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Climate Change and Food Security in Kenya

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Climate Change and Food Security in Kenya

Jane Kabubo-Mariara and Millicent Kabara

Abstract

The paper investigates the effects of climate change on food security in Kenya. Fixed and random effects regressions for food crop security are estimated. The study further simulates the expected impact of future climate change on food insecurity based on the Special Report on Emissions Scenarios and Atmospheric Oceanic Global Circulation Models. The study is based on county-level panel data for yields of four major crops and daily climate variables data spanning over three decades. The results show that climate variability and change will increase food insecurity. Food security responds positively to favourable agro-ecological zones, soil drainage and depth, and high population density. The paper recommends strengthening policies on mitigation against and adaptation to climate change.

Key Words: climate change, crop productivity, food security, Kenya

JEL Classification: Q10, Q51, Q54

Contents

Climate Change and Food Security in Kenya

Jane Kabubo-Mariara and Millicent Kabara*

1. Introduction

Climate change has intensified the risk of catastrophic natural disasters all over the world. Residents of developing countries are particularly vulnerable to these catastrophic risks for three reasons: first, they rely primarily on natural resource dependent income sources for their livelihoods; second, they have few resources with which to adapt to the anticipated change in climatic patterns; and, third, lack of planning and poor management at the central level impedes or delays recovery from climate-related shocks, and in some cases even leads to increased economic and social damage.

The World Food Programme (2011) notes that climatic change threatens to significantly increase the number of people at risk of hunger and under-nutrition. Predictions are that more powerful and more frequent droughts and storms will wreak greater devastation. Rising sea levels will ruin fertile farmland. Changing rainfall patterns will deplete harvests. Increasingly scarce resources will exacerbate social tensions and may spark conflict. Millions more people will be at risk of hunger and under-nutrition. Most of them will be in the world's poorest countries, where hunger, under-nutrition and food insecurity are already widespread. Sub-Saharan Africa is the region worst affected by hunger and under-nutrition. In some countries, yields from rain-fed agriculture could fall by 50 percent by 2020 (World Food Programme 2011).

According to the Inter-governmental Panel on Climate Change (IPCC), climate change will lead to increases in the frequency and intensity of natural disasters and extreme weather events, such as droughts, floods and hurricanes; rising sea levels and the contamination/salinization of water supplies and agricultural lands; changes in rainfall patterns, with an expected reduction in agricultural productivity in already fragile areas, especially in sub-Saharan Africa, and declining water quality and availability in arid and semiarid regions.

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Diminishing water availability and quality, together with rising water demand, have created immense challenges in poor and vulnerable communities. The effects of these changes on hunger and under-nutrition have been felt across the world, with a disproportionate impact on vulnerable communities in less developed countries – those with the least resources and capacities to adapt and respond.

Climate change is expected to affect food security in several respects: increased vulnerability to climate change due to dependence on rain-fed agriculture; high levels of poverty; and low levels of human and physical capital as well as generally poor infrastructure. IPCC predicts that, by 2050, crop yields in Sub-Saharan Africa will have declined by 14% (rice), 22% (wheat) and 5% (maize), pushing the vast number of already poor people, who depend on agriculture for their livelihoods, deeper into poverty and vulnerability. It also predicts decreased food availability by 500 calories less (a 21% decline) per person in 2050 and a further increase in the number of malnourished children by over 10 million - a total of 52 million in 2050 in Sub-Saharan Africa alone.

Against this background, this paper analyses the effect of climate variables on food security in Kenya, a low income country characterized by low and declining crop productivity. The country can be divided into seven agro-climate zones (Sombroek et al. 1982). These zones differ in terms of moisture index, rainfall, vegetation and farming systems. High potential areas (zones I, II and III) have a moisture index greater than 50%, but account for only 12% of Kenya's land area. These are located above an altitude of 1200m and have mean annual temperatures of below 18˚C. These areas are mainly suitable for livestock farming (mostly cattle and sheep), cash crops (coffee, tea and pyrethrum) and key food crops (maize, beans and wheat). Medium potential zones favor farming systems similar to the high potential areas, but barley, cotton, cassava, coconut and cashew nuts also are cultivated. Areas with moisture indexes of less than 50% are semi-humid to arid regions (zones IV, V, VI and VII) and account for about 80% of the land area. Most arid and semi-arid areas lie below 1260m, have relatively high temperatures and are less suited for arable agriculture. Sorghum, millet, livestock and wildlife are the main farming systems (Table A1).[1]

Given this agro-ecological setting, agricultural production is undermined by unpredictable weather and climate variations, especially in the less arable zones. Climatic

[1] This section borrows from Kabubo-Mariara and Karanja (2007).

variations affect crop and livestock systems both directly and indirectly and could have severe socio-economic impacts such as shortages of food, water, energy and other essential basic commodities, as well as long-term food insecurity (Kabubo-Mariara 2008a). There is a growing body of literature on the impact of climate change in Africa. Most studies have concentrated on the impact of climate change on crop and livestock productivity, while other studies have assessed adaptation to climate change (see, for instance, Kabara and Kabubo-Mariara 2011; Herrero et al. 2010; Kabubo-Mariara, 2008b, 2009; Deressa et al. 2009; Dinar et al. 2008; Hassan and Nhemachena 2008; Kabubo-Mariara and Karanja 2007; Deressa et al. 2005; Gbetibouo and Hassan 2005; Turpie et al. 2002). To design policy measures for averting catastrophes such as those experienced in the Horn of Africa in 2011, there is a need for research on the impact of climate change on food security. There is, however, a dearth of literature on the relationship between climate change and food security in Kenya. This study addresses the gap. The general objective of this study is to analyze the linkages between climate change and food security in Kenya, and to formulate policy options for mitigating the effect of climate change on food security in Kenya.

The rest of the paper is organized as follows. Section 2 discusses the data; Section 3 presents the framework for analysis and methods; Section 4 presents the results and discussion; and Section 5 concludes.

2. Data

This study uses county level data for the period 1975 to 2012. Crop data was sourced mainly from the Ministry of Agriculture,[2] supplemented by data from the International Livestock Research Institute (ILRI), which provided more refined data at the division level. The data sets for four climate variables (precipitation, temperature, runoff, and total cloud cover) were obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis-Interim (ERA-Interim) Model, which archives the data in both daily and twice daily

[2] Source: Ministry of Agriculture (2009). Kenya Agricultural Sector Data Compendium, Vol. 2 - Crop Production.

ten-day and monthly formats. The resolution of the data is 1.5 deg by 1.5 deg (approx 150 km).[3] ECMWF is the most comprehensive model in terms of archiving most of the common and uncommon weather parameters. Precipitation and runoff data are measured in millimeters, while temperature data is measured in degrees Celsius. Cloud cover or precipitable moisture/cloudiness, which indicates the amount of water vapor in a vertical column of the atmosphere (Revuelta et al. 1985), is measured as a percentage of the sky covered by clouds. Population data was sourced from the Kenya National Bureau of Statistics. The soil database used in this study is a combination of the Kenya Soil Survey (KSS) soil map of 1982 (Sombroek et al. 1982), revised in 1997, and the FAO et al. (2012) classification. The agro-ecological zone layer was sourced from the Food and Agriculture Organization (1998). Base maps were generated from the Kenya census of 1999. The layers were sourced from the ILRI GIS database, which was generated in collaboration with the Kenya National Bureau of Statistics (KNBS).

