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Does Adoption of Multiple Climate-Smart Practices Improve Farmers' Climate Resilience?

Empirical Evidence from the Nile Basin of Ethiopia

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Abstract

There is a paucity of information on the conditions under which multiple climate-smart practices are adopted and on the synergies among such practices in increasing household resilience by improving agricultural income. This study analyzes how heat, rainfall, and rainfall variability affect farmers' choices of a portfolio of potential climate-smart practices – agricultural water management, improved crop seeds and fertilizer – and the impact of these practices on farm income in the Nile Basin of Ethiopia. We apply a multinomial endogenous switching regression approach by modeling combinations of practices and net farm income for each combination as depending on household and farm characteristics and on a set of climatic variables based on geo-referenced historical precipitation and temperature data. A primary result of this study is that farmers are less likely to adopt fertilizer (either alone or in combination with improved varieties) in areas of higher rainfall variability. However, even when there is high rainfall variability, farmers are more likely to adopt these two yield-increasing inputs when they choose to (and are able to) include the third part of the portfolio: agricultural water management. Net farm income responds positively to agricultural water management, improved crop variety and fertilizer when they are adopted in isolation as well as in combination. But this effect is greater when these practices are combined. Simulation results suggest that a warming temperature and decreased precipitation in future decades will make it less likely that farmers will adopt practices in isolation but more likely that they will adopt a combination of practices. Hence, a package approach rather than a piecemeal approach is needed to maximize the synergies implicit in various climate-smart practices.

Key Words: multiple climate-smart practices, precipitation, temperature, multinomial endogenous switching, farm income, Ethiopia

JEL Codes: Q01, Q12, Q16, Q18

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1. Introduction

Smallholder farmers in Sub-Saharan African countries (SSA) are confronted with changing patterns of temperature and precipitation and increased occurrences of extreme events like droughts and floods. Meteorological data show a persistent upward trend in both mean temperatures and variation in seasonal and annual rainfall patterns. Changes in temperature and precipitation patterns will expose the region's agricultural production systems to tremendous risks, causing more short-term crop failures and long-term production declines (Ngigi 2009; Lasco et al. 2014). It is particularly important to understand the vulnerability of farmers in Ethiopia, because around 85% of the population are farmers and climate change impacts are expected to be significant. Climate change in Ethiopia will not only increase rainfall variability and lead to more frequent droughts and higher risk of floods; it will also continue to intensify the degradation of soil fertility, which causes agricultural productivity to decline.

Empirical studies measuring the economic impacts of climate change on agriculture (Kurukulasuriya and Mendelsohn 2006; Seo and Mendelsohn 2006a; Mano and Nhemachena 2006; Benhin 2006) show that such impacts can be significantly reduced through adaptation. A substantial literature provides empirical evidence on climate-induced choices among crop types, livestock selection, resilience of mixed farms and the decision to irrigate under variable climate conditions in different parts of the

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world (Seo and Mendelsohn 2008; Seo 2010; Kurukulasuriya et al. 2011). Adaptation measures that build upon risk-reducing options through improved water management enhance soil fertility, while development and dissemination of improved germplasm are fundamental in boosting overall resilience to climate change (Hellin et al. 2012). In the context of agriculture and climate change, there are substantial potential benefits from applying available climate-smart agricultural practices that have been developed for use in existing agro-climatic systems.

Climate-smart agriculture reflects smart agricultural practice informed by climate impacts on agriculture. This refers to practices that seek, first of all, to increase agricultural productivity in order increase income and food security (Brown and Funk 2008; Bryan et al. 2011); secondly, to strengthen farmers' resilience to climate change; and, thirdly, to decrease greenhouse gas emissions and increase carbon sinks (FAO 2011; Campbell et al. 2014; Arslan et al. 2014). The relative priority of each objective varies across locations, with, for example, greater emphasis on productivity and adaptive capacity in smallholder farming systems in developing countries (Campbell et al. 2014). Efforts to improve adaptation to climate change are numerous; highlights include on-farm practices to improve the soil's water holding capacity, as well as switching to water efficient or drought and heat tolerant crop varieties better suited to a warmer and drier climate (Hellin et al. 2012; Lobell et al. 2008; Arslan et al. 2014). In fact, the growth and transformation plan in Ethiopia intends to continue efforts on adoption and diffusion of agricultural soil and water management technologies, which are considered central to building a climate resilient green economy.

We consider the application of various combinations of climate-smart agricultural practices. One salient area for research on technology adoption that has not been very thoroughly studied is that of multiple technology adoption (Teklewold et al. 2013; Wu and Babcock 1998). Farmers may face technology alternatives that can be adopted either as substitutes or in combination (as complements or supplements) to deal with their overlapping constraints such as pest infestations, low soil fertility and moisture stress (Dorfman 1996; Khanna 2001; Moyo and Veeman 2004). However, while previous studies of choice and impact of adaptation have focused on either a single practice or a set of practices considered as a single unit (Deressa et al. 2009; Deressa et al. 2010; Di Falco et al. 2011; Di Falco et al. 2012), there is limited information on how adoption of multiple strategies by smallholder farmers responds to climate change or on the synergies between various adaptation strategies in improving agricultural productivity and farm income. While individual climate-smart practices provide multiple benefits, there are complementarities and synergies when more than one practice is adopted together. For instance, in smallholder subsistence farming in much of SSA, one of the major sources of risk is moisture stress, where fertilizer will not be applied if application to a crop is perceived as too risky (Rockström et al. 2002). This happens because smallholder farmers are averse to risk, given their precarious financial situation and their poor access to credit and insurance. The risk of moisture stress is increasing as a result of increased variability of seasonal distribution of rainfall throughout most of Africa, coupled with a reduction in rainfall in much of the SSA (Lobell et al. 2008). Under these circumstances, agricultural water management can reduce the risk created by moisture stress and thus make farmers more confident about applying fertilizer.

If researchers ignore the inter-relatedness of various agricultural practices, this suggests that farmers make each adoption decision exogenously, an approach that may underestimate or overestimate the influences of various factors on the choice and effect of the decision. Treating farmers' adoption choices as bundle of practices, rather than as isolated decisions, is important in order to better understand the synergistic effect of inter-related practices. Furthermore, a joint analysis may still be needed for determining the total effect of the simultaneous application of the practices (Wu and Babcock 1998; Teklewold et al. 2013). This will enable policy makers and development practitioners to promote combinations of technologies/practices that perform well together.

In this study, we consider three climate-smart agricultural practices. The first is the adoption of agricultural water management practices. This is one of the "best bet" strategies for adapting agricultural production to climate change and variability, because agricultural water management practices improve water balance and availability, infiltration and retention by the soil, reduce water loss due to runoff and evaporation, and improve the quality and availability of ground and surface water (Ngigi et al. 2005; Arslan et al. 2013). Water management (irrigation, drainage and water conservation and control) stabilizes crop production by maintaining soil conditions close to the optimum for crop growth. Water management practices (such as terracing) that change slope profile can reduce runoff speed – especially on erosion-prone highlands – thus reducing soil erosion. It also allows some water to seep into the soil (infiltration), improving the soil to allow more vegetation cover. This practice also increases groundwater recharge and protects the topsoil (FAO 2014). Agricultural water management works best when it is accompanied by other crop management practices such as modern crop varieties and fertilizer that can use moisture more efficiently. Thus, we next consider two other technologies: improved crop varieties and inorganic fertilizer.

Food security in an era of climate change may be possible if farmers transform agricultural systems via the use of improved crop seed and fertilizer (Brown and Funk 2008; Bryan et al. 2011). Appropriate use of fertilizer is required both to enhance crop productivity and to produce sufficient crop residues to ensure soil cover under smallholder conditions (Vanlauwe et al. 2013).

This study, therefore, has two objectives: to examine the effect of both climate-related and socio-economic factors on the probability that farmers will adopt climate-smart practices, individually and in combination, in the Nile Basin of Ethiopia; and to quantify the impact of adopting various combinations of these practices on crop net income (net of fertilizer, seed, labor and pesticide costs) as an outcome indicator.

We do this by controlling for selection bias using a multinomial endogenous switching treatment effects approach. In the first part, we estimate a selection model to investigate the extent to which various combinations of climate-smart practices are related to climate and socio-economic conditions. In the second part, a set of linear models conditional on each combination of the practices is used to examine farm profitability. Empirical assessment uses a recent novel data set that combines household characteristics with geo-referenced data on historical temperature and rainfall as well as plot-level farm characteristics in the Nile basin of Ethiopia.

This paper complements previous work by Di Falco and Veronesi (2013) that aimed to answer how adaptation has occurred in terms of various types of adaptation practices, using structural Ricardian models at a fairly aggregate level of household data. From a data utilization point of view, ours is the more detailed dataset, where we know each practice actually implemented at plot level.

Our study further adds to the literature on the economics of climate change adaptation in the following ways. First, we contribute to the limited literature on adoption of a portfolio of climate-smart practices in the face of changing climate conditions. To our knowledge, no similar empirical articulation of the relationship between climate variables and alternative combinations of climate-smart practices in the smallholder farming system has been done. Second, we investigate – for the first time, to our knowledge – whether adoption of a combination of climate-smart practices will provide more economic benefits than individual adoption. For Ethiopia, a country that has a vision of building a climate-resilient economy, identifying a combination of climate-smart practices that deliver the highest payoff is a valuable contribution to help government and development agencies design effective extension policies.

The rest of the paper is organized as follows. The next section provides a description of the study areas. Section 3 provides a brief discussion of the data and empirical specification of our estimation model. Section 4 presents a conceptual and econometric framework for a multinomial endogenous switching regression model. Section 5 presents our estimation of average treatment effects. This is followed by presentation of our estimation results in Section 6. The final section concludes and draws key findings and policy implications.

