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Weather Vulnerability, Climate Change, and Food Security in Mt. Kilimanjaro

Francis M. Muamba* and David S. Kraybill PhD

Abstract

This study estimates the impact of rainfall variation on livelihood in Mt. Kilimanjaro using the *Ricardian* approach to capture farmers' adaptation strategies to cope with climate change risks. The data for the analysis were gathered from a random sample of over 200 households in 15 villages and precipitation from rainfall observation posts placed in each of the surveyed villages. The precipitation data provide information on the effect of moisture at critical months in the growing season. Due to prevalence of intercropping among local farmers, the present study develops a multivariate model that assumes endogeneity between crop yields. Doing so allows the study to capture adaptation strategies that smallholders use by diversifying farm portfolio. The results indicate that Mt. Kilimanjaro agriculture is vulnerable to precipitation variation. However, farm vulnerability is heterogeneous across space, crops and, months. Location varying inputs are responsible for substantial percentage of crop yield. The study found ambiguous evidence about the ability of irrigation usage to reduce crop vulnerability to precipitation variation, but suggests that proper cost benefit analysis ought to be done in order to measure the welfare value of irrigation. In terms of future food security, climate simulations reveal that by 2029, it will no longer be ideal to produce coffee in Mt. Kilimanjaro if precipitation annually decreases by a minimum rate of 2%. While maize production will also suffer severe production reduction, banana production will decrease but not in an alarming rate by 2029.

Keywords: Climate Change, Precipitation Variability, Food Security, Irrigation

JEL Classification: Q1, Q5, Q54, Q56

1. Introduction

As more than 80% of Mt. Kilimanjaro[1] glaciers have retreated over the past 90 years, lower-altitude agriculture faces serious precipitation variations (Thompson et al, 2002; Kaser et al, 2004). Although rainfall volume is not necessarily the problem in Mt. Kilimanjaro, rainfall distribution within each year is the biggest threat to the heavily rain

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[1] Mt. Kilimanjaro is the tallest mountain in Africa. It is located on the Tanzania-Kenya border in Eastern Africa. Data for this study were gathered on the southern and eastern slopes in Tanzania.

dependent agriculture. For example, figure (1) below shows that although annual rainfall volume is no different from long run average, rainfall distribution varies a lot within the year when compared against long run average. These precipitation anomalies are so alarming that some scientists suggest the short rainy season may soon disappear (Aggarwal et al., 2003). One of the questions that policy makers are yet to answer is "what could be the impact of these climatic changes on food security in Mt. Kilimanjaro?" Agricultural production on Mt. Kilimanjaro provides a unique setting to analyze the impact of climate change. The variation of precipitation and temperature across altitudes provides a setting for a natural experiment to effectively capture yield responses to weather conditions that approximate the climatic change projected to occur in East Africa. On the other hand, high prevalence of intercropping among local farmers requires the analyst to be mindful of the effects of intercropping on crop yield as failing to account for such risk coping mechanism may overestimate (underestimate) the negative (positive) impacts of climate change.

Various approaches have been used to estimate the impact of climate change on agriculture. First, the agronomic approach uses agronomic models to simulate crop growth over the life cycle of the plant and measures the effect of climatic change on crop yield (Parry et al, 1999). One of the main advantages of the agronomic method is its inclusion of the effects of carbon fertilization in plants. This incorporation is valuable since failing to do so will overestimate the negative impact of climate change. On the other hand, critics of this approach argue that it tends to overestimate negative impact and underestimate positive impact because it fails to account for adaptations that farmers undertake in order to cope with climate pressures (Mendelsohn et al., 1994, 1999).

Other researchers have used Computational General Equilibrium (CGE) models to estimate the impact of climate change on economic outcomes (Roston, 2003). CGE is an economy-wide model suitable for environmental issues, as it is capable of capturing complex economy-wide effects of exogenous changes while at the same time providing insights into the micro-level impacts on producers, consumers, and institutions. Usage of CGE has some drawbacks. Key limitations include the sensitivity of results to model assumptions, the weak empirical grounding of many of the model parameters, the absence of statistical tests for the model specification, and the complexity of the models (Gillig and McCarl, 2002).

Deschenes and Greenstone (2007) use a time series approach to estimate the economic impact of climate change on US agriculture. The benefit of their approach lies in the richness of their data. Their production data comes from the 1978, 1982, 1987, 1992, 1997, and 2002 Censuses of Agriculture in US Counties. These data allow the paper to account for the presumably random year-to-year variation in temperature and precipitation on agricultural profits. Unfortunately, this approach can only be applied to developed countries given the availability of excellent and reliable county or regional level records of agricultural production. Most developing countries do not hold reliable records of long run crop production data unfortunately.

The *Ricardian* approach was developed to account for farmers' adaptation (Mendelsohn et al. 1994). This approach uses cross-sectional data to capture the influence of climatic change on land value or farm income. The *Ricardian* approach is based on the notion that the value of a piece of land capitalizes the discounted value of all future profits that can be derived from the land. Since land value is hard to estimate in rural areas of

developing countries, most researchers use farm profit or crop yield assuming a fixed price across space. The model addresses climate change by including weather variables as determinants of land value. Last, since climate is a long run variable as opposed to weather, the *Ricardian* model in reality estimates the impact of weather variation on crop yield or farm profit and makes inferences from the results about the potential impact of future climate change by simulating farm profit response to predicted future climatic change.

The present study estimates the impact of climate change on agriculture in Mt. Kilimanjaro using the *Ricardian* model. The *Ricardian* model is chosen because of its ability to capture the effects of adaptation strategies that farmers undertake to mitigate expected risks. Short rainy season is projected to suffer the most from climate change in East Africa (Aggarwal et al, 2003). Therefore this study focuses on measuring the impacts of short rainy season precipitation variance on agricultural yield. This is important because the decline of the short rainy season is the main cause of food insecurity since its stretches the dry period (Devereux et al, 2008). The data for the analysis were gathered from a random sample of over 200 households in 15 villages and precipitation from rainfall observation posts placed in each of the villages. The precipitation data provides information on monthly distributions to pinpoint the effect of moisture at critical times in the growing season. Farmers in the region practice intercropping, and so the study develops a multivariate model that assumes interrelationships between crops. Specifically, the study estimates the impact of climate change on maize, banana, and coffee yields. Maize, banana, and coffee are chosen because they have great influence on household's livelihood since they are the three main crops cultivated in Mt Kilimanjaro. The author recognizes that the three crops chosen above may not be all annual crop types for which the farmer can easily adjust his acreage

allocation. The author assumes that every year the farmer decides whether to continue cropping the perennial crops or stop producing them as opposed to decide whether to plant or not. As a proxy for temperature, a second climate variable that affects crop yield, the study uses altitude.

The layout of the paper is as follow. Section 2 discusses climate change and food security in Africa. Section 3 presents a literature review on the application of the Ricardian approach. Section 4 presents a description of both the study area and the livelihood of *chagga* farmers, Mt. Kilimanjaro's most dominant tribal group. Section 5 conceptually explains the *Ricardian* model. Section 6 describes the data and the survey method. Section 7 presents and discusses the results. Finally, section 8 concludes and proposes policy recommendations.