3. Framework for Analysis and Methods

This study adopts the framework on climate change and food security developed by FAO (2008). The framework illustrates how adaptive adjustments to food system activities will be needed all along the food chain to cope with the impacts of climate change. Climate change affects food security outcomes for the four components of food security – food availability, food accessibility, food utilization and food system stability – in various direct and indirect ways (FAO 2008, Schmidhuber and Tubiello 2007). The transmission mechanism from climate change to food insecurity is complex. Climate change variables influence biophysical factors and how they are managed through agricultural practices and land use for food production. They also influence physical and human capital, which indirectly affect the economic and socio-political factors that govern food access and utilization. The framework shows that the impact of climate change on food security occurs through the following mechanisms: the CO2 fertilization effect of increased greenhouse gas concentrations in the atmosphere; increasing mean, maximum and

[3] Data with finer resolutions were available, but the problem was the time span. For instance, we have daily precipitation satellite data retrieved from the Climate Prediction Centre (CPC) of the National Oceanic and Atmospheric Administration (NOAA) with a resolution of 0.1 deg by 0.1 deg (about 10km). We also have precipitation from the UK Met Office with a resolution of 50km by 50km. This data was used mostly for exploratory spatial analysis to compare climate variability, agro-ecological zones, and population density, among other variables, and crop yields. A collection of daily parameters from the ECMWF model can be found at http://data-portal.ecmwf.int/data/d/interim_daily/.

minimum temperatures; gradual changes in precipitation; increase in the frequency, duration and intensity of dry spells and droughts; changes in the timing, duration, intensity and geographic location of rain and snowfall; increase in the frequency and intensity of storms and floods; and greater seasonal weather variability and changes in the start/end of growing seasons. These climate change variables have been shown in the literature to impact agricultural productivity and global food supply. Following this framework, the study assesses the impact of climate change on the food availability dimension of food security. We investigate the impact of climate variability and change on major food crops (maize, beans, sorghum and beans).

This paper uses a modified form of the Massetti and Mendelsohn (2011) approach to estimate the effects of climate change on food insecurity. This is a modified Ricardian approach applied to panel data – an extension of the Deschenes and Greenstone (2007) approach. The basic starting point is the Ricardian approach, which assumes that the value of farm land per acre is affected by climate change (Mendelsohn et al. 1994). Deschenes and Greenstone (2007) extended the Ricardian model and used county-level panel data to estimate the effect of weather on agricultural profits, conditional on county and state-by-year fixed effects. Their approach differs from the hedonic approach in a few key ways. First, under an additive separability assumption, its estimated parameters are purged of the influence of all unobserved time-invariant factors. Second, land values cannot be used as the dependent variable once the county fixed effects are included because land values reflect long-run averages of weather, rather than annual deviations from these averages, and there is no time variation in such variables. Third, the approach can be used to approximate the effect of climate change on agricultural land values, though land value is not the independent variable. Deschenes and Greenstone (2007) caution that there are two issues that could undermine the validity of using annual variation in weather to infer the impacts of climate change. First, short-run variations in weather may lead to temporary changes in prices that obscure the true long-run impact of climate change. Second, farmers cannot undertake the full range of adaptations in response to a single year's weather realization. The authors, however, show evidence to discount the possibility that the results obtained were affected by either of these two concerns.

Deschenes and Greenstone (2007) start with the hedonic cross-sectional model (Mendelsohn et al. 1994) and estimate the following equation:

$$Y_{ct} = \alpha_c + \gamma_t + X'_{ct}\beta_t + Z'_c\varphi_t + W'_c\theta_t + \varepsilon_{ct} \tag{1}$$

where Y_{ct} is the value of agricultural land per acre in county c in year t, measured by county-level agricultural profits. α_c and γ_t are the county fixed effects and year indicators respectively – γ_t controls for annual differences in the dependent variable that are common across counties. $\mathbf{X}_{ct}$ is a vector of observable time-varying determinants of farmland values. Z_c is a vector of time-invariant control variables. $W_c^{'}$ is a vector of climate variables (annual realizations of weather). ε_{ct} is the stochastic error term, which has two components: a permanent, county-specific component, α_c, and an idiosyncratic shock, u_{ct}. β, γ and θ are all time-variant coefficients. θ captures the true effect of climate on farmland values. Equation (1) is further extended to include interactions of irrigated and non-irrigated farms and climate variables. Deschenes and Greenstone (2007) make appropriate assumptions and adjustments[4] to correct for econometric problems arising in the estimation of equation (1), including omitted variable bias.

Deschenes and Greenstone estimate the above model using repeated cross sections. Masseti and Mendelshon (2011), however, argue that equation (1) is mis-specified because, in an ideal panel data model, the coefficients of the time-invariant variables should not change over time. They propose the following modified form of equation (1), with β, γ and θ as time-invariant coefficients:

$$Y_{ct} = X_{ct}^{'}\beta + Z_c^{'}\varphi + W_c^{'}\theta_t + \varepsilon_{ct} \tag{2}$$

We estimate two variants of equation (2) in this study. First, we use crop productivity as a proxy for food security, as has been done in the literature (Gregory et al. 2005; Parry et al. 2004; Xiong et al. 2007). The dependent variable in this paper is, however, crop yields (production per acre) rather than land values or profits. Second, we estimate another variant where the dependent variable is the probability of being food insecure.[5] The explanatory variables include climate-related variables (temperature and precipitation), runoff, population, agro-ecological zones, and

[4] The assumptions and adjustments relate to: (i) lack of correlation between W_c and $\mathbf{X}_{ct}$; (ii) possible spatial correlation of the error terms; and (iii) weighting of equation (1) to take into account county variations in cropland and revenue.

[5] Food insecurity is based on the FGT index. The FGT poverty measures can be defined as $P_\alpha = 1/n\sum\left[(z-y_i)/z\right]^\alpha ; \alpha \geq 0$, for y < z, where z is the poverty line and y_i is a measure of the economic welfare of household *i* (say, consumption expenditure), ranked as $y_1 \leq y_2 ... y_q \leq z \leq y_{q+1....} \leq y_n$. The household equivalents of the headcount index, poverty gap index and squared poverty gap index are obtained when α = 0, 1 or 2, respectively (Foster et al. 1984). In this paper, the probability that a county is food insecure at time *i* is based on $P_\alpha = 0$. Relative rather than absolute definitions of poverty are, however, used (see Section 4).

soil variables. Fixed effects and random effects models are estimated for both crop productivity and food insecurity, with the random effects model testing the effect of time-invariant variables (Mundlak 1978). Sensitivity analysis is carried out through simulations based on the Special Report on Emissions Scenarios (SRES) and Atmospheric Oceanic Global Circulation Models (AOGCMs).

4. Results and Discussion

4.1 Descriptive Statistics

The summary statistics are presented in Table 1. The data shows that, on average, yields ranged from 1.81 to 3.13 tons per hectare. Millet reported the highest mean yields, while the lowest was from beans, which also recorded the highest variability. Average total yields were estimated at 2.15 tons per hectare.

