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CROSS-SECTIONAL ANALYSES OF CLIMATE CHANGE IMPACTS

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ABSTRACT

This working paper explores the use of cross-sectional analysis in order to measure the impacts of climate change on agriculture. The impact literature, using experiments on crops in laboratory settings combined with simulation models, suggests that agriculture will be strongly affected by climate change. The extent of these effects varies by country and region. Therefore, local experiments are needed for policy purposes, which becomes expensive and difficult to implement for most developing countries. The cross-sectional technique, as an alternative approach, examines farm performance across a broad range of climates. By seeing how farm performance changes with climate, one can estimate long-run impacts. The advantage of this approach is that it fully captures adaptation as each farmer adapts to the climate they have lived in. The technique measures the full net cost of climate change, including the costs as well as the benefits of adaptation. However, the technique is not concern-free. The four chapters in this working paper examine important potential concerns of the cross-sectional method and how they could be addressed, especially in developing countries. Data availability is a major concern in developing countries. The first chapter looks at whether estimating impacts using individual farm data can substitute using agricultural census data at the district level that is more difficult to obtain in developing countries. The study, conducted in Sri Lanka, finds that the individual farm data from surveys are ideal for cross-sectional analysis. Another anticipated problem with applying the cross-sectional approach to developing countries is the absence of weather stations, or discontinued weather data sets. Further, weather stations tend to be concentrated in urban settings. Measures of climate across the landscape, especially where farms are located, are difficult to acquire. The second chapter compares the use of satellite data with ground weather stations. Analyzing these two sources of information, the study reveals that satellite data can explain more of the observed variation in farm performance than ground station data. Because satellite data is readily available for the entire planet, the availability of climate data will not be a constraint. An ever continued debate is whether farm performance depends on just climate normals—the average weather over a long period of time—or on climate variance (variations away from the climate normal). Chapter 3 reveals that climate normals and climate variance are highly correlated. By adding climate variance, the studies can begin to measure the importance of weather extremes as well as normals. A host of studies have revealed that climate affects agricultural performance. Since agriculture is a primary source of income in rural areas, it follows that climate might explain variations in rural income. This is tested in the analysis in Chapter 4 and shown to be the case. The analysis reveals that local people in rural areas could be heavily impacted by climate change even in circumstances when the aggregate agricultural sector in the country does fine.

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SUMMARY

This working paper explores the use of cross-sectional analysis in order to measure the impacts of climate change on agriculture. Although these methods have been applied to study the United States and other developed countries, they have been only sparsely applied to developing countries. Before a major investment was made in using these methods in a host of low-latitude countries, a number of technical issues needed to be addressed. This working paper addresses specific questions about applying cross-sectional methods to developing countries.

The impacts from climate change are difficult to measure. We have no direct experience with new future climates. Past climate change has been very slow and difficult to discern, and technological changes have obscured any possible signal historic climate could have given. Despite these difficulties, the impact literature has made many strides toward understanding and quantifying climate impacts. Experiments on crops in laboratory settings have confirmed that most crops are highly sensitive to climate. Although the ideal climate varies across crops, each crop tends to have an optimal climate setting where it grows best. Alternative experiments reveal that increased carbon dioxide will also help plants grow, increasing the yields of most crops substantially. Combining these experiments with simulation models suggests that agriculture will be strongly affected by climate change.

Although the experimental–simulation approach is an important methodology, it is expensive and difficult to implement for most developing countries. This working paper reports on another approach to measuring the impacts of climate change: cross-sectional analysis. The cross-sectional approach examines farm performance across a broad range of climates. By seeing how farm performance changes with climate, one can estimate long-run impacts. The advantage of this approach is that it fully captures adaptation as each farmer adapts to the climate they have lived in. The technique measures the full net cost of climate change, including the costs as well as the benefits of adaptation.

The four chapters in this working paper examine important potential limitations of the cross-sectional method and how they could be addressed. The first chapter looks at estimating impacts using individual farm data. Past cross-sectional studies have focused on aggregate data for a county or district. The information at this level was available in secondary sources (agricultural census). However, many developing countries do not have adequate census data. This study addresses whether having individual farm level data from a survey would be an acceptable substitute for district level data. The study, conducted in Sri Lanka, finds that individual farm data from surveys is ideal for cross-sectional analysis. By having more detailed information on each farm, one can control for many of the differences between one farm and another that are not related to climate. Uncontrolled variables are more likely to be captured in the analysis using individual farm data. The Sri Lankan study also illustrates the importance of precipitation in addition to temperature. At least in Sri Lanka, what happens to the monsoons may be more important than warming itself.

Another anticipated problem with applying the cross-sectional approach to developing countries is the absence of weather stations. Although there are weather

stations throughout the world, they tend to be concentrated in urban settings. Measures of climate across the landscape, especially where farms are located, are difficult to acquire. The second chapter compares the use of satellite data with ground weather stations. The weather stations provide more accurate measures of ground level conditions in their vicinity. However, climate between weather stations must be inferred using sophisticated interpolation methods. Alternatively, satellite measures of climate directly observe the surface pattern of climate. Although the satellites have trouble measuring some relevant phenomenon such as precipitation, they have substitute measures such as soil moisture that can be used instead. Analyzing these two sources of information, the study reveals that satellite data can explain more of the observed variation in farm performance than ground station data. Only in Brazil where precipitation is key, do ground measurements outperform satellites. The results support the use of satellite data for cross-sectional analysis. Because satellite data are readily available for the entire planet, the availability of climate data will not be a constraint.

Chapter 3 examines how climate should be measured—it addresses the role of climate versus weather. The analysis tests whether farm performance depends on just climate normals- the average weather over a long period of time- or on climate variance (variations away from the climate normal). The study reveals that climate normals and climate variance are highly correlated. Either set of variables can explain a great deal of the variation in farm performance. However, when they are introduced together, the climate normals explain the bulk of the variation in farm performance and the variance terms explain only a little more. The results imply that it would be attractive to include both climate normals and climate variance to the extent possible. The satellite data can support measures of both sets of climate variables. By capturing climate variance, the studies can begin to measure the importance of weather extremes.

Chapter 4 explores the role of climate in rural income. A host of studies have revealed that climate affects agricultural performance. Since agriculture is a primary source of income in rural areas, it follows that climate might explain variations in rural income. This is tested in the analysis and shown to be the case. The very same variables that explain farm performance also explain why some rural districts and counties have higher income per capita than others. The results demonstrate the importance of climate to rural livelihood. The results also reveal that even if aggregate country-wide outcomes in agriculture are minimal, there may still be local distributional effects from climate change that are quite severe. That is, the study reveals that local people in rural areas could be heavily impacted by climate change even in circumstances when the aggregate agricultural sector in the country does fine.

The working paper reveals that the cross-sectional approach can be applied to developing countries to explore the impact of climate on agricultural performance. Combining an agricultural survey conducted across a range of climate zones with satellite climate data will yield a rich data set to study climate impacts. The approach will be able to study the effect of both climate normals and climate variance. The working paper thus provides strong support for continued work in this area.

The papers also suggest that climate will have a large impact on developing countries. Agriculture is a large fraction of GDP in many low-latitude countries. Labor-intensive agriculture appears to be especially sensitive to warming. Many low-latitude countries are already on the hot side of global temperatures, and thus are particularly vulnerable to global warming.

The working paper also suggests that rural livelihoods will also be vulnerable. Because rural areas are especially dependent on agriculture, climate impacts will be felt directly in rural income. Even in circumstances where agriculture in general does well in a country, some regions may still be particularly vulnerable to climate change. Rural people in these regions will have little ability to buffer climate impacts. Climate change will likely cause new hardships for rural people who happen to live in the most marginal locations.

The world community should anticipate a policy response to these new distributional problems. Although mitigation is likely to reduce the magnitude of potential impacts, it is not expected to eliminate global warming. Adaptation will also help to mute the damages from warming. However, preliminary results suggest that adaptation, by itself, will not be enough to prevent damages in low latitude marginal settings. Some rural people will invariably be hurt by global warming. Policy makers may want to develop effective long-term responses for such cases. A dialogue is called for between the scientific community and the policy makers in low latitude and high latitude countries in order to examine different types of policy-enhancing adaptation interventions.

1. RICARDIAN STUDY OF SRI LANKAN FARMERS[1]

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ABSTRACT

This study applies the Ricardian technique to estimate the effect of climate change on the smallholder agriculture sector in Sri Lanka. The main contribution of the paper is the use of household-level data to analyze long-term climate impacts on farm profitability. This level of detail allows control for a host of factors such as human and physical capital available to farmers as well as adaptation mechanisms at the farm level. At the household level, about half the variation in net revenues is explained by non-climate variables. The household data have the advantage of providing more detailed controls in Ricardian analyses. The results suggest that climate change will have a significant impact on smallholder profitability. Reductions in precipitation during key agricultural months can be devastating for temperatures. At the aggregate level, a change in net revenues of between –23% and +22 percent can be expected depending on the climate change scenario. These effects will vary considerably across geographic areas from losses of 67% to gains that more than double current net revenues. The largest adverse impacts are expected to be in the dry zones of the North Central region and the dry zones of the South Eastern regions of Sri Lanka. On the other hand, the intermediate and wet zones are likely to benefit, mostly due to the predicted increase in rainfall.

INTRODUCTION

The vulnerability of the agricultural sector to exogenous shocks continues to be of interest to policymakers working on rural development issues. This is especially a problem for low-income countries because agriculture accounts for a larger fraction of their economy, accounting for about 60 percent of the labor force and producing on average 25 percent of GDP. In contrast, agriculture accounts for only 15% of GDP in middle-income countries and only 5% of GDP in the United States (World Bank 2003). Climate change has increasingly been recognized as a longer-term threat to the agriculture sector (IPCC 2001). The general consensus is that changes in temperature and precipitation normals will lead to adjustments in land and water regimes that will affect agricultural productivity (IPCC 1997). The temperature and precipitation normals reflect long-term weather patterns and are defined as the average of 30 years of weather. Qualitative evidence suggests that developing countries in the low latitudes will be especially vulnerable. Not only are such regions near or beyond optimal temperature conditions for agricultural production (so any warming will only worsen existing production conditions), but also many of the countries are subject to technological, resource, and institutional constraints that are likely to constrain productivity (Mendelsohn and Dinar 1999). Yet, the magnitude of likely impacts from climate change in developing countries is not well understood.

Although research suggests that global food production is likely to be robust, experts predict tropical regions will see a reduction in agricultural yields (Mendelsohn and Dinar 1999; Kurukulasuriya and Rosenthal 2003). Large adverse impacts on productivity, especially among smallholders who depend on farm productivity as a source of livelihood and subsistence can lead to a rise in poverty levels (World Bank 2003). Consequently, this study contributes to the limited quantitative research on measuring the potential impacts of climate change in low-latitude developing countries where detailed quantitative estimates of the impact of climate change and variability are scarce.

The primary interest of the study is to estimate the impact of changes in long-term climate (temperature and precipitation normals) on the agricultural performance of smallholders (i.e. households that cultivate less than 10 acres of farmland) in Sri Lanka. Perhaps fortunately, there are no observed changes in climate normals over time yet in Sri Lanka. We consequently cannot turn to time series analysis to understand how farms are affected by climate change. Instead, we adopt a cross-sectional approach, the Ricardian approach (Mendelsohn et al 1994). The intuition here is that if climate conditions in region A become more like current climate conditions in region B, then farmers in region A will adapt and become more like farmers are currently in region B. Past Ricardian studies have strictly depended on aggregate district or county level data (Mendelsohn et al 1994; 1999; 2001). In this study, we use observations about individual farmers, rather than aggregate data, to conduct the analysis.

The use of individual farm data poses new opportunities and challenges. One of the opportunities is that there is a rich set of data about individual farmer characteristics that can serve as better controls. The individual farm data have many socio-economic and demographic characteristics that are likely to affect farm productivity. This micro data is generally not available at the district or county level. Consequently, a micro level study may be able to control for non-climatic factors more carefully than the studies that depend on aggregate data. On the other hand, detailed farm-level data may pose new challenges as the analysis will have to explain variations between farmers within a specific climate zone in addition to variations among farmers between climate zones. As a result, the choice of the type of dataset crucially depends on the nature of the question being posed. Whether it is advantageous to move to individual data is therefore an empirical question that needs to be resolved.

The remainder of this paper is organized as follows. The next section outlines the empirical strategy relied on in this study. The third section outlines the data used in the analysis along with some background about the agriculture sector in Sri Lanka. The fourth section presents results of applying the economic approach using household-level data from Sri Lanka. The fifth section then presents our predictions for climate change on the smallholder agriculture sector in Sri Lanka for three climate models. Finally, the sixth section concludes.

METHODOLOGY

Much of the existing quantitative evidence of the magnitude of climate impacts in developing countries is based on agronomic (also known as the production function) studies. Carefully controlled crop simulation experiments that measure damages on crop growth due to variation in inputs such as temperature, precipitation and $C0_2$ are used for this purpose (see for example, Rosenzweig and Parry 1994).

However, economists assert that agronomic studies tend to overestimate negative climate impacts and underestimate positive impacts because they fail to account for adaptations that farmers continuously undertake in order to cope with climate pressures (Adams et al 1990; 1999; Mendelsohn *et al.* 1994; 1999). In other words, the agronomic studies ignore that sufficient reductions in yields will lead farmers to switch to a different crop that will better suit the new climatic conditions. Similarly, any positive impacts of climate change are likely to be underestimated in an agronomic model because it does not account for the behavioral response of farmers not producing the optimal crop who will switch into cultivating the optimal crop.

In response, Mendelsohn *et al.* (1994) propose an alternative economic approach, which makes use of cross-sectional data to capture the influence of climatic as well as economic and other factors on land values (or farm income). The Ricardian technique captures the flexibility of farmers better than the agronomic method. The method examines how land values (or rents) shift with climate and other control variables. Because farmer adaptations are reflected in land values, the approach accounts for the costs and benefits of adaptation. The Ricardian model has been applied in a variety of countries, including the United States (Mendelsohn et al 1994; Mendelsohn and Dinar 2003), England and Wales (Maddison 2000), India (Dinar et al 1998; Mendelsohn et al 2001), and Cameroon (Molua 2002). Notably, all of these studies are based on aggregate district level data except for Maddison (2000) and Molua (2002). Madison (2000) measures the productivity of farmland characteristics in England and Wales using individual farmland values. Molua (2002) examines revenues of farmers in a single agro-ecological zone of Cameroon.

We examine the impact of long-term climate impacts on agriculture productivity by relying on an empirical econometric specification similar to that adopted in the Mendelsohn *et al.*(1994). That is, farmland value (H) reflects the present value of future net revenues, and depends on a host of exogenous determinants:

$$H = \int P_{LE} e^{\varphi t} dt = \int \left(\sum P_i \cdot Q_i \left(X, F, M, G \right) - R \cdot X \right) e^{\varphi t} dt \qquad [1]$$

where P_{LE} is the net revenue per hectare, t is time, and φ is the discount rate. We assume that the net revenue per hectare, P_{LE}, depends upon P_i, the market price of crop i; Q_i, the output of crop i; R, a vector of input prices, and X, a vector of purchased inputs (other than land). The crop output, Q_i, is in turn a function of the purchased inputs (X); a vector of climate variables (F), a vector of labor characteristics (M), and a set of farm characteristics such as market access and access to infrastructure (including irrigation), (G).