2. Study Areas and Sampling

Our basic data come from the farm household survey conducted in five regional states of the Ethiopian part of the Blue Nile Basin: Amhara, Oromia, Tigray, Benshangul-Gumuz and SNNP. The data were collected from March through May, 2015. The basin covers about two-thirds of the country's land mass and contributes nearly 40% of its agricultural products and 45% of its surface water (Erkossa et al. 2014). The areas selected represent different agro-ecological settings and are characterized by highly rugged topography with altitudes ranging from 800 to over 3000 meters above sea level. The farming system of the basin can be broadly categorized as a mixed crop-livestock farming system, where over 90% of the cultivated area is covered by a cereal-based farming system (Erkossa et al. 2014).

The sampling frame considered the traditional typology of agro-ecological zones in the country (i.e., *Dega* (cool, humid, highlands), *Weina-Dega* (temperate, cool sub-humid, highlands), *Kolla* (warm, semi-arid lowlands), and *Bereha* (hot and hyper-arid)). The sampling frame selected the *woredas*[1] in such a way that each class in the sample matched the proportions for each class in the entire Nile basin. Accordingly, a multistage sampling procedure was employed to select villages from each woreda and households from each village. First, 20 woredas from the five regional states were selected (three each from Tigray and Benshangul-Gumuz, six from Amhara, seven from Oromia, and one from SNNP). This resulted in a random selection of 50 farmers from each woreda, and, after cleaning inconsistent responses, a total of 929 farm households and 4702 farming plots.

The areas selected for this study have two periods of rainfall: the main rainy season (*Meher*) runs from June to October, and the short rainy season (*Belg*) is from

[1] An administrative division equivalent to a district.

January to April. Although both annual and perennial crops are grown in the area, the annual crops cover more than 98% of the plots. We thus limit our analysis to the annual crop plots, where most of the land and water management practices are applied. The main crops grown in the study areas are maize, wheat, teff, barley and legumes.

3. Data Description and Empirical Specification

The climate-smart practices considered in this study include agricultural water management, improved crop seeds and inorganic fertilizer, providing eight mutually exclusive combinations of practices (2^3). Table 1 presents the proportions of area cultivated under the different combination of practices. Of all the 4702 farming plots, about 28% did not receive any of the adaptation practices ($Va_0Fe_0Aw_0$), while all three practices were simultaneously adopted on only 9% of the plots ($Va_1Fe_1Aw_1$).

Table 2 shows the interdependence of adaptation practices. Agricultural water management is used on 41% of the plots, improved crop seeds on 24% and inorganic fertilizer on 53% of the plots. The sample unconditional and conditional probabilities presented in Table 2 also highlight the existence of interdependence across the three adaptation practices. For instance, the probability of adopting agricultural water management increased by 3% conditional on adoption of improved crop variety. Similarly, the probability of water management increased by 6% conditional on adoption of fertilizer. The conditional probability of a household adopting fertilizer is significantly increased, from 52% to 60%, when farmers practiced agricultural water management. In addition, the conditional probability of adoption of improved crop varieties increased from 23% to 25% when farmers practiced agricultural water management. Similarly, adoption of inorganic fertilizer increased in the presence of modern seeds and vice versa. The results indicate complementarity between the adoption of water management, modern crop seeds and fertilizers.

Table 3 presents the description and summary statistics of the control variables used in the empirical analysis for the full sample and the eight sub-groups. The specification of our empirical model is based on a review of theoretical work and previous similar empirical adoption and impact studies on integrated natural resource management and sustainable land management (D’Souza et al. 1993; Neill and Lee 2001; Arellanes and Lee 2003; Gebremedhin and Scott 2003; Lee 2005; Bandiera and Rasul 2006; Marenya and Barrett 2007; Knowler and Bradshaw 2007; Deressa et al. 2009; Ricker-Gilbert and Jayne 2009; Deressa et al. 2010; Kassie et al. 2010; Wollni et al. 2010; Di Falco et al. 2011; Di Falco et al. 2012; Holden and Lunduka 2012). According to this literature, factors affecting adaptation and net crop income include natural capital (soil depth, slope and fertility), social capital and networks (membership in community-based institutions and spillover effects), shocks (self-reported rainfall shocks and plot-level crop production disturbances), physical capital (farm size and livestock holdings), access to services and constraints (distance to main market, access to credit, extension service and climate information), human capital (family size, household head education, gender and age), plot distance to dwelling, geographic location and climate variables (temperature, intensity and variability of rainfall). Below, we focus on describing these variables in relation to climate change adaptation literature.

Farmers' education level as a factor influencing technology adoption is commonly discussed in the adoption literature. Education may increase an individual's ability to acquire, understand and implement knowledge-intensive adaptation practices, and may increase returns from using these practices relative to the old practices. The more farmers are educated, the more they perceive climate change, and the more likely they are to respond to climate change by implementing adaptation strategies (Maddison 2006). The average educational attainment of household heads is about two years of education across the study areas. About 88% of the sample households are male-headed. The justification for including age of the household head is straightforward. An older household head means that the farmer has more experience in climate change, environmental conditions, and adaptation strategies, as well as a greater accumulation of physical and social capital, all of which facilitate adaptive capacity. However, age can also be associated with a shorter-term planning horizon, poorer health, and loss of energy, as well as being more risk averse. Thus, the *a priori* effect of age on adaptation is indeterminate. The average age of the household head is 52 years.

Based on related literature, the resource constraint variables (farm size, livestock, credit and household expenditure) are expected to have a positive association with adoption because these variables often represent wealth or financial capital, which tend to relax liquidity constraints in implementing adaptation practices. The vast majority of the households in the sample can be characterized as small-scale farmers, with average farm size of 1.8 ha.

We followed the approach of Feder et al. (1990) to construct a credit-access variable. This measure of credit tries to distinguish between farmers who choose not to use available credit and farmers who do not have access to credit. In our study, credit-constrained farmers are defined as those who need credit but are unable to get it.

In addition to the classical household characteristic and endowment variables, we also study the ways in which individuals relate to wider social networks and the effects of these networks on adaptation decisions. In Ethiopia, where information is scarce and markets are ill-functioning, social networks are considered a means to facilitate the exchange of information, enable farmers to access inputs on schedule, and overcome credit constraints and shocks (Fafchamps and Minten 2002; Isham 2002; Barrett 2005; Bandiera and Rasul 2006; Marenya and Barrett 2007; Wossen et al. 2015). Particularly for smallholder farmers, local institutions play a pivotal role in building resilience and reducing vulnerability to climate change (Agrawal et al. 2009). In this study, we distinguish three social networks as social capital variables: whether a household is a member of a rural institution in the village; the number of agricultural groups in which the household is a member; and the number of social groups in which the household is a member. Such classification is important because different forms of social capital and networks may affect the implementation of adaptation strategies in various ways, such as information sharing, stable market outlets, labor sharing, relaxing of liquidity constraints, and mitigation of risks.

There is increasing evidence on the role of neighborhood effects in the adoption of agricultural technologies (Bandiera and Rasul 2006; Knowler and Bradshaw 2007; Wollni and Andersson 2014). The role of perceived spillover effects in the uptake of adaptation practices is captured by recording farmers' expectations that adoption of a given practice might have positive effects on their neighbors' plots. For some agricultural practices, not all the benefits accrue to the individual who adopts them, but the practice may also directly benefit the neighboring farmer by reducing soil erosion and increasing soil fertility, as well as through pest control. In addition, farmers who adopt a new technology may generate positive externalities for neighboring farmers in the form of information about how to use the technology (Besley and Case 1994).

Agricultural extension service is the major source through which many climate-related adaptation practices and information are channeled. We control for access to extension service by including a dummy variable for whether the farmer has had contact with the extension agent during the last cropping season. However, access to extension service per se may not impact technology adoption, because the quality of information provided to farmers depends on the skill of extension workers. Unlike the previous adoption studies, we control for not only the extension contact but also farmers' perceptions regarding the skill of extension workers in providing the required services, by including a dummy variable taking the value of one if the farmer indicates confidence in the qualification of extension agents and zero if the farmer lacks confidence.

There has been relatively little research on the effects of climate-related shocks (such as droughts, water-logging, untimely or uneven distribution of rainfall, and incidence of pests and diseases) on the implementation of adaptation practices. This study includes self-reported rainfall shocks and plot-level crop production shocks. We followed Quisumbing (2003) to construct the rainfall disturbance variable based on respondents' subjective rainfall satisfaction in terms of timeliness, amount, and distribution. The individual rainfall index was constructed to measure the farm-specific experience related to rainfall in the preceding seasons, based on such questions as whether rainfall came on time at the start of the growing season, whether there was enough rain at the beginning of and during the growing season, whether the rain stopped on time and whether there was rain at harvest time. Responses to each of these questions (either yes or no) were coded as favorable or unfavorable rainfall outcomes. By averaging over the number of questions asked (five questions), we created an index that provides a value close to one for the best outcome and zero for the worst outcome. Plot-level disturbance is captured by the five most common shocks affecting crop production: pest and disease pressure, drought, flood, hailstorm, and erratic rainfall. The effect of these shocks on the use of adaptation practices depends on the type of practices (Teklewold et al. 2013).

We also control for the possible role of farmers' perceptions of government assistance, by including a dummy variable taking the value of one if the farmer can rely on government support when events beyond his control cause output or income to drop. In the developing world, where production risks are high, farmers are less likely to adopt technologies in the absence of farm insurance, which can protect farmers in case of lost income or crop failure. Whether in the form of social safety nets or formal insurance, farm insurance can build confidence among farmers so that they invest despite uncertainty, and can help farm households smooth consumption and maintain productive capacity by reducing the need to liquidate assets that might arise in case of shocks (Barrett 2005). A better understanding of this issue can be obtained by examining the effect of farmers' judgments and perceptions of the policy environment of government assistance on different types of climate-smart practices. In our study, only about 40% of farm households believe they can rely on government assistance.

