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## Crop switching as a strategy for adapting to climate change

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### Abstract

This paper examines the impact of climate change on primary crops grown in Africa. An innovative approach is presented that bridges the gap between agro-economic and traditional Ricardian models. We label it a 'structural Ricardian model'. It first captures the type of crop a farmer will select and then examines the conditional net revenue of that crop. The model is estimated using a sample of over 5000 farmers across 11 countries in Africa. The analysis finds that farmers shift the crops they plant to match the climate they face. Studies that fail to account for crop switching will overestimate the damages from climate change and underestimate the benefits.

**Keywords:** Adaptation; Climate change; Crops; Africa

### Résumé

*Cet article étudie l'impact du changement climatique sur les principales cultures en Afrique. On y présente une approche innovatrice qui comble l'écart entre les modèles agro-économiques et les traditionnels ricardiens. Nous la qualifions de « modèle structurel ricardien ». Elle distingue tout d'abord le genre de culture qu'un fermier choisira et examine ensuite le revenu conditionnel net de cette culture. Le modèle est calculé sur la base d'un échantillon de plus de 5 000 fermiers répartis sur 11 pays en Afrique. L'analyse démontre que les fermiers alternent leurs cultures afin de s'adapter au climat auquel ils font face. Les études qui ne tiennent pas en compte la culture alternée surestimeront les dommages imputés au changement climatique et en sous-estimeront les bénéfices.*

**Mots clés :** Adaptation ; Changement climatique ; Cultures ; Afrique

## 1. Introduction

There are four competing strands of research into the economic impacts of climate change on agriculture: agronomic, panel data, agro-economic and Ricardian. The agronomic literature predicts large and dire yield losses (Rosenzweig & Parry, 1994) especially in many areas of Africa

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(Deressa et al., 2005; Gbetibouo & Hassan, 2005). Panel data studies examine weather surprises and also suggest climate change will be harmful, though their predictions are not as dire as those of the agronomic studies (Deschenes & Greenstone, 2007). Agro-economic models take farmers' yield losses as given, but predict that farmers can reduce the impact by switching crops (Adams et al., 1990). Finally, the Ricardian model captures the actual adaptations that farmers make and measures the final net impact (Mendelsohn et al., 1994; Mendelsohn & Dinar, 2003). The problem with the first two approaches is that they do not capture adaptation and so overestimate damages. The problem with the agro-economic approach is that the burden of capturing adaptation falls on the analyst. Finally, the problem with the traditional Ricardian approach is that it is a 'black box' so that the actual adaptations by farmers are not revealed.

This paper develops a new approach that attempts to bridge the gap between the agro-economic and Ricardian models in a 'Structural Ricardian model'. A simple model of the farm is developed where a farmer first chooses a desired crop or crop combination and then earns a conditional income given the crop chosen. By modeling crop choice, this approach reveals one of the explicit adaptations that farmers make. Crop choice has been modeled in the agricultural literature before and it has been found to be sensitive to climate (e.g. Moore & Negri, 1992). But this empirical research is limited to the US and the authors did not explore what implications their research might have for climate change. Empirical work on crop choice is virtually nonexistent in the low latitudes where climate change is expected to have a devastating effect on agriculture (Mendelsohn et al., 2006).

In this paper we quantify the climate sensitivity of specific crop choices made by farmers in Africa. The modeling follows earlier research on the impact of irrigation (Kurukulasuriya & Mendelsohn, 2007) and especially livestock choice (Seo & Mendelsohn, 2007). We first examine farmer' crop choices across different climates, measuring the role that climate plays in these choices. We then estimate conditional net revenue functions for each crop. The resulting model is used to predict the effect of two global warming scenarios on expected net revenue, both with and without changing crops.

The next section outlines the formal modeling framework. Crop selection is analyzed within the framework of a multinomial logit model (MNL) and the conditional net revenue functions are estimated using a Dubin-McFadden selection bias correction model. Section 3 outlines the available data, Section 4 presents the results of the empirical modeling of crop choice and the conditional income equations, and Section 5 uses these empirical results to predict what would happen to African farmers in two climate scenarios. The paper concludes in Section 6 with a discussion of the crop model results and the implications of climate change for African crops.

## 2. Theory

The paper takes the amount of cropland as given<sup>1</sup> and examines the impact of climate change on the income a farmer earns per hectare of cropland. The analysis takes explicit account of the farmer's choice of crops. We assume each farmer makes crop decisions to maximize expected profit. We define profit broadly to include the value a farmer may get from consuming his own crops. We examine choices of both a single crop and combinations of specific crops in each season. For example, farmers might combine two different crops as a choice. The full set of choices is mutually exclusive: the farmer must pick one choice from the full set.

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<sup>1</sup> Clearly, if climate changes then the amount of cropland is likely to change as well. However, in this paper we do not address this issue but leave it for future analysis.

We employ a discrete-continuous (DM) model (Dubin & McFadden, 1984) that is a generalization of Heckman's (1979) two-step selection model. It takes into account the polychotomous first choice of which crop to grow. The DM two-step estimation uses a multinomial logit model in the first stage to choose a specific crop (or combination of crops) and then estimates a conditional net revenue model for each choice using ordinary least squares (OLS) with selection terms.<sup>2</sup>

The probability that a species is chosen depends on the profitability,  $V(Z_{ji})$ , of crop  $j$  ( $j=1,2,\dots,J$ ):

$$\pi_{ji} = V(Z_{ji}) + \varepsilon_{ji} \quad (1)$$

where  $Z$  is a vector of independent variables that include climate variables, soils and other socioeconomic variables such as household characteristics. The profit function in equation (1) is composed of two components: the observable component  $V$  and an error term  $\varepsilon$ . The error term is unknown to the researcher, but may be known to the farmer. The farmer will choose the livestock that gives him the highest profit. The farmer will choose crop  $j$  over all other crops if:

$$\pi^*(Z_{ji}) > \pi^*(Z_{ki}) \text{ for } \forall k \neq j. [\text{or if } \varepsilon_k - \varepsilon_j < V(Z_{ji}) - V(Z_{ki}) \text{ for } k \neq j] \quad (2)$$

The probability  $P_{ji}$  for the  $j$ th crop to be chosen is then

$$P_{ji} = \Pr[\varepsilon_k - \varepsilon_j < V_j - V_k] \quad \forall k \neq j \text{ where } V_j = V(Z_{ji}) \quad (3)$$

Assuming  $\varepsilon$  is independently and identically Gumbel distributed,<sup>3</sup> the probability that farmer  $i$  will choose crop  $j$  (McFadden, 1981; Chow, 1983) is:

$$P_{ji} = \frac{\exp(Z_{ji}\gamma_j)}{\sum_{k=1}^J \exp(Z_{ki}\gamma_k)} \quad (4)$$

<sup>2</sup> We also examine an OLS version of the model and the Lee (1983) model as alternative specifications. Contact the corresponding author for results.