Given that we use a cross-sectional one period dataset of net revenue, H reflects net revenue in that particular year. We make the strong assumption that returns in the specific year of the study reflect long run profitability. Clearly, it would be preferable to gather multiple year data to get a better measure of long run profitability. In the absence of multiple year data, one must be careful to choose a year that is as close to normal as possible.

We assume farmers make a series of production choices aimed at maximizing profit given household preferences and endowments. In addition, the farm households are price takers in the model and hence individual farmers have no impact on market prices. Then the estimated specification of net revenues per hectare, P_{LE}, can be written as:

$$P_{LE} = \beta_0 + \beta_1 F + \beta_3 G + \beta_4 M + \varepsilon \qquad [2]$$

where β_i are estimated coefficients, ε is the unexplained portion, which is assumed to be independent and identically distributed. Implicit in this specification is that relative crop prices and input prices remain fixed despite the impact of climate or any other factor[2].

The aggregate impact of climate change on farm profitability is estimated as the difference between the fitted values of net revenues per hectare evaluated with climate variables set to those before the climate change ($\hat{P}^b_{LE}$) with the fitted values of net revenues per hectare with climate variables set to those after the change ($\hat{P}^a_{LE}$). In other words, the value of a change in climate is equal to $\hat{P}^a_{LE} - \hat{P}^b_{LE}$.

We include households that make losses in the empirical analysis. It is our assertion that there is important information embedded in these losses. It is likely that some households will not only make losses in the short run today but also into the future.

[2] One of the main criticisms of the Ricardian approach has been the omission of price (Cline 1996; Darwin 1999). Mendelsohn and Nordhaus (1999) contend that the assumption of constant prices does bias the estimates, but that this bias is relatively limited if standard demand and supply elasticities apply.

The long-run average outcome for an area will often include some fraction of losses. Although the individual data capture these short-run outcomes, we assume that the estimated cross-sectional model reflects long run consequences. The model captures how farmers adjust to climate over decades not weather year by year. We consequently assume that the predictions we make using this model are long-run not short-run predictions. We consequently censor losses when they occur in future climate scenarios to avoid giving the impression that farmers would continue to grow food in places that are permanently unprofitable. If areas become permanently unsuitable for growing food, we assume that there will be no farming activity. We assume that farm income will go to zero in these cases.

DATA

By the close of the 1990s, the agriculture sector in Sri Lanka accounted for 26% of GDP and employed nearly 50% of the total rural labor force. The most important export crops are tea, rubber and coconut. Other important crops include paddy rice, fruits, vegetables, spices and cereals.

The island is characterized by diverse agro-ecological zones including dry, wet and intermediate climatic regions (RRDI 2003). Two annual monsoonal seasons produce significant geographical variation on temperature and precipitation. The monsoons lead to two distinct cropping seasons in the island. The most significant season (*Maha* season) is from October to February and brings rain to the entire country. The second season (Yala season) is from May to September but only a part of the country receives rain during this period. These monsoons lead to a substantial dry and intermediate zone in the lowlands and some very wet highlands. The majority of irrigated and drought-prone farms are in the dry and intermediate lowlands.

We utilize a unique dataset that combines the detailed household-level information from the Sri Lanka Integrated Survey (SLIS) 1999-2000 (World Bank 2001) with climate data from the FAO (FAO 2000). The SLIS survey was conducted across all 25 administrative districts (9 provinces) in the country between October 1999 and the third quarter of 2000. The dataset is based on interviews of 7,500 households and includes data on 35,181 individuals. Included in the sample are farming households who were administered a detailed farm production (input and output) questionnaire. Given reservations by the World Bank regarding the quality of the data from the North and Eastern Provinces of the country due to regional hostilities at the time, these two regions are excluded from our analysis. These two regions contain 8 districts, leaving 17 districts in our sample. This is an important area for paddy cultivation and it is our intention to examine this region when more reliable data become available. In this paper, we limit our analysis to smallholder agricultural producers[3]. The resulting sample contains 1,552 households, which represent (when weighted) around 900,000 smallholders in Sri Lanka.

[3] In order to reduce measurement error, 10 extreme observations (in terms of net revenue per hectare) were removed from the sample. Quantile analysis at the median, with the extreme observations included, are similar to the results in the paper.

We estimate net revenue by valuing all variable inputs (except land) and outputs at the market price[4]. Total annual farm income includes annual earnings from crop and livestock, and revenues from the sale of farm produce (milk, butter, etc). We exclude subsidies received from the government, and income received from hiring out farm equipment in the calculation of net revenues. However, we include controls for households that receive subsidies and for households that receive income from hiring out their own capital, to control for any selection bias associated with these indicators. Total costs include variable costs associated with hired labor, seeds, fertilizer and chemical sprays, tractor charges, irrigation costs, transport/packaging costs, other incidental farm expenses, rent paid to leased land, rent paid to sharecropped land, costs of maintaining livestock (including feed, veterinary fees, other costs). Net revenues per hectare are defined as the difference between revenues and costs divided by the number of hectares farmed.

We combine the household data with data on long-term climate normals. In particular, we rely on FAO data that provides weather station measurements of temperature and rainfall over the period 1960 to 1995. However, available climate data are limited in geographic coverage by the number of weather monitoring stations in Sri Lanka. As a result, we use estimates of temperature and precipitation for all the regions in which no weather station is present. Estimates are obtained with data from the eight weather stations by interpolating using an inverse-distance weighted quadratic regression approach, limiting each regression model to weather stations within a 250-kilometer radius from the centroid of each district (Mendelsohn et al 1994; Dinar et al 1998). Observed climate is regressed against latitude, longitude, altitude, and distance to sea, weighting each observation by the square of the distance from the district's centroid. Interaction terms are also used. Nonlinearities are accommodated by utilizing a quadratic weighted regression for the interpolation. The estimated predicted value of temperature and precipitation at the centroid of each district is used in the Ricardian analysis.

The accuracy of the climate model we specify is tested by predicting the temperature and precipitation for a weather station using the model and then comparing the predicted climate values with the actual observation. Our tests for a sample of weather stations in different locations across the country indicate that the temperature and precipitation predictions were close to the actual measurements although the predicted precipitation estimates were less precise. In addition, the reliability of the climate estimates was also compared with separate estimates provided by the Department of Meteorology of Sri Lanka (MET). We find that both temperature and precipitation estimates were relatively close to the actual measurement, albeit precipitation estimates are less close (in absolute terms) than the temperature estimates (see Figure 1).

Because the model relies on annual weather in 2000 and not climate, we tested whether the climate in 2000 was close to the long-term average. The year 2000 is considered an average climatic year in terms of temperature and precipitation in Sri Lanka (IRI 2003). There is consequently empirical support for the assumption that the weather in 2000 reflects climate normals.

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[4] Ideally, we would have preferred to use land value or land rents but such data were not available.

RESULTS

Table 1 presents the basic summary statistics of the dataset for the relevant variables of the study. The precipitation and temperature means and standard deviations show that despite Sri Lanka's small surface area, there is considerable variation across geographic regions. In general temperature appears to be driven by elevation, with cooler temperatures in the high elevation areas (Kandy - 22° C and Nuwara Eliya - 15° C) and warmer temperatures in the southern and northern plains (average 26-28° C). Rainfall averages are lowest in the Hambantota and Matara districts (in the south), Puttalam and Anuradhapura districts (in the dry zone in the North). The average smallholder has approximately 5 people living in the household. The head of the household is on average 50 years old and has more than 7 years of education completed. Fifty-six percent of all smallholders depend on rain for their irrigation needs and cultivate around 1.4 acres of land. The channels to market produce vary, with one third of all smallholders marketing their produce in the local markets and a little more than a third marketing their produce through a middle-man. Around two-thirds of all farmers were born in the place in which they currently reside.

In order to capture the effect of climate variables on key months for agriculture in Sri Lanka, we tested various models. The inclusion of mean monthly precipitation estimates to reflect seasonal effects or the range of rainfall patterns across the year as independent variables poses several challenges. First, mean monthly rainfall is serially correlated across months and hence, estimated coefficients will be inefficient. We therefore include quarterly averages, instead of monthly averages, to avoid any serious serial correlation in the independent variables. Taking a three month average of rainfall and temperature (by including the months on either side of a key month of interest) is an effective measure to capture precipitation effects relative to using a monthly mean. The strategy of using quarterly averages permits a more thorough reflection of the accumulation of precipitation in soils over a period relative to the use of a single month. In addition, since climate variables could have non-linear impacts on net revenues, linear and quadratic terms are included (as in Mendelsohn *et al* 1994; Mendelsohn and Dinar 2003). However, to ensure that the linear and quadratic terms are not collinear all precipitation variables are expressed in terms of differences from the means across the 30 years of data. By demeaning the climate data, the linear term in the model can be interpreted as the marginal effect of that variable evaluated at the mean.

Similarly, the analysis attempted to recognize that temperature at key times in the production cycle is important for farmers. However, although there is significant variation in temperatures across geographic locations (driven primarily by elevation), temperatures are largely unchanged across time in Sri Lanka. We therefore include only the annual average temperature rather than separate variables for seasonal temperatures. We could not isolate the impact of elevation on farm profitability because it is too strongly correlated with our temperature measure.

Besides attempting a variety of specifications, a series of diagnostic tests are performed. First, strong heterogeneity is present as revealed by the Breusch-Pagan test and hence, the variance-covariance matrix is white corrected (White 1980). Second, the Shapiro-Wilks asymptotic test for normality in residuals is rejected, indicating that estimated coefficients are consistent but are distributed as Student-t only asymptotically.

Third, because household surveys are conducted in two stages, we report robust standard errors clustered over districts.

Table 2 presents the White-corrected, district clustered, OLS estimates of the determinants of net revenues per hectare using two models. Our specification is entirely driven by the literature on the Ricardian technique and the literature on the determinants on farm net revenues. Model 1 presents the marginal impacts of the quarterly precipitation rates and annual temperatures, while model 2 also includes socioeconomic characteristics. Demeaning the climate variable does not correct for multicollinearity associated with the linear and quadratic variables for quarters 1 and 4 respectively. We exclude the quadratic precipitation measures on the grounds of collinearity as well as insignificance[5].

Several key insights permeate through these regressions. In Model 1, precipitation in the 2nd and 3rd quarters exerts a significant impact on net revenues per hectare along with annual temperature. Precipitation has a concave effect in the 2nd quarter (indicating diminishing returns) and a convex effect in the 3rd quarter.

Model 2 presents the impacts of climate and socioeconomic characteristics on net revenues per hectare[6]. We find that the R^2 more than doubles from 0.14 when only climate is used to 0.30 when climate and socioeconomic characteristics are included. The inclusion of many of the socioeconomic characteristics is jointly highly significant[7]. We believe that our finding of high explanatory power of the included socioeconomic characteristics is not a special case and is likely to be found in other countries. However, the significance of marketing channels as an explanatory variable of net revenues has not been considered previously in Ricardian studies to examine climate impacts.

The importance of precipitation in the second quarter gathers significance when its quadratic is removed[8]. Three specific variables, irrigation, land tenure and cropping intensity, render the precipitation effect in the 3rd quarter insignificant. The strong negative impact of temperature remains important in model 2. The importance of precipitation in quarters 2 and 4 is not surprising given that these periods correspond with the beginning of the main agricultural seasons.

Due to the importance of the interpretation of the climate variables on net revenues per hectare, two tests were conducted to validate the robustness of the chosen measure of climate. First, we compare the same regressions using temperature and

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5 The collinearity between the linear and quadratic terms of the demeaned climate variables in quarters 1 and 4 is very strong with correlation coefficients of 0.98 and 0.99. The collinearity between the 2nd and 3rd quarter is weak with correlation coefficients of 0.84 and 0.83, respectively. As a result, the precision with which the coefficients can be estimated makes inferences unreliable.

6 Although we only report 2 models, numerous other variants were attempted to assess the stability of the estimated coefficients. There were no interesting differences between coefficients across models and in no case did a variable go from being positively significant to being negatively significant and *vice versa*.

7 The F-statistic of the test of the joint significance of the climate variables are 1,211 and 11,833 – both of which are highly significant at the 1 percent level.

8 However, the convex relation to precipitation in the 3rd quarter (as observed in Model 1) looses significance when other socioeconomic variables are included. This implies that other included variables are capturing the effect that the negative impact of precipitation in the 3rd quarter exhibited when only climate variables are included.

precipitation estimated from the FAO data against data from the meteorological department of Sri Lanka. We find that there is no significant difference between the estimated climate coefficients from the two different sources.

Our second test is a range of specifications using climate data from different months. We select the months that minimize the residual sum of squares. We use the natural logarithm of temperature and precipitation rather than the linear and quadratic terms. We try months that we believe to be important to each growing season. However, none of the results leads to an improved model. All the other specifications suffer from strong collinearity across the climate variables. In some instances the collinearity is between linear terms of different months, but more often it is the collinearity between the linear and the quadratic terms that makes the estimated coefficients unreliable. In the case when the climate variables are transformed using the natural logarithm, the collinearity between months was too strong to obtain reliable results.

In addition to the climate variables, we also got interesting results about farmer characteristics. We include the household head's education level to capture effects such as ability of households to adopt new technologies, ability to better optimize on farming and marketing practices, etc. Farmer education has a concave effect on net revenues per hectare. In other words, higher levels of education generally imply higher net revenues per hectare but the rate at which the increase occur decreases with each incremental year of education. The survey does not contain information about the farmer's experience, which is expected to have a positive impact on farm profitability. As such we use farmer's age to proxy for experience. The age of the farmer does not have a significant impact on net revenues per hectare. This may be explained by the fact that in our sample, where the average farmer is 50 years old, more experience is countered by the hardships of manual work experienced by older workers. We also include the gender of the household head in the model. Male heads of households appear to be more profitable than equivalent households with a female head. This may be because considerable manual labor is required in farming in developing countries, or because of possible discrimination faced by women when selling the produce. Another explanation is that female-headed households generally have only one adult while a majority of male-headed households have two adults, which improves the potential labor position of the farm. Interestingly, however, the size of the household does not have a significant impact on farm profitability. In Sri Lanka, as in many other developing countries, household members substitute for paid labor on the farm, but the available data does not show this to lead to higher net revenues.

