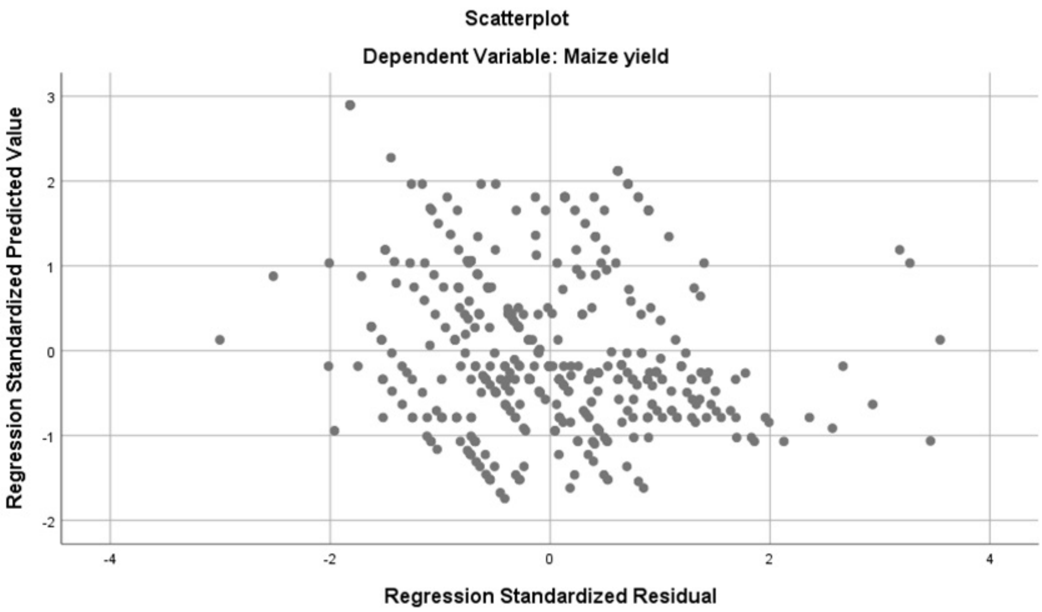

Figure C.15: A scatterplot of the standardised residuals, showing only few standardised residuals are outside the range of -3.3 and 3.3.

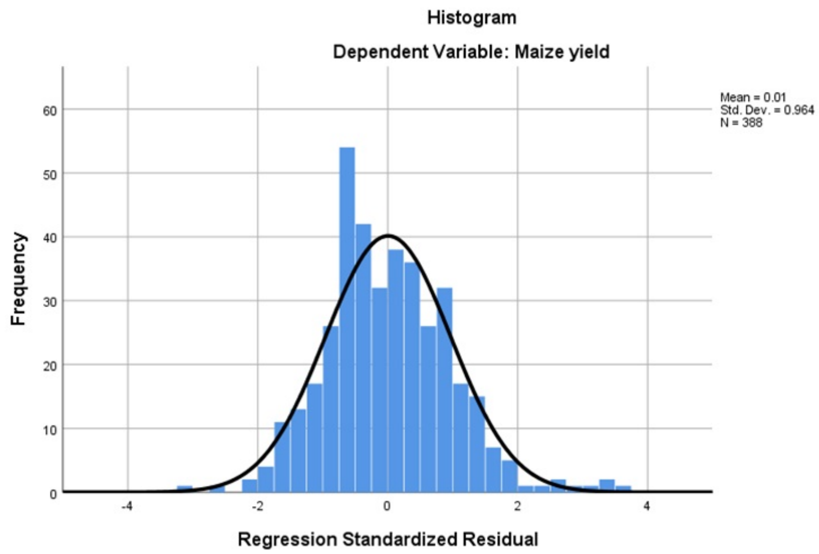

Figure C.16: A histogram showing a normal distribution of the standardised residuals for the dependent variable, maize yield, with sample size = 388, mean = 0.01 and standard deviation = 0.964.

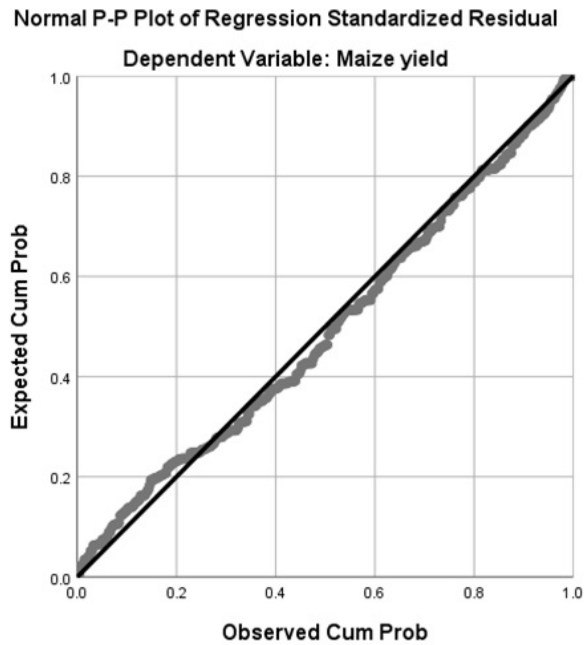

Figure C.17: A P-P plot showing the residuals for the dependent variable, maize yield. No major deviations are apparent, hence normality can be assumed.

C.1.4. MRA: Potato Yield

Below the output of the MRA conducted with potato yield as the dependent variables is shown. For potato none of the assumptions are violated. The scatterplot of residuals (see Figure C.26) shows a few values outside the range of -3.3 and 3.3, from which the statistics are shown in Table C.22. However, since the Cook's Distance indicated in Table C.23 is 0.160, and thus lower than 1, it is assumed the outliers are not causing any problems for the outcome of the model. Although, the scatterplot of residuals does not show a complete random distribution, it also does not show a clear shape (see Figure C.26). Hence, homoscedasticity is assumed. Also normality can be assumed, since the residuals barely show any deviation from the straight diagonal line in the P-P plot (see Figure C.25). Therefore, since normality and homoscedasticity are assumed, also linearity can be assumed. At last, the coefficients table (see Table C.21) shows the tolerance and VIF values of each variable included in the model. The tolerance values of the final model are within 0.639 and 0.876, and thus remain above the minimum threshold of 0.1, whereas the VIF values range from 1.191 to 1.566, and thus remain below the maximum threshold of 10. Hence, multicollinearity is not present in the model.

