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What explains agricultural performance: climate normals or climate variance?

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Abstract This paper measures the influence of climate normals (average long-term surface wetness and temperature) and interannual climate variance on farms in the United States and Brazil using satellite data. The paper finds that just climate normals or just climate variance variables can explain both net revenues and how much land is used for cropland. However, because they are correlated with each other, it is important to include both normals and variance in the same statistical model to get accurate measures of their individual contribution to farm outcomes. In general, higher climate variance increases the probability that land is used for cropland in both countries and higher temperatures reduce both cropland and land values. Other annual effects were not consistent across the two countries.

1 Introduction

Provided that there is enough climatic variation across a sample, cross-sectional analysis can reveal the influence of climate, soils, and other relevant production conditions on farm

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value per hectare (Mendelsohn and Nordhaus 1999; Mendelsohn et al. 1994, 2001). Crop experiments have confirmed a hill-shaped relationship between crop productivity and temperature normals (e.g., Rosenzweig and Parry 1994). Further, agronomic studies suggest that daily climate variance is more important than climate normals (Mearns et al. 1997). In this paper, we use cross sectional methods to explore the relative importance of climate normals versus interannual climate variance on agriculture. There is an important difference between this economic analysis and the earlier agronomic work. If farmers can adapt to the observed weather they see in a season, they can take advantage of good years and avoid losses in bad years making climate variance helpful. If they cannot adapt, then variance should be harmful. The agronomic researchers may be correct in assuming that farmers cannot adapt to daily variance. However, it is important to test whether farmers are able to adapt to interannual variance or not.

The paper tests the relative importance and effect of climate normals versus interannual climate variance on both value per hectare of farmland and the fraction of land used for cropland in both Brazil and the United States. The analysis begins by including just normals and then just variance in a pair of regressions to compare the two measures. For both sets of variables, the percent of cropland and the value per hectare of cropland is regressed on climate and other important control variables such as soils and socioeconomic data. The study finds that interannual variance and climate normals can both explain what land is used for cropland and how valuable it is. The study surprisingly finds that interannual variance generally increases both farm values per hectare and the fraction of land in cropland.

We then test a hypothesis first raised by Schneider (1997) that argues the effect of climate normals would be different if climate variance was included in cross-sectional analysis. To test the hypothesis, a third regression is estimated that includes both normals and variance together. This final set of regressions explores the individual contribution of each climate variable controlling for the other. Because climate normals and interannual variance are correlated, the results of this final set of regressions sometimes differ from the earlier analysis, confirming the Schneider hypothesis. Specifically, higher temperature is more harmful to cropland controlling for variance.

2 Methodology

The Ricardian method is a cross-sectional approach to study agricultural production. The method was named after Ricardo because of his original observation that land rents would reflect the net productivity of farmland. Net revenue (NR) consequently reflects net productivity and costs across crops i:

$$NR = \sum P_i Q_i(X, F, Z, G) - \sum RX \tag{1}$$

where P_i is the market price of crop i, Q_i is the output of crop i, F is a vector of climate variables, Z is a set of soil variables, G is a set of economic variables such as market access, X is a vector of purchased inputs (other than land), and R is a vector of input prices (see Mendelsohn et al. 1994). The farmer is assumed to choose X and crops i to maximize net revenues given the characteristics of the farm and market prices. The Ricardian model is a reduced form model that examines how a set of exogenous variables, F, Z, and G, affect net revenue. Land values are simply the present value of net revenues, so an intertemporal variation of the formula above also applies to land value.

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

$$NR = B_0 + B_1F + B_2F^2 + B_3Z + B_4G + u \tag{2}$$

where u is an error term. Both a linear and a quadratic term for temperature and surface wetness are introduced. This paper extends this simple formula to include temperature and surface wetness interannual variance terms as well. We introduce squared terms for the variance expressions because there is no *a priori* reason to believe the effect of variance is strictly linear. The marginal influence of each climate variable consequently depends upon its level:

$$dNR/df_i = b_{1,i} + 2*b_{2,i} * f_i \tag{3}$$

The quadratic term reflects the nonlinear shape of the climate response function. When the quadratic term is positive, the response function is U-shaped and when the quadratic term is negative, the function is hill-shaped. Based on agronomic research and previous cross-sectional analyses, there is a temperature range where each crop grows best across the seasons. Sites that are either too cool or too hot have lower productivity. Crops consistently exhibit a hill-shaped relationship with annual temperature, although the maximum of that hill varies with each crop. Seasonal variables, however, can take on many shapes. The Ricardian model, however, is estimated across crops so that its shape depends upon the relative profitability of different crops at different temperatures.

