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The impacts of global warming on farmers in Brazil and India

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ABSTRACT

How big a threat is global warming to climate-sensitive and economically important sectors such as agriculture in developing countries? How well will farmers be able to adapt to the threats of global warming? This paper attempts to shed light on these two important questions. A cross-sectional analysis is employed to estimate the climate sensitivity of agriculture in Brazil and India. Using panel data from both countries, the study measures how net farm income or property values vary with climate, and consequently, how farmers in India and Brazil react and adapt to climate. The estimated relationships are then used to predict the consequence of alternative climate scenarios. Global warming by the end of the next century could cause annual damages in Brazil between 1% and 39% and between 4% and 26% in India, although some of this effect may be potentially offset by carbon fertilization. These estimates do not factor into account climate-induced extreme weather events.

1. Introduction

With the growing confidence that emissions of greenhouse gases will lead to climate change (IPCC, 2007a), it is increasingly important to understand what might happen when climate changes. One of the world's greatest fears is that warming will endanger global agricultural and food production. Most economic analyses of climate change impacts on agriculture have focused on developed countries and specifically the United States (Adams et al., 1990, 1995, 1999; Easterling et al., 1993; Kaiser et al., 1993a, b; Mendelsohn et al., 1994, 1999; Mendelsohn and Dinar, 2003). Although these studies have contributed to our understanding of climate impacts in the United States, they serve as a poor reference for what is likely to happen in large developing countries such as Brazil and India. Economic analyses of global trade impacts, such as Reilly et al., 1994, have assumed climate responses in developing countries and then explored the trade implications. However, these trade studies did not actually measure what would happen in developing countries.

There are two general approaches to measure the impact of climate on agriculture. The "scientific-modeling approach" begins with controlled scientific experiments measuring the effect of climate on crops and builds the results into agronomic and economic simulation models. The "cross-sectional" approach begins with cross-sectional data and estimates the effects of climate using empirical analysis across space. Both approaches have different strengths and weaknesses. The scientific approach has the strength of careful controls and explicit mechanisms. The scientific approach, however, is expensive so the results may not be representative. The scientific approach is also only as good as the model. There is an enormous burden on the researcher to include all relevant factors. The cross-sectional approach automatically includes hidden mechanisms brought on by climate because such mechanisms (for example, insects) are already present in every climate. Specifically, the cross-sectional approach includes farmer behavior, how farmers adjust to the climate in their region. The cross-sectional approach also tends to be representative because the empirical data is often measured in the places of interest. However, the cross-sectional approach does not have the careful controls of the scientific method and the mechanisms are often not clear. Furthermore, the cross-sectional approach cannot assess phenomenon that do not vary across space such as carbon dioxide levels. We advocate the use of both methods because they provide different insights. Both methods also serve as good checks on each other, alerting the researcher and the policy maker alike to possible problems when they differ and to more confidence when they agree.

Early information about what might happen to agriculture in developing countries came from agronomic studies (Reilly et al., 1996). Additional agronomic studies have recently been completed in India (Gadgil, 1995; Kumar, 1998; Lal et al., 1998). However, because of the reasons cited above, one must be cautious about interpreting these results. The studies have been

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done in only a few places, the studies have focused largely on grains and adaptation has been explored only to a limited degree (the most ambitious study to date is Rosenzweig and Parry, 1994). Lacking an economic component, the agronomic studies cannot determine optimal adaptation strategies for farmers and so tend to underestimate the beneficial effects of adaptation. Embedding agronomic results in economic frameworks has revealed that including efficient adaptation strategies is extremely important (Adams et al., 1990, 1995, 1999; Easterling et al., 1993; Kaiser et al., 1993a, b). Unfortunately, these agronomic–economic models have been applied mostly to the United States.

This paper provides a detailed empirical estimate of the impact of climate change on the agricultural sector in Brazil and India. Brazil and India were chosen because it is critical to do empirical studies of the impacts of climate warming in tropical countries. Both of these countries have large landmasses that span a variety of climate zones ranging from tropical to temperate. Both countries also have large and carefully measured agricultural sectors, which constitute 6% of Brazilian GDP and 23% of Indian GDP in 2002 (World Bank, 2008). Finally, both countries contain a broad range of agricultural activities from modern to relatively primitive farms. Thus, India and Brazil provide excellent opportunities to measure the climate sensitivity of developing country agriculture.

This study uses the Ricardian method to estimate the climate sensitivity of Brazilian and Indian farms. The Ricardian method was developed by Mendelsohn et al. (1994) to estimate climate effects using cross-sectional data. The method was named after Ricardo, an Italian economist who first noted that farm property values reflect the net productivity of the land. By looking at a cross-section of existing farms, the cross-sectional technique examines not only the direct impact of different environments on farms but also the indirect effects of farmer adaptation. Farmer adaptation is automatically included in the analysis because every farmer has adapted to where they live. When farm performance in one place is compared to another, the observation already includes all the changes each farmer has made to get the most from his own farm. Of course, comparisons across space may capture other differences as well. For example, in a developing country context, social and cultural conditions may also vary from one place to another and if they are not accounted for, they can bias the results.

The initial Ricardian studies in the United States revealed that farmer adaptation is extensive and important. These adaptations soften the blow of being in less than ideal environments and have allowed farmers to survive in a wide variety of settings. The Ricardian studies suggest that farmers are less sensitive to extreme environments than the agronomic models suggest. Furthermore, the Ricardian models estimated in the United States are consistent with results from agronomic–economic models that incorporate efficient adaptation (Adams et al., 1999). However, one must be cautious interpolating from the capital-intensive farms of the US to developing country farms. The same results may not be present or be as strong in the agricultural systems of developing countries.

The next section briefly reviews the Ricardian method, including its limitations. Section 3 presents the data and empirical methodology. Section 4 presents the results of the multiple regression analyses. Section 5 utilizes these empirical results to estimate the impacts from several climate change scenarios for India and Brazil. The paper concludes with a discussion of the policy implications.

2. Theory

In this study, we assume that individual farmers maximize their net revenues subject to their constraints. The constraints could be prices, land, water, climate, and technology. But the constraints could also be education and family size. Net revenue is defined broadly in this study to include own consumption. Thus, the modeling is quite consistent with economic models where farmers maximize utility instead of profit (Bardhan and Udry, 1999). The dependent variable in the Ricardian analysis is *agricultural net revenue per hectare.*

If use i is the best use for the land given a vector of environmental variables $\mathbf{E}$ and factor prices $\mathbf{R}$, the observed market rent on the land will be equal to the annual net revenues from the production of good i. Land rent per hectare, P_{L}, will be equal to net revenue per hectare:

$$P_{\mathrm{L}} = \frac{P_i Q_i(R, E) - C_i(Q_i, \mathbf{R}, \mathbf{E})}{L_i}, \tag{1}$$

where P_i and Q_i are, respectively, the price and quantity of good i; $C_i()$ is the relevant cost function; and L_i is the land area. The present value of land i is

$$V_i = \int [P_i Q_i(R, E) - C_i(Q_i, \mathbf{R}, \mathbf{E})]\, \mathrm{e}^{-rt}\, \mathrm{d}t. \tag{2}$$

The land value is equal to the discounted value of all future rents. This is the basic insight of Ricardo and it is this reason that the method was given the label, Ricardian method. The welfare value of a change in the environment from state A to B is

$$W = \sum V_{i\mathrm{B}} L_i - \sum V_{i\mathrm{A}} L_i, \tag{3}$$

where $V_{i\mathrm{A}}$ is the value per hectare of land in environmental state A and $V_{i\mathrm{B}}$ is the value per hectare of land in environmental state B. If there is no change in output prices, the welfare value of the change in the environmental variable is captured by the change in farm values, the change in the present value of net revenues, across differing environmental conditions.