Descriptive Statistics

	Mean	Std. Deviation	N
Potato yield	150.9157895	57.56692001	95
Elevation	2386.94	145.489	95
Education	1.66	.678	95
Experience	31.42	11.268	95
Household farmers	4.374	1.5281	95
Crop area	1.38200	.682395	95
Market distance	3.816	2.2134	95
Livestock (TLU)	3.787368421	1.678603910	95
Chemical use (liquid)	.9263	.37166	95
Chemical use (powder)	.1985	.33515	95
Fertiliser use	285.2631579	110.0951436	95
Capital	14342.11	6566.057	95
Borrowing money	.16	.367	95
Weather forecast	.49	.503	95
Climate adaptation	.97	.176	95
Potato irrigation	.46	.501	95
Potato seeds	2120.42	1062.696	95

Figure C.18: "Descriptive statistics" table: the descriptive statistics, including the mean and standard deviation, for the dependent variable, potato yield, and all independent variables taken into account in the MRA.

Model Summary[f]

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.496[a]	.246	.238	50.24255075	.246	30.404	1	93	.000
2	.561[b]	.314	.300	48.17851448	.068	9.139	1	92	.003
3	.600[c]	.360	.339	46.81293813	.045	6.446	1	91	.013
4	.634[d]	.401	.375	45.51837476	.042	6.250	1	90	.014
5	.667[e]	.445	.414	44.07145419	.044	7.007	1	89	.010

a. Predictors: (Constant), Weather forecast

b. Predictors: (Constant), Weather forecast, Potato irrigation

c. Predictors: (Constant), Weather forecast, Potato irrigation, Chemical use (liquid)

d. Predictors: (Constant), Weather forecast, Potato irrigation, Chemical use (liquid), Experience

e. Predictors: (Constant), Weather forecast, Potato irrigation, Chemical use (liquid), Experience, Potato seeds

f. Dependent Variable: Potato yield

Figure C.19: "Model Summary" table: a summary of the model containing the significant predictors for potato yield, namely access to a weather forecast, irrigation, chemical use, experience, and seed use, with $R^2 = 0.45$. Together, these five variables account for 45% of the variance in potato yield.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	76750.133	1	76750.133	30.404	.000[b]
	Residual	234761.193	93	2524.314		
	Total	311511.326	94			
2	Regression	97963.755	2	48981.877	21.102	.000[c]
	Residual	213547.572	92	2321.169		
	Total	311511.326	94			
3	Regression	112089.269	3	37363.090	17.049	.000[d]
	Residual	199422.057	91	2191.451		
	Total	311511.326	94			
4	Regression	125038.307	4	31259.577	15.087	.000[e]
	Residual	186473.020	90	2071.922		
	Total	311511.326	94			
5	Regression	138647.243	5	27729.449	14.277	.000[f]
	Residual	172864.084	89	1942.293		
	Total	311511.326	94			

a. Dependent Variable: Potato yield

b. Predictors: (Constant), Weather forecast

c. Predictors: (Constant), Weather forecast, Potato irrigation

d. Predictors: (Constant), Weather forecast, Potato irrigation, Chemical use (liquid)

e. Predictors: (Constant), Weather forecast, Potato irrigation, Chemical use (liquid), Experience

f. Predictors: (Constant), Weather forecast, Potato irrigation, Chemical use (liquid), Experience, Potato seeds

Figure C.20: "ANOVA" table: the overall regression model was significant, F(5, 89) = 14.277, $p < 0.001$, $R^2 = 0.45$.

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	95.0% Confidence Interval for B Upper Bound	Correlations Zero-order	Correlations Partial	Correlations Part	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	179.042	7.252		24.689	.000	164.641	193.442					
	Weather forecast	-56.850	10.310	-.496	-5.514	.000	-77.324	-36.376	-.496	-.496	-.496	1.000	1.000
2	(Constant)	196.251	8.987		21.838	.000	178.402	214.100					
	Weather forecast	-62.993	10.093	-.550	-6.241	.000	-83.040	-42.947	-.496	-.545	-.539	.959	1.042
	Potato irrigation	-30.594	10.120	-.266	-3.023	.003	-50.694	-10.495	-.156	-.301	-.261	.959	1.042
3	(Constant)	166.978	14.463		11.545	.000	138.249	195.708					
	Weather forecast	-70.640	10.259	-.617	-6.886	.000	-91.019	-50.261	-.496	-.585	-.578	.877	1.141
	Potato irrigation	-28.812	9.858	-.251	-2.923	.004	-48.395	-9.230	-.156	-.293	-.245	.955	1.048
	Chemical use (liquid)	34.794	13.705	.225	2.539	.013	7.571	62.017	.065	.257	.213	.899	1.113
4	(Constant)	196.104	18.262		10.738	.000	159.823	232.385					
	Weather forecast	-58.919	11.022	-.514	-5.345	.000	-80.817	-37.021	-.496	-.491	-.436	.718	1.392
	Potato irrigation	-26.279	9.639	-.229	-2.726	.008	-45.429	-7.129	-.156	-.276	-.222	.944	1.059
	Chemical use (liquid)	35.269	13.327	.228	2.646	.010	8.792	61.745	.065	.269	.216	.898	1.113
	Experience	-1.163	.465	-.228	-2.500	.014	-2.087	-.239	-.420	-.255	-.204	.802	1.246
5	(Constant)	178.159	18.937		9.408	.000	140.532	215.786					
	Weather forecast	-48.944	11.318	-.427	-4.324	.000	-71.432	-26.456	-.496	-.417	-.341	.639	1.566
	Potato irrigation	-35.002	9.897	-.305	-3.536	.001	-54.668	-15.336	-.156	-.351	-.279	.839	1.191
	Chemical use (liquid)	29.810	13.067	.192	2.281	.025	3.845	55.774	.065	.235	.180	.876	1.141
	Experience	-1.334	.455	-.261	-2.933	.004	-2.238	-.430	-.420	-.297	-.232	.786	1.272
	Potato seeds	.013	.005	.239	2.647	.010	.003	.023	.264	.270	.209	.763	1.311

a. Dependent Variable: Potato yield

Figure C.21: "Coefficients" table showing the direction and value of the significant predictors for potato yield. In addition, the tolerance and VIF values are shown, and exceed the thresholds of 0.1 and 10, respectively. Hence, there is no violation of multicollinearity in the model.