Model 2 also includes a variable to capture the household's access to irrigation and whether or not the farmer has a legal claim to the land being cultivated. The results surprisingly indicate that rain-fed farms are more profitable than irrigated farms and that farms that relied on both rain fed and surface and ground water irrigation are more profitable than households that used one or the other source of water. This finding has to be interpreted with caution. On one hand, rain-fed agriculture is good for normal years in which an appropriate amount of rain falls at the appropriate time. In such a year, rain-fed agriculture would be superior to irrigated agriculture because there is a cost associated with the latter and not with the former. On the other hand, households with no access to irrigation in a drought year will stand to lose. At the time of the survey (1999-2000) the rainfall patterns and timing relative to long run patterns were normal and hence, the household dependence on irrigation may have been limited.

We also include a variable to capture land tenure, which is whether or not the household has legal rights to the property that is cultivated. In our sample, land tenure is a positive and significant determinant of net revenues per hectare[9]. Ownership reduces the uncertainty of reaping the benefits of effort (in terms of capital investment, labor and time inputs) and hence the adoption of efficient farming techniques is likely.

We include a linear and quadratic term for the number of hectares of land cultivated by the household. We define area as the sum of hectares planted in each season. The estimated coefficients of crop area suggest that there are increasing returns to scale in farm size, which is not surprising given that the average farm is 1.5 hectares. An alternative interpretation is that large farms are large because the farmer is particularly good at what he/she does and therefore can buy more land. Households that cultivate a single crop are less profitable than households that plant multiple crops. A similar result is observed by Collier and Gunning (1999) in research on farmers in Africa. This is interesting because crop diversification provides insurance against unforeseen adverse effects such as poor weather and price fluctuations. If crop diversification provides both higher expected returns and more reliable returns, it is clearly superior to single crop farming.

The chosen avenue for selling the produce of the farm is an important determinant of net revenues and one that has also not previously been explored in the climate impacts economic literature. The survey identifies the following choices available to farmers: local market, urban market, middle man, government agent, and other. We find that farm profitability is significantly determined by farmers who market their produce through local, urban channels as well as through middlemen relative to the other two alternatives. As indicated in Model 2, smallholders that are able to market their produce through middlemen are the most profitable (perhaps due to transaction costs), while those that use urban markets also do better than if they had used local markets or other means of marketing.

Whether or not the household receives a subsidy from the government does not appear to have a significant impact on farm profitability. Only 2 percent of the households receive subsidies and hence limited inferences can be made with this variable. Households that receive income from renting land or machinery do not impact farm profitability significantly. This variable helps control for households that have made investments in their farming techniques and are sufficiently enterprising to rent out their capital. We did not include the amount of the subsidy or the rental income of machinery in our definition of farm net revenue. The coefficients indicate that farm outcomes were largely independent of these variables.

Finally, whether or not the household head was born at his present location (district) is not a significant determinant of farm profitability. On one hand, local birth

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[9] We do not believe that this variable reflects selection bias because the Sri Lankan government has been providing land titles based on geographic region rather than any other kind of criteria.

implies knowledge about the local conditions. On the other, people migrate in pursuit of better pastures or opportunities. It is not clear whether this variable would be important.

PREDICTIONS

In this section, we utilize the coefficients from Model 2 in order to estimate the impact on net revenues in Sri Lanka of global warming. We rely on the climate forecasts of four different climate models (PCM (Washington et al 2000), CCSR (Emori et al 1999), CSIRO (Gordon and O'Farrell 1997), and HAD3 (Gordon et al 2000). Each model predicts precipitation and temperature by 2100 assuming greenhouse gas emissions continue unabated. We use the climate scenarios specific to Sri Lanka to analyze the impact on farm profitability (see table 3). The four models predict different annual increases in temperature normals of 1.7˚C (PCM), 2.7˚C (CCSR), 2.8˚C (CSIRO) and 3.3˚C (HAD3) and in precipitation normals of 50% (PCM), 6% (CCSR), 5% (CSIRO) and 10% (HAD3). Both temperature and precipitation are playing a role in the predicted agricultural impacts.

The very large increase in precipitation coupled with the very small warming predicted by PCM leads to large increases in overall productivity and benefits (30%). CCSR and CSIRO predict medium warming scenarios for Sri Lanka with small increases in precipitation that lead to gains for the aggregate agricultural sector of 11% and 6% respectively. HAD3, which reflects large reductions in precipitation and increases in temperature for Sri Lanka, predicts that net revenues per hectare could reduce by 23%.

The results of our study highlight the importance of precipitation relative to temperature for agriculture in tropical countries. While scientists demonstrate greater confidence regarding temperature changes in the tropics under climate change, there is far greater uncertainty about precipitation. The results from the four climate models reveal that change in precipitation levels, not temperature, drives productivity. In particular, reductions in precipitation especially when it is needed for local agricultural practices (as evident from HAD3) can have large adverse effects. In contrast, beneficial rainfall during key agricultural months can lead to substantial dividends even if accompanies by higher annual temperatures. Additional research in tropical countries must thus focus on measuring impacts on agricultural productivity due to changes in rainfall.

These aggregate effects for the country however mask the diversity of impacts likely to affect the heterogeneous geographic regions. Table 4 presents the net revenues per hectare for 17 districts under the four separate climate scenarios and current conditions (see also Figure 3). Effects vary from losses of 35% to gains of more than 50% in net revenues depending on the climate scenario. In general, the South East and the North Central regions experience a large negative impact from climate change. Conversely, the Central province is positively affected and the South West is also spared or stands to benefit marginally. From an agro-ecological standpoint, the large negative impacts are experienced in the predominantly dry zone climates. The dry zones are also currently the most stressed from climate pressures, although these regions are currently used for rice cultivation when combined with effective irrigation. On the other hand, positive impacts are expected in the higher elevation intermediate zones (these regions contain tea crops and other high value fruits and vegetables). In general the higher elevation areas appear the most able to cope, and in some cases gain from climate change. It should also be noted that the parts of the country that stand to benefit, or stand to lose the least from climate change, i.e. the South Western and Central regions of the country, are also in the path of the South West monsoons which bring rains between May and September.

CONCLUSION

This study makes two main contributions to the literature. First, from a methodological standpoint, this study applies a Ricardian framework with which to employ detailed farm-level data on net revenues across a diverse range of agro-ecological zones, available in most recent household surveys, together with climate data. In estimating the impacts of climate change, we argue that the use of farm level surveys is essential to tap into the within-district variation and also to capture the many socio-economic controls that can be obtained from household surveys and that serve to proxy for the adaptive abilities of farmers in the face of climate change. Our second contribution is that we empirically estimate the likely impacts of climate change on the smallholder sector in Sri Lanka using a single cross section of data. In carrying out the estimation, we are careful to handle some of the estimation problems, namely multicollinearity, which affects the cross-sectional climate impacts in the literature.

We find that climate variables can explain about 14% of the variation in net revenues across farms. Adding farmer, household and community characteristics increases the explanatory power of the model to 31%. About half of the explained variation is therefore due to climate and half is due to other micro level characteristics. This underscores the importance of controlling for a more diverse array of determinants of farm net revenues in conducting Ricardian valuations. For instance, we find that the manner in which produce is marketed, whether the farmer has legal property rights to cultivate the land, the size of the individual plots, and the number of crops cultivated each year are very significant determinants of net revenues per hectare. These variables have not previously been considered in the Ricardian literature.

The effect of predicted climate change scenarios depends heavily on the scenario. With a mild warming and a large increase in precipitation, we predict benefits (+22%). With medium warming and only a small increase in precipitation, we predict losses of 23%. We also predict that the climate change impacts will have considerable regional variation, which we assert is crucial from both a climate and poverty perspective (forthcoming paper). The wet, high-elevation areas may well benefit from warming whereas the hot, dry North Western and South Eastern lowlands are expected to be adversely affected. Irrigation has been used to moderate climate limitations in the lowland dry zones. However, future analyses will have to determine whether warming will threaten this adaptation by reducing runoff.

The results of our study also highlight the importance of precipitation relative to temperature for agriculture in tropical countries. Changes in precipitation dominate temperature especially during key months for local agricultural practices. Policies to address climate change concerns should therefore place a greater emphasis on dealing with long-term changes in precipitation.

It should also be noted that this analysis did not adjust for carbon fertilization. Carbon fertilization from the higher levels of CO_2 in the atmosphere is expected to increase production on average by 30% by 2100 (Reilly 1995). This effect would dominate the impacts measured here, suggesting an overall net benefit for Sri Lankan agriculture. On the other hand, we did not examine more severe climate scenarios that are likely to predict more dramatic losses in Sri Lanka.

REFERENCES

Adams, R., Rosenzweig, C., Pearl, R., Ritchie, J., McCarl, B., Glyer, J., Curry, R., Jones, J., Boote, K. and Allen, L.: 1990. "Global Climate Change and U.S. Agriculture." *Nature* **345,** 219-24.

Adams, R., McCarl, B., Segerson, K., Rosenzweig, C., Bryant, K.J., Dixon, B.L., Conner, R., Evenson, R.E., and Ojima, D.: 1999. "The Economic Effects of Climate Change on U.S. Agriculture." In Robert Mendelsohn and James Neumann, eds., *The Impact of Climate Change on the United States Economy*. Cambridge, U.K.: Cambridge University Press.

Collier, P and Gunning, J.W.: 1999. "Explaining African Economic Performance", *Journal of Economic Literature*, **37**, 62-111.

Dinar, A., Mendelsohn, R., Evenson, R., Parikh, J., Sanghi, A., Kumar, K., McKinsey, J., and Lonergan, S. (eds): 1998. *Measuring the Impact of Climate Change on Indian Agriculture*. World Bank Technical Paper 402. Washington, D.C.

Emori, S., Nozawa, T., Abe-Ouchi, A., Namaguti, A., and Kimoto, M.: 1999. "Coupled ocean-atmospheric model experiments of future climate change with an explicit representation of sulphate aerosol scattering" *Journal of Meteorological Society,* Japan **77,** 1299-1307.

Gordon, H. and O'Farrell, S.: 1997. "Transient climate change in the CSIRO coupled model with dynamic sea ice." *Mon. Weather Research* **125**, 875-907.

Gordon, C., Senior, C., Banks, H., Gregory, I., Johns, J., Mitchell, J., and Wood, R.: 2000. "The simulation of SST, sea ice extents, and ocean heat transports in a version of the Hadley Centre coupled model without flux adjustments", *Climate Dynamics* **16**, 147-168.

International Research Institute for Climate Prediction (IRI): 2003. "IRI Net Assessment Predictions for Sri Lanka", http://iri.columbia.edu/%7Emahaweli/clim/forecast.html.

Intergovernmental Panel on Climate Change (IPCC): 1997. *The regional impact of climate change: an assessment of vulnerability. Special report of IPCC Working Group II: Summary for policy makers,* New York.

Intergovernmental Panel on Climate Change (IPCC): 2001. "*Climate Change 2001: Impacts, Adaptation and Vulnerability.* Cambridge University Press, Cambridge, UK.

Kurukulasuriya, P. and Rosenthal,: 2003. Climate Change and Agriculture:A Review of Impacts and Adaptations, *Climate Change Series, 91,* Agriculture and Rural Development Department and Environment Department Joint Publication, The World Bank, Washington DC.

Maddison, D.: 2000. "A Hedonic Analysis of Agricultural Land Prices in England and Wales." *European Review of Agricultural Economics* **27**: 519-532.

Mendelsohn, R., Nordhaus, W. and Shaw, D.: 1994. "The Impact of Global Warming on Agriculture: A Ricardian Analysis." *American Economic Review* **84**: 753-771.

Mendelsohn, R, Dinar, A and Sanghi, A.: 2001. "The effect of development on the climate sensitivity of agriculture", *Environment and Development Economics*, **6,** 85-101.

Mendelsohn, R., and Dinar, A.: 1999. "Climate Change, Agriculture, and Developing Countries: Does Adaptation Matter?" *The World Bank Research Observer* **14**: 277-93.

Mendelsohn, R. and Dinar, A.: 2003. "Climate, Water, and Agriculture." *Land Economics,* **79,** 328-341.

Molua, E.: 2002. "Climate Variability, Vulnerability and Effectiveness of Farm-Level Adaptation Options: the Challenges and Implications for Food Security in Southwestern Cameroon." *Environment and Development Economics* **7,** 529–545.

Reilly, J.: 1995. "Climate Change and Global Agriculture: Recent Findings and Issues." *American Journal of Agricultural Economics* **77,** 727-733.

Rice Research and Development (RRDI): 2003. "Agroecological zones in Sri Lanka and Rice Cultivation", webpage (http://www.rice.ac.lk/research_disciplines2_map.html).

Rosenzweig, C., and Parry, M.: 1994. "Potential Impacts of Climate Change on World Food Supply." *Nature* **367**: 133-138.

Washington, W., Weatherly, J. Meehl, G., Semtner, J., Bettge, T., Craig, A., Strand, W., Arblaster, J., Wayland, V., James, R., and Zhang, Y.: 2000. "Parallel Climate Model (PCM): control and transient scenarios". *Climate Dynamics*, **16,** 755-774.

White, H.: 1980. "A Heteroscedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroscedasticity." *Econometrica.* **48,** 817-830.

World Bank: 2001. Sri Lanka Integrated Survey (SLIS) 1999-2000, Washington DC

World Bank: 2003. Global Economic Prospects, Washington, DC, USA.