We also merge the household survey data with a novel set of climate variables based on geo-referenced historical temperature and precipitation data at household level for the period 2000-2013. Monthly rainfall and temperature data were collected from all the meteorological stations near the study areas. Then, the Thin Plate Spline method of spatial interpolation was used to impute household-specific rainfall and temperature values, using geo-referenced information such as elevation, longitude and latitude. The Thin Plate Spline is a two-dimensional interpolation scheme for arbitrarily spaced tabulated data. The spline surface represents a thin metal sheet that is constrained not to move at the grid points, which ensures that the generated rainfall and temperature data at the weather stations are exactly the same as data at the weather station sites that were used for the interpolation (see Wahba 1990).

This method is one of those most commonly used to create spatial climate data sets (e.g., Di Falco et al. 2011; Deressa and Hassan 2010). Its strengths are that it is readily available and relatively easy to apply, and it accounts for spatially varying elevation relationships.[2] Given that our area of the study is characterized by significant terrain features, the choice of the Thin Spline method is reasonable. These climatic variables are included in our empirical model to capture whether differences in seasonal temperature and precipitation influence our two outcome variables: farmers' choice of combination of climate-smart practices and farm income.

We summarize rainfall and temperature data of the main growing season by districts and regions included in the study.[3] The distribution of the growing season rainfall and temperature in our data conforms to the traditional agro-ecology classification of the country. The Tigray region in the semi-arid zones (Kolla) receives the least rainfall. The other regions, which are traditionally classified in the highland zones (Dega and Woindega), have higher rainfall. Our data also show variability across regions in rainfall patterns during the growing season. In order to identify the monthly pattern of rainfall heterogeneity in our study areas, we used Oliver's (1980) Precipitation Concentration Index (PCI),[4] analyzed at seasonal scale (April-September). The PCI value calculated on a seasonal scale varies across the area under study, ranging from values

[2] This method only simulates an elevation relationship, and it has difficulty handling very sharp spatial gradients. However, very sharp gradients are typical of coastal areas, and our study region has no climatically important coastlines.

[3] Results are not shown here for brevity of space.

[4] The PCI is described as: $PCI = 50X\left[\sum r_m^2 / \left(\sum r_m\right)^2\right]$, where r_m is amount of rainfall in the m^{th} month. The PCI is a powerful indicator of temporal distribution of precipitation; as the value increases, the precipitation is more concentrated. PCI values of less than 10 indicate uniform monthly distribution of rainfall (low precipitation concentration); values between 11 and 15 indicate moderate precipitation concentration; PCI between 16 and 20 indicate irregular distribution; and values above 21 indicate very high precipitation concentration, i.e., strong irregularity (Oliver 1980).

higher than 16 in Tigray to lower than 11 in Benshangul-Gumuz. This indicates a much higher concentration of growing season rainfall in Tigray than in Benshangul-Gumuz. Similarly, monthly rainfall variability is much higher in all study districts in the Tigray region (PCI ranging from 16-20) than in the districts in the other study areas in the highland zones.

The survey asked farmers whether they have noticed changes in climate over their lifetime. In response, more than half of the farmers reported an increase in temperature and erratic and low rainfall distribution, with delayed onset of rains at planting season. These perceptions are in harmony with our climate data from 2000 to 2013. For instance, the observed average monthly temperature difference between those who report increasing temperature and those who do not is about 0.34 0^{C}, and the difference is statistically significant. Similarly, the difference in PCI between those farmers who observe increasing variability of rainfall and those who do not is about 1.69. These results are consistent with the recent studies in the Nile Basin of Ethiopia by Amdu et al. (2013) and in some African countries by Hassan and Nhemachena (2008).

To account for farm features, we include several plot-specific attributes, including soil fertility,[5] soil depth,[6] plot slope,[7] spatial distance of the plot from the farmer's home (in minutes walking) and choice of crops grown. On average, 75% of landowners operate on about four parcels, each with about 0.25 ha, and these plots are often not spatially adjacent (as far as 15 minutes walking time from the farmer's residence). The variable distance to plot is an important determinant of adaptation practices through its effect on increasing transaction costs on the farthest plot, particularly costs for transporting bulky materials/inputs. Distant plots usually receive less attention and it is difficult to frequently monitor (watch or guard) them.

4. Conceptual Framework and Econometric Specification

As discussed above, farmers' adoption choices among agricultural water management practices, modern crop seeds and fertilizers lead to eight (2^3) possible combinations of adaptation practices. Adoption of these combinations may not be random; instead, farmers may endogenously self-select into using or not-using decisions, so decisions are likely to be influenced by unobservable characteristics (for example,

[5] The farmer's perception of each plot's soil fertility is ranked as "poor," "medium" or "good."

[6] The farmer's perception of each plot's soil depth is ranked as "deep," "medium deep" or "shallow."

[7] The farmer's perception of each plot's slope is ranked as "flat," "medium slope" or "steep slope."

expectation of yield gain from adoption, managerial skills, motivation) that may be correlated with the outcomes of interest, i.e., combination of techniques adopted and farm income. We model farmers' choice of combinations of climate-smart practices and impacts of adoption in a setting of a multinomial endogenous switching regression framework, a relatively new selection-bias correction methodology based on the multinomial logit model (Bourguignon et al. 2007). This approach allows for getting both consistent and efficient estimates of the selection process and a fairly good correction for the outcome equations, even when the independence of irrelevant alternatives (IIA) assumption is not achieved (Bourguignon et al. 2007).

This framework also has the advantage of evaluating adoption of adaptation practices both individually and in combination, capturing the interactions among choices of alternative practices (Wu and Babcock 1998). The estimation is done in two steps. In the first stage, the farmer's choice of individual and combined climate-smart practices is modeled using a multinomial logit selection model, while recognizing the inter-relationship among the practices. In the second stage, we follow Mendelsohn et al. (1996) and estimate Ricardian models conditional on the impacts of various combinations of climate-smart practices on the outcome variables with selectivity correction terms.

4.1 Multinomial Adoption Selection Model

The farmer faces a decision in which multiple climate-smart practice combinations are simultaneously available and she has to select at least one of the combinations. The appropriate econometric approach to modeling such a decision process is to use a polychotomus choice framework, such as the multinomial logit model. Farmers are assumed to use the combination of climate-smart practices that maximizes their expected utility over their planning horizon. Let U_{ij}^{*} be the i^{th} farmer's expected utility from adopting combination of practices j, $j(j=1,..,J)$, with respect to adopting alternative combination of practices m:

$$U_{ij}^{*} = X_i\beta_{,} + \varepsilon_{ij} \qquad (1)$$

where X_i is observed exogenous variables (household, farm and location characteristics) and ε_{ij} is unobserved characteristics. The farmer's utility from choosing a combination of climate-smart practices is not observable but the choice is.

Climate-smart practice combination j is chosen if U_{ij}^* is the highest for household i. Therefore, the farmer will choose combination of adaptation practices j in preference to adopting any other combination of practices m if:

$$U = \begin{cases} 1 \text{ iff } U_{i1}^* > \max_{m \neq 1}(U_{im}^*) \text{ or } \eta_{i1} < 0 \\ \quad . \qquad . \qquad\qquad . \\ \quad . \qquad . \qquad\qquad . \\ \quad . \qquad . \qquad\qquad . \\ J \text{ iff } U_{iJ}^* > \max_{m \neq J}(U_{im}^*) \text{ or } \eta_{iJ} < 0 \end{cases} \qquad \text{for all } m \neq j \tag{2}$$

where $\eta_{ij} = \max_{m \neq j}\left(U_{im}^* - U_{ij}^*\right) < 0$ (Bourguignon et al. 2007). Equation (2) implies that the i^{th} farmer will adopt a combination of practices j to maximize his expected profit if it provides greater expected profit than any other package $m \neq j$, that is, if $\eta_{ij} = \max_{m \neq j}\left(U_{im}^* - U_{ij}^*\right) < 0$.

Assuming that ε are identically and independently Gumbel distributed, the probability that farmer i with characteristics X will choose combination of practices j can be specified by a multinomial logit model (MNL) (McFadden, 1973):

$$P_{ij} = \Pr(\eta_{ij} < 0 \mid X_i) = \frac{\exp(X_i \beta_j)}{\sum_{m=1}^{J} \exp(X_i \beta_m)}. \tag{3}$$

4.2 Multinomial Endogenous Switching Regression

The relationship between the outcome variables and a set of exogenous variables Z (farm, household and location characteristics) is estimated for the chosen combination of practices. This yields eight conditional specifications, one for each combination of practices. The conditional Ricardian specification for each possible regime j for j=1, . . ., 8 is given as:

$$\begin{cases} \text{Regime 1: } Q_{i1} = Z_i\alpha_1 + u_{i1} \quad \text{if } I = 1 \\ . \qquad\qquad . \\ . \\ . \qquad\qquad . \\ . \qquad\qquad . \\ \text{Regime 8:} Q_{i8} = Z_i\alpha_8 + u_{i8} \quad \text{if } I = 8 \end{cases} \tag{4}$$

where $Q'_{ij}s$ are the outcome variables of the i^{th} farmer in regime j, and the error terms $(u's)$ are distributed with $E(u_{ij}|X,Z)=0$ and $\text{var}(u_{ij}|X,Z)=\sigma_j^2$. Q_{ij} is observed if and only if combination of climate-smart practices j is used, which occurs when $U_{ij}^* > \max_{m\neq j}(U_{im}^*)$. If the $\varepsilon's$ and $u's$ are not independent, a consistent estimation of α_j requires inclusion of the selection correction terms of the alternative choices in (4). Bourguignon et al. (2007) show that consistent estimates of α_j in the outcome equations (4) can be obtained by estimating the following selection bias-corrected net crop income:

$$\begin{cases} \text{Regime 1: } Q_{i1} = Z_i\alpha_1 + \sigma_{1\varepsilon}\hat{\lambda}_{i1} + \omega_{i1} \quad \text{if } U = 1 \\ . \qquad\qquad . \\ . \qquad\qquad . \\ . \qquad\qquad . \\ \text{Regime 8: } Q_{i8} = Z_i\alpha_8 + \sigma_{i8}\hat{\lambda}_{i8} + \omega_{i8} \quad \text{if } U = 8 \end{cases} \tag{5}$$

where σ_j is the covariance between ε's and u's and λ_j is the inverse Mills ratio computed from the estimated probabilities in (3) as follows:
$\lambda_j = \sum_{m\neq j}^{J} \rho_j \left[\frac{\hat{P}_{im}\ln(\hat{P}_{im})}{1-\hat{P}_{im}} + \ln(\hat{P}_{ij}) \right]$; ρ is the correlation coefficient of ε's and u's and $\omega's$ are error terms with an expected value of zero. In the multinomial choice setting, there are J-1 selection correction terms, one for each alternative combination of adaptation practices. The standard errors in (5) are bootstrapped to account for the heteroskedasticity arising from the two-stage estimation procedure.