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

The cross-sectional approach captures the direct effect of long-term climate. Because it is a long-term measurement, it also captures indirect effects. For example, the method captures the long-term changes in ecosystems that are tied to climate. Each farm is experiencing the insects and pests that are associated with the climate that the farm is in. Indirect effects of climate on ecosystems are therefore reflected in the measurements. One potential problem with this, however, is if the relationships change over time. For example, if future farmers can overcome pests at much lower cost, having a farm in a place with pest problems would be less problematic in the future compared to today. Because the Ricardian technique measures long-term impacts, it is also important to understand that it does not capture transition costs, and neither does it distinguish short-term resiliency from long-term adaptation (Easterling, 1996). The results are not intended to measure dynamic adjustments but rather simply comparisons of steady state outcomes (with and without climate change).

The Ricardian model has other limitations and assumptions. One drawback of the Ricardian model is that it assumes prices are constant. As argued by Cline (1996, 2007), this introduces a bias in the analysis. By assuming constant prices, the method overestimates benefits and damages (Mendelsohn and Nordhaus, 1996). The Ricardian approach, by relying on a cross-section, cannot adequately control for prices as all farms in the same country effectively face the same price set. However, calculating price changes is not a straightforward task for any country study as prices are a function of the global market. Studies that have claimed to take price changes into account have had to make gross assumptions about how world output would change with climate change (Adams et al., 1990, 1995, 1999). These global assumptions also may introduce bias, if they are not correct. Furthermore, even analysts who have assumed large agronomic impacts from global warming, predict that greenhouse gases would have only a small net effect on aggregate global food supply (Reilly et al., 1996). If aggregate supplies do not change a great deal, the bias introduced by the Ricardian assumption of constant prices is likely to be small (Mendelsohn and Nordhaus, 1996). If the supplies of some commodities increased and others decreased, welfare effects would offset each other. In this case, the bias could be large relative to the remaining small net effect. However, even in this case, the absolute size of the bias would remain small. In a separate analysis, Kumar and Parikh (1998) include prices in their interannual analysis of Indian agriculture. The inclusion of the price terms appears to have little impact on the climate coefficients.

Another valid criticism that has been leveled against the Ricardian analysis concerns the absence of explicit inclusion of irrigation. Cline (1996) and Darwin (1999) both argued that irrigation should be explicitly included in the analysis. Schlenker et al. (2006) note that the climate sensitivity of rain-fed farms is greater than the climate sensitivity of all farms in the US. Mendelsohn and Dinar (2003) show that farm value is significantly affected by the availability of water but that including water availability does not change the climate sensitivity of farms in the US. Perhaps more relevant to this argument, Kurukulasuriya and Mendelsohn (2008) in Africa, Seo and Mendelsohn (2008) in South America, and Wang et al. (2008) in China show that the climate sensitivity of rain-fed farms is indeed much higher than the climate sensitivity of irrigated farms. These results explain the Schlenker et al. (2006) results for the US while revealing that irrigation does not lead to a bias in the overall Ricardian results.

A final concern with the Ricardian method is that it reflects current agricultural policies. If countries subsidize specific inputs or specific crops, these subsidies will affect farmer choices. The Ricardian results will consequently have these distortions embedded in the results. For example, India subsidizes electricity for irrigation. This will tend to make irrigation less costly which will reduce the sensitivity of farms to low precipitation and high temperatures. If future policies eliminate these subsidies or introduce new ones, the empirical results may no longer hold.

The model assumes individual profit-maximizing behavior of farmers. However, this is a standard assumption in economic modeling and analyses, and not a limitation of the Ricardian methodology per se. The results of the paper are contingent on the extent that this assumption may not be a valid one. Finally, the model does not factor the impact of low-probability, high-consequence climate-induced catastrophic events.

3. Empirical methodology

All the variables used in the analysis are carefully defined in Appendix A for Brazil and Appendix B for India. The units of observation in Brazil are all the 3941 municipios measured in the four Agricultural Censuses: 1985, 1980, 1975, and 1970 undertaken by the Instituto Brasileiro de Geographia e Statistica (IBGI). Each census measures detailed data on farm values, annual and perennial crop production, and areas used in pastures and forests. Farmers reported a separate assessment of farm value from the value of residences and buildings.[1] These separate assessments by farmers yield an *intrinsic* measure of farm values, making the Brazilian census data an ideal case study for the Ricardian analysis.[2] Farm value per hectare was computed by dividing aggregate farm value by the total number of hectares in farms. The land-use allocation within farms was not used as an explanatory variable as land use is an endogenous choice of farmers.

The unit of observation in India is a district. There were 271 agricultural districts from 13 states in the sample, which cover most of India where crops are grown. Farmland values were not available in India so we relied on annual net farm income. Net income was computed as gross revenue minus costs. Data were available from 1966 through 1986. The districts thus represent a panel dataset.

The climate variables used in this study are the "climate normals", the 30-year averages of temperatures and precipitation. The Brazilian observations range from 1961 to 1990 and the Indian observations range from 1931 to 1960. Although the Indian values are old, the climate normals in this earlier period and in 1960–1990 are expected to be similar. The Brazilian climate data come from the Ministerio do Agricultura de Reforma Agraria, Secretaria Nacional de Irrigacao, Departmento Nacional do Metrologia and the Food and Agricultural Organization (FAO, 1990)[3]. The climate measurements come from 310 weather stations across Brazil. The Indian climate data come from the Food and Agricultural Organization (FAO, 1990) and represent 160 weather stations around India. We measure normal temperatures (°C) and rainfalls (mm) in both countries for four seasons. The months of June (winter), September (spring), December (summer), and March (fall) are used in Brazil and the months of January (winter), April (spring), July (summer), and October (fall) are used in India.

The focus on seasons rather than on shorter time frames is both an econometric and a practical choice. In principle, we could have included every month of the year. However, the climates of many months are closely correlated with adjacent months. Inclusion of all the 12 months leads to insignificant results. The seasonal effects, however, are significant so that using longer time frames such as annual climate or limited time frames such as just the growing season do not capture important effects that happen over the year. The United States analyses revealed that the climate during the nongrowing season was important, possibly because of its effects on weeds and pests (Mendelsohn et al., 1994, 1999; Mendelsohn and Dinar, 2003). Finally, the climate models that predict future climate cannot make reliable predictions any finer than by season.

Although earlier research indicates the importance of interannual and diurnal climate variation (Mendelsohn et al., 1999), measures of climate variance were not available to this study. Interannual and diurnal variance effects could not be included. Hopefully, this limitation will be overcome in future studies.

In order to assign the climates measured at the weather stations to each municipio or district, we interpolate from the

[1] It is likely that there are measurement errors in reporting farm value estimates. However, there is no reason to expect that these errors are correlated with the independent (climate and edaphic) variables.

[2] The Brazilian data separate the value of land from the value of buildings. One problem with previous US studies is that farm values included buildings on site.

[3] Normal climate variables are treated as the expected climate variables perceived by agents in the land market. It is true that in any given year, current weather may depart from normal weather, but this is not expected to influence farm value assessments.