Table 1: Unweighted and weighted summary statistics for variables of interest

	Unweighted			Weighted by population		
Variable	Number of Obs.	Mean	Std. Dev	Number of Obs.	Mean	Std. Dev
nr4ha	1,552	169.68	365.47	901,727	153.24	352.05
Precipitation_1st Quarter (mm)	1,552	-62.70	47.59	901,727	-67.04	45.31
Precipitation_2nd Quarter (mm)	1,552	60.47	58.88	901,727	60.42	57.95
Precipitation_3rd Quarter (mm)	1,552	29.13	76.81	901,727	32.23	76.17
Precipitation_4thQuarter (mm)	1,552	104.49	27.69	901,727	106.28	25.32
Average Annual Temperature (C)	1,552	26.03	2.41	901,727	26.05	2.28
Size of Household	1,552	4.66	1.66	901,727	4.59	1.67
Male head of household	1,552	0.88	0.33	901,727	0.88	0.33
Age of the Household head (years)	1,552	50.76	13.46	901,727	50.46	13.81
Years Education of the Household head	1,395	7.07	3.27	822,028	7.25	3.26
Farms practicing rainfed agriculture	1,552	0.60	0.49	901,727	0.57	0.50
Farms practicing rainfed and irrigated agriculture	1,552	0.06	0.23	901,727	0.05	0.22
Household has land tenure	1,552	0.64	0.48	901,727	0.64	0.48
Size of cropping area (HA)	1,552	1.54	3.29	901,727	1.41	2.11
Farm cultivating single crop	1,552	0.67	0.47	901,727	0.71	0.45
Sell produce at Local market	1,552	0.38	0.48	901,727	0.33	0.47
Sell produce at Urban market	1,552	0.08	0.27	901,727	0.08	0.27
Sell produce to Middleman	1,552	0.33	0.47	901,727	0.35	0.48
Receive Subsidy	1,552	0.02	0.13	901,727	0.01	0.12
Receive income from renting crop land	1,552	0.03	0.18	901,727	0.04	0.19
Born in current location	1,552	0.71	0.45	901,727	0.71	0.46

Notes: Authors' estimation using SLIS 1999-2000

Table 2: Determinants of net revenues per hectare

	Model 1	Model 2
Precipitation 1st Quarter	-0.56	-1.620+
	(0.79)	(0.78)
Precipitation 2nd Quarter	2.539+	-1.499**
	(1.30)	(0.59)
Precipitation 3rd Quarter	-2.869+	0.497
	(1.55)	(0.66)
Precipitation 4th Quarter	-1.70	-2.499**
	(1.02)	(0.95)
Precipitation 2nd Quarter Squared.	-0.014*	
	(0.00)	
Precipitation 3rd Quarter Squared	0.035*	
	(0.01)	
Average Annual Temperature	-21.104**	-27.858*
	(9.90)	(7.46)
Size of Household		-3.714
		(5.97)
Male head of household		79.123**
(1: male head: 0: female head)		(32.18)
Age of the Household head		-0.416
		(4.51)
Age of household head squared.		-0.003
		(0.04)
Education of the Household head		19.093
		(14.10)
Education of Household head squared		-1.398+
		(0.79)
Farms practicing rainfed agriculture		54.291**
		(25.06)
Farms practicing rainfed and irrigated agriculture		68.079
		(62.67)
Household has land tenure		57.054**
(1: has tenure; 0: none)		(25.03)
Size of cropping area		-24.600*
		(7.52)
Size of cropping area squared		0.292*
		(0.10)
Farm cultivating single crop		-122.951*
(1: single crop; 0: multiple crops)		(21.56)
Sell produce at Local market		205.879*
		(17.36)
Sell produce at Urban market		241.611*
		(50.85)
Sell produce to Middleman		266.735*
		(46.94)
Born in current location		-6.327
		(20.63)
Receive Subsidy		-7.838

		(42.92)
Receive income from renting crop land		124.408
		(86.78)
Constant	656.87	912.588*
	(383.38)	(213.68)
Observations	1552.00	1395
R-squared	0.14	0.302

Source: Authors' estimation using SLIS 1999-2000.

Notes: Robust standard errors in parentheses. Omitted variables include female household heads, farms that rely on irrigation only, households with no land tenure, households planting multiple crops, selling in informal markets, households not receiving subsidy, households not receiving income from renting capital and household heads not born in the current location.

Table 3: Climate Scenarios for Sri Lanka

	CURRENT	CCSR	PCM	HAD3	CSIRO
TEMPERATURE	(Celsius)	*(Change in temperature (C))*			
Quarter 1 (FEB)	25.38	2.86	1.98	3.31	2.91
Quarter 2 (MAY)	27.18	2.65	1.58	3.41	2.96
Quarter 3 (SEPT)	26.23	2.61	1.43	3.33	2.74
Quarter 4 (NOV)	25.23	2.69	1.75	3.15	2.88
Annual Average		2.70	1.69	3.30	2.87
PRECIPITATION	(mm)	*(Change in precipitation (%))*			
Quarter 1 (FEB)	8.18	-33.99	72.98	-55.50	55.50
Quarter 2 (MAY)	20.83	-5.81	-33.22	-7.06	-9.70
Quarter 3 (SEPT)	17.91	109.00	39.14	27.97	31.71
Quarter 4 (NOV)	29.74	-42.80	48.66	-24.95	6.76

Source: Mendelsohn (2003).

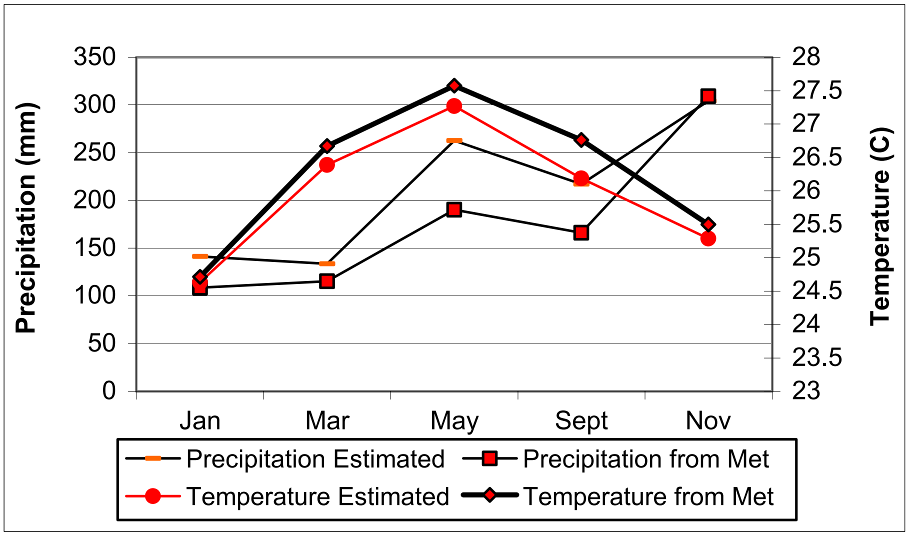
Note: Given our definition of the quarterly averages for each of the climate variables, the middle month in the quarterly average was used to model each of the climate scenarios.

Table 4: Simulated net revenues per hectare (US $) by climate

District	Province	Current	CCSR	HAD3	PCM	CSIRO
Kandy	Central	178.42	248.72	182.28	205.00	189.05
Matale	Central	115.31	113.38	118.74	165.61	91.24
Nuwara Eliya	Central	430.29	514.47	465.90	413.04	419.09
Anuradhapura	North Central	101.00	99.21	37.58	56.13	84.48
Polonnaruwa	North Central	107.04	121.59	41.96	38.22	87.39
Kurunegala	North Western	62.62	80.03	33.89	119.65	80.31
Puttalam	North Western	210.19	210.95	134.03	235.37	214.79
Kegalle	Sabaragamuwa	67.09	76.17	42.73	166.47	88.31
Ratnapura	Sabaragumuwa	345.85	404.11	302.27	581.33	435.09
Galle	Southern	425.07	477.78	368.91	717.66	533.79
Hambantato	Southern	184.95	172.74	130.34	152.14	150.17
Matara	Southern	306.20	336.59	251.77	515.80	372.88
Badulla	Uva	258.84	258.71	184.73	94.70	200.00
Moneragala	Uva	108.74	134.96	87.87	35.64	77.74
Gampaha	Western	117.84	107.75	51.01	166.32	124.10
Kalutara	Western	112.45	128.79	65.13	344.86	182.03
Sri Lanka		186.49	207.55	143.76	228.29	196.31
		(4.67)	(5.06)	(4.53)	(6.61)	(5.22)

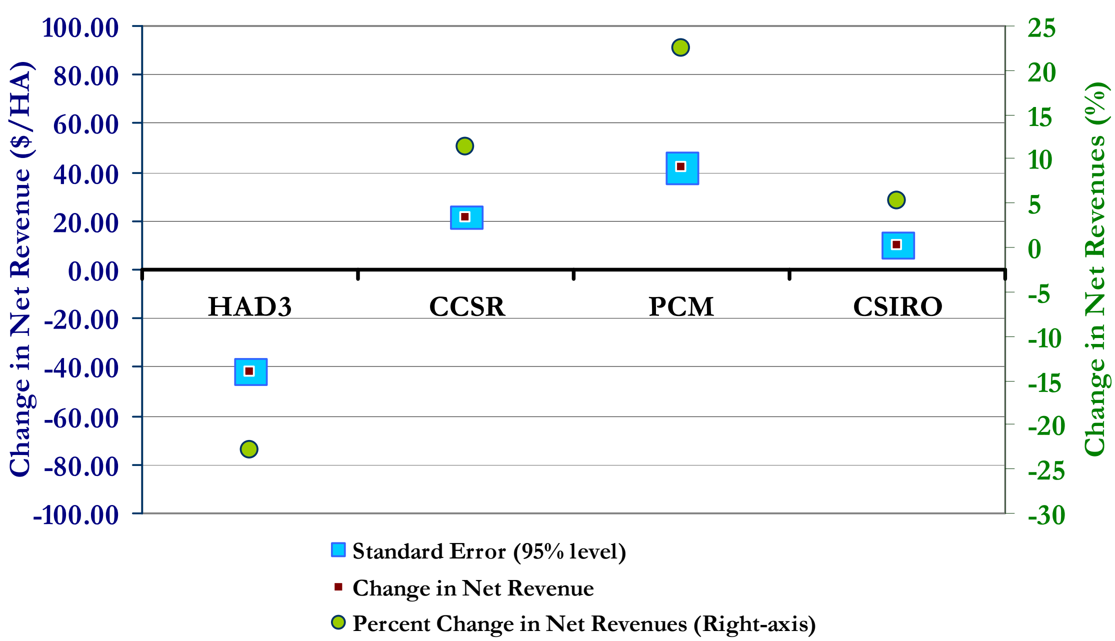
Note: North and Eastern Provinces are excluded. The district of Colombo has been omitted from the table because only 16 households in the survey are agricultural smallholders in Colombo. Standard errors in parentheses.

Figure 1: Comparison of authors' estimated temperature and precipitation (using quadratic distance weighted model) with Meteorological Department climate data for Sri Lanka (by district)



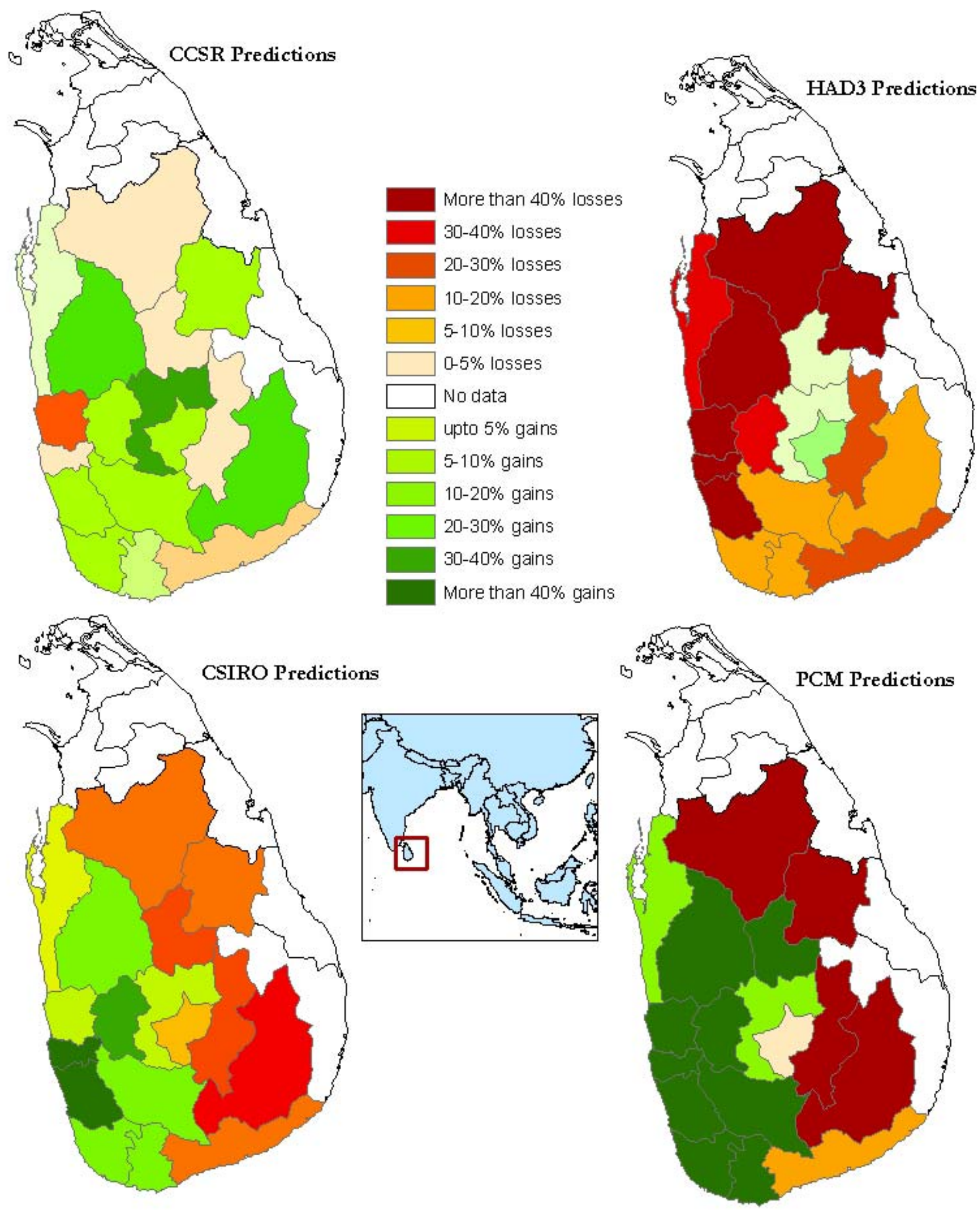
Notes: Authors' estimation using SLIS 1999-2000.

Figure 2: Aggregate National Impacts of Climate Change Based on Various Climate Models



Notes: Authors' estimation using SLIS 1999-2000.

Figure 3: Distribution of climate impacts on small holder agriculture in Sri Lanka based on alternative climate scenarios*



* Based on aggregating impacts at the household level. North and Eastern Provinces excluded.

2. CLIMATE ANALYSIS WITH SATELLITE VERSUS WEATHER STATION DATA

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ABSTRACT

This paper examines the effectiveness of satellites versus weather stations for analyzing the role that climate plays in agriculture. Although weather stations give accurate measures of ground conditions, they entail sporadic observations that require interpolation into areas where observations are missing. In contrast, satellites have trouble measuring some ground phenomenon, such as precipitation, but they provide complete spatial coverage of various parameters over a landscape. This study compares the effectiveness of ground measurements and satellite observations in a climate analysis of agriculture over Brazil, India, and the United States. The differences between the two measurement sources are small. However, except where precipitation is key, the satellite measures of climate provide more accurate accounts of agricultural performance across the landscape than the weather stations.

INTRODUCTION

As the threat of climate changes becomes more evident, there is increased interest in understanding the role of climate on agriculture and other facets of our lives and economy (Houghton et al., 2001; McCarthy et al 2001). In order to use cross-sectional data to quantify the effects of climate on farm productivity and various other activities, analysts need climate measures across space. This paper examines how best to measure climate carefully over the landscape. There are two available tools at the moment: ground measurements from weather stations or satellite observations. The weather station data are very accurate at recording what is happening at ground level but only in the immediate vicinity of the station. However, weather stations are expensive and require constant recording of measurements and periodic maintenance. Weather stations are consequently sparsely distributed, especially in developing countries. Subject areas are rarely closely covered and require interpolation between stations. In contrast, satellites see entire landscapes and so they are able to provide precise measurements at every location. However, satellites cannot make ground measurements as accurately as weather stations. Whether the accuracy of the individual measurements or the completeness of the spatial coverage provides superior observations is an important empirical question.