Casewise Diagnostics[a]

Case Number	Std. Residual	Potato yield	Predicted Value	Residual
16	-3.537	50.00000000	205.8812547	-155.881255
271	3.043	290.0000000	155.9008698	134.0991302
360	4.271	290.0000000	101.7705944	188.2294056

a. Dependent Variable: Potato yield

Figure C.22: "Casewise Diagnostics" table showing all outliers in the model with the dependent variable potato yield.

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	61.97080231	227.2691040	157.6684981	36.74902072	143
Std. Predicted Value	-2.316	1.988	.176	.957	143
Standard Error of Predicted Value	7.570	22.320	10.978	2.666	143
Adjusted Predicted Value	56.10955429	238.2202606	157.8223711	37.18162328	143
Residual	-155.881256	188.2294006	-4.33496204	47.78796900	143
Std. Residual	-3.537	4.271	-.098	1.084	143
Stud. Residual	-3.608	4.188	-.097	1.094	143
Deleted Residual	-162.225845	188.2294006	-4.48883510	50.06255582	143
Stud. Deleted Residual	-3.883	4.188	-.098	1.107	143
Mahal. Distance	1.784	23.121	5.034	3.225	143
Cook's Distance	.000	.160	.016	.029	143
Centered Leverage Value	.019	.246	.053	.034	143

a. Dependent Variable: Potato yield

Figure C.23: "Residual Statistics" table showing the statistics of the residuals. Cook's Distance is 0.160, from which it can be concluded that the outliers are no potential problem for the outcome of the MRA.

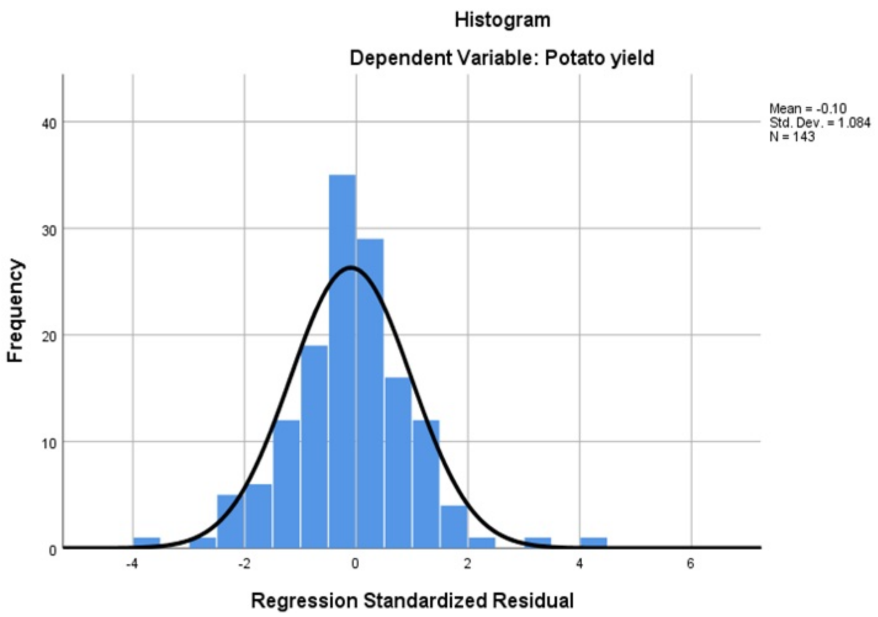

Figure C.24: A histogram showing a normal distribution of the standardised residuals for the dependent variable, potato yield, with sample size = 143, mean = -0.10 and standard deviation = 1.084.

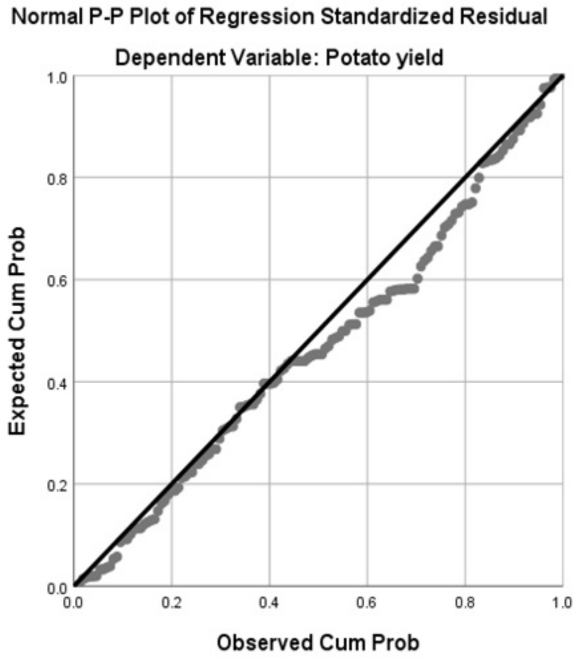

Figure C.25: A P-P plot showing the residuals for the dependent variable, potato yield. No major deviations are apparent, hence normality can be assumed.

