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The economic impact of climate change on Kenyan crop agriculture: A Ricardian approach ☆

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Abstract

This paper measures the economic impact of climate on crops in Kenya. We use cross-sectional data on climate, hydrological, soil and household level data for a sample of 816 households. We estimate a seasonal Ricardian model to assess the impact of climate on net crop revenue per acre. The results show that climate affects crop productivity. There is a non-linear relationship between temperature and revenue on one hand and between precipitation and revenue on the other. Estimated marginal impacts suggest that global warming is harmful for crop productivity. Predictions from global circulation models confirm that global warming will have a substantial impact on net crop revenue in Kenya. The results also show that the temperature component of global warming is much more important than precipitation. Findings call for monitoring of climate change and dissemination of information to farmers to encourage adaptations to climate change. Improved management and conservation of available water resources, water harvesting and recycling of wastewater could generate water for irrigation purposes especially in the arid and semi-arid areas.

Keywords: climate change; agriculture; crop revenue; adaptations

1. Introduction

Agriculture continues to be the leading sector in the Kenyan economy in terms of its contribution to real GDP (about 24%). The sector is the largest contributor to employment (with more than 70% of the labor force based in rural areas) and accounts for about 50% of principal export earnings (Republic of Kenya, 2006). Agriculture is also responsible for providing food security for both the rural and urban populations. However, rapidly expanding population, rapid urbanization and the shortage of high potential arable land cause occasional imbalances between the national demand for food and its supply. In addition, the sector has over time experienced declining agricultural productivity and fluctuations in contribution to real GDP and export earnings.

The performance of the agricultural sector is determined by crop production, which depends on a large number of factors. Most important is the country's endowment of soils and climate resources. Kenya has climate and ecological extremes, with altitude varying

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from sea level to over 5000 m in the highlands. The mean annual rainfall ranges from less than 250 mm in the arid and semi-arid areas to 2500 mm in high potential areas. Kenya has a total area of 580,367 km^2, of which only 12% is considered high potential for farming or intensive livestock production. A further 5.5%, which is classified as medium potential, mainly supports livestock, especially sheep and goats. The other 82% of the total land in the country is classified as arid and semi-arid and is largely used for extensive livestock production, as well as being the habitat for wildlife both in and outside national parks and game reserves. Because of differences in soil, climate and hydrological factors, agricultural productivity and incomes are highest in the high and medium potential zones and lowest in the arid and semi-arid areas.

The declining performance of the sector is worrisome and a real challenge for a government with a population of approximately 30 million to feed. Worse still is the expected adverse impact of global warming on agriculture in the future. The highest damages from climate change are predicted to be in the agricultural sector in sub-Saharan Africa because the region already endures high heat and low precipitation (Kurukulasuriya and Mendelsohn, 2006). Global circulation models also predict that global warming will lead to increased temperatures of about 4 °C and cause variability of rainfall by up to 20% in Kenya by the year 2100. From these predictions, the two extreme climate events that may adversely affect the agricultural sector are drought and flooding in both the arid and semi-arid areas and the high potential areas. Even with the predicted climate change scenarios, unpredicted climate events (e.g. the 1997–98 El Nino rains) may still occur with devastating effects, in more vulnerable areas. The overall adverse weather events that may occur because of the projected climate change 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.

Though a few studies have been conducted to assess the impact of climate change on agriculture in developing countries (see for instance (Molua, 2002; Gbetibouo and Hassan, 2005; Deressa et al., 2005; Seo et al., 2005)), there is a dearth of literature on this impact in Kenya. A growing body of literature on the determinants of agricultural productivity concentrate on impacts of factors such as soil conservation and other farm technologies. In addition, adaptive mechanisms used by farmers to circumvent the welfare impact of climate change have not been studied in Kenya. This paper addresses these research gaps. It uses the Ricardian approach to analyze the impact of climate on crop productivity in Kenya. The Ricardian method is a cross-sectional technique that measures what determines net revenues to farmers (Mendelsohn et al., 1994) and has been used to study the impact of climate change on agriculture in the literature. Understanding the impact of long-term climate change on agriculture is crucial for future agricultural policies and interventions in Kenya, particularly interventions to mitigate potential adverse impacts of climate change, which would have important implications for future food security and the overall growth of the sector. Such growth would in turn trickle down to the rest of the economy, increasing employment and incomes in agriculture and related sectors and boosting overall economic growth.

The general objective of this paper is to analyze the effect of long-term climate change on Kenyan agriculture and to identify the adaptation options of agro-ecological systems. The specific objectives are: first to assess farmers' awareness of climate change and to investigate the various adaptation measures they employ to counter adverse effects of climate change. Second, to carry out an economic analysis of the effect of climate on agricultural production under baseline climate conditions. Third, to simulate the expected effect of various long-term climate change scenarios on future agricultural productivity. Based on research findings, the paper then recommends interventions for mitigating the potential impact of climate change in the future.