For climate/weather-related variables, we use two different definitions of seasons to estimate a series of models for the main food crops. First, there are two main cropping seasons in Kenya: the extended long rains season, which runs from March to August, and the short rains season, which runs from September to February. The long and short rains refer to the extended wet and dry conditions, respectively. In Kenya, long rains fall between March and May and short rains between October and December. The extended rain seasons are, however, longer, covering the whole cropping season. Long rains crops planted in early March are harvested in August. Farms are then prepared and planted in September and the crops harvested in February. In this paper, the long rains season is therefore defined as March to August and the short rains season as September to February. We further define seasons to correspond to three-month spells, or short seasons, where each of the two rain seasons are broken down into two seasons: March to May (summer), June to August (winter), September to November (spring) and December to February (fall).[6] The same definition of seasons is applied to runoff.

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[6] The rainy seasons vary depending on the region. For instance, the long rains in the Western, Nyanza and Rift Valley highlands are longer and extend from February to September. Long rains in the Central and Eastern areas are much shorter, spanning from March to June, and coincide very closely with long rains in pastoral areas and cropping in the South Eastern and Coastal areas (Source http://www.fews.net/Pages/timelineview.aspx?gb=ke&tln=en&l=en, accessed 18 July 2013). The definition of summer, fall, spring and winter is also variable depending on location and so the definition adopted here is indicative (Kabubo-Mariara 2009).

The data shows little variation in long versus short rains temperatures, which are on average about 18^{o}C. There is more variation in the spell-length seasonal temperatures, with the highest recorded for summer and lowest for winter, with a range of almost 2^{o}C. Precipitation shows more significant variation between seasons. Average runoff varies from 0.07 to 0.2 cubic meters. Summer experiences the highest runoff and variability, compared to fall, which exhibits the lowest runoff and least variability. Long rains runoff was much lower than short rains runoff. The average population density stood at 269.06 persons per square kilometer. Agro-ecological zones are based on the length of the growing period (LGP), that is, the period in which the soil has enough moisture to sustain plant growth. The country is subdivided into seven major agro-ecological zones, ranging from humid to very arid, with the regions varying in rainfall, moisture availability and temperature highs and lows. Regarding soils, the only information available at the county level is on three types of soil (clay, silt and sand, with clay soils being the dominant type, followed by sand), soil depth and soil drainage. The distribution of type of soil, depth and drainage varies by agro-ecological setting. Agro-ecological zone and soil data are time-invariant.

4.2 Effect of Climate Variables on Food Security

4.2.1 Crop Productivity Analysis

Regression Results

Table 2 presents fixed effects regression results using the short and long rain season definitions. The results show that both short and long rains precipitation exhibit an inverted U-shaped relationship with most crops. The coefficients are significant for maize (for both long and short rains) and for sorghum (only for long rains), but are insignificant for beans and millet.[7] Long rains precipitation has larger impacts than short rains precipitation. The results suggest that high rainfall is crucial for increased crop productivity and thus food security, but excessive rainfall is harmful. This is because flooding and waterlogging destroy crops at the formative periods, while heavy rains during the harvest season lead to rotting of mature crops. Short rains temperature exhibits a U-shaped relationship with maize and sorghum yields, while long rains temperature exhibits a U-shaped relationship, which is significant for maize only. The results support literature that has found non-linear effects of temperature and precipitation on

[7] Beans and millet are found to be largely unresponsive to weather variability and, for this reason, the discussion is based on results for maize and sorghum.

agricultural production (Mendelsohn et al. 1994, 2003; Kurukulasuriya and Mendelsohn 2008; Kabubo-Mariara and Karanja 2007).[8] Short rains runoff is associated with higher yields, while long rains runoff is associated with lower yields. Earlier studies found a non-linear relationship between hydrological factors and crop revenue (Kabubo-Mariara and Karanja 2007), but we uncovered no significant effect when we introduced the quadratic term.

We further investigate the impact of population density on crop yields.[9] The literature suggests that population density is a proxy for agricultural adaptation options (Kurukulasuriya and Mendelsohn 2008). Population density could also capture availability of farm labor. The positive significant effect on maize and beans could be interpreted as suggesting that adaptation to climate change and availability of family labor are associated with increased yields and thus food security. Similar conclusions were also drawn by Nhemachena et al. (2010), who found that factor endowment (land, labor, capital, technology) contributes to higher net revenue. However, sorghum and millet are found to be unresponsive to population density.

Table 3 shows the effect of short seasonal weather variability on crop yields. The results once again suggest that beans and millet are largely unresponsive to weather variability. We find that both spring and winter precipitation exhibit an inverted u-shaped (hill) relationship with maize and sorghum yields, which supports the results for short and long rains seasons' precipitation. Summer precipitation exhibits a U-shaped relationship with maize and sorghum yields, but the effect of fall precipitation is insignificant for all crops. This implies that high summer precipitation is not necessarily beneficial for crops, as this is the formative period for crop growth. Previous studies have shown that high precipitation is not always beneficial for farmers (Kabubo-Mariara 2009) and could therefore also be associated with food insecurity. Turning to temperature, we find that fall temperature exhibits a U-shaped relationship with maize and beans yields, while similar relationships are found between summer temperature and all crop yields except beans. Winter temperatures exhibit a hill-shaped relationship with most crops, but this is only significant for maize. High temperatures during the planting period slow down or destroy crop growth, while moderately high winter temperatures are crucial for crop maturity (Kabubo-Mariara and Karanja 2007). The results for the short spell-length seasonal climate

[8] These findings, however, contrast with Roberts and Schlenker (2013), who argue that the relationship between temperature and ethanol production is nothing like quadratic and that only very high temperature are harmful.

[9] It is possible, however, that good crop yields could lead to high population density on average, but this has not been explored in this paper. Future research may want to look into this.

variables support the results for the short and long rain season variables and illustrate the non-linear relationship between climate variables and crop productivity.

We further investigate the effect of summer and fall runoff on crop yields. We find that summer runoff has a positive impact on crop yields, but the effect is significant only for maize. Fall runoff exhibits a negative impact, but the coefficient is only significant for maize and sorghum. As with the first model, the impact of population density is positive and significant for maize and beans yields, suggesting that population density is associated with higher productivity and thus better food security.

In Table 4, we introduce time-invariant variables into the model, following Mundlak (1978). The variables include agro-ecological zones and soil characteristics. First, we find that the results of all the time-variant variables are consistent with the fixed effects estimates presented in Table 2. The results for the new variables show that maize is the only crop that is responsive to time-invariant variables. Specifically, maize productivity responds positively to favorable agro-ecological zones, soil drainage and depth, but performs poorly on silt soils. Sorghum productivity responds positively to favorable agro-ecological zone, but the effect of other time-invariant factors is insignificant. We also uncover no significant effect of the time-invariant factors on beans and millet. The results support literature that has shown that favorable development domain dimensions and population density are associated with higher crop productivity (Kabubo-Mariara 2012) and thus better food security.

Simulating the Effect of Climate Change on Crop Productivity

To estimate possible effects of future climate change on crop productivity, the study used a set of climate change scenarios (Atmosphere–Ocean Global Circulation Models (AOGCM)) predicted by the Intergovernmental Panel on Climate Change (IPCC). We used estimated model coefficients and corresponding variable means to examine how changes in climate are likely to affect future productivity of Kenyan crops. Predicted changes in temperature and precipitation are used to adjust benchmark values of crop yields and the impact evaluated. The simulations in this paper are based on the A2 and B2 Special Report on Emissions Scenarios (SRES), as the two have been integrated by many AOGCMS because of the assumptions on which each is based.[10]

[10] The scenarios related to future greenhouse gases and aerosols emissions have been developed based on certain assumptions of population and economic growth, land use, technological change and energy availability (Hounghton et al. 2001). See Kabubo-Mariara (2009) for a discussion of the SRES and simulations.

