CLIMATE CHANGE AND AFRICAN AGRICULTURE

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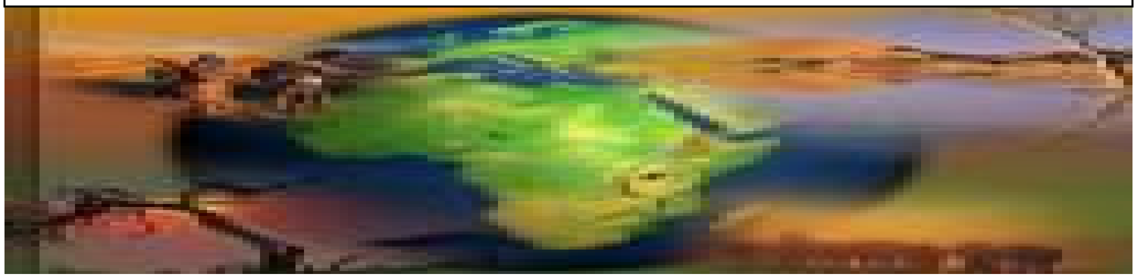

Adapting to climate change: Using irrigation in Africa[1]

The cross-section (Ricardian) method for estimating the impacts of climate change on agriculture is a regression of land values (or net revenue) against climate and other exogenous characteristics. A consistent criticism that has been leveled at the first Ricardian study is that it did not properly take into account irrigation. Adding a dummy variable to control for the effect of irrigation does not resolve the key problem, however. Based on results from analysis of US samples showing different climate response functions for dryland and irrigated land, Schlenker et al. (2005) argue that the welfare effects from climate change should be estimated separately for irrigated and dryland farms and then added. However, this approach is problematic because it treats irrigation as though it is exogenous. The decision to irrigate is a choice and this choice is influenced by climate. Further, there may be sample selection bias if we rely on farms that are observed to use either dryland or irrigation.

Studies that assume irrigation is exogenous fail to take into account how irrigation will change as climate changes and therefore provide biased estimates of the impact of climate change. Moreover, to analyze separately farms that use irrigation and farms that use only dryland is to rely on self-selected samples (not random samples). Studies that fail to account for this non-randomness in the modeling framework will be biased (Heckman 1979; Lee 1983). This study develops a model that improves on past Ricardian efforts to model irrigation by explicitly addressing farmer choice and selection bias. The new Ricardian approach developed examines dryland and irrigated land separately but treats the choice of irrigation as endogenous (an adaptation choice made by the same decision-making farmer). The model is then empirically tested and used to examine how irrigation and net revenues of African crop farmers may be affected under various climate change scenarios. The study then compares the results of the model with endogenous irrigation with a model that assumes irrigation is exogenous.

Modeling endogenous irrigation

[1] This Policy Note is prepared by R Hassan based on Kurukulasuriya & Mendelsohn (2006), Endogenous irrigation: The impact of climate change on farmers in Africa, *CEEPA Discussion Paper No. 18, CEEPA, University of Pretoria.*

This study assumes that the amount of cropland is fixed, in order to focus on the issue of irrigation. Formally, we rely on an approach similar to the sample selection model for labor (Heckman 1979). However, there is an important difference. In the labor example, people who did not work had no observed income. In this model, farmers who choose not to irrigate still have observed income from dryland farming. We assume that a farmer irrigates if irrigation is more profitable than dryland farming. In the first stage, we estimate a dichotomous choice model of irrigation (Y=1 for irrigation and Y=0 for dryland farming). In the second stage, we estimate a conditional profit function for each type of farming with selected explanatory variables.

The data and empirical model

The empirical analysis is based on a household survey conducted in 11 countries across Africa: Burkina Faso, Cameroon, Egypt, Ethiopia, Kenya, Ghana, Niger, Senegal, South Africa, Zambia and Zimbabwe. It was difficult to collect land values from all these countries. We consequently relied on measures of net revenue per hectare. Net revenue is defined as gross revenue minus the cost of transport, packaging and marketing, storage, post-harvest losses, hired labor (valued at the median market wage rate), light farm tools (files, axes, machetes, etc.), rental on heavy machinery (tractors, ploughs, threshers, etc.), fertilizer and pesticide. Household labor costs are not included as a cost in net revenues because it was not clear what value to assign to wages. We controlled for household labor by using household size as a proxy.