The rest of the paper is organized as follows. Section 2 analyzes the relationship between climate and agriculture in Kenya; Section 3 discusses the study site and data; Sections 4 and 5 present the methods and results respectively; and Section 6 concludes.

2. Climate and agriculture in Kenya

2.1. Agro-climate zones and farming systems

Kenya is divided into seven agro-climate zones using a moisture index based on annual rainfall expressed as a percentage of potential evaporation (Sombroek et al., 1982). Areas with an index greater than 50% have high potential for cropping and are designated zones I, II and III (Table 1). These zones account for about 18% of Kenya's land area. The semi-humid to arid regions (zones IV, V, VI and VII) have indexes of less than 50% and a mean annual rainfall of less than 1100 mm. These zones are generally referred to as the Kenyan rangelands and account for about 80% of the land area. Most of the high potential areas are located above an altitude of 1200 m and have mean annual temperatures of below

Table 1
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: Sombroek et al. (1982); Jaetzold and Schmidt (1982).

18 °C. These areas are mainly suitable for livestock farming, cash crops and key food crops. The medium potential zones favor farming systems similar to the high potential areas, but temperatures are higher and productivity lower. Ninety percent of the arid and semi-arid areas lies below 1260 m and mean annual temperatures range from 22 °C to 40 °C. These areas are less suited for arable agriculture.

2.2. Drainage basins

Kenya is endowed with a large potential of water resources including groundwater, river flows, lakes and oceans. The surface water resources are contained within five main drainage basins whose hydrological characteristics are related to moisture availability, rainfall and climate (Table 2). Except for the water resources in the oceans and lakes, rainfall is also a major water resource in Kenya and sustains most of the water resources in the country. Rainfall is the main cause of variability in the water balance over space and time, and changes in precipitation have significant implications for hydrology and water resources.

2.3. Rainfall and temperature

The country receives a bimodal type of rainfall where the 'long rains' fall between March and May and the 'short rains' between October and December. The average annual rainfall ranges from 250 mm to 2500 mm; the average potential evaporation ranges from less than 1200 mm to 2500 mm; and the average annual temperature ranges from less than 10 °C to 30 °C. The annual rainfall generally follows a strong seasonal pattern, with variations being strongest in the dry lowlands, but weakest in the humid highlands. Mean temperatures in Kenya are closely related to ground elevation. The highest temperatures are recorded in the arid regions where the night minimum may be as high as 29 °C during the rainy seasons. Coldest areas are the tops of the mountains where night frost occurs above 10,000 feet and permanent snow or ice covers the area above 16,000 feet (Mt Kenya). Annual temperature variations are generally small (less than 5 °C) throughout the country.

2.4. Soils and topography

Kenya is a country with varying climate, vegetation, topography and underlying parent rock. Climate is the most important factor influencing soil formation and affects soil type directly through its weathering effects and indirectly as a result of its influence on vegetation. In most parts of Kenya, soils are deficient in nitrogen, phosphorous and occasionally potassium. In dry areas,

Table 2
Characteristics of the main drainage basins in Kenya

Drainage basin	Area (km^2)	Mean annual rainfall (mm)	Mean annual runoff (mm)	Climate classification
Lake Victoria	49,210	1000	270	Humid to sub-humid
Rift Valley	126,910	600	120	Arid to semi-arid
Athi River	69,930	650	200	Semi-arid
Tana River	132,090	520	170	Semi-humid (headlands), semi-arid to arid
Ewaso Nyiro	204,610	400	80	Arid to semi-arid

Source: Sombroek et al. (1982).

the soils have low organic matter mainly because rainfall is low, variable, unreliable and poorly distributed. The distribution of soils varies by agro-ecological zones. The humid regions have volcanic rocks and soils range from loam, sandy clay, alluvial soils, sand dunes and soils covered by mangrove swamps. The sub-humid regions have volcanic and basement rocks and soils are red clay and generally productive. Dark red clays, sandy loams and alluvial deposits of eroded material from the uplands are common along the flood plains of big rivers in these regions. Peat swampy soils and black cotton soils dominate the lowlands. The semi-arid regions have shallow and generally infertile soils.

3. The data

3.1. Sampling and data collection

The primary data for this study were based on a sample of 816 households in Kenya. The data were collected using a common questionnaire designed jointly by the School of Forestry and Environmental Studies of Yale University and the Centre for Environmental Economics and Policy in Africa (CEEPA), University of Pretoria for 11 countries participating in the regional Global Environmental Facility/World Bank project. The questionnaire details the socio-economic characteristics of the sampled households and their economic activities. The questionnaire also included a module for perceptions and adaptations of households to climate change. The data were collected from 38 districts drawn from six out of eight provinces in Kenya between June and August 2004. The districts chosen captured variability in a wide range of agro-climatic conditions (rainfall, temperatures and soils), market characteristics (market accessibility, infrastructure, etc.) and agricultural diversity, among other factors. Each district was divided into agro-ecological zones and samples of three different farm types/sizes: large (>8 ha), medium (2–8 ha) and small (0–2 ha) chosen from each ecological zone. Detailed information from the Ministry of Agriculture and from the *Farm Management Handbook* (Jaetzold and Schmidt, 1982) was used to help identify agro-ecological zones and farm types. Except for the tropical alpine zone which is found on the top of the mountains, all zones in a selected district were sampled. The sampling procedure was purposely designed to target at least four households from each agro-ecological zone, comprising at least one household from each farm type. However, in some districts, only small farmers could be interviewed due to the scale of production prevailing in the district. The final sample comprised of 66% small scale, 22% medium scale and 12% large scale farms.