Table 1
Sample municipio climate interpolation (Paranapua)

Independent variables	Temperature		Rainfall	
	June	September	June	September
Constant	−49.4[a]	−112[a]	1337[a]	−1002
Altitude	−0.005	−0.176[a]	−0.029	−0.107
Latitude	−0.381[a]	2.79	32.4[a]	132[a]
Longitude	−3.37[a]	−7.97[a]	51.1	−110
Distance to sea	−0.078	−0.130[a]	0.51	−2.28[a]
Latitude × longitude	−0.133[a]	0.065	0.17	6.00[a]
Latitude × altitude	−3.70E−4	3.75E−4	−0.017[a]	−0.012[a]
Altitude × longitude	−1.87E−4[a]	5.29E−4[a]	0.009[a]	0.006
Altitude squared	−7.64E−8	1.43E−6[a]	1.67E−5	3.86E−5[a]
Latitude squared	0.104	−0.008	0.279	−2.919
Longitude squared	−0.004	−0.111[a]	0.724	−2.703[a]
Distance to sea squared	3.15E−7[a]	−4.57E−5[a]	6.06E−4	−8.82E−4
Distance × altitude	1.36E−5	−5.55E−6	4.68E−4[a]	3.45E−4[a]
Distance × latitude	−0.0023	1.79E−3	−0.045	0.0964
Distance × longitude	−0.3.89E−4	4.13E−3[a]	0.043[a]	−0.974
Adjusted R^2	0.90	0.92	0.88	0.81
Number of observations	114	114	114	114

Temperature in °C and rainfall in mm/months.
[a] Statistically significant at the 5% level.

stations to the farms using a climate surface.[4] The interpolations predict what the climate is likely to be between the weather stations as not every farming area is adjacent to a weather station. A weighted regression for each climate variable is estimated for each farm location that includes all the weather stations within a 600 miles radius.[5] The weight in the regressions is the inverse of the square root of a station's distance to the geographical center of the municipio or district. The dependent variable in each regression is the climate variable of interest, temperature or precipitation, in a specific month. Fourteen exogenous variables were used to predict climate: latitude, longitude, altitude, distance from nearest shoreline, and their corresponding square and interaction terms. The regression procedure is a sophisticated method of interpolating between measurements across space. A separate regression was done for each climate variable and each location. Given the eight climate variables for temperature and precipitation, the 3941 municipios and the 271 districts, a total of 31,528 regressions were estimated for Brazil and 2168 regressions for India. Table 1 shows a sample prediction and the variables used for one municipio.

Interpolation regressions were then utilized to predict the climate at the geographic center of each municipio and district. The temperatures and precipitation estimates from this interpolation procedure are the independent variables used in the Ricardian regressions. To assess the reliability of the interpolation, we use the same method to predict the climate at each weather station (dropping the weather station itself). The interpolation predicts between 90% and 96% of actual weather station temperatures and between 75% and 85% of actual weather station precipitation. The estimates suggest that there is very little measurement error in our interpolated temperature variables but there is some in our precipitation measurements. The precipitation measurements are more difficult to derive because there are subtle geographic variations in precipitation from place to place caused by mountains, river valleys, and oceans. Our inability to capture these geographic variations in precipitation will bias the precipitation coefficients towards zero.

Edaphic variables (soils), which vary significantly over the municipios and districts, need to be controlled in order to isolate climate from soils. We have data on Brazilian micro-region soil types and erosion potential (Atlas Nacional do Brazil, 2nd Edigvo, IBGE, Rio de Janeiro, 1992). In India, data on soil slope, type, texture, and topsoil depth were available by district (Sanghi et al., 1998). Care was taken in both datasets not to include soil variables that might be "hidden climate indicators" such as the agricultural potential of soils (Index V3), rainfall classes (Index IV1), or thermic efficiency variables (Index IV2).[6]

Additional control variables were introduced to control for extraneous factors. For example, latitude is included to control for day length. Population density is used to control for the opportunity cost of the land and market access. Literacy is included in the Indian study as a rough approximation of alternative wage rates. To account for household/nonhired labor in India, we use the number of cultivators (self-employed males who list their primary job classification as cultivators) as a proxy. This enables us to compute an implicit shadow wage for self-employed labor. This, of course, is an imperfect measure as household labor is an endogenous variable.

Another important concern of this study was how to account for technology. Although India has modern farms and equipment, it also has many labor-intensive traditional farms. As a proxy for technology, we include several variables: tractors per hectare, bullocks per hectare, and fraction of land planted in high yield variety crops (rice, wheat, maize, jowar, and bajra). Although it is possible that these variables are endogenous, it was important to make some distinctions between commercial and household farms. The technology variables attempt to reflect the effects of the Green Revolution in each district.

All the values in the study were deflated to adjust for inflation. In addition, yearly dummies are used to control for unmeasured interannual variations in weather, prices, and other factors affecting agricultural activity in each of the four censuses, with 1985 as the reference year. Including these dummies is especially important in Brazil because of hyperinflation between 1970 and 1985.

Agronomic research and casual observation reveal that many crops have preferred temperature zones. Temperatures either below or above this optimum reduce productivity. There is consequently evidence to suggest that the relationship between net revenue and annual temperature should be concave. Of course, the shape of a seasonal variable may not follow this pattern. We attempt to capture nonlinear shapes using a quadratic functional form:

$$V_i = a_0 + \sum (a_s T_s + b_s T_s^2 + c_s P_s + d_s P_s^2 + f_s T_s P_s) + \sum_c g_c Z_c + \sum_y h_y Y_y + e, \qquad (4)$$

where V_i is net revenue per hectare; T_s and P_s ($s = 1, \ldots, 4$) represent normal (demeaned) temperature and precipitation variables in each season; Z_c represents the soil, economic, and climate control variables; Y_y are yearly dummies, e represents an error term; and a_0, a_s, b_s, c_s, d_s, f_s, g_c, h_y are parameters to be estimated. In the Brazilian analysis, V_i is the farm value per hectare and in the Indian analysis, V_i is the annual net revenue per hectare.

The independent climate variables include a linear and a quadratic temperature and precipitation term for winter, spring, summer and fall. In addition to the linear and quadratic terms for

[4] The interpolation approach is similar to the one adopted in Mendelsohn et al. (1994). Please see Sanghi (1998) for maps on the spatial distribution of weather stations.

[5] A 600 miles radius was determined to give the best predictions after trying several alternatives.

[6] A detailed description of the variables can be found in Sanghi (1998).

India, a rainfall–temperature interaction term was introduced in each season. We demean all the climate variables (subtract the mean) to make the coefficients easier to interpret. Taking the derivative of Eq. (4) with respect to temperature, for example, yields

$$\frac{\mathrm{d}V}{\mathrm{d}t} = a_s + b_s T_s. \tag{5}$$

With the demeaning, the value of T_s is set equal to zero. The linear climate terms consequently measure the marginal effect of each climate variable evaluated at the sample mean for each country. The quadratic term measures the nonlinear shape of the climate response function. A positive coefficient for b_s implies a hill-shaped response function and a negative coefficient implies a U-shaped function.

Each observation is weighted by the area in cropland in each municipio or district (acreage weights). Larger municipios or districts, including more farms, have lower measurement errors and therefore deserve more weight. The weighting adjusts for heteroscedasticity, the fact that the variance is higher in municipios and districts with few farms. The weighting also has the beneficial effect of reducing the importance of net revenue measurements from urban areas where farms tend to have high values because of their proximity to markets rather than their net productivity.

4. Results

The results of the Brazilian pooled farm value regressions are presented in Table 2. The control variables in the pooled regressions behave as expected. Farm values and net revenues are sensitive to the different soil types. The soil erosion variables are being measured relative to an omitted class of soils that are the least predisposed to erosion. The soil type variables are being measured against a fertile soil. Consequently, the coefficients on the soil erosion variables are generally positive and the soil type coefficients are generally negative. Higher latitudes are more negative implying lower farm values. This is consistent with agronomic models that argue that increased solar radiation is beneficial to crops. Higher population density increases farm values but the effect diminishes as population increases. These population effects reflect both the proximity to markets and the opportunity cost of land.