<sup>3</sup> Two common assumptions about the error term are either the normal or the Gumbel distribution. Normal random variables have the property that any linear combination of normal varieties is normal. The difference between two Gumbel random variables has a logistic distribution, which is similar to the normal, but with longer tails. Thus the choice is somewhat arbitrary with large samples (Greene, 2003).

Because the farmer may know the  $\varepsilon$  that applies to his farm, it is possible that conditional income is correlated with the choice of crops. This is the standard Heckman (1979) selection problem. OLS estimates of the conditional income equation will consequently be biased. Following McFadden (1973), we can correct for this problem by introducing a selection correction term in the second stage conditional income equation:

$$\pi_j = X_j \phi_j + \sigma \cdot \sum_{i \neq j}^J r_i \cdot \left( \frac{P_i \cdot \ln P_i}{1 - P_i} + \ln P_j \right) + w_j \quad (5)$$

where  $w_j$  is an independent error term. This equation can be estimated using OLS. The choice regressions are identified in this system with cross price terms.

The agronomy literature has revealed through laboratory experiments that temperature and precipitation have non-linear impacts on crop yields (Reilly et al., 1996). We consequently introduce both long-run mean temperature and precipitation as quadratic functions. We also follow agronomic results that suggest temperature and precipitation have different effects during each phase of a crop's growth and use seasonal temperature and precipitation measures. We calculate the marginal impacts of temperature and precipitation and 95% confidence intervals using bootstrapping.

The expected income is the sum of the conditional revenues earned across all crop choices times the probability each crop is chosen. The probability ( $\theta_j$ ) of choosing crop ( $j$ ) is obtained from the estimates of the first stage regression (4) and the conditional income ( $Q_j$ ) comes from the second stage (5). The expected income associated with the current climate ( $C_0$ ) is:

$$Y(C_0) = \sum \theta_j(C_0) * Q_j(C_0) \quad (6)$$

The welfare effect of a change in climate from ( $C_0$ ) to ( $C_1$ ) is therefore:

$$W = Y(C_1) - Y(C_0) \quad (7)$$

We rely on bootstrapping to predict the median and 95% confidence intervals for the welfare effects.

### 3. Data

The data for this study was collected in 11 countries – Burkina Faso, Cameroon, Egypt, Ethiopia, Kenya, Ghana, Niger, Senegal, South Africa, Zambia and Zimbabwe – by national teams (Dinar et al., 2008). The countries were chosen to represent the diverse climates of Africa. Further, within each country, districts were chosen to get a wide representation of the climates that support

farming in that country. The districts are not representative in that some climatic regions in each country tend to produce a preponderance of agricultural production. In this sample we wanted to make sure there was sufficient variation in the climate conditions facing farms. However, the farms are representative of the farms in each district and climatic zone. The sampling is clustered within a district.

The number of surveys in each country varied, but a total of 9597 surveys was administered. Some farmers did not grow crops. Some surveys contained incorrect information about the size of the farm or area of cropland. Impossible values were judged to be missing. It is not clear what the sources of these errors were. They may reflect field errors due to a misunderstanding of the question or the units of measurement, or they may be intentionally incorrect answers. Other surveys did not contain clear information on crop type and are therefore excluded. The final number of useable surveys for this analysis was 7296.

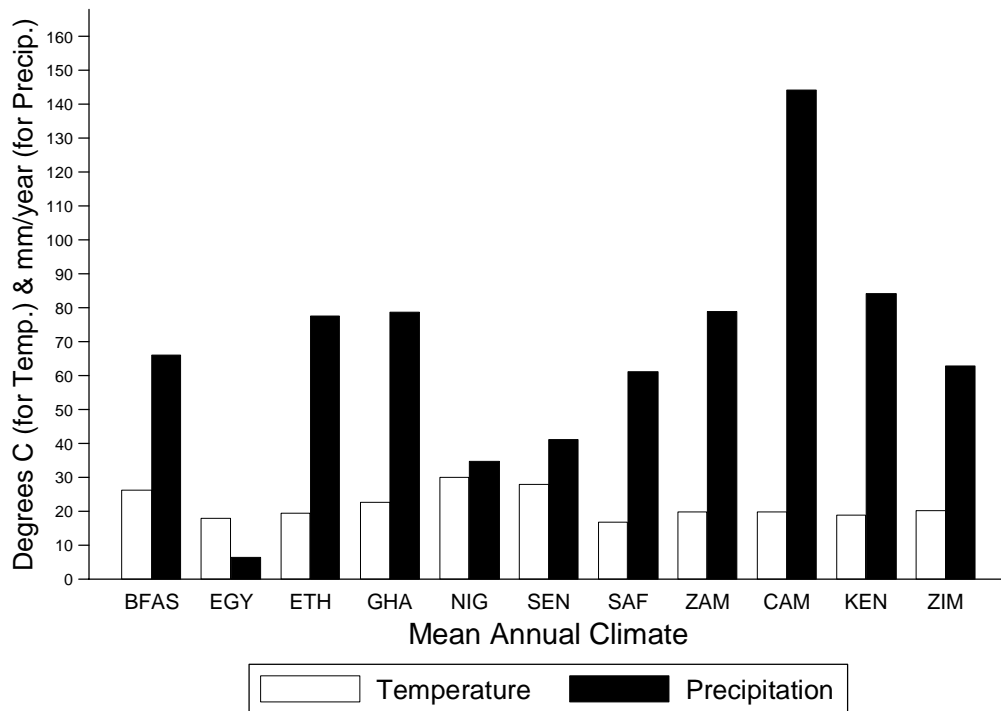
Most of the surveys of farm production and input data are for the 2002–2003 agricultural year.<sup>4</sup> In this paper, the analysis is undertaken at the plot level. Plot specific data on crops grown is summarized to obtain the suite of crops grown throughout the year. The full dataset revealed 130 distinct combinations of crops. However, some of the combinations were rare, with only a handful of observations. We only examine crop alternatives where there are at least 100 observations. We are restricted to analyzing this subset of the data given that the district specific climate and soil variables place a limit on the number of covariates that can be accommodated in the analytical framework.<sup>5</sup> We therefore do not analyze relatively rare crop selections. Using this restricted dataset, the median district-level yield price of each crop is measured and used to identify the crop choice equations (see Table 5).

Data on climate are from two sources. Long-term temperature data comes from US Department of Defense satellites. These satellites pass over every location on earth between 6 am and 6 pm every day. They are equipped with sensors that detect microwaves that can pass through clouds and detect surface temperature (Weng & Grody, 1998). Precipitation data comes from the Africa Rainfall and Temperature Evaluation System (ARTES) (World Bank, 2003). This dataset, created by the National Oceanic and Atmospheric Association's Climate Prediction Center, interpolates between ground station measurements. The mean annual temperature and precipitation for each country in the sample is shown in Figure 1.

