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An Analysis of Crop Choice:

Adapting to Climate Change in Latin American Farms[1]

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Abstract

This paper explores how Latin American farmers adapt to climate by changing crops. We develop a multinomial choice model of farmer's choice of crops. Estimating the model across over 2000 farmers in seven countries, we find that both temperature and precipitation affects the crops that Latin 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, and squash and in dryer locations maize and potatoes. Global warming will cause Latin American farmers to switch away from wheat and potatoes towards fruits and vegetables. Predictions of the impact of climate change must reflect not only changes in yields or net revenues per crop but also crop switching.

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1. Introduction

This paper uses cross-sectional evidence to explore how farmers adapt to exogenous environmental factors such as climate and soils. By comparing choices of farmers who face different conditions, the model uncovers how farmers adapt. In this paper, we apply this technique to study how climate affects the crop choice of Latin 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 (Smit and Pilifosova 2001). However, understanding adaptation is also important if one is interested in quantifying the impacts of climate change. Forecasts of the impact of climate on agriculture cannot rely solely on how climate affects a specific crop. The forecasts must also capture crop switching. Unfortunately, data limitations make it difficult to study the crop specific impacts of climate change in this paper. However, independent data on the effect of climate on yields of specific crops could be combined with the crop switching results of this study to obtain an overall measure of damages.

Climate impact studies have consistently predicted extensive impacts to the agricultural sector from climate change across the globe (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 (Adams et al. 1999; Mendelsohn et al 1994) predict that farmers will move away from crops with low yields and substitute new crops that will perform better in the new climate. Studeis 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 2006). This paper follows the approach taken in the African paper but explores the choices of farmers in Latin 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 Latin America. Section 4 discusses the estimation procedure and the empirical results. Three climate change scenarios from Atmospheric Oceanic General Circulation Models (AOGCM's) are then examined in Section 5. 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,…, 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. For example, K could include climate, soils, and price variables and S could include the age of the farmer and family size. The profit function is composed of two components: the observable component V and an error term, ε. The error term is unknown to the researcher, but may be known to the farmer. 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. However, the number of combinations is large and becomes difficult to model. Given the assumption that only the most important crop matters, we look at all available choices. 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:

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

More succinctly, farmer *i*'s problem is:

$$\arg\max_j [\pi_1^*(Z_i), \pi_2^*(Z_i), \ldots, \pi_J^*(Z_i)] \qquad (3)$$

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

$$P_{ji} = \Pr[\varepsilon_k(Z_i) - \varepsilon_j(Z_i) < V_j - V_k] \ \forall \text{ k} \neq \text{j where } \mathrm{V_j = V_j(Z_i)} \qquad (4)$$

Assuming ε is independently Gumbel distributed and $V_k = Z_{ki}\gamma_k + \alpha_k$,

$$P_{ji} = \frac{e^{Z_{ji}\gamma_j}}{\sum_{k=1}^{J} e^{Z_{ki}\gamma_k}} \qquad (5)$$

which gives the probability that farmer *i* will choose crop j among J species (McFadden 1973, Train 2001).

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. Data

The data this study relies upon came from a World Bank project to study climate change impacts on agriculture in Latin America. The project collected economic surveys at the farm level from the following seven countries: Argentina, Brazil, Chile, Colombia, Ecuador, Uruguay, and Venezuela. The countries were selected to represent the wide range of climate throughout South America and include representatives from both the Southern Cone and Andean regions. Districts within each country were selected to provide as much within country climate variation as possible. The original survey interviewed over 2000 farmers of which 949 farmers selected one of the crops that we are modeling. Some farmers focused strictly on livestock, some farmers picked other crops, and some farmers did not reveal which crops they grew.

Climate data came from two sources: US Defense Department satellites and weather station observations. We relied on satellite temperature observations and interpolated precipitation observations from ground stations (see Mendelsohn et al 2006 for a detailed explanation). Soil data were obtained from the FAO digital soil map of the world CD ROM. The soil data were extrapolated to the district level using GIS (Geographical Information System). The data set reports 26 dominant soil types.

4. Empirical results

In this analysis, we focus on the seven most important crops in the region: fruits and vegetables (31%), maize (24%), wheat (15%), squash (11%), rice (8%), potatoes (7%), and soybeans (4%). Altogether these seven crops generated about 85 % of the total revenue from crops.

In Table 1, we estimate the probability each species is selected using a multinomial choice model. 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. Other explanatory variables included three soil variables, farmer age, farmer education, household size, prices, and a dummy variable for a computer. The model is significant according to three tests of global significance. Most of the individual coefficients are significant. P-values show how significant each variable is. The positive coefficients imply that the probability of choosing each crop increases as the corresponding variable increases.

