A Ricardian analysis of the impact of climate change on African cropland

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Abstract

This study examines the impact of climate change on cropland in Africa, using a Ricardian cross-sectional approach. Relying on farm data from an 11-country survey of over 9500 farmers, annual net revenue is regressed on climate and other variables. The study confirms that current climate affects the net revenues of farms across Africa. Applying these results to possible future climates reveals that dryland farms are especially climate sensitive. Even as early as 2020, climate change could have strong negative impacts on currently dry and hot locations. By 2100, dryland crop net revenues could rise by 51% if future warming is mild and wet but fall by 43% if future climates are hot and dry. The crop net revenues of currently irrigated farms are likely to be least affected.

Keywords: Climate change; Agriculture; Valuation; Africa

JEL codes: Q12; Q25

Résumé

Cette étude examine l'impact du changement climatique sur les terres cultivées en Afrique, en utilisant une analyse transversale ricardienne. Se basant sur les données concernant des fermes et issues d'une étude regroupant 11 pays et plus de 9 500 fermiers, on note que le revenu annuel net est régressé sur les variables climat et autres. L'étude confirme que le climat actuel affecte les revenus nets des fermes dans toute l'Afrique. Lorsqu'on applique ces résultats à de futurs climats éventuels, on s'aperçoit que les fermes situées sur les terres sèches sont particulièrement sensibles au climat. Même à partir de 2020, le changement climatique pourrait influer de manière extrêmement négative sur les zones actuellement chaudes et arides. A partir de 2100, les revenus nets des cultures des terres sèches pourraient augmenter de 51% si le réchauffement est doux et humide mais chuteraient de 43% si les futurs climats s'avèrent chauds et secs. Les revenus nets des cultures provenant de fermes actuellement irriguées ont de grandes chances d'être moins affectés.

Mots clés : *Changement climatique ; Agriculture ; Evaluation ; Afrique*

Catégories JEL : *Q12 ; Q25*

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1. Introduction

African agriculture is predicted to be especially vulnerable to climate change because the region already endures high heat and low precipitation, agriculture is a large fraction of the economy, and African farmers rely on relatively basic technology (Pearce et al., 1996; McCarthy et al., 2001). Despite this dire prediction, there have been relatively few empirical studies of African agriculture (Kurukulasuriya & Rosenthal, 2003). There has been a handful of agronomic studies, largely of grains, that suggest that warming would have extensive harmful effects (see for example Rosenzweig & Parry, 1994). There have also been a few economic analyses of specific crops or specific regions (Molua, 2002; Gbetibouo & Hassan, 2005; Deressa et al., 2005). These studies all suggest that warming would have large effects. However, empirical analysis of farmer adaptation is limited in current research.

This study is based on a cooperative research effort amongst 11 African countries: Burkina Faso, Cameroon, Egypt, Ethiopia, Ghana, Kenya, Niger, Senegal, South Africa, Zambia, and Zimbabwe. The sample of farmers was distributed across many different climate zones so that the study would cover a wide range of climate variation. A total of 9064 surveys of individual farmers were analyzed (Table 1). An earlier analysis of this data revealed that African crop net revenues are sensitive to climate (Kurukulasuriya et al., 2006). This study extends that research by exploring how these impacts are distributed across Africa depending on a set of future climate scenarios.

Table 1: Useable surveys by country

Country	Dryland	Irrigated	Total
Burkina Faso	990	41	1031
Cameroon	646	105	751
Egypt	0	802	802
Ethiopia	874	66	940
Ghana	849	29	878
Kenya	675	79	754
Niger	849	48	897
Senegal	1037	31	1068
South Africa	199	87	286
Zambia	956	14	970
Zimbabwe	597	90	687
Total	**7672**	**1392**	**9064**

The study uses the Ricardian method to measure how climate affects current net revenues. This method is a cross-sectional technique that regresses net revenues on independent variables (Mendelsohn et al., 1994; Mendelsohn et al., 2001). It has been applied to selected countries in the low latitudes, namely Brazil and India (Sanghi, 1998; Mendelsohn et al., 2001), using district level data, and Sri Lanka and Cameroon (Molua, 2002; Seo et al., 2005; Kurukulasuriya & Ajwad, 2007), using household level data.

The next section briefly reviews the theory behind the Ricardian method, the potential advantages and disadvantages of the method, and the empirical specification. Section 3 then discusses the empirical results for Africa, examining regression models for all farms in Africa, dryland farms and irrigated farms. In Section 4 we simulate the impacts implied by these empirical results for a set of future climate scenarios in 2020 and 2100 from three different Atmospheric-Oceanic Global Circulation Models (AOGCMs). The paper concludes with a summary and general policy implications.

2. Theory

The Ricardian method is a cross-sectional approach to studying agricultural production. It was named after David Ricardo (1772–1823) because of his original observation that the value of land would reflect its net productivity. Farmland net revenues (V) reflect net productivity. This principle is captured in the following equation:

$$V = \Sigma P_i Q_i (X, F, H, Z, G) - \Sigma P_x X \tag{1}$$

where P_i is the market price of crop i, Q_i is the output of crop i, X is a vector of purchased inputs (other than land), F is a vector of climate variables, H is water flow, Z is a vector of soil variables, G is a vector of economic variables such as market access and P_x is a vector of input prices (see Mendelsohn et al., 1994). 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 several exogenous variables, F, H, Z and G, affect net revenues.

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

$$V = B_0 + B_1F + B_2 F^2 + B_3H + B_4 Z + B_5 G + u \tag{2}$$

where u is an error term. Both a linear and a quadratic term for temperature and precipitation are introduced. The expected marginal impact of a single climate variable on farm net revenue evaluated at the mean is:

$$E[dV/df_i] = b_{1,i} + 2 * b_{2,i} * E[f_i] \qquad 3)$$

The quadratic term reflects the nonlinear shape of the net revenue climate response function (equation 2). When the quadratic term is positive, the net revenue function is U-shaped and when the quadratic term is negative, the function is hill-shaped. We expect, based on agronomic research and previous cross-sectional analyses, that farm value will have a hill-shaped relationship with temperature. For each crop, there is a known temperature at which that crop grows best across the seasons. The relationship of seasonal climate variables, however, is more complex and may include a mixture of positive and negative coefficients across seasons.

The change in annual welfare, ΔU, resulting from a climate change from C_0 to C_1 can be measured as follows.

$$\Delta U = V(C_1) - V(C_0) \tag{4}$$

If the change increases net income it will be beneficial and if it decreases net income it will be harmful.

Cross-sectional observations across different climates can reveal the climate sensitivity of farms. The advantage of this empirical approach is that the method includes not only the direct effect of climate on productivity but also the adaptation response by farmers to local climate. This farmer behavior is important because it mitigates the problems associated with less than optimal environmental conditions. Analyses that do not include efficient adaptation (such as the early agronomic studies) overestimate the damages associated with any deviation from the optimum. Adaptation can explain the more optimistic results found with the Ricardian method compared to more pessimistic results found in purely agronomic studies.

Adaptation is clearly costly. The Ricardian model takes into account the costs of different alternatives. For example, if a farmer decides to introduce a new crop on his land as climate warms, the Ricardian model assumes the farmer will pay the costs normally associated with growing that new crop. That is, the farmer will have to pay for new seeds and new equipment specific to the crop. The Ricardian model does not, however, measure transition costs. For example, if a farmer has crop failures for a year or two as he learns about a new crop, this transition cost is not reflected in the analysis. Similarly, if the farmer makes the decision to move to a new crop suddenly, the model does not capture the cost of decommissioning capital equipment prematurely. Transition costs are clearly very important in sectors where there is extensive capital that cannot easily be changed. For example, studies of timber (Sohngen et al., 2002) show that modeling the transition from one stock to another is important. Although agriculture adapts quickly to changes in prices, some intertemporal analyses argue that transitional costs attributable to climate change will also be substantial for farms as well (Kaiser et al., 1993a,b; Kelly et al., 2005). Given how slowly some innovations in modern agriculture have spread in Africa in particular, transition costs may be important.