Self-selection models that are estimated in a two-stage procedure have been criticized for being sensitive to misspecification (Wu and Babcock 1998). The lack of identification is particularly a problem when variables affecting the adoption decisions

(Z) are the same as those affecting the subsequent outcome equations (X). This is because, though the correction term (λ) is non-linear, this may not be sufficient in some cases, leading to problems of multicollinearity (Khanna 2001; Wu and Babcock 1998). Accordingly, to enable identification, we established a set of selection instruments hypothesized to directly affect the choice decisions but not the outcome variable of net crop income. A simple falsification test following Di Falco and Veronesi (2011) was used to test the assumption that the instrumental variables affect the practice choice decision but do not influence the crop income outcome. The results confirm that in nearly all cases the sets of instruments are successful at enabling identification.

In addition, to overcome the possible correlation of plot-invariant unobserved heterogeneity with observed covariates, we use Mundlak's (1978) approach, where the unobserved heterogeneities are parameterized by including the mean value of plot-varying explanatory variables (e.g., average of plot characteristics, plot distance to residence) as additional covariates in the regression model. For application of this approach using cross-sectional multiple plot observations, see Di Falco et al. (2012).

5. Estimation of Average Adoption Effects

In this section, we show how to estimate the average adoption effect of a combination of climate-smart practices from the econometric approach outlined above. The estimands that are most commonly of interest are the average adoption effect on the population (ATE), the average adoption effect on the adopter (ATT) and the average treatment effect on the non-adopter (ATU). The ATE is the unconditional average adoption effect, which answers the question of how, on average, the net farm income would change if everyone in the population of interest had been "treated" with a particular combination of adaptation practices relative to none of them adopting any practices. The ATT and ATU answer the question of how the average outcome would change if everyone who received one particular treatment had instead received another particular treatment.

The ATE of combination of practices (j) versus package (1) is defined from equation (5) as:

$$ATE = E(Q_{ij} - Q_{i1} | Z = z_i) = Z_i(\alpha_j - \alpha_1) \text{ for } j = 2, \ldots, 8 \tag{6}$$

In observational studies, where the investigators have no control over the assignment of the package of adaptation practices, the adoption status is likely to be dependent on outcomes and thus a biased estimator of the ATE. However, the ATT and ATU are used to compare expected net farm income of adopters and non-adopters with the counterfactual hypothetical case that adopters did not adopt and vice versa. Following Carter and Milon (2005), the expected net farm income under the actual and counterfactual hypothetical cases are computed as follows, by applying Equation (5).

Adopters with adoption (actual): $E(Q_{ij} \mid I = j) = Z_{ij}\alpha_j + \sigma_j\lambda_{ij}$ (7)

Non-adopters without adoption (actual): $E[Q_{i1} \mid I = 1] = Z_{ij}\alpha_1 + \sigma_1\lambda_{i1}$ (8)

Adopters had they decided not to adopt (counterfactual): $E[Q_{i1} \mid I = j] = Z_{ij}\alpha_1 + \sigma_1\lambda_{ij}$ (9)

Non-adopters had they decided to adopt (counterfactual): $E[Q_{ij} \mid I = 1] = Z_{ij}\alpha_j + \sigma_j\lambda_{i1}$. (10)

Equations (7) and (8) represent the expected outcomes of adopters and non-adopters that were actually observed in the sample, whereas Equations (9) and (10) denote the counterfactual expected outcomes of adopters and non-adopters, respectively. These expected values are used to compute unbiased estimates of the effects of adoption on adopters and on non-adopters. The average climate-smart practices adoption effect on the adopters (ATT) is defined as the difference between Equations (7) and (9):

$$ATT = [Q_{ij} \mid I = j] - E[Q_{i1} \mid I = j] = Z_i(\alpha_j - \alpha_1) + \lambda_{ij}(\sigma_j - \sigma_1) \quad (11)$$

Similarly, the average effects of adoption of a combination of climate-smart practices on non-adopters (ATU), i.e., the counterfactual effects of adoption on those who did not adopt if they had adopted, is computed as the difference between Equations (8) and (10):

$$ATU = E[Q_{ij} \mid I = 1] - E[Q_{i1} \mid I = 1] = Z_i(\alpha_j - \alpha_1) + \lambda_{i1}(\sigma_j - \sigma_1) \quad (12)$$

The ATT and ATU parameters give the expected outcome effect of adoption, controlling for selection bias, on a randomly chosen household in the groups that do and do not adopt a combination of adaptation practices, respectively.

6. Estimation Results

We begin to discuss our results with the choice analysis. Table 4 reports the estimated results of the multinomial logit model for the combination of climate-smart practices, including mean of plot-variant explanatory variables. We assessed the effect of introducing the Mundlak (1978) approach. Almost all equations reject the null hypothesis that all coefficients of the mean of plot-varying covariates are jointly statistically equal to zero. Hence, we confirm the presence of correlation between unobserved household fixed effects and observed covariates. Keeping non-adoption of all practices ($Va_0Fe_0Aw_0$) as the base category to which results are compared (i.e., the estimated effects are relative to being non-adopters), the table shows seven sets of parameter estimates, one for each mutually exclusive combination of practices. The estimation results shed light on the difference between adoptions of various combinations of adaptation practices. The Wald test that all regression coefficients are jointly equal to zero is rejected [$\chi^2(420) = 38992$; p = 0.000].

There is no significant correlation between adoption of climate-smart practices and gender of household head, except that male-headed households are more likely to adopt the combination of the two externally purchased inputs – modern crop seeds and inorganic fertilizers ($Va_1Fe_1Aw_0$). As expected, there is significant and positive association between education level of the household head and adoption of modern crop seeds when combined with inorganic fertilizers ($Va_1Fe_1Aw_0$) or water management practices ($Va_1Fe_0Aw_1$). Education may increase an individual's ability to acquire and absorb information on climate change and various farm management practices (Chander et al. 2003; Maddison 2006). Households with more education may have greater access to non-farm income and thus be more able to purchase inputs. Results also reveal that modern crops seeds, when combined with water management ($Va_1Fe_0Aw_1$) and inorganic fertilizer ($Va_1Fe_1Aw_1$), are more likely to be adopted by households with larger family size.

The results reveal a significant wealth or liquidity constraint effect on the adoption of combinations of climate-smart practices. For example, the extent of livestock holdings influences the adoption of a combination of modern seeds and fertilizer ($Va_1Fe_1Aw_0$). This indicates that modern seeds and inorganic fertilizer, which are externally purchased inputs, are not adopted by resource-poor farmers. This is likely because wealthier farmers have both the capacity to purchase external inputs and the ability to bear risk. Similarly, adoption of $Va_0Fe_1Aw_0$ (only fertilizer) or $Va_0Fe_0Aw_1$ (only agricultural water management practice) is less likely for credit-constrained farm households. This suggests that liquidity-constrained households (those who need credit but are unable to get it) are less likely to adopt practices that require cash outlay.

The results also reveal that households with confidence in the skills of extension agents are more likely to adopt improved seed varieties or fertilizer. These practices are relatively capital- and knowledge-intensive, requiring considerable cash outlays and management knowledge about proper application. However, whether the farmer has been in contact with extension services has no impact on adoption of these two inputs. This may indicate that it is not the extension contact per se that affects adoption, but rather the quality of the extension services. This underscores the importance of upgrading the skills of extension workers to speed up adoption of climate-smart practices.

The role of trusted intermediaries is particularly important in providing climate information to the farmers because, as empirical research has shown, farmers resist using climate forecasts. Many farmers, especially those in less developed regions, place a low priority on climate-related concerns, and farmers often think that climate information does not fit their needs because they perceive it to be inaccurate (spatially and temporally) and unreliable, because of high levels of uncertainty (Lemos et al. 2014). Here, however, we find that access to climate information makes it more likely that farmers use water management practices ($Va_0Fe_0Aw_1$). This result suggests that climate change information is an important step to increase awareness and knowledge of farmers by providing evidence-based critical climate change information to build resilience and reduce uncertainty (Iwuchukwu and Udoye 2014). Thus, it is of particular importance to develop appropriate outreach materials about climate-smart practices and provide them to farmers, in order to promote farm management alternatives and reduce vulnerability to a changing climate.

The social capital and network variables have positive effects on adoption of a combination of climate-smart practices. With imperfect markets for credit and insurance, including high transaction costs and scarce or inadequate information sources, these types of social capital and networks could facilitate the exchange of information, enable farmers to access inputs on schedule and overcome credit constraints.

The perception that adoption of climate-smart practices has positive productivity effects on neighboring plots has mixed effects depending on the type of practice. Farmers are more likely to adopt agricultural water management and modern crop seeds on their plots if they believe that there have been positive productivity effects on their neighbors' plots. Other-regarding preferences behind altruistic behavior may offer insights into the circumstances under which individuals are most likely to adopt modern crop seeds and water management that generate positive externalities. Adoption of water management techniques reduces soil erosion and increases soil moisture content, which to a certain extent benefits neighboring plots. However, farmers are less likely to adopt inorganic fertilizer when they perceive that their adoption has beneficial effects that are captured by their neighbors and experience disutility from the feeling that others free-ride on their application of fertilizers. The latter result is consistent with that of Wollni and Andersson

(2014), who suggest that farmers tend to forgo agricultural investments to prevent others from free-riding on their efforts because not all the benefits accrue to the individual who adopts them.