In each country, districts were chosen to identify farms across a wide range of climate conditions in that country. In each chosen district, a random but clustered sample of farms was selected. Out of a total of 9597 surveys 8463 were found usable. We conducted the analysis at the plot level of each farm, as each farm provided plot specific data on whether or not irrigation was used, crop production (including crop type, amount harvested, quantity sold, quantity consumed and amount of sales receipt) and crop costs (fertilizer, pesticide and seed data). Net revenue estimates are at the farm level because the input data, including labor (both hired and household) and machinery, were available only at that unit of measurement. The dataset we used contains 1750 irrigated plots and 9183 dryland plots.

In this study, we relied on monthly temperature data collected from US Department of Defense satellites. The monthly precipitation data came from the Africa Rainfall and Temperature Evaluation System (ARTES) (World Bank 2003).

It is not possible to use every month of climate in a Ricardian regression because of the high correlation between one month and the next. Consequently we had to cluster the monthly data into seasons. However, it is not self-evident how to cluster monthly temperatures into a limited set of seasonal measurements. After exploring several ways of defining three-month average seasons, 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 implies that February, March and April would be spring, May, June and July would be summer, and August, September and October would be fall (in the north). We then adjusted for the fact that seasons in the southern and northern hemispheres occur at exactly the opposite months of the year.

Soil data was obtained from FAO (2003). Hydrology data was predicted from a hydrological model for Africa (Strzepek & McCluskey 2006). The model calculated the water flow through each district in the surveyed countries. Data on elevation at the centroid of each district was obtained through GIS manipulation using data from the United States Geological Survey (USGS 2004).

In the first stage of the analysis, we estimated a probit model of whether to irrigate or not. We relied on the 10,880 plots for which we have complete information for the regression. The explanatory variables in the first stage included seasonal climate variables, various soils, and flow (millions of m^3). We tested the inclusion of quadratic climate variables but found the linear model to be more reliable. The coefficients (which are highly significant) suggest that the probability of adoption of irrigation increases with higher temperatures and precipitation in each season except spring. The probability of adopting irrigation increases in regions with lower temperatures (for example Egypt and South Africa), while it decreases in warmer regions. Irrigation in cooler regions is more profitable because it requires less water and the crops are more productive. Similarly, in regions of higher precipitation or available flow, the probability of adopting irrigation decreases. Irrigation is less profitable in wetter locations because the fixed cost of irrigation remains the same but the net increment to production declines.

The coefficient on the long run average (30 years) of estimated mean flow variable is positive and significant. We included in the probit model only those soils that are jointly significant for both irrigated and dryland farms.

We then turned to estimating the second stage model of net revenue conditional on type of farm. Following the standard Heckman model, we included the Mills ratio as an additional explanatory variable to control for self-selection bias in the second stage OLS model (Dubin & McFadden 1984). We examined two sets of second stage OLS models: one for dryland and one for irrigated land. The coefficient on the estimated Mills ratio is significant in the dryland regression and negative as anticipated but not significant in the irrigated model. We tested several control variables in each regression (including gender, education and whether the head of the household was a full-time farmer), but dropped them because they were not significant.

A comparison of the OLS coefficients confirms our hypothesis that irrigated and dryland farms are different. The log of size of household has a positive effect on net revenue per hectare for both irrigated and dryland farms. Household size is logged because productivity per worker is expected to fall as households become too large. In addition, our findings lend support to the controversial but often observed inverse relationship between farm size and productivity. Controlling for labor, machinery and other farm inputs, including irrigation and technology, small farms have higher net revenues per hectare than large ones.

We also included a dummy variable that denotes whether or not a farm has electricity. It is clear that electrified farms outperform farms that do not have electricity in both the irrigated and dryland models. Electrification might directly enhance productivity and earnings or it may simply be a proxy for farms that are closer to markets or more modern.