The key household variables of interest for the Ricardian analysis include net crop revenue, wage rates and a few other household variables. We define net revenue as gross revenue less all total variable costs, costs of hired labor, farm tools, machinery, fertilizers and pesticides. Costs of household labor were not netted out due to difficulties of accurate measurement. Instead we introduce household wage rates for adults and children as independent variables in the net revenue regression. A summary of the key variables used in the analysis is presented in Table 3.

3.2. Secondary data

In addition to the household data, the study also made use of satellite and ARTES (Africa Rainfall and Temperature Evaluation System) climate data. Satellite data were provided by the US Department of Defense. The data values were derived from a set of polar orbiting satellites that are equipped with sensors to detect microwaves through clouds and estimate surface temperature and surface wetness (Weng and Grody, 1998; Basist et al., 1998, 2001). The ARTES dataset was created by the National Oceanic and Atmospheric Association's Climate Prediction Center based on ground station measurements of precipitation and minimum and maximum temperature (World Bank, 2003). The data were constructed from a base with data for each month of the survey year and for morning and evening. The monthly means were estimated from approximately 14 years of data (1988–2003) to reflect long-term climate change. In the final estimating equations, we use seasonal climate variables (see Table 4 for summary statistics) because we uncover neither important nor significant impact of wet, dry and annual climate variables on net crop revenue.

Hydrological data (run off and flow) were obtained from the IWMI (International Water Management Institute) and the University of Colorado and were based on monthly values from the 1961 to 1990 time series. The final values were estimated using hydrological models for Africa (IWMI and UOC, 2003). The mean runoff for the country was estimated at about 39 mm, with a high standard deviation of 25 mm, implying that there is high variability in the mean runoff across the six provinces. Provinces with very high runoff estimates also have the highest estimates for surface flow, with a national estimate of 301,000 m^3.

Soil data were obtained from the Food and Agricultural Organization (FAO, 2003). Kenya has at least 28 different types of soil but the key types in the six sampled provinces can be divided into only 8 main groups. These include nitosols (28%); ferrasols (22%); Luvisols (11%);

Table 3
Distribution of selected variables by agro-ecological zone

Variable	Medium and low potential		High potential		All zones	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Net revenue (US$)	339.2	376.9	352.38	317.14	344.60	353.44
Temperature summer	20.2	2.9	17.47	1.46	19.07	2.74
Temperature winter	19.5	2.4	17.12	1.35	18.50	2.36
Precipitation fall	101.1	75.4	57.40	24.68	83.20	63.74
Precipitation summer	97.2	19.3	145.94	24.91	117.18	32.41
Log (mean flow)	5.3	0.3	5.50	0.21	5.40	0.26
Soils (andosols)	0.1	0.1	0.06	0.09	0.06	0.11
Livestock ownership dummy	0.9	0.3	0.89	0.32	0.88	0.32
Primary occupation of household head is farming	0.8	0.4	0.70	0.46	0.73	0.44
Secondary occupation of household head is farming	0.2	0.4	0.23	0.42	0.21	0.41
Household head is Christian	0.9	0.2	0.98	0.14	0.96	0.20
Average years of education of household members	8.5	3.1	8.46	2.78	8.46	2.99
Farm size	8.5	55.8	2.53	2.81	6.02	42.87
Household size	6.8	2.9	6.26	1.88	6.60	2.53
Male wage rates	115.6	52.7	97.29	34.63	108.11	47.02
Child wage rates	57.4	17.6	51.55	13.25	54.98	16.18
Irrigation dummy	0.2	0.4	0.07	0.26	0.14	0.34
Sample size	427		297		724	

cambisols and lithosols (each 8%); andosols (6%); vertisols, planosols and arensols (each less than 4%) (see Kabubo-Mariara and Karanja, 2006 for a detailed description of the major soil types in Kenya).