With regard to the importance of rainfall and plot-level shocks in determining the adoption of a combination of adaptation practices, the results indicate that in areas/years where rainfall is worst in terms of timing, amount and distribution, it is more likely that a household shifts to a combination of practices that are more climate-smart. This finding suggests that smallholder farmers who are aware of rainfall variability are using water management practices in combination with modern seeds ($Va_1Fe_0Aw_1$) and inorganic fertilizer ($Va_1Fe_1Aw_1$) as adaptation strategies to mitigate the risk of climate variability. This is important evidence of the synergy among climate-smart practices as a form of climate adaptation. Plot-level disturbances such as flooding and incidence of pests and diseases negatively affect the adoption of modern seeds and fertilizer ($Va_1Fe_1Aw_0$). However, households that believe that the government will provide support when crops fail are more likely to adopt fertilizer ($Va_0Fe_1Aw_0$) or a combination of seed variety and inorganic fertilizer ($Va_1Fe_1Aw_0$), probably because the benefit of these technologies is uncertain and farmers want insurance in order to adopt them.

Farmers are more likely to adopt agricultural water management on plots that they own. This is probably because of tenure security and the hypothesis of Marshallian inefficiency, i.e., lower efficiency or input use on rented plots as compared to owned plots. Given the fact that the benefits from establishing water management systems on the farm accrue over time, this inter-temporal aspect suggests that secure land access or tenure will positively impact adaptation decisions. We also found significant effects of farm characteristics on the choice of alternative combinations of climate-smart practices. Slope of the farm and depth of the soil are particularly associated with the likelihood of climate-smart practices. The type of crops grown is also important in the choice of adaptation practices. While adoption of modern seeds and/or inorganic fertilizer is more likely for cereal than vegetable crops, adoption of water management is more likely for vegetable crops than for cereal and legume crops. As expected, fertilizer application is less likely on legume crops. Growing legume crops is usually considered a key component of integrated soil fertility management.

We now move to the results of the climate variables. Not all individual climate variables are statistically significant. However, the set of climate variables are jointly highly significant determinants of the choice of a combination of climate-smart practices. We found that the amount of rainfall in the growing season is important for the choice of fertilizer ($Va_0Fe_1Aw_0$) and for the choice of a combination of water management practices with improved seed ($Va_1Fe_0Aw_1$) or fertilizer ($Va_0Fe_1Aw_1$). The positive first degree and negative second degree terms for growing season precipitation indicate an inverted U-shaped response to the likelihood of these combinations of climate-smart practices. However, the non-significance of the quadratic term coefficients of ($Va_1Fe_0Aw_1$) and ($Va_0Fe_1Aw_1$) suggests that adoption of modern seeds and fertilizer might be quite resilient to changes in precipitation when they are combined with water management practices. This result suggests the need for careful agro-ecological targeting when developing, promoting and scaling up adaptation practices. Water management seems to be a key element because it can minimize the risk of a yield shortfall arising from application of fertilizer and new seeds in the event of unfavorable rain (Monjardino et al. 2013).

This study also shows that the adoption of agricultural water management in combination with modern seeds ($Va_1Fe_0Aw_1$) or inorganic fertilizer ($Va_0Fe_1Aw_1$) responds to annual temperature in a hill-shaped pattern, where the linear coefficient is positive and the quadratic term coefficient is negative; all are statistically significant. This result suggests that these combinations of practices are important options for adapting agricultural production to warmer climatic conditions. Agricultural water management is a risk-reducing option, so increased frequency of unfavorable weather conditions favors its adoption.

Increasing rainfall variability significantly decreases the likelihood of adoption of fertilizer, either in isolation or in combination with modern seeds, thus reflecting the adverse effects of rainfall variability on adoption of risk-increasing inputs. In high rainfall variability conditions, agricultural water management, whether in isolation ($Va_0Fe_1Aw_1$) or in combination with inorganic fertilizer ($Va_0Fe_1Aw_1$) or modern seeds ($Va_1Fe_0Aw_1$) or both ($Va_1Fe_1Aw_1$), is more important as an adaptation strategy for smallholder farming systems. As a risk-decreasing practice, water management is the most common response to rainfall variability; it strengthens farmers' resilience when adopted in combination with modern seeds and/or inorganic fertilizer.

Finally, we tested an interaction term between amounts of growing season precipitation and growing season rainfall variability and found important lessons for climate change adaptation. The result shows that, in low rainfall areas, adoption of improved crop seeds and/or fertilizer in combination with agricultural water management is more likely under high variable rainfall conditions. More variable rainfall and lower amounts of rain could bring challenges to agricultural production in general and to adoption of risk-increasing externally purchased inputs in particular. However, agricultural water management can be combined with modern seeds and inorganic fertilizers to present opportunities for farmers to make the farming system more resilient to decreased rain intensity and increased variability.

A schematization of choice behaviors with point predictions at varying levels of rainfall intensity, annual temperature and rainfall variability is shown in Figs. 1, 2 and 3, respectively. Fig. 1 shows that, if the climate becomes wetter, the probability of choosing agricultural water management practices in isolation or in combination with modern seeds and inorganic fertilizer increases. Farmers tend to move away from adoption of modern seeds and inorganic fertilizer when annual rainfall is higher or lower than an optimal level 800 mm. Agricultural water management is chosen more frequently as the climate becomes hotter, as shown in Fig. 2. On the other hand, Fig. 3 depicts that, under high rainfall variability, the likelihood of adoption of agricultural water management is increasing, whether it is adopted in isolation or in combination with modern seeds and inorganic fertilizer.

6.1 Impacts of Multiple Adaptation Practices

As we described above, in the second stage, we estimate the least squares regression of net crop income for each combination of climate practices, taking care of the selection bias correction terms from the first stage. The estimation result is shown in Table 1A in the appendix. In brief, many of the selection correction terms are significant at least at the 10% level, suggesting that these combinations of climate-smart practices will not have the same effects on non-adopters should they choose to adopt. This is evidence of self-selection in the adoption of packages of practices. It also suggests that a number of variables in the model have significant correlation with the net crop income variables and that there are differences between the outcome equations' coefficients among the different combination adopter groups. This illustrates the heterogeneity in the sample with respect to crop net income.

From the regression estimates, we derive the unconditional and conditional average effects of adoption of various combinations of agricultural water management practices, modern crop seeds and inorganic fertilizers. The unconditional average effect is presented in Table 5. The unconditional average effects indicate that adopters of any of the climate-smart practices in isolation or in combination earn more net crop income, on average, than non-adopters. This naive comparison would drive misleading conclusions because the approach doesn't consider that the difference in the outcome variable may be caused by observable and unobservable characteristics.

Table 6 presents the true average adoption effects of net crop income under actual and counterfactual conditions. In this table, the net farm income variable of farm households who adopted the combination of climate-smart practices is compared with the outcome variables that would have been found if the households had not adopted. This is done by applying Eq. (11). In order to determine the average adoption effects, we compare Columns A and B of Table 6. Column C presents the impacts of adoption of climate-smart practices in isolation and in combination on net crop income, computed as the difference between the above columns.

Results show that the adoption of any of the climate-smart practices, whether in isolation or combination, provides higher net crop income compared with non-adoption (Table 6). In all counterfactual cases, farm households who actually adopted would have earned less if they did not adopt. Adoption of inorganic fertilizers in isolation provides higher net income than adoption of other practices in isolation. Adoption of inorganic fertilizers in combination with agricultural water management practices ($Va_0Fe_1Aw_1$) or in combination with modern crop seeds ($Va_1Fe_1Aw_0$) also provides higher farm income than a combination of water management and modern crop seeds ($Va_1Fe_0Aw_1$). However, the largest farm income (10.5 thousand Birr/ha) is obtained from adoption of agricultural water management practices jointly with inorganic fertilizers and modern crop seeds ($Va_1Fe_1Aw_1$).

The productivity-enhancing effect of modern seeds or/and inorganic fertilizer is significantly higher when agricultural water management practices are added into the package. The net revenue of adopting a combination of agricultural water management with modern seeds or inorganic fertilizer is significantly higher, by 7.6 and 1.5 thousand Birr/ha, respectively, than adopting modern seeds or inorganic fertilizer alone. The net farm income from adoption of a combination of modern seeds and fertilizer is 14 thousand Birr/ha. The net farm income from modern seeds and fertilizer is significantly increased by about 45% if agricultural water management is combined with modern seeds and fertilizers. This is a clear indication of complementarity among the three climate-smart practices.

6.2 Simulation of Future Combination of Practices and Income

The observed distributions and farm income associated with the different combinations of climate-smart practices are the consequences of long-term adjustment by farmers to the existing climate. If the current climate were to shift significantly, as many climate models predict, this would change the current distribution of practices, as farmers will learn that the current practices do not provide as much return as in the past. Based on our previous results, we now intend to simulate the effects of possible substantial future changes in climate on the choice of climate-smart practices and the net farm income half a century in the future.

We use a climate scenario predicted by the regional climate model BCM.2 to get estimates using the A2 emission scenario from the special report on emission scenarios (SRES) of the IPCC (2000). At the district level, the SRES A2 emission scenario predicts an average annual temperature increase of 1.8^0C (+8% from the 1980-99 period) and an average total annual rainfall decrease of 34 mm (-2%) by 2060. We summarize the potential behavior of the combination of climate-smart practices in the adaptation model by calculating the scenario-predicted probabilities, which are cross-tabulated against the base fitted ones in Table 7. In the net income impacts module, we measure the impacts of climate change on net crop income for each alternative combination of climate-smart practices half a century in the future by taking the difference between the base-fitted and scenario-predicted net farm income (Table 8). An important remark to note in interpreting the results in Table 7 and 8 is that these results are partial equilibrium changes, which ignore the effects of other possible determinants of adaptation and farm profitability.