Another drawback of the Ricardian approach is that it cannot measure the effect of variables that do not vary across space. Specifically, this approach cannot detect the effect of different levels of carbon dioxide since carbon dioxide levels are generally the same across the world. Changes in carbon dioxide levels have occurred over recent decades. In principle, one might be able to detect the effect of these increases in CO_2 by looking at productivity over time. However, it is difficult to distinguish the effect of the carbon dioxide changes from the much larger effect of technical changes that have occurred across the same time period (Mendelsohn, 2006). The best evidence about the magnitude of the fertilization effects of carbon dioxide comes from controlled experiments. These studies report an almost universal fertilization effect for all crops, although the magnitude of this effect varies from crop to crop (Reilly et al., 1996). Reilly reports an average improvement in productivity of 30% associated with a doubling in CO_2. However, these results must be interpreted cautiously because the conditions in the controlled experiments may not be representative of farms across the world. In most cases, the laboratory experiments have been done in near ideal conditions where other nutrients are freely available. In practice, if nutrients are scarce, the fertilization benefits from increased carbon dioxide levels may be lower. Thus, in many developing countries, where fertilizers are not fully applied, the actual carbon fertilization benefits may be less than 30%.

Another potential drawback is that the variation in climate that one could observe across space may not resemble the change in climate that will happen over time. For example, the temperature range across space could be small relative to the change in temperature over the next century. This explains why one may not be able to estimate a Ricardian model in small countries. If the range of climates in a country is small, one cannot detect how climate might affect crops. This specific problem does not apply to this study as there is a wide range of climate variation across the sample. However, it may still be true that climates in the future will not resemble any existing climates. For example, the climate could become erratic, leading to precipitation events that are simply not common today. The analysis cannot measure the impact of such changes.

The Ricardian model also assumes that prices remain constant. As argued by Cline (1996), this introduces a bias in the analysis, overestimating benefits and underestimating damages. The Ricardian approach, by relying on a cross section, cannot adequately control for prices since all farms in the same country effectively face the same prices. However, calculating price changes is not a straightforward task since prices are a function of the global market. Studies that have claimed to take price changes into account have had to make gross assumptions about how world output would change with climate change. These global assumptions also may introduce bias if they are not correct. Further, even analysts who have assumed large agronomic impacts from global warming predict that greenhouse gases would have only a small net effect on aggregate global food supply (Reilly et al., 1996). If aggregate supplies do not change a great deal, the bias introduced by the Ricardian assumption of constant prices is likely to be small (Mendelsohn & Nordhaus, 1996). If the supplies of some commodities increased and others decreased, welfare effects would offset each other. In this case, the bias could be large relative to the remaining small net effect. However, even in this case, the absolute size of the bias would remain small. In a separate analysis, Kumar and Parikh (2001) include prices in their interannual analysis of Indian agriculture. The inclusion of the price terms appears to have little impact on the climate coefficients.

Another criticism that has been leveled against the Ricardian analysis concerns the absence of explicit inclusion of irrigation. Cline (1996) and Darwin (1999) both argue that irrigation should be explicitly included in the analysis. This problem has been addressed in the literature by explicitly modeling irrigation (Mendelsohn & Nordhaus, 1999; Mendelsohn & Dinar, 2003; Schlenker et al., 2005). This study explicitly examines dryland and irrigated land and also includes measures of district water flow (Strzepek & McCluskey, 2006). The Ricardian analysis in this paper clearly does take irrigation into account.

A final concern about the Ricardian method is that it reflects current agricultural policies. If countries subsidize specific inputs or regulate crops, these policies will affect farmer choices. The Ricardian results will consequently have these distortions embedded in the results. For example, if a country mandates that a fraction of cropland be devoted to a certain crop, one may well see more of that crop in that country than elsewhere. We can control for such effects using country dummies. In general, we prefer not to place dummies unless there is evidence of a distortion. We did examine the implications of using country specific dummy variables and the results did not change significantly.[1] Nonetheless, if future decision makers eliminate these subsidies or introduce new ones, the empirical results may no longer hold. Policies that differ across countries could contribute to some of the differences in farm net revenue.

3. Data and empirical analyses

The data for this study was collected in 11 countries, Burkina Faso, Cameroon, Ethiopia, Egypt, Kenya, Ghana, Niger, Senegal, South Africa, Zambia and Zimbabwe, by national teams. In each country, districts were chosen to get a wide representation of farms across climate conditions in that country. The districts are not representative of the distribution of farms in each country as there are more farms in more productive locations. In each chosen district, a survey was conducted of randomly selected farms. The sampling was clustered in villages to reduce sampling costs.

[1] The results with country dummy variables can be obtained from the authors.

A total of 9597 surveys was administered across the 11 countries in the study. The number of surveys across countries varied. (For more information on the survey method and the data collected see Dinar et al., 2008.) Not all the surveys could be used. Some farms did not grow crops (they only raised livestock). Some surveys contained incorrect information about the size of the farm, cropping area or some of the farm operating costs. Impossible values were treated as missing values. It is not clear what the sources of these errors were but field and measurement errors are most likely. They may reflect a misunderstanding of the units of measurement, they may reflect a language barrier, or they may be intentional incorrect answers. The final number of useable surveys was 9064 and their distribution by country is shown in Table 1.

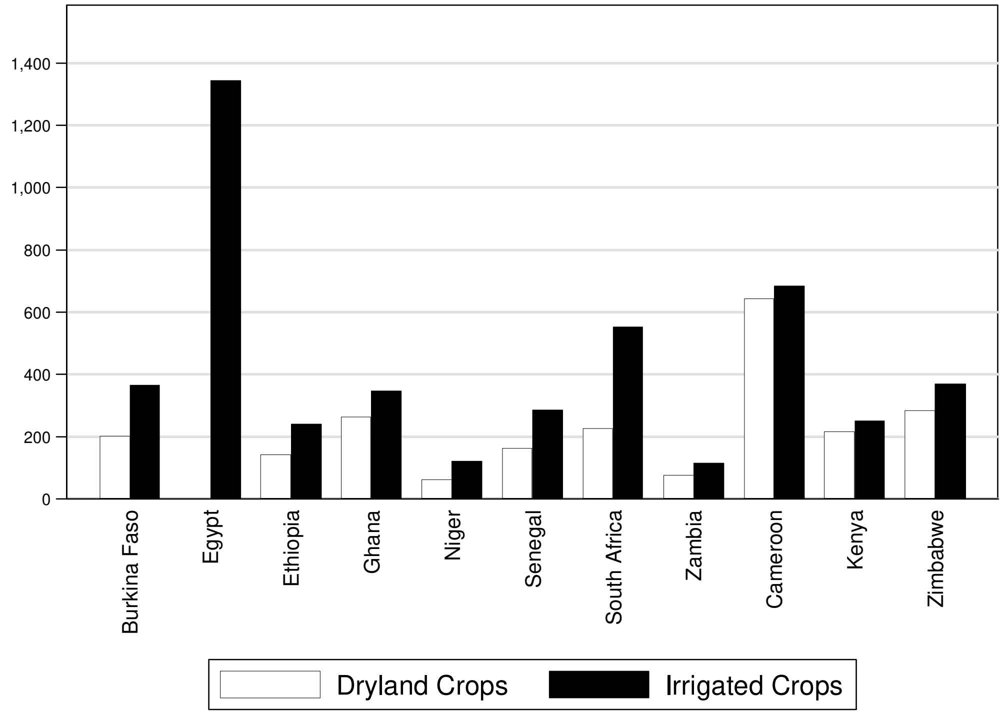
Data on climate was gathered from two sources. We relied on temperature data from satellites operated by the US Department of Defense (Basist et al., 2001). The Defense Department uses a set of polar orbiting satellites that pass over each location on earth between 6am and 6pm every day. The satellites are equipped with sensors that measure surface temperature by detecting microwaves that pass through clouds (Weng & Grody, 1998). The 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, is based on ground station measurements of precipitation.