Although the Ricardian technique carefully measures the influence of climate, it has been criticized for omitting the influence of irrigation and water from runoff (Cline 1996; Darwin 1999). Irrigation is clearly quite important as irrigated farms have different climate sensitivities compared to dryland farms (Mendelsohn and Dinar 2003; Schlenker et al. 2005). In this study, separate information is not available for dryland versus irrigated farms. The early empirical models also did not include runoff from other sources and so they did not capture the value of exogenous water supplies (compare Mendelsohn et al. 1994 to Mendelsohn and Dinar 2003). In this study, water runoff is not available for Brazil and so it is not included.

3 Data and empirical specifications

Past cross sectional studies have relied on global land surface temperature and precipitation from weather stations. Unfortunately, these stations are neither located evenly nor densely around the globe. Ground stations are mainly in populated and industrialized regions (for example, airports). Observations are sparse over rural regions of Africa, tropical South America, and southeastern and central Asia. An alternative technique based on satellite observations was consequently developed to derive the global distribution of land surface temperature and surface wetness (Williams et al. 1999; Basist et al. 2001).

The Defense Department has maintained a set of polar orbiting satellites that pass over the entire earth at 6 A.M. and 6 P.M. every day. These orbits are particularly attractive because they pass over the same location at the same time daily. These satellites are equipped with sensors that detect microwaves that can pass through clouds. The Special Sensor Microwave Imager (SSM/I) can detect both surface temperature (McFarland et al. 1990, Neale et al. 1990, Njoku 1994, Weng and Grody 1998) and surface wetness (Basist et al. 1998). Unfortunately, the satellite cannot measure climate conditions in frozen conditions so that winter climate variables were not available for the US.

A major difficulty in deriving surface temperature from passive microwave measurements is the variable emissivity associated with different surfaces. For the microwave spectrum the emissivity of soil depends on its water and/or mineral content, as well as the effects of vegetation and surface roughness. Since the microwave emissivity is variable, the brightness temperature is not a function of surface temperature alone. Therefore, any algorithm that attempts to estimate surface temperature must first infer the particular surface condition for a microwave measurement, and either make appropriate emissivity adjustments to the microwave measurement, or filter the measurement if reliable adjustments are not possible. The approach used here assumes no *a priori* information about the surface conditions, allowing the satellite observations to provide a dynamic assessment of the surface type and current emissivity.

The Basist Wetness Index (BWI) is simply the emissivity adjustment associated with water on the radiating surface. Surface wetness has strong correspondence with the upper level surface wetness and we rely on surface wetness as our measure of moisture throughout this paper. Wetness originates from multiple sources (i.e., precipitation, snowmelt, and irrigation).

There is an important difference between the satellite surface wetness measures and precipitation. Surface wetness measures the amount of water at the surface. From an agronomic perspective, surface wetness may be a more attractive measure than rainfall as it reflects the moisture actually available to crops. Surface wetness, however, is a complex measure. First, surface wetness has a memory, it reflects not just precipitation but also past precipitation. Second, surface wetness varies with soil type. Soils with more organic material can hold moisture longer whereas sandy soils cannot. Third, surface wetness can be affected by management decisions. Irrigated land, for example, has more surface wetness simply from diverted water. Fourth, surface wetness can be distorted by nearby water bodies. Fifth, surface wetness over closed canopy forests tends to measure the wetness at the top of the canopy, not at the soil surface.

The products used in this study are monthly climatologies for surface wetness and temperature from the period January 1988 to 2002 for the United States and Brazil. We use both the average value of each measure in each month and the interannual variance. The spatial resolution is one third degree (approximately 30 Km) for both data products. The centroid of each pixel is associated with the centroid of counties in the United States and municipios in Brazil. All of these divisions have approximately the same resolution, although the municipios are slightly smaller.

One concern with the satellite data is that it includes only 15 years of data. Although this may be sufficient to get a reasonable estimate of climate normals (averages), it is probably too short a period to get a reliable estimate of climate variance. The 15-year period will not capture longer term cycles in weather.

Brazil and the US were selected because they are both large countries, they are located in different climate zones, and they have different development levels (Mendelsohn et al. 2001). They were also chosen because they have existing farm data at a fine geographic detail.