This paper compares climate measurements by satellites and interpolated weather station data in an analysis of agricultural net revenues in order to determine which measurement tool is more effective. The study examines broad cross sections in the United States, Brazil, and India. The Ricardian model is used to test how well climate explains agricultural performance across the landscape in each country (Mendelsohn, Nordhaus, and Shaw 1994). The Ricardian approach regresses climate, soils, and other control variables on farm value or net revenues per hectare. Past Ricardian studies of the United States, Brazil, and India relied strictly on ground weather station observations alone (Mendelsohn et al 1994; Mendelsohn et al 2001; Mendelsohn and Dinar 2003). This analysis compares the ground measurement results directly with satellite results in order to make a full assessment of the effectiveness of satellite data in each country.

We obtain long-term temperature and precipitation data from weather stations in all three countries. We interpolate between weather stations to provide climate estimates for each agricultural area (county, district, or municipio, in the United States, India, and Brazil, respectively) in the study. We also collect corresponding climate measurements from polar orbiting meteorological satellites from the Department of Defense. We also collect the maximum temperature from National Oceanic and Atmospheric Administration (NOAA) satellites. Using this satellite data, we calculate the temperature, maximum temperature, and surface wetness for the centroid (center) of each studied agricultural district.

In addition to these climate measures, we also examine two other satellite measures that directly examine crops. From the NOAA satellites, we calculate the Net Difference Vegetation Index (NDVI). From the Defense satellites, we calculate polarization. These two measures are direct measures of plants on the surface, not climate. However, it was interesting to test how well the satellite observations explained economic crop performance. A more detailed description of all the measurements and the interpolation technique is described in the next section.

The third section describes the data analyses. The climate measurements are regressed on net revenue per hectare, along with soils and economic control variables. Separate regressions are estimated for each country. By comparing the weather station and the satellite results, we test the predictive power of each variable in the climatic dataset and determine which variables are statistically significant. The paper concludes with some general observations and findings.

DATA

We gathered climate normal data from available weather stations in Brazil, India, and the continental United States. There were 751 stations in Brazil, 378 stations in India, and 5,511 stations in the United States. We specifically collected January, April, July, and October monthly means for precipitation and average temperature for the period from 1961-90. Because the counties (districts or municipios) did not all have weather stations, we interpolated between available weather stations to the centroid of each county. We used a quadratic weighted regression for interpolation. The interpolation is based on weather stations in a 500-mile radius from each county. We then regressed the observed climate on latitude, longitude, altitude, and distance to sea weighting each observation by the square of the distance from the county. A separate regression was estimated for each county. This weighted regression obviously places much greater emphasis on weather stations that are close to the county. The predicted value at the centroid of each county was then used for each county. We present an example of this interpolation method in Table 1. In places that are relatively flat, the regressions explain a great deal of the variation. However, in mountainous terrain, the models cannot capture the complexity of the surface and the explanatory power falls.

We tested this interpolation method on the actual stations and found that temperature was very accurate but that there was some error associated with precipitation in all three countries. Table 2 presents the R-squared results from the regression of the predicted values on the actual values for all the weather stations in each country. Note that the temperature predictions are reasonably accurate. The surrounding weather stations do give a good prediction of what to expect at each station. The precipitation predictions are not at all accurate. The geographical complexity of the precipitation patterns is great and the simple model is not able to predict precipitation accurately at each location. Although weather stations are much better at measuring precipitation at the station than satellites, they do not lead to good predictions of what is happening between stations.

We rely on polar orbiting satellites from two programs: the Defense Meteorological Satellite Program (DMSP) and NOAA. The Defense satellite used channel measurements from the Special Sensor Microwave Imager (SSM/I) sensor on three separate DMSP polar orbiting satellites (F08, F11, and F13) from 1987 to 2002. These DMSP satellites provide sun synchronized overpasses at 6 A.M. and 6 P.M over the entire planet. These twice-daily satellite overpasses are processed into 1/3 x 1/3 degree "pixels" by NESDIS and archived at the National Climatic Data Center (NCDC). The SSM/I instrument measures the brightness temperature (reflections) at four frequencies: 19, 37, and 85 GHz with vertical and horizontal polarization and 22 GHz with only vertical polarization. All of these frequencies are in atmospheric window regions with the 22 and 85 GHz channels having weak water vapor absorption. The measurements consequently can be made through clouds. Various signatures among the seven channel measurements were used to identify surface types and calculate dynamic emissivity adjustments (reflections by surface type)(Basist et al 1998).

The primary difficulty in deriving surface temperature from passive microwave measurements is the variable emissivity associated with different surface types. 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 currently 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 in the radiating surface. Surface wetness has strong correspondence with the upper level surface wetness at many locations (Basist et al. 2001). Moreover, wetness can originate from multiple sources (i.e. precipitation, snow melt, irrigation).

The difference between precipitation and surface wetness deserves some discussion. Precipitation captures the water falling through the air at any one moment. Surface wetness captures the stock of water in the top soil. Surface wetness consequently is affected by irrigation whereas precipitation is not. Further, surface wetness has a memory. It reflects not only the current weather but also recent history. Finally, surface wetness is also sensitive to the soil as some soil types can hold moisture better than others.

Three inputs from the DMSP satellites are used in this study: monthly climatologies for temperature, surface wetness, and polarization from the period January 1988 to 2002 for Brazil, India, and the United States. The spatial resolution is approximately 30 km. January temperatures for the United States had to be dropped because the satellite could not measure values accurately when the ground is covered by snow. Polarization provides a measure of the land use, as different surfaces (soils, crops, trees) reflect light differently. Generally the lower the polarization, the more vegetation covers the surface. Unfortunately, both water on the surface and bare ground increase polarization. Even with this potential confusion in the interpretation, the study allows us to test whether polarization can be used as a significant predictor

We also rely on the Advanced Very High Resolution Radiometer (AVHRR) instrument on board NOAA-9, 11, 14 and 16 polar-orbiting spacecrafts. The data were collected from the NOAA/NESDIS archive using the Global Vegetation Index (GVI) product covering the period 1985-2001 (Kidwell 1997). The GVI is produced by sampling and mapping the AVHRR-based 4-km (global area coverage format, GAC) daily radiances in the visible-VIS (0.58-0.68 μm), near infrared- NIR (0.72-1.1 μm), and infrared-IR (10.3-11.3 and 11.5-12.5 μm) spectrums. These values were truncated to 8-bit precision, and mapped to a (16 km^2) latitude/longitude grid. To minimize cloud effects, the maps were composited over a 7-day period by saving radiances for the day that had the largest difference between NIR and VIS (Kidwell 1997). The reflectances in the VIS and NIR and emission in the IR (CH4, 10.3-11.3 μm) were used for studying application of AVHRR indices as a proxy for climate and land use in Brazil and India.

The AVHRR-based radiances are known to have both inter-annual and intra-annual noise due to variable illumination and viewing conditions, sensor degradation, satellite navigation and orbital drift, atmospheric and surface conditions, methods of data sampling and processing, communication and random errors (Gutman 1991). The initial processing included post launch calibration of VIS and NIR following Rao and Chen (1999), calculation of NDVI ([NIR-VIS]/[NIR+VIS]), and conversion of CH4 (methane) radiance to brightness temperature (BT). The latter measure was corrected for the non-linear behavior of the sensor (Kidwell 1997). As the result, long-term noise was reduced substantially. Furthermore, temporal high frequency noise was completely removed from NDVI and BT annual time series using statistical smoothing techniques. The 1985-2000 climatology (extreme values) were then calculated (Kogan 1997, 2001).

The climatology of NDVI and BT was approximated by the multi-year extreme (maximum and minimum) values for each pixel and week. These extremes are known to characterize carrying capacity of land ecosystems and climate. It is important to emphasize that NDVI and BT are very unique parameters. NDVI characterizes the distribution of vegetation on the earth surface. NDVI values reflect the combined impact of moisture and thermal resources on vegetation and this impact is cumulative. Brightness temperature from the GVI data set characterizes the highest temperature in the diurnal cycle. These properties make the indices valuable for agricultural and water resource applications.

RESULTS

The purpose of the following analysis is to compare the effectiveness of weather station versus satellite measurements of climate. We begin the analysis in the US examining the effectiveness of just the temperature measurements from the ground and satellite data sets. We regress April, July, and October average monthly temperature measurements and their squared values on US land values in Table 3 (columns 1 and 4). The coefficients are significant for both the linear and squared terms for all three months for both the weather station and the satellite data. However, the R-squared is slightly higher for the satellite data. The satellite data does a better job of describing the pattern of farmland values across the US landscape. Presumably, this is because it is doing a better job of measuring the actual temperatures in each county.

In the second analysis in Table 3 (columns 2 and 5), we add other climate measures as well, including precipitation for the weather stations, surface wetness for the satellite, and interannual variance for both. The coefficients of most of these additional measurements are significant. The overall R-squared for the satellite measurements remain slightly higher. In the third analysis in Table 3 (columns 3 and 6), we also include soils and economic control variables. Including these remaining variables improves the overall fit. Climate normals, however, continue to play a large role in explaining land values across the US. Overall, the satellite data continues to give slightly higher R squares than the weather station results. This is an interesting result given the abundance of weather station data in the US.

Another interesting result in these final regressions is to compare the marginal impact of higher annual temperatures evaluated at the mean temperature of agricultural production in the US. Summing across the seasons, the marginal impact of higher temperatures would reduce land values by 13.1% according to the weather station data but only 7.3% according to the satellite data. The weather station data implies that the negative slope of the land value temperature relationship is steeper. It is also interesting to note that although the marginal impact of surface wetness is slightly negative (-2.0%) that increased precipitation is positive (13.4%). This, of course, may have less to do with the measuring device and more to do with the difference between surface wetness and precipitation that was discussed earlier. Interannual variance has mixed effects depending upon the season, the climate variable, and the measuring device.

In Table 4, we conduct a similar analysis for Brazil. In columns 1 and 4, we regress only temperature and temperature squared for the months of January, April, July, and October onto average net revenue per hectare. Since the vast majority of Brazil's agricultural land is in the Southern Hemisphere, January represents the middle of the growing season. The weather station temperature coefficients are generally not significantly different from zero. Approximately half of the satellite temperature coefficients are significant. The overall results, however, indicate that the satellite data can explain only slightly more of the cross sectional variation in average net revenue than the weather station data.

Columns 2 and 5 of Table 4 contain the remaining climate variables of precipitation, surface wetness, and interannual variance. The precipitation variables are highly significant whereas the surface wetness variables are generally insignificant. In addition, more of the interannual variance measures taken by the weather stations are significant, as compared with the satellite variance measures. The overall result is that the weather station data explains more of the variance in the second analysis than the satellite data.

In the third analysis (columns 3 and 6 in Table 4), we include soils and economic variables as further controls. This weakens the significance of some of the climate coefficients indicating that they are correlated with soil and economic parameters. Overall, the power of the regression improves, but it remains that the weather station data is slightly more effective in explaining net revenues than the satellite data. At least in Brazil, it appears that having precipitation data rather than surface wetness data is important, giving the weather station data an advantage. This may reflect the numerous low-lying wet areas scattered across Brazil, which affect the surface wetness measure at a 30 km resolution.

We also compare the marginal impact of temperature in Brazil. According to the weather station data, a one degree increase in annual temperature would reduce net revenue by -4.5%. The negative marginal effect of temperature according to the satellite data is -14.2%. The marginal effect of increased precipitation is virtually zero on annual net revenues in Brazil. Increasing surface wetness increases net revenues by 7.6%. According to the satellite data, interannual variance is harmful in the few seasons that it is significant. The interannual results are more mixed with the weather station data with both positive and negative effects.

In Table 5, we examine the results for India. In the first case, climate measures were regressed on net revenues in a single year, 1997 (columns 1 and 4). The results for the temperature only case reveal that the satellite data slightly outperformed the weather station data. The overall explanatory power of both regressions is weak. Using only a single year of net revenue data is problematic because it reflects the weather of that year not just the long-term climate. Adding the other climate variables (columns 2 and 5) improves the performance of the regression notably. In India, precipitation and surface wetness may be more important than temperature in explaining cross-sectional variation. With the surface wetness variables and interannual effects, the satellite data clearly outperforms the weather station data, since it generates a much higher R squared value.

The third analysis (columns 3 and 6 in Table 5) includes locational and socioeconomic data. This considerably improves both models even further, but especially the weather station model. Nonetheless, even with all the control data in the equation, the satellite data still clearly outperforms the weather station data in this last set of regressions.

With all the controls, April and October linear and squared temperature coefficients are significant. The same two seasons are significant with precipitation as well. Examining marginal impacts reveals that the weather station data predicts that higher temperature has a large positive effect on net revenue (26%). With the satellite data, higher temperatures reduce net revenues by 17.5%. Given the already high temperatures in India, it was expected that higher temperatures would be harmful. The satellite results reflect what was expected. Higher precipitation is beneficial, increasing net revenues by 3.5%. Higher surface wetness is also very beneficial, increasing net revenues by 61.3%. The weather station data suggests that April interannual temperature variation is beneficial and that April and July precipitation variance is also mildly beneficial. The satellite data suggests that temperature variance is insignificant in India and that precipitation variance is mixed with positive effects in January and negative effects in April. The satellite results conform more closely to expectations. Off-season weather variation (January) is easier for farmers to adapt to since crops have not yet been planted. However, in-season weather variation (April) is more harmful because often the growing season has already begun and little adaptation is possible.

In addition to the measures of climate discussed above, the satellites provided additional measurements that have never been tested in a Ricardian study before: maximum temperature, Normalized Difference Vegetation Index (NDVI), and polarization. In all three cases, these variables have been added to the final regressions (column 6) in Tables 3, 4, or 5. Table 6 presents the results for maximum temperature for Brazil and India. Maximum temperatures could be important to crops because they may reflect heat stress in warm seasons and reduced frost in cold seasons. Only the coefficients of the additional variables are reported in Table 6. All four seasonal coefficients for maximum temperature in India are significant. The coefficients have an interesting pattern with a positive value in January and October and a negative value in April and July. Given that April and July are the hottest months, one could interpret the negative results as reflecting heat stress. In the cooler months of January and October, the maximum temperature turns into a beneficial force. The results for Brazil are less compelling with January and July effects no different from zero. The results for April and October are almost significant. They suggest that maximum temperature has a negative effect in April (harvest season) and a positive effect in October (planting season).

In Table 7, we present the results for NDVI. The NDVI depends heavily on the inverse of maximum temperature. It consequently works in exactly the opposite direction as the maximum temperature variable. In India, that means positive coefficients for April and July and negative coefficients for January and October. Once again the interpretation for NDVI would be similar to the maximum temperature interpretation above. Higher NDVI indices in January and October are harmful but higher indices in April and July are beneficial. The results in Brazil are again weak except for July (winter), which is very significant. Again, a high NDVI in winter is a bad thing inferring that high maximum temperatures in winter are beneficial.