There are many ways one could represent monthly temperatures and precipitation data in a Ricardian regression model. It is not advisable to include every month, because there is a high correlation between adjacent months. We explored several ways of defining three-month average seasons. 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 months after that would be summer, and August, September and October would be fall (in the north). These seasonal definitions were chosen because they provided the best fit with the data and reflected the mid-point for key rainy seasons in the sample. We adjusted for the fact that seasons in the southern and northern hemispheres occur at exactly the opposite months of the year. We also explored the idea of defining seasons by the coldest month, the month with highest rainfall, and solar position, but found these definitions did a poorer job of explaining current agricultural performance.

Soil data was obtained from the Food and Agriculture Organization of the United Nations (FAO 2003). The FAO data provides information about the major and minor soils in each location as well as slope and texture. Hydrology data was obtained from the University of Colorado (IWMI/University of Colorado, 2003). Using a hydrological model for Africa, the hydrology team calculated flow and runoff for each district in the surveyed countries. Flow is an especially important variable because it describes the amount of water coming into a district from higher elevations. Data on elevation at the centroid of each district was obtained from the United States Geological Survey (USGS, 2004). The USGS data is derived from a global digital elevation model with a horizontal grid spacing of 30 arc seconds (approximately one kilometer).

The literature has made it clear that irrigation and water availability are important variables in crop production. Irrigated land is generally considered to be of the highest value. However, in Africa, most agricultural areas rely on rain (nearly 80%). We explore in this analysis the effect of irrigation on the climate response functions of farmers in different regions of Africa. The irrigation variable is based on plot specific data on water sources. Farms that relied on rainwater alone were considered dryland. Those that relied at least in part on surface water resources, ground water or stored water in any season of the survey year were assumed to be irrigated. Table 1 provides a breakdown of where irrigation is employed by country, based on the survey data. It is evident that irrigation plays a prominent role in Egypt and South Africa but also in places such as Cameroon, Kenya, and Zimbabwe.

Figure 1 depicts the mean net revenue for dryland and irrigated farms in each country in the sample. Egypt is a unique case in Africa. Farming in Egypt is predominantly irrigated and technology intensive, leading to significantly higher earnings. A large fraction of Egyptian farmers take advantage of cultivating for two seasons, which gives them another advantage over farmers in the rest of our sample.



Note: Net revenue = Gross revenue less total cost of hired labor, small tools and heavy machinery, fertilizer and pesticide.

Figure 1: Average net revenue per hectare of dryland and irrigated cropland by country ($/ha)

Net revenue is gross revenue minus the costs of transport, packaging and marketing, storage, post-harvest losses, hired labor (valued at the median market wage rate), light farm tools (such as files, axes and machetes), heavy machinery (tractors, ploughs, threshers and others), fertilizer and pesticide. The median prices per district were used to value both crops and inputs whenever possible. In some circumstances it was necessary to rely on median provincial or national prices. We excluded household labor in the definition of net revenue because including it led to many households having negative net revenues. This was the case whether we used the payments each household alleged it gave to household workers or whether we assigned market wage rates to household labor. The inclusion of household labor in net revenues is problematic, as reported in the agricultural development literature (Bardhan & Udry, 1999). We therefore defined net revenues without household labor costs and controlled for the effect of household labor by including household size as an independent variable. Table 2 provides a summary of the mean of variables used in the analysis.

Table 2: Descriptive statistics

Variable	Obs	Mean	Std dev	Min	Max
Net revenue (USD/ha)	8622.00	461.86	767.99	-2272.65	6972.42
Temp – winter (°C)	9064.00	19.82	4.71	6.99	28.45
Temp – spring (°C)	9064.00	23.35	5.46	9.06	32.79
Temp – summer (°C)	9064.00	24.52	5.61	15.34	36.27
Temp – fall (°C)	9064.00	22.23	4.11	14.09	32.42
Precip – winter (mm/mo)	9064.00	25.86	36.08	0.26	158.83
Precip – spring (mm/mo)	9064.00	39.84	43.79	0.67	214.60
Precip – summer (mm/mo)	9064.00	96.04	63.24	0.19	289.31
Precip – fall (mm/mo)	9064.00	102.39	65.90	0.54	330.88
Mean flow (m3)	9037.00	1.87	5.42	0.00	49.54
Farmland area (ha)	8988.00	60.05	1481.09	0.04	80958.23
Elevation (m)	9023.00	683.27	659.03	1.00	3042.00
Size of household	8991.00	7.32	4.13	1.00	48.00
Irrigation (1/0)	9064.00	0.15	0.36	0.00	1.00
Electrified (1/0)	9064.00	0.29	0.45	0.00	1.00
Eutric gleysols, coarse to undulating	9037.00	0.01	0.04	0.00	0.50
Lithosols, hilly to steep slope	9037.00	0.01	0.06	0.00	0.60
Orthic luvisols, medium texture, hilly slope	9037.00	0.00	0.02	0.00	0.50
Chromic vertisols, fine texture, undulating slope	9037.00	0.00	0.04	0.00	0.60
Chromic luvisols, medium to fine texture, undulating	9037.00	0.01	0.06	0.00	0.70
Cambic arenosols	9037.00	0.00	0.02	0.00	0.50
Luvic arenosols	9037.00	0.01	0.04	0.00	0.40
Chromic luvisols, coarse to medium texture, steep slope	9037.00	0.00	0.01	0.00	0.30
Dystric nitosols	9037.00	0.01	0.05	0.00	0.50
Gleyic luvisols	9037.00	0.01	0.08	0.00	0.80
Rhodic ferralsols, fine texture, hilly to steep slope	9037.00	0.00	0.02	0.00	0.30
Calcic yermosols, coarse to medium texture, undulating to hilly slope	9037.00	0.01	0.08	0.00	0.60

In Table 3, we present the results of the multiple regression models of net revenue across three samples. This initial set of regressions does not control for regional differences across Africa. It examines three models: the entire sample (all farms), just irrigated farms, and just dryland farms. The coefficients for irrigated and dryland farms are not the same, which suggests they have different relationships with the independent variables. While we do not present the results here, a number of farmer specific variables, such as gender, education and whether or not the farmer was a full time farmer or not, were not significant and so were dropped as they were not jointly significant. Overall, the three regressions explain 35%, 17% and 29% of the variation in net revenues from farm to farm. The coefficients of the models are significantly different from zero. The variables identify many reasons why farm net revenue varies from place to place. However, a great deal of the variation remains unmeasured. This is especially true of dryland farms that vary from small backyard systems to large commercial operations. There are several sources of possible error, including misreporting of net revenue, omitted variables, local or national restrictions, and random annual phenomena.