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<sup>4</sup> Data from Cameroon, Ethiopia, Kenya and Zimbabwe were collected in 2003–2004.

<sup>5</sup> There are in total 394 districts in the sample. This places a restriction on the number of observations that can be in the model, given the district specific variables that we use to analyze the climate sensitivity of crops.



Note: BFAS: Burkina Faso, EGY: Egypt, ETH: Ethiopia, GHA: Ghana, NIG: Niger, SEN: Senegal, SAF: South Africa, ZAM: Zambia, CAM: Cameroon, KEN: Kenya, ZIM: Zimbabwe

**Figure 1: Mean annual temperature and precipitation**

As outlined in Kurukulasuriya et al. (2006), although monthly climate measures were available, individual months are highly correlated with neighboring months. Previous research indicates it is useful to aggregate monthly data into seasons (Mendelsohn et al., 2001). However, it is not self-evident how to cluster monthly temperatures into a limited set of seasonal measurements. We explored several ways of defining three-month average seasons, starting with November, December and January for winter. Comparing the results, we found that defining winter in the northern hemisphere as the average of November, December and January provided the most robust results for Africa. This assumption in turn implies that the next three months would be spring, the three after that would be summer, and August, September and October would be fall (in the north). The choice of these particular seasonal definitions is motivated by the fact that they provided the best fit with the data and reflect the mid-point for key rainy seasons in the sample. We adjusted for the fact that seasons in the southern hemisphere occur at exactly the opposite months of the year from northern hemisphere seasons. We did not use the temperature and precipitation for the growing season to define climate because the growing season would clearly change with future climate scenarios. In other words, it is an endogenous length of time and would lead to confusion between the effects of warmer temperatures for a specific time and measuring temperature over a longer time period.

Soil data was obtained from FAO (2003). The FAO data provides information about the major and minor soils in each location. Data for the hydrology was obtained from the University of Colorado (IWMI & University of Colorado, 2003). Using a hydrological model for Africa, the hydrology team calculated the potential flow for each district in the surveyed countries.

#### 4. Results

Table 1 presents the major crop choices that farmers make by country. The study looks at the eight most popular choices. Note that to a large extent they reflect farmers' choices in all countries except Egypt. Egyptian agriculture is entirely irrigated and many farmers chose crops not common in the rest of Africa. The most popular crop choice in the sample is maize, which is capable of growing across a range of climates because there are a number of varieties grown in Africa. The second most popular crop portfolio is maize-groundnut. (We hyphenate crop combinations throughout the paper.) Cowpea-sorghum, sorghum and millet-groundnut are also popular choices. While growing maize alone is the most popular choice in Zambia and Ghana, farmers in Cameroon prefer to grow maize-groundnut. Drought tolerant crops were the revealed preference of farmers in Burkina Faso, Niger and Senegal (sorghum, cowpea or cowpea-sorghum). In Egypt and South Africa, the popular choices are maize, wheat, and fruits and vegetables. Farmers in Zambia and Zimbabwe indicated a preference for maize and maize-groundnut.

In order to have sufficient observations to model each crop choice we analyze only the eight most popular choices. We assume that these are independent of the more minor crops. These choices are maize (1071 observations), maize-groundnut (811), cowpea-sorghum (666), sorghum (569), millet-groundnut (568), fruits-vegetables (556), maize-beans (399), cowpea (388) and maize-millet (331). The farmers who made these choices account for almost three quarters of all farmers in the dataset.

**Table 1: Farms choosing major crops by country**

Major crop	Burkina Faso	Cameroon	Egypt	Ethiopia	Ghana	Kenya	Niger	Senegal	South Africa	Zambia	Zimbabwe	Total
Cowpea	11	8	0	3	25	41	271	0	1	16	12	388
Maize	0	62	6	122	364	47	2	3	44	312	109	1,071
Sorghum	100	2	61	223	9	28	11	27	3	50	55	569
Fruits-vegetables	0	90	45	23	47	176	3	10	88	45	29	556
Maize-beans	0	79	4	16	6	189	0	1	27	37	40	399
Cowpea-sorghum	189	0	0	5	0	28	432	0	0	5	7	666
Maize-groundnut	14	200	0	5	58	25	0	24	9	249	227	811
Maize-millet	14	4	0	32	15	55	22	100	1	35	53	331
Millet-groundnut	25	0	0	4	33	0	59	440	0	7	0	568
<b>Farms choosing major crops</b>	<b>353</b>	<b>445</b>	<b>116</b>	<b>433</b>	<b>557</b>	<b>589</b>	<b>800</b>	<b>605</b>	<b>173</b>	<b>756</b>	<b>532</b>	<b>5,359</b>
<b>Total farms</b>	<b>716</b>	<b>518</b>	<b>478</b>	<b>644</b>	<b>664</b>	<b>692</b>	<b>871</b>	<b>906</b>	<b>243</b>	<b>920</b>	<b>644</b>	<b>7,296</b>



Table 2 presents the multinomial logit (MNL) regression results of crop choice. Elevation, surface flow availability and several soil variables affect crop choice. Higher elevation encourages cowpea, sorghum, maize and beans, cowpea-sorghum, maize-groundnut and maize-millet and discourages millet-groundnut. Lower flow is associated with farmers choosing maize-beans, cowpea-sorghum, maize-groundnut, maize-millet, millet-groundnut and fruits-vegetables. Lower flow probably implies that farmers cannot irrigate. Choosing low-water-intensive crop combinations is one way for farmers to adapt to dryland farming in Africa. Farms that have electricity are more likely to choose minor crops but less likely to choose every other crop. Electricity may help in the production of fruits-vegetables or it may simply signal access to urban markets, which often accompanies access to electricity (particularly in the context of rural Africa where electricity distribution networks are predominantly in the vicinity of towns and cities). Farmers whose farms have steep slopes and fine-textured soils are more likely to choose millet-groundnut but less likely to choose cowpea, sorghum, cowpea-sorghum, maize-beans and fruits-vegetables. Farms whose soils are eutric gleysols and solodic planosols are more likely to choose cowpea and maize and less likely to choose every other crop. Farms with lithosols or medium-textured soils in steep areas are more likely to choose cowpea, maize-beans and minor crops, but less likely to choose sorghum. Finally, those whose farms have orthic ferrasols and chromic luvisols are more likely to choose millet-groundnut but less likely to choose sorghum and maize-millet.