Ten scenarios have been derived for Kenya by using five different models in conjunction with two different emission scenarios: A2 and B2 (Strzepek and McCluskey 2006). The five models are: CGCM (Coupled General Circulation Model), CSIRO (the Commonwealth Scientific and Industrial Research Organization Model), ECHAM (the European Centre Hamburg Model), HADCM (the Hadley Centre Coupled Model) and PCM (the Parallel Climate Model). Based on these models, Strzepek and McCluskey (2006) predicted various temperature and precipitation changes for Kenya for various years up to 2100. This paper uses the predictions for 2050 and 2100 to simulate the likely effect of future climate change on crop yields (Appendix Table A2). The figures present the predicted decadal average changes in annual climate variables for 2050 and 2100, relative to the year 2000.[11]

To evaluate the effect of climate change of crop yields, we first added the predicted change in temperature from each AOGCM to the mean temperature values for each county, and then evaluated the impact on crop yields. We further adjusted the mean precipitation by the predicted percentage to get the new precipitation levels. We then compared the predicted crop yield to the baseline yield and computed the percentage change. The results (Table 5) show that, except for HADCM3, which predicts a modest gain in maize yield in 2100, farms are expected to suffer declining crop yields due to climate change. Specifically, for the year's crop yield in 2050, the largest damage from a combination of increased temperatures and precipitation is predicted from the CSIRO2, HADCM3 and CGCM2 for both A2 and B2 SRES. The largest damage is estimated at a 69% decline in yields. The lowest potential damage is from the ECHAM B2 scenario, at 44%. For the year 2100, the greatest damages are predicted to come from the B2 SRES scenario and the CGCM2, PCM and CSIRO2 models. A2 SRES predicts rather modest losses for 2100. Kenya is therefore likely to suffer severe food insecurity by the year 2100 unless farmers mitigate and undertake adaptation measures against climate change. The simulation results support other results that have shown that global warming will damage crop production, alter crop choices and diversification, reduce livestock productivity and influence livestock adaptation options. The results also reveal differential effects predicted by different AOGCMs, as in the literature (Kabubo-Mariara 2009, 2008a, 2008b; Kabubo-Mariara and Karanja 2007).

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[11] Comparing the data that we have for various years, there is little variation between climate variables from the year 2000 to 2012, so the base of 2000 used by Strzepek and McCluskey (2006) is still valid for our predictions. The advantage of using these scenarios is that decadal predictions are available for each county.

4.2.2 Food Security Analysis

Regression Results

We use subjective definitions of food availability to capture food security. The data available for this study is for crop productivity measured by yields. Productivity directly translates into food availability in that the lower the productivity, the lower the amount that will be available for consumption. In this paper, we define households as food insecure if they fall short of a relative poverty line. The poverty literature suggests that relative poverty lines can be set at various percentiles of the welfare measure: 25th Percentile, 40th percentile and 60th percentile. In this case, our measure of food availability is yield and so we construct poverty thresholds based on the three percentiles of yields. A county would have experienced food insecurity if yields fell short of the 25th, 40th and 60th percentile of the yields in any one period.

Using this 60th percentile poverty threshold, the highest incidence of food insecurity is associated with maize (52%), followed by beans and sorghum (39% each). Millet is lowest at 27%. The same trend is observed for the other two percentile definitions of poverty, with maize recording an incidence of 23% and 35% for the 25th and 40th percentiles, respectively; beans and sorghum at 16% and 26% for the 25th and 40th percentiles, respectively; and millet only 11% and 18% for the two percentiles, respectively. The incidence of food insecurity taking into account all crops is basically equivalent to that of maize. This is probably because maize is the main food crop and so anyone insecure in maize is likely to be food insecure.

We estimate panel regression models for the probability of being food insecure at the three poverty thresholds for two variants of weather variability – the short and long rains definition, and also seasonal spells definitions. The discussion of the results is based on the 60th percentile poverty line.[12] The results for the short vs. long rain seasons' definition of weather variability are presented in Table 6. The results suggest that short rains and long rains precipitation exhibit U-shaped relationships with food insecurity for all crops, suggesting a non-linear relationship between precipitation and food insecurity. The impact of short rains precipitation is largest for millet crops, followed by maize. The largest impact of long rains precipitation is on maize insecurity. The impact of the quadratic term is significant only for maize.

[12] The results for the 25th and 40th percentiles are consistent in terms of signs of coefficients, though levels of significance differ. They are not presented to save space, but are available from the authors.

The short rains temperatures exhibit inverted U-shaped relationships with food insecurity, again highlighting a non-linear relationship between temperature and food insecurity, but we find no significant effect of long rains temperature, although it has an inverted U-shaped relationship with all food crop insecurity. The short rains effect is largest for millet and maize, while the long rains effect is insignificant for all food crops. The results support other studies which have found a non-linear relationship between climate variables and farm values (Mendelsohn et al. 1994, 2003; Kabubo-Mariara and Karanja 2007; Kurukulasuriya and Mendelsohn 2008; Deressa et al. 2005). The results also support earlier studies that have found that global warming is likely to have adverse effects on farm productivity in Africa (Massetti and Mendelsohn 2011; Kabara and Kabubo-Mariara 2011; Mohamed et al. 2002; Molua 2008; Molua 2002; Nhemachena et al. 2010).

We do not uncover any significant effect on short and long rains runoff on food insecurity. Population density is, however, associated with lower food insecurity. This is because areas of high population density are associated with higher crop productivity. The effects are, however, quite marginal. Favorable agro-ecological zones are associated with reduced food insecurity, but the effect is significant only for beans. Good soil drainage and silt soil are also associated with lower millet and bean crop insecurity. The effect of these time-invariant factors could be explained by the expected positive correlation between food crop production and favorable development domains (Kabubo-Mariara 2012).

Table 7 presents results for the effect of seasonal weather variability on food insecurity. The results suggest that food insecurity responds to seasonal precipitation and the latter generally exhibits a U-shaped relationship with the probability of being food insecure. Spring precipitation is significant for maize, beans and millet. Beans and millet insecurity respond significantly to fall precipitation, while only millet responds to summer precipitation. Insecurity for all crops responds significantly to winter precipitation. Very high summer precipitation will damage crops at the early cropping season up to some threshold. Turning to temperatures, the results suggest that spring and fall temperatures exhibit an inverted U-shaped relationship with food insecurity. Insecurity in maize and sorghum respond significantly to spring temperature, while only sorghum insecurity responds significantly to fall temperatures. Summer runoff exhibits a significant negative effect on beans insecurity, but we uncover no significant effect of fall runoff on food insecurity. Population density is associated with lower food insecurity and the effect is significant for all crops except sorghum. Favorable agro-ecological zones reduce food insecurity, but the effect is significant only for beans.