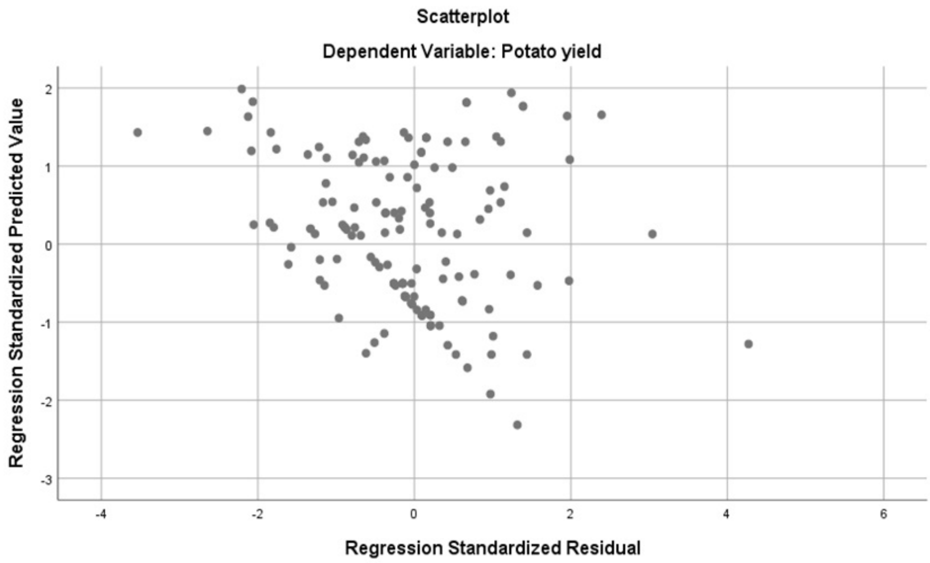

Figure C.26: A scatterplot of the standardised residuals, showing few of the standardised residuals to be outside the range of -3.3 and 3.3.

C.1.5. MRA: Teff yield

Below the output of the MRA conducted with teff yield as the dependent variables is shown. For teff none of the assumptions are violated. The scatterplot of residuals (see Figure C.35) shows a few values outside the range of -3.3 and 3.3, from which the statistics are shown in Table C.30. However, since the Cook's Distance indicated in Table C.32 is 0.617, and thus lower than 1, it is assumed the outliers are not causing any problems for the outcome of the model. In addition, homoscedasticity can be assumed since the residuals do not show a particular shape. The residuals in the P-P plot follow the straight diagonal line rather well, without showing major deviations (see Figure C.34). Hence, normality is assumed. Therefore, since normality and homoscedasticity are assumed, also linearity can be assumed. At last, the coefficients table (see Table C.31) shows the tolerance and VIF values of each variable included in the model. The tolerance values of the final model are within 0.465 and 0.888, and thus remain above the minimum threshold of 0.1, whereas the VIF values range from 1.126 to 2.152, and thus remain below the maximum threshold of 10. Hence, multicollinearity is not present in the model.

Descriptive Statistics

	Mean	Std. Deviation	N
Teff yield	13.51373626	5.564893738	182
Elevation	2282.32	216.068	182
Education	1.57	.803	182
Experience	28.30	11.178	182
Household farmers	4.522	1.6924	182
Crop area	1.19368	.599252	182
Market distance	4.725	3.4655	182
Livestock (TLU)	3.924725275	1.814244948	182
Chemical use (liquid)	1.0591	.89212	182
Chemical use (powder)	.6805	1.63695	182
Fertiliser use	332.8021978	153.2172631	182
Capital	15604.40	9094.658	182
Borrowing money	.20	.404	182
Weather forecast	.37	.484	182
Climate adaptation	.85	.356	182
Teff irrigation	.07	.249	182
Teff seeds	42.269	30.3617	182

Figure C.27: "Descriptive statistics" table: the descriptive statistics, including the mean and standard deviation, for the dependent variable, teff yield, and all independent variables taken into account in the MRA.

Model Summary[g]

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.691[a]	.477	.474	4.034081991	.477	164.432	1	180	.000
2	.738[b]	.544	.539	3.777359931	.067	26.298	1	179	.000
3	.766[c]	.586	.579	3.609345916	.042	18.053	1	178	.000
4	.791[d]	.626	.618	3.439740253	.040	18.986	1	177	.000
5	.801[e]	.642	.631	3.378835146	.015	7.439	1	176	.007
6	.807[f]	.651	.639	3.343390936	.009	4.751	1	175	.031

a. Predictors: (Constant), Weather forecast

b. Predictors: (Constant), Weather forecast, Fertiliser use

c. Predictors: (Constant), Weather forecast, Fertiliser use, Chemical use (liquid)

d. Predictors: (Constant), Weather forecast, Fertiliser use, Chemical use (liquid), Crop area

e. Predictors: (Constant), Weather forecast, Fertiliser use, Chemical use (liquid), Crop area, Experience

f. Predictors: (Constant), Weather forecast, Fertiliser use, Chemical use (liquid), Crop area, Experience, Capital

g. Dependent Variable: Teff yield

Figure C.28: "Model Summary" table: a summary of the model containing the significant predictors for teff yield, namely access to a weather forecast, fertiliser use, chemical use, crop area, experience, and capital, with R^2 = 0.65. Together, these three variables account for 65% of the variance in teff yield.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2675.929	1	2675.929	164.432	.000[b]
	Residual	2929.287	180	16.274		
	Total	5605.216	181			
2	Regression	3051.163	2	1525.582	106.920	.000[c]
	Residual	2554.052	179	14.268		
	Total	5605.216	181			
3	Regression	3286.342	3	1095.447	84.088	.000[d]
	Residual	2318.873	178	13.027		
	Total	5605.216	181			
4	Regression	3510.985	4	877.746	74.185	.000[e]
	Residual	2094.231	177	11.832		
	Total	5605.216	181			
5	Regression	3595.907	5	719.181	62.995	.000[f]
	Residual	2009.309	176	11.417		
	Total	5605.216	181			
6	Regression	3649.020	6	608.170	54.406	.000[g]
	Residual	1956.196	175	11.178		
	Total	5605.216	181			

a. Dependent Variable: Teff yield

b. Predictors: (Constant), Weather forecast

c. Predictors: (Constant), Weather forecast, Fertiliser use

d. Predictors: (Constant), Weather forecast, Fertiliser use, Chemical use (liquid)

e. Predictors: (Constant), Weather forecast, Fertiliser use, Chemical use (liquid), Crop area

f. Predictors: (Constant), Weather forecast, Fertiliser use, Chemical use (liquid), Crop area, Experience

g. Predictors: (Constant), Weather forecast, Fertiliser use, Chemical use (liquid), Crop area, Experience, Capital

Figure C.29: "ANOVA" table: the overall regression model was significant, $F(6, 175) = 54.406$, $p < 0.001$, $R^2 = 0.65$.