4. Methodology

Most studies of the impact of climate change on agriculture employ the Ricardian analysis (see for instance Mendelsohn et al., 1994) while traditional studies have used the production function approach (for example Rosenzweig and Iglesias, 1994). The latter approach has been criticized for having an inherent bias and tending to overestimate the damage climate change causes to farming because of failing to take into account the enormous variety of substitutions, adaptations and old and new activities that may displace obsolete activities as climate changes. The Ricardian approach is based on the observation by David Ricardo (1772–1823) that land rents reflect the net productivity of farmland and it examines the impact of climate and other variables on land values and farm revenues (Ricardo, 1817, 1822). This approach has been found attractive because it corrects the bias in the production function approach by using economic data on the value of land. By directly measuring farm prices or revenues, the Ricardian approach accounts for the direct effects of climate on the yields of different crops as well as the indirect substitution of different inputs, the introduction of different activities and other potential adaptations to different climates (Mendelsohn et al., 1994). It is also attractive because it includes not only the direct effect of climate on productivity but also the adaptation response by farmers to local climate.

The Ricardian approach is a cross-sectional model applied to agricultural production. It takes into account how variations in climate change affect net revenue or land value. Following Mendelsohn et al. (1994), the approach involves specifying a net productivity function of the form:

$$R = \Sigma P_i Q_i(X, F, Z, G) - \Sigma P_x X \quad (1)$$

where R is net revenue per hectare, P_i is the market price of crop i, Q_i is output of crop i, X is a vector of purchased inputs (other than land), F is a vector of

Table 4
Sample statistics for temperatures and precipitation by season

Season	Temperatures (°C)		Precipitation (mm/month)	
	Mean	Standard deviation	Mean	Standard deviation
Fall (December–February)	19.29	2.67	88.80	41.45
Summer (March–May)	19.07	2.74	103.71	31.57
Winter (June–August)	18.50	2.36	62.40	40.82
Spring (September–November)	19.09	2.66	71.89	26.95
Annual average	18.99	2.58	84.53	18.60
Long rains (March–August)	19.33	2.73	90.90	34.97
Short rains (September–February)	18.65	2.46	81.27	23.71

climate variables, Z is a set of soil variables, G is a set of economic variables such as market access and P_x is a vector of input prices. The farmer is assumed to choose X to maximize net revenues given the characteristics of the farm and market prices. The Ricardian model is a reduced form model that examines how a set of exogenous variables F, Z, and G affect farm value.

The standard Ricardian model relies on a quadratic formulation of climate:

$$R = B_0 + B_1 F + B_2 F^2 + B_3 Z + B_4 G + u \qquad (2)$$

where u is an error term, and F and F^2 capture levels and quadratic terms for temperature and precipitation. The introduction of quadratic terms for temperature and precipitation reflects the non-linear shape of the response function between net revenues and climate. From the available literature, we expect that farm revenues will have a concave relationship with temperature. When the quadratic term is positive, the net revenue function is U-shaped, but when the quadratic term is negative, the function is hill-shaped. For each crop there is a known temperature where that crop grows best across the seasons, though the optimal temperature varies by crop (Mendelsohn et al., 1994). From Eq. (2), we can derive the mean marginal impact of a climate variable on farm revenue as well as the mean marginal impact of runoff and flow on farm revenue.

The Ricardian analysis has, however, been criticized on several accounts: firstly, it does not measure transition costs, where a farmer changes from one crop to another suddenly, yet transition costs are clearly very important in sectors where there is extensive capital that cannot easily be changed. Secondly, it cannot measure the effect of variables that do not vary across space. Thirdly, it fails in that the change in climate that can be observed across space may not resemble the change that will happen over time. Fourthly, it generally assumes prices to be constant, which introduces bias in the analysis, overestimating benefits and underestimating damages. Fifthly, it explicitly includes irrigation, and lastly it reflects current agricultural policies (Kurukulasuriya and Mendelsohn, 2006).

5. Research findings

5.1. Results of Ricardian analysis

Our empirical implementation of the Ricardian model discussed above is based on three different model results. First we test the impact of climate variables only in model 1, then we introduce hydrological and soil variables in model 2 and last we introduce selected household characteristics in model 3 (Table 5). For climate variables, we present results for summer and winter temperatures only because fall and spring are collinear with summer and winter temperatures. For precipitation, we retain fall and summer precipitation for the same reason.

The results are robust across the three models. High summer temperatures are harmful to crop production while high winter temperatures are beneficial. This is because summer (March–May) is the planting period followed by formative crop growth, while winter (June–August) is the period for ripening and maturing of crops. High summer temperatures would therefore slow down or destroy crop growth, while higher winter temperatures are crucial for ripening and harvesting. In the Kenyan highlands, winters can be quite chilly and excessively low winter temperatures have been associated with crop damage from frost. The negative coefficient for the quadratic term suggests, however, that excess winter temperatures would be harmful for crop productivity. Summer temperatures exhibit a U-shaped relationship with net crop revenue and winter temperatures a hill-shaped one. Both fall and summer precipitation are, however, positively correlated with net crop revenue and exhibit a hill-shaped relationship with it. The results further show that climate exhibits a non-linear relationship with net revenue, which is consistent with the available literature (Mendelsohn et al., 1994, 2003, Kurukulasuriya and Mendelsohn, 2006). The Chow test results show that the overall models are significant at the 1% level of significance, but the R^2 shows that the models explain only between 3 and 13% of the total variation in net revenue.[1]