The results in Table 8 concern polarization, which also is a measure of vegetation cover. We tested polarization in Brazil, India, and the United States. Very few of the polarization coefficients are significant. April (fall) and July (winter) polarization are negative and positive respectively in Brazil. But in the United States, only October (fall) polarization is significant and it is positive. Polarization measurements are thus generally insignificant and the coefficients that are significant are inconsistent across countries.

CONCLUSION AND POLICY IMPLICATIONS

This study compares satellite and weather station data with agricultural performance across the landscape. In Brazil, India, and the United States, we examine how well the various climate measures explain land values or net revenue per hectare across municipios, districts, and counties, respectively. Climate measures from both satellites and weather stations are closely comparable. Temperature measurements from the satellites slightly outperform the weather station temperatures. In this case, the satellite's ability to see the entire landscape is a clear advantage over the scattered weather station observations. However, the weather stations are able to measure precipitation more accurately. In countries where precipitation is important, such as Brazil, these measures give the weather stations an advantage. In India, by contrast, the surface wetness measures of the satellites are especially effective, giving the satellite's measures even more explanatory power. However, part of this advantage may actually be reflecting irrigation (since the wetness product senses all sources of liquid water, not just precipitation). Therefore, the wetness product is not just a measure of climate, it is also a reflection of farmer choices.

The study also tests the importance of additional measurements made by the satellites. Maximum temperature has a significant and interesting pattern in India. In warmer months, it increases stress on plants and reduces productivity. In cooler months, warmer maximum temperatures are helpful, possibly by reducing risk of frost and drying fall harvests. In Brazil, the pattern was less clear, having no effect in the winter or summer and reducing productivity in the fall but increasing it in the spring. Normalized difference vegetation indices were also explored. Maximum temperature is in the denominator of the NDVI, so the NDVI coefficients exhibit a pattern exactly opposite maximum temperature. Higher NDVI measures lead to higher production in the spring and summer in India, but lower production in the fall and winter. The negative winter results were repeated in Brazil but the other seasons were not quite significant. A final measure tested was polarization, which tended to be unable to predict either land values or net revenues per hectare in the three countries tested.

The study shows that satellite data could well support analyses of agricultural performance across the landscape. Specifically, the satellite data did a very good job of capturing climate effects in the Ricardian analyses in Brazil, India, and the United States. Although it would be prudent to collect weather station data, especially of precipitation, future studies could rely solely on the satellite data in remote locations. Thus, the satellites may be particularly valuable for studying agriculture in developing countries where reliable weather station data may be sparse.

Another policy question that could be of great relevance is whether satellite technology is mature enough to replace weather station data for climate related decision-making. For example, satellites may be able to identify droughts, floods, and other emergency conditions in a timely and cost-effective manner. This information could be used to help relief programs anticipate problems at an early stage before a crisis is reached. The information could help insurance programs identify where and when they might have to pay large claims. The information could help develop effective predictions of crop production. Given the difficulty of maintaining an extensive network of weather stations in many developing countries, satellite data show great potential.

The Ad-Hoc Group on Earth Observations recently argued that "…despite the existence of numerous remote sensing and *in situ e*arth observation capabilities, a critical need persists for improved availability, quality, and assured continuity of data in the systematic observation of the planet." (GEO 2003) Climate has been identified on the top of the list of the possible activities that can benefit from use of satellite data. Our paper clearly demonstrates the potential of satellites for studying climate change impacts.

REFERENCES

Basist, A., Williams Jr., C., Grody, N., Ross, T.E., Shen, S., Chang, A., Ferraro, R., Menne, M. J.: 2001. “Using the Special Sensor Microwave Imager to monitor surface wetness”. *J. of Hydrometeorology,* **2,** 297-308.

Basist, A., Peterson, N., Peterson, T., and Williams, C.: 1998. “Using the Special Sensor Microwave Imager to monitor land surface temperature, wetness, and snow cover”. *J. Appl. Meteor.,* **37**, 888-911.

Gutman, G.G.: 1991. “Vegetation Indices from AVHRR Data: An Update and Future Prospects”. *Remote Sens. Environ.*, **35**, 121-136.

Group on Earth Observation, 2003. Draft Framework, *http://earthobservations.org*

Houghton, J., Ding, Y., Griggs, D., Noguer, M., van der Linden, P., Dai, X., Maskell, K., and Johnson, C. (eds.): 2001. *Climate Change 2001: The Scientific Basis*. Third Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge.

Kidwell, K. B.: 1997. *Global Vegetation Index User's Guide*. Department of Commerce, NOAA/NESDIS, National Climate Data Center, Washington D.C., 52p.

Kogan. F.N.: 2001. “Operational Space Technology for Global Vegetation Assessment”. *Bull. Amer. Meteor. Soc*. **82**, 1949-1964.

Kogan, F.N.: 1997. “Global Drought Watch from Space”. *Bull. Amer. Meteor. Soc.*, **78**, 621-636.

Kogan, F.N.: 1990. “Remote sensing of weather impacts on vegetation in non-homogeneous areas”. *Int. J. Remote Sens.,* **11**, 1405- 1419.

Kogan, F.N.: 1995. “Droughts of the Late 1980s in the United States as Derived from NOAA Polar Orbiting Satellite Data”. *Bull. Amer. Meteor. Soc*. **76**, 655-668.

McCarthy, J., Canziani, O., Leary, N., Dokken, D., and White, K. (eds.): 2001. *Climate Change 2001: Impacts. Adaptation, and Vulnerability*. Third Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge.

Mendelsohn, R., Nordhaus, W., and Shaw, D.: 1994. "The Impact of Global Warming on Agriculture: A Ricardian Analysis” *American Economic Review* **84**: 753-771.

Mendelsohn, R., Dinar, A., and Sanghi, A.: 2001. "The Effect of Development on the Climate Sensitivity of Agriculture", *Environment and Development Economics* **6,** 85-101.

Mendelsohn, R. and Dinar, A.: 2003. “Climate, Water, and Agriculture”, *Land Economics* **79,** 328-341.

Rao, C.R.N. and Chen, J.: 1999. “Revised post-launch calibration of the visible and near-infrared channels of the Advanced Very High Resolution Radiometer on the NOAA-14 spacecraft”. *Int. J. Remote Sens.,* **20**, 3485-3491.

Table 1

Interpolation Regression for Temperature in Anantpur, Andra Pradesh, India

Independent Variables	January	Season April	July	October
Constant	52.3	17.2	-6.1	24.6
	(9.60)	(2.73)	(0.74)	(5.50)
Latitude	-0.34	0.12	0.11	0.04
	(6.41)	(1.94)	(1.37)	(0.87)
Longitude	-0.29	0.14	0.42	0.03
	(4.16)	(1.80)	(4.00)	(0.58)
Altitude	-5.2e-3	-1.2e-3	-5.7e-3	-3.3e-3
	(3.67)	(0.71)	(2.62)	(2.80)
Distance to Sea	7.9e-3	9.6e-3	1.1e-3	3.2e-3
	(0.82)	(0.86)	(0.77)	(0.40)
Altitude Squared	-4.0e-6	-2.3e-6	-0.1e-6	1.0e-6
	(0.76)	(3.75)	(0.13)	(2.33)
Distance to Sea	-2.2e-6	-9.7e-6	-2.9e-6	-8.4e-6
Squared	(0.77)	(0.29)	(0.66)	(0.35)
Adjusted R-Squared	0.96	0.95	0.92	0.97
N	21	21	21	21

Table 2

Predictive Ability of Interpolated Climate Normals

Country and Variable	Month			
	January	April	July	October
Brazil				
Temperature	.916	.959	.977	.775
Precipitation	.089	.765	.815	.103
India				
Temperature	.985	.793	.833	.934
Precipitation	.557	.466	.324	.776

The reported values are the R-squared from regressing predicted values on actual values for all weather stations. Values for the United States ranged from .97 to .99 for temperature and from .87 to .97 for precipitation.

Table 3

Climate Regressions for the United States

Independent Variables	Dependent Variable: Cropland Value in 1997					
	Weather Station			Satellite		
	Temp	Climate	All	Temp	Climate	All
Constant	-2520	3780	4780	8070	6530	5550
	(2.36)	(3.47)	(5.04)	(11.22)	(9.29)	(8.63)
April Temp	589.	757.	553.	579.	591.	393.
	(9.52)	(13.03)	(10.43)	(10.29)	(10.45)	(8.32)
July Temp	350.	-242.	-406.	-601	-484.	–476.
	(3.70)	(2.44)	(4.75)	(8.79)	(7.42)	(8.18)
October Temp	-186.	-628.	-414.	-166.	-261.	–76.
	(2.12)	(7.49)	(5.48)	(2.52)	(3.94)	(1.40)
Apr Temp Squared	-29.9	-39.9	-25.0	-26.9	-30.4	-16.6
	(13.82)	(18.66)	(12.66)	(11.28)	(12.74)	(8.20)
Jul Temp Squared	-15.1	2.37	7.1	6.5	6.0	7.0
	(7.61)	(1.15)	(4.02)	(4.31)	(4.03)	(5.28)
Oct Temp Squared	23.6	35.8	18.8	17.7	23.3	7.6
	(8.31)	(12.09)	(6.99)	(6.36)	(8.19)	(3.21)
April Prec	…	239.	177.	…	6.6	-39.6
		(8.53)	(6.97)		(0.97)	(1.65)
July Prec	…	-57.	-80.	…	60.2	3.0
		(3.30)	(5.30)		(7.26)	(0.09)
October Prec	…	147.	48.	…	-36.6	0.7
		(4.69)	(1.74)		(3.89)	(0.02)
Apr Prec Squared	…	-5.62	-3.10	…	1.14	6.01
		(3.89)	(2.37)		(3.04)	(4.50)
Jul Prec Squared	…	3.95	5.35	…	-1.83	2.77
		(4.47)	(6.95)		(2.48)	(0.83)

Table 3-continued

Independent Variables	Weather Station Temp	Weather Station Climate	Weather Station All	Satellite Temp	Satellite Climate	Satellite All
Oct Prec Squared	…	-8.80	-3.49	…	-0.99	-7.44
		(3.92)	(1.79)		(1.45)	(2.81)
April Interannual Temp Variance	…	134.	83.5	…	-354.	-243.
		(10.62)	(7.26)		(11.47)	(9.09)
July Interannual Temp Variance	…	-179.	–154.	…	…	...
		(10.52)	(10.38)			
October Interannual Temp Variance	…	-29.	13.	…	389.	194.
		(1.96)	(1.04)		(12.29)	(6.91)
April Interannual Prec Variance	…	-27.1	-20.1	…	21.0	53.8
		(6.42)	(5.55)		(1.22)	(3.64)
July Interannual Prec Variance	…	-12.7	-5.8	…	-87.4	-46.2
		(4.31)	(2.30)		(3.02)	(1.94)
Income per capita	…	…	84.2	…	...	773.
			(12.02)			(9.60)
Population density	…	…	4.26	…	…	3.91
			(12.25)			(10.00)
% Urban	…	…	…	…	…	94.0
						(2.88)
Population change	…	…	1.83	…	…	3.94
			(2.47)			(4.62)
Permeability	…	…	3.35	…	…	…
			(1.99)			
Altitude	…	…	-146	…	…	-177.
			(10.53)			(9.65)
% Clay	…	…	83.3	…	…	49.1
			(3.69)			(1.96)
% Flooding	…	…	-316.	…	...	-155.
			(5.54)			(2.54)

Table 3-continued

Independent Variables	Weather Station Temp	Weather Station Climate	Weather Station All	Satellite Temp	Satellite Climate	Satellite All
Soil erosion	…	...	-1970.	…	…	-1130.
			(9.43)			(4.71)
Salinity	…	…	322.	…	...	1140.
			(1.88)			(5.39)
% Sand	…	…	-356.	…	…	-263.
			(5.82)			(4.06)
%Wetland	…	…	-1170.	…	...	-667.
			(7.64)			(3.60)
Water capacity	…	…	543.	…	...	533.
			(10.98)			(9.85)
Adj R^2	.507	.658	.761	.597	.677	.792

There were 1942 observations in each regression, weighted by acres of cropland.

Table 4

Climate Regressions for Brazil

Independent Variables	Dependent Variable: Cropland Value in 1997					
	Weather Station			Satellite		
	Temp	Climate	All	Temp	Climate	All
Constant	-623.	1970	1760	6970	12300	8960
	(1.01)	(3.06)	(2.88)	(5.39)	(8.07)	(6.15)
January Temp	74.7	-12.8	-26.3	-100.	–121.	140.
	(1.70)	(0.29)	(0.64)	(0.51)	(0.50)	(0.61)
April Temp	49.2	-119.9	-112.	-646.	-930.	-115.
	(0.70)	(1.65)	(1.62)	(2.73)	(3.64)	(4.68)
July Temp	48.8	-32.2	-61.2	626.	855.	654.
	(1.15)	(0.71)	(1.42)	(7.79)	(9.23)	(7.47)
October Temp	0.2	51.5	66.7	-261.	-738.	-385.
	(0.04)	(0.89)	(1.22)	(2.12)	(5.58)	(2.95)
Jan Temp Squared	-1.95	0.87	0.50	2.11	3.63	-1.94
	(1.87)	(0.83)	(0.51)	(0.46)	(0.65)	(0.37)
Apr Temp Squared	1.00	3.18	3.71	14.6	21.2	26.8
	(0.62)	(1.85)	(2.26)	(2.64)	(3.49)	(4.62)
Jul Temp Squared	-0.58	1.64	2.22	-13.9	-22.7	-16.1
	(0.53)	(1.38)	(1.97)	(6.34)	(8.87)	(6.62)
Oct Temp Squared	-2.76	-3.18	-2.97	2.4	16.5	7.6
	(2..13	(2.37)	(2.40)	(0.81)	(5.12)	(2.41)
January Precipitation	…	2.19	0.98	…	-85.6	53.3
		(4.92)	(2.23)		(1.63)	(1.06)
April Precipitation	…	-1.46	-1.54	…	6.1	-77.4
		(2.59)	(2.87)		(0.11)	(1.51)
July Precipitation	…	1.66	1.62	…	-24.9	74.6
		(3.68)	(3.75)		(0.63)	(1.94)

Table 4-continued

Independent Variables	Weather Station Temp	Weather Station Climate	Weather Station All	Satellite Temp	Satellite Climate	Satellite All
October Precipitation	…	-0.42	-0.63	…	179.	13.0
		(0.92)	(1.44)		(4.32)	(0.32)
Jan Prec Squared	…	-2.87e-3	–1.41e-3	…	0.02	-2.20
		(3.94)	(1.99)		(0.00)	(1.93)
Apr Prec Squared	…	2.92e-3	2.96e-3	… …	5.53	4.97
		(2.98)	(3.17)		(2.40)	(2.30)
Jul Prec Squared	…	-2.35e-3	-2.19e-3	…	-0.63	-1.69
		(3.22)	(3.15)		(0.44)	(1.24)
Oct Prec Squared	…	-0.17e-3	0.23e-3	…	-4.97	-1.34
		(0.23)	(0.32)		(3.19)	(0.91)
April Interannual	…	...	-20.9	…	-97.9	-70.2
Temp Variance			(2.05)		(5.40)	(4.09)
July Interannual	…	39.2	17.5	…	-46.3	-50.1
Temp Variance		(4.67)	(2.08)		(3.47)	(4.00)
October Interannual	…	-75.3	-37.8	…	…	...
Temp Variance		(6.54)	(3.40)			
January Interannual		0.68	0.78	…	-17.6	-18.2
Prec Variance		(5.26)	(6.22)		(3.96)	(4.34)
April Interannual	…	-0.77	-0.64		...	…
Prec Variance		(3.79)	(3.30)			
July Interannual	…	0.64	0.58	…	…	…
Prec Variance		(3.59)	(3.44)			