2. Climate Change and Food Security in Africa

Some of the most profound and direct impacts of climate change over the next few decades in Africa will be on agricultural and food security. Kurukulasuriya et al (2006) predict that revenues from agricultural activities practiced in dry lands and livestock sales will suffer the most from climate change in Africa. Further, Parry et al (1999) predict that by 2080, between 55 and 70 million extra Africans will be at risk of hunger due to climate change. They argue that decrease in expected crop yields are likely to be caused by a shortening of the growing season and decrease in soil water retention capabilities due to high rate of evapotranspiration. Eastern Africa's agriculture may no longer benefit from its bimodal annual rainy seasons (Aggrawal et al, 2004). The risks of climate change are threatening the disappearance of the short rainy season and increasing the prevalence of hunger seasons (seasonal food insecurities) each year.

Hunger seasons take place during the last few months before the harvest when the household runs out of its food supply from the previous harvest. This season usually occurs in places where there is only one growing season per year or where the second growing season has become highly volatile. Hunger seasons are also common in areas where farmers have no access to irrigation, practice subsistent farming, and cultivate marginal and degraded lands. These setbacks unfortunately lock the next generation in a vicious cycle of poverty because the land deterioration problem will only get worse and worse each year.

Farmers in countries such as Niger and Malawi as a well as those in low input agriculture in developing countries are already facing the risks of hunger seasons. Consequently, they prefer planting crops that store better while yielding less, or having less selling value. Faced with hunger seasons, households are also tempted to prematurely harvest their crops in order to assure the survival of their malnourished and/or dying children. In terms of farm revenue, farmers find themselves tempted to sell their harvest quicker to keep the cash that will be use to diversify their diet and purchase food as needed. Unfortunately, lower harvest prices do not permit them to gain enough to at least break even from their agricultural activities. Saving crop sale profits is also very difficult because households have to repay their high interest debts incurred during the hunger season to pay medical bills or to purchase food, or agricultural inputs.

Irrigation or small scale water harvesting units are practical means to reduce the impact of climate change on the prevalence of food insecurity in Africa. In addition to lowering crop vulnerability to precipitation shock, access to irrigation will encourage

farmers to invest in new technology such as high yield varieties which in most cases require more water and care than the traditional seed varieties. Access to irrigation will also increase farm return. In fact, by providing adequate water, crops will be able to reach their full growth potential and become more valuable.

Investing in drought early warning infrastructures can also be useful to communities threatened by increased weather variability. Such infrastructures will enable farmers to tailor farm management decisions in the season ahead. Although such technology has yet taken ground in Africa, researchers have found considerable demand for them in various countries. For example, using Contingent Valuation Methods (CVM), Makaudze (2005) found the existence of a substantial welfare benefit of a wide scale improved seasonal forecast system among Zimbabwean farmers. In Tanzania, studies were done to identify the trends of onset, cessation dates and variability of rainfall seasons particularly during El-Nino/La Nina years (Mhita et al, 2003). The outcomes are very important for agricultural planning since ENSO accounts for about 50 to 60 percent of precipitation variability (Mhita et al, 2003). The results can also be used to establish weather forecasting infrastructures that will warn farmers against potential dry spell.

Finally, there has been increasing interest in introducing weather based crop insurance contracts as means to help peasant farmers break out of the vicious cycle of poverty (Barnett et al, 2008). These contracts can be sold at the farm level, district level, or to country level to help speed up the relief effort after a systemic shock. Sarris et al (2006) estimates the demand for rainfall based crop insurance in Mt. Kilimanjaro in terms of willingness to pay. They found existence of welfare benefit of a rainfall based crop insurance. Similar results were found when estimating the welfare benefit of a rainfall

based crop insurance among Zimbabwean farmers (Makaudze, 2005). In terms of application, the International Livestock Research Institute (ILRI) recently launched livestock insurance for Northern Kenya's pastoral farmers. The insurance scheme is supposed to indemnify farmers based on a satellite imagery of land forage of that region since forage is highly correlated with livestock mortality rate.

3. Literature Review

The *Ricardian* model has been applied in a variety of countries, including the US (Mendelsohn et al., 1994; Mendelsohn and Dinar, 1999; Schlenker and Roberts, 2006), Canada, India (Mendelsohn et al., 2001), Cameroon (Molua, 2002), Sri Lanka (Kurukulasuriya and Ajurad, 2006), Africa (Kurukulasuriya et al, 2006), and Ethiopia (Deressa and Hassan, 2009). Notably, all of these studies are based on aggregate district-level data, except for Molua (2002), Kurukulasuriya and Ajurad (2007), Kurukulasuriya et al (2006), and Deressa and Hassan (2009) who applied the Ricardian approach using farm level data in developing countries.

Molua (2002) examines the relationship between farm revenue and climate in a single agro-ecological zone in Southwest Cameroon. Using a sample size of about 110 farmers, Molua (2002) used village level precipitation volume and controlled for indigenous soil and water conservation practices to capture the marginal effects of precipitation on farm income. The results indicate that marginal impact of precipitation on farm income is 38%.

Kurukulasuriya and Ajurad (2007) examine the relationship between climate variables such as precipitation and temperature and smallholder farm profitability in Sri

Lanka. Using farm level data of more than 1500 farmers, Kurukulasuriya and Ajurad (2007) found that climate variables explains about 30% of net revenue variation when controlling for other variables. The study predicts that wet and high elevation areas may benefit from warming whereas hot dry Northwester and Southeastern lowlands are expected to be negatively affected.

Kurukulasuriya et al (2006) apply the Ricardian model to estimate the impact of climate change in Africa using farm level data from more than 9000 farmers across 11 difference African countries. The study estimates the impact of climate change on farm revenue from dry land, irrigated land, and from livestock. Controlling for soil properties, the study used precipitation and temperature as measures of climate. The results of this study reveal that dry land agricultural crop revenue and livestock revenue are most vulnerable to temperature increase than irrigated land crop revenue. Similarly, farm revenue from dry land and livestock are most vulnerable to precipitation change than farm revenue from irrigated land. Specifically, access to irrigation reduces farm revenue precipitation elasticity from 0.4 to 0.1.

Deressa and Hassan (2009) regress net farm revenue on climate, household variables, and soil variables to estimate the vulnerability of Ethiopian farmers to climate change. The results indicate that net revenue vulnerability is not uniform across agri-ecological zones. Also, marginal increase in precipitation during spring would increase revenue, while marginal increase in temperature during summer and winter would reduce net revenue. After forecasting future climate using three climate scenario models, Deressa and Hassan (2009) predict that there would be a reduction of net farm revenue in 2050 and 2100.