Based on our parameter results and the A2 storyline, adoption of a combination of climate-smart practices by 2060 would be expected to change in about 40% of the farming plots (around 1840 plots – the sum of the off-diagonal components of Table 7). While plots with none of the climate-smart practices are predicted to decrease by about 22% (38% vs. 16%), adoption of climate-smart practices in isolation as well as in combination would be expected to increase by up to 18% in half a century. Under the SRES A2 scenario, the net crop income for farms without climate-smart practices would be expected to decline compared to the baseline levels but the profit of farms with agricultural water management practices would increase (Table 8). Similarly, although there is a decrease in net crop income from farms with modern seeds alone or in combination with inorganic fertilizer, the profit increases when these two externally purchased inputs are combined with agricultural water management practices. Although profit from farms with agricultural water management increases, the increase from farms with a combination of agricultural water management, modern seeds and inorganic fertilizer is very high. The overall conclusion of net income changes, shown in Table 8, confirms the hypothesis that farms with a combination of climate-smart practices are more resilient under climate change than are farms with climate-smart practices in isolation. A farm with a combination of climate-smart practices will have a relative advantage in the future in a warmer and moisture-stressed climate. These patterns should encourage more farmers to adopt modern inputs (fertilizer and modern seeds) in combination with agricultural water management practices.

7. Conclusions

Under climate change, increasing and sustaining food production is a scientific and policy challenge that must be met to sustain and increase benefits of intensive agricultural production. In the developing world, where vulnerability is greatest and farmers may face overlapping constraints (such as weeds, pest and disease infestations, and low soil fertility and crop productivity), promising climate-related management innovations, which may be adopted simultaneously as complements, substitutes or supplements, are underutilized because of the lack of empirically tested actionable information. In this article, we contribute to the existing empirical literature on whether a combination of multiple climate-smart practices is more resilient against climate change. We developed a multinomial endogenous switching regression model, where selectivity is modeled as a multinomial logit for the climate dependent occurrence of a combination of climate-smart practices (agricultural water management, modern crop seeds and fertilizers) at farm-plot level. We also develop a least squares model in the second stage to include self-selection bias correction terms for net farm income for those combinations of practices. In addition, we simulate the possible effects of climate change in the future on both the choice of practices and on farm income, using nationally representative comprehensive household-plot level data collected in 2015 in the Nile Basin of Ethiopia.

Our results indicate that the current choices of alternative combinations of practices and related farm income in the Nile basin of Ethiopia are heavily influenced by climate. When the climate is hot and the rainfall is variable, farmers more often prefer a combination of practices over a practice in isolation. Adoption of fertilizer, whether alone or in combination with improved seed varieties, is less likely in areas of higher precipitation variability. However, under conditions of high rainfall variability, adoption of fertilizer and improved seeds are more likely when they are combined with agricultural water management practices.

The multinomial logit model results also revealed that the likelihood of adoption of agricultural water management, modern crop seeds and inorganic fertilizers is influenced by plot-level shocks, soil characteristics, social capital and extension services. The effect of these variables can be used to target policies aimed at increasing adoption rates of different types of practices. For example, the significant role of social capital and extension services suggests the need for establishing and strengthening local institutions, service providers and extension systems to accelerate and sustain adoption. In a country where there is information asymmetry and both input and output markets are missing or incomplete, local institutions can play a critical role in providing farmers with timely information, inputs (e.g., labor, credit, and insurance), and technical assistance. Furthermore, the adoption of climate-smart practices is more likely on owner-cultivated plots than on rented-in plots, suggesting a number of supplementary policy measures to guarantee long-term tenure security.

With regard to the results of adoption effects, net farm income displays a positive response to agricultural water management, improved crop variety and fertilizer when they are adopted in isolation as well as in combination. But this effect is greater when these practices are combined than used in isolation. Based on these results, simulating the effects of climate scenarios by 2060, we find that the share of plots with none of the climate-smart practices is predicted to decrease by about 22%, while the share of plots with adoption of climate-smart practices in isolation as well as in combination is expected to increase by up to 18%.

An important message from our findings is that the observed changes in intensity and variability of rainfall in the Nile Basin of Ethiopia could have negative impacts on agriculture if these changes persist. However, there are opportunities for agricultural producers to improve their resilience in a changing world; agricultural water management is among the ways that producers in the region are presently adjusting management to improve production and to be ready for the possibility of a more challenging rainfall regime. Increasing water retention and improving infiltration of soils might become a greater priority for producers looking to capture and efficiently use scarce rainfall, in order to minimize the risks associated with adopting yield-enhancing inputs under conditions of extreme variability of rains and increasing temperature.

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Tables and Figures

Table 1. Package of Climate-Smart Practices Used on Farming Plots in the Nile Basin of Ethiopia

Choice (j)	Package of climate-smart practices[Ψ]	Improved crop varieties (Va)		Fertilizer (Fe)		Water managment (Aw)		Frequency (%)
		Va_1	Va_0	Fe_1	Fe_0	Aw_1	Aw_0	
1	$Va_0Fe_0Aw_0$		√		√		√	28.25
2	$Va_1Fe_0Aw_0$	√			√		√	2.72
3	$Va_0Fe_1Aw_0$		√	√			√	17.50
4	$Va_0Fe_0Aw_1$		√		√	√		14.50
5	$Va_1Fe_1Aw_0$	√		√			√	10.36
6	$Va_1Fe_0Aw_1$	√			√	√		1.83
7	$Va_0Fe_1Aw_1$		√	√		√		16.16
8	$Va_1Fe_1Aw_1$	√		√		√		8.57

[Ψ]Each element in the adaptation practices combinations consists of a binary variable for a practice (Improved crop varieties (Va), Inorganic fertilizer (Fe) and Agricultural water management (Aw)), where the subscript refers 1= if adopted and 0 = otherwise.

Table 2. Sample Conditional and Unconditional Adoption Probabilities of Climate-Smart Practices in Ethiopia

	Improved crop varieties (Va)	Fertilizer (Fe)	Water managment (Aw)
$P(Y_k = 1)$	23.5	52.6	41.1
$P(Y_k = 1 \mid Y_{Va} = 1)$	100.0	80.6***	44.3***
$P(Y_k = 1 \mid Y_{Fe} = 1)$	35.9***	100.0	47.0***
$P(Y_k = 1 \mid Y_{Aw} = 1)$	25.3***	60.2***	100.0
$P(Y_k = 1 \mid Y_{Va} = 1, Y_{Fe} = 1)$	100.0	100.0	45.3***
$P(Y_k = 1 \mid Y_{Va} = 1, Y_{Aw} = 1)$	100.0	82.4***	100.0
$P(Y_k = 1 \mid Y_{Fe} = 1, Y_{Aw} = 1)$	34.7***	100.0	100.0

Y_k is a binary variable representing the adoption status with respect to choice k (k = Improved crop varieties (Va), Inorganic fertilizer (Fe) and Agricultural water management (Aw)).

*, ** and *** indicate statistical significance difference at 10%, 5% and 1% respectively. The comparison is between unconditional probability and conditional probabilities in each practice.

Table 3. Explanatory Variables by Combination of Climate-Smart Practices

Variable	Description	$Va_0Fe_0Aw_0$	$Va_1Fe_0Aw_0$	$Va_0Fe_1Aw_0$	$Va_0Fe_0Aw_1$	$Va_1Fe_1Aw_0$	$Va_0Fe_0Aw_0$	$Va_0Fe_0Aw_0$	$Va_0Fe_0Aw_0$	All Mean	Std.dev
Household features											
Gender	Sex of the head (1=if male)	0.872	0.867	0.855	0.890	0.930	0.872	0.876	0.916	0.882	-
Age	Age of the head. Years	51.39	48.62	52.64	51.39	51.81	49.55	53.15	51.23	51.81	12.72
Education	Education level of the head in years	1.80	2.35	1.24	1.95	2.11	2.87	1.76	1.98	1.80	3.03
Famlysize	Family size	8.07	8.45	8.27	8.03	8.55	8.29	8.10	8.55	8.21	2.40
Resource constraints											
Farmsize	Farm size in ha	1.74	2.28	1.90	1.80	1.84	2.04	1.90	1.83	1.84	1.20
Tlu	Livestock size	4.71	4.84	4.84	4.68	5.13	4.79	4.85	5.13	4.83	3.53
Credit	Credit constraint (1=if yes)	0.485	0.492	0.408	0.440	0.419	0.558	0.417	0.404	0.442	-
Expend	Annual household expenditure in '000 Birr	14.69	16.23	16.97	13.18	19.10	14.79	16.14	19.36	16.00	15.33
Extension. information and market											
Distmkt	Walking distance to main market in minutes	68.65	65.51	69.05	69.55	57.96	62.97	67.84	59.49	66.64	53.03
Extcont	1=if contact extension agents	0.959	0.992	0.968	0.972	0.979	1.000	0.971	0.983	0.970	-
Extconfd	1=if confident with the skill of extension agents	0.952	0.984	0.959	0.955	0.964	0.957	0.961	0.957	0.958	-
Infoclimat	1=if farmer has access to climate information	0.496	0.539	0.447	0.595	0.575	0.547	0.503	0.620	0.524	-
Social capital and network											
Member	1=if the household is member of groups	0.923	0.938	0.983	0.969	0.994	0.977	0.978	0.973	0.962	-
Agrigroup	Number of agricultural groups where a farmer is a member	0.789	0.953	0.656	0.802	0.951	1.105	0.807	1.097	0.824	1.098
Socgroup	Number of social groups where a farmer is a member	2.428	2.508	2.495	2.567	2.669	2.384	2.607	3.017	2.566	1.461
Spillover effects on neighbors' plots											
Vapos	1=if perceived positive effects of improved variety	0.258	0.336	0.337	0.189	0.359	0.291	0.228	0.395	0.282	-
Fepos	1=if perceived positive effects of fertilizer	0.336	0.328	0.396	0.306	0.374	0.349	0.379	0.412	0.360	-
Awpos	1=if perceived positive effects of water management	0.593	0.688	0.652	0.818	0.630	0.733	0.822	0.779	0.698	-
Shocks											
Rainindex	Rainfall disturbance index (1=best)	0.706	0.706	0.683	0.695	0.727	0.630	0.731	0.673	0.702	0.283
Plotindex	Plot level disturbance index (1=worst)	0.185	0.150	0.200	0.184	0.157	0.165	0.199	0.215	0.188	0.178
Relygovt	1=if rely on government support in case of crop failure	0.364	0.359	0.482	0.334	0.437	0.360	0.434	0.479	0.409	-
Farm features											
Plotdist	Walking distance of the plot from home (minutes)	14.64	14.20	14.50	16.05	13.41	16.88	15.08	14.35	14.77	18.73
Tenure	1=if own the plot	0.867	0.898	0.814	0.897	0.850	0.919	0.832	0.849	0.855	-
Highfert	1=if highly fertile soil plot	0.349	0.305	0.367	0.384	0.386	0.488	0.393	0.427	0.376	-
Midfert	1=if medium fertile soil plot	0.516	0.578	0.490	0.515	0.509	0.453	0.508	0.469	0.506	-
Flatslop	1=if flat slope plot	0.580	0.492	0.683	0.565	0.602	0.709	0.617	0.613	0.607	-
Midslop	1=if medium slope plot	0.392	0.445	0.279	0.389	0.366	0.267	0.367	0.347	0.360	-
Depdepth	1=if deep depth soil plot	0.464	0.484	0.482	0.479	0.478	0.558	0.501	0.467	0.480	-
Middepth	1=if medium depth soil plot	0.408	0.414	0.405	0.411	0.394	0.337	0.417	0.400	0.406	-
Manure	1=if manure was applied in the plot	0.260	0.414	0.283	0.330	0.298	0.523	0.292	0.385	0.303	-
Cereal	1=if cereal crops grown	0.593	0.758	0.871	0.588	0.938	0.593	0.820	0.871	0.742	-
Legume	1=if legume crops grown	0.283	0.148	0.064	0.220	0.031	0.221	0.064	0.037	0.148	-
Climate											
Rain	Amount of rainfall in the growing season in mm (2000-2013)	698.39	790.70	616.24	775.88	719.19	818.02	695.72	694.97	701.38	233.67
PCI	Precipitation concentration index	20.09	21.02	19.39	20.79	19.62	21.66	19.56	19.86	19.97	2.59
Temperature	Average temperature in ^{0}C (2000-2013)	27.36	26.34	26.04	28.19	24.31	27.20	29.35	29.14	27.38	5.85
Elevation	Location of the household with respect to altitude (m.a.s.l)	2218	1979	2279	2251	2211	2001	2250	2214	2227	416
Number of observations		1333	128	823	682	487	86	760	403	4702	