Despite using different approaches, the results support earlier studies on the impact of climate change on food security (Arndt et al. 2011; Schmidhuber and Tubiello 2007). Xiong et al. (2007) found that, in the absence of adaptation, climate change is likely to adversely affect rice, wheat, and maize production in China. Similarly, Yates and Strzepek (1998) found that, despite increased water availability in Egypt, production was still likely to be adversely affected by climate change. Other studies have found differential effects of climate change on food insecurity. Arndt et al. (2011) found that the impact of climate change is likely to vary by climate scenario, sector and region. Parry et al. (2004) found that climate change is likely to lead to declining crop yields and to increase the disparities in cereal yields between developed and developing countries. Gregory et al. (2005) also found that the impact of climate change on food security varies between regions and between different societal groups within a region. Kabubo-Mariara (2009) found that, in the long term, climate change is likely to lead to increased poverty, vulnerability and loss of livelihoods.

Simulating the Effect of Climate Change on Food Insecurity

Table 8 presents the predicted changes in food crop insecurity based on the A2 and A3 SRES and the five AOGCMs for the years 2050 and 2100. The results show that the largest predicted increases in food insecurity will be from the A2, relative to B2, SRES. B2 actually predicts very minor changes in food insecurity for all crops. This supports findings by Parry et al. (2005), who found that the impact of climate change on the risk of hunger under the B2 SRES is characterized by much lower levels of risk than under A2. The greatest increases in food insecurity are predicted to be for maize, Kenya's staple food crop, estimated at 21% for the year 2100 by the HADCM3 model. This suggests that, unless measures are adopted to adapt to or mitigate against climate change effects, about 73% (base of 52% + 21%) of all Kenyan may be maize insecure by 2100. The lowest predicted increase in maize insecurity by the year 2100 is from the PCM model, which predicts an 8.56% increase in insecurity, suggesting that 60% of all Kenyans are likely to be maize insecure by 2100. The predictions for sorghum are more promising, probably because it is more drought-resistant than maize. The results suggest that sorghum crop insecurity may actually witness modest improvements by the year 2050, as predicted by the PCM, ECHAM and CGCM2 models, but modest increases are predicted by all AOGCMS for the two SRES for the year 2100. The models also predict rather modest increases in beans and millet insecurity. The results support the simulation results for crop productivity.

5. Conclusion

Climate change affects food security in several respects: increased vulnerability to climate change due to dependence on rain fed agriculture; high levels of poverty; low levels of human and physical capital; and poor infrastructure. Severe droughts in Kenya have continued to interrupt rainfall patterns, leaving behind serious consequences such as harvest failure, deteriorating pasture conditions, decreased water availability and livestock losses. To design policy measures for averting famine catastrophes in parts of Kenya, there is a need for research on the impact of climate change on food security. This study sought to address this gap. Fixed and random effects regressions for food crop security were estimated. The study further simulated the expected impact of future climate change on food insecurity based on the Special Report on Emissions Scenarios (SRES) and Atmospheric Oceanic Global Circulation Models (AOGCMs). The study is based on county-level panel data for yields of four major crops (maize, beans, sorghum and millet) and daily climate data spanning over three decades.

The results show that climate variability affects food security irrespective of how food security is defined. First, food security is proxied by food crop yields. The results show that rainfall during short seasonal spells, as well as during long vs. short rains, exhibit an inverted U-shaped relationship with most food crops; the effects are most pronounced for maize and sorghum. Beans and millet are found to be largely unresponsive to climate variability and also to time-invariant factors. We find that long rains precipitation has larger impacts than short rains precipitation. The results suggest that high rainfall is therefore crucial for increased crop productivity and thus food security, but that excessive rainfall is harmful. Short rains and fall and summer temperature exhibit a U-shaped relationship with yields for most crops, while long rains temperature exhibits an inverted U-shaped relationship. Winter temperatures, however, exhibit a hill-shaped relationship with most crops. The differential impacts of temperature are explained by the fact that high temperatures during the planting period slow down or destroy crop growth, while moderately high winter temperatures are crucial for crop maturity. Simulations of the effects of future climate change scenarios on crop productivity show that climate change will adversely affect food security, with up to 69% decline in yields by the year 2100. Population density has a positive effect on crop yields, suggesting that population density is associated with higher productivity. Maize productivity responds positively to favorable agro-ecological zones, soil drainage and depth, but performs poorly on silt soils. Sorghum productivity responds positively to favorable agro-ecological zone.

The results for food insecurity show that climate variables have a non-linear relationship with food insecurity. Increased seasonal precipitation is associated with reduced food insecurity, but excessive precipitation will increase insecurity due to damage to crops. Temperature generally exhibits an inverted U-shaped relationship with food insecurity, suggesting that increased temperatures will increase food crop insecurity. Maize and millet may, however, benefit from increased summer and winter temperatures. Population density and favorable agro-ecological zones are associated with lower food insecurity. Good soil drainage and silt soil are also associated with lower millet and bean crop insecurity. High river runoff is associated with lower bean crop insecurity. The simulated effects of different climate change scenarios on food insecurity suggest that adverse climate change will increase food insecurity in Kenya. The largest increases in food insecurity are predicted for the A2 SRES, relative to B2. Climate change is likely to have the largest effects on maize insecurity, which is likely to increase by between 8.56% and 21% by the year 2100, other factors constant. The results further suggest that sorghum, a relatively more drought-resistant crop than maize, may actually witness modest improvements in terms of food insecurity by the year 2050, followed by modest increases in insecurity by the year 2100. The models also predict rather modest increases in beans and millet insecurity.

The results of this paper point at the need for policies that safeguard agriculture against the adverse effects of climate change in order to alleviate food insecurity in Kenya. Food insecurity is found to be responsive to climate variability and change. Different food crops respond differently to climate change variables. It is therefore important that climate change mitigation is given much more priority in policy planning and also implementation. Mitigation against global warming can take two main forms: reduction of human emission of greenhouse gases and increasing the capacity of carbon sinks through reforestation. Though Kenya makes a relatively small contribution to greenhouse gas emission, a bigger role in mitigation can be played by encouraging reforestation throughout the country, especially in the more arid areas, where drought-resistant trees and crops could be introduced. This is supported by Thorlakson and Neufeldt (2012), who found that agro-forestry increased farm productivity.

The government can also play a bigger role by ensuring policy-driven adaptation to climate change, especially in more vulnerable counties. Though farmers may be aware of the effects of climate change, they may not always have full information about adaptation options available to them. Continuous climate change monitoring, intensified early warning systems and dissemination of relevant information to farmers, are crucial. Even where farmers have information, they may not have the means to adopt suggested adaptation options. Yet, previous studies suggest that adaptation strategies are important for very vulnerable farm households who have the least capacity to produce food (Di falco et al. 2011). For instance, one of the key strategies to reduce vulnerability is by encouraging irrigation, especially in drier and more marginal areas. This is, however, constrained by water availability, and, even where water is available, by lack of finances for required irrigation infrastructure. Lessons from FAO agricultural projects in Turkana county in the recent past serve as a good illustration of how irrigation interventions can serve as a solution in vulnerable areas. Lessons can also be learnt from practices from relatively dry countries such as Israel, where agriculture thrives, and the United Arab Emirates, where trees and other vegetation are grown using recycled water. There is also a need to encourage intensive rain water harvesting, particularly in drier areas, to supplement any available water. In the dry counties, a lot of water could be harvested during heavy rains (when severe floods hit such areas) and stored for use during the dry seasons.