One of the contributions that the present study brings to the application of the *Ricardian* approach is its disaggregation of crop yield. Unlike farmers in developed countries, smallholder farmers in developing countries plant more than one crop type in their parcels. This portfolio diversification decision is taken to reduce farm vulnerability to shocks. Consequently, the present paper will use a multivariate model to estimate the impact of climate change on crop yields to account for the interrelationship between crop types. This is a very important modeling approach because by aggregating farm profit in the context of smallholder farmers, the analyst implicitly assumes that each crop type is equally affected by climate change and consequently fails to capture adaptation strategies that smallholder famers undertake by substituting between crop types to reduce risks. Failing to capture smallholders' portfolio diversification strategy will overestimate the negative impact of precipitation variation and underestimate the positive impact of climate change on crop yield. Disaggregation will also help in terms of suggesting specific policy recommendations. In fact, by identifying the crops most and least vulnerable to precipitation variation, farmers should be able to effectively reconsider their crop allocation strategies in order to minimize farm vulnerability.

Also, previous studies of climate change in Africa have used spatial variation across vastly different localities to estimate climate impacts. A drawback of that approach is potential bias from unobservables that vary across disparate regions and affect crop yields. A fixed effect model can take care of this problem, but if the climate variables are fixed by localities, a locality fixed effect model will no longer be valuable since it will cancel the impact of those weather variables. In contrast, this study uses the spatial variation in

climate in a relatively small mountainous area with a high degree of ethnic homogeneity, similar crops, similar soil types, and similar access to markets.

Finally, the present study performs a per season analysis rather than mixing all seasonal output together. Specifically, this study separately estimates the vulnerability (here measured by crop yield elasticity to precipitation) of short and long rainy season crop yield on climatic variables instead of estimating the vulnerability of annual crop yield on seasonal rain. This seasonal study is important because the results will help farmers effectively plan their risk minimizing decisions by season rather than applying the same strategy every season. Also, given the threats of climate change on seasonal weather variations, the present analysis will allow the paper to make proper inferences about the impact of climate change on food security.

4. Description of the Study Area

Located 300 km south of the equator in the East African country of Tanzania, Mt Kilimanjaro is the highest point of Africa and one of the second highest free-standing mountains in the world with an altitude nearing 5,895 meters (19,650 feet). It consists of two peaks, Kibo, 5,895 meters (19,455 feet), and Mawezi, 5,149 meters (15,840 feet). Mt Kilimanjaro rises 4,800 meters (15,840 feet) from the plains, covers 4 square km and at its widest is 40 km (25 miles) across.

Mt. Kilimanjaro is characterized by a typical equatorial day-time climate. Due to its near-equatorial location, it experiences two distinct rainy seasons: the long rains from March to May constituting the main rainy season (Masika); and the short rainy season (Vuli) from October to December. The driest months falls between July to October while

April and May are the wettest months. However, precipitation and temperature vary with altitude and exposure due to the dominant wind blowing from the Indian Ocean. Annual precipitation reaches a maximum of around 3,000 mm at 2,100 meters on the central southern slope in the lower part of the forest belt (Hemp 2001).

Mt. Kilimanjaro is a critical water catchment for both Tanzania and its northern neighbor, Kenya. High precipitation and extensive forests give Mt. Kilimanjaro its high catchment value. The southern and the south-eastern forest slopes form the main upper catchments of the Pangani River, one of Tanzania's largest rivers, which drains into the Indian Ocean. Despite the great dryness of the northern slope of Mt Kilimanjaro, the area forms a catchment for the Tsavo River, a tributary of the Galana River, one of Kenya's major rivers (TANAPA, 2004).

The mountain forest belt between 1,600 and 3,100 m above sea level (asl) is said to provide most of the water coming from the mountain with a substantial quantity of water harvested from the clouds forest. These water supplies come from cloud forests, and various springs which are replenished by the abundant precipitation hitting the forest area. In this zone the precipitation is very high while evaporation losses are low due to an almost permanent cloud cover and it is considered as the quintessential source of water supply to Mt Kilimanjaro farmers living below.

The main source of livelihood of *chagga* households is agriculture. The *chagga* people mainly produce maize, bananas, coffee, beans, and vegetables where crop choice depends on both altitude and availability of reliable irrigation canals. With coffee as one of the main cash crop, changes in water supply are making it more and more difficult to

produce coffee in the region. Kilimanjaro region dropped from the number one producer of coffee in Tanzania to number three over the past 30 years. Despite the introduction of resistant and high yielding seeds by Tanzania Coffee Research Institutes (TACRI), a local research center now partly sponsored by the European Union (EU), weather uncertainty is making it difficult for farmers to adopt the new seeds since the new seed variety is more demanding in terms of inputs such as water.

Poor access to markets is another important risk factor faced by *Chagga* farmers. Because of high transaction cost to access markets, lack of adequate market information, and weakening of government supported cooperatives, farmers are forced to sell most of their output at low farm gate prices. Therefore, stronger market participation must be encouraged through policy incentives. In fact, as farmers are given adequate incentive to participate into the market, this participation will promote the transformation from subsistent or semi-subsistent stage to specialized farmers producing mainly crops for which they have a comparative advantage. This ultimate stage will eventually allow them to commercialize and direct their production to regional, national, and international markets, and consequently improving and insuring household well-being.

Water from traditional irrigation schemes is a very important element of the livelihood of *chagga*. In fact, farmers' ability to cope with the growing climatic risk depends on their capacity to adequately store and allocated irrigated water. A slight alteration of the normal flow of irrigation water and/or precipitation volume will have damaging impacts on their livelihood. As a consequence of greater uncertainty of future rainfall, farmers have developed methods such as shaping village paths to help divert rain water toward their

parcels. Also, some farmers are adopting certain land management practices in order to increase soil water retention capacity. These practices include mulching, bunds, and terracing.

5. Conceptual Model

The *Ricardian* technique assumes that each farmer maximizes profit subject to the exogenous conditions of the farm, which includes climate and access to irrigation. Although the *Ricardian* model estimates the impact of climate change on farm profits, the present study uses crop yield assuming price to be constant across space. This assumption is legitimate here because the study is estimating the impact of climate change in a relatively small area. The concept assumes that each farmer chooses a mix of agricultural techniques and inputs that achieve the highest crop yield across all parcel *i* and crop type *j* such that:

$$y_{ij} = X_{ij}\phi + R_i\beta_1 + R^2{}_i\beta_2 + H\theta + I_i\lambda + T_i\rho + S_i\gamma + \varepsilon_{ij} \quad (1)$$

where y is per acre crop yield, X is a vector of input, R is a vector of a monthly rainfall, H is household characteristics, I is a dummy for irrigated land, T represents altitude which is used here as a proxy for temperature, S is a vector of soil characteristics, and ε is an error term which is identically and independently normally distributed. Because this analysis is applied across multiple districts, it is quite possible that there are variables at the district level that are not taken into account in the analysis. Consequently, the study explores a district fixed effects model that controls for district specific factors where L is a set of district dummies.

$$y_{ij} = X_{ij}\phi + R_i\beta_1 + R^2{}_i\beta_2 + H\theta + I_i\lambda + T_i\rho + S_i\gamma + L\eta + \varepsilon_{ij} \quad (2)$$

In order to measure the marginal impact of a precipitation on crop yield, a partial derivative of equation (2) is taken with respect to R_i as shown in equation (3).

$$E\left[\partial y_{ij} \big/ \partial R_i\right] = \beta_1 + 2\beta_2 E[R_i] \tag{3}$$

If equation (3) is positive (negative), yield increases (decreases) with precipitation increase.

