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ANALYSIS

An analysis of crop choice: Adapting to climate change in South American farms[☆]

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ABSTRACT

This paper explores how South American farmers adapt to climate by changing crops. We develop a multinomial logit model of farmer's choice of crops. Estimating the model across 949 farmers in seven countries, we find that both temperature and precipitation affect the crops that South American farmers choose. Farmers choose fruits and vegetables in warmer locations and wheat and potatoes in cooler locations. Farms in wetter locations are more likely to grow rice, fruits, potatoes, and squash and in dryer locations maize and wheat. Global warming will cause South American farmers to switch away from maize, wheat, and potatoes towards squash, fruits and vegetables. Predictions of the impact of climate change on net revenue must reflect not only changes in yields per crop but also crop switching.

1. Introduction

This paper uses cross-sectional evidence to explore how farmers would adapt to exogenous environmental factors such as climate and soils (Seo and Mendelsohn, 2007a). By comparing choices of farmers who face different environmental conditions across the landscape, we examine quantitatively how farmers would adjust their current choices in response to future climate. In this specific paper, we apply this technique to study how climate affects the choice of crops by South American farmers. We quantify which crops farmers are likely to choose and how dependent this choice is on climate. Understanding adaptation is an important goal in itself to assist planning by policy makers and private individuals (Smith, 1997; Smit et al., 2000; Smit and Pilifosova, 2001). However, understanding adaptation is also important if one is interested in quantifying the impacts of climate change (Mendelsohn et al., 1994). Forecasts of the impact of climate on agriculture cannot rely solely on how climate affects the yield of a specific crop. The forecasts must also capture crop switching. That is, the forecasts must recognize that farmers will change what they plant in order to maximize profits in each new climate. Studies that assume farmers will continue to grow what they currently grow even as yields decline will overestimate damages (Examples in Latin America are Downing, 1992; De Siqueira et al., 1994; Magrin et al., 1997; Hofstadter et al., 1997; Conde et al., 1997).

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Climate impact studies have consistently predicted extensive impacts to the agricultural sector from climate change across the globe (Cline, 1992; Rosenzweig and Parry, 1994; Pearce et al., 1996; Tol, 2002). A large set of these studies have focused on the reduction of yields of specific crops in warmer temperatures (Reilly et al., 1996; McCarthy et al., 2001). Because these studies assume that farmers make no changes in crops, these studies predict large yield losses from climate change and therefore large losses in net revenue. Studies that do allow crops to change (Mendelsohn et al, 1994; Adams et al., 1999; Seo and Mendelsohn, 2007b) predict that farmers will move away from crops with low yields and substitute new crops that will perform better in the new climate. Studies that allow adaptation predict smaller damages. However, empirical analyses of just how much farmers are likely to switch crops in response to climate are rare in low latitude countries. The only exception is a new study of farmers in Africa (Kurukulasuriya and Mendelsohn, 2007). This paper follows the approach taken in the African paper but explores the choices of farmers in South America.

The theoretical choice model is developed in the next section. Section 3 discusses how data were collected from over 2000 farmers in seven countries across South America. Analysis of the sample reveals 949 farmers who chose to grow crops. A multinomial logit model is then estimated to reveal the role that climate plays in crop choice. Section 4 discusses this estimation procedure and the empirical results. Three climate change scenarios from Atmospheric Oceanic General Circulation Models (AOGCM's) are then examined in Section 5 to simulate the effects of climate change on the choice of crops in the coming century. The paper concludes with a summary of results and policy implications.