**Table 2: Multinomial logit crop choice model**

	Cowpea	Sorghum	Fruits-vegetables	Maize-beans	Cowpea-sorghum	Maize-groundnut	Maize-millet	Millet-groundnut
Temp winter	-2.81*	1.14*	-1.27*	-0.83	2.12*	-0.87	1.12	-5.41**
Temp winter sq	.06*	-.04*	.04*	0.01	-.05*	0.00	-0.03	0.13**
Temp spring	2.19	-2.73**	-0.10	-0.29	-2.85*	-0.79	-3.09**	6.16*
Temp spring sq	-0.03	.07**	-0.01	0.01	.07*	.048*	.08**	-0.10*
Temp summer	-5.81**	0.89	-0.75	-0.69	-1.06	-3.37**	0.43	6.62**
Temp summer sq	0.11**	-0.01	0.01	0.00	0.03	0.07**	0.00	-0.11**
Temp fall	4.58**	-1.90*	0.39	1.26	-0.15	6.60**	-0.94	-6.31**
Temp fall sq	-0.10**	0.03*	0.01	-0.01	0.00	-0.16**	0.00	0.11**
Precip winter	-0.12**	-0.11**	0.06**	-0.03	-.17**	-0.02	0.09**	0.03
Precip winter sq	0.001**	0.001**	-0.0002*	0.0002*	0.001**	0.0003**	-0.0005**	0.00
Precip spring	0.03	.06**	-.06**	0.01	-0.03	0.01	-0.10**	-0.04
Precip spring sq	0.00	-.0003**	.0002**	0.00	0.00	0.00	0.0004**	0.00
Precip summer	.21**	-.05**	0.00	0.01	.15**	0.02	-.05**	-.12**
Precip summer sq	-.001**	.0002**	0.00	0.00	-.001**	0.00	.0002**	.0003**
Precip fall	-.16**	0.01	.02*	0.00	-.103**	0.01	.04*	.22**
Precip fall sq	.001**	-0.0001	-0.00003	0.00	.0003*	0.00	-.0001*	-0.0008**

Notes: Base category crop: maize. \*\* significant at 1% \* significant at 5%  
 Multinomial logistic regression: Number of obs = 5251; LR chi2(200) = 10042; Prob > chi2 = 0.0000;

Pseudo R2= 0.45; Log likelihood = -6184

**Table 2 (continued): Multinomial logit crop choice model**

	Cowpea	Sorghum	Fruits-vegetables	Maize-beans	Cowpea-sorghum	Maize-groundnut	Maize-millet	Millet-groundnut
Mean flow (mm)	0.1*	-0.06*	-0.08**	-0.04	0.00	-0.06	-0.24**	-0.19*
Elevation (m)	0.0002	0.00	0.0004	.001*	0.00	0.00	.001**	.003**
Log (farmland area)	0.04	0.10	-.14*	-.19**	.19*	0.05	.187*	0.00
Log (household size)	.69**	.69**	.41*	.43*	1.50**	.81**	.80**	.67*
Electricity dummy	-.67*	-1.83**	0.19	-0.20	-1.81**	-0.48*	-0.98**	-0.66*
Soil type 1	0.99	2.49**	-2.83**	-0.72	0.20	0.75	-0.74	2.06*
Soil type 2	-1.42**	-.62*	-1.00*	-1.00*	-1.01*	-.57*	-.70*	-1.17*
Soil type 3	-0.76	-2.11*	2.47**	2.06*	-1.90*	-0.75	1.50	-1.87*
Soil type 5	0.58	-0.39	-0.48	-0.01	-0.28	-0.46	-0.95	-1.95
Price of groundnut	1.68*	4.37**	1.32*	4.00**	5.66**	1.59**	4.55**	3.54**
Price of cotton/kg	-5.34**	0.47	-2.55*	-1.92*	0.13	0.50	1.45	-9.78**
Price of wheat/kg	6.62**	-4.10**	.33*	0.43	-12.94**	4.33**	0.23	-5.43
Price of cowpea/kg	-3.26**	0.34	-0.70	-0.32	0.96	-0.42	0.57	-0.61
Price of sorghum/kg	-0.79	-1.11	1.70*	3.42**	0.92	-0.44	-1.10	-1.05
Constant	10.20	29.24**	14.33**	1.05	18.84*	-20.70*	22.70**	-53.81**

Notes: Base category crop: maize. \*\* significant at 1% \* significant at 5%

Multinomial logistic regression: Number of obs = 5251; LR chi2(200) = 10042; Prob > chi2 = 0.0000; Pseudo R2 = 0.45; Log likelihood = -6184

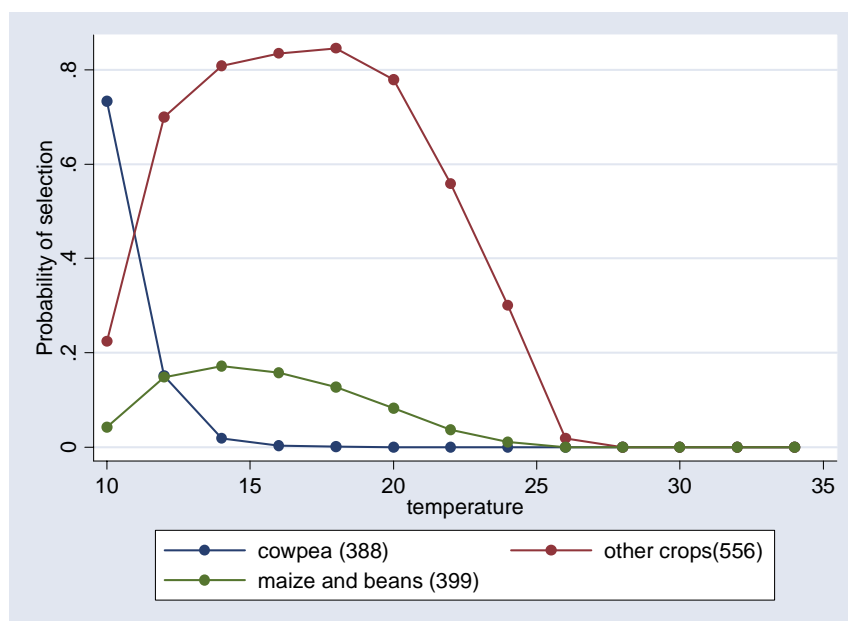
From the perspective of this study, the most important coefficients in Table 2 concern the seasonal climate. The choice of different crops is sensitive to seasonal climate variables. For example, in comparison to maize, cowpea reacts to summer and fall temperatures and winter, summer and fall precipitation, whereas sorghum reacts to winter, spring and fall temperatures and precipitation in every season. Millet-maize in comparison reacts to winter and spring temperature and precipitation in all seasons. In order to get a sense of the impact of climate on crop choice, we calculate the climate elasticity in Table 3. The climate elasticity measures the percentage change in the probability of selecting a crop with respect to a percentage change in annual temperature or precipitation. The temperature elasticity is generally much larger than the precipitation elasticity. Crop choices are more sensitive to temperature than precipitation. Warmer temperatures reduce the probability of maize-millet, maize-groundnut, and fruits-vegetables, and especially cowpea but increase the probability of all other crops and especially sorghum. Increased precipitation reduces the probability of maize, maize-millet and maize-groundnut, but increases the probability of sorghum and cowpea-sorghum.