The results of the Indian pooled net revenue regressions are presented in Table 3. Many effects resemble the results in Brazil. Soils have significant effects on farm revenue in India. Higher population density increases net values. Low latitudes have higher farm values. A new variable, higher literacy rates, is also associated with higher incomes. Some of the new variables, the number of bullocks per hectare and the number of cultivators, are not significant. More bullocks mean more animal power (a positive effect) but also less capital-intensive technology (a negative effect). Similarly, more household labor reflects inexpensive labor costs but also less efficient technology. Although the coefficients on these two variables may be difficult to interpret, the variables serve a useful purpose of controlling for the influence of missing data. In contrast to these two variables, the number of tractors and the fraction of hectares under high yield varieties both have positive coefficients as expected. The results suggest that these technological advances have increased Indian net revenues.

The economic values in the Brazilian dataset are nominal so the time dummy variables in Table 2 are largely correcting for inflation. Inflation increased dramatically across the study period but there was a reevaluation of the currency before 1985. The time dummies for Brazil consequently increase over the study period but 1980 is no greater than 1985. The time dummies for Brazil also capture other changes across time in prices and climate. The time dummies in India suggest fluctuations in annual values because of unmeasured weather and economic effects. Inflation has been corrected in the Indian data so that there is no trend in the time coefficients in Table 3.

Most of the climate coefficients are statistically significant. In Table 2, 15 of the 16 climate terms are significant. In Table 3, 19 of the 20 climate coefficients are significant. The quadratic coefficients reveal strong nonlinear climate impacts. The shape of the temperature functions varies between India and Brazil. The winter and fall temperature functions are concave for India but the spring and summer temperature functions are convex. In Brazil, the spring and fall temperature functions are concave, while the other temperature functions are convex. The temperature results indicate a more convex function than the results from the United States. Hotter places are less productive but at a decreasing rate. The difference in the results is likely due to the increased reliance on irrigation, especially in India. Agriculture can continue to exist even in the tropics as long as there is sufficient water for irrigation.

The precipitation response functions are not similar in Brazil and India. In India, the summer and spring precipitation functions are convex, the winter function is linear, and the fall function is concave. In Brazil, all the precipitation functions are concave. The monsoons in India that deliver large amounts of rain in the late spring–early summer may explain these differences.

The climate variables exhibit some consistent patterns across both India and Brazil. In both countries, temperature has a more powerful effect on farm values and net revenues than precipitation. The study suggests that warmer winters are harmful to farmers. Most agronomic studies ignore winter because it lies outside of the growing season for their target crop. However, winters are important, probably because of their effect on pests. Pests are not directly measured in the study. However, if pests were important, they would lead to lower net revenues in places with warmer winters. This phenomenon has been observed not only in Brazil and India but also across the United States (Mendelsohn et al., 1994, 1999). Although frosts are necessary to completely kill many pests, cold but not freezing temperatures nonetheless reduce populations. The effect of warmer winters is one of the more harmful consequences of warming.

The coefficients during the growing season largely act as expected. Warmer summer temperatures stress plants in both countries. In India, the impact of warmer springs is particularly harmful but spring temperatures in India are often higher than summer. Warmer springs in Brazil, in contrast, are beneficial. Warmer falls are mildly beneficial to both countries. Warmer falls allow for a longer growing season and they help ripen crops. Wetter winter and falls tend to increase farm values, allowing cropping to extend beyond just the post-monsoon period. Wetter summers are harmful because spring–summer monsoons provide sufficient moisture and clouds in the summer reduce solar radiation. Spring responses to precipitation are quite different between India and Brazil. Wetter springs have no effect in Brazil but they are distinctly harmful in India.

In order to examine the interannual stability of the climate coefficients, we estimate the Brazil model independently for each of the four census years (see Table 2). The climate coefficients across the four regressions remain stable suggesting that the climate sensitivity is consistent and robust. Although the magnitude of coefficients varies, most of the climate coefficients retain their signs and significance with few exceptions. The edaphic coefficients are also markedly stable. Coefficients on latitude and population density retain their signs as well.

Table 2
Brazil pooled and cross-sectional regressions[a]

	Parameter ($\times 10^5$)				
	Pooled	1970	1975	1980	1985
Intercept	234 (2.01)	−63.1 (0.93)	211 (0.66)	−49.6 (0.24)	353 (1.84)
Summer temperature	−171 (6.08)	−44.8 (2.76)	−222 (2.89)	−182 (3.57)	−82.7 (1.72)
Fall temperature	79.4 (2.89)	4.3 (0.27)	150 (1.96)	74.9 (1.49)	10.2 (0.22)
Winter temperature	−175 (−11.83)	−57.2 (−6.13)	−203 (4.50)	−267 (9.19)	−177 (8.02)
Spring temperature	198 (10.99)	78.7 (7.50)	171 (3.36)	346 (10.19)	167 (5.65)
Summer temperature sq.	12.2 (3.35)	−2.77 (1.30)	8.81 (0.86)	−0.19 (0.03)	24.9 (4.15)
Fall temperature sq.	−8.66 (2.84)	0.47 (0.28)	−12.2 (1.45)	−1.92 (0.33)	−11.7 (2.30)
Winter temperature sq.	20.0 (9.96)	5.20 (4.47)	27.3 (4.78)	21.1 (5.54)	22.4 (7.04)
Spring temperature sq.	−31.5 (16.80)	−7.94 (1.30)	−34.4 (6.60)	−29.7 (8.60)	−41.6 (13.46)
Summer precipitation	−2.97 (9.17)	−1.47 (7.94)	−3.75 (4.21)	−2.64 (4.53)	−1.88 (3.41)
Fall precipitation	3.90 (11.28)	1.02 (5.09)	4.51 (4.76)	3.62 (5.70)	4.43 (7.74)
Winter precipitation	1.30 (2.81)	0.73 (2.67)	0.48 (0.36)	1.58(1.91)	1.34 (1.78)
Spring precipitation	−1.11 (1.47)	−0.14 (0.29)	−0.85 (0.39)	0.90 (0.65)	−0.72 (0.60)
Summer precipitation sq.	−14.7E−3 (9.46)	−2.78E−3 (2.98)	−19.8E−3 (4.53)	−11.6E−3 (4.02)	−21.4E−3 (8.66)
Fall precipitation sq.	−10.1E−3 (7.75)	−2.09E−3 (2.63)	−12.1E−3 (3.28)	−6.82E−3 (2.92)	−12.1E−3 (5.66)
Winter precipitation sq.	−7.47E−3 (3.20)	−3.60E−3 (2.80)	−0.68E−3 (0.10)	−11.0E−3 (2.57)	−16.4E−3 (4.20)
Spring precipitation sq.	−55.0E−3 (10.02)	−17.5E−3 (5.52)	−65.0E−3 (4.31)	−61.3E−3 (6.23)	−78.5 (8.43)
Soil type 1	−135 (4.50)	32.6 (2.04)	−104 (1.30)	−236 (4.29)	−189 (3.53)
Soil type 2	−41.0 (1.29)	17.8 (1.07)	66.0 (0.77)	−169 (2.89)	−97.5 (1.71)
Soil type 3	−499 (10.49)	−101 (3.97)	−465 (3.61)	−653 (7.62)	−624 (7.38)
Soil type 4	−203 (3.28)	1.5 (0.04)	−134 (0.78)	−362 (3.29)	−232 (2.21)
Soil type 5	−409 (4.91)	−26.9 (0.47)	−139 (0.56)	−740 (5.14)	−482 (3.66)
Soil type 6	157 (1.74)	67.7 (1.36)	386 (1.57)	−163 (0.99)	275 (1.77)
Soil type 7	29.4(0.51)	39.7 (1.33)	194 (1.23)	9 (0.08)	−184 (1.81)
Soil type 8	−423 (−10.93)	−52.7 (2.48)	−334 (3.22)	−554 (7.84)	−601 (8.92)
Erosion potential 1	2.0 (0.01)	−28.3 (1.38)	−97.6 (0.98)	−10.8 (0.17)	68.8 (1.14)
Erosion potential 2	545 (17.63)	141 (7.89)	541 (6.22)	515 (9.15)	687 (13.40)
Erosion potential 3	309 (9.09)	43.4 (2.22)	127 (1.33)	433 (6.98)	411 (7.34)
Erosion potential 4	675 (9.12)	235 (6.25)	1133 (5.66)	884 (6.25)	67.7 (0.51)
Latitude	−64.9 (9.99)	−21.9 (−5.71)	−58.9 (3.30)	−73.3 (6.18)	−65.80 (6.09)
Population density	0.81 (23.75)	0.11 (4.61)	0.33 (2.77)	2.95 (29.88)	1.21 (18.99)
Population sq.	−23.6E−6 (22.15)	−3.10E−6 (4.70)	−9.84E−6 (2.85)	−163E−6 (28.15)	−41.8E−6 (10.36)
Dummy year (1970)	−947 (37.83)				
Dummy year (1975)	−114 (4.79)				
Dummy year (1980)	0.63 (0.03)				
Adjusted R^2	0.469	0.428	0.312	0.583	0.611