Introducing flow and hydrological variables reduces the F statistic marginally from 3.73 to 3.27. However the R^2 increases by almost 100%. The results imply a hill-shaped relationship between mean flow and net revenue, and both coefficients are statistically different from zero at the 10% level. All soils except andosols turned out to be insignificant and reduce the significance

[1] The results presented here omit households we suspected to be outliers, 92 in all. Most of the outlying households reported zero or very low revenues, or very high revenues or very high costs, making net revenues negative. We also excluded five households that reported very high crop land (group ranches). When these variables are included in the regression models, most variables are insignificant but they do not affect the signs of the coefficients. Their impact on the overall explanatory power of the model is also minimal. Median regressions which control for outliers are robust with Ordinary Least Squares (OLS) and so we present and discuss the latter.

Table 5
Ricardian regression estimates of the net crop revenue model

Variable	Model 1 [a]	Model 2 [a]	Model 3 [a]
Temperature summer	−542.02 (−2.44)***	−397.71 (−1.85)**	−479.31 (−2.21)**
Temperature summer squared	11.76 (2.03)**	8.68 (1.58)*	11.03 (1.96)**
Temperature winter	716.22 (2.55)***	567.73 (2.08)**	702.63 (2.64)***
Temperature winter squared	−17.09 (−2.30)**	−13.48 (−1.92)**	−17.44 (−2.51)***
Precipitation fall	13.70 (2.64)***	19.51 (2.98)***	19.79 (2.86)***
Precipitation fall squared	−0.04 (−2.21)**	−0.06 (−2.82)***	−0.07 (−2.68)***
Precipitation summer	82.97 (2.49)***	83.00 (2.38)***	76.29 (2.08)**
Precipitation summer squared	−0.33 (−2.49)***	−0.33 (−2.40)***	−0.31 (−2.11)**
Log (mean flow)		3953.32 (1.86)**	3494.69 (1.64)*
Log (mean flow squared)		−367.62 (−1.88)**	−326.70 (−1.65)*
Soils (andosols)		602.84 (1.62)**	887.29 (2.34)***
Livestock ownership dummy			−120.25 (−2.58)***
Primary occupation of household head is farming			21.22 (0.51)
Secondary occupation of household head is farming			132.46 (2.62)***
Household head is Christian			154.70 (2.26)**
Average years of education of household members			1.17 (0.31)
Farm size			−3.59 (−3.14)***
Farm size squared			0.01 (2.94)***
Household size			9.15 (1.59)*
Male wage rates			−0.81 (−2.10)**
Child wage rates			−2.57 (−2.41)***
Irrigation dummy			136.43 (2.46)***
Constant	−6567 (−2.33)	−17510 (−2.52)	−16194 (−2.16)
Number of observations	724	724	715
F	3.73***	3.27***	5.30***
R^2	0.0297	0.0558	0.1291

* significant at 10% level, ** significant at 5% level, *** significant at 1% level.
[a] Model 1 uses only climate variables as regressors, model 2 introduces hydrological and soil factors and model 3 introduces household characteristics.

of other variables considerably and we therefore dropped all other soils. The results indicate that andosols have a positive and significant impact on net crop revenue, which conforms to a priori expectations because andosols are quite fertile and thus suited for crop production.

Introduction of the household level variables raises the F statistic from 3.27 to 5.30, while the R^2 doubles. Most of the household level variables have a significant impact on crop revenue. Livestock ownership dummy, farm size and wage rates are inversely correlated with crop revenue. Farm size exhibits a U-shaped relationship with crop revenue, implying that large farm size may be associated with higher productivity. Main and secondary occupation of household head, religion of household head and average number of years of education of the household members are positively correlated with net crop revenue. Household size, introduced as a proxy for household labor (or remotely population density), has a positive and significant impact on net crop revenue.

Livestock ownership dummy has a negative and significant impact on net revenue. This implies competition rather than complementarity between farming and livestock keeping. Irrigation has a large positive impact on crop revenue, implying the importance of adaptations to counter the impact of climate change.[2] We did not discover any significant effect of education on crop productivity but the sign of the coefficient implies that education is associated with higher crop revenue.

5.2. Marginal impacts and elasticities

The estimated marginal impacts of climate on crop agriculture are presented in Table 6. The results are

[2] It is important to note that though livestock ownership and irrigation are important adaptations by farming households to climate change, they are potentially endogenous and can be quite sensitive to climate change. To test for the robustness of the results with these two variables, we re-estimate model 3 excluding these variables. The results (not presented) show that the magnitudes of the coefficients of the other variables change very marginally but the levels of significance remain the same, implying that they do not present a serious problem. However, omitting these variables affects the estimated marginal impacts and predicted impacts of different climate change scenarios, confirming their sensitivity to climate change.