**Table 3: Marginal effects of climate on choosing crop i**

Crop	Temperature	Precipitation
Cowpea	1.26	-0.06
Maize		
Sorghum	-0.08	-0.06
Fruits-vegetables	-0.06	0.01
Maize-beans	-0.08	0.01
Cowpea-sorghum	1.10	-0.17
Maize-groundnut	-0.01	0.02
Maize-millet	0.34	0.0003
Millet-groundnut	0.90	-0.06

Note: Marginal effects estimated from coefficients in Table 4.

It is helpful to see how crop choice changes as temperature and precipitation move away from the mean. Figure 2 (a, b, c) shows how crop probabilities change at different temperatures and Figure 3 (a, b) how they change with different precipitation levels. In these figures, annual temperature changes are adjusted equally across all seasons. The relative temperatures and precipitation between seasons are important.<sup>6</sup> For example, if the model is estimated using annual temperature rather than seasonal temperature, cowpea, maize-millet and minor crops all behave quite differently.<sup>7</sup> Figure 2 (a, b, c) shows that farmers are more likely to choose cowpea, maize-beans and fruits-vegetables in relatively cool temperatures; maize, maize-millet, sorghum and cowpea-sorghum in more average African temperatures; and millet-groundnut in the hottest regions of Africa. Figure 3 (a, b) shows that farmers tend to select maize-millet, sorghum and millet-groundnut in dry but not desert regions; maize, fruits-vegetables and maize-beans in regions with moderate rainfall; and cowpea and cowpea-sorghum in the wettest regions.



**Figure 2a: Probability of crops by annual temperature**

<sup>6</sup> Regressions based on annual temperature and precipitation give slightly different results for the crop choice model.

<sup>7</sup> The annual model assumes that seasonal differences shrink as temperatures increase, whereas the seasonal model holds the difference fixed. The results of these additional regressions are available from the corresponding author.