Data concerning farms for the United States was collected from US Census of Agriculture survey in 1997. The value of farms per hectare is used as the measure of land value. Soil data was collected from the National Resource Inventory for each county (see Mendelsohn et al. 1994 for details). US socioeconomic data come from the US Census of Population (2000 and 1990). In both Brazil and the US, net area sown divided by total area is the measure of the fraction of land in cropland. Data concerning Brazil was collected by the Instituto Brasiliero de Geografia e Estatica (IBGE) from the Census of Agriculture http://www.ibge.gov.br). The net revenue per year was used to measure land value in Brazil.

Table 1 Means and standard deviations of climate and economic variables in the US and Brazil

Variable	Mean US	Brazil mean
Land value (net revenue)	3,100 (1,994)	1,000 (917)
% Cropland	33 (26)	2 (2)
January temperature	...	21.0 (2.3)
April temperature	12.7 (3.3)	19.2 (2.8)
July temperature	22.0 (2.8)	17.0 (4.2)
October temperature	12.7 (2.7)	20.1 (3.6)
January soil wetness	...	3.1 (3.9)
April soil wetness	4.1 (3.1)	3.5 (4.0)
July soil wetness	2.8 (2.6)	3.7 (4.5)
October soil wetness	3.1 (2.7)	3.4 (4.3)

Standard deviations are in parentheses.

Three years of data (1990, 1995, 2000) were combined to provide a long run measure of net revenue.

The means and standard deviations of land value, net revenues, % cropland, and the climate normals are presented in Table 1. The sample only includes counties that have some cropland. Urban counties were also dropped from the sample because urban land values are determined by many non-climatic factors. Note that there is substantial variation in land values and percent cropland across the sample in each country. There is also substantial variation in the climate variables. Although Brazil is on average hotter than the US, summer temperatures in the US (July) are hotter than summer temperatures in Brazil (January).

4 Results

The first set of regressions compares the influence of using just climate normals versus just interannual climate variance variables. We measure two responses by agriculture: changes in land value per hectare and changes in the percent of land used for cropland. Table 2 presents the results for the United States. The first column explores the effect of climate normals on land value and the second column reflects the effect of climate variance on land value. Both regressions include an identical set of control variables for soils, altitude, and economic forces. Looking at the R squares of both regressions reveals that the climate normals slightly outperform the climate variance terms. Most of this superior performance is because of the temperature variables. The seasonal temperature coefficients are significantly different from zero, whereas the temperature variance effects are insignificant. Looking at the joint effects of the linear and squared normal terms, higher spring and fall temperatures increase land value but higher summer temperatures reduce land values. The spring and fall effects reflect the benefits of longer growing seasons and the summer effect reflects the harm of extreme summer temperatures.

The surface wetness normal coefficients are less significant than the surface wetness variance coefficients although both are statistically different from zero. Combining the linear and squared normal terms, the only significant effect is that higher surface wetness values in the fall are beneficial. Combining the linear and squared terms of the surface wetness variance coefficients reveals a positive significant effect in the summer and a negative significant effect in the fall. Most of these seasonal surface wetness effects are the opposite of earlier results found with precipitation and are difficult to explain. Moisture in the summer is usually beneficial whereas moisture in the fall can be harmful as many crops ripen. Moisture variance is generally expected to be harmful during the growing season.

Table 2 Climate normal and variance regressions for the United States (2,000 USD/year/hectare)