Table 6
Marginal impacts of climate on net crop revenue (US$/ha)

Marginal impacts	Climate variables (model 1)	All variables (model 3)
Summer temperature	−94.77**	−64.82
Winter temperature	84.87***	74.51
Overall temperature	−9.90	9.69
Temperature elasticity	−0.55	0.53
Fall rainfall	7.11***	11.31***
Summer rainfall	5.95**	6.45***
Overall rainfall	13.06***	17.76***
Precipitation elasticity	3.18	4.34

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

based on the regression results for the climate variable only model (second column of Table 5 and the all variable model (column 4), but omitting livestock and irrigation). The marginal impacts for winter temperatures are positive, but summer temperatures have larger negative impacts on net crop revenue. Using the climate only model, crop revenue is inelastic (−0.55) with respect to changes in temperature. The seasonal marginal impacts with respect to temperature are statistically significant and thus different from zero. These results show that high temperatures are harmful for productivity (elasticity is negative), confirming that global warming is likely to have devastating effects on agriculture unless farmers take adaptation measures to counter the impact of climate change (Kurukulasuriya and Mendelsohn, 2006). Using the model with all variables, the elasticity of crop revenue with respect to changes in temperature reverses signs from −0.55 to 0.53. This is because the absolute value of the positive marginal impacts for winter is higher than the absolute value of the negative impacts for summer, leading to an overall positive impact. Since this model includes household characteristics and endowments, the results imply that, with adaptation to climate change, high winter temperatures would be beneficial for crop agriculture in Kenya. This is consistent with the signs of regression coefficients for winter temperatures.

The marginal impacts of precipitation are more modest than for temperatures, but the elasticities are higher. The last row of Table 6 shows that crop revenue is highly elastic with respect to changes in precipitation, and that increased precipitation increases productivity. The elasticity of revenue with respect to precipitation in the all variable model is larger (4.34) than in the first model. A 1% increase in rainfall would lead to a 4.34% increase in net crop revenue, though a similar change in temperature would lead to a 0.53% increase in revenue.

5.3. Predicting impact of global warming on Kenyan agriculture

Results from the Ricardian analysis show that climate has important effects on agriculture in Kenya. In this subsection, we use the regression results for the full model (excluding livestock ownership and irrigation) to project the impact of global warming on Kenyan agriculture. To simulate the impact of different climate scenarios, two General Circulation Models (GCMs) were used, namely the Canadian Climate Model (CCC) and the Geophysical Fluid Dynamics Laboratory model (GFDL). These models have been found to give reasonable climate forecasts for Kenya. The CCC and GFDL models predict an average increase in temperature of 3.5 °C and 4 °C respectively with the doubling of CO_2 by the year 2100. For rainfall, evidence from Kenya shows that there have been very large geographical disparities in the trend patterns. Estimates show that there has been a tendency for annual rainfall to decrease in the arid and semi-arid areas and increase over Lake Victoria and the coastal and neighboring regions. This implies that some regions may gain from global warming while others may be adversely affected. Both models predict, however, that changes in precipitation will range from −20% to +20% by the year 2100.

Using the regression results and variable means, we simulated the expected impact of climate change on net crop revenue, using the CCC and GFDL models. We added the predicted change in temperature to the benchmark values, and then evaluated the impact on the baseline net crop revenue. We also adjusted benchmark precipitation by the predicted percentage to get the new precipitation levels. For the CCC model, we simulated the impact of an increase in temperature of 3.5 °C combined with a 20% decrease in rainfall and took a similar scenario for the GFDL model but with a 4 °C change in temperature. We applied the scenarios separately for medium and low potential zones on the one hand and high potential zones on the other, and then for the country as a whole. This was because it is expected that the effects of climate change on agriculture will not be uniform across continents or even within a country (Gbetibouo and Hassan, 2005; Deressa et al., 2005; Seo et al., 2005).

The results (Table 7) show that with precipitation remaining the same, changes in temperature predicted by the CCC model would result in a −0.03% (US$0.11 per hectare) gain in high potential zones but a 28% (US $97 per hectare) loss in medium and low potential zones. The results further suggest that medium and low potential zones will bear the brunt of global warming in

Table 7
Predicted impacts of different climate scenarios by zone (loss in US$) [a]

Climate change scenario	Medium and low potential	High potential	All zones
CCC (+3.5 °C temperature)	97.01 (28)	−0.11 (−0.03)	57.91 (17)
GDFL (+4 °C temperature)	125.31 (37)	15.67 (4)	80.80 (23)
(CCC and GDFL) 20% reduction in rainfall	111.33 (33)	47.67 (13)	80.92 (23)
+3.5 °C temperature +20% reduction in precipitation	208.34 (61)	47.56 (13)	138.71 (40)
+4 °C temperature +20% reduction in precipitation	236.63 (69)	63.34 (18)	161.69 (47)

[a] Percentage loss in brackets.