2. Theory

In this paper, farmers are assumed to maximize their profits. Farmers choose the desired species to yield the highest net profit. Hence, the probability that a crop is chosen depends on the profitability of that crop. We assume that farmer i's profit in choosing crop j ($j=1,2,\ldots,J$) is

$$\pi_{ij} = V_j(K_i, S_i) + \varepsilon_j(K_i, S_i) \tag{1}$$

where K is a vector of exogenous characteristics of the farm and S is a vector of characteristics of the farmer. The vector K includes climate, soils, and price variables and S includes the age of the farmer and family size. The profit function is composed of two components: the observable component V and an unobservable component that is in the error term ε. The farmer will choose the crop that gives him the highest profit. When farmers select multiple crops, the crop choice is defined as the single crop with the greatest net revenue. Alternatively, we could have examined all combinations of crops that farmers select (Seo and Mendelsohn, 2007a). However, the number of combinations is large and becomes difficult to model because farmers reported more than 50 different crops. We assume that only the primary crop (the crop that yields the highest net revenue) matters. The choices are consequently mutually exclusive and exhaustive, i.e. the farmer must pick one and only one of the available crops.

Defining $Z=(K,S)$, the farmer will choose crop j over all other crops k if:

$$\pi_j^*(Z_i) > \pi_k^*(Z_i) \text{ for } \forall k \neq j. \left[\text{or if } \varepsilon_k(Z_i) - \varepsilon_j(Z_i) < V_j(Z_i) - V_k(Z_i) \text{ for } k \neq j\right]. \tag{2}$$

More succinctly, his problem is:

$$\underset{j}{\operatorname{argmax}} \quad \left[\pi_1^*(Z_i), \pi_2^*(Z_i), \ldots, \pi_J^*(Z_i)\right] \tag{3}$$

The probability P_{ij} for the jth crop to be chosen is then

$$P_{ij} = \Pr\left[\varepsilon_k(Z_i) - \varepsilon_j(Z_i) < V_j - V_k\right] \forall k \neq j \text{ where } V_j = V_j(Z_i). \tag{4}$$

Assuming that ε is independently Gumbel distributed and the profit function can be written linearly in its parameters, the probability can be calculated as follows:

$$P_{ij} = \frac{e^{Z_{ij}\gamma_j}}{\sum_{k=1}^{J} e^{Z_{ik}\gamma_k}} \tag{5}$$

which gives the probability that farmer i will choose crop j among J species (McFadden, 1973; Train, 2003). The parameters can be estimated by the Maximum Likelihood Method, using an iterative nonlinear optimization technique such as the Newton–Raphson Method. These estimates are CAN (Consistent and Asymptotically Normal) under standard regularity conditions (McFadden, 1999).

3. Description of data

This study is part of a World Bank project entitled 'Incorporation of Climate Change to the Strategies of Rural Development' (Mendelsohn et al., 2007). The project collected economic surveys at the farm level from seven South American countries: Argentina, Brazil, Chile, Columbia, Ecuador, Uruguay, and Venezuela. The countries were selected to represent the wide range of climate throughout South America and included representatives from both Southern Cone and Andean regions. Districts within each country were selected to provide as much within country climate variation as possible. Sampling was clustered in villages within districts to reduce the costs.

The surveys asked detailed questions on farming activities during the one year period of July 2003 to June 2004 (Mendelsohn et al, 2007). Initial surveys were designed and pretested with country team members cooperating in the project. Data collection and initial coding were completed by each country team. The data was then cleaned to remove errors and omissions. The original survey interviewed over 2000 farmers. We removed observations with important missing data. About half the remaining farms were household farms and the other half were commercial farms.

The study focuses on the seven major crops grown in South America: fruits and vegetables (31%), maize (24%), wheat (15%), squash (11%), rice (8%), potato (7%), and soybeans (4%). The frequency that each of these crops is the primary crop is shown in parentheses above. Altogether these seven crops generated about 85% of the total revenue from crops in the sample. Farmers that chose other crops as the primary crop were dropped. This process of identifying observations leaves 949 farms in the analysis.