[a] The dependent variable is the log of farm value per hectare, the *t*-statistics are in parentheses, and the regression is weighted by the acreage of farmland in the municipio.

Table 3
Pooled and averaged regressions for India[a]

Variable	Pooled	Average	Variable	Pooled	Average	Variable	Pooled
Intercept	4660 (8.92)	5390 (2.8)	Winter rain × temperature	−3.62 (4.57)	−3.58 (1.23)	dmyr66	377 (6.77)
Winter temperature	−133 (3.38)	−185 (−1.28)	Spring rain × temperature	8.21 (11.59)	8.31 (3.20)	dmyr67	541 (9.92)
Spring temperature	−372 (16.71)	−305 (3.61)	Summer rain × temperature	−0.21 (1.97)	−0.02 (0.05)	dmyr68	292 (5.37)
Summer temperature	−103 (2.84)	−124 (0.92)	Fall rain × temperature	3.01 (5.83)	2.86 (1.51)	dmyr69	289 (5.38)
Fall temperature	486 (7.35)	504 (2.06)	Soil type 1	193 (9.28)	169 (2.20)	dmyr70	411 (7.75)
Winter temperature sq.	−39.3 (11.4)	−39.4 (3.10)	Soil type 2	221 (8.59)	211 (2.23)	dmyr71	365 (6.93)
Spring temperature sq.	80.3 (12.48)	80.9 (3.41)	Soil type 3	−153 (4.39)	−116 (0.90)	dmyr72	354 (6.74)
Summer temperature sq.	35.0 (4.62)	42.2 (1.51)	Soil type 4	13 (0.41)	48 (0.40)	dmyr73	611 (11.80)
Fall temperature sq.	−68.1 (6.77)	−60.5 (1.63)	Soil type 5	−10 (0.22)	−8 (0.05)	dmyr74	563 (10.77)
Winter precipitation	18.5 (6.11)	16.5 (1.47)	Soil type 6	81 (1.56)	70 (0.37)	dmyr75	519 (10.07)
Spring precipitation	−14.4 (8.00)	−16.6 (2.49)	Cultivators/ha	−27 (0.78)	79 (0.56)	dmyr76	351 (6.77)
Summer precipitation	−0.4 (2.11)	−0.0 (0.01)	Bulls/ha	50 (1.16)	−77 (−0.44)	dmyr77	431 (8.40)
Fall precipitation	2.28 (2.23)	3.41 (0.90)	Tractors/ha	28680 (8.98)	62670 (3.44)	dmyr78	338 (6.61)
Winter precipitation sq.	−0.16 (1.57)	−0.20 (0.54)	Population density	13.6 (2.16)	9.2 (0.39)	dmyr80	330 (6.46)
Spring precipitation sq.	0.28 (10.58)	0.32 (3.22)	Literacy	770 (6.85)	529 (1.22)	dmyr81	206 (4.06)
Summer precipitation sq.	0.01 (3.89)	0.01 (1.33)	High-yield variety	137 (1.87)	475 (1.25)	dmyr82	160 (3.13)
Fall precipitation sq.	−0.04 (7.34)	−0.04 (2.29)	Latitude	−174 (−7.83)	−195 (−2.38)	dmyr83	307 (6.05)
dmyr84	155 (2.96)		dmyr85	80 (1.52)		dmyr86	−12 (0.23)
No. of observations	5690	270					
Adjusted R^2	0.44	0.51					

[a] The dependent variable is net revenue per hectare, the *t*-statistics are in parenthesis, and the regressions are weighted by area of farmland. dmyr*x* are dummy variables for year *x*.

We also explore an alternative regression for the Indian data (see Table 3). Instead of treating each year as an observation, we average the net income for the entire time period and explore whether the independent variables can explain this average return. This is a purely cross-sectional analysis. The results, however, are almost identical to the pooled regression. All the coefficients are almost the same size for every variable. Because of the much smaller sample size, however, the *t*-statistics are much smaller for the average regression.

5. Climate impact simulations

The empirical regressions measure the climate sensitivity of current Brazilian and Indian agriculture. In this section, we explore the impact a broad range of climate scenarios might have on each country. These simulations provide a sense of the magnitude of potential impacts for developing countries. The estimates, however, must be interpreted cautiously because many factors may change over the next hundred years and they may well change the results. For example, population growth, economic development, changing prices, and changing technology may all have profound impacts on the agriculture sector in these countries. We do not make forecasts of these drivers. It is important to note that we are looking solely at the effect of climate change. Future analyses must take these other important factors into account as well.

The climate simulations rely on the climate response functions estimated in Tables 2 and 3. Global temperatures are predicted to increase from 1.5 to 5.8 °C by 2100 (IPCC, 2007a). Global precipitation is predicted to increase from 0% to 14% with a best guess of an 8% increase (IPCC, 2007a).

These scenarios represent the consensus of climate scientists for the entire world by 2100. Of course, we are interested in the predictions for Brazil and India, not the results for the world. We consequently predict temperature and precipitation changes for Brazil and India using COSMIC (Schlesinger and Williams, 1997). In each case, we assume that the global temperature sensitivity is 2.5 °C and that CO_2 increases to 840 ppmv by 2100. We then generate country predictions using 14 different GCMs (General Circulation Models). The 14 GCMs predict that India's temperature would increase between 1.4 and 3.5 °C and Brazil's temperature would increase from 1.5 to 3.5 °C. These results are consistent with the general expectation that temperature increases near the equator will be less than the world average. These estimates suggest that policy makers should place greater emphasis on the 2.0 °C warming scenario as the best guess for the tropics.