Kenya. Using the GFDL model, we estimated losses of up to US$125 per hectare by the year 2100 for these zones compared to losses of only US$16 for high potential zones and US$81 for the whole country. Though these results may sound surprising, they can be interpreted to mean that a small increase in global warming would have immediate adverse effects on already dry areas. This is what is happening to Kenya at the time of writing this paper (2006) because of the prolonged drought in the arid and semi-arid areas which has already claimed lives of both human beings and livestock, yet the effect is still not pronounced in high potential zones. The results confirm that long-term climate change has important implications for agriculture and support findings in related literature for Africa and beyond (see for instance Mendelsohn et al., 2000, 2003; Gbetibouo and Hassan, 2005; Deressa et al., 2005).

The GDFL prediction results show that medium and low potential zones are likely to suffer more from rising temperatures resulting from global warming than from a fall in precipitation. However, the reverse is the case for high potential zones and this may be because such zones are located in the highlands where temperatures are quite low and so a rise in temperature may have a lower impact than a fall in precipitation. The whole country is also expected to suffer more from decreases in rainfall than from rising temperatures, just as in medium and low potential zones.

5.4. Perceptions of and adaptations to climate change

Economic adaptation has been argued to significantly reduce vulnerability to anticipated future impacts of climate change. Previous studies have shown that the potential contribution of adaptation to reducing the negative impacts of global warming is large. The basic forms of adaptation identified in the literature including micro-level adaptations, market responses, institutional changes and technological developments (Darwin et al. 1995; Reilly 1999; Kurukulasuriya and Rosenthal, 2003). In this paper, we focused on micro-level adaptations which include farm production adjustments such as diversification and intensification of crop and livestock production, changing land use, irrigation and altering the timing of operations.

5.4.1. Perceptions of and adaptations to short-term climate variations

Analysis of the perceptions and adaptations of farmers to short-term climate variations reveal that though households practice a range of adaptation measures, the most popular are crop diversification or mixed cropping, adopted by 37% of all households, and tree planting, adopted by 16%. A relatively low proportion adopted adjustments to livestock management probably due to land scarcity in more arable areas, which may hinder large scale livestock production. Nevertheless, such a measure is expected to reduce soil erosion and improve moisture and nutrient retention (Kurukulasuriya and Rosenthal, 2003). Most other measures were adopted by between 11% and 14% of all households. Though the percentage of households involved is small, results for irrigation, water and soil conservation support the argument that a range of management practices such as water and soil conservation can help reduce vulnerability by reducing runoff and erosion and promoting nutrient restocking in soils, while other techniques may improve the soil structure and fertility. 13% of households reported that they did not do anything to counter the impact of short-term variations in weather. Analysis by agro-ecological potential reveals that the use of mixed cropping, different planting dates and soil conservation techniques are more common in high potential zones, while livestock, irrigation, water conservation and shading/sheltering are more important in medium and low potential zones.

Table 8 tabulates the constraints on adaptations to climate change. About 60% of all households are hindered from adapting by lack of credit and savings (poverty). This supports findings in the literature that diversification is costly in terms of the income opportunities that farmers forgo (Kurukulasuriya and Rosenthal, 2003). Another 19% fail to adopt any measure because of lack of knowledge about appropriate adaptations. The other constraints are reported by a relatively small proportion of households. Only 8% of households reported that there were no barriers to adaptation. Poverty and lack of knowledge seem to be more critical constraints in medium and low potential zones than in high potential zones.

5.4.2. Perceptions of and adaptations to long-term climate variations

Turning to long-term adaptation, results show that farmers are aware of increased global warming: 47% of all households reported to have noticed long-term increases in mean temperatures, while only 5% noticed decreased temperatures; 18% noticed climate variations but did not indicate the direction of change; and 28% reported that they had not noticed any change. Farmers in high potential zones were more aware of long-term climate change than their counterparts in medium and low potential zones. 56% of all households reported having noticed changes in precipitation levels over the years, but there were no clear patterns in the differences in perceptions of high potential zone farmers and medium and low potential zone farmers.

The analysis further shows that only 60% of all households made any effort to counter long-term temperature changes (40% reported no adaptations), compared to 78% in the case of precipitation (Table 9). For long-term temperature changes, two main adaptations emerge: crop diversification and shading/sheltering or planting of trees. However, the low percentages adopting crop diversification (25% and 34% for temperature and precipitation changes respectively) could be due to lack of knowledge, skills and finances (Kurukulasuriya and Rosenthal, 2003). Shading/sheltering/tree planting (adopted by 22% of household) is important because in addition to countering climate change it is also a form of soil conservation. Improved water management measures (increased water conservation and increased use of irrigation) were adopted by a relatively low proportion of households. The low overall adoption rates could be attributed to scarcity of resources, including water for irrigation, and lack of knowledge about the importance of these options. Indeed, only about 10% of the overall sample of 816 households reported having used any irrigation at all.