Climate data came from two sources: US Defense Department satellites and weather station observations recorded by the World Meteorological Organization (WMO, 2004). We relied on satellite observations for temperature and interpolated ground station data for precipitation (see Mendelsohn et al., 2007 for a detailed explanation). Monthly climate data was averaged to construct seasonal climate data. In the southern hemisphere, summer is the average of December, January and February; fall is the average of March, April and May, winter is June, July, and August, and spring is September, October and November. The northern hemisphere seasons are six months apart. For example, summer in the northern hemisphere corresponds to winter in southern hemisphere.

Soil data were obtained from the Food and Agriculture Organization's (FAO) digital soil map of the world CD ROM (FAO 1999). The Latin American soil data was assigned to each district using GIS (Geographical Information System) by overlapping the dominant soil map of Latin America over a district map of Latin America. The data set reports 26 dominant soil types.

4. Empirical results

In Table 1, we estimate the probability each species is selected using a multinomial choice model (Eq. (5)). The choice of fruits and vegetables has been left out of the regression as the base case. The probability of choosing each crop was assumed to be a function of summer and winter temperature and summer and winter precipitation. Previous empirical research of temperate countries suggests that all four seasons of the year may be significant (Mendelsohn et al., 1994). Although we explored a four season model, we were not able to estimate significant results for each season. This sample is heavily dominated by tropical observations, where the four seasons are not as distinct. Other explanatory variables included soil variables, farmer age, farmer education, household size, prices, and a dummy variable for computer. Other variables such as gender were not significant. The model is significant according to three tests of global significance. Most of the individual coefficients are significant. Positive (negative) coefficients imply that the probability of choosing each crop increases (decreases) as the corresponding variable increases.

The coefficient on education is positive and significant for every crop in Table 1 except for rice and maize which are not significant. This result implies that lower educated farmers tend to grow fruits and vegetables, the omitted choice. Potatoes are more often chosen when the dominant soil at the farm is a Lithosol. When the dominant soil is a Luvisol, farms tend to choose maize less often, but potatoes more often. Wheat, potatoes, and soybeans are more likely to be chosen if a farm has Planosol soils. Farms with computers are more likely to choose potatoes and rice. It is not clear whether this equipment actually enhances the profitability of these crops or whether the computer is a proxy for a missing variable such as technology or market access. Larger farm families are less likely to choose maize, potatoes, soybeans, and wheat. These crops are easily mechanized and so may be selected by farmers with smaller families. Older farmers are more likely to choose wheat. The remaining effects are not significant.

Only two of the own prices are significant: maize and wheat. Both coefficients are positive as expected. Farmers are more likely to choose these crops when their prices are higher. The remaining significant price effects are cross price terms. When wheat prices are higher, farmers are more likely to pick maize, rice and soybean. When maize prices are higher, they are more likely to pick rice but less likely to pick squash. When

Table 1 – Multinomial logit crop selection model for July 2003 to June 2004 season

Variable	Maize	Potatoes	Rice	Soybeans	Squash	Wheat
Intercept	4.444	−23.338	−11.823	−6.536	7.774	5.292
Temperature summer	0.025	0.130	4.046*	0.528	−1.255	−0.091
Temperature summer sq	−0.001	−0.029	−0.151*	−0.010	0.036	0.006
Precipitation summer	−0.004	0.234*	0.045*	0.002	0.044*	0.009
Precipitation summer sq	0.00003	−0.002*	−0.00007*	0.00002	−0.00008*	0.00002*
Temperature winter	−0.122	1.844*	−1.380*	0.088	−0.149	−0.561*
Temperature winter sq	0.003	−0.073*	0.078*	−0.013	−0.002	0.004
Precipitation winter	0.005	−0.058*	0.097	0.052**	0.014	−0.005
Precipitation winter sq	0.0001	0.0004*	0.0002	−0.001*	−0.00001	0.0003*
Soil Lithosols	0.013	0.074*	−0.007	0.006	0.011	−0.015
Soil Luvisols	−0.021**	0.039*	0.031	−0.015	−0.152	−0.015
Soil Planosols	0.007	0.024*	−0.052	0.026*	−0.005	0.031*
Computer dummy	0.269	0.761	0.656	−0.108	−0.066	0.057
Age head	0.009	0.038	0.004	0.017	0.005	0.035*
Log household size	−0.909*	−1.215*	−0.937	−0.998*	−0.031	−0.841*
Log education	0.106	1.004*	−0.030	1.085*	0.629*	1.512*
Maize price	0.460*	0.688	1.563*	0.099	−2.45**	0.104
Wheat price	18.724*	−44.745*	27.75**	16.910*	4.026	33.562*
Squash price	−26.401*	79.127	−113.900	−20.114*	−7.197	−27.264*
Mango price	−2.015	−7.649	−11.59**	0.391	−1.387*	−2.009
Tomato price	4.290*	−2.876	10.581	−2.765	0.451	−19.580*