Table 4-continued

Independent Variables	Weather Station Temp	Climate	All	Satellite Temp	Climate	All
Income per capita	…	…	54.7	…	...	58.0
			(10.73)			(11.56)
Soils 517	…	…	-337.	…	…	-403.
			(4.62)			(4.46)
Soils 521	…	…	83.	…	…	151.
			(2.17)			(3.33)
Soils 524	…	…	1570	…	…	2220
			(15.17)			(15.07)
Adj R^2	.243	.325	.402	.264	.303	.392
N	3173	3173	3173	2750	2750	2750

Table 5

Climate Regressions for India

Independent Variables	Dependent Variable: Cropland Value in 1997					
	Weather Station			Satellite		
	Temp	Climate	All	Temp	Climate	All
Constant	-37000	-82500	-53700	3680	3964	8470
	(2.35)	(6.11)	(4.24)	(0.39)	(0.57)	(1.22)
January Temp	39.	–1160	-1240	-390.	180.	–238.
	(0.10)	(3.27)	(3.50)	(0.84)	(0.50)	(0.63)
April Temp	965.	2030	1160	504.	-1130	-1300
	(1.08)	(2.63)	(1.60)	(0.55)	(1.74)	(2.04)
July Temp	1810.	1800	976.	-446.	-160.	–230.
	(1.97)	(2.10)	(1.25)	(0.40)	(0.22)	(0.32)
October Temp	-177.	2190	1880	137.	1260	1540
	(0.21)	(2.27)	(2.14)	(0.10)	(1.50)	(1.87)
Jan Temp Squared	3.70	27.3	25.7	7.6	-9.3	1.0
	(0.40)	(3.26)	(3.17)	(0.53)	(0.82)	(0.09)
Apr Temp Squared	-21.3	-34.7	-17.6	-13.6	24.7	29.3
	(1.39)	(2.62)	(1.42)	(0.76)	(1.95)	(2.34)
Jul Temp Squared	-28.2	-28.8	-15.9	4.1	3.5	4.0
	(1.87)	(2.08)	(1.26)	(0.20)	(0.26)	(0.31)
Oct Temp Squared	4.23	-33.9	-30.6	8.3	-34.6	-41.9
	(0.31)	(2.17)	(2.16)	(0.28)	(1.79)	(2.18)
January Prec	…	-57.6	-25.1	…	-59.0	-49.0
		(2.82)	(1.17)		(0.43)	(0.36)
April Prec	…	91.8	50.4	…	1320	1230
		(3.68)	(2.13)		(6.83)	(6.41)
July Prec	…	7.2	6.0	…	-39.1	-1.8
		(2.15)	(1.99)		(0.40)	(0.02)

Table 5-continued

Independent Variables	Weather Station Temp	Weather Station Climate	Weather Station All	Satellite Temp	Satellite Climate	Satellite All
October Prec	…	24.2	20.9	…	-550.	-557.
		(3.17)	(2.72)		(4.00)	(4.13)
Jan Prec Squared	…	0.41	0.12	…	24.5	23.7
		(1.93)	(0.62)		(4.01)	(3.96)
Apr Prec Squared	…	-0.29	-0.19	…	-81.7	-76.1
		(4.46)	(3.08)		(6.91)	(6.47)
Jul Prec Squared	…	-0.01	-0.01	…	5.7	4.9
		(1.88)	(1.62)		(1.47)	(1.28)
Oct Prec Squared	…	-0.10	-0.07	…	22.7	21.8
		(2.87)	(2.08)		(4.19)	(4.09)
April Interannual	…	155.	281.	…	...	…
Temp Variance		(2.44)	(4.68)			
January Interannual	…	…	…	…	169.	148.
Prec Variance					(3.41)	(3.03)
April Interannual	…	8.6	15.4	…	-216.	–200.
Prec Variance		(1.00)	(1.96)		(6.31)	(5.86)
July Interannual	…	3.0	2.3	…	…	…
Prec Variance		(2.76)	(2.29)			

Table 5-continued

Independent Variables	Weather Station Temp	Weather Station Climate	Weather Station All	Satellite Temp	Satellite Climate	Satellite All
Distance to sea	…	…	-6.2	…	...	-2.9
			(5.71)			(3.21)
Population density	…	…	1.6	…	…	…
			(4.58)			
Latitude	…	…	162.	…	…	…
			(2.78)			
Adj R^2	.078	.464	.566	.128	.683	.695
N	296	296	296	268	268	268

Table 6

Maximum Temperature (MT)

Independent Variables	Brazil	India
January MT	-3.4	119.
	(0.35)	(2.09)
April MT	-24.5	-267.
	(1.75)	(4.62)
July MT	5.8	-128.
	(0.59)	(2.17)
October MT	14.8	187.
	(1.86)	(3.80)
R^2	.397	.724

The maximum temperature variables have been added to the regression in column 6 in Table 4 for Brazil and column 6 in Table 5 for India. The dependent variable is net revenue per hectare. Only the added variables are shown here.

Table 7

Normalized Difference Vegetation Index (NDVI)

Independent Variables	Brazil	India
January NDVI	-452.	-3780
	(1.16)	(2.32)
April NDVI	643.	14300
	(1.53)	(5.13)
July NDVI	-1860	3140
	(5.68)	(1.50)
October NDVI	630.	-8480
	(1.64)	(4.27)
R^2	.399	.736

The NDVI variables have been added to the regression in column 6 in Table 4 for Brazil and column 6 in Table 5 for India. The dependent variable is net revenue per hectare. Only the added variables are shown here.

Table 8

Polarization

Independent Variables	Brazil	India	United States
January Polarization	65.7	74.6	…
	(1.33)	(0.84)	
April Polarization	-93.7	-112.	7.6
	(1.92)	(1.10)	(0.52)
July Polarization	93.5	-188.	-13.6
	(2.16)	(0.81)	(0.69)
October Polarization	-0.4	-25.9	91.7
	(0.01)	(0.15)	(4.38)
R^2	.405	.696	.803

The polarization variables have been added to the regression in column 6 of Table 3 for the United States, column 6 in Table 4 for Brazil, and column 6 in Table 5 for India. The dependent variable is net revenue per hectare for Brazil and India and land value for the United States. Only the added variables are shown here.

3. 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 temperature and precipitation) and interannual climate variance on farms in the United States, India, and Brazil. The paper finds that both climate normals and climate variance are important, explaining both net revenues and how much land is used for cropland. In all three countries, higher temperature and higher precipitation variance are harmful. But only in the United States are higher precipitation levels also harmful and only in Brazil are higher temperature variances harmful. The set of variables that is most important varies by country. In the United States, climate normals are more important in explaining net revenue but climate variance is more important in explaining cropland. In Brazil, climate variance is just as powerful in explaining net revenues and even more powerful in explaining the distribution of cropland across the country. In India, climate normals and especially surface wetness explain net revenues but only temperature normals explain cropland.

INTRODUCTION

Agronomic-economic and cross-sectional models are two major economic approaches that have been employed to study the interaction between climate, water, and agriculture. The agronomic-economic approach begins with calibrated agronomic models and predicts outcomes, using economic simulations. For example, an economic model and agronomic experimental results have been combined to make numerous simulations of the impact of climate change on US agricultural production (Adams et al 1990; 1999; 2001). The cross-sectional approach compares the choices and performance of existing farms that face different climate, soil, and other relevant production conditions. For example, the Ricardian approach links farm values to climate (Mendelsohn, Nordhaus, and Shaw 1994; 1999; 2001). Both the cross-sectional and agronomic-economic models have provided independent insights into how climate and soils affect farming. The two approaches have also jointly confirmed a number of hypotheses, such as the hill-shaped relationship between crop productivity and temperature. This confirmation should be reassuring to all practitioners because it shows that the results are robust across all the assumptions inherent in each method.

In this paper, we use cross-sectional methods to explore the relative importance of climate normals versus climate variation on agriculture. Earlier Ricardian studies showed that climate normals and climate variance had significant effects on cropland value per hectare (Mendelsohn, Nordhaus, and Shaw 1999; 2001). This paper extends the earlier studies by quantifying the relative importance of climate normals versus climate variance. The paper also explains the percentage of cropland across the landscape. Where crops are grown also depends on climate.

The study examines two key economic measures of agriculture: net revenue per hectare and the fraction of land used for cropland. In all three countries, net area sown divided by total area was used to measure the fraction of land in cropland. These dependent variables are regressed on climate and other important control variables, such as soils and socioeconomic data. Satellites were used to provide consistent climate measures across countries.

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:

$$NR = \Sigma P_i Q_i (X, F, Z, G) - \Sigma RX \qquad [1]$$

where P_{LE} is the net revenue per hectare per year, 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, Nordhaus and Shaw 1994). The farmer is assumed to choose X 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.

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

$$NR = B_0 + B_1F + B_2 F^2 + B_3 Z + B_4 G + u \qquad [2]$$

where u is an error term. Both a linear and a quadratic term for temperature and precipitation are introduced. The marginal influence of each climate variable consequently depends upon the level of temperature or precipitation:

$$[dNR/df_i]= [b_{1,i} + 2*b_{2,i} * f_i] \quad .$$

The quadratic term reflects the nonlinear shape of the net revenue of the climate response function. When the quadratic term is positive, the net revenue function is U-shaped and when the quadratic term is negative, the function is hill-shaped. We expect, based on agronomic research and previous cross-sectional analyses, that farm value will have a hill-shaped relationship with temperature. For each crop, there is a temperature range where that 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.

There is one important difference between the satellite data in this study and the ground station data that has been used in past studies. The ground stations measure precipitation. Satellites find measuring rainfall very difficult. They can detect when rain clouds are present but they have a hard time measuring actual precipitation. The satellites, however, can measure surface wetness (soil moisture). From an agronomic perspective, surface wetness may be a more attractive measure than rainfall as it reflects the moisture actually available to crops. Soil moisture, 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.

Although the Ricardian technique carefully measures the influence of climate, it has been criticized for omitting the influence of water from runoff (Cline 1996; Darwin 1999). The early empirical models did not include runoff from other sources and so they did not capture the value of exogenous water supplies (Mendelsohn et al 1994). This criticism was addressed in Mendelsohn and Nordhaus (1999) and again in Mendelsohn and Dinar (2003) who show that although both irrigation and irrigation water supplies are important, including them has only a minor effect on the measurement of climate sensitivity. Water runoff is not available in this study for all countries and so it is not included.

DATA AND EMPIRICAL SPECIFICATIONS

Historically, global land surface temperatures and wetness have been obtained from weather stations on the ground mainly in populated and industrialized regions (for example, airports). Unfortunately, these stations are neither located evenly nor densely around the globe. Specifically, observations are sparse over large 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 wetness (Williams et al. 2000 and Basist et al. 2001).

The Defense Department has maintained a set of polar orbiting satellites that pass over the entire earth at 6AM and 6PM 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).

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

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, Brazil and India. We use both the average value of each measure in each month and the interannual variance. The spatial resolution is 1/3 degree (approximately 30 Km) for both data products. The centroid of each pixel is associated with the centroid of counties in the United States, districts in India, and municipios in Brazil. All of these divisions have approximately the same resolution, although the municipios are slightly smaller.

The three countries were selected for several reasons. First, they encompass large land masses and thus allow spatial variation in both climate and other variables (e.g., soil and adaptation techniques). Second, the three countries are placed in various locations around the globe, so that the results could be extrapolated to other countries with similar climatic conditions. Third, these countries represent various development levels (Mendelsohn et al 2001), which allow us to predict what could be the different impacts and adaptation measures most likely to be effective in countries with different levels of development.

Data concerning farms for the United States were collected from US Census of Agriculture surveys in 1997. Soil data were 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). Data concerning Brazil were collected by the Instituto Brasiliero de Geografia e Estatica (IBGE) from the Census of Agriculture (www.ibge.gov.br). The Census of Agriculture data from India were made available through Indiastat (www.indiastat.com).

The model is estimated using weighted OLS. We rely on the smallest administrative unit in each country that records agricultural activity: a county in the United States, a municipio in Brazil, and a district in India. Only rural observations are included to eliminate the unwanted influence of urban areas. Observations with population densities above 500 people/km^2 were dropped. The observations are weighted by the aggregate amount of cropland.

RESULTS

This study explores the interaction between climate and agriculture in three countries: the Unite States, Brazil, and India. We measure two responses by agriculture: changes in net revenue and changes in the percent of land used for cropland. Both measures reflect net productivity and are sensitive to climate, soils, and economic conditions. We specifically test the relative importance of average climate (normals) versus climate variance (interannual variation).

Table 1 presents the net revenue results for the United States, Brazil, and India. The three regressions use net revenue as the dependent variable. The independent variables include climate normals, climate variance, soils, and economic variables. The coefficients in the three regressions are stable, indicating a robust relationship between these variables and net revenue. Only significant coefficients for climate variance, soils, and economic variables were kept unless omitting the variable strongly affected the model. The US and India regressions do a particularly good job of explaining the distribution of net revenues per hectare across the landscape, explaining over 80% of the variation. The results in Brazil are more mixed, explaining only 40% of the variation.

Both climate normal and climate variance terms are significant in every equation. Coefficients for every season are also significant implying that a seasonal description of climate is important. Quite often, quadratic terms are significant implying a nonlinear functional form for surface wetness and temperature.

Because many of the climate variables have both a linear and quadratic term and there are several seasonal variables, it is difficult to see exactly what each set of climate variables are doing. Table 2 takes the coefficients in Table 1 and calculates the marginal annual effect of temperature, soil moisture, temperature variance, and surface wetness variance. The central values presented in Table 2 show the effect of increasing each term by one standard deviation. For example, taking the standard deviation in temperature across the US, the value in Table 2 for temperature shows what a warming of this magnitude would do to land values. This is one way to understand the relative importance of temperature versus surface wetness and one way to compare climate normals against climate variance. The values in parentheses are the marginal effects of one more degree C or one more unit of surface wetness.

Table 2 reveals that climate normals are far more important than climate variance in the United States, almost an order of magnitude more important. In India, climate normals are still more important than climate variance but only about three times more important. In Brazil, in contrast, climate normals and climate variance are both equally important. The relative importance of climate normals versus climate variance thus depends on the climate one starts with. In relatively stable settings like the US, climate variance is less important. In monsoon settings such as in India, surface wetness variance has a relatively large role to play. In equatorial climates, such as in Brazil, climate normals appear to be less important.