In order to measure the welfare value (W) of a change from today's climate (C_1) to n years from today's climate (C_2), yield before the change is subtracted from the yield after the change for each farm household. Previous research derived C_2 data from Atmospheric Oceanic General Circulation Models (AOGCM). But for this study, the author will assume a uniform weather variation over the next 20 years. The welfare change is the difference between yields under the two climate scenarios. If the value is negative (positive), yield decline (increase), leading to a conclusion that the climate change has caused damage (benefit):

$$W = y(C_2) - y(C_1) \tag{4}$$

The *Ricardian* model is a comparative static analysis. It reflects all the adjustments that farmers and ecosystems have made in response to climate. It is a measure of the long-term consequences of climate change. Because the *Ricardian* function is estimated across space at a moment in time, the level of prices as a function of aggregate output is constant. The model cannot capture how prices would change if global quantities of output were to change. With international trade, this bias is not expected to be large (Mendelsohn and Nordhaus, 1996). However, if price changes were to occur, they would offset changes in quantity, leading to a smaller change in net revenues.

Also, the *Ricardian* model does not control for variables that do not vary across space. For example, the *Ricardian* model does not control for the level of carbon dioxide. Controlled experiments and crops simulation modeling are required to learn about the likely positive effect of carbon fertilization (Kurukulasuriya et al, 2006). This shortcoming may lead the *Ricardian* model to overestimate the negative impact of climate change on crop yield.

The present study seeks to test two null hypotheses. The first null hypothesis stipulates that Mt. Kilimanjaro agriculture is not vulnerable to climate change. In other words, the elasticity of crop yield to monthly precipitation is statistically equal to zero. The second null hypothesis stipulates that access to irrigation does not reduce crop yield vulnerability to precipitation.

6. Fieldwork and Data Source

Funded by the University of Ohio States Climate, Water, and Carbon (CWC) program, the Kilimanjaro Livelihood and Climate Survey (KLCS) first started in September 2008 (Kraybill, 2009). The project is a two year mission to collect household level data on agricultural production, household socio-economic characteristics, and geographical coordinates of each household's location; and village level climatic variables such as precipitation in Mt Kilimanjaro, Tanzania. The project surveys fifteen villages where fifteen households were randomly chosen in each village to make up a sample size of 225 respondents. The fifteen villages are located within the three districts that surround Mt. Kilimanjaro. The three districts include Hai, located in the western slope of the mountain, Moshi Rural, located in the southern slope of the mountain, and Rombo, located in the

eastern slope of the mountain (see figure 1). The Northern slope of the mountain is mostly inhabited. Table 1 presents demographics of the three surveyed districts.

The survey project was implemented with the collaboration of Sokoine University of Agriculture (SUA) which provided enumerators and field technical support. Respondents were visited during the planting season to collect information about pre harvest activities and then again after the harvest season to collect post harvest information. The precipitation data were collected with the cooperation of designated village leaders and local primary and secondary school officials and reported at the end of every month.

Summary statistics are presented in table 2. The average household size of a *chagga* family is 6 individuals per household. The average age of a households head is 55 years old and about 83% of households head are male. The average schooling years of a household head is 7 years. Forty percent of the respondents have user right of portion of land that does not belong to them. The average daily labor hour is 4 hours per day. For this study, average daily labor hour is weighted by household size since households size will impact the average time spent by a household member doing agricultural work. Average rent per acre farmers are willing to accept is 46,782 TZ Shillings per season.

The average yield for coffee is 58 kg per acre. The average yield of banana was found to be 1793 kg per acre. Finally the average yield of maize was found to be 1017 kg per acre. Most respondents live on an average altitude ranging from 836 m asl and 1895m asl. The average monthly precipitation received during the key agricultural months of the second rainy season (October, November, and December) is 228 mm with a maximum of 395 mm and a minimum of 87 mm. The average precipitation received in October is 28 mm, 156

mm in November, and 43.2 mm in December. In the analysis, only November and December rain is considered because some villages have missing information for October since the precipitation data gathering started in mid October 2008. Only 16% of the respondents used fertilizers during the second rainy season and 44% of the respondents had access to traditional irrigation. Eighteen percent of farmers used pesticides against coffee disease, and 57% applied mulching in their home plots.

7. Results

Location-varying production inputs are important determinants of crop yield, and failing to capture their effects will bias the estimates. Fortunately, using the geographical coordinates of respondents' parcels, this study captures the effects of these and other location-varying inputs by assuming the error terms to be spatially correlated and applying the Generalized Spatial Three Stage Least Squares (GS3SLS) model introduced by Kelejian and Prucha (2004). The procedure as discussed in detail in the appendix is a data corrective approach that allows the analysis to control for the spatially dependent nature of the error terms while capturing the interrelationship between crop types. The procedure is a four-step approach and consists of : (1) estimating each equation using 2SLS, (2) using the residual of each equation to estimate spatial autoregressive parameters ρ_j using a GMM procedure, (3) using the estimate of ρ_j to transform the data using an Cochran-Orcutt-type transformation, (4) use the transformed data to estimate the GS3SLS specifications.

To estimate the autoregressive parameters ρ_j, a distance decay weight matrix is built assuming that *n* and *m* are neighbors if and only if *n* and *m* live in the same village[2]. Row standardization of the weight matrix and Lagragian Multiplier diagnostic test for both a distance decay weight matrix and a squared distance weight matrix to test for both spatial dependence and robustness are performed. Tables 3, 4, and 5 indicate that there is sufficient evidence to claim that banana production function has a spatially autocorrelated error term. Since crops are interrelated, it is fair to assume that the coffee and maize error terms will also be spatially autocorrelated. Therefore, a Cochran-Orcutt-type transformation as discussed in the appendix is performed on all three crop equations. This procedure embeds heteroskedsticity corrective procedures.

Table 7 reveals that maize is more vulnerable to November rain than to December rain. This justifies the importance of early planting to ensure proper crop growth. Estimated elasticity (or vulnerability) of second season precipitation on maize yield is 6.6%. This means that for a 1% decrease (increase) in rainfall volume, maize yield will decrease (increase) by 6.6%. Years of education of the head of the household, and age of the household's head have a positive impact on maize yield. Further, altitude and fertilizer usage have a significant positive relationship with maize yield. Usage of traditional irrigation has no direct effect on maize yield; access to improved maize seeds has a strong positive impact on maize yield. Hours spent doing agricultural work, manure, and gender of the head of the household have no effect on maize crop yield.

[2] Detail estimation procedure are provided in the appendix

Coffee is also vulnerable to November and December rain. The estimated elasticity of second season precipitation on coffee yield is 6.9%. While usage of traditional irrigation has no direct effect on coffee yield, altitude is positively related to coffee yield and fertilizer usage has a positive impact on coffee yield. Farmers who used pesticides are more likely to have higher coffee yield.

Hours allocated to agricultural activities, and mulching have a positive effect on banana yield. Altitude has a positive effect on banana yield while fertilizers have no effect on banana yield. Similarly to the other crops discussed above, banana is most vulnerable to November rain than December rain. But unlike the other crops, banana yield is the least vulnerable to second season precipitation with elasticity of 0.4%.