Note: 1) Fruit is the omitted choice. 2) Likelihood ratio test: $P<0.0001$, Lagrange multiplier test: $P<0.0001$, Wald test: $P<0.0001$. 3) * implies significance at 5% and ** implies significance at 1% level.

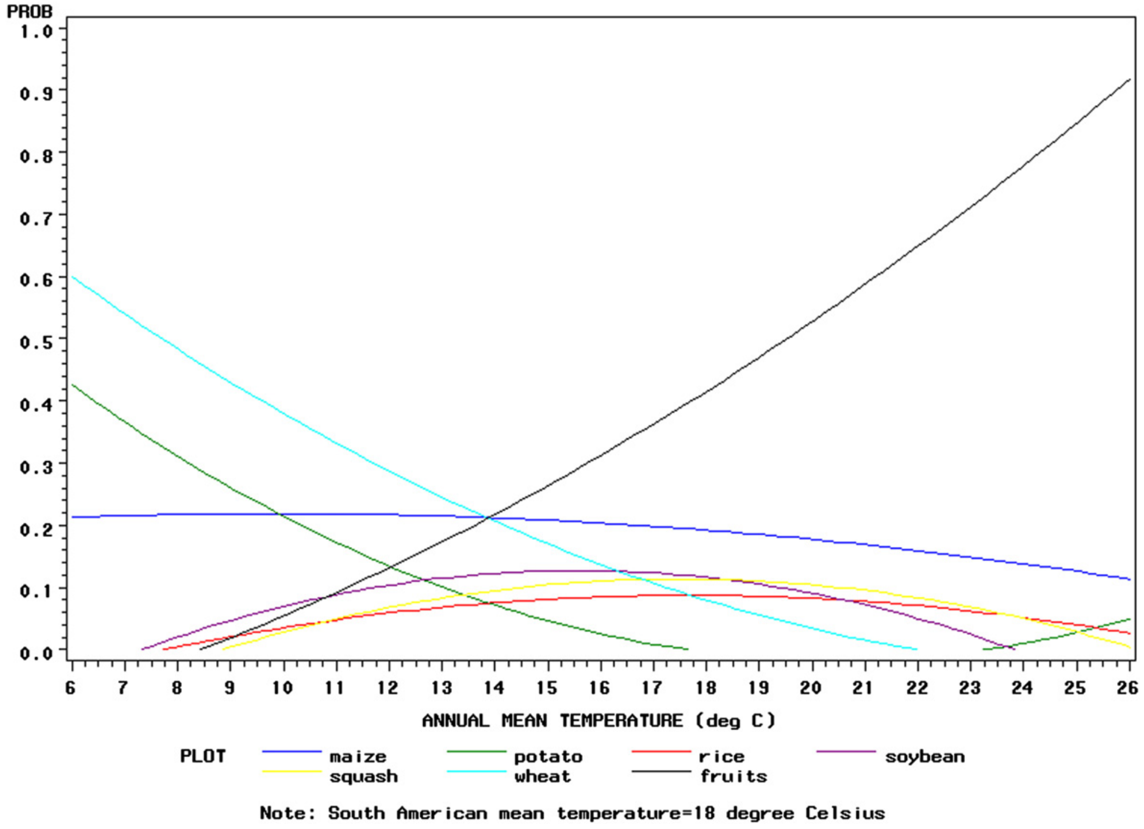

Fig. 1 – Estimated probabilities for crops to be chosen over temperature (°C).