Casewise Diagnostics[a]

Case Number	Std. Residual	Teff yield	Predicted Value	Residual
155	3.144	14.00000000	3.487817685	10.51218231
186	3.064	20.00000000	9.756553280	10.24344672
226	-3.105	7.000000000	17.37978068	-10.3797807

a. Dependent Variable: Teff yield

Figure C.30: "Casewise Diagnostics" table showing all outliers in the model with the dependent variable teff yield.

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	95.0% Confidence Interval for B Upper Bound	Correlations Zero-order	Correlations Partial	Correlations Part	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	10.587	.376		28.143	.000	9.845	11.329					
	Weather forecast	7.950	.620	.691	12.823	.000	6.727	9.174	.691	.691	.691	1.000	1.000
2	(Constant)	13.661	.695		19.648	.000	12.289	15.033					
	Weather forecast	8.106	.581	.705	13.944	.000	6.959	9.254	.691	.722	.704	.997	1.003
	Fertiliser use	-.009	.002	-.259	-5.128	.000	-.013	-.006	-.222	-.358	-.259	.997	1.003
3	(Constant)	14.274	.680		20.996	.000	12.933	15.616					
	Weather forecast	6.863	.628	.596	10.932	.000	5.624	8.102	.691	.634	.527	.781	1.281
	Fertiliser use	-.016	.002	-.432	-6.842	.000	-.020	-.011	-.222	-.456	-.330	.584	1.712
	Chemical use (liquid)	1.822	.429	.292	4.249	.000	.976	2.669	.268	.303	.205	.492	2.034
4	(Constant)	12.393	.779		15.917	.000	10.856	13.929					
	Weather forecast	5.373	.689	.467	7.796	.000	4.013	6.733	.691	.506	.358	.588	1.700
	Fertiliser use	-.017	.002	-.477	-7.813	.000	-.022	-.013	-.222	-.506	-.359	.567	1.763
	Chemical use (liquid)	2.209	.418	.354	5.282	.000	1.384	3.035	.268	.369	.243	.469	2.130
	Crop area	2.148	.493	.231	4.357	.000	1.175	3.121	.445	.311	.200	.749	1.335
5	(Constant)	10.843	.953		11.381	.000	8.963	12.724					
	Weather forecast	5.235	.679	.455	7.711	.000	3.895	6.575	.691	.503	.348	.585	1.709
	Fertiliser use	-.016	.002	-.454	-7.500	.000	-.021	-.012	-.222	-.492	-.338	.556	1.797
	Chemical use (liquid)	2.194	.411	.352	5.339	.000	1.383	3.005	.268	.373	.241	.469	2.130
	Crop area	1.629	.520	.175	3.130	.002	.602	2.656	.445	.230	.141	.649	1.541
	Experience	.069	.025	.139	2.727	.007	.019	.119	.388	.201	.123	.783	1.278
6	(Constant)	11.480	.987		11.631	.000	9.532	13.428					
	Weather forecast	5.304	.673	.461	7.887	.000	3.977	6.632	.691	.512	.352	.584	1.713
	Fertiliser use	-.016	.002	-.432	-7.108	.000	-.020	-.011	-.222	-.473	-.317	.541	1.849
	Chemical use (liquid)	2.282	.409	.366	5.585	.000	1.476	3.089	.268	.389	.249	.465	2.152
	Crop area	1.620	.515	.174	3.147	.002	.604	2.636	.445	.231	.141	.649	1.541
	Experience	.068	.025	.137	2.717	.007	.019	.118	.388	.201	.121	.782	1.278
	Capital	-6.322E-5	.000	-.103	-2.180	.031	.000	.000	-.073	-.163	-.097	.888	1.126

a. Dependent Variable: Teff yield

Figure C.31: "Coefficients" table showing the direction and value of the significant predictors for teff yield. In addition, the tolerance and VIF values are shown, and exceed the thresholds of 0.1 and 10, respectively. Hence, there is no violation of multicollinearity in the model.

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	3.487817764	22.41856766	13.24487857	4.221875345	235
Std. Predicted Value	-2.233	1.983	-.060	.940	235
Standard Error of Predicted Value	.354	2.845	.658	.277	235
Adjusted Predicted Value	3.487817764	22.79429054	13.25520678	4.227244393	235
Residual	-10.3797808	10.51218224	.6179336367	3.578512016	235
Std. Residual	-3.105	3.144	.185	1.070	235
Stud. Residual	-3.147	3.082	.174	1.067	235
Deleted Residual	-10.6647224	10.51218224	.6076054345	3.683793736	235
Stud. Deleted Residual	-3.231	3.161	.174	1.073	235
Mahal. Distance	1.032	75.457	6.819	7.889	235
Cook's Distance	.000	.617	.011	.044	235
Centered Leverage Value	.006	.415	.038	.043	235

a. Dependent Variable: Teff yield

Figure C.32: "Residual Statistics" table showing the statistics of the residuals. Cook's Distance is 0.617, from which it can be concluded that the outliers are no potential problem for the outcome of the MRA.