The GCM models have more difficulty predicting precipitation, especially on a country basis. The same 14 GCM models discussed above predict precipitation changes of between −5% and +10% for Brazil and between −8% and +14% for India. In order to capture this range, we must explore a wider range of precipitation effects in both countries than are expected for the world. We consequently explore a range of precipitation changes effects from −8% to +14% in both countries. Although we do not directly use each GCM climate scenarios, the GCMs have been used to inform the climate modeling.

With each climate scenario, the predicted change in climate is added to the current climate of each district and municipio. We analyze only uniform change scenarios within each country. In practice, climates may not change uniformly within a country with the size of Brazil or India. Within-country changes in climate would cause larger (smaller) damages if warm areas increased more (less) than average and cool areas increased less (more) than average. The effects could vary if precipitation and temperature change differently in each season. For example, increased precipitation in the fall and winter would be beneficial but the same increase in the spring or summer would be harmful in India.

The climate scenarios only consider changes in the climate normals. Greenhouse gases may cause other changes as well including changes arising from extreme events. We were unable to test for these effects in this study. Analyses in the United States, however, reveal that climate variation is likely to be harmful. If global warming increases the frequency of extreme events, it will cause additional damage not measured in this study. In contrast, if the frequency of extreme events declines, this will be a benefit. For example, the expected reduction of diurnal variation from global warming would be an added benefit to farmers not measured in this study.

Of course, the climate scenario is not the only uncertain aspect of these predictions. By 2100, Brazilian and Indian agriculture are expected to modernize significantly. It is likely that this increased technology will reduce climate sensitivity (Mendelsohn et al., 2001). Agronomic studies concerning carbon fertilization also suggest that higher levels of carbon dioxide will increase crop productivity on an average of 30% (Reilly et al., 1996). Many of the harmful effects of changing climates could be offset by increased carbon fertilization.

The net revenue of agriculture is computed for each district and municipio for the current climate and the predicted new climate. The pooled regression coefficients for each climate variable from Tables 2 and 3 are used to make the computation. The welfare effect is calculated as the change in net revenue in each area. The aggregate welfare effect is the sum of all the changes across every district and municipio. The benefits of carbon fertilization are not included in these estimates. The effects represent the impact of climate change in isolation.

The Brazilian estimates are presented in Table 4. A 2 °C warming and an 8% precipitation increase scenario results in a 20% loss of net farm income for Brazil of $3 billion. The 95% confidence interval surrounding this scenario is $1–$5 billion annual damages. Given the full range of climate scenarios possible by 2100 considered in this paper, annual damages for Brazil could range between a damage of $0.1 billion–$7 billion. Increased precipitation or temperature increases damages according to the Brazilian climate response function. In the 3.5 °C, +14% precipitation scenario, damages are expected to be 40% or $6 billion.

The Indian estimates are presented in Table 5. The 2 °C warming and an 8% precipitation increase scenario leads to a loss in India of 12% or $4 billion per year. The 95% confidence interval surrounding this climate scenario is from $2.6 to $6.0 billion damages. Given the full range of climate scenarios, damages in India could range between $1 and $11 billion per year by 2100. Higher temperatures and lower precipitation result in higher damages in India. The worst climate scenario for India, the 3.5 °C warming with an 8% loss of precipitation, results in expected annual damages of 26% or $9 billion.

Even though the climate change scenario is assumed to be uniform, the impacts are not felt identically in every region within each country. There are substantial regional variations within each country as shown in Map 1 of Brazil and Map 2 of India. Both maps show the effect of the 2 °C, +8% precipitation scenario on each country. Map 1 of Brazil reveals that the *cerrados* (mid-west) is the most negatively impacted region. The low-value agricultural regions of Amazonas and neighboring states are also damaged but their current low value limits the magnitude of the damages. In contrast, the southern (more temperate) municipios of Rio Grande do Sul and parts of Santa Catarina benefit overall.

Map 2 indicates that the coastal and inland regions of Gujarat, Maharashtra and Karnataka are the most adversely affected regions in India. The high-value wheat growing regions

Table 4
Damages to agriculture in Brazil from climate change[a]

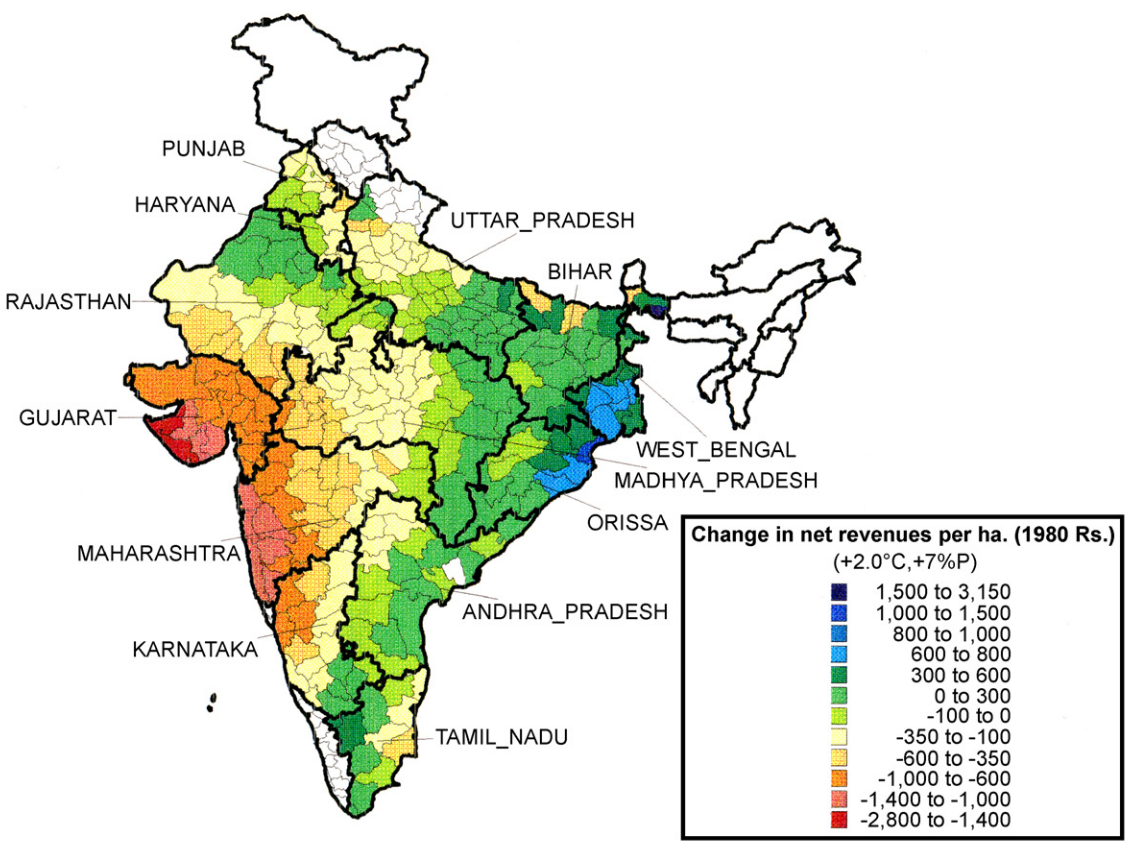
Change in precipitation (%)	Increase in temperature (°C)			
	+0.0 °C	+1.0 °C	+2.0 °C	+3.5 °C
−8%	+5.0% (8 to 2)	−1.3% (4 to −6)	−9.2% (−4 to −14)	−22.7% (−12 to −38)
+0%	0.0% (0.0)	−6.4% (−1 to −11)	−14.2% (−7 to −21)	−28.7% (−14 to −42)
+8	−5.4% (−2 to −8)	−11.7% (−5 to −16)	−19.6% (−10 to −30)	−34.1% (−17 to −51)
+14%	−9.8% (−6 to −14)	−16.1% (−8 to −24)	−24.0% (−12 to −36)	−38.5% (−19 to −57)

[a] Damages measured in percent reductions in farm property value. Net revenue for Brazil in 1990 is $14.7 billion. Figures in parenthesis are 95% confidence intervals.