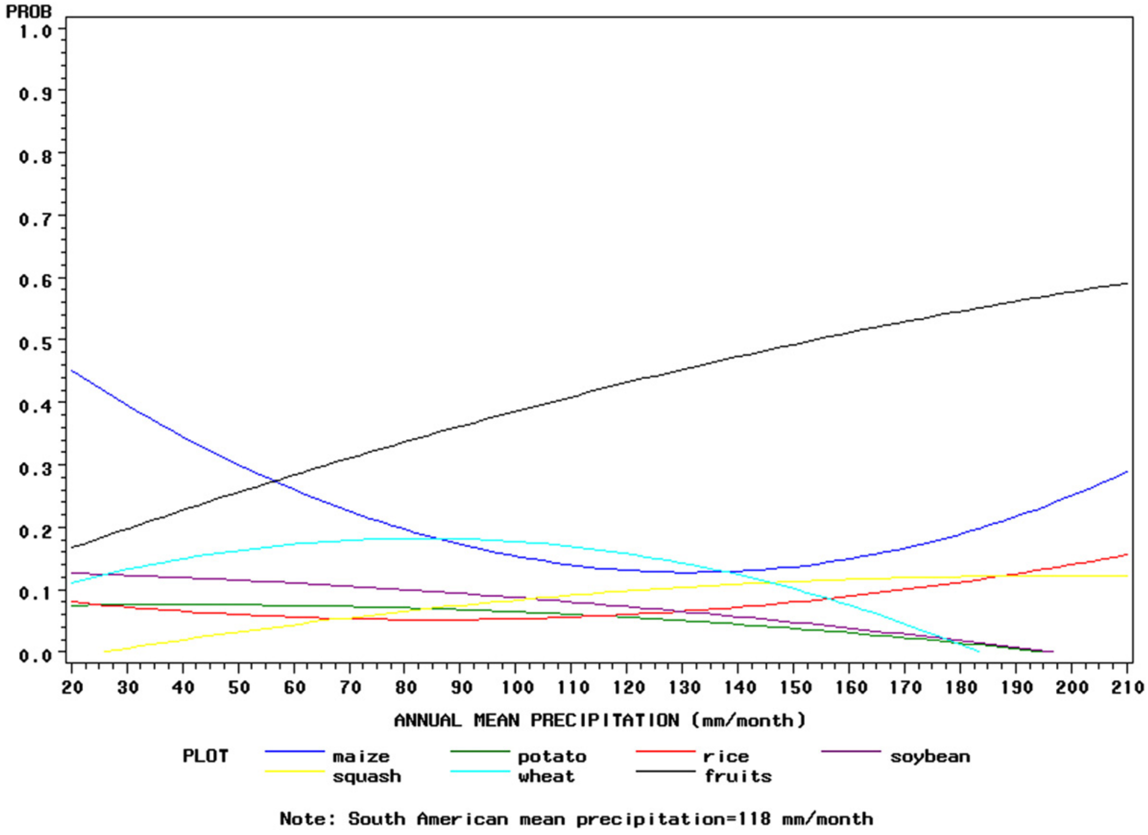

Fig. 2 – Estimated probabilities for crops to be chosen over precipitation (mm/month).

Table 2 – Marginal effect of climate change on crop choice in South America

	Maize (%)	Potato (%)	Rice (%)	Soybean (%)	Squash (%)	Wheat (%)	Fruit (%)
Baseline (%)	19.5	6.8	4.8	7.9	8.0	14.4	38.6
Temperature (°C)	−0.2	+0.5	+0.4	+0.2	+0.7	−2.3	+0.8
Precipitation (mm/month)	−0.3	+0.2	+0.1	0.0	+0.1	−0.1	−0.2

squash prices are higher, they are less likely to pick maize, soybean, and wheat. Higher tomato prices are associated with higher likelihood to choose maize but lower likelihood to choose wheat. These positive cross price terms imply a complementarity between the two crops in question.