Independent	Dependent variable					
Variables	Land value ($/hectare)			Percent cropland		
	Normals	Variance	Nor. + var.	Normals	Variance	Nor. + var.
Constant	34,300	4,370	3,120	−407	−1,870	−2,820
	(15.58)	(1.63)	(9.18)	(1.57)	(6.03)	(7.54)
April temp.	1,360	...	858	100	...	35.3
	(6.36)		(3.46)	(3.40)		(1.18)
July temp.	−3,280	...	−3,200	83.8	...	187
	(14.61)		(13.33)	(3.12)		(7.00)
October t.	−120	...	376	−220	...	−150
	(0.51)		(1.42)	(6.96)		(4.77)
April t. sq.	−54.0	...	−38.5	−2.7	...	1
	(6.67)		(4.21)	(2.43)		(0.50)
July t. sq.	59.6	...	59.2	−0.6	...	−4.2
	(12.22)		(11.16)	(0.91)		(6.69)
Oct. t. sq.	18.4	...	1.3	5.2	...	3.2
	(1.98)		(0.13)	(4.40)		(2.74)
April t. variance	...	−267	148	...	284	377
		(0.32)	(0.19)		(2.78)	(3.86)
July t. variance	...	−169	−467	...	50	−47.9
		(0.55)	(1.63)		(1.28)	(1.27)
October t. variance	...	−687	1,120	...	326	276
		(0.94)	(1.65)		(3.73)	(3.38)
April t. var. squared	...	−25.6	3.0	...	−29.4	−39.7
		(0.34)	(0.04)		(3.13)	(4.40)
July t. var. squared	...	−9.4	34.2	...	−4.2	9.2
		(0.31)	(1.24)		(1.07)	(2.38)
October t. var. sq.	...	41.0	−115	...	−25.1	−20.4
		(0.57)	(1.73)		(2.79)	(2.44)
April surface wetness	40.	...	−218	50.0	...	−45.2
	(0.53)		(2.03)	(4.43)		(3.27)
July surface wetness	−204	...	−446	187	...	133
	(2.33)		(3.52)	(14.87)		(8.42)
October surf. wetness	212	...	639	−175	...	−98
	(2.15)		(4.34)	(12.17)		(5.28)
Apr. surface wetness sq.	5.7	...	10.2	−0.6	...	3.7
	(1.29)		(1.84)	(0.88)		(5.22)
Jul. surface wetness sq.	37.2	...	46.4	−4.9	...	−3.7
	(4.27)		(4.51)	(4.08)		(2.93)
Oct. surface wetness sq.	−42.3	. ...	−55.0	2.5	. ...	−0.4
	(2.33)		(5.14)	(2.03)		(0.33)
April surface wetness var.	...	−301	−94	...	87	76
		(3.45)	(0.96)		(7.63)	(6.01)
July surface wetness var.	...	598	334	...	105	6
		(6.15)	(2.82)		(8.31)	(0.38)
October surf. wetness var.	...	−355	−193	...	−73	16.3
		(3.39)	(1.59)		(5.64)	(1.07)
April surface wet var. sq.	...	50.5	24.4	...	−3.0	−4.1
		(7.84)	(3.55)		(3.45)	(4.57)
July surface wet var. sq.	...	−45.6	−19.4	...	−7.2	−1.3

Table 2 (Continued)

Independent Variables	Dependent variable					
	Land value ($/hectare)			Percent cropland		
	Normals	Variance	Nor. + var.	Normals	Variance	Nor. + var.
		(4.18)	(1.72)		(5.58)	(0.96)
October surf. wet var. sq.	...	−6.4	−1.6	...	1.5	−0.5
		(0.60)	(0.15)		(1.19)	(0.41)
Income per capita	215	297	205	17.7	14.7	8.9
	(9.88)	(12.54)	(8.95)	(6.75)	(5.72)	(3.58)
Population density	770	1,390	800	−0.1	0.4	0.3
	(7.65)	(12.98)	(7.82)	(0.72)	(2.99)	(2.25)
% Urban	301	184	296	4.1	−8.6	−1.6
	(3.41)	(1.87)	(7.38)	(0.36)	(0.763.41)	(0.15)
Population change	14.2	7.5	14.5	−1.8	−2.4	−1.1
	(5.88)	(2.76)	(5.78)	(6.36)	(8.55)	(3.91)
Altitude	−0.44	−0.52	−0.46	−0.03	0.00	−0.05
	(7.95)	(8.84)	(7.02)	(4.85)	(0.71)	(7.79)
% Flooding	−742	−998	−797	−144	−175	−122
	(4.62)	(5.57)	(4.84)	(8.26)	(10.02)	(7.56)
Soil erosion	−2,790	−4,020	−1,960	447	650	461
	(4.36)	(6.01)	(2.93)	(5.58)	(8.31)	(6.04)
Salinity	3,820	4,520	3,420	−247	−177	−222
	(6.03)	(6.41)	(5.30)	(2.14)	(1.58)	(2.11)
% Sand	−444	−1,160	−395	42.2	33.6	10.6
	(2.67)	(6.46)	(2.37)	(2.38)	(1.92)	(0.64)
Water capacity	1,460	992	1,360	33.3	210	46.6
	(9.65)	(6.05)	(8.50)	(1.54)	(1.01)	(2.29)
R^2	0.818	0.771	0.826	0.711	0.710	0.768

There are 1,580 observations in each regression. T statistics are in parenthesis. Crop coefficients are multiplied by 1,000.