In order to motive policy recommendations, a comparison of the elasticities of precipitation on crop yields for households that used irrigation against the elasticity of precipitation for households that did not use irrigation is performed. Recall that the results in table 7 state that usage of irrigation has no direct effect in any crop yield. This may be the case because irrigation water may not be reliable enough to constantly supply water to parcels to improve yields. By introducing interaction terms between access to irrigation and monthly rainfall, table 8 shows that when precipitation is below average, irrigation water can serves as a cushion against rain water shortage for maize. In other words, usage of irrigation reduces the vulnerability of maize to short rainy season precipitation vulnerability. Banana and coffee produced in parcels with access to irrigation seem to be no less vulnerable to precipitation change than banana and coffee produced in dry lands. In other words, irrigation does not have a significant effect on coffee and banana yield.

Additional information on the frequency of irrigation water must be obtained in order to make further inferences on the nature of these relations. Farmers with access to irrigation schemes were later asked about the frequency of irrigation water over the past 10 years. The results presented in figure (3) show that on average, farmers who have access to traditional irrigation report irrigation water flow was much below normal in 2.4 out of the past 10 years, somewhat below normal in 3.0 out of the past 10 years, normal in 4.3 out of the past 10 years, somewhat above normal in 0.2 out of the past 10 years, and much above normal in 0.5 out of the past 10 years. The right truncated distribution of irrigation water flow may be one explanation of the ineffectiveness of traditional irrigation usage on yield.

Table 9 shows the change in average precipitation elasticity caused by access to irrigation. Joint test for significance of irrigation and monthly rain interaction variables reveal that access to irrigation indeed affects the elasticity of precipitation on crop yield. Table 9 states that access to irrigation reduces the elasticity of short rain season on maize by 0.2% at 10% confidence interval. On the other hand, access to irrigation does not affect vulnerability of coffee and banana yield. Although additional information is needed to make further inferences, the results suggest that policy makers should be cautious before recommending irrigation as a policy instrument to help farmers cope with the risk of precipitation vulnerability. The results also support the importance of disaggregating the analyses to the crop level rather than to the farm level as climate change simultaneously but differently affect crop yields. Disaggregation helped render policy recommendations more effective in terms of indentifying the type of farmer that will be most affected by climate change and will benefit the most from the policy intervention. This study for example found that coffee growers are the most affected by weather vulnerability while

banana growers are the least affected by weather vulnerability. In terms of policy, maize will benefit the most from irrigation while coffee and banana grower may not have significant benefits from irrigation.

To provide insights about future food security and climate change in Mt. Kilimanjaro, table 10 presents simulation results of the impact of climate change on crop yield by 2029. Unlike previous application of the *Ricardian* model, this paper does not use climatic model such General Circulation Model (CGM) or the (AOGCM) to predict future climate in Mt. Kilimanjaro. This study simply estimates yield reaction to a 1%, 2%, and 3% annual precipitation decrease in the second rainy season to gain better insight about the potential impact of climate change on future food security. For a 1% precipitation decrease, the simulation predicts that maize, coffee, and banana yield will decrease by 74.8%, 76%, and 8.4% respectively. For a 2% precipitation decease, the simulation predicts that maize, coffee, and banana yield will decrease by 94%, 95%, and 11% respectively. For a 3% decrease in rainfall, the model predicts that maize, coffee, and banana yield will decrease by 98.7%, 99%, and 23.3% respectively.

8. Conclusion and Policy Implications

This study uses the *Ricardian* approach proposed by Mendelsohn et al. (1994) to make inferences about the impact of climate change on food security in Mt Kilimanjaro. Unlike previous studies, this paper disaggregates both precipitation and crop yield to capture the true relationship between climatic variable and crop yield and capture any adaptation that smallholder may use by diversifying their farm portfolio. Second, the study also estimates a system of spatial equations to address both the spatial dependence of the

error terms and the correlation of the error terms using a robust GS3SLS model (Kelejian and Prucha, 2004). By simulating precipitation decrease over the next 20 years, the study is able to make adequate inferences about the impact of climate change on food security.

This study does not predict the future as most applications of the *Ricardian* model do. Predicting the future is a heavy task because it requires one to examine the projection of several climate models and how agriculture is likely to change in the future. The analysis in this paper examines the climate sensitivity of current crop yields gives insights on potential food insecurity problem assuming annual precipitation decrease of 1%, 2%, and 3% for the next 20 years. The study later motivates policy recommendations by testing for the significance of access to irrigation as means to abet the negative impacts of climate change on crop yield.

Results indicate strong evidence of a negative impact of climate change on all three crops used in this analysis. Specifically, crop yield is greatly impacted by November rain. On average, the elasticity of precipitation on maize, coffee, and banana is 6.6%, 6.9%, and 0.4% respectively. The study concludes that a change in November rain is the driving force behind short rainy season crop yield variation experienced by many Mt. Kilimanjaro farmers.

Further, the analyses conclude that location varying inputs such as parcel exposure to sun radiation, soil quality, soil slope and other significantly affect crop yield. These are powerful results because they justify the importance of investing in soil preservation technologies. As average annual temperature rises, farmers may reduce soil evapotranspiration rate by changing their soil management strategies in favor of improving soil water retention capabilities by heavily investing in mulching, terracing, increasing soil

residue cover, and no till farming just to name a few. Climate simulations reveal that by 2029, it will no longer be ideal to produce coffee in Mt. Kilimanjaro if precipitation uniformly decreases by a rate of 2%. While maize production will also suffer severe production reduction, banana production will decrease but not in an alarming rate.

One way to assist Mt. Kilimanjaro farmers cope with the risks of climate change is to introduce water storage infrastructures such as improved irrigation schemes. In fact, this study concludes that maize raised in irrigated land is on average 0.2% relatively less vulnerable to precipitation decline while coffee and banana planted in irrigated land are statistically no less sensitive to precipitation variation. The study cautions that serious cost benefit analyses and field experiments must be undertaken in order to indentify farmers who will benefit from the irrigation infrastructure.

Last, considering the heterogeneous vulnerability of each crop types to change in rain, this study suggests a study that will identify optimal crop allocation given the risks of climate change and the heterogeneous sensitivity of each crops to change in precipitation level. It is important for farmers to have adequate information to guide them in their crop allocation decisions to help maximize farm profit.