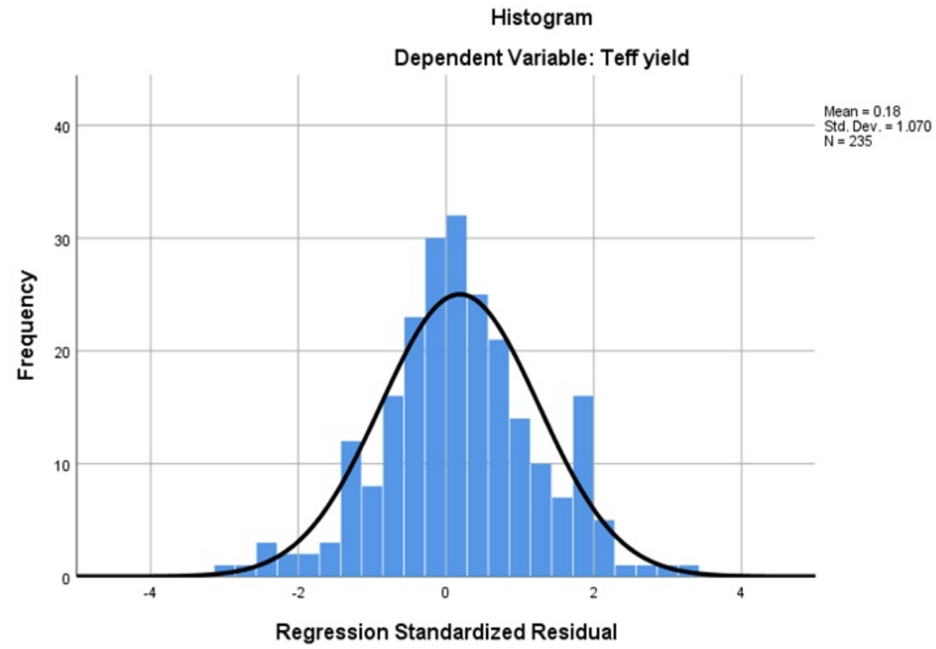

Figure C.33: A histogram showing a normal distribution of the standardised residuals for the dependent variable, teff yield, with sample size = 235, mean = 0.18 and standard deviation = 1.070.

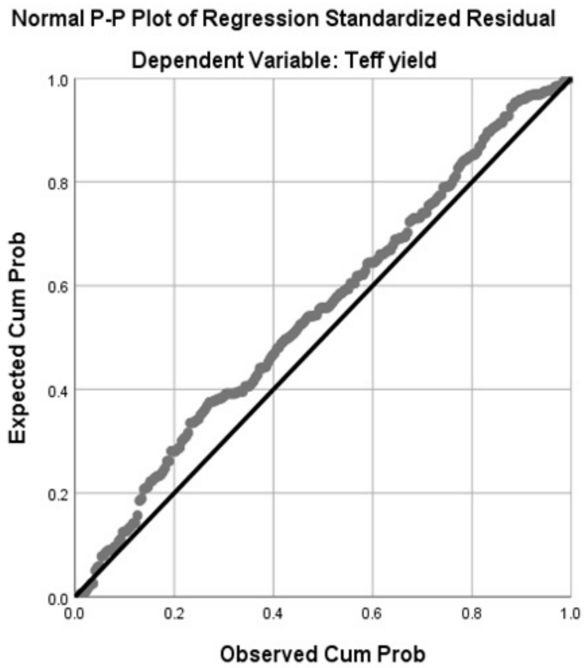

Figure C.34: A P-P plot showing the residuals for the dependent variable, teff yield. No major deviations are apparent, hence normality can be assumed.

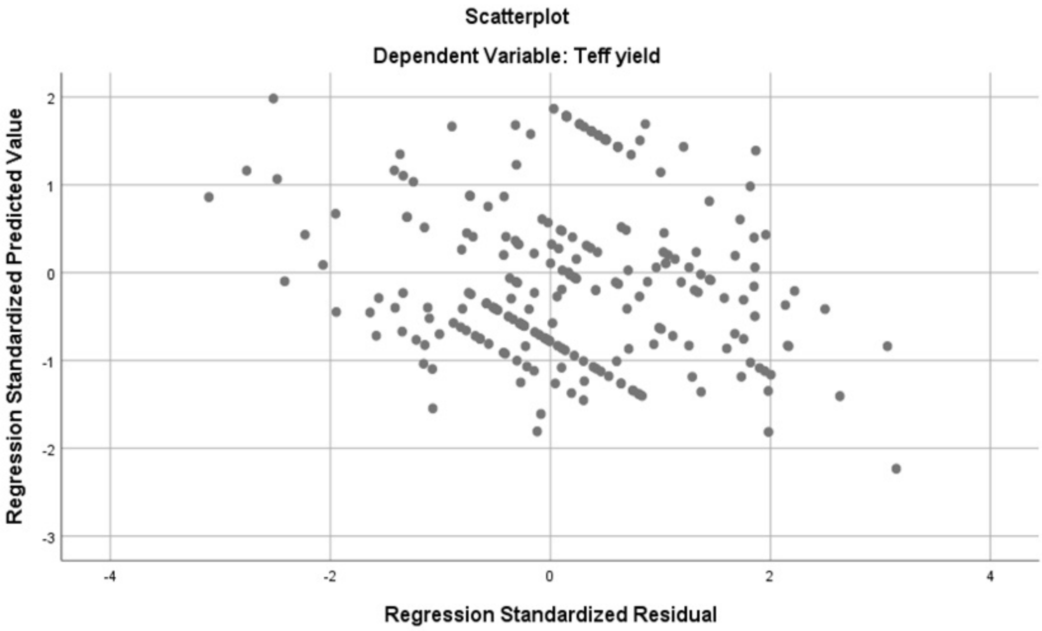

Figure C.35: A scatterplot of the standardised residuals, showing a few standardised residuals falling outside the range of -3.3 and 3.3.

C.2. Binary Logistic Regression Analysis

In this section the output of each binary logistic regression analysis conducted in Section 4.4 is presented. In addition, the statistical variables included in the results of the binary logistic regression shown in this Section are explained. Hereby, the textbook of Julie Pallant is followed (Pallant and Manual, 2010).