Column 3 of Table 2 combines both normal and variance terms in the land value regression. Because climate normals and variance are correlated, it is important to include them both in a cross-sectional regression. Otherwise, the included climate variables can serve as a proxy for the omitted climate variables. Comparing columns 1 and 2 with column 3 reveals that the temperature normal coefficients become more negative in the combined regression but the temperature variance terms become more positive. That is controlling for temperature variance, higher temperature normals are predicted to be slightly more harmful. Controlling for temperature normals, higher temperature variance actually increase land value. Controlling for surface wetness variance, reduces the beneficial effects of higher surface wetness normals. Controlling for surface wetness normals, surface wetness variance is more beneficial.

Columns 4 and 5 in Table 2 explore the effect of climate normals and climate variance on percent cropland. Examining the R squares for the two regressions reveals that both regressions are equally able to explain the observed variation in percent cropland. In the cropland regressions, both seasonal temperature and seasonal temperature variance coefficients are significant. Examining the combined effect of both the linear and squared normal temperature terms, the only significant effect is the increase in cropland with higher spring temperature. Again this positive effect was expected because of longer growing seasons. The only significant effect of higher temperature variance is an increase in cropland in the fall. Higher soil wetness normals have no significant effects. The only significant effect of higher soil wetness variance is an increase in cropland from higher April variance. The beneficial effect of climate variance on the percent of cropland was not expected.

Column 6 in Table 2 combines both climate normals and climate variance in the percent cropland regression. As with the value regressions, the climate variance effects are strongly positive. Higher variance in both temperature and soil wetness lead to more land being used for cropland. Controlling for variance makes the temperature normal effect significantly negative, implying that warmer areas have less cropland. Controlling for variance changes the effect of the precipitation normal from being positive to insignificant. This implies that the soil wetness normal is not actually important, it only appears to be important in column 1 as a proxy for soil wetness variance.

In Table 3, we examine the identical set of regressions for Brazil. The dependent variable has changed to net revenue instead of land value, but we use the average of 1990, 1995, and 2000 net revenue so that the estimate reflects more than just a single year effect. Comparing the two regressions for land value with just climate normals and climate variance terms, we see that both regressions have the same overall explanatory power. In column 1, only the coefficients for the climate normal temperatures in winter and spring are significant. The temperature variance coefficients, in contrast, are significant in the spring, summer, and fall, which would be expected because this is the primary growing season. Combining the linear and squared terms, higher winter normal temperatures are beneficial and higher spring temperatures are harmful. These effects were not expected. Examining the temperature variance effects, higher spring and fall variances increase net revenue but higher summer temperature variance decreases net revenue. The variance effects could be explained if farmers cannot adjust to unusual summer temperatures but can make adjustments in planting and harvesting to accommodate unusual spring and fall temperatures. This is an adaptation by farmers to annual weather.

In column 3 of Table 3, we observe the effect of including both the climate normals and the variance terms in the net revenue regression. In the Brazilian data, climate variance is strictly a harmful effect, in direct contrast to the US results. Controlling for climate normals, the effect of both temperature variance and soil wetness variance become more negative. Controlling for variance, the effect of the temperature normals does not change but the effect of soil wetness normals becomes more positive.

Examining columns 4 and 5 in Table 3, reveals the effect of climate normals and climate variance on the percent of cropland in Brazil. The climate normal temperature coefficients are significant in every season. The climate variance coefficients are even more significant in every season except winter. Combining the effects of the linear and squared terms, higher normal temperatures in the fall and winter reduce cropland but higher spring and summer temperatures increase cropland. It is not clear why one is seeing this pattern across seasons. Higher soil wetness normals increase cropland in the summer and decrease cropland in the fall. The beneficial effect of soil wetness in the summer is expected with the high summer temperatures. Soil wetness may be more problematic in the fall when crops are ripening. Higher temperature variance increases cropland in the spring and fall but decreases cropland in the summer. Higher soil wetness variance increase cropland in the spring and fall but decreases cropland in the winter. The positive climate variance effects in the spring