Table 4. Parameter Estimates for the Selection Model of Various Combinations of Climate-Smart Practices in Ethiopia

Variables	$Va_1Fe_0Aw_0$		$Va_0Fe_1Aw_0$		$Va_0Fe_0Aw_1$		$Va_1Fe_1Aw_0$		$Va_1Fe_0Aw_1$		$Va_0Fe_1Aw_1$		$Va_1Fe_1Aw_1$	
	Coefficient	SE	Coefficient	SE.	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Household features														
Gender	-0.030	0.365	0.057	0.206	-0.024	0.242	0.529**	0.255	-0.029	0.421	0.199	0.241	0.475	0.330
Age	-0.010	0.009	-0.000	0.006	0.009	0.006	-0.002	0.006	0.005	0.016	0.010	0.007	-0.007	0.010
Education	0.031	0.035	-0.032	0.029	0.006	0.029	0.048*	0.026	0.084*	0.047	0.022	0.027	-0.000	0.033
Famlysize	0.067	0.049	0.027	0.028	-0.003	0.036	0.029	0.032	0.163**	0.078	-0.022	0.036	0.083*	0.043
Resource constraints														
Farmsize	0.170**	0.069	0.104	0.072	-0.005	0.072	0.042	0.090	-0.041	0.090	0.033	0.076	-0.004	0.109
Tlu	0.002	0.040	0.020	0.024	0.004	0.023	0.047*	0.024	0.009	0.042	-0.029	0.024	0.024	0.031
Credit	-0.002	0.237	-0.220*	0.144	-0.279*	0.153	-0.160	0.161	0.172	0.318	-0.220	0.165	-0.231	0.195
Expend	-0.006	0.007	0.001	0.005	-0.012*	0.007	0.005	0.004	-0.018	0.016	0.007	0.006	0.006	0.005
Extension. information and market														
Distmkt	-0.002	0.002	0.001	0.001	0.001	0.001	-0.003**	0.001	-0.001	0.003	0.003**	0.001	-0.003	0.002
Extcont	1.379	0.936	-0.166	0.423	0.145	0.463	0.196	0.402	14.830***	0.520	0.083	0.504	0.224	0.818
Extconfd	2.044***	0.698	0.592*	0.315	-0.120	0.385	0.585	0.494	-0.312	0.733	0.560	0.405	0.744	0.507
Infoclimat	-0.132	0.250	-0.148	0.141	0.304*	0.157	0.045	0.169	0.010	0.331	0.027	0.160	-0.004	0.211
Social capital network														
Member	0.580	0.506	0.587	0.457	0.878*	0.529	1.514*	0.810	1.274	0.882	0.504	0.481	-0.318	0.626
Agrigroup	0.056	0.098	-0.061	0.066	0.124	0.088	-0.052	0.069	0.247**	0.121	0.061	0.079	0.181**	0.086
Socgroup	0.236**	0.112	-0.047	0.056	0.062	0.062	0.079	0.063	0.034	0.124	0.027	0.061	0.199***	0.068
Spillover effects on neighbors' plots														
Vapos	0.658*	0.387	0.654***	0.214	-0.293	0.246	1.235***	0.265	0.113	0.463	-0.231	0.263	0.987***	0.321
Fepos	-0.746**	0.355	-0.519***	0.201	-0.297	0.216	-0.888***	0.229	-0.386	0.425	-0.372*	0.230	-0.901***	0.292
Awpos	0.340	0.307	-0.077	0.167	0.981***	0.198	-0.133	0.198	0.374	0.401	1.027***	0.199	0.668***	0.231
Shocks														
Rainindex	-0.037	0.400	-0.304	0.237	-0.184	0.263	-0.293	0.275	-1.128***	0.437	0.339	0.251	-0.632**	0.288
Plotindex	-0.001	0.654	-0.601	0.437	-0.435	0.403	-1.253**	0.512	-0.927	0.900	0.192	0.425	0.139	0.546
Relygovt	-0.034	0.264	0.465***	0.139	-0.223	0.165	0.288*	0.155	-0.257	0.329	0.007	0.169	0.242	0.200
Farm features														
Plotdist	0.002	0.010	0.011**	0.005	0.005	0.005	0.003	0.005	-0.009	0.008	0.010**	0.004	0.001	0.005
Tenure	-0.333	0.442	0.076	0.207	0.669***	0.233	0.041	0.233	0.871*	0.473	0.370*	0.202	0.253	0.256
Highfert	-0.177	0.536	-0.111	0.281	-0.389	0.314	0.107	0.338	-0.587	0.744	-0.160	0.299	-0.209	0.334
Midfert	-0.101	0.479	0.058	0.229	-0.383	0.270	0.254	0.292	-0.503	0.766	-0.001	0.272	-0.153	0.300
Flatslop	-1.404**	0.627	-0.748*	0.388	-0.974***	0.369	-0.047	0.446	0.096	1.195	-1.083**	0.520	-1.649***	0.451
Midslop	-1.047*	0.586	-0.505	0.373	-0.564	0.346	0.230	0.428	-0.336	1.247	-0.328	0.512	-1.090**	0.450
Depdepth	1.343**	0.619	0.478*	0.299	0.579	0.381	0.265	0.339	0.350	0.663	0.727**	0.289	0.424	0.389
Middepth	0.761	0.727	0.671**	0.265	0.569*	0.336	0.335	0.295	0.050	0.609	0.662**	0.278	0.482	0.354
Manure	0.838***	0.225	0.083	0.150	0.082	0.153	0.407**	0.176	0.803***	0.300	-0.028	0.161	0.457**	0.182
Cereal	0.873**	0.355	1.097***	0.192	-0.320**	0.162	1.815***	0.320	-0.059	0.337	0.225	0.177	0.606**	0.252

Legume	-0.272	0.453	-0.860***	0.238	-0.514***	0.174	-1.029**	0.410	-0.512	0.383	-1.581***	0.257	-1.920***	0.344
Climate														
Rainfall	-0.011	0.036	0.055***	0.019	0.013	0.014	-0.001	0.020	0.048**	0.023	0.036**	0.015	0.016	0.017
Rainfall-squared	0.001	0.002	-0.003***	0.001	-0.000	0.001	0.000	0.001	-0.001	0.001	-0.001	0.001	0.000	0.001
Temperature	18.361**	8.841	1.508	4.278	2.215	1.941	1.663	3.495	17.231***	4.403	4.632*	2.690	3.294	4.267
Temperature-squared	-0.425**	0.194	-0.029	0.122	-0.063	0.051	-0.037	0.096	-0.446***	0.114	-0.128*	0.074	-0.094	0.119
PCI	0.055	0.046	-0.175***	0.017	0.090***	0.014	-0.232***	0.023	0.062***	0.023	0.080***	0.018	0.065***	0.022
Rainfall X PCI	0.030	0.072	-0.060*	0.037	-0.025	0.030	-0.011	0.038	-0.217***	0.046	-0.086***	0.030	-0.061*	0.029
Elevation	-0.000	0.001	0.001	0.001	-0.001	0.001	-0.001	0.001	-0.002	0.002	-0.003***	0.001	-0.002	0.001
Constant	-206.782**	102.1	-34.391	37.409	-26.473	20.334	-16.390	35.789	-178.65***	47.146	-52.420**	26.384	-34.321	39.05
Joint significance of selection instruments χ^2 (7)	21.08***		17.07***		28.33***		25.55***		1083.32***		33.73***		41.28***	
Joint significance of plot varying covariates χ^2 (6)	4.19		11.25		21.25***		12.28		20.98***		17.23**		24.19***	
Joint significance of location variables χ^2 (6)	23.60**		1298.76***		35.30***		136.08*		485.35***		867.06*		89.08***	
Number of observations = 4702; Wald $\chi^2(420)$ =38992 ; p >χ^2 = 0.000														

Note: SE is robust standard errors; *, ** and *** indicate statistical significance at 10%, 5% and 1% level; $Va_0Fe_0Aw_0$ is the reference category; Location fixed effects are statistically significant, but not shown here for the sake of space.