Table 5
Effects on agriculture in India from climate change[a]

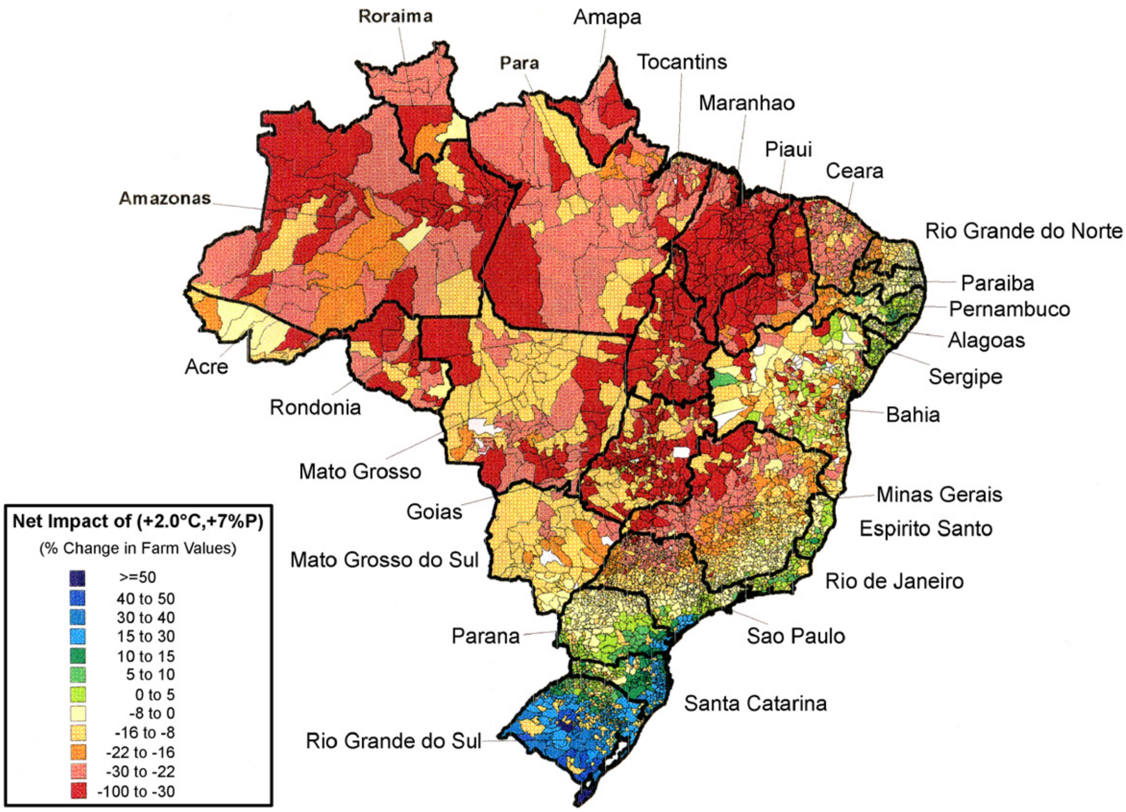
Change in precipitation (%)	Increase in temperature (°C)			
	+0.0 °C	+1.0 °C	+2.0 °C	+3.5 °C
−8%	−1% (−2 to 0)	−12% (−6 to −18)	−20% (−14 to −26)	−26% (−20 to −32)
+0%	0.0% (0.0)	−9% (−6 to −12)	−16% (−11 to −21)	−21% (−13 to −29)
+7%	+1% (0 to 2)	−6% (−5 to −7)	−12% (−7 to −17)	−16% (−8 to −24)
+14%	+2% (1 to 4)	−4% (−3 to −5)	−9% (−5 to −13)	−10% (−6 to −14)

[a] Damages measured in percent reductions in farm net revenue. Net revenue in India in 1990 is $34.8 billion. Figures in parenthesis are 95% confidence intervals.



Map. 1.

of Punjab, Haryana and Western Uttar Pradesh are also damaged but only slightly. The low-value, hot and dry districts of Rajasthan and Central India also are damaged only slightly. In contrast to the rest of India, the eastern districts of Andhra Pradesh, Orissa, and West Bengal actually benefit mildly from warming. The regional variation in impacts is even greater if one takes into account the range of possible climate changes across regions as well.



Map. 2.

6. Conclusions and policy implications

Panel data are used to measure the climate sensitivity of agriculture in Brazil and India. The cross-sectional nature of the data includes actual farmer adaptation in the estimation of climate sensitivity. The measured climate sensitivity is less than what agronomic models would predict. Agronomic models suggest that a warming of 3.5 °C with a 7% precipitation increase would result in large yield losses of 30–40% in India (Kumar, 1998). The cross-sectional evidence suggests that such warming would result in net revenue reductions of 7–17% in India and 10–30% loss in Brazil. The difference between the two results can be explained by adaptation. The Ricardian method takes adaptations such as crop switching into account whereas the traditional agronomic approach does not. Farmers make planting adjustments in suboptimal climate conditions to increase net revenue on each farm. Farmers as a group also change where crops are planted. The combination of adjustments suggests that the net revenue reductions are smaller than the predicted reductions in yields (Reilly et al., 1996; Adams et al., 1999).

Agriculture in Brazil, India, and the United States exhibits similar relationships with climate. Warmer summers and winters are harmful and warmer falls are beneficial. Wetter winters and springs are helpful but wetter summers are harmful. These results are consistent with agronomic studies of major crops. Warming, however, has a different overall effect in each country. Examining similar climate scenarios for all the three countries, Brazil and India have larger impacts than the United States. Earlier Ricardian studies (Mendelsohn et al., 1994) suggest the United States would have smaller percentage damages. This result is likely due to the fact that the US is more temperate. The climate sensitivities may also be different because of differences in irrigation. India may be slightly less sensitive than Brazil because it has far more irrigated farmlands.

The study finds that if temperatures rise by 2.0 °C with an 8% increase in precipitation, agricultural net revenue may fall 12% in India and 20% in Brazil without carbon fertilization. Given a broader range of possible climates, the range of annual damages lies between 4% and 26% for India and between 1% and 39% for Brazil.

These predicted effects measure the consequences of changes in seasonal temperature and precipitation normals but do not count other possible changes to climate. For example, the study does not take into account possible changes in interannual precipitation and temperature caused by greenhouse gases. Increases of interannual variation would be harmful to crops whereas reductions would be helpful (Mendelsohn et al., 1999). Unfortunately, these effects could not be included in this study. Climate scientists do predict that diurnal temperature variation will likely fall because of greenhouse gases (IPCC, 2007a). These reductions will likely benefit crops (Mendelsohn et al., 1999) but this effect could not be assessed in this study as well.

The rising levels of carbon dioxide may also have a carbon fertilization effect on crops (Reilly et al., 1996). Although the magnitude of this effect varies by crop, higher levels of carbon dioxide are likely to increase crop productivity (IPCC, 2007b). The damages from climate change could therefore, to some degree, be offset by potential benefits from carbon fertilization. Aggregate production in India and Brazil may consequently experience little net change from greenhouse gases. However, with the expected increase in agricultural productivity in polar and temperate zones, low latitude countries may still find themselves in a relatively less competitive situation with climate change.