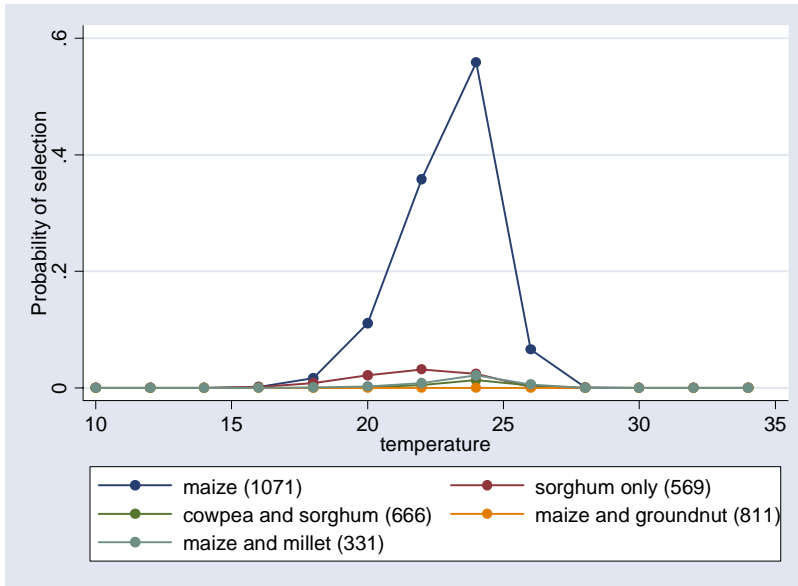


Figure 2b: Probability of crops by annual temperature

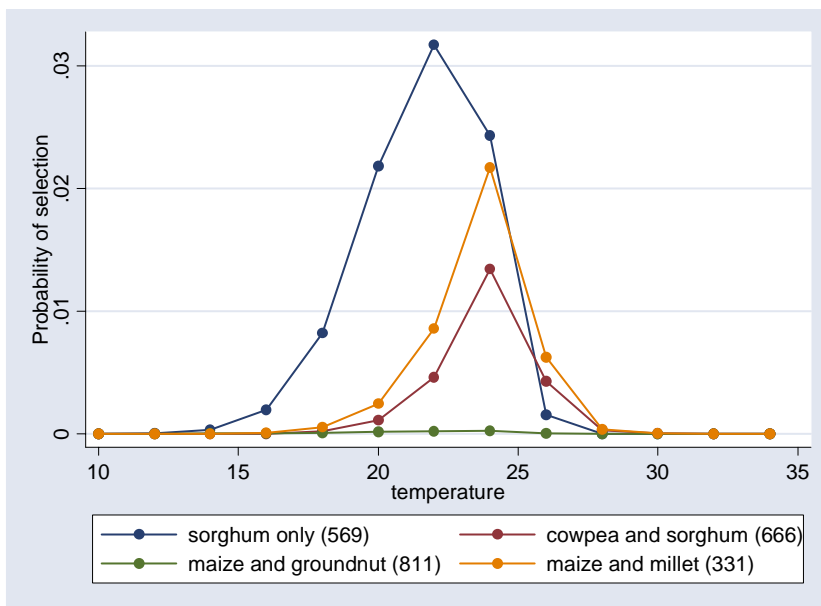


Figure 2c: Probability of crops by annual temperature

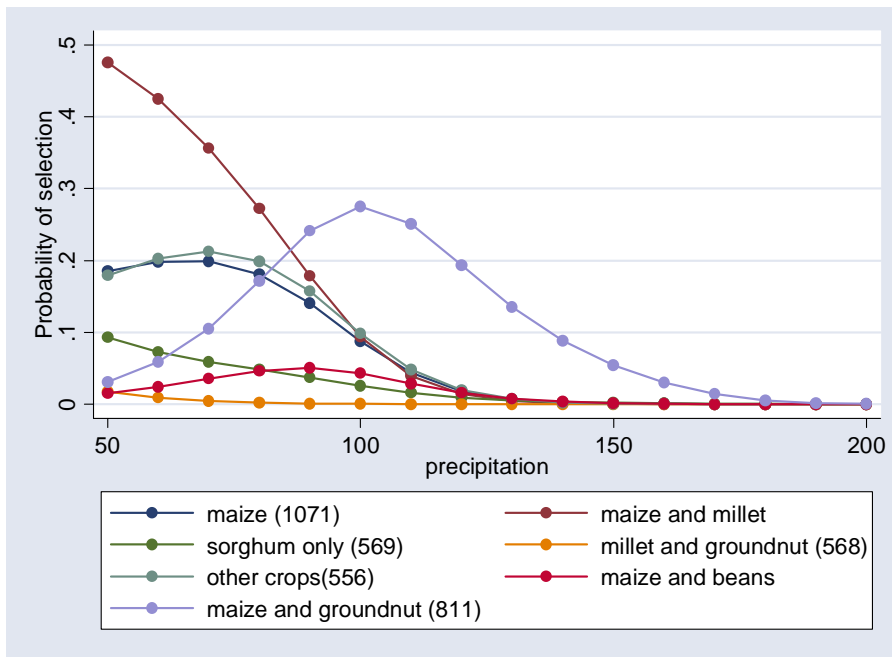


Figure 3a: Probability of crops by annual precipitation

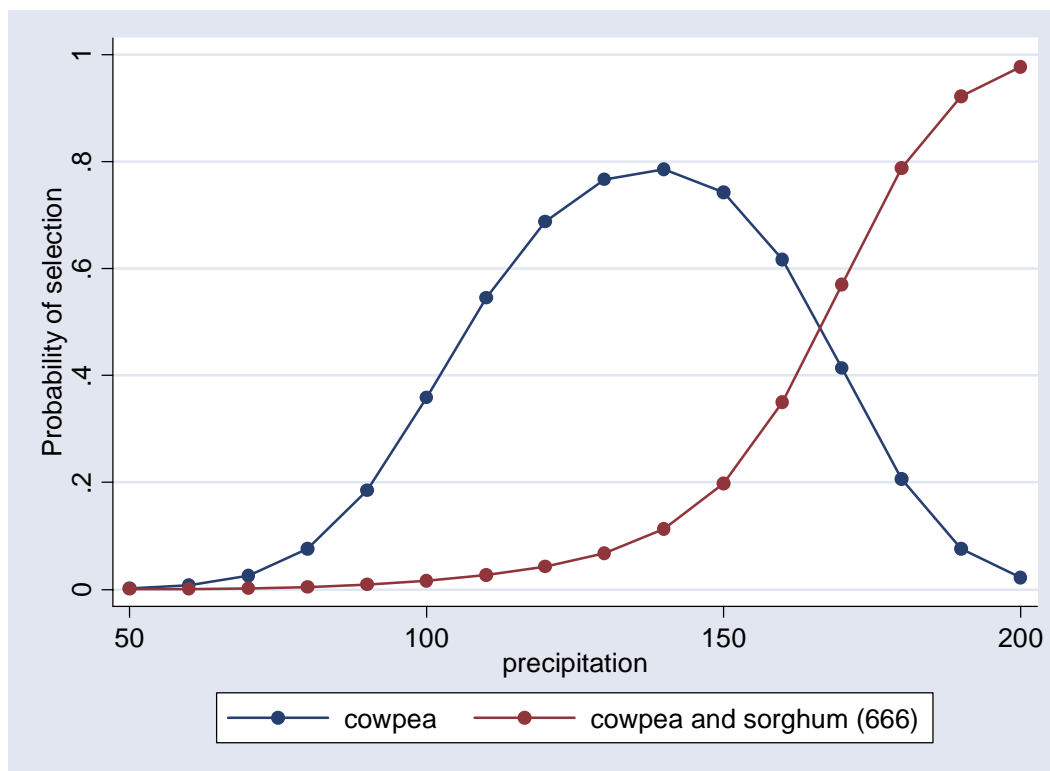


Figure 3b: Probability of crops by annual precipitation

Table 4 presents the results of the second stage regressions of net revenue by crop. Selection bias is controlled using the Durbin-McFadden selection bias correction.<sup>8</sup> Many of the seasonal climate variables in Table 4 are statistically significant, although many of the squared terms are not significant. Because there are fewer observations in each conditional income equation compared to the choice model, the individual coefficients of the model are less significant. The significant selection term coefficients in Table 4 are all negative. A negative selection term coefficient implies there is a negative correlation between the errors in the selection and conditional income equations. For example, the selection term in the cowpea regression for maize-millet is negative. This implies that if the selection equation predicts a farm is more likely to choose maize-millet, but instead the farmer chooses to grow cowpea, that farm will earn more than would be expected by growing cowpea.

An additional test we undertook was to assess the effect that clustering of the data is likely to have on the coefficients. We controlled for clustering effects by clustering at the district level. We find that the clustering does not affect the magnitude or sign of the coefficients. Clustering does increase the size of the standard errors, but we rely on bootstrapping to estimate the statistical confidence of this analysis.

**Table 4: Conditional income by crop regressions**

	Cowpea	Maize	Sorghum	Fruits-vegetables	Maize-beans	Cowpea-sorghum	Maize-groundnut	Maize-millet	Millet-groundnut
<b>Independent variable</b>									
Price of cowpea/kg	296.2*					40.0			
Price of sorghum/kg			1238**			181.4*			
Price of maize/kg					1698*		118.1	400.3	
Price of groundnut/kg		-445.5					-296.9		-115.8
Price of millet/kg								45.9	720.5*
Temp winter	-887.5*	-248.5	281.8	353.8	423.3	641.1	-681.5*	67.7	-24.2
Temp winter sq	17.8*	14.3**	-5.2	-7.6	-12.1	-14.5*	25.1*	1.1	1.9
Temp spring	829	-4.1**	-374	-338	-572	-204	715	-50	-275
Temp spring sq	-15.04	-7.9	5.29	2.9	12.01	3.96	-21.28	-1.3	4.16
Temp summer	-522	1054.0**	214	1207*	458	-115	182	127	466
Temp summer sq	11.41	-23.5**	-5.07	-23.11*	-2.23	3.45	-0.72	-1.78	-7.36
Temp fall	662*	-840.8**	-320	-1235	728	-2	1237	-97	-1
Temp fall sq	-14.86*	22.3**	8.91	29.94	-26.39	-1.1	-33.99	1.46	-0.67
Precip winter	-20.2	7.49	4.15	-16.63	27.53	-24.4	-3.47	-0.29	43.99

<sup>8</sup> A similar analysis using the Lee correction model is available from the corresponding author.