There are two key caveats to the results in this paper. First, the study does not take into account household-level characteristics and other factors that could affect the response of food insecurity to climate change. Future research should incorporate the impact of household-level factors, farm characteristics, and other development domains in order to test the effect of climate change controlling for other factors. Second, in this paper, simulations predict the impact of climate change over time, *ceteris paribus*. In the very long run, it is likely that other factors (such as prices of inputs and outputs and technology) may change and thus affect crop farming and food security. Farmers may also adopt appropriate adaptation measures to counter the effect of climate change on agriculture. Future research should address these concerns.

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Tables

Table 1. Summary statistics

Variable	Mean	Std. Dev.
Maize yields	2.21	3.98
Bean yields	1.81	22.54
Millet yields	3.13	10.45
Sorghum yields	1.92	3.41
Spring precipitation (Sept-Nov)	10.54	12.62
Fall precipitation (Dec-Feb)	7.58	9.45
Summer precipitation (Mar-May)	15.82	19.29
Winter precipitation (June- Aug)	7.63	10.29
Short rains (Sept- Feb) precipitation	9.06	10.28
Long rains (Mar-Aug) precipitation	11.72	13.89
Spring temperature (Sept-Nov)	17.95	3.37
Fall temperature (Dec-Feb)	18.12	3.61
Summer temperature (Mar-May)	18.96	3.50
Winter temperature (June- Aug)	17.22	3.46
Short rains temperature	18.03	3.47
Long rains temperature	18.09	3.46
Summer runoff (mm)	0.20	0.40
Winter runoff	0.12	0.23
Spring runoff	0.13	0.26
Fall runoff	0.07	0.15
Short rains runoff	0.16	0.31
Long rains runoff	0.10	0.19
Population density	269.06	577.57
Agro- ecological zone	2.49	1.47
Soil drainage	7.13	2.17
Soil depth	4.62	2.67
Silt soil	18.03	14.47

Table 2. Fixed effect estimates of weather variability on crop yields, short and long rains seasons

Variables	Maize	Sorghum	Bean	Millet
Short rains (Sept- Feb) precipitation	0.2170***	0.0478	0.0004	-0.0231
	[0.065]	[0.062]	[0.002]	[0.256]
Short rains precipitation squared	-0.0056***	-0.001	0.0000	-0.0002
	[0.001]	[0.001]	[0.000]	[0.005]
Long rains (Mar-Aug) precipitation	0.2974***	0.1279**	0.0011	-0.1748
	[0.052]	[0.050]	[0.001]	[0.195]
Long rains precipitation squared	0.0002	-0.0003	0.0000	0.0028
	[0.001]	[0.001]	[0.000]	[0.003]
Short rains temperature	-7.8370***	-4.2380**	-0.0333	3.1717
	[1.795]	[1.751]	[0.056]	[9.457]
Short rains temperature squared	0.1609***	0.0851*	0.0009	-0.1009
	[0.049]	[0.047]	[0.002]	[0.284]
Long rains temperature	3.8528**	0.3461	-0.0143	-3.6579
	[1.601]	[1.589]	[0.050]	[7.994]
Long rains temperature squared	-0.0721*	-0.0035	0.0004	0.0953
	[0.043]	[0.042]	[0.001]	[0.236]
Short rains runoff	4.2094***	0.7331	0.0171	-0.6717
	[1.304]	[1.302]	[0.038]	[4.595]
Long rains runoff	-5.5259***	-1.4086	0.0215	0.7192
	[2.074]	[2.040]	[0.060]	[7.300]
Population density	0.0016***	0.0011	0.0001**	-0.0041
	[0.001]	[0.001]	[0.000]	[0.010]
Constant	38.7435***	40.3589***	0.8992**	14.9148
	[13.637]	[13.754]	[0.407]	[65.367]
Observations	1,362	1,105	1,462	696
R-squared	0.198	0.055	0.01	0.003
Number of code	47	44	43	24

Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1.

Table 3. Fixed effect estimates of seasonal weather variability on crop yields

Variables	Maize	Sorghum	Bean	Millet
Spring precipitation (Sept-Nov)	0.1865***	0.0253	0.0009	-0.0231
	[0.045]	[0.045]	[0.001]	[0.179]
Spring precipitation squared	-0.0046***	-0.0016**	0.0000	0.0000
	[0.001]	[0.001]	[0.000]	[0.003]
Fall precipitation (Dec-Feb)	-0.0406	-0.0124	-0.0008	-0.1105
	[0.046]	[0.045]	[0.001]	[0.250]
Fall precipitation squared	0.0009	0.0012	0.0000	0.0015
	[0.001]	[0.001]	[0.000]	[0.007]
Summer precipitation (Mar-May)	-0.0815**	-0.0584*	0.0006	-0.3171**
	[0.035]	[0.034]	[0.001]	[0.136]
Summer precipitation squared	0.0019***	0.0010**	0.0000	0.0026*
	[0.000]	[0.000]	[0.000]	[0.002]
Winter precipitation (June- Aug)	0.6052***	0.3758***	0.0009	0.238
	[0.054]	[0.052]	[0.002]	[0.204]
Winter precipitation squared	-0.0064***	-0.0051***	0.0000	-0.0022
	[0.001]	[0.001]	[0.000]	[0.004]
Spring temperature (Sept-Nov)	0.5032	1.0839	0.0888	5.6035
	[1.669]	[1.666]	[0.054]	[8.968]
Spring temperature squared	-0.0146	-0.031	-0.0024	-0.1751
	[0.046]	[0.045]	[0.002]	[0.272]
Fall temperature (Dec-Feb)	-4.3586***	-2.6975**	-0.1034**	3.7938
	[1.348]	[1.355]	[0.045]	[7.403]
Fall temperature squared	0.0889**	0.0562	0.0028**	-0.0901
	[0.036]	[0.035]	[0.001]	[0.216]
Summer temperature (Mar-May)	-3.2914**	-3.6622**	0.0207	-18.0565**
	[1.584]	[1.601]	[0.053]	[7.964]
Summer temperature squared	0.0473	0.0853**	-0.0003	0.4017*
	[0.039]	[0.039]	[0.001]	[0.215]
Winter temperature (June- Aug)	3.2444**	1.7625	-0.0532	7.0621
	[1.423]	[1.411]	[0.045]	[6.356]
Winter temperature squared	-0.04	-0.0374	0.0013	-0.1404
	[0.040]	[0.038]	[0.001]	[0.191]
Summer runoff	1.8362***	0.7027	0.0214	0.2446
	[0.666]	[0.677]	[0.020]	[2.547]
Fall runoff	-4.3032**	-2.7322	0.02	-1.3764
	[1.726]	[1.569]	[0.052]	[8.003]
Population density	0.0017***	0.0012	0.0001**	-0.003
	[0.001]	[0.001]	[0.000]	[0.010]
Constant	43.2779***	39.4000***	0.8652**	40.3216
	[13.613]	[14.048]	[0.427]	[68.552]
Observations	1,362	1,105	1,462	696
R-squared	0.28	0.111	0.015	0.024
Number of code	47	44	43	24

Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1.