Table 3: Regression coefficients of all farms, dryland and irrigated farms without regional dummies

Variable	All farms	Dryland	Irrigated
Winter temperature	-83.9	-117.1*	91.0
Winter temperature squared	2.98*	3.62*	-2.16
Spring temperature	-18.4	-20.9	-186.3
Spring temperature squared	-1.61	-1.10	2.21
Summer temperature	212.4**	118.9	1093.0**
Summer temperature squared	-2.74**	-1.36	-19.01**
Fall temperature	-116.6*	-22.8	-1067.4**
Fall temperature squared	1.68	-0.23	22.28**
Winter precipitation	-3.32**	-4.79**	7.86
Winter precipitation squared	0.018**	0.025**	-0.043
Spring precipitation	3.42*	5.38**	-11.99
Spring precipitation squared	-0.002	-0.017**	0.099*
Summer precipitation	3.90**	3.43**	23.84**
Summer precipitation squared	-0.016**	-0.015**	-0.093**
Fall precipitation	-1.63*	-1.76**	-19.82**
Fall precipitation squared	0.012**	0.013**	0.074**
Mean flow	12.20**	-8.48*	10.54**
Farm area	-0.074**	-0.320**	-0.042*
Farm area squared	0.000**	0.000**	0.000*
Elevation	-0.077**	-0.115**	0.234*
Log (household size)	27.3*	20.93	64.5
Irrigate (1/0)	251.3**		
Household access to electricity (1/0)	117.4**	95.47**	297.8**
Eutric gleysols, coarse, undulating	-692.4**	-393.3**	-1265.7**
Lithosols and luvisols, hilly and steep	-454.4**	-228.1**	-1038.0**
Orthic luvisols, medium, hilly	-2322.0**	-1999.8**	
Chromic vertisols - fine, undulating	-1065.1**	-894.3**	-1585.5**
Chromic luvisols - medium, fine, undulating	-261.2**	-250.2**	
Cambic arenosols	1642.8**	1709.0**	
Luvic arenosols	-539.9**	-269.6**	
Chromic luvisols, medium, steep	-2267.6		-5812.3**
Dystric nitosols	370.7		7343.7**
Gleyic luvisols	-179.0**	-125.2**	
Rhodic ferralsols, fine, hilly, steep	992.4*		3540.0
Calcic yermosols, coarse, medium, undulating, hilly	1279.6**	-636.3**	
Constant	141.8	702.4	-243.3
N	8459	7238	1221
R2	0.351	0.171	0.29
F	68.59	33.81	52.45

Note: * significant at 5% level ** significant at 1% level

Many of the control variables were significant. More water flow increases the value of irrigated farms but not dryland farms. Dryland farms are no better off with water flow because the only water they use comes from on-farm precipitation. Farm area reduces the value per hectare of farms at a decreasing rate. That is, small farms are more productive on a per hectare basis. Small farms may appear to be more productive because they are using a fixed resource such as household labor over a much smaller piece of land. This is consistent with the finding that the log of household size is positive in the all-Africa and dryland models. Higher elevation reduces the value of dryland farms but increases the value of irrigated ones. In general, high elevation is associated with high diurnal temperature variance, which is often hard on crops. However, high elevation may reduce the cost of irrigation as the slopes can be used to capture and move water at low cost.

Technology variables also matter. Whether or not the farm has access to electricity has a positive effect. This may reflect either higher technology or better access to markets. Whether a farm has irrigation increases farm net revenue substantially. This dummy reflects the gross not net value of irrigation because the irrigation costs were not counted in the net revenues.

Soils also were quite important in the model. Altogether 12 types were identified as significant in the Africa sample. Types such as cambic arenosols, rhodic ferralsols with fine texture in hilly to steep regions and calcic yermosols with coarse to moderate texture and in undulating to hilly regions were identified as high productivity soils. By contrast, eutric gleysols with coarse texture in undulating areas, orthic luvisols in moderate to hilly areas, chromic vertisols with fine texture in undulating areas and chromic luvisols in moderate to steep areas were all particularly unproductive soils. Some of these soil types were unique to small areas and so could not be included in the dryland and irrigated equations.

The effects of the seasonal climate variables vary across the three models in Table 3. Both linear and squared terms are significant in certain seasons, implying that climate has a nonlinear effect on net revenues. One can see from the negative/positive sign of the quadratic term that the relationship is hill-shaped/U-shaped. However, depending on what seasonal temperature or precipitation is being examined, the marginal impact of a climate variable could be either positive or negative. The relationship between temperature and net revenues is depicted in Figure 2. As temperatures rise, the net revenues from irrigated farms rise whereas the net revenues from dryland fall. The relationships between net revenues and precipitation for dryland and irrigated farms are shown in Figure 3. Precipitation increases net revenues in both types of farms but it has a comparatively larger impact on dryland farms. Drying and warming is especially harmful to dryland farms. By contrast, irrigated farms are likely to be robust against climate changes, provided there is enough water flow for irrigation.

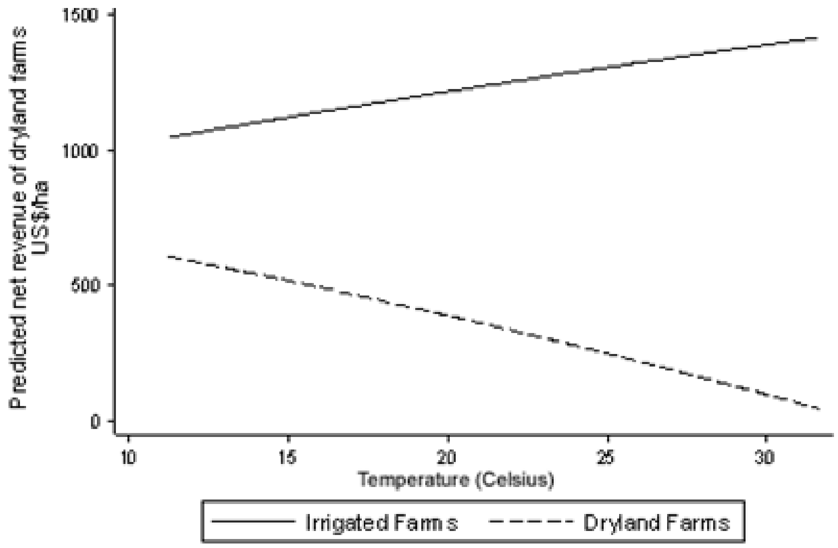


Figure 2: Temperature response functions

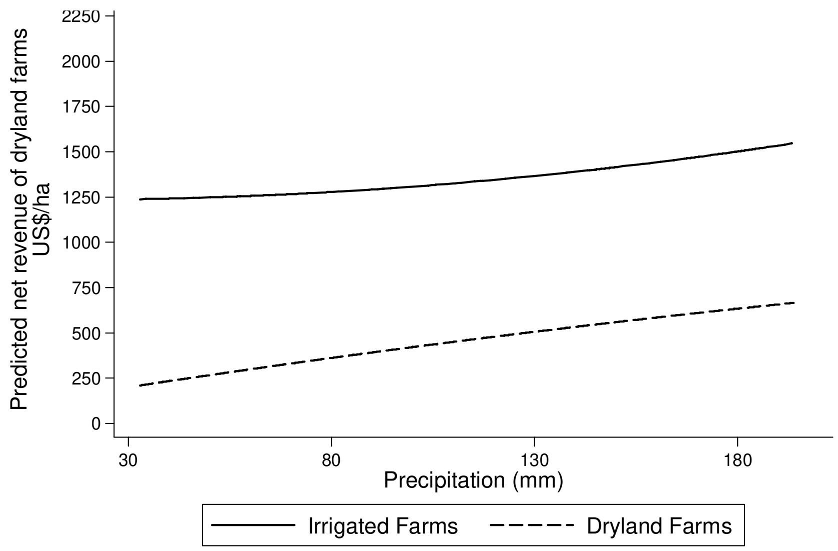


Figure 3: Precipitation response functions

In Table 4 we present an alternative specification of the model. We have added regional variables to capture differences across broad regions and a few more technology variables. The regional variables reflect trade arrangements, common language and colonial history, and proximity. The regional dummies suggest that West Africa and North Africa are more productive than southern Africa. East Africa, on the other hand, is less productive. The results of the technology variables are mixed. The coefficient for whether a farm uses heavy machinery is positive in the dryland equation, which probably reflects modern technology. The coefficient for whether a farm depends on animal power depends on whether it is dryland or irrigated. The dummy variable for animal power has a positive effect on dryland farms but a negative effect on irrigated ones. It is also possible that in irrigated lands the negative coefficient implies that some farmers of irrigated land have a lower level of technology than others. Animal power may be a proxy on the one hand for household labor and on the other for the absence of capital and technology.