The second stage regressions give an important insight into the climate sensitivity of farms. The results clearly show that dryland and irrigated farms are both sensitive to climate. Evaluating the marginal impact of temperature and precipitation at the mean climate for the sample reveals many significant seasonal impacts. In most seasons (except for winter temperature and winter and spring precipitation), the signs of the coefficients for both types of farms are in the same direction. However, the marginal effects of changes in temperature are not the same across seasons. In spring and fall, the marginal temperature effect is negative, whereas in summer and winter it is positive.

These offsetting seasonal effects make annual impacts more ambiguous. The annual marginal impacts of temperature and precipitation are shown in Table 1. The magnitudes of the annual temperature effects for dryland and irrigated farms are different. The resulting elasticity of net revenue with respect to temperature is -0.81 and 0.31 for dryland and irrigated farms respectively. The precipitation results for dryland and irrigated land are also quite different. Dryland farms are sensitive to precipitation (elasticity of 0.28) whereas precipitation has virtually no effect on the net revenues of irrigated farms. As long as there is sufficient water, irrigation appears to buffer farms from insufficient precipitation.

We also estimated a pair of regressions that treat irrigation as exogenous. Further, the climate coefficients in the two dryland and two irrigated regressions are quite similar. Sample selection bias does not appear to be a significant problem in this dataset. Figures 1 and 2 plot the resultant response functions from the selection model as well as the second stage conditional models for dryland and irrigated farms by varying temperature and precipitation respectively.

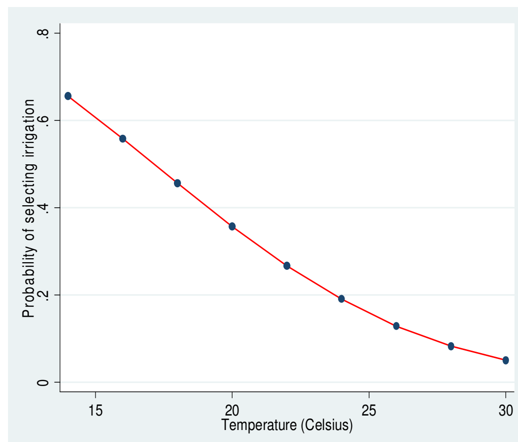

Figure 1: Relationship between annual temperature and the probability of adopting irrigation

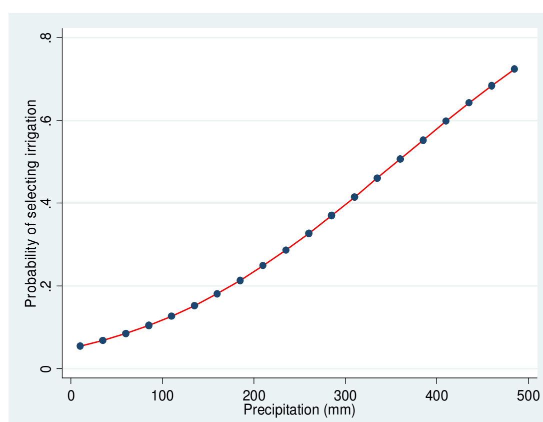

Figure 2: Relationship between annual precipitation and the probability of adopting irrigation

Climate change simulation

In this section, we calculate the welfare effect of changing climate. We compare the welfare results from our endogenous modeling approach with the welfare results from the exogenous model of irrigation (Schlenker et al. 2005). Note that with the exogenous model of irrigation it is assumed that climate change has no effect on the probability of irrigation. The endogenous model allows this probability to change with the climate scenario.