Table 4. Random effects estimates of seasonal weather variability on crop yields

Variables	Maize	Sorghum	Beans	Millet
Spring precipitation (Sept-Nov)	0.1364***	-0.0114	-0.0008	-0.0023
	[0.043]	[0.041]	[0.001]	[0.172]
Spring precipitation squared	-0.0041***	-0.0011	0.0000	-0.0003
	[0.001]	[0.001]	[0.000]	[0.003]
Fall precipitation (Dec-Feb)	-0.0406	0.0212	-0.0004	-0.087
	[0.043]	[0.042]	[0.001]	[0.237]
Fall precipitation squared	0.0018**	0.0013	0.0000	0.0007
	[0.001]	[0.001]	[0.000]	[0.006]
Summer precipitation (Mar-May)	-0.1738***	-0.0840***	0.0004	-0.3072**
	[0.032]	[0.031]	[0.001]	[0.129]
Summer precipitation squared	0.0023***	0.0011***	0.0000	0.0026*
	[0.000]	[0.000]	[0.000]	[0.001]
Winter precipitation (June- Aug)	0.2380***	0.2256***	0.0049***	0.2287
	[0.038]	[0.038]	[0.001]	[0.186]
Winter precipitation squared	0.0003	-0.0023***	-0.0001***	-0.0022
	[0.001]	[0.001]	[0.000]	[0.004]
Spring temperature (Sept-Nov)	0.1819	1.6345	0.0419	5.3659
	[1.562]	[1.533]	[0.052]	[8.730]
Spring temperature squared	-0.0009	-0.0457	-0.001	-0.1697
	[0.043]	[0.042]	[0.001]	[0.265]
Fall temperature (Dec-Feb)	-0.9203	-1.095	0.024	3.3393
	[1.069]	[1.076]	[0.039]	[7.159]
Fall temperature squared	0.0198	0.027	-0.001	-0.0724
	[0.028]	[0.028]	[0.001]	[0.211]
Summer temperature (Mar-May)	-3.6934**	-3.6612**	0.0201	-17.3613**
	[1.484]	[1.460]	[0.051]	[7.727]
Summer temperature squared	0.0602	0.0908**	-0.0008	0.3846*
	[0.037]	[0.036]	[0.001]	[0.209]
Winter temperature (June- Aug)	3.2681**	2.6516**	-0.0920**	6.9111
	[1.280]	[1.267]	[0.043]	[6.289]
Winter temperature squared	-0.0592*	-0.0674**	0.0029**	-0.1419
	[0.035]	[0.034]	[0.001]	[0.190]
Summer runoff	0.0363	0.1497	0.0375*	0.1732
	[0.640]	[0.631]	[0.020]	[2.494]
Fall runoff	-3.8253**	-2.5774	-0.026	-1.5876
	[1.657]	[1.640]	[0.051]	[7.761]
Population density	0.0004	0.0005	0.00001**	-0.0052
	[0.000]	[0.000]	[0.000]	[0.009]
Agro-ecological zone	0.5970***	0.4734**	-0.0073	-1.1662
	[0.154]	[0.206]	[0.007]	[1.492]

Soil drainage	0.2122***	0.0067	0.0034	0.061
	[0.076]	[0.082]	[0.004]	[1.374]
Soil depth	0.0962	-0.009	-0.0033	-0.408
	[0.061]	[0.080]	[0.003]	[0.691]
Silt soil	-0.0201*	-0.0141	0.0014	-0.0112
	[0.011]	[0.012]	[0.001]	[0.185]
Constant	15.0954**	7.7277	0.5485**	45.7872
	[6.432]	[6.879]	[0.262]	[54.145]
Observations	1,362	1,105	1,462	696
Number of code	47	44	43	24

Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1.

Table 5. Predicted damage to maize crop yields from different AOGCM climate scenarios

Scenario	A2				B2			
Model	year	Predicted yield	net loss	% damage	year	Predicted yield	net loss	% damage
HADCM3								
	2050	0.88	-1.43	-62	2050	0.81	-1.50	-65
	2100	2.44	0.13	6	2100	1.10	-1.21	-52
PCM								
	2050	1.18	-1.13	-49	2050	1.14	-1.17	-51
	2100	0.95	-1.36	-59	2100	0.84	-1.47	-64
ECHAM								
	2050	1.19	-1.12	-48	2050	1.29	-1.02	-44
	2100	1.98	-0.33	-14	2100	1.37	-0.94	-41
CSIRO2								
	2050	0.89	-1.42	-62	2050	0.71	-1.60	-69
	2100	2.11	-0.20	-9	2100	0.90	-1.41	-61
CGCM2								
	2050	0.89	-1.42	-61	2050	0.92	-1.39	-60
	2100	1.50	-0.81	-35	2100	0.72	-1.59	-69

* Base yield = 2.31 Tons per Hectare.

Table 6. Random effects estimates of short & long rains seasons weather variability on food security - poverty line set at 60% percentile of yields

Variables	Maize	Sorghum	Bean	Millet
Short rains (Sept- Feb) precipitation	-0.0866***	-0.0408**	-0.0840***	-0.1177***
	[0.024]	[0.021]	[0.022]	[0.031]
Short rains precipitation squared	0.0011**	0.0002	0.0010*	0.0012*
	[0.001]	[0.000]	[0.001]	[0.001]
Long rains (Mar-Aug) precipitation	-0.0821***	-0.0303*	-0.0366**	-0.0186
	[0.021]	[0.017]	[0.019]	[0.025]
Long rains precipitation squared	0.0007*	0.0003	0.0003	0.0003
	[0.000]	[0.000]	[0.000]	[0.000]
Short rains temperature	2.2624***	1.3781**	1.1282*	3.7882***
	[0.633]	[0.545]	[0.684]	[1.138]
Short rains temperature squared	-0.0554***	-0.0321**	-0.0273	-0.1092***
	[0.017]	[0.014]	[0.019]	[0.033]
Long rains temperature	-0.5985	-0.0237	-0.4578	-0.7621
	[0.552]	[0.515]	[0.656]	[0.942]
Long rains temperature squared	0.0069	0.0031	0.0084	0.0207
	[0.014]	[0.013]	[0.018]	[0.027]
Short rains runoff	-0.0941	0.2334	-0.725	0.5319
	[0.573]	[0.483]	[0.564]	[0.616]
Long rains runoff	0.4206	-0.5356	0.4589	-0.7515
	[0.922]	[0.782]	[0.914]	[0.992]
Population density	-0.0013***	-0.0001	-0.0007***	-0.0065***
	[0.000]	[0.000]	[0.000]	[0.001]
Agro-ecological zone	0.0797	-0.0839	-0.3186*	-0.3451
	[0.284]	[0.127]	[0.163]	[0.375]
Soil drainage	-0.0856	0.0400	0.102	0.3183*
	[0.163]	[0.068]	[0.093]	[0.187]
Soil depth	-0.0077	0.0322	-0.099	0.0179
	[0.136]	[0.056]	[0.076]	[0.186]
Silt soil	0.017	0.0002	-0.0357*	-0.0278
	[0.024]	[0.010]	[0.019]	[0.054]
Constant	-11.8841**	-13.2540***	-3.9975	-25.9010***
	[5.041]	[3.887]	[4.293]	[7.955]
lnsig2u	1.5830***	-0.3012	0.2669	1.7535***
	[0.440]	[0.295]	[0.312]	[0.327]
Observations	1,598	1,598	1,598	1,598
Number of code	47	47	47	47

Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1.