The coefficient on education is positive and significant for every crop in Tab1e 1. This effectively implies that lower educated farmers tend to grow fruits and vegetables, the omitted choice. Fruits and vegetables tend to be grown in more tropical climates. The association with lower education may simply reflect the fact that farmers in tropical zones are less educated. Maize and squash are more likely to be chosen if a farm has lithosols and luvisols. Potatoes and soybeans are more likely to be chosen if a farm has planasols. Farms with computers are more likely to choose potatoes, rice and squash. 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. Larger farm families are less likely to choose maize and soybeans. These crops are easily mechanized and so may be selected by farmers with smaller families. Older farmers are more likely to choose wheat.

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 remainder of the price effects are cross price terms. When wheat prices are higher, farmers are more likely to pick potato and soybean. When maize prices are higher, they are more likely to pick rice but less likely to pick squash. When squash prices are higher, they are more likely to pick maize, soybean, and wheat. Higher tomato prices are associated with maize and wheat. These positive cross price terms imply a complementarity between the two crops in question.

Maize and soybeans do not have any significant climate coefficients but all the other crop choices do. There are many varieties of maize and soybeans so that they can effectively grow in many climate zones in Latin America. The two crops are in this sense "generalists". In contrast, the other crops are specialized to grow under certain temperature or precipitation ranges. Rice for example is temperature sensitive. Potatoes and squash are precipitation sensitive. Wheat is both temperature and precipitation sensitive. Fruits and vegetables generally prefer warmer temperatures.

Figure 1 reveals that the choice of crop varieties in Latin America is temperature sensitive. The graph describes the relationship between the probability of choosing a crop and annual mean temperature measured in ˚C. Note that the mean annual temperature in Latin America is 18°C. The probability of choosing wheat and potatoes is high in the farms at the cooler place but much lower in the farms at the warmer place. By contrast, the probability of choosing fruits and vegetables is low in cool farms but much higher in warmer farms. The rest of the crops have hill-shaped relationships with temperature. The probability of being selected at first increases as one moves from cool to warm farms and then it decreases as one moves to even warmer farms. With maize, the peak probability of being chosen is about 13˚C. With rice and soybeans, the peak is closer to 16˚C. With squash, the peak is closer to 20˚C.

Figure 2 displays the estimated relationship between the probability of choosing a crop and annual precipitation measured in mm/mo. The mean annual precipitation in Latin America is 118 mm/month. The probability of choosing maize and potatoes declines precipitously as one moves from dry to wet farms. By contrast, moving from dry to wet farms increases the probability of selecting fruits, rice, and squash. Wheat and soybeans exhibit a hill-shaped pattern. They are less likely to be picked in very dry farms, more likely to be picked in moderately dry farms, and then less likely to be picked in wet farms. The peak condition for wheat and soybeans is around 70 mm/mo which is well below the average precipitation in Latin America.

5. Climate scenarios

In this section, we simulate the consequences of climate change using the parameter estimates in the previous section. We examine a set of climate change scenarios predicted by AOGCMs. The climate scenarios reflect the A1 SRES 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 (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 gave us a new climate for every district in Latin America for each scenario.

Table 2 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 (Intergovernmental Panel on Climate Change) report (Houghton et al. 2001). In 2100, PCM predicts a 2°C temperature increase in Latin 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%. 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.

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 2.

Table 3 describes the results. The dryer and hotter CCC and CCSR scenarios predict that farmers would choose fruits and vegetables more often and maize, potatoes, squash, and wheat less often by 2020. There is no noticeable effect on rice. With the milder and wetter PCM scenario, farmers will pick potatoes, rice, and wheat more often in addition to fruits and vegetables. In all three climate scenarios, the magnitude of the crop changes grow over time as the climate scenario becomes more severe. For example, the crop switching in 2060 and 2100 is more common. The more severe is the scenario, the more crop switching is predicted.

6. Conclusion

This paper uses a multinomial choice model to capture the choice of crops made by farmers. The model is estimated across almost 1000 farmers in Latin America. We observe that the choice of species 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 Colombia. 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.

The crop choice model is quite consistent with the response functions from Africa (Kurukulasuriya and Mendelsohn 2006). 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 fruits and vegetables more often and maize, potatoes, squash, and wheat less often by 2020. There is no noticeable effect on rice. With the milder and wetter PCM scenario, farmers will pick potatoes, rice, and wheat 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.

Unfortunately, it was not possible to estimate incomes per crop as a function of climate because there were not enough observations. However, results from other studies that predict the yields of crops in different climates could be combined with the crop switching results in this paper in order to predict the overall economic impacts of climate change on Latin American farmers.