We examined four simple scenarios to illustrate the importance of modeling irrigation correctly. The scenarios assume a uniform change in either temperature or precipitation across Africa. We examined two temperature increases of 2.5°C and 5.0°C, and a +20% and a -20% change in precipitation. In Table 1, we present the results of each scenario. First, we demonstrate that the different climate change scenarios change the fraction of farms that are irrigated. Second, we show that the welfare estimates using a model that addresses endogeneity (referred to herein as the 'endogenous model') and the model that assumes that irrigation is exogenous when it is not (referred to as the 'exogenous model') are quite different. Our endogenous model indicates the overall changes in welfare from a 2.5 and 5 degree increase in temperature are -8% and -14% respectively. The exogenous model overestimates the welfare losses in both cases. Our endogenous model predicts that a 20% decrease in precipitation reduces overall welfare by 21% while a 20% increase in precipitation increases it by 18%. The exogenous model underestimates both the damages and benefits of these two scenarios. By failing to take into account how farmers change their irrigation decision as climate changes, the exogenous model leads to biased welfare estimates.

Table 1: Comparison of irrigation and welfare estimates for endogenous and exogenous models across different climate scenarios

	Climate scenario	**Endogenous approach**	**Exogenous approach**
Mean probability of irrigation	2.5˚C Δ in T	0.166	0.162
	5˚C Δ in T	0.171	
	-20% Δ in P	0.157	
	+20% Δ in P	0.167	
Δ in welfare	2.5˚C Δ in T	-8%	-12%
	5˚C Δ in T	-14%	-21%
	-20% Δ in P	-21%	-16%
	+20% Δ in P	18%	14%

Note: The current probability of irrigation is 0.162.

Conclusions and implications

This paper provided an improved modeling framework for the Ricardian method in analyzing the effect of irrigation on farm performance. We explicitly modeled irrigation as recommended (Cline 1996; Darwin 1999; Schlenker et al. 2005), but we controlled for the endogeneity of irrigation that plagues a recently suggested remedy (Schlenker et al. 2005). Our results indicate that treating irrigation as exogenous leads to biased welfare estimates from climate change. If dryland and irrigation are to be estimated separately in the Ricardian model, irrigation must be modeled endogenously.

The results also indicate that African agriculture is sensitive to climate change. Many farmers in Africa will experience net revenue losses from warming. Any reduction in precipitation will be especially deleterious to dryland farmers, generally the poorest segment of the agricultural community. Irrigation is an effective adaptation against loss of rainfall and higher temperatures provided there is sufficient water available. This will be an effective remedy in regions of Africa with sufficient water (FAO 1997). However, for many regions, there is no available surface water, so that warming scenarios with reduced rainfall are particularly deleterious. On the other hand, mild warming scenarios with increased rainfall may not be harmful at all.

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The agricultural sector in sub-Saharan Africa is predicted to be especially vulnerable to climate change because this region already endures high heat and low precipitation, provides the livelihoods of large segments of the population, and relies on relatively basic technologies, which limit its capacity to adapt. This series of Policy Notes reports on the methods and results of the first continent-wide study of this kind assessing how the economic well-being of African farming communities is currently affected by climate, predicts how future climate change effects may unfold under various possible global warming scenarios, and evaluates the roles adaptation to climate change could play. The study is based on collaborative research efforts conducted in 11 countries: Burkina Faso, Cameroon, Egypt, Ethiopia, Ghana, Kenya, Niger, Senegal, South Africa, Zambia and Zimbabwe. The sampled districts used as the unit of analysis cover all key agro-climatic zones and farming systems in Africa. This is the first analysis of climate impacts and adaptation in Africa on such a scale and the first in the world to combine cross-country, spatially referenced survey and climatic data for conducting an analysis that uses economic impact assessment methods, river-basin hydrological modeling and crop growth simulation techniques.

All the reports produced under this GEF/WB/CEEPA funded project, *Regional Climate, Water and Agriculture: Impacts on and Adaptation of Agro-ecological Systems in Africa*, are found on CEEPA e-Library at its website link (www.ceepa.co.za/discussionp2006.html) and can also be accessed directly through the project link (www.ceepa.co.za/Climange_Change/project.html)

Centre for Environmental Economics and Policy in Africa (CEEPA)*, University of Pretoria, Room 2-7, Agricultural Annex, 0002 PRETORIA, South Africa. Tel: +27 (0)12 420 4105, Fax: +27 (0)12 420 4958, Web address: www.ceepa.co.za*

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The Centre for Environmental Economics and Policy in Africa
University of Pretoria

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