Table 4: Regression coefficients of all farms, dryland and irrigated farms with regional dummies

Variable	All farms	Dryland	Irrigated
Winter temperature	-173.6**	-106.7	-93.5
Winter temperature squared	6.1**	3.9*	4.9
Spring temperature	115.1	-82.8	58.7
Spring temperature squared	-5.0**	-0.3	-4.1
Summer temperature	173.9**	198.6**	827.5**
Summer temperature squared	-1.9	-3.2*	-13.1*
Fall temperature	-98.1	-92.4	-824.2*
Fall temperature squared	1.1	1.5	15.3*
Winter precipitation	-2.9*	-1.9	5.8
Winter precipitation squared	0.0**	0.00	0.00
Spring precipitation	3.5*	3.6**	-10.6
Spring precipitation squared	-0.001	-0.011*	0.091*
Summer precipitation	3.4**	1.9*	21.4**
Summer precipitation squared	-0.012**	-0.005	-0.086**
Fall precipitation	-0.5	-0.6	-14.7**
Fall precipitation squared	0.0055*	0.0053*	0.0586***
Mean flow	9.4**	-5.4	8.8**
Farm area	-0.1**	-0.3**	-0.0**
Farm area squared	0.0*	0.0**	0.0*
Elevation	0.035	-0.0009	0.229
Log (household size)	22.9	10.1	62.4
Irrigate (1/0)	237.5**		
Access to electricity (1/0)	66.6**	47.7**	233.2*
Eutric gleysols, coarse, undulating	-631**	-287**	-540
Lithosols and luvisols, hilly, steep	-387**	-156**	-1147**
Orthic luvisols, medium, hilly	-2181**	-1959**	
Chromic vertisols - fine, undulating	-1180**	-1006**	-1719**
Chromic luvisols - medium, fine, undulating	-295**	-241**	
Cambic arenosols	1633**	1726**	
Luvic arenosols	-482**	-188**	
Chromic luvisols, medium, steep	-2153		-6157**
Dystric nitosols	214		7051**
Gleyic luvisols	-199**	-154**	
Rhodic ferralsols, fine, hilly, steep	1428**		3212
Calcic yermosols, coarse, medium, undulating, hilly	1071**	148	
West Africa dummy	136**	208**	-285
North Africa dummy	457**		675*
East Africa dummy	-186**	-154**	-361
Heavy machinery dummy	51.8**	55.5**	-60.8
Animal power dummy	10.4	49.3**	-185.5**
Constant	-388	1081	-549
N	8459	7238	1221
R2	0.4	0.2	0.3
F	63.6	32.4	46.3

Note: * significant at 5% level ** significant at 1% level

In order to interpret the climate coefficients, we calculated the marginal impacts of a change in each climate variable evaluated at the mean climate for each specific regression sample. So, the marginal impacts for the dryland model are evaluated at the mean climate of the dryland sample while those for the irrigated sample are assessed at the mean climate of irrigated farms. The marginal values depend on the regression equation that is being used and the climate that is being evaluated. Table 5 displays the results of using the three regressions from Tables 3 and 4. In each case the marginal effect of temperature and precipitation is evaluated at the mean for each sample. For example, the marginal effect of temperature on irrigated land is evaluated at the mean temperature of irrigated land and the marginal impact of precipitation on dryland is evaluated at the mean precipitation for dryland. Irrigated farms are located in cooler (19.7°C) and drier (38.3 mm/mo) locations than dryland farms (22.2°C and 74.1 mm/mo). The marginal temperature results are almost identical with or without regional dummies. However, the marginal precipitation results are larger with the regional dummies.

Table 5: Marginal impacts of climate on net revenue (USD/ha)

(Elasticities in parentheses)

Without regional dummies

(From coefficients in Table 2)

Sample	Africa regression	Irrigated regression	Dryland regression
Temperature	-28.3**	33.6	-23.0**
	(-1.3)	(0.5)	(-1.6)
Precipitation	2.65**	2.08	2.02**
	(0.36)	(0.06)	(0.47)

With regional dummies

(From coefficients in Table 3)

Annual	Africa regression	Irrigated regression	Dryland regression
Temperature	-28.5**	35.04	-26.7**
	(-1.4)	(0.6)	(-1.9)
Precipitation	3.28**	3.82	2.70**
	(0.44)	(0.13)	(0.63)

Notes: ** significant at 1% level
Marginal impacts evaluated at the mean of the all-Africa, irrigated and dryland samples.

Comparing the results of dryland farms with irrigated ones reveals that they are quite different. The marginal temperature effect for dryland farms is -USD27/°C. By contrast, the marginal effect of a temperature increase on irrigated farms evaluated at their mean temperature is positive at USD35/°C. Higher temperatures increase the net revenues of irrigated farms because the mean temperature of these farms is relatively cool and because irrigation buffers crops from temperature effects. The marginal precipitation effects for dryland and irrigated farms are more similar (3.8 mm/mo for irrigated farms and 2.7 mm/mo for dryland). Irrigated farms may benefit more than dryland farms from small increases in precipitation because they are located in such dry locations.

In addition to marginal effects, another important perspective to look at is the climate elasticities (the percentage change in net revenues for a percentage change in climate). The mean net revenue of irrigated cropland (USD1367/ha) is much higher than the net revenue from dryland cropland (USD360/ha). The temperature elasticity for dryland is −1.9 but the elasticity for irrigated land is +0.6. Similarly, the precipitation elasticity for dryland is +0.6 but the elasticity for irrigated land is only +0.1. The net revenues from dryland are much more climate sensitive than those from irrigated land.

In Figure 4 we present the marginal temperature and precipitation impacts across all irrigated and dryland farms. The results suggest that a marginal increase in temperature will cause substantial damage in West Africa and in areas along the Rift Valley. Drier parts of East Africa (especially in northwest Ethiopia) will also suffer adversely. By contrast, higher rainfall is most likely to benefit large parts of southern Africa and the currently dry North Africa. Some of the gains in, for example, the Sahara Desert area are exaggerated, as there is limited agriculture in deserts without water.