Table 3 Climate normal and variance regressions for Brazil

Independent Variables	Dependent variable					
	Net revenue (cruzeiros/hectare/year)			Percent cropland		
	Normals	Variance	Nor. + var.	Normals	Variance	Nor. + var.
Constant	4,690	924	4,940.	−76.3	−39.5	−36.5
	(3.76)	(9.29)	(3.50)	(1.52)	(11.28)	(0.65)
January temperature	139	...	5,726	32.6	...	15.5
	(0.55)		(2.21)	(3.04)		(1.40)
April temp.	−363	...	−860	−62.5	...	−59.7
	(1.38)		(3.17)	(5.50)		(5.04)
July temp.	544	...	409	−176	...	−5.7
	(5.40)		(3.56)	(3.97)		(1.16)
October temperature	−642	...	−499	470	...	47.5
	(4.68)		(3.41)	(9.28)		(8.37)
Jan. t. sq.	−4.7	...	−12.8	−0.6	...	−0.30
	(0.80)		(2.11)	(2.39)		(1.12)
April t. sq.	−11.4	...	22.8	1.3	...	1.29
	(1.80)		(3.44)	(4.91)		(4.55)
July t. sq.	−12.8	...	−10.3	0.4	...	0.14
	(4.59)		(3.17)	(3.29)		(1.02)
Oct. t. sq.	12.0	...	9.7	1.0	...	−1.02
	(3.60)		(2.71)	(7.84)		(7.44)
Jan. t. variance	...	89.5	1,540	...	−10.0	−5.4
		(4.43)	(6.33)		(12.47)	(5.90)
April t. variance	...	−151	−217	...	11.6	10.0
		(6.56)	(7.90)		(12.64)	(9.44)
July t. variance	...	−27.6	−50	...	1.3	0.4
		(1.14)	(1.80)		(1.52)	(0.47)
October t. variance	...	−131	−197	...	16.9	12.0
		(3.12)	(3.86)		(10.88)	(6.63)
Jan. t. var. squared	...	−2.1	−7.6	...	0.5	0.26
		(1.48)	(4.35)		(9.76)	(4.16)
April t. var. squared	...	6.0	11.6	...	−0.6	−0.53
		(3.35)	(5.35)		(9.16)	(6.72)
July t. var. squared	...	1.5	3.4	...	−0.0	−0.11
		(0.78)	(1.64)		(0.43)	(1.73)
October t. var. sq.	...	12.2	19.0	...	−1.8	−1.33
		(2.58)	(3.37)		(10.46)	(6.84)
Jan. surface wetness	−354	...	−186	15.3	...	11.6
	(6.41)		(3.03)	(6.75)		(4.87)
April surface wetness	296	...	175	−11.2	...	−12.6
	(4.54)		(2.48)	(4.73)		(5.04)
July surface wetness	−126	...	−148	1.2	...	4.6
	(2.72)		(2.96)	(0.70)		(2.47)
October surf. wetness	192	...	248	−3.4	...	−3.4
	(4.76)		(5.25)	(2.01)		(1.87)
Jan. surface wetness sq.	8.1	...	3.5	−0.4	...	−0.32
	(3.91)		(1.59)	(5.93)		(4.22)
Apr. surface wetness sq.	−6.6	...	−4.4	0.3	...	0.35
	(2.62)		(1.69)	(3.62)		(4.00)

Table 3 (Continued)

Independent Variables	Dependent variable					
	Net Revenue (cruzieros/hectare/year)			Percent cropland		
	Normals	Variance	Nor. + var.	Normals	Variance	Nor. + var.
Jul. surface wetness sq.	3.8	...	3.3	−0.0	...	−0.09
	(2.08)		(1.66)	(0.61)		(1.25)
Oct. surface wetness sq.	−5.4	...	−5.0	0.1	...	0.05
	(3.18)		(2.47)	(1.65)		(0.74)
Jan. surface wetness var.	...	−15.7	−2.9	...	0.0	−0.2
		(1.81)	(0.29)		(0.16)	(0.76)
April surface wetness var.	...	−10.5	−5.5	...	0.8	1.2
		(0.92)	(0.45)		(2.22)	(3.14)
July surface wetness var.	...	16.9	15.8	...	−1.9	−1.6
		(1.46)	(1.29)		(4.45)	(3.71)
October surf. wetness var.	...	6.3	−29.4	...	1.1	0.9
		(0.61)	(2.47)		(2.75)	(2.27)
Jan. surface wet var. sq.	...	0.1	−0.01	...	0.00	0.00
		(0.71)	(0.19)		(1.10)	(1.23)
April surface wet var. sq.	...	0.1	0.01	...	−0.01	−0.01
		(1.06)	(0.07)		(2.05)	(2.62)
July surface wet var. sq.	...	−0.2	−0.16	...	0.01	0.01
		(1.95)	(1.90)		(3.57)	(3.28)
October surf. wet var. sq.	...	0.1	0.30	...	−0.01	−0.01
		(0.89)	(3.66)		(2.38)	(2.24)
Income per capita	56.8	60.6	49.0	1.1	2.1	1.4
	(12.98)	(15.19)	(11.10)	(5.76)	(12.22)	(7.66)
Soils 517	−304	−337	−350	7.5	8.6	8.0
	(3.51)	(3.87)	(4.06)	(2.60)	(3.06)	(2.89)
Soils 521	95	172	93	−3.0	−7.5	−4.1
	(2.40)	(4.51)	(2.38)	(2.12)	(5.46)	(2.96)
Soils 524	1,520	1,930	1,820	−10.6	−28.2	−19.1
	(11.08)	(14.02)	(12.95)	(3.03)	(8.14)	(5.35)
R^2	0.375	0.376	0.419	0.255	0.260	0.326