C.2.1. Explanation of Statistical Variables

The figures showing the results of the binary logistic regression in Subsection 4.4.9 include a few statistical variables. Each of these statistical variables are explained in this subsection. As an example, we look at Figure C.38.

The regression coefficients are indicated by B. The statistical variable B represent the value for the logistic regression equation for predicting the dependent variable from the independent variable, and are in log-odds units. The value for B indicates the relationship between the independent variable and the dependent variable, whereby the independent variable is on a logit scale. They indicate the amount of change in the predicted log odds of, in this example, the climate adaptive capacity that would be predicted by a 1 unit increase in the predictor, holding all other predictors constant.
Since the value for B is often difficult to interpret, they are often converted into odds ratios, indicated by Exp(B), which are the exponentiation of the coefficients B. The value for Exp(B) indicates the increase in the log-odds ratio of, in this example, the climate adaptive capacity by a one unit increase of one of the independent variables, holding all other independent variables constant. It is assumed that the independent variable with the highest odds ratio, is the strongest predictor.

The standard errors associated with the coefficients B are indicated by S.E. The standard error is used to test whether the parameter is significantly different from 0.

The Wald column provides the Wald chi-square values. The Wald test is used to determine statistical significance for each of the independent variables. The statistical significance of the test is found in the Sig. column. If the sig. value is smaller than 0.05, the independent variable adds significantly to the prediction of the dependent variable. The df column lists the degree of freedom for each variable for the Wald chi-square test.

The 95% C.I. (Confidence Interval) for EXP(B) are ranges of values that are likely to contain the true values of the odds ratio.

C.2.2. Climate Adaptive Capacity

In this binary logistic regression analysis only those farmers without access to a weather forecast are taken into account, hence N = 278.

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	60.542	3	.000
	Block	60.542	3	.000
	Model	60.542	3	.000

(a) Model summary

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	198.373[a]	.196	.323

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

(b) Omnibus test of model coefficients

Figure C.36: Figure a) shows the model to be statistically significant with a chi-square value of 60.54 and $p < 0.001$. Figure b) shows the combined predictive capacity of the independent variables, hence the independent variables explain between 19.6% and 32.3% of the variance in climate adaptive capacity.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	6.987	8	.538

(a) Hosmer and Lemeshow Test

Classification Table[a]

	Observed		Predicted: Climate adaptation 0	Predicted: Climate adaptation 1	Percentage Correct
Step 1	Climate adaptation	0	15	34	30.6
		1	15	214	93.4
	Overall Percentage				82.4

a. The cut value is .500

(b) Classification table

Figure C.37: Figure a) presents the Hosmer and Lemeshow test with a p-value larger than 0.05, from which can be assumed the model is not a poor fit of the data. Figure b) presents the classification table, which indicates the number of correctly and wrongly predicted farmers by the model with respect to the climate adaptive capacity.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Step 1[a]	Farm size	.550	.261	4.425	1	.035	1.733	1.038	2.893
	Use of onset of rains(1)	2.121	.375	31.949	1	.000	8.339	3.997	17.400
	Household labour	.034	.013	6.663	1	.010	1.035	1.008	1.062
	Constant	-1.355	.543	6.231	1	.013	.258		

a. Variable(s) entered on step 1: Farm size, Use of onset of rains, Household labour.

Figure C.38: The three variables significantly predicting the dependent variable, climate adaptive capacity. The use of onset is the strongest predictor as it has the highest odds ratio indicated by Exp(B).

```
                 Step number: 1

                 Observed Groups and Predicted Probabilities

      40 +                                                                                                    +
         I                                                                                              1     I
         I                                                                                              1     I
F        I                                                                                              1     I
R     30 +                                                                                              1     +
E        I                                                                                              1     I
Q        I                                                                                              1  1  I
U        I                                                                                              1  1  I
E     20 +                                                                                              11 1  +
N        I                                                                                        1     11 1  I
C        I                                                                                        1   1 11 1  I
Y        I                                                                                        1  11 11 1  I
      10 +                                                                                       11 11111111  +
         I                                            1        1  1                            1 11111111111  I
         I                                         1  1    1 1 0  1       11                 1 11111111111111 I
         I                                  0 1  1 0  1  0 0 0 00 0       01    1    1       1 111010011101111I
Predicted ---------+---------+---------+---------+---------+---------+---------+---------+---------+----------
  Prob:   0        .1        .2        .3        .4        .5        .6        .7        .8        .9        1
  Group:  0000000000000000000000000000000000000000000000000011111111111111111111111111111111111111111111111111

              Predicted Probability is of Membership for 1
              The Cut Value is .50
              Symbols: 0 - 0
                       1 - 1
              Each Symbol Represents 2.5 Cases.
```

Figure C.39: An overview of observed groups and the predicted probabilities. The threshold is set at 0.5.

C.2.3. Changing Crop Type

In this binary logistic regression analysis the probability of a farmer to adapt by changing the crop type is assessed. Hereby, only non-rice growing farmers claiming to adapt to climate variability are taken into account, hence N = 285.

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	37.767	5	.000
	Block	37.767	5	.000
	Model	37.767	5	.000

(a) Model summary

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	316.153[a]	.124	.175

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

(b) Omnibus test of model coefficients

Figure C.40: Figure a) shows the model to be statistically significant with a chi-square value of 37.77 and $p < 0.001$. Figure b) shows the combined predictive capacity of the independent variables, hence the independent variables explain between 12.4% and 17.5% of the variance in climate adaptive capacity.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	10.494	8	.232

(a) Hosmer and Lemeshow Test

Classification Table[a]

			Predicted		
			Changing to short cycle crop		Percentage Correct
	Observed		0	1	
Step 1	Changing to short cycle crop	0	23	66	25.8
		1	22	174	88.8
	Overall Percentage				69.1

a. The cut value is .500

(b) Classification table

Figure C.41: Figure a) presents the Hosmer and Lemeshow test with a p-value larger than 0.05, from which can be assumed the model is not a poor fit of the data. Figure b) presents the classification table, which indicates the number of correctly and wrongly predicted farmers by the model with respect to the climate adaptive capacity.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	Farm size	.543	.255	4.527	1	.033	1.722	1.044	2.840
	Elevation	-.005	.001	15.751	1	.000	.995	.993	.998
	Education	.383	.185	4.284	1	.038	1.467	1.021	2.110
	Livestock (TLU)	.231	.111	4.373	1	.037	1.260	1.015	1.565
	Capital	.000	.000	10.006	1	.002	1.000	1.000	1.000
	Constant	10.289	2.696	14.563	1	.000	29416.066		

a. Variable(s) entered on step 1: Farm size, Elevation, Education, Livestock (TLU), Capital.