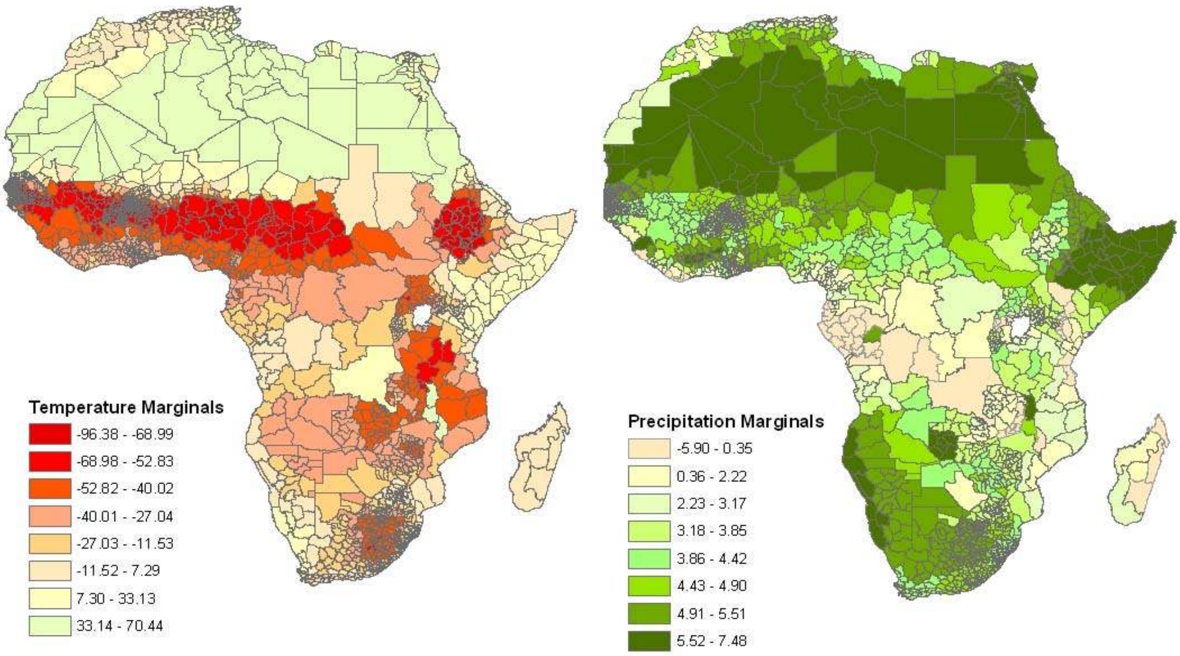


Figure 4: Marginal impacts ($/ha) from a small change in temperature and precipitation

4. Forecasts of climate impacts

We used the estimated regressions in the previous section to explore how climate change scenarios might affect cropland in all of Africa. The Ricardian results above estimate how net revenues vary across existing climates on the African continent. In this projection, we predict how future climates might affect future farm net revenues. These projections assume that all other conditions hold constant and that the results of the cross section can be used for long-term intertemporal analysis.

We examine a set of climate change scenarios predicted by three AOGCMs: the Canadian Climate Centre (CCC) (Boer et al., 2000), the CCSR (Emori et al., 1999), and the Parallel Climate Model (PCM) (Washington et al. 2000). The AOGCMs project how climate will change in the near term (2020) and in the long run (2100) for each country in Africa. For each climate scenario, we added the predicted change in temperature from the climate model to the baseline temperature in each district. We also multiplied the predicted percentage change in precipitation from the climate models by the baseline precipitation in each district or province. This gave us a new climate for every district in Africa. Table 6 presents the mean temperature and rainfall predicted by the three models for the years 2020 and 2100. The PCM scenarios are relatively mild and the CCC ones are relatively severe. The temperature change predicted by the CCSR is between these two models but the CCSR has a particularly dry 2100 scenario. There is a clear trend of warming in both scenarios over time but precipitation varies.

Table 6: Climate predictions of AOGCM models for 2020and 2100

	Current	2020	2100
Temperature (°C)			
CCC	23.3	24.9 (+1.6)	30.0 (+6.7)
CCSR	23.3	25.3 (+2.0)	27.4 (+4.1)
PCM	23.3	23.9 (+0.6)	25.8 (+2.5)
Rainfall (mm/month)			
CCC	79.8	76.8 (-3.7%)	65.1 (-18.4%)
CCSR	79.8	74.0 (-7.3%)	62.44 (-22%)
PCM	79.8	89.8 (+12.5%)	83.2 (+4.3%)

Note that each model also has a slightly different precipitation prediction for each region of Africa. For 2020 and 2100, the PCM model predicts a large increase in precipitation in East Africa and West Africa, but only a small increase in North, Central and southern Africa. By contrast, the CCC model predicts that precipitation will increase in Central and West Africa but fall in the rest of Africa. By 2100, the CCC model also predicts an unusually large increase in temperature in West Africa (7.3°C) and in Central and southern Africa (6.5°C) compared to the rest of Africa (5.5°C). Finally, the CCSR predicts a substantial increase in precipitation in West Africa (30%) and a small increase elsewhere in 2020. In this same period, West and Central Africa experience larger temperature changes (more than 2 degrees) than the rest of the continent. The 2100 prediction of warming is also a little higher for North Africa (4.8°C) than for the rest of Africa (3.7°C). North, East and West Africa are likely to experience relatively higher precipitation in 2100 than Central and southern Africa.[2]

[2] Detailed country and seasonal changes in the climate variables used in the analysis are available from the authors.

In order to extrapolate from the sample to the entire continent, we began by projecting how many hectares of cropland there are in each district. In this paper, we relied on estimates by the International Food Policy Research Institute (IFPRI) and the FAO of the amount of cropland in each district (FAOStat, 2005; Lotsch, 2006). The primary arable land areas are in the temperate regions of North Africa, the coastal belt in West Africa (south of the Sahel) and along the Rift Valley in East and southern Africa.

Because we intended to explore the effects of climate on dryland and irrigated land, we needed to determine which land across Africa is irrigated. We relied on FAO estimates of the total hectares of irrigated cropland in each country (FAOStat, 2005; Siebert & Döll, 2005). We allocated these hectares across districts within each country on the basis of the districts' respective climates. The probability of irrigation in each district was interpolated using a probit model that regressed irrigation on a set of independent climate variables including climate, soils and flow.[3] The results suggest that coastal regions in North and southern Africa have a higher likelihood of irrigation. Other regions of Africa, particularly Central Africa and regions along the Rift Valley either have sufficient rainfall or lack the investment necessary to undertake irrigation. Note that the amount of cropland and irrigated land in each country is based solely on current estimates and is assumed not to change.

Using the estimated regression coefficients in Table 3, we calculated the change in net revenue for each climate scenario in each district throughout Africa. We then multiplied the change in net revenue per hectare by the number of hectares of cropland in each district to get an aggregate impact in each district. This value was then summed across all the districts of Africa to get a total impact for a country or for the continent:

$$\text{Aggregate Climate Impact}_d = \text{Sum}(\Delta Y_i * W_j) \qquad (5)$$

where ΔY_i = change in net revenue per hectare from a climate change

W_j =hectares of cropland, irrigated cropland or dryland cropland

d= district d

Table 7 presents the results of the six scenarios for the three climate models for 2020 and 2100. The PCM results suggest that with ample rainfall and only a small increase in temperature the net effect on all African farms would be a marginal gain of from USD59 to USD69 billion/yr. The predicted effects would begin in 2020 and become slightly larger by 2100. With CCSR, the results decrease from modest gains of USD5.5 to losses in excess of USD15 billion/yr. With CCC, the results suggest that even by 2020 losses of USD22 billion are likely. By 2100, a large warming of 6°C would lead to substantial losses across African farms equal to USD47 billion. Irrigated farms are predicted to be the least affected across all the climate scenarios partly because they are climate insensitive and partly because they are currently located in relatively cool areas. Dryland farms are likely to be affected the most, whether it is a benefit of USD57 billion or a loss of USD43 billion, depending on the climate scenario.

[3] The regression results can be requested from the authors.