**Table 4: (Continued) Conditional income by crop**

Precip winter sq	-0.02	-0.04	-0.05	0.11	-0.07	0.12*	0.05	-0.02	-0.22
Precip spring	36.39**	-16.3**	2.92	14.32	-12.17	26.64*	-8.49	-1.66	-7.28
Precip spring sq	-0.07	0.10**	-0.02	-0.08	0.02	-0.12*	0.02	0.02	-0.12
Precip summer	21	-0.01	4.71	4.31	3.65	4.12	-7.64	-3.3	-5.45
Precip summer sq	-0.11*	0.0002	-0.01	-0.02	0.00	0.02	0.01	0.00	0.03
Precip fall	-36.34**	5.40	-15.42*	2.73	5.84	-1.97	8.24	3.4	11.41
Precip fall sq	0.14**	-0.01	0.06	0.00	-0.01	-0.04	-0.01	-0.01	-0.06
Log (area of farmland)	-68.5*	-60.8**	-7.0	-101.4*	-115.8**	-27.6*	-160.0**	-21.9	-72.3*
Log (household size)	-14.18	-48.9	-61.11	33.06	0.38	25.76	178.75*	-37.88	-22.38
Dummy household with electricity	-154.6*	275.7**	170.9	516.1**	280.3*	-15.7	152	112.0	32.6
Soil type 1	188.6	-233.9	157.6	378.4	-967.6	239.2	1044.4	-247.7	-75.1
Soil type 2	-34.5	64.7	232.8*	53.2	146.2	-77.0	107.4	12.7	26.9
Soil type 3	202.9	-60.8	367.0*	-358.9	-141.4	-193.1	-1583*	119.5	181.7
Soil type 5	117.7	124.2	-87.2	-169.7	315.9	332.4	-154.3	412.7	386.0
Selection cowpea		-469.4	370.8	-385.6	-736.6	111.6	-724.2	313.6	-323.9
Selection maize	-160.27		183.4	881.0*	700.8	423.3	323.8	737.5*	753.1
Selection sorghum	509.9	162.5		171.3	-247.4	466.5	529.8	-502.0	-476.0
Selection fruits-vegetables	372.3	1538**	-243.09	0.0	1692.6*	269.1	994.9	-63.7	-713.6
Selection maize-beans	-91.4	-718**	1338.8*	-285.5		-295.5	-2017.2**	19.9	1424.0
Selection cowpea-sorghum	-243.1	-231.5	-902.4**	309.7	625.7		415.1	-56.6	61.3
Selection maize-groundnut	-591.9	-729.2**	-409.5*	-611.5	2111.0*	-418.7		-691.0*	-887.7*
Selection maize-millet	996.2*	-148.6	-128.8	-1233.0*	272.5	-572.1	-682.0		139.0
Selection millet-groundnut	-732.6*	704.3	-216.0	1145.9	-4273.0*	-10.9	1062.7	211.2	
Constant	-1253.4	-242.6	3216.6**	-456.5	-8745.0	-3274.3	-15325.0*	-141.8	-3239.0

Note: Dependent variable is net revenue.

Selection terms are consistent estimators of conditional expected values of the residuals derived from the MNL model in Table 2.

**Table 4 (continued): Conditional income by crop**

	Cowpea	Maize	Sorghum	Fruits-vegetables	Maize-beans	Cowpea-sorghum	Maize-groundnut	Maize-millet	Millet-groundnut
<b>Ancillary</b>									
Sigma2	822574	2245430	1106193	2148307	6178184	318609	3714124	793803	423232
Rho cowpea		-0.40	0.45	-0.34	-0.38	0.25	-0.48	0.45	-0.64
Rho maize	-0.23		0.22	0.77	0.36	0.96	0.22	1.06	1.48
Rho sorghum	0.72	-0.14		0.15	-0.13	1.06	0.35	-0.72	-0.94
Rho fruits-vegetables	0.53	1.32	-0.3		0.87	0.61	0.66	-0.09	-1.41
Rho maize-beans	-0.13	-0.61	1.63	-0.25		-0.67	-1.34	0.03	2.81
Rho cowpea-sorghum	-0.34	-0.20	-1.1	0.27	0.32		0.28	-0.08	0.12
Rho maize-groundnut	-0.84	-0.62	-0.5	-0.54	1.09	-0.95		-0.99	-1.75
Rho maize-millet	1.41	-0.13	-0.16	-1.08	0.14	-1.3	-0.45		0.27
Rho millet-groundnut	-1.04	0.60	-0.26	1	-2.2	-0.02	0.71	0.3	
Number of obs	367	1023	540	503	381	630	780	313	554
F-stat	9.63		29.06	7.8	5.11	7.07	10.49	1.64	2.11
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.02	0
R-squared	0.48	0.25	0.65	0.34	0.32	0.28	0.32	0.16	0.12
Adj R-squared	0.43	0.23	0.62	0.3	0.26	0.24	0.29	0.06	0.06
Root MSE	268.05	571.93	372.05	928.15	582.55	200.22	639.86	349.86	272.07

*Note:* Dependent variable is net revenue.

Selection terms are consistent estimators of conditional expected values of the residuals derived from the MNL model in Table 2.

To interpret the results of the empirical modeling, we examine the marginal impact on conditional income of a 1 degree increase in temperature and a 1 mm increase in precipitation. This is shown in Table 5. Warming will reduce net revenues per hectare by USD10 for maize-beans, USD14 for cowpea-sorghum and USD19 for sorghum but increase net revenues per hectare by USD32 for maize-groundnut and by USD86 for fruits-vegetables. These results are consistent with the choices made by farmers (warming will increase the probability that they will select maize-groundnut and fruits-vegetables). Curiously, the results using the Lee estimation procedure or OLS are not similar. All but the cowpea and the millet-groundnut estimates are different. Controlling for sample selection bias is quite important.



**Table 5: Marginal effects of climate on conditional net revenue**

Crop	Temperature (C°)	Precipitation (mm/mo)
Cowpea	-5.29*	0.06
Maize	31.6*	0.78
Sorghum	-19.43*	3.55*
Fruits-vegetables	86.42*	0.03
Maize-beans	-10.40*	14.04*
Cowpea-sorghum	-14.12*	3.85*
Maize-groundnut	31.86*	-5.61*
Maize-millet	3.03*	-3.43*
Millet-groundnut	6.57*	38.19*

Note: Marginal effects estimated from coefficients in Table 4.

#### 4.1 Climate change scenarios

The empirical research compares the results in one farm against another in different climate zones. In this section, we use these empirical results to forecast the impact of climate change. Note that to the extent that we did not capture the correct functional form of this relationship, the intertemporal forecasts will be biased. One must also be careful to use the intertemporal forecasts appropriately. They are intended to capture the effect of long-term shifts in climate, not short-term fluctuations in weather. To the extent that farmers fail to adjust to climate changes there may be additional adjustment costs not considered in this analysis (Kelly et al., 2005).

We examine how alternative future climate scenarios may affect the choice of irrigation and net revenue per hectare. We rely on two climate models, the Parallel Climate Model (PCM) (Washington et al., 2001) and the Canadian Climate Centre model (CCC) (Boer et al., 2000), to provide a range of climate outcomes for each African country in 2100.<sup>9</sup> The PCM scenario is relatively mild and wet whereas the CCC scenario is relatively hot and dry. With both scenarios, we examine how the predicted changes in climate would affect both the probability of choosing each crop and the conditional income. Table 6 shows the results of the changes in the mean predicted probabilities based on 300 bootstrapped runs. It is evident that the probability of selecting cowpea decreases under the PCM estimates of future climate but increases under the CCC scenario. Cowpea is a dry weather crop so it is understandable that it should increase with the relatively dry CCC scenario but not with the relatively wet PCM scenario. The crop combinations maize-millet and millet-groundnut are more likely with the PCM scenario but especially with the CCC scenario. The adoption of sorghum, maize-beans and maize-groundnut is likely to decrease according to both scenarios. Fruit and vegetables, cowpea and sorghum are more likely to be adopted under the mild PCM climate scenario than the severe CCC one.