9. Reference

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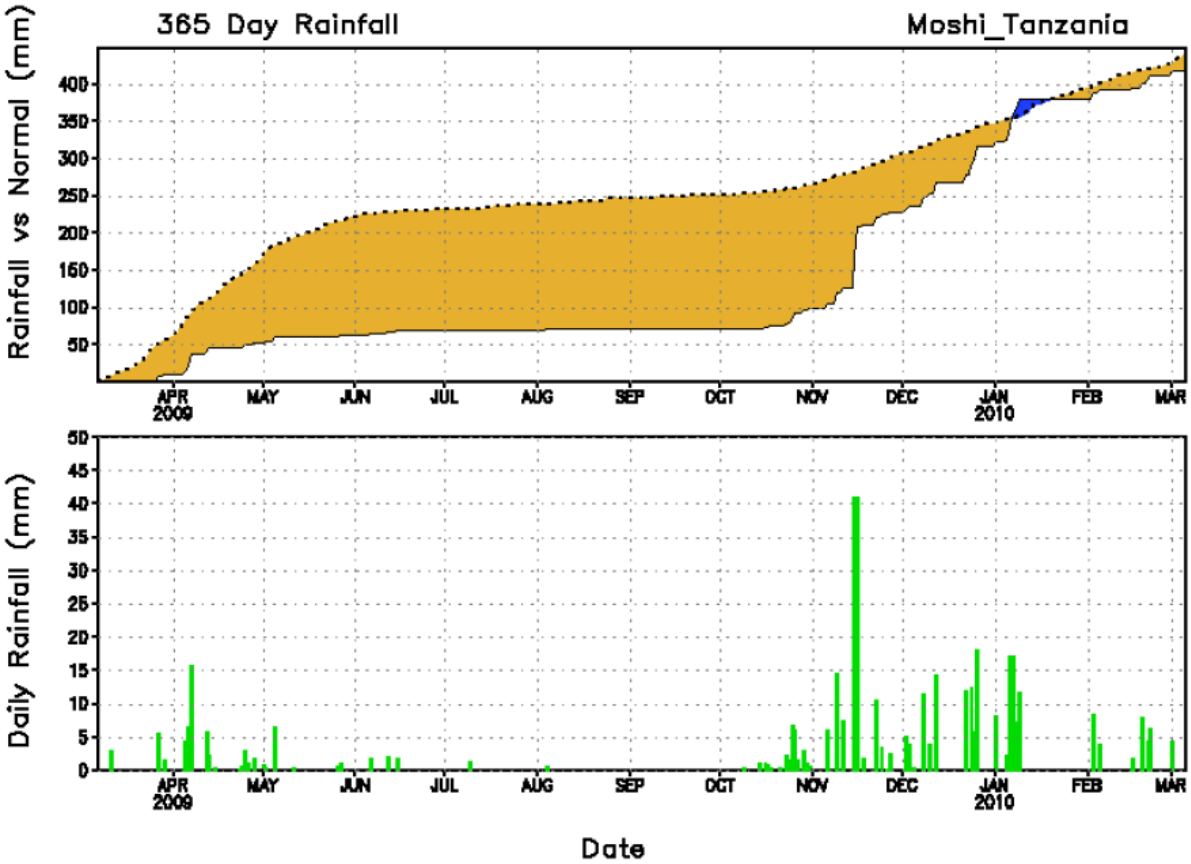
10. Appendix

10.1. Rainfall Distribution

Figure 1: Current vs. Normal Rainfall Distribution



Source: National Oceanic and Atmospheric Administration (NOAA)

10.2. Appendix A: Regional Descriptions

Figure 2: Map of Kilimanjaro region showing the study area

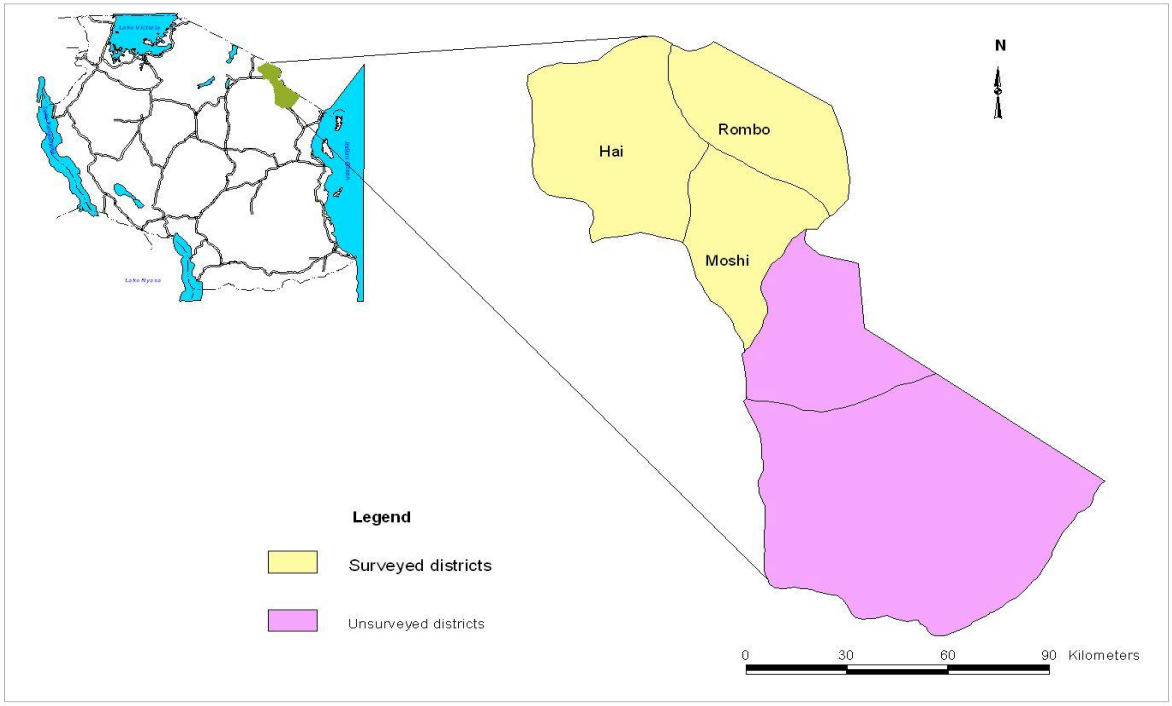


Table 1: Kilimanjaro Region (surveyed districts) demographics

District	Area	Administrative units			Population size	Annual growth rate	Average h'hold size	No. of h'holds
		div	ward	Villages.				
Hai	2,112	4	14	82	200,136	1.3	5.4	33,899
Moshi	1,713	4	31	165	504,287	1,9	5.4	62,890
Rombo	1,442	5	20	62	417,602	2.4	5.7	35,078

Source: URT, 1998; URT, 2002; Kilimanjaro Socio-economic Profile

10.3. Appendix B: Spatial Econometrics Model

10.3.1. Building The Weight Matrix

A row standardized distance decay weight matrix $\boldsymbol{W}$ is estimated and Lagragian Multiplier (LM) diagnostic tests are performed to verify if the error term of at least one crop is spatially autocorrelated (Anselin and Bera, 1998). Although efficiency is gained by jointly performing the diagnostic test, an equation by equation diagnostic test is preferred in order to avoid bias from cross equation misspecification[3].