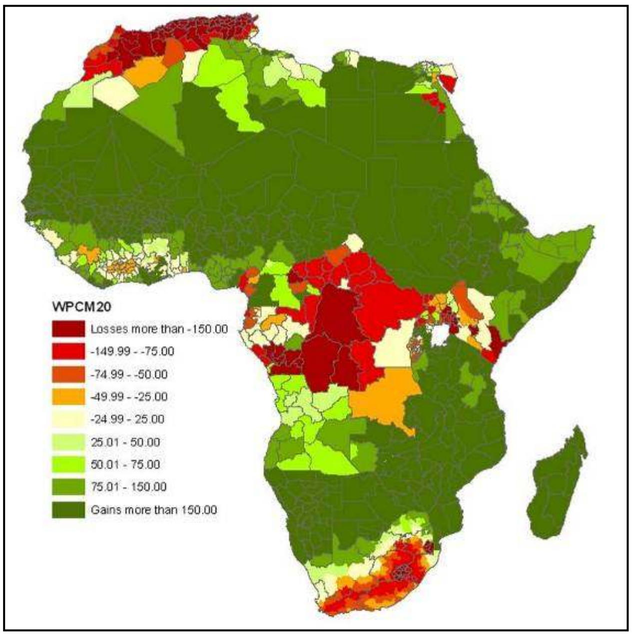
Table 7: African impacts from AOGCM climate scenarios

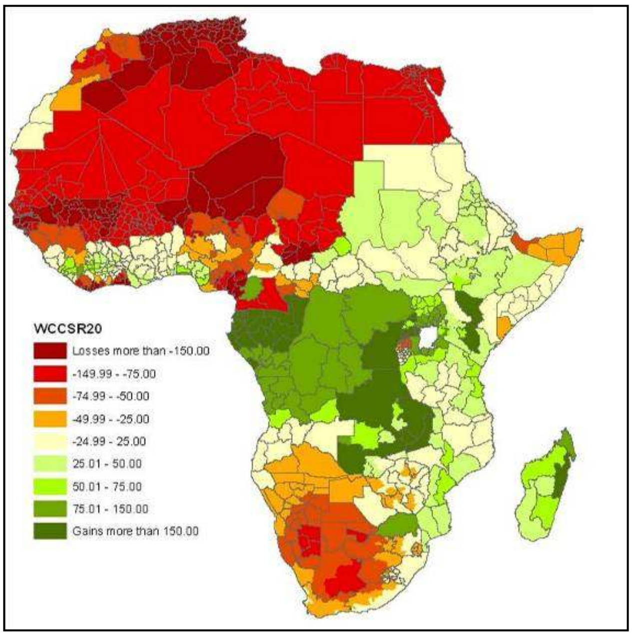
Impacts	PCM 2020	PCM 2100	CCSR 2020	CCSR 2100	CCC 2020	CCC 2100
Dryland						
ΔNet revenue (USD/ha)	181.1 [181, 182] *(53.3%)*	160.6 [160.5, 162.] *(50.8%)*	-22.9 [-23.6, -22.8] *(-7%)*	-116.6 [-118, -115.8] *(-36%)*	-67.5 [-67.9, -67.3] *(-21%)*	-137.4 [-138.9, -136.8] *(-43%)*
ΔTotal net revenue (billions USD)	57.3	50.8	-7.3	-36.9	-21.4	-43.5
Irrigated						
ΔNet revenue (USD/ha)	31.3 [9.3, 36.8] *(2.7%)*	352.0 [326.3, 359.7] *(30%)*	99.5 [92.2, 98.1] *(8.7%)*	-416.6 [-427.1, -404] *(-36%)*	58.0 [55, 57.8] *(5.1%)*	341.4 [333, 345] *(29%)*
ΔTotal net revenue (billions USD)	0.4	4.6	1.3	-5.4	0.8	4.4
All Africa						
ΔNet revenue (USD/ha)	180.2 [179.7, 182.3] *(41%)*	212.5 [212, 214] *(48%)*	16.8 [16.3, 17.2] *(4%)*	-46.3 [-48, -44] *(-10%)*	-61.1 [-61.7, -60.9] *(-14%)*	-143.7 [-145.6, -143] *(-33%)*
ΔTotal net revenue (billions USD)	58.7	69.2	5.5	-15.1	-22.4	-46.8

Note: Using coefficients in Table 6 and AOGCM country specific climate scenarios. The numbers in parentheses represent the percentage change in net revenue per hectare relative to the mean of the sample. The numbers in the square brackets represent bootstrapped confidence intervals based on 1000 repetitions where 50% of the sample is randomly dropped.

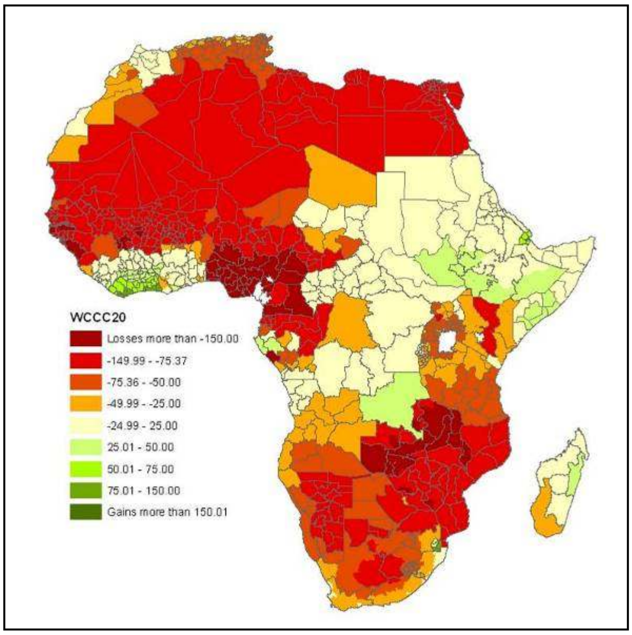
In order to show how the climate effects in 2020 are distributed across Africa, in Figure 5 we map the predicted impacts in each district for each of the three AOGCM scenarios. The figure suggests a wide range of country specific impacts across Africa. Across the three scenarios, increases in precipitation in West Africa offset increases in temperature so that there are muted net effects. With the CCC scenario, southern Africa experiences large losses in net revenue per hectare, as does most of Saharan and North Africa. However, there is a wide swath of land across Central Africa that is hardly affected. A similar pattern appears in the CCSR scenario except that Central and West African farmers increase their net revenues. By contrast, the PCM climate scenario, which predicts a significant increase in rainfall with moderate warming, depicts increases in net revenues almost everywhere in Africa. The major exception is Central Africa, where the marginal impact of more rain is harmful because this area already receives a great deal of precipitation.

Figure 6 depicts the impact on net revenue per hectare from the 2100 climate change scenarios. Compared to the 2020 scenarios, the damages generally get larger and the benefits shrink. However, the general spatial patterns that were visible in the 2020 scenarios in each of the three models remain. The CCC scenario hits farmers the hardest in North and southern Africa but has smaller impacts in Central Africa. The CCSR scenario also leads to large predicted losses in North and southern Africa but gains in Central Africa. In the PCM scenario, there remain benefits to most of Africa but the benefits are smaller. The higher temperatures by 2100 reduce the benefits found earlier by the PCM model. Looking across the models, the impact in each location is uncertain. The outcome will depend on the climate scenario. Further, the entire continent will not be affected uniformly in any scenario. Impacts will vary in each scenario, from being harmful in some locations to being beneficial in others across all of Africa.