Maize does not have any significant climate coefficients but all the other crop choices have at least one significant climate coefficient. There are many varieties of maize so that it can effectively grow in many climate zones in South America. The crop is a "generalist" in the sense that it is grown throughout South America. In contrast, the other crops are more specialized and grow in narrower temperature or precipitation ranges. The climate variables consequently significantly influence their choice. Rice, for example, is very sensitive to summer and winter temperatures and to summer precipitation. Potatoes are very sensitive to winter temperatures and summer and winter precipitation. Squash is sensitive to summer precipitation. Wheat is sensitive to winter temperature and summer and winter precipitation. Fruits and vegetables generally prefer warmer temperatures. Soybeans are sensitive to winter precipitation.

Fig. 1 reveals that the choice of crop varieties in South America is generally temperature sensitive. The graph describes the relationship between the probability of choosing a crop and annual mean temperature measured in Celsius. Crops that are not very temperature sensitive tend to have flat response functions; the probability of adoption remains the same regardless of the temperature. For example, maize is grown across the full range of temperatures in the sample. The remaining crops tend to have preferred temperature ranges. For example, the probability of choosing wheat and potatoes is higher in farms at the coolest end of the sample. The reader should disregard the reappearance of potatoes at very high temperatures as potatoes are not chosen at these very high temperatures. By contrast, the probability of choosing fruit is high in farms that are at the warmest end of the sample. The rest of the crops have specific ranges within the sample. Rice and soybeans are chosen most often when temperatures are close to 16°C. Squash is most often chosen when temperatures are close to 18 °C. The average temperature in the sample is 18 °C.

Fig. 2 displays the estimated relationship between the probability of choosing the seven crops and annual precipitation measured in millimeters per month. The mean annual precipitation in South America is 118 mm/month.[2] Almost all farms in our sample are located in areas with less than 200 mm/month of precipitation. The probability of choosing soybeans and potatoes declines, the wetter the farm is. By contrast, moving from dry to wet farms increases the probability of selecting fruit. Wheat and squash exhibit a hill-shaped pattern, peaking at around 70 and 200 mm/month respectively. Maize and rice have a U-shaped relationship with precipitation with a minimum of 140 and 90 mm/month respectively.

Because the coefficients and shapes in Table 1 and Fig. 1 are nonlinear, it is not transparent what effect changes in temperature or precipitation would have on crop choice. In Table 2, we calculate the marginal effects of a slight temperature increase and a slight increase in precipitation evaluated at the mean climate of the sample. As temperature increases by 1 °C, farmers tend to choose maize and wheat less often while they choose potatoes, rice, soybean, and fruits more often. If precipitation increases by 1 mm, farmers move away from maize, wheat, and fruits to potato, rice, and squash. Symmetrically, if climate change caused precipitation to fall, farmers would move in the opposite direction.

5. Simulations of crop switching

In this section, we simulate the consequences of climate change on crop selection behaviors using the parameter estimates in the previous section. We start with a baseline scenario that assumes farmers will continue to plant their current crops if climate remains unchanged. That is, we do not model other possible reasons why crop choice might change over the next hundred years. We look at only the effects of climate change. We examine a set of climate change scenarios predicted by Atmospheric Oceanic General Circulation Models (AOGCM's). The climate scenarios reflect the A1 SRES (Special Report on Emissions Scenarios of the Intergovernmental Panel on Climate Change) scenarios from the following three models: the Canadian Climate Center (CCC) scenario (Boer et al. 2000), Centre for Climate System Research (CCSR) scenario (Emori et al. 1999), and the Parallel Climate Model