Let w_{nm} be the element of spatial weighting matrix $\boldsymbol{W}$ and, d_{nm} the geographical distance between households n and m, then:

If households are not too far apart, $w_{nm} = 1/d_{nm}$ (B.1)

If distance between households is too far, $w_{nm} = p_{nm}/d_{nm}$ (B.2)

$$\text{where,} \quad p_{nm} = \begin{cases} 1 \ if \ n \ and \ m \ are \ in \ the \ same \ village \\ 0 \ if \ n \ and \ m \ are \ not \ in \ the \ same \ village \end{cases} \tag{B.3}$$

In other words, the above weight matrix allow the study to assume that the effect of soil slope, soil quality, and soil moisture on crop yield is the same for farmers who are closer than farmers living further away from each other but in the same village. To check for robustness of the weight matrix specifications, a LM diagnostic test for two weight matrices is performed. The first weight matrix includes the distance decay property as defined above. The second weight matrix incorporates a distance squared in order to test the robustness of the spatial autocorrelation.

[3] Thanks to Professor Harry Kelejian for the useful clarifications.

10.3.2. Generalized Spatial Three Stage Least Squares (GS3SLS)

Assuming that at least one crop type proves to be spatially autocorrelated, the model is estimated following the procedures described below. Testing the second hypothesis will necessitate multiple steps. Drawing from Kelejian and Prucha (2004), a Generalized Spatial three Stage Least Squares (GS3SLS) model that investigates the inter-relationship between crop types and their spatial autocorrelation is estimated. First, considering the following spatial system of simultaneous equations:

$$Y = X\Gamma + U \qquad (B.4)$$

$$U = \boldsymbol{W}UC + E$$

where,

$$\boldsymbol{W}U = \boldsymbol{W}u_1, \dots, \boldsymbol{W}u_G \ ,$$

$$C = diag_{j=1}^{G}\rho_j \ ,$$

$$E = \varepsilon_1, \dots, \varepsilon_G,$$

$$Y = y_1, \dots, y_G,$$

$$X = x_1, \dots, x_K \ ,$$

$$U = u_1, \dots, u_G$$

Where y_j is the n x 1 vector of cross sectional observations on the dependent variable in jth equation, x_l is an n x 1 vector of cross sectional observations on the lth exogenous variable, u_j is an n x 1 vector of error terms in the jth equation, and Γ is a parameter matrix of

dimension K x G. ρ_j denotes the spatial autoregressive parameter in the jth equation and since C is taken to be diagonal, the specification relates the disturbance vector in the jth equation only to its own spatial lag. Since it is assumed that $E\varepsilon = 0$ and $E\varepsilon\varepsilon' = \Sigma \otimes I_n$, the disturbances, however, will be spatially correlated across units and across equations. Finally, **W** is the spatial weighting, or *contiguity,* matrix, which influences the form of the spatial dependence.

The 4 steps procedure outlined by Kelejian and Prucha (2004) to estimate the above model is as followed: Let each jth equation be expressed as:

$$y_{j,n} = Z_{j,n}\delta_j + u_{j,n} \qquad (B.5)$$

$$u_{j,n} = \rho_j \boldsymbol{W}_n u_{j,n} + \varepsilon_{j,n}$$

With $Z_{j,n} = Y_{j,n}, X_{j,n}$ and their corresponding parameter estimates $\delta_j = \beta_j', \gamma_j'\ '$, where $Y_{j,n}, X_{j,n}$ are matrices of observations on the endogenous variables, and exogenous variable appearing in the jth equation (j=1 and 2).

In the first step, equation (B.5) is estimated using a 2SLS approach. In step two, the autoregressive parameter ρ_j and the variance σ_j are estimated by the generalized method of moments (GMM). In the third step, using the estimate for ρ_j, a Cocrhran-Orcutt-type transformation, T, is performed on equation (B.5) to account of spatial autocorrelation in the disturbances $u_{j,n}$:

$$y_{j,n}^T(\rho_j) = Z_{j,n}^T(\rho_j)\delta_j + \varepsilon_{j,n} \qquad (B.6)$$

where $$y_{j,n}^T(\rho_j) = y_{j,n} - \rho_j W_n y_{j,n}$$

$$Z_{j,n}^{T}(\rho_j) = Z_{j,n} - \rho_j W_n Z_{j,n}$$

In the fourth step, the vector parameters δ_j are obtained by estimating the transformed model in (B.6) using the GS3SLS model to account for the endogeneity of the dependent variables.

10.4. Appendix C: Summary Statistics

Table 2. Summary Statistics

Variable	Observation	Mean	St Dev	Min	Max
HH size	225	6.3	2.4	1	15
Age Head	225	55	14	23	90
Head Gender(male=1, female=0)	225	0.83	0.37	0	1
Head Education (years)	225	6.6	3.2	0	15
Labor (hour/ day)	225	4.8	1.5	0	8
Manure (total in kg)	225	1428	1545	0	7300
Land Size (acre)	225	2.2	1.7	0.11	14
Coffee Yield (Kg/acre)	225	58	65	1.7	350
Maize Yield (Kg/acre)	225	1017	2478	3.4	25539
Banana Yield (Kg/acre)	223	1793	2581	2.77	13290
Altitude (m asl)	225	1279	257	836	1895
October Rain (mm)	225	28	27	0	89
November Rain (mm)	225	156	93	34.6	319.7
December Rain (mm)	225	43.9	39.4	0	140
Pesticides (1=used, 0=not used)	221	0.185	0.38	0	1
Fertilizer (1=used, 0=not used)	225	0.16	0.37	0	1
Rent Land (1=rented, 0=not rented)	225	0.4	0.49	0	1
Rent price per acre	177	46782	49951	2500	419120
Mulching (1=used, 0=not used)	224	0.57	0.50	0	1
Irrigation (1=used, 0=not used)	225	0.44	0.5	0	1

Source: Kilimanjaro Livelihood and Climate Survey 2008

10.5. Appendix D: Error Spatial Dependence and Error Correlation

Table 3: Testing for Error Autocorrelation for Coffee

Model	Distance Decay	Distance Decay Squared
Robust LM Error	0.22	0.41
	(0.636)	(0.52)

( ) p-value ***1%, ** 5%, * 10%

Table 4: Testing for Error Autocorrelation for Maize

Model	Distance Decay	Distance Decay Squared
Robust LM Error	0.72	0.01
	(0.40)	(0.9134)

( ) p-value ***1%, ** 5%, * 10%

Table 5: Testing for Error Autocorrelation for Banana

Model	Distance Decay	Distance Decay Squared
Robust LM Error	2.97*	2.90*
	(0.085)	(0.088)

( ) p-value ***1%, ** 5%, * 10%

10.6. Appendix E: Ordinary Three Stage Least Squares (3SLS)

Table 6

Variables	Maize		Coffee		Banana	
	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
Irrigation	1.47*	1.66	0.98	1.52	0.50	0.78
Education	1.20**	1.98	0.45	0.74	0.46	0.81
Age	1.58	1.62	1.03	1.45	0.30	0.39
Gender	0.12	0.16	-0.06	-0.09	-0.50	-0.7
November rain	-36.60**	-1.81	-26.52***	-2.56	26.59	0.96
December rain	0.42	1.05	0.51**	2.39	-0.68	-1.13
November rain2	4.06**	1.88	2.73**	2.34	-3.20	-1.05
December rain 2	-0.02	-0.18	-0.06	-0.83	0.22	1.46
Labor	0.03	0.09	0.25	0.80	0.69**	2.10
Manure	0.04	0.4	0.09	1.13	0.03	0.29
Altitude	11.10	1.57	10.59***	3.08	0.47	0.08
Fertilizer	1.95**	1.87	0.82	1.25	-1.15	-0.85
Land Rent Price	0.16	0.84	0.09	0.53	-0.18	-0.85
Maize seed	2.87***	5.49				
Coffee	-1.12*	-1.72			1.37	1.23
Banana	-0.22	-0.41	-0.76*	-1.83		
Maize			0.09	0.49	0.19	1.17
Pesticide			1.16*	1.74		
Mulch					2.06**	2.06
Constant	-5.66	-0.18	-14.28	-0.5	-56.28**	-1.95
Fixed Effect	Yes		Yes		Yes	

*significant at 10%, **significant at 5%, ***significant at 1%.