Table 7. Random effects estimates of seasonal weather variability on food insecurity-poverty line set at 60% percentile of yields

Variables	Maize	Sorghum	Bean	Millet
Spring precipitation (Sept-Nov)	-0.0655***	-0.0138	-0.0342**	-0.0695***
	[0.016]	[0.015]	[0.015]	[0.022]
Spring precipitation squared	0.0009***	0.0000	0.0003	0.0003
	[0.000]	[0.000]	[0.000]	[0.000]
Fall precipitation (Dec-Feb)	0.0052	-0.0057	-0.0451**	-0.0452
	[0.022]	[0.020]	[0.018]	[0.030]
Fall precipitation squared	-0.0001	-0.0002	0.0009**	0.0018**
	[0.001]	[0.001]	[0.000]	[0.001]
Summer precipitation (Mar-May)	-0.014	0.0057	0.0055	0.0290*
	[0.014]	[0.012]	[0.012]	[0.016]
Summer precipitation squared	-0.0001	0.0000	-0.0001	0.0000
	[0.000]	[0.000]	[0.000]	[0.000]
Winter precipitation (June- Aug)	-0.1239***	-0.0827***	-0.0816***	-0.1206***
	[0.022]	[0.019]	[0.020]	[0.030]
Winter precipitation squared	0.0019***	0.0011***	0.0012***	0.0017***
	[0.000]	[0.000]	[0.000]	[0.001]
Spring temperature (Sept-Nov)	1.6415***	-0.5138	0.9402	3.7155***
	[0.632]	[0.576]	[0.716]	[1.085]
Spring temperature squared	-0.0528***	0.0085	-0.0332	-0.1112***
	[0.017]	[0.015]	[0.021]	[0.032]
Fall temperature (Dec-Feb)	0.7444	1.4264***	0.4237	0.6085
	[0.525]	[0.453]	[0.565]	[0.903]
Fall temperature squared	-0.0096	-0.0320***	-0.0054	-0.0205
	[0.014]	[0.012]	[0.016]	[0.026]
Summer temperature (Mar-May)	-0.9411	0.6344	0.3242	1.1303
	[0.625]	[0.560]	[0.686]	[1.025]
Summer temperature squared	0.0300**	-0.0076	-0.0015	-0.0174
	[0.015]	[0.013]	[0.018]	[0.027]
Winter temperature (June-Aug)	0.2922	0.0188	-0.7021	-1.9908***
	[0.539]	[0.497]	[0.571]	[0.765]
Winter temperature squared	-0.0188	-0.0083	0.0131	0.0505**
	[0.015]	[0.013]	[0.016]	[0.022]

Summer runoff	-0.0709	-0.1761	-0.8972***	0.5384
	[0.313]	[0.268]	[0.342]	[0.383]
Fall runoff	-0.2089	0.0092	1.2754	-1.7497
	[0.857]	[0.740]	[0.906]	[1.170]
Population density	-0.0012***	-0.0001	-0.0007***	-0.0065***
	[0.000]	[0.000]	[0.000]	[0.001]
Agro-ecological zone	-0.1931	-0.2048	-0.4360**	-0.3047
	[0.253]	[0.141]	[0.177]	[0.383]
Soil drainage	-0.1673	-0.0172	0.0463	0.2764
	[0.145]	[0.075]	[0.101]	[0.180]
Soil depth	-0.0578	0.0083	-0.12	0.0681
	[0.120]	[0.062]	[0.082]	[0.176]
Silt soil	0.024	0.0072	-0.0336	-0.021
	[0.022]	[0.011]	[0.021]	[0.037]
Constant	-11.4608**	-14.7019***	-6.7598	-31.5097***
	[5.192]	[4.296]	[4.739]	[8.609]
lnsig2u	1.3098***	-0.1049	0.4347	2.0331***
	[0.439]	[0.305]	[0.324]	[0.330]
Observations	1,598	1,598	1,598	1,598
Number of code	47	47	47	47

Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1.

Table 8. Predicted changes in food insecurity from different AOGCM climate scenarios

Scenario		**A2**				**B2**			
Model	year	Maize	Sorghum	Beans	Millet	Maize	Sorghum	Beans	Millet
HADCM3									
	2050	4.04	0.15	0.55	0.58	3.96	0.17	0.53	0.58
	2100	21.15	5.08	2.83	2.67	11.34	2.06	1.52	1.50
PCM									
	2050	1.68	-0.22	0.23	0.28	1.8	-0.21	0.24	0.20
	2100	8.56	1.28	1.15	1.15	4.44	0.26	0.60	0.63
ECHAM									
	2050	2.79	-0.05	0.39	0.39	2.91	-0.02	0.41	0.39
	2100	15.21	3.19	2.05	1.90	7.7	1.04	1.05	0.97
CSIRO2									
	2050	3.63	0.09	0.49	0.53	3.82	0.12	0.51	0.58
	2100	18.90	4.36	2.53	2.40	11.09	2.00	1.48	1.50
CGCM2									
	2050	2.80	-0.07	0.38	0.43	2.25	-0.16	0.30	0.36
	2100	15.36	3.27	2.05	1.99	6.43	0.73	0.86	0.90

Appendix

Table A1. Characteristics of agro-climate zones and farming systems in Kenya

Zone	Moisture index (%)	Climate classification	Average annual rainfall (mm)	Average annual potential evaporation (mm)	Vegetation	Farming system
I	>80	Humid	1100-2700	1200-2000	Moist forest	Dairy, sheep, coffee, tea, maize, sugarcane
II	65-80	Sub-humid	1000-1600	1300-2100	Moist and dry forest	Maize, pyrethrum, wheat, coffee, sugarcane
III	50-65	Semi-humid	800-1400	1450-2200	Dry forest and moist woodland	Wheat, maize, barley coffee, cotton, coconut, cassava
IV	40-50	Semi-humid to semi-arid	600-1100	1550-2200	Dry woodland and bush land	Ranching, cattle sheep, barley, sunflower, maize, cotton, cashew nuts, cassava
V	25-40	Semi-arid	450-900	1650-2300	Bush land	Ranching, livestock, sorghum, millet
VI	15-25	Arid	300-550	1900-2400	Bush land and scrubland	Ranching
VII	<15	Very arid	150-350	2100-2500	Desert scrub	Nomadism and shifting grazing

Source: Kabubo-Mariara and Karanja (2007).

Table A2. Predicted decadal average changes in precipitation and temperature: 2050-2100

	Precipitation (Percentage change)									
	CGCM2		CSIRO2		ECHAM		HADCM3		PCM	
Year	2050	2100	2050	2100	2050	2100	2050	2100	2050	2100
A2- Scenarios	106	116	109	123	113	134	110	124	106	115
B2- Scenarios	104	109	105	109	116	129	108	115	106	110
	Temperature (increases ^{o}C)									
	CGCM2		CSIRO2		ECHAM		HADCM3		PCM	
Year	2050	2100	2050	2100	2050	2100	2050	2100	2050	2100
A2- Scenarios	3.0	7.4	3.4	8.2	2.8	7.2	3.6	8.7	2.2	5.4
B2- Scenarios	2.7	4.7	3.6	6.3	2.8	4.9	3.6	6.3	2.3	3.8

Source: Strzepek and McCluskey, (2006) and associated district level database for Kenya.