Table 5.The Unconditional Average Effect of Adoption of a Combination of Climate-Smart Practices on Crop Net Income ('000 Birr/ha)

Practices	Net crop income, Birr/ha	Adaptation effects
$Va_0Fe_0Aw_0$	7.99(0.22)	-
$Va_1Fe_0Aw_0$	10.09(0.21)	2.09(0.30)***
$Va_0Fe_1Aw_0$	16.25(0.26)	8.25(0.34)***
$Va_0Fe_0Aw_1$	10.96 (0.07)	2.96 (0.23)***
$Va_1Fe_1Aw_0$	14.34 (0.07)	6.34 (0.23)***
$Va_1Fe_0Aw_1$	27.45 (0.94)	19.45 (0.97)***
$Va_0Fe_1Aw_1$	14.31 (0.091)	6.31 (0.24)***
$Va_1Fe_1Aw_1$	21.05 (0.08)	13.05 (0.23)***

Note: figures in parentheses are standard errors; *, ** and *** indicate statistical significance at 10%, 5% and 1% level, respectively.

Table 6. Average Expected Net Crop Income ('000 Birr/ha) with Adoption of Combination of Climate-Smart Practices Effects

Outcome	Descriptions	Adopter sample farm households (A) Actual Net crop income if farm households did adopt (Birr/ha)	(B) Counterfactual Net crop income if farm households didn't adopt (Birr/ha)	(C) Adoption Effects (Birr/ha)
$Va_1Fe_0Aw_0$	Varieties	12.19 (0.56)	7.32 (3.15)	4.88(3.19)***
$Va_0Fe_1Aw_0$	Fertilizer	12.87 (0.13)	5.99 (0.39)	6.89 (0.41)***
$Va_0Fe_0Aw_1$	Water management	12.83 (0.20)	9.58 (0.11)	3.24 (0.23)***
$Va_1Fe_1Aw_0$	Varieties & Fertilizers	13.42 (0.16)	5.84 (0.47)	7.58 (0.49)***
$Va_1Fe_0Aw_1$	Varieties & Water managment	17.34 (1.08)	10.39 (0.48)	6.94 (1.19)***
$Va_0Fe_1Aw_1$	Fertilzer & Water managment	15.06 (0.12)	5.99 (0.71)	9.06 (0.72)***
$Va_1Fe_1Aw_1$	Varieties, Fertilzer & Water managment	20.55 (0.20)	10.04 (1.45)	10.51 (1.46)***

Note: figures in parenthesis are standard errors; *. ** and *** indicate statistical significance at 10%. 5% and 1% level.

Table 7. Changes in the Choice Probabilities (%) of Combinations of Climate-Smart Practices for Future Decades

Baseline (model-fitted) combinations of climate-smart practices	Scenario simulated combinations of climate-smart practices								
	$Va_0Fe_0Aw_0$	$Va_1Fe_0Aw_0$	$Va_0Fe_1Aw_0$	$Va_0Fe_0Aw_1$	$Va_1Fe_1Aw_0$	$Va_1Fe_0Aw_1$	$Va_0Fe_1Aw_1$	$Va_1Fe_1Aw_1$	Sum
$Va_0Fe_0Aw_0$	40.09	1.01	18.47	21.51	6.19	0.73	9.74	2.25	37.77
$Va_1Fe_0Aw_0$	0.00	94.74	0.00	0.00	5.26	0.00	0.00	0.00	0.40
$Va_0Fe_1Aw_0$	1.33	0.00	76.48	2.42	6.06	0.00	11.52	2.18	17.55
$Va_0Fe_0Aw_1$	3.16	0.53	2.63	85.44	0.35	0.18	4.91	2.81	12.12
$Va_1Fe_1Aw_0$	0.25	0.49	11.03	0.98	74.51	0.00	8.82	3.92	8.68
$Va_1Fe_0Aw_1$	0.00	0.00	0.00	6.25	6.25	81.25	6.25	0.00	0.34
$Va_0Fe_1Aw_1$	0.00	0.00	22.25	7.42	3.01	0.00	64.19	3.13	18.35
$Va_1Fe_1Aw_1$	0.00	0.00	21.78	1.33	5.33	0.89	7.11	63.56	4.79
Sum	15.78	0.87	26.80	20.44	10.76	0.62	19.20	5.53	100.00

Table 8. Changes in Conditional Net Farm Income ('000 Birr/ha) for Future Decades

Mean net income	$Va_0Fe_0Aw_0$	$Va_1Fe_0Aw_0$	$Va_0Fe_1Aw_0$	$Va_0Fe_0Aw_1$	$Va_1Fe_1Aw_0$	$Va_1Fe_0Aw_1$	$Va_0Fe_1Aw_1$	$Va_1Fe_1Aw_1$
Simulated	8.87	9.94	13.04	14.03	12.90	18.79	16.10	23.09
	(1.46)	(5.33)	(2.38)	(2.73)	(3.03)	(10.89)	(2.09)	(4.78)
Baseline	9.44	12.07	12.87	12.85	13.43	16.99	15.09	20.57
	(2.03)	(6.05	(3.09)	(4.58)	(3.21)	(6.92)	(3.16)	(4.04)
Absolute change	-0.56***	-2.12**	0.17	1.18***	-0.54***	1.79	1.01	2.52***
Percentagechange	-5.40	-17.94	1.33	9.18	-3.99	10.55	6.69	12.20***

Note: Numbers in parentheses are standard deviations; *, ** and *** indicate statistical significance at 10%, 5% and 1% level.

Figure 1. Choice Probabilities Response of Combination of Climate-Smart Practices to Amount of Rainfall

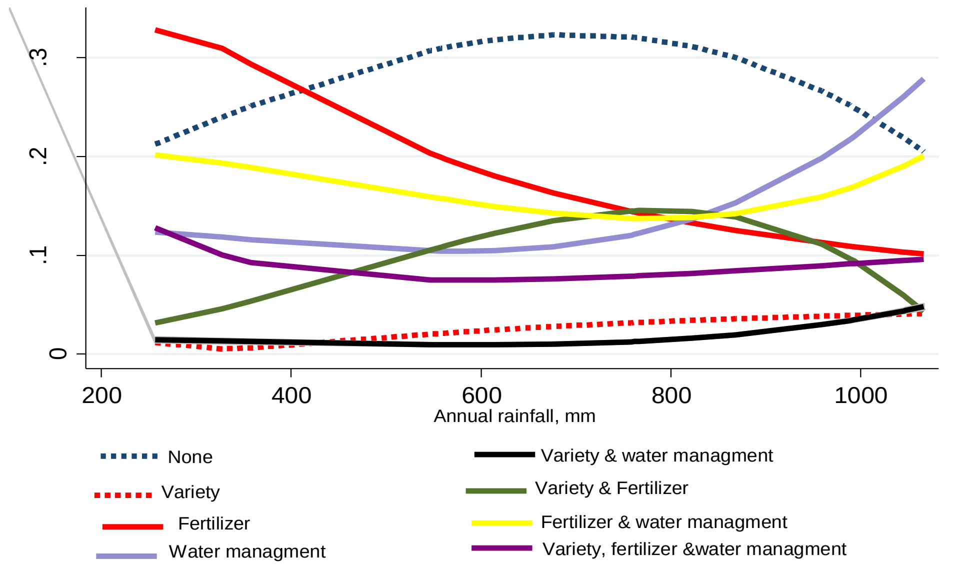

Figure 2. Choice Probabilities Response of Combination of Climate-Smart Practices over Temperature

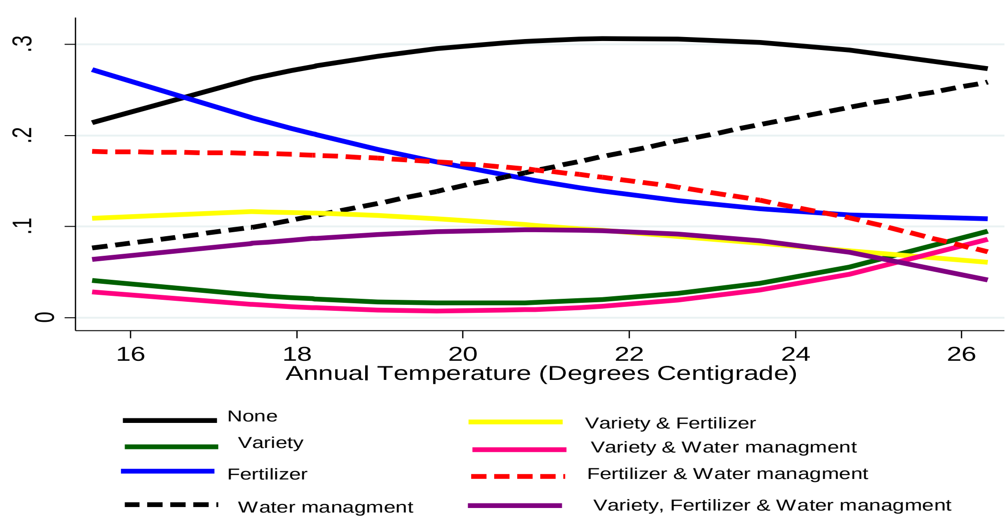

Figure 3. Choice Probabilities Response of Combination of Climate-Smart Practices to Rainfall Variability