10.7. Appendix F: Generalized Spatial Three Stage Least Squares (GS3SLS)

Table 7

Variables	Maize		Coffee		Banana	
	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
Irrigation	0.70	1.52	0.31	0.97	0.80	1.64
Education	0.81**	1.95	0.12	0.36	0.46	0.90
age	0.86*	1.68	0.43	1.11	0.61	1.02
gender	0.09	0.19	0.11	0.29	-0.26	-0.46
November Rain	-26.71**	-2.11	-22.70***	-4.33	15.07	1.33
December Rain	0.29	1.11	0.46***	4.30	-0.43*	-1.77
November Rain2	3.14**	2.32	2.51***	4.23	-1.92	-1.51
December Rain2	-0.02	-0.30	-0.10***	-2.51	0.16**	2.18
Labor	-0.11	-0.50	-0.03	-0.18	0.60**	2.22
Manure	-0.009	-0.14	0.04	0.95	0.06	0.94
Altitude	4.68*	1.82	5.02***	4.36	3.46*	1.70
Fertilizer	1.23**	2.35	0.77**	2.02	-0.66	-0.99
Land Rental Price	0.09	0.69	0.07	0.71	-0.10	-0.64
Maize seed	2.46***	6.97				
Coffee	-0.70***	-2.90			0.86***	2.52
Banana	0.32**	2.38	-0.05	-0.47		
Maize			-0.06	-0.69	0.20	1.37
Pesticides			1.12***	3.11		
Mulch					1.75***	3.73
Constant	16.27	0.66	13.26	1.00	-53.46**	-2.61
Fixed Effect	Yes		Yes		Yes	
Rho	0.203*	1.70	0.18	1.28	0.178***	3.20

*significant at 10%, **significant at 5%, ***significant at 1%.

10.8. Appendix G: Irrigation and Weather Vulnerability

Table 8

Variables	Maize		Coffee		Banana	
	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
Irrigation *Nov rain	-46.87*	-1.87	-4.73	-0.42	23.10	1.33
Irrigation *Dec rain	-0.22	-0.54	0.24	1.34	-0.34	-1.20
Irrigation *Nov rain2	5.18*	1.83	0.61	0.48	-2.47	-1.26
Irrigation *Dec rain2	0.02	0.13	-0.11	-1.55	0.14	1.21
Irrigation	84.28*	1.90	11.49	0.38	-63.04	-1.38
Education	0.70*	1.72	0.20	0.62	0.35	0.72
Age	0.64	1.25	0.47	1.22	0.71	1.21
Gender	0.28	0.58	-0.0005	-0.00	-0.49	-0.85
November Rain	-13.61	-1.05	-23.58***	-3.54	-0.64	-0.05
December Rain	0.34	1.18	0.29*	1.75	-0.09	-0.34
November Rain2	1.81	1.42	2.57***	3.55	-0.32	-0.24
December Rain 2	-0.06	-0.68	-0.04	-0.84	0.07	0.91
Labor	-0.20	-0.90	-0.01	-0.08	0.62**	2.31
Manure	-0.02	-0.35	0.05	1.06	0.08	1.24
Altitude	3.10	1.33	4.64***	3.89	4.85***	2.56
Fertilizer	1.09**	2.12	0.78**	2.10	-0.60	-0.94
Land Rental Price	0.09	0.66	0.09	0.93	-0.07	-0.49
Maize Seed	2.31***	6.68				
Coffee	-0.69***	-3.25			0.70**	2.40
Banana	0.43***	3.76	-0.03	-0.36		
Maize			-0.10	-1.15	0.30**	2.25
Pesticides			1.20***	3.37		
Mulch					1.53***	3.50
Constant	-4.09	-0.15	17.91	1.20	-25.19	-1.05
Fixed Effect	Yes		Yes		Yes	
Rho	0.203*	1.70	0.18	1.28	0.178***	3.20

*significant at 10%, **significant at 5%, ***significant at 1%.

10.9. Appendix I: Crop Simulation

Table 9: Comparison of Precipitation Elasticities

Crop	Elasticity	Δ in elasticity with Irrigation
Coffee	6.90*	0.00*
Maize	6.65*	-0.20*
Banana	0.44*	0.00*

*significant at 10%, **significant at 5%, ***significant at 1%.

Table 10: Precipitation Simulation Results

	Change in Crop Yield by 2029		
	1%	**2%**	**3%**
Maize	-74.7%	-94%	-98.8%
Coffee	-76.1%	-95%	-99.0%
Banana	-8.4%	-16%	-23.3%

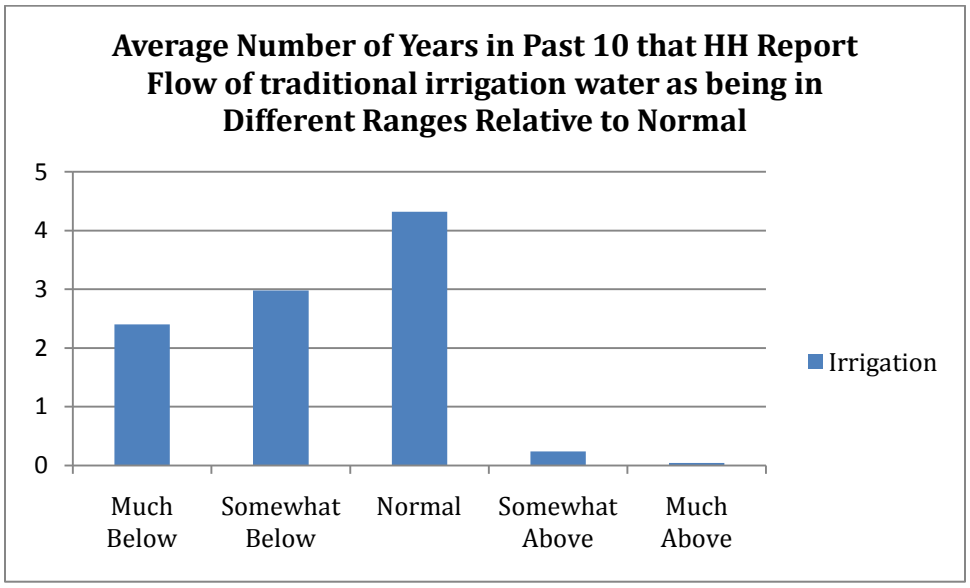



Figure 3