Table 8
Constraints to short-term adaptations (% of households)

Constraint faced	% Constrained	Standard deviation
Lack of information about short-term climate variation	8	0.27
Lack of knowledge concerning appropriate adaptations	19	0.39
Lack of credit or savings	59	0.49
No access to water	8	0.27
Lack of appropriate Seed	5	0.21
Other constraints	13	0.33
No barriers to adaptation	8	0.28

Table 9
Adaptation to long-term climate change (% of households)

Adaptation options	Temperature		Precipitation	
	% adopting	Standard deviation	% adopting	Standard deviation
Crop diversification/ mixed/multi-cropping	25	0.43	37	0.47
Different planting dates	6	0.23	15	0.36
Adjustments to livestock management	4	0.19	6	0.23
Increased use of irrigation/ groundwater/watering	6	0.23	16	0.37
Increased water conservation techniques	7	0.25	21	0.41
Decreased water conservation techniques	6	0.24	13	0.34
Shading and shelter/tree planting	22	0.41	9	0.28
No adaptation	40	0.49	22	0.41

6. Conclusions and implications for policy

This paper explores the impact of climate on crop revenue in Kenya, using primary household level data enriched with secondary climate, hydrological and soil data. We concentrated on a seasonal Ricardian model to assess the impact of climate on net crop revenue per acre. We first assessed the impact of climate on agriculture by estimating models with climate factors only, and then tested the impact of hydrological, soil and household variables.

Our results suggest that climate affects agricultural productivity. Increased winter temperatures increase net crop revenue, while high summer temperatures decrease it. Increased precipitation increases net crop revenue. The results further show that there is a non-linear relationship between temperature and crop revenue on the one hand and between precipitation and crop revenue on the other. This finding is consistent with studies on the impact of global warming on agriculture (Mendelsohn et al., 1994, 2003; Kurukulasuriya and Mendelsohn, 2006). Another key result is a hill-shaped relationship between mean flow and net crop revenue. Furthermore, we also find that andosols, irrigation and household size are positively correlated with crop revenue, while livestock ownership, farm size and wage rates are inversely correlated with revenue.

Estimated marginal impacts further show that crop revenue is elastic with respect to climate change, but less elastic with respect to temperature than to precipitation. The temperature elasticities suggest that global warming is harmful for agricultural productivity. Though precipitation elasticities are much higher than temperature elasticities, the magnitude of marginal impacts suggests that the temperature component of global warming may have more serious repercussions than rainfall. The results further suggest that with adaptation to climate change, farming households can counter the adverse impacts of global warming on crop agriculture.

This study further predicts the impact of different climate change scenarios on Kenyan agriculture. We used two GCMs to do so: CCC and GFDL, which predict 3.5 °C and 4 °C changes in temperature by the year 2100 respectively and a 20% change in precipitation over the same period. The predictions show that long-term changes in temperatures and precipitation will have a substantial impact on net revenue and that the impact will be more pronounced in medium and low potential zones than in high potential zones. The latter are expected to receive some marginal gains from mild temperature increases, holding precipitation constant.

Our analysis of perceptions and adaptation of farmers to climate change show that farming households in Kenya are aware of both short- and long-term climate change and some have implemented various adaptation mechanisms. The analysis also shows differences between the perceptions and adaptations of medium/low potential zone farmers and their counterparts in high potential zones. Diversification (changing the crop mix) is the most common adaptation measure, particularly in high potential zones, while water conservation, irrigation and shading/sheltering of crops are the main adaptation measures in drier regions.

These results imply that adaptation to climate change in Kenya is important if households are to counter the expected impacts of long-term climate change. The government should therefore play a more critical role in encouraging adaptations. Monitoring of climate change and disseminating information to farmers would be a critical intervention, while knowledge on adaptation measures could encourage both short- and long-term adaptations to climate change. To gather such knowledge requires a multidisciplinary approach involving soil scientists, hydrologists, climate experts and agronomists. Using this knowledge, farmers and local leaders should be sensitized, through extension network, on the implications of climate change, including the vulnerability of crop production and the necessity for adaptation strategies. Management of the scarce water resources in the country could generate more water for irrigation purposes, especially in the drier zones. Given the dwindling and fluctuating water resources in the country, the government needs to embark on recycling of waste water, which can then be used to save on available water. In addition, water harvesting techniques should be introduced to farmers and adoption encouraged, particularly in drier areas, to supplement any available water. Protection, conservation and rehabilitation of water catchment areas and river basins are also critical to ensure sustainable water supply. Policies that improve household welfare as well as access to credit are also a priority for both short- and long-term adaptation measures.

Studies on climate change in Kenya are still limited. There is room for further studies focusing on individual crops, livestock production and the use of time series data to capture long-term changes in agricultural production which may better reflect the impact of long-term climate change than cross-sectional estimates.

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