Other important changes might occur by 2100 independently of climate change. It is highly likely that developing countries will continue to modernize their agricultural sectors. Farms are likely to adopt more capital-intensive irrigation methods, more mechanization, and higher yield varieties. This modernization may well reduce climate sensitivity in low latitude countries (Mendelsohn et al., 2001). Productivity is expected to increase as well, which could affect crop choice, land use, and prices. Of course, urbanization will take away agricultural land, which will not help. However, given the small amount of land devoted to urban uses, this effect may not be as important as the others. These effects should be taken into account in future studies.

The net effect of all these changes will vary from one country to another and within most large countries. First, climate change impacts will vary depending on initial climates. Farms in temperate climates will likely become more productive with carbon fertilization, and farms in more tropical climates will remain at their current level of productivity. Second, climate change itself is not likely to be uniform. Some areas will suffer from larger than average temperature increases and possibly even reductions in precipitation.

Aggregate production may depend more on what happens in the more productive areas of a country than in the marginal areas. The regression coefficients suggest that the effect of warming in each district depends on the climate of that district. Farms in more marginal areas may be more vulnerable than the entire agricultural sector.

The adaptation captured in the cross-sectional studies reflect private adaptation by individual farmers. This is expected to occur as each farmer seeks the crops and production methods that are best suited for the climate they live in. However, there may also be opportunities for public adaptation as a result of governmental policies and actions. The government could help by monitoring climate and keeping farmers informed of the climate as it changes. As decades progress, historical records may become out of date and will need revision. New crops could be developed which are more suited for a warmer carbon-enriched world. New crops with increased heat and drought tolerance may help reduce potential damages. Policies that increase farmer flexibility would also help allow farmers to adjust to new conditions. The government could also help disseminate new farming techniques that prove successful in the field. Finally, the government could help organize irrigation and other development projects. As temperatures rise in semi-arid parts of the low latitudes, the supply of irrigation water and the availability of modern irrigation technologies could become increasingly valuable. Although this analysis does not consider public assistance, governments have important roles in helping their agricultural sectors adapt. Finally, along the lines suggested by Hanemann (2000), Polsky (2004) and others, future research should pay more attention to investigating factors that may constrain efficient adaptation (for example, by undertaking empirical research at household or even individual levels) and by exploring how human–environment relationships vary over time, which would also incorporate social dimensions of adaptation.

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Appendix A. Description of variables for Brazil[7]

Altitude: meters above sea level
Distance to sea: in kilometers to nearest ocean
Latitude: in degrees and minutes
Longitude: in degrees and minutes
Erosion potential 1: moderate predisposition to erosion
Erosion potential 2: strong predisposition
Erosion potential 3: very strong predisposition
Erosion potential 4: extreme predisposition
Population density: people per square kilometer
Spring precipitation: 30-year average precipitation in mm in September
Summer precipitation: 30-year average precipitation in mm in December
Fall precipitation: 30-year average precipitation in mm in March
Winter precipitation: 30-year average precipitation in mm in June

Soil type 1:	Latossolo Amarelo; Latossolo Bruna; Latossolo Vermelho-Escuro; Latossolo Roxo; Latossolo Vermelho-Amarelo [Old, highly weathered, acidic soils with low to moderate base saturation and exchange capacity]
Soil type 2:	Podzolico Amarelo; Podzolico Vermelho-Escuro; Podzolico Vermelho-Amarelo [Old, highly acidic, and not productive]
Soil type 3:	Solos Litolicos; Afloramento Rochoso; Solos Indiscriminados de Mangue [Rocky soils and bedrocks]
Soil type 4:	Areias Quartzoas; Areias Quartzoas Hidromorficas [Sandy in nature and can be productive in conjunction with water]
Soil type 5:	Plintossolo; Plintossolo Petrico [Low pH content]
Soil type 6:	Regessolo [Range from dry and sandy to very good in terms of potential productivity]
Soil type 7:	Planosolos; Planosolos Solodico
Soil type 8:	Cambissolo; Cambissolo Bruno; Gleissolos; Rendzina; Solos Aluvias [Intermediate and young soils which could be productive but are slightly impermeable]

Spring temperature: 30-year average temperature in Celsius in September
Summer temperature: 30-year average temperature in Celsius in December
Fall temperature: 30-year average temperature in Celsius in March
Winter temperature: 30-year average temperature in Celsius in June

Appendix B. Description of variables for India

Altitude: meters above sea level
Bulls/ha: number of bulls in district/cropland hectares
Cultivators/ha: number of cultivators in district/cropland hectares
Distance to sea: distance in kilometers to nearest ocean
High-yield variety: percent of farms using high-yield varieties
Latitude: latitude in degrees and minutes
Literacy: percent of literate population
Longitude: longitude in degrees and minutes
Population density: people per kilometer squared
Spring precipitation: 30-year average precipitation in mm for April
Summer precipitation: 30-year average precipitation in mm for July
Fall precipitation: 30-year average precipitation in mm for October
Winter precipitation: 30-year average precipitation in mm for January
Spring temperature: 30-year average temperature in Celsius for April
Summer temperature: 30-year average temperature in Celsius for July
Fall temperature: 30-year average temperature in Celsius for October
Winter temperature: 30-year average temperature in Celsius for January
Tractors/ha: Number of tractors in district/hectares in cropland

[7] All micro-region variables are taken from maps in Atlas Nacional do Brazil, 2nd Edigvo, IBGE, Rio de Janeiro, 1992. Edaphic variables are from Folha V.1 (DM51(j)), Folha V.2 (DM(52(k)) and Folha V.3 (DM531-DM5310). For each map, an overlay of the 361 1985 micro-regions (Folha 1.2) was used to locate micro-regions. The dominant class or type was then recorded. Dummy variables are equal to one if the dominant class is in the dummy category.

Table B.1 Description of soil types—India[a]

Variable name	Description
DMS01	Not used
DMS02	Laterite
DMS03	Red and yellow
DMS04	Shallow black
DMS05	Medium black
DMS06	Deep black
DMS07	Mixed red and black
DMS08	Coastal alluvial
DMS09	Deltaic alluvium
DMS10	Calcerous
DMS11	Gray brown
DMS12	Desert
DMS13	Tarai
DMS14	Black (Karail)
DMS15	Saline and alkaline
DMS16	Alluvial river
DMS17	Skeletal
DMS18	Saline and deltaic
DMS19	Red
DMS20	Red and gravely

Source(s): Visual inspection of soil maps for each state. Found in S.P. Raychaudhuri et al., 1963. Soils of India, Indian Council of Agricultural Research, New Delhi.

[a] Although a number of organizations such as The National Bureau of Soil Survey and Land Use Planning, Nagpur (India), collect and compile soil data, there are no district-level soil datasets covering the entire country available in India as of now. James McKinsey of Yale University has carefully compiled the soil data from various sources, maps, and prepared one aggregate soil dataset, which is described below. The dataset includes 19 dummy variables (variables names DMS02 through DMS20) specifying soil type. The value of a particular dummy variable in a given district equals one if that dummy's soil type is one of the two predominant soil types in the district; that is, if that soil type covers the largest, or second largest, amount of area in the district. Two caveats, however, are in order, one concerning the construction of the dummy variables used in this paper and the other concerning their interpretations. First, most districts contain more than two soil types: the soil maps display four or even five types for many districts. And the third-most prevalent soil type in some districts may cover more area than the second-most prevalent type in other districts. Second, because two of the dummy variables in each district can have the value of one, the coefficients of the dummy variables cannot be interpreted as usual.

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