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Table 1: Multinomial logit crop selection model

	Maize			Potato		
Variable	**Est.**	χ^2	**P-value**	**Est.**	χ^2	**P-value**
Intercept	4.444	1.35	0.246	-23.338	2.10	0.147
Temperature summer	0.025	0.00	0.944	0.130	0.03	0.857
Temperature summer sq	-0.001	0.02	0.890	-0.029	1.45	0.228
Precipitation summer	-0.004	0.42	0.519	0.234	112.40	<.0001
Precipitation summer sq	0.000	0.00	0.991	-0.002	1008.65	<.0001
Temperature winter	-0.122	0.50	0.480	1.844	15.75	<.0001
Temperature winter sq	0.003	0.25	0.620	-0.073	16.78	<.0001
Precipitation winter	0.005	0.73	0.393	-0.058	4.50	0.034
Precipitation winter sq	0.000	0.16	0.691	0.000	8.34	0.004
Soil_Lithosols	0.013	2.39	0.122	0.074	17.49	<.0001
Soil_Luvisols	-0.021	3.11	0.078	0.039	4.01	0.045
Soil_Planasols	0.007	0.84	0.361	0.024	4.98	0.026
Computer_dummy	0.269	1.37	0.241	0.761	2.49	0.115
Age_head	0.009	0.56	0.456	0.038	2.22	0.137
Log household size	-0.909	8.40	0.004	-1.215	5.11	0.024
Log education	0.106	0.21	0.645	1.004	4.32	0.038
maize_pr	0.460	11.95	0.001	0.688	2.31	0.129

wheat_pr	18.724	21.92	<.0001	-44.745	5.86	0.016
squash_pr	-26.401	17.74	<.0001	79.127	2.02	0.156
mango_pr	-2.015	1.80	0.179	-7.649	0.43	0.513
tomato_pr	4.290	4.92	0.027	-2.876	0.43	0.511

Table 1: continued

		Rice			Soybean	
Variable	**Est.**	χ^2	**P-value**	**Est.**	χ^2	**P-value**
Intercept	-11.823	0.49	0.486	-6.536	0.52	0.471
Temperature summer	4.046	4.29	0.038	0.528	0.37	0.543
Temperature summer sq	-0.151	4.79	0.029	-0.010	0.18	0.670
Precipitation summer	0.045	5.63	0.018	0.002	0.09	0.762
Precipitation summer sq	0.000	6.95	0.008	0.000	0.16	0.691
Temperature winter	-1.380	3.85	0.050	0.088	0.09	0.760
Temperature winter sq	0.078	6.89	0.009	-0.013	1.92	0.165
Precipitation winter	0.097	2.56	0.110	0.052	3.06	0.081
Precipitation winter sq	0.000	1.72	0.190	-0.001	4.16	0.041
Soil_Lithosols	0.000	0.00	0.996	0.006	0.32	0.573
Soil_Luvisols	0.031	1.74	0.187	-0.015	0.96	0.328
Soil_Planasols	-0.052	0.00	0.996	0.026	10.67	0.001
Computer_dummy	0.656	2.19	0.139	-0.108	0.19	0.667
Age_head	0.004	0.03	0.867	0.017	0.95	0.330
Log household size	-0.937	1.95	0.163	-0.998	5.39	0.020
Log education	-0.030	0.00	0.953	1.085	7.21	0.007
maize_pr	1.563	15.83	<.0001	0.099	0.08	0.771

wheat_pr	27.751	2.87	0.090	16.910	5.96	0.015
squash_pr	-113.900	2.09	0.148	-20.114	6.78	0.009
mango_pr	-11.597	2.88	0.090	0.391	0.01	0.911
tomato_pr	10.581	2.43	0.119	-2.765	0.50	0.478

Table 1: continued

	Squash			Wheat		
Variable	**Est.**	χ^2	**P-value**	**Est.**	χ^2	**P-value**
Intercept	7.774	0.66	0.418	5.292	1.07	0.301
Temperature summer	-1.255	1.86	0.173	-0.091	0.04	0.846
Temperature summer sq	0.036	2.30	0.130	0.006	0.22	0.642
Precipitation summer	0.044	7.19	0.007	0.009	0.60	0.438
Precipitation summer sq	0.000	4.85	0.028	0.000	5.66	0.017
Temperature winter	-0.149	0.23	0.630	-0.561	3.96	0.047
Temperature winter sq	-0.002	0.06	0.809	0.004	0.13	0.714
Precipitation winter	0.014	1.18	0.278	-0.005	0.14	0.708
Precipitation winter sq	0.000	0.44	0.506	0.000	4.77	0.029
Soil_Lithosols	0.011	1.40	0.237	-0.015	1.44	0.231
Soil_Luvisols	-0.152	0.44	0.506	-0.015	1.00	0.316
Soil_Planasols	-0.005	0.20	0.652	0.031	14.36	0.000
Computer_dummy	-0.066	0.09	0.759	0.057	0.05	0.828
Age_head	0.005	0.10	0.752	0.035	4.12	0.042
Log household size	-0.031	0.01	0.940	-0.841	3.78	0.052
Log education	0.629	4.83	0.028	1.512	15.03	0.000