<sup>9</sup> The choice of 2100 as a scenario is for exposition purposes. The analysis can easily project impacts for other scenarios.

**Table 6: Change in probability of crops under alternative climate scenarios**

	Current climate	PCM	CCC
Cowpea	7.3%	-0.8%	+8.0%
Maize	19.8%	-14.6%*	-15.8%*
Sorghum	10.6%	-6.7%*	-6.6%*
Fruits-vegetables	10.2%	+22.1%*	+8.0%
Maize-beans	7.5%	-6.3%*	-4.1%
Cowpea-sorghum	12.3%	+7.1%	-3.5%
Maize-groundnut	15.2%	-14.3%*	-14.8%*
Maize-millet	6.2%	+7.4%	+5.8%
Millet-groundnut	10.8%	+6.1%	+23.0%*

\* Significant differences

PCM - Parallel Climate Model; CCC - Canadian Climate Centre model

Table 7 highlights the conditional incomes under alternative climate change scenarios using the DM method. The reported values reflect the mean of 300 bootstrapped runs. According to these results the continued adoption of cowpea under both the PCM and CCC 2100 scenario results in a significant reduction in conditional revenues. While losses under the PCM scenario (relative to current climate) are significantly larger, even under the CCC scenario there are losses. In the case of sorghum, the conditional net revenues increase to nearly USD600 per hectare under the CCC scenario while decreasing to USD268 under the PCM scenario (relative to USD426 under current climate). The conditional incomes of fruits and vegetables increase under both the PCM and CCC scenario. By contrast, the conditional incomes of maize-beans stay relatively similar to current levels under the PCM scenario but decrease substantially under the CCC scenario. Farms that grow maize-millet and millet-groundnut earn higher conditional revenues under both the CCC and PCM scenarios relative to earnings under the current climate. Farms that grow cowpea-sorghum are predicted to earn less conditional revenue under the PCM and CCC scenarios.

We then calculate the expected income from current climate by summing the product of the probability of selecting crop  $i$  multiplied by the conditional net revenue from crop  $i$ . After this we calculate the expected income of each farmer for each future climate scenario. The change in expected income is the welfare effect of climate change. We compare the results from the DM approach with the estimates from the OLS and Lee approaches. We also examine the predicted effect if one assumes there is no crop switching; that is, if one assumes the probability of crop choice is exogenous to climate. We employ bootstrapping with 300 replications to obtain unbiased standard errors for the mean of the estimates of each draw.

**Table 7: Change in conditional incomes under alternative climate scenarios**

<b>Crop</b>	<b>Current conditional income (USD/hectare)</b>	<b>PCM (USD/hectare)</b>	<b>CCC (USD/hectare)</b>
Cowpea	157	-1760	-139
Maize	464	+1210	+554
Sorghum	427	-160	+125
Fruits-vegetables	318	+343	+432
Maize-beans	178	+12	-2110
Cowpea-sorghum	99	+62	-302
Maize-groundnut	296	+1521	-1829
Maize-millet	248	-0	+19
Millet-groundnut	-266	+681	+530

PCM – Parallel Climate Model, CCC - Canadian Climate Centre model

Table 8 shows the results of the welfare analysis. We first present the welfare effect of climate change if farmers do not change their crops. With the current climate, farmers earn USD157/ha. With the same crops but the PCM climate scenario for 2100, predicted revenues are expected to increase by 82%. By contrast, under a CCC climate scenario for 2100, which includes a reduction in rainfall and a large increase in temperature, predicted net revenues are likely to fall by 68%. We then calculate the expected welfare effect allowing the farmer to adjust his crop mix. Welfare increases by 49% under the PCM scenario and falls by only 5% in the CCC scenario.

**Table 8: Change in expected welfare from alternative climate scenarios**

<b>Calculation</b>	<b>PCM welfare USD/hectare</b>	<b>% Change in welfare with PCM</b>	<b>CCC welfare USD/hectare</b>	<b>% Change in welfare with CCC</b>
Constant crops	+129	+82%	-106	-68%
Crop switching	+77	+49%	-8	-5%

PCM – Parallel Climate Model, CCC - Canadian Climate Centre model

*Note:* The expected income with current climate is USD157/ha.

Constant crops measures the change in expected income assuming there is no change in cropping patterns. The endogenous crop measure allows farmers to switch crops to match the future climate.

These results reveal that crop switching is an important adaptation for farmers. If they could not switch crops, the magnitude of the damages would be exceedingly high in the CCC scenario (losses of near 70%). However, with crop switching these losses virtually disappear. It is evident from the analysis that African farmers are already adapting, albeit with several constraints, to current climate; that is, they are selecting the crops most suitable for the climate in which they must be grown. If this practice is extended into the future, the likely impacts of climate change on agriculture will be small. This study has provided an indication of the extent to which adaptation can affect overall household welfare.

## 5. Conclusion and policy implications

This paper examines the choices that farmers in Africa make across a wide spectrum of climate conditions. The study finds that crop choice is highly sensitive to both temperature and precipitation. Farmers adapt their crop choices to suit the local conditions they face. For example, farmers in cooler regions of Africa choose maize-beans and sorghum, whereas those in hot regions choose cowpea and millet. Farmers in dry regions choose millet and sorghum, whereas those in wet regions choose maize-beans, cowpea-sorghum and maize-groundnut. Other crops, such as maize, are grown throughout Africa. The study also found that farmers often choose crop combinations to survive the harsh conditions in Africa, such as maize-beans, cowpea-sorghum and millet-groundnut. These combinations provide the farmer with more flexibility across climates than growing a single crop on its own.

However, the focus of this analysis is on climate change. This study has shown that African farmers have adapted crop choice to climate. There is every reason to believe that they will alter future crop choices as the climate changes, provided there are no barriers to the adoption of appropriate crops. Analyses of the agricultural impacts of climate change must take into account crop selection. Studies that treat crop choice as exogenous will seriously overestimate the damages from global warming. For example, agronomic studies or empirical studies that use weather as a proxy must be careful not to assume crop choices are exogenous. Farmers will probably change crops in response to a new climate. They will match future crops to future climates. Although some climate scenarios may still lead to losses in agricultural income in Africa, the predicted losses appear to be much smaller with endogenous crop choice.

On a cautionary note, this paper only examines choices across currently available crops. Agronomic research could develop new varieties that are more suitable for higher temperatures. These new varieties could substantially improve farmers' welfare, especially in hot locations such as Africa. Such research could substantially expand the choices available to low latitude farmers and help them adapt not only to current conditions but to future climates as well. The paper does not address every factor that might be important to crop choice and outcomes in the distant future, including sudden changes in weather, technical change, carbon fertilization, irrigation and changes in cropland. The quantitative results must consequently be taken as suggestive, not conclusive.

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