Table 3 – South American average AOGCM climate scenarios

	Current	2020	2060	2100
Temperature (°C)				
CCC	18.1	19.5 (+1.4)	20.8 (+2.7)	23.2 (+5.1)
CCSR	18.1	19.4 (+1.3)	20.4 (+2.2)	21.3 (+3.2)
PCM	18.1	18.7 (+0.6)	19.5 (+1.3)	20.1 (+2.0)
Rainfall (mm/month)				
CCC	119	116 (−2.6%)	107 (−9.5%)	109 (−7.7%)
CCSR	119	120 (+1.5%)	119 (0.0%)	114 (−3.8%)
PCM	119	128 (+8.2%)	133 (+11.9%)	129 (+8.4%)

Note: 1) CCC refers to the Canadian Climate Center scenario, CCSR the Center for Climate Systems Research scenario, and PCM the Parallel Climate Model scenario. 2) 'Current' refers to the baseline climate for 1970–2000.

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[2] In contrast, African annual mean temperature is 23° degree Celsius and annual mean precipitation is around 67mm/month. South America is much cooler and wetter than Africa.

Table 4 – Effect of climate change scenario on crop choice in South America

	Maize (%)	Potato (%)	Rice (%)	Soybean (%)	Squash (%)	Wheat (%)	Fruits (%)
Baseline	19.5	6.8	4.8	7.9	8.0	14.4	38.6
2020							
CCC	−0.7	−1.4	1.3	−0.5	1.9	−0.7	0.2
CCSR	−1.5	−1.8	1.7	−0.4	2.2	−0.2	0.0
PCM	1.9	4.9	0.0	−1.2	−2.2	−4.9	1.4
2060							
CCC	−1.2	−0.8	0.3	−1.1	4.3	−2.2	0.7
CCSR	−0.3	−2.0	0.3	0.3	3.2	−3.1	1.6
PCM	2.2	3.8	0.9	−1.1	−1.7	−6.3	2.1
2100							
CCC	−3.3	2.2	1.1	−3.3	9.7	−5.0	−1.3
CCSR	−0.7	−2.5	0.1	−0.6	5.5	−3.0	1.1
PCM	3.1	2.7	−0.1	−1.2	−1.3	−6.5	3.2

Note: 1) CCC refers to the Canadian Climate Center scenario, CCSR the Center for Climate Systems Research scenario, and PCM the Parallel Climate Model scenario. 2) 'Baseline' refers to the observed distribution in the sample.

(PCM) scenario (Washington et al. 2000). We use country level climate change scenarios in 2020, 2060, and 2100 from each climate scenario. The change in temperature predicted by each climate model is added to the baseline temperature in each district. The percentage change in precipitation is multiplied by the baseline precipitation in each district. This gives us a new climate prediction for every district in South America for each scenario.

Table 3 summarizes the climate scenarios of the three models for the years 2020, 2060, and 2100. The models predict a broad set of scenarios consistent with the range of outcomes in the most recent IPCC report (Intergovernmental Panel on Climate Change, 2007). In 2100, PCM predicts a 2 °C temperature increase in South America whereas CCC predicts a 5 °C increase. Rainfall predictions are noisier: PCM predicts rainfall to increase by 8% by 2100 whereas CCC predicts rainfall to decrease by 8%. CCSR scenario predicts changes of the magnitude between that of PCM and of CCC for both temperature and precipitation. Examining the path of climate change over time reveals that temperatures are predicted to increase steadily until 2100 for all three models but precipitation will vary across time. The climate models also predict slightly different climate changes in each country.

We assume that the cross-sectional evidence used in the estimation is appropriate to predict future changes in long run equilibriums. The parameters from the estimated choice model in Table 1 are used to simulate the impacts of climate change on the probabilities of choosing a particular crop for each climate scenario in Table 3.