There are 2,153 observations in each regression. T-statistics are in parentheses. Crop coefficients multiplied by 1,000.

and fall may be due to the fact that farmers can adjust planting an harvesting to unusual weather outcomes in these seasons whereas they can do very little in the summer.

Column 6 in Table 3 explores the combined effect of both climate normals and climate variance on cropland in Brazil. The regression reveals that climate variance on net is beneficial to cropland. Places with more annual variation, especially temperature variation, have more cropland. Controlling for climate variance, the effect of temperature normals becomes slightly more negative (though not significant) and the effect of soil wetness goes from being positive and significant to being insignificant. Controlling for climate normals, the effect of climate temperature variance becomes slightly more positive and the effect of soil wetness variance becomes significantly more positive. The combined regression suggests that the individual climate coefficients in columns 4 and 5 were often biased.

Table 4 Elasticities of annual climate from combined regressions

Variable	Land value		Percent cropland	
	US	Brazil	US	Brazil
Annual temp.	−0.88*	−1.12	−0.82*	−1.58
Surface wetness	0.01	0.21*	−0.02	0.04
Annual t. var.	0.29	−0.78*	4.92*	2.04*
Surface w. var.	0.30*	−0.22*	0.95*	0.12

Note: Results measure the influence of a percentage change in the dependent variable for a percentage change in the climate variable using the coefficients from the combined regressions in Tables 2 and 3 and the mean values for each country.

*Statistically significant effects (at the 5% level)

Comparing the results in Tables 2 and 3, it is apparent that the R2 is much higher in the US. There are more independent variables available in the US and they clearly do a better job of explaining the range of land values across counties in the US. Another factor that hampers Brazil concerns land restriction laws that limit how much land a farmer can put into production. Because these laws are enforced unevenly, it can lead to substantial variation in land values across municipios. Although this problem clearly handicaps farmers in Brazil, it is not apparent that the regulations bias the climate results of this study.

In order to get an overall impression of the effect of temperature and surface wetness, Table 4 presents the elasticities of annual climate normals and variance from the combined regressions in Tables 1 and 2. The elasticities in Table 4 measure the percent change in the dependent variable for a percent change in the annual climate variable. For example, the US value for temperature in the land value regression implies that for every 10% increase in annual temperature, land values in the US would decline by 8.8%. Both the US and Brazilian results consistently suggest that higher temperatures would reduce land values and cropland although this latter effect is significant only in the US. Higher surface wetness would increase land values in Brazil but otherwise have no effect. The signs of the climate normal impacts are consistent across the two countries. Higher temperature variance would reduce cropland in the US but increase both land value and cropland in Brazil. Finally, higher surface wetness variance would reduce land value in Brazil but increase land value and cropland in the US. The different predicted effects of variance on land value between the US and Brazilian regressions reflect changes in the coefficients on the variance variables, not differences in the mean levels of variance between the two countries. It is not clear why they are different and which coefficients are more reliable.

5 Conclusion

The paper tests the relative importance of climate normals and interannual variance in explaining both the net revenue from cropland and the fraction of all land used for cropland. Samples are drawn from the United States and Brazil. Satellite data is used to provide consistent measures of climate across both countries.

The data analysis concludes that climate normals and climate variance play almost an equal role in determining net revenue and percent cropland. Both sets of variables have almost identical explanatory power. Despite having the same overall explanatory power, the seasonal effects of normals and variance are often different. For example, in the US, higher fall surface wetness increases land value but higher surface wetness variance decreases land value. In Brazil, higher spring surface wetness increases land value but higher surface wetness variance in the spring decreases land value. Higher fall surface wetness and temperature decrease cropland in Brazil but higher fall surface wetness and temperature increase cropland.

Climate normals are expected to be important because they determine the climate conditions for individual crops. Agronomic research has clearly identified that certain crops are more suited for certain climates. The more valuable the crops that can be grown in an area, the higher are the net revenues of farmers. Overall, there is a hill-shaped relationship between temperature and land value. The mean US temperature is near the top of that hill and so the temperature elasticities are lower for the US. Brazil is much warmer and so on a steeper portion of that hill. The temperature elasticities in Brazil are steeper.