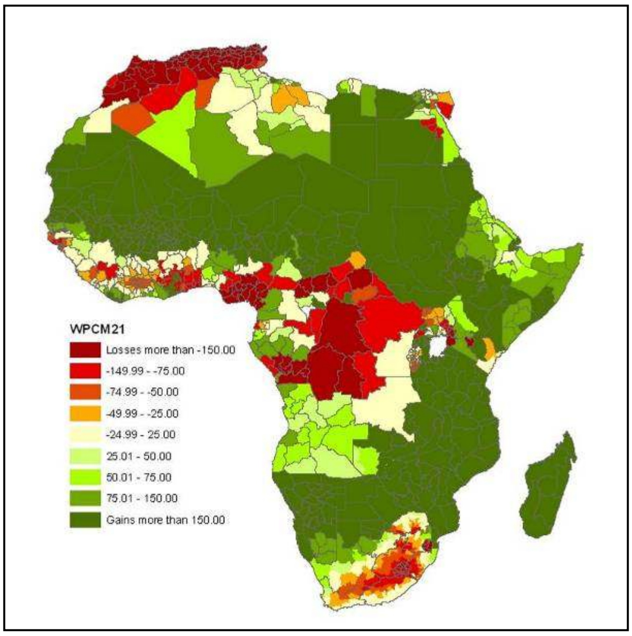


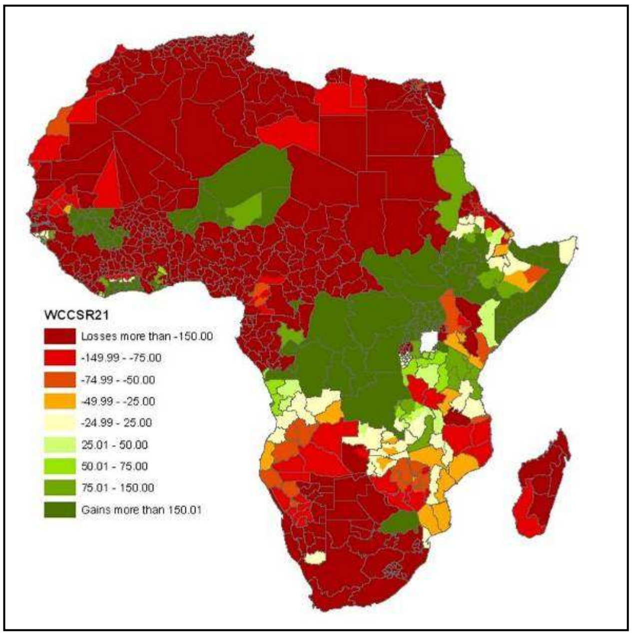
(a) Impacts based on PCM climate scenario **(b) Impacts based on CCSR climate scenario**



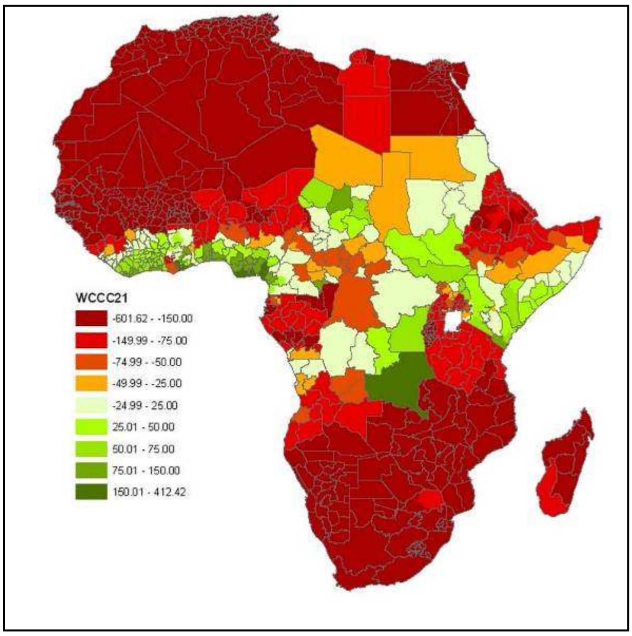
(c) Impacts based on CCC climate scenario

Figure 5: Predicted change in net revenue per hectare by 2020





(a) Impacts based on PCM climate scenario (b) Impacts based on CCSR climate scenario



(c) Impacts based on CCC climate scenario

Figure 6: Predicted change in net revenue per hectare by 2100

5. Conclusions and implications for policy

This study is a cross-sectional analysis of the crop net revenues of African farms, relying on the Ricardian method to investigate the current impact of climate on crop net revenues, and building on the back of a massive data effort to collect information about farmers in 11 African countries.

Surveys of 9064 African farms were combined with detailed measurements of soils, climate, hydrology and elevation from a number of sources.

The study found that African farms are sensitive to climate and especially temperature. It finds that farm net revenues are lower in places with higher temperatures. Specifically, the temperature elasticity with respect to the net revenue of African farms is estimated to be -1.3. That is, a 10% increase in temperature will lead to a 13% decline in net revenue. The precipitation elasticity is estimated to be 0.4. African farms are more sensitive to changes in temperature than changes in precipitation. Similar results were also found for US farms (Mendelsohn et al., 1994; Mendelsohn & Nordhaus, 1999; Mendelsohn et al., 2001; Mendelsohn & Dinar, 2003). The sensitivity is the greatest for dryland farms with a temperature elasticity of -1.6 and a precipitation elasticity of 0.5. Irrigated farms, by contrast, are resilient to temperature changes and may actually increase in value (partly because of their location in temperate regions of Africa). These results are similar to preliminary analyses using the same data (Kurukulasuriya et al., 2006).

The study then predicts the impacts of future scenarios from climate models. Irrigated farms will benefit slightly across all scenarios. The fate of dryland farms depends on the scenario. Mild climate scenarios will probably benefit dryland farmers. Harsh scenarios will lead to large losses. Impacts are expected to be evident as early as 2020 and to become larger over time as warming increases.

The results provide some insights into the consequences of doing separate analyses of dryland and irrigated land (Schlenker et al., 2005). The dryland regression alone is more sensitive than a regression that includes all farms. Schlenker et al. mistakenly conclude from this result that separating dryland and irrigated farms indicates that climate warming is more dangerous. However, they omit the results of irrigated farms. The dryland analysis alone provides a biased forecast of the overall effect of climate change on all farms. Irrigated farms are much more robust to warming than dryland farms. If dryland and irrigated farms are to be separated, one must use the results from both samples to predict the effects of climate change.

The study also finds that impacts are not likely to be uniform across Africa. The hotter and drier regions of Africa are likely to be hurt the most. Further, the climate changes themselves are not likely to be uniform, with some areas getting wetter and others dryer. How many people are affected depends on where they are located. Putting all these factors together, there remains a wide range of plausible outcomes.

The study suggests that African countries should begin to plan for climate contingencies. Governments should develop contingency plans if certain climate outcomes come to pass. They should anticipate what farmers will do, how markets will react, and what role governments need to play. They should be prepared to help people adapt to these new circumstances.

Some actions can also be taken before the climate changes. Actions that make agricultural sectors more immune to climate can be taken in advance. Developing new crops that are more suited to hot and dry conditions will help countries to adapt to many current climate zones as well as future ones. Encouraging profitable irrigated systems will reduce the climate vulnerability of the agriculture sector. Developing the economy away from agriculture will reduce the climate sensitivity of the entire economy. Increasing wealth so that firms and households can explore more alternatives will make adaptation easier.

There are three important factors that must be considered that were not included in this analysis. First, this study takes the technology of each farmer as given. There is no doubt about the importance of technology. The average dryland farmer earns USD319/ha whereas the average irrigated farmer earns USD1261/ha. The more advanced irrigated farms earn even more. What will happen to technology in Africa's future is very important. A second factor is that all-Africa results are contingent on the current distribution of dryland and irrigated agriculture. Future analysis should take into account impacts where irrigation adjusts as climate changes (Mendelsohn, 2006). The third important factor left out of this analysis is carbon fertilization. Experimental results suggest that yields could increase on average by 30% if CO_2 doubles (Reilly et al., 1996). If these gains are realized in the field, they will help to offset a great deal of the predicted harmful effects of warming. Of course, agriculture in Africa will nonetheless be handicapped compared with agriculture in cooler regions even with carbon fertilization.

Acknowledgements

This paper was funded by the Global Environmental Facility and the World Bank. It is part of a larger study on the effect of climate change on agriculture coordinated by the Centre for Environmental Economics and Policy in Africa (CEEPA), Pretoria, South Africa. The authors would like to thank Rashid Hassan, David Maddison, Ariel Dinar and the individual country teams for their assistance in this project, and the entire research team of the GEF/World Bank/CEEPA project for their efforts in collecting the data. The views expressed are the authors' alone.

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