Table 4 describes the results. The dryer and hotter CCC and CCSR scenarios predict that farmers would choose rice, squash, and fruits and vegetables more often, but maize, potatoes, soybean, and wheat less often by 2020. With the milder and wetter PCM scenario, farmers will pick maize and potatoes more often in addition to fruits and vegetables. There is no noticeable effect on rice. They tend to choose soybean, rice and wheat less often under PCM scenario. In all three climate scenarios, the direction of the change in crops remains the same but the magnitude of the crop switching grows. More farmers switch as the climate scenario becomes more severe. For example, the amount of crop switching increases in 2060 and again in 2100. Further, comparing the climate scenarios, the more severe the climate scenario, the more likely farmers switch crops.

6. Conclusion and policy discussions

This paper uses a multinomial choice model to capture the choice of crops made by farmers. The model is estimated across 949 farmers in South America. We observe that the choice among the seven most popular crops in South America varies with climate. Farms that are cooler are more likely to choose potatoes and wheat, average temperature farms tend to choose maize, soybeans and rice, and farms in warm locations choose fruits and vegetables and squash. Farms in dry locations tend to choose maize and potatoes, farms in moderately dry conditions tend to pick soybeans and wheat, farms in wet conditions choose fruits and vegetables, squash, and rice. These cross-sectional results suggest that farmers have adjusted crop choice to fit their local climate conditions.

Although crop switching has not generally been captured by the climate change impact literature, crop switching is quite consistent with broad observations of where species are currently located. Maize is grown from Argentina to Venezuela. Potatoes are concentrated in the mountains of Chile and Columbia. Rice is the crop of choice in Ecuador. Soybeans and squash are concentrated in Uruguay, northern Argentina, and southern Brazil. Wheat is chosen in cooler parts of Chile. Fruits are the primary choice of hot Brazilian farms. If climate changes, this current distribution of crops across the landscape in South America will shift as individual farmers switch crops to respond to a new climate. The model anticipates how farmers might switch from cool loving crops in South America to warm loving crops currently grown in South America. The model does not consider new crops that might get introduced into the crop mix from either importation or research. The model therefore underestimates the likely substitution available in the future. On the other hand, the research is focusing on long term adaptation. These changes may take farmers a long time to make. It is important to recognize these adaptations will not be instantaneous.

The crop choice model is quite consistent with the response functions from Africa (Kurukulasuriya and Mendelsohn 2007). This study also found that maize was grown across many temperature zones, that wheat favored cool dry regions, and that fruits and vegetables tended to be chosen in warmer wetter places.

We simulate climate change impacts for the three AOGCM scenarios based on the parameter estimates from the choice model. The dryer and hotter CCC and CCSR scenarios predict that farmers would choose squash, fruits and vegetables more often and maize, potatoes, soybeans, and wheat less often by 2020. There is no noticeable effect on rice. With the milder and wetter PCM scenario, farmers will pick potatoes and maize more often in addition to fruits and vegetables. These differential effects on crops are magnified over time.

In interpreting these results, there are several caveats that should be kept in mind. First, this analysis does not include price effects. Large changes in crop prices may alter the results. Second, the analysis does not take into account carbon fertilization. If it affects all crops identically, it may not matter. However, evidence suggests that some crops may benefit more from carbon fertilization than others. Third, we assume that adaptations can take place as needed. For example, farmers can switch from one crop to another as temperature increases and rainfall decreases. However, this may not be the case if the adjustment requires a heavy capital investment. Fourth, we assume that in forecasting climate change impacts, the only thing that changes in the future is climate. Many things, however, will change over the century such as population, technologies, institutional conditions, and reliance on animal power. Future studies should address these issues and provide ever more accurate measures of climate change impacts. Finally, the model does not include every variable that might influence crop choice. There remains the possibility that an omitted variable has biased the results.

Unfortunately, it was not possible to estimate incomes per crop as a function of climate because there were not enough observations of each crop. If conditional incomes could be estimated by crop, researchers could explicitly model crop switching and predict the overall economic impacts of climate change on South American farmers.

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