Climate variance is also expected to be important, though it was not clear how important. Interannual variance explains how much weather may differ from year to year. The higher the variance, the more difficult it is for farmers to plan which crops to plant. If farmers cannot adapt to changes in weather, variance is harmful. However, if farmers can anticipate the differences across years, they can tailor crops to the actual weather conditions of each year. This analysis shows that variance is beneficial to US farmers and harmful to Brazilian farmers. The analysis implies that farmers in the US are more able to adapt to interannual variance. There are similar results for cropland. Places with more climate variance are more likely to be used as cropland in the US compared to Brazil.

Because variance and normals are correlated, controlling for both normals and variance together tends to change their individual effects. The variance terms become more negative in Brazil and more positive in the US. In both countries, the temperature normal effects became more negative and the precipitation normal effects went from positive to insignificant. The results suggest that including both normals and variance is important if one is trying to measure the individual influence of each variable. For example, if one were trying to determine what would happen if temperature rose but temperature variance did not, the combined regression is a better functional form.

The results indicate that global warming could have a large influence on agriculture as it changes the climate normals and possibly also climate variance. Warming will tend to decrease net revenues per hectare and probably also cropland. If warming reduces surface moisture, this will have additional harmful effects on Brazil. If warming increases temperature or precipitation variance, this may have beneficial effects on both US land values and cropland acreage. In Brazil, higher climate variance is expected to harm land values but at least temperature variance is likely to increase cropland. Warming impact specialists must consequently pay close attention to not only the changes in climate normals, but also possible changes in climate variance.

Of course, warming may cause more changes than just to normals and interannual variation. Warming might also affect El Nino cycles, intensity and frequency of storms, and diurnal cycles. These other possible changes in climate were not examined in this paper.

Global warming is also expected to lead to carbon dioxide fertilization. The widespread field and laboratory evidence that crops will be more productive in a CO2 enhanced world (Reilly et al. 1996) is not reflected in this cross sectional evidence. The beneficial CO2 fertilization effects must be added to these cross sectional results to get an unbiased expected net effect.

As global warming unfolds, successful adaptation must adjust to the new climate normals and variance. Although a lot of these adjustments will be made by farmers without any explicit government policies, it is clear that governments can help the private sector by publicizing both shifts in climate and successful responses by innovative farmers. Governments may also have other key adaptation roles to play in the agriculture sector.

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Appendix

1 Definition of Variables

January normal temperature average of December, January and February temperatures in Celsius from 1988–2002
April normal temperature average of March, April, and May temperatures in Celsius from 1988–2002
July normal temperature average of June, July, and August temperatures in Celsius from 1988–2002
October normal temperature average of September, October, and November temperatures in Celsius from 1988–2002
January temperature variance average of December, January and February interannual temperature variance from 1988–2002
April temperature variance average of March, April, and May interannual temperature variance from 1988–2002
July temperature variance average of June, July, and August interannual temperature variance from 1988–2002
October temperature variance average of September, October, and November interannual temperature variance from 1988–2002
January normal surface wetness average of December, January and February Basist Surface Wetness Index from 1988–2002
April normal surface wetness average of March, April, and May Basist Surface Wetness Index from 1988–2002
July normal surface wetness average of June, July, and August Basist Surface Wetness Index from 1988–2002
October normal surface wetness average of September, October, and November Basist Surface Wetness Index from 1988–2002
January surface wetness variance average of December, January and February interannual variation in the Basist Surface Wetness Index from 1988–2002
April surface wetness variance average of March, April, and May interannual variation in the Basist Surface Wetness Index from 1988–2002
July surface wetness variance average of June, July, and August interannual variation in the Basist Surface Wetness Index from 1988–2002
October surface wetness variance average of September, October, and November interannual variation in the Basist Surface Wetness Index from 1988–2002
Income per capita thousands of USD or cruzeiros per person
Soils 517 Planosolo
Soils 521 Moderate predisposition to erosion
Soils 524 Extreme predisposition to erosion
Population density people per kilometer squared
% Urban fraction of land in urban use
Population change change in thousands of people in county between decades
Altitude meters above sea level
% Flooding fraction of land in floodplain

Soil Erosion k factor
Salinity fraction of land with serious salt problems
% Sand fraction of land that is sandy
Water capacity ability of soil to hold moisture
Land value USD/hectare of farmland used for crops
Net revenue Cruzeiros/hectare per year
% Cropland fraction of land in county planted for crops

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