maize_pr	-2.459	3.76	0.053	0.104	0.15	0.703
wheat_pr	4.026	0.53	0.468	33.562	23.18	<.0001
squash_pr	-7.197	1.13	0.288	-27.264	9.51	0.002
mango_pr	-1.387	4.92	0.027	-2.009	0.64	0.425
tomato_pr	0.451	0.02	0.882	-19.580	6.29	0.012

Fruits and vegetables are the omitted choice. Likelihood ratio test: P<0.0001, Lagrange multiplier test: P<0.0001, Wald test: P<0.0001.

Table 2: Marginal Effect of Climate Change on Crop Choice in Latin America

	Maize	Potato	Rice	Soybean	Squash	Wheat	Fruits
Baseline	19.5%	6.8%	4.8%	7.9%	8.0%	14.4%	38.6%
Temp	-0.2%	0.5%	0.4%	0.2%	0.7%	-2.3%	0.8%
Prec	-0.3%	0.2%	0.1%	0.0%	0.1%	-0.1%	-0.2%

Table 3: Latin 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%)

Table 4: Effect of Climate Change Scenario on Crop Choice in Latin 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%

Figure 1: The effect of annual temperature on the probability of choosing a crop.

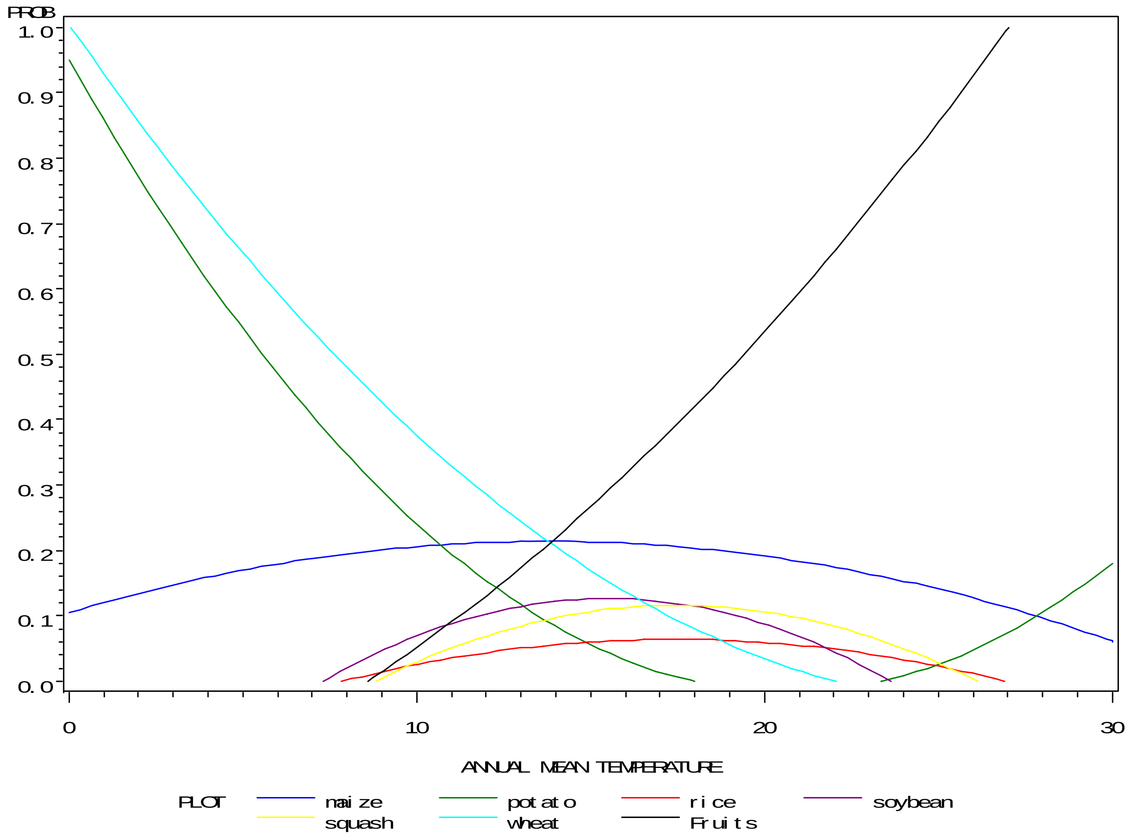

Figure 2: The effect of annual precipitation on the probability of choosing a crop