Figure C.42: The five variables significantly predicting the dependent variable, climate adaptive capacity. The farm size is the strongest predictor as it has the highest odds ratio indicated by Exp(B).

```
              Step number: 1

              Observed Groups and Predicted Probabilities

      16 +                                                                                                    +
         I                                                                                                    I
         I                                                                                                    I
F        I                                                                              1                     I
R     12 +                                                                              1                     +
E        I                                                                      1       1  1                  I
Q        I                                                                      1    1  1  1                  I
U        I                                                                      1 1  1 11  1        1         I
E      8 +                                                   1                  1 1  1 11 11 1      1         +
N        I                                                1  11 1             1 1 1  1 11 11 1      1         I
C        I                                                0  11 11            1 1 1  1 11 11 1  1   1         I
Y        I                                     1        1 0  01 01  1   1  11 111 1  1 11 11 1  1 1 1         I
       4 +                                     1     1  1 0  00 01  11 111 10 11111  1111111 11 111111 11     +
         I                                     1  1  1111101 000011 11 111110101011 111011011111111111 11     I
         I                                     1  10 0011100 000000111 1011101000000101011011111111111 11 1   I
         I           0        1       1    0 0 0000 1000000000000000011010000000000010000000000110110111111 11I
Predicted ---------+---------+---------+---------+---------+---------+---------+---------+---------+----------
  Prob:   0        .1        .2        .3        .4        .5        .6        .7        .8        .9         1
  Group:  0000000000000000000000000000000000000000000000000011111111111111111111111111111111111111111111111111

          Predicted Probability is of Membership for 1
          The Cut Value is .50
          Symbols: 0 - 0
                   1 - 1
          Each Symbol Represents 1 Case.
```

Figure C.43: An overview of observed groups and the predicted probabilities. The threshold is set at 0.5.

C.2.4. Changing Planting and Harvesting Dates

In this binary logistic regression analysis the probability of a farmer to adapt by changing the planting and harvesting dates is assessed. Hereby, only non-rice growing farmers claiming to adapt to climate variability are taken into account, hence N = 285.

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	161.322	6	.000
	Block	161.322	6	.000
	Model	161.322	6	.000

(a) Model summary

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	213.931[a]	.433	.591

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

(b) Omnibus test of model coefficients

Figure C.44: Figure a) shows the model to be statistically significant with a chi-square value of 161.32 and p < 0.001. Figure b) shows the combined predictive capacity of the independent variables, hence the independent variables explain between 12.4% and 17.5% of the variance in climate adaptive capacity.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	9.412	8	.309

(a) Hosmer and Lemeshow Test

Classification Table[a]

			Predicted		
			Changing planting and harvesting dates		Percentage Correct
	Observed		0	1	
Step 1	Changing planting and harvesting dates	0	80	26	75.5
		1	27	151	84.8
	Overall Percentage				81.3

a. The cut value is .500

(b) Classification table

Figure C.45: Figure a) presents the Hosmer and Lemeshow test with a p-value larger than 0.05, from which can be assumed the model is not a poor fit of the data. Figure b) presents the classification table, which indicates the number of correctly and wrongly predicted farmers by the model with respect to the climate adaptive capacity.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Step 1[a]	Elevation	-.006	.001	17.948	1	.000	.994	.992	.997
	Education	1.011	.227	19.886	1	.000	2.747	1.762	4.283
	Livestock (TLU)	-.736	.129	32.628	1	.000	.479	.372	.617
	Experience	.064	.017	13.792	1	.000	1.066	1.031	1.103
	Weather forecast	-1.389	.440	9.984	1	.002	.249	.105	.590
	Household labour	.105	.016	44.875	1	.000	1.111	1.077	1.146
	Constant	9.680	2.842	11.597	1	.001	15991.262		

a. Variable(s) entered on step 1: Elevation, Education, Livestock (TLU), Experience, Weather forecast, Household labour.

Figure C.46: The six variables significantly predicting the dependent variable, climate adaptive capacity. Education is the strongest predictor as it has the highest odds ratio indicated by Exp(B).

```
             Step number: 1

             Observed Groups and Predicted Probabilities

      32 +                                                                                                     +
         I                                                                                                     I
         I                                                                                                     I
F        I                                                                                                    1I
R     24 +                                                                                                    1+
E        I                                                                                                    1I
Q        I                                                                                                    1I
U        I                                                                                                    1I
E     16 +                                                                                                    1+
N        I                                                                                                  111I
C        I                                                                                              1  111I
Y        I                                                                                           1  1  111I
       8 +                    1                    1                                                 1  1  111+
         I               1    0                    0                                    1        1 1 111111111I
         I 010  000 0  100   00        1       1   0       1   11                 1 111  1   1111 1 11111111111I
         I000001000000 0000000001  0  000 0100000010000001110 000001100101 0 10 10110001 0 100001 0111100111111I
Predicted ---------+---------+---------+---------+---------+---------+---------+---------+---------+----------
  Prob:   0        .1        .2        .3        .4        .5        .6        .7        .8        .9         1
  Group:  00000000000000000000000000000000000000000000000000111111111111111111111111111111111111111111111111111

          Predicted Probability is of Membership for 1
          The Cut Value is .50
          Symbols: 0 - 0
                   1 - 1
          Each Symbol Represents 2 Cases.
```

Figure C.47: An overview of observed groups and the predicted probabilities. The threshold is set at 0.5.