Table 2 also shows that the marginal effect of warming, increased soil wetness, or increased variance may also vary by climate. In all three countries, higher temperatures lead to lower net revenues, though the effect is largest in the US. Higher summer temperatures are particularly harmful. Higher temperature variance, however, is beneficial though not significant in the US and India whereas it is harmful and significant in Brazil. Higher surface wetness is harmful in the US whereas it is distinctly beneficial in Brazil and especially India. The sufficient precipitation in the US reduces the beneficial effects of more rain. The increased clouds required to bring more rain reduce net revenue. Conditions are drier in Brazil and India so that the additional rains in those countries are strictly beneficial. In all three countries, increased surface wetness variance is harmful. The results confirm one age-old fear of farmers that needed rains won't come each year.

Table 3 presents the results for the percentage of cropland in each country. The results are again particularly powerful in the United States and India, explaining over 80% of the variation across the landscape. The results are more mixed in Brazil with 37% of the variance explained. The poorer land use results in Brazil may be due to another unmeasured influence such as subsidies or land use regulation in Brazil or that the data is more poorly measured there. Climate normals and climate variance terms are significant explanatory variables for land use in every country as they were for net revenues. Climate variables reflecting quadratic terms and each season were also significant, although the importance of winter variables in India and the United States was less pronounced with the land use regressions.

Table 4 displays how important each set of climate variables is in explaining the percentage of cropland. Using the coefficients in Table 3, Table 4 shows the effect of increasing each set of climate variables one standard deviation. The marginal effects of each climate variable are shown in parentheses. Higher temperatures are expected to reduce the amount of cropland in the United States and especially India whereas they have almost no effect on Brazil. Increased temperature variance, in contrast, is expected to increase cropland in both the United States and Brazil. This variance effect is larger than the effect of the temperature increase implying temperature variance is important in both countries. There is no observed effect of temperature variance on cropland in India. The greater reliance on irrigation in India may make their farming system somewhat resilient against temperature variance.

Table 4 shows that higher surface wetness would increase cropland in the US but it would have only a negligible effect in Brazil and no effect at all in India. It may seem strange that a relatively dry country such as India appears not to respond to soil moisture. Irrigation once again may explain this phenomenon. Most areas may naturally be dry and they are farmed strictly because they have irrigation water. Cropland thus appears to be independent of soil moisture. Surface wetness variance curiously increases the likelihood of cropland in both the US and Brazil. Once again, this effect is larger than the effect of the surface wetness normals. The results suggest that the advantages of occasional wet years outweigh the disadvantages of occasional dry years. Farmers appear to be attracted to the very phenomenon they most bitterly complain about-climate variance.

CONCLUSION

The paper tests the relative importance of climate normals and climate 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, Brazil, and India. For the first time in this type of analysis, satellite data are used to provide consistent measures of climate across all three countries.

The data analysis concludes that climate normals and climate variance both play a role in determining net revenue and percentage of cropland. Interestingly, the results are mixed across the three countries in determining which set of variable is most important. In the United States, climate normals are far more important than climate variance in explaining net revenue per hectare but climate variance is slightly more important in explaining percentage of cropland. Temperature variables in general are slightly more important than surface wetness variables. In Brazil, climate variance and climate normals are equally important in explaining net revenues but climate variance is more important in explaining percentage of cropland. Surface wetness variables are more important explanatory variables for net revenues and but temperature is slightly better explaining percentage of cropland. Finally in India, climate normals, especially surface wetness variables, are more important than climate variance in explaining net revenue but only temperature normals explain percentage of cropland.

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 soil moisture, this will have additional harmful effects on dry countries such as India and Brazil, although it might actually help the United States. If warming simultaneously increases temperature variance, this may have beneficial effects in the United States and India but harmful effects in Brazil. However, if warming increases the variance of soil moisture, it is expected to be harmful to all countries, although it may increase the amount of 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, the net effect of global warming on agriculture must also take into account the effects of carbon dioxide fertilization. The widespread field and laboratory evidence that crops will be more productive in a CO_2 enhanced world (Reilly et al 1996) is not reflected in this cross-sectional evidence. The beneficial CO_2 fertilization effects must be added to these cross sectional results to get an unbiased expected net effect.

Efforts to adapt to global warming must focus closely on how to react to changing normals and variance. Successful adaptation will depend first and foremost on adjusting farmer activities and decisions to new climate normals and variance as they unfold. 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 also have key roles to play in making sure that public infrastructure is kept up to date with changing needs and that public resources such as water are allocated to their highest use.

Observers who are concerned about the impacts of weather extremes should note that the climate variance reflects the likelihood of extremes. The standard deviation of weather is the square root of the variance. The weather at the 95% edge of the distribution is two standard deviations away from the mean (at least in a normal distribution). The magnitude of the damages associated with being plagued by extreme weather consequently is reflected in the coefficients on climate variance.

REFERENCES

Adams, R., Glyer, D. and McCarl, B.: 1989. "The Economic Effects of Climate Change in US Agriculture: A Preliminary Assessment." In D. Tirpak and J. Smith (eds.) *The Potential Effects of Global Climate Change on the United States: Report to Congress*, Washington D.C.: US Environmental Protection Agency, EPA-230-05-89-050.

Adams, R., McCarl, B., Segerson, K., Rosenzweig, C., Bryant, K., Dixon, B., Conner, R., Evenson, R., and Ojima, D.: 1999. "The Economic Effects of Climate Change on US Agriculture." In. *The Impact of Climate Change on the Economy of the United States,* eds. R. Mendelsohn and J. Neumann, Cambridge, UK: Cambridge University Press.

Adams, R. and McCarl, B.: 2001. "Agriculture: Agronomic-Economic Analysis" in R. Mendelsohn (ed) *Global Warming and the American Economy* Cheltenham, UK: Edward Elgar.

Basist, A., Williams Jr., C., Grody, N., Ross, T.E., Shen, S., Chang, A., Ferraro, R., Menne, M.: 2001. "Using the Special Sensor Microwave Imager to monitor surface wetness." *J. of Hydrometeorology* **2,** 297-308.

Basist, A. N., Peterson, N., Peterson, T., Williams, C.: 1998. Using the Special Sensor Microwave Imager to monitor land surface temperature, wetness, and snow cover. *J. Appl. Meteor.,* **37**, 888-911.

Cline, W.: 1996. "The Impact of Global Warming on Agriculture: Comment." *American Economic Review* **86**: 1309-12.

Darwin, R.: 1999. "Comment on The Impact of Global Warming on Agriculture: A Ricardian Analysis." *American Economic Review* **89**: 1049-52.

Ferraro, R. R., Weng, F., Grody, N., and Basist, A.: 1996. "An eight-year (1987-1994) time series of rainfall, clouds, water vapor, snow cover, sea ice derived from SSM/I measurements". *Bull. Amer. Meteor. Soc.*, **77**, 891-905.

Grody, N.C. and Basist, A.: 1996. "Global identification of snowcover using SSM/I measurements". IEEE Trans. *On Geoscience and Rem. Sensing*. **34,** 237-249.

Houghton, J., Ding, Y., Griggs, D., Noguer, M., Van der Linden, P., Dai, X., Maskell, K., Johnson, C. (eds.): 2001. *Climate Change 2001: The Scientific Basis*. Intergovernmental Panel on Climate Change, Cambridge University Press: Cambridge.

McFarland, J.M., Miller, R., and Neale, C.: 1990. "Land surface temperature derived from the SSM/I passive microwave brightness temperatures". *IEEE Transactions Geoscience and Rem. Sens*., **28**, 839-845.

Mendelsohn, R., Nordhaus, W., and Shaw, D.: 1994. "The Impact of Global Warming on Agriculture: A Ricardian Analysis." *American Economic Review* **84,** 753-71.

Mendelsohn, R., Nordhaus, W., and Shaw, D.: 1996. “Climate Impacts on Aggregate Farm Values: Accounting for Adaptation.” *Agriculture and Forest Meteorology* **80,** 55-67.

Mendelsohn, R. and Nordhaus, W.: 1999. “Reply to Darwin”, *American Economic Review* **89,** 1053-1055.

Mendelsohn, R., Dinar, A., and Sanghi, A.: 2001. "The Effect of Development on the Climate Sensitivity of Agriculture", *Environment and Development Economics* **6,** 85-101.

Mendelsohn, R and Dinar, A.: 2003. “Climate, Water, and Agriculture”, *Land Economics* **79,** 328-341.

Neale, C.M.U., McFarland, M., Chang, K.: 1990. “Land-surface-type classification using microwave brightness temperatures from the Special Sensor Microwave/Imager”.

Njoku, E. G.: 1994. “Surface temperature estimation over land using satellite microwave radiometry”. *Remote Sensing of Land-Atmosphere Interactions*, St. Laury, France. 509-530.

Prigent, C., Rossow, W., Matthews, E.: 1997. “Microwave land surface emissivities estimated from SSM/I”. *J. Geophys. Res*., **102**, 21867-21890.

United States Department of Agriculture (USDA): 1997. “1997 Census of Agriculture.” Washington, D.C.: National Agricultural Statistics Service, CD-ROM set.

Vinnikov, K. Y., Robock, A., Qui, S., Entin, J., Owe, M., Choudhury, B., Hollinger, S., Njoku, G.: 1999. “Satellite remote sensing of surface wetness in Illinois, United States”. *J. Geophys. Res*., **104**, 4145-4165.

Weng. F. and Grody, N.: 1998. “Physical retrieval of land surface temperature using the Special Sensor Microwave Imager”. *J. Geophys. Res*., **103**, 8839-8848.

Williams, C., Basist, A., Peterson, T., Grody, N.: 1999. “Calibration and validation of land surface temperature anomalies derived from the SSM/I”. *Bull. Amer. Meteorol. Soc.*

Table 1 Net Revenue Results (2000 USD/yr/ha)

Independent	Dependent Variable		
Variables	United States	Brazil	India
Constant	1340	809.	4330
	(11.73)	(3.69)	(2.89)
Jan Temp	...	78.6	-202.
		(1.97)	(3.75)
April Temp	33.8	-125.	...
	(6.65)	(2.93)	
July Temp	-134.	79.7	-631.
	(13.93)	(4.49)	(3.68)
October Temp	17.4	-91.1	585.
	(6.59)	(4.04)	(3.48)
Jan Temp Squared	…	-1.87	4.99
		(2.00)	(3.07)
Apr Temp Squared	-1.54	3.41	...
	(9.65)	(3.33)	
Jul Temp Squared	2.48	-1.96	11.2
	(11.57)	(4.01)	(3.58)
Oct Temp Squared	…	1.73	-13.2
		(3.20)	(3.43)
Jan Interannual	...	25.0	...
Temp Variance		(6.53)	
April Interannual	...	-38.0	...
Temp Variance		(8.38)	
July Interannual	-26.7	…	83.2
Temp Variance	(2.37)		(1.75)
October Interannual	52.3	-32.8	…
Temp Variance	(1.84)	(4.27)	
Jan Temp	...	-1.44	...
Variance Squared		(5.28)	
April Temp	...	2.11	…

Table 1-continued

	United States	Brazil	India
Variance Squared		(5.95)	
July Temp	2.24	…	-5.91
Variance Squared	(2.07)		(1.80)
October Temp	-5.28	3.35	…
Variance Squared	(1.90)	(4.01)	
Jan Surface Wetness	...	-16.6	-130.
		(2.92)	(3.28)
April Surface Wetness	-10.1	11.8	133.
	(2.72)	(2.53)	(3.87)
July Surface Wetness	-18.9	...	54.4
	(3.84)		(2.27)
October Surface Wetness	28.4	17.8	-51.4
	(5.17)	(4.33)	(2.99)
Jan Surface Wetness	…	…	16.3
Squared			(11.66)
Apr Surface Wetness	0.55	-0.40	…
Squared	(2.83)	(5.48)	
Jul Surface Wetness	1.94	…	-1.88
Squared	(5.14)		(1.53)
Oct Surface Wetness	-2.45	…	…
Squared	(6.55)		
Jan Interannual	...	…	22.5
S. W. Variance			(2.52)
April Interannual	…	…	-36.6
S. W. Variance			(7.41)
July Interannual	12.4	…	…
S. W. Variance	(3.27)		
October Interannual	-9.55	-2.98	...
S. W. Variance	(4.21)	(5.72)	

Table 1 (continued)

	United States	Brazil	India
Jan S. W.	...	...	-0.11
Variance Squared			(1.52)
April S. W.	0.76	…	...
Variance Squared	(6.46)		
July S. W.	-0.65	-0.016	…
Variance Squared	(2.23)	(3.56)	
October S. W.	…	0.034	…
Variance Squared		(5.42)	
Income per capita	847.	7.87	...
	(8.85)	(11.02)	
Population density	0.35	…	…
	(8.13)		
% Urban	12.2	...	...
	(3.34)		
Population change	0.65	…	…
	(6.32)		
Altitude	-18.2	…	…
	(6.87)		
% Flooding	-32.4	…	...
	(4.73)		
Soil erosion	-80.2	…	…
	(2.96)		
Salinity	147.	...	…
	(5.44)		
% Sand	-17.0	...	…
	(2.45)		
Water capacity	59.3	...	…
	(9.20)		
Distance to sea	…	…	-0.27
			(1.40)

Table 1 (continued)

	United States	Brazil	India
Literacy Rate	…	…	0.65
			(0.33)
Soils 517	…	-68.8	…
		(5.38)	
Soils 521	…	18.1	…
		(2.89)	
Soils 524	…	325.	…
		(15.50)	
R^2	.821	.419	.844
Number of Observations	1580	2744	218

Table 2 Climate Influence on Net Revenue/Hectare (USD/yr)

Variable	United States	Brazil	India
Annual Temp	-735	-26.9	-185
	(-201)	(-11.9)	(-61.5)
Annual T Var	78.6	-27.9	23.5
	(116)	(-19.7)	(23.7)
Annual Surface W.	-630	43.7	938
	(-164)	(10.4)	(178)
Annual SW Var	-36.9	-44.8	-376
	(-14.8)	(-2.7)	(-13.1)

Note: Results measure the influence of a standard deviation change in set of variables evaluated from the mean of the country in USD/yr. Marginal effects are in parenthesis. Net revenues are assumed to be equal to 4% of asset value to calculate US results.

Table 3 Regression on Percent Cropland

Independent		Country	
Variables	United States	Brazil	India
Constant	232. (7.53)	-49.4 (5.07)	103. (1.29)
Jan Temp	...	...	-22.6 (7.63)
April Temp	2.47 (3.63)	-8.19 (6.40)	36.6 (4.92)
July Temp	18.4 (8.86)	-12.9 (13.87)	…
October Temp	-15.6 (12.62)	23.3 (17.81)	-33.8 (2.43)
Jan Temp Squared	…	...	0.52 (6.14)
Apr Temp Squared	…	0.18 (5.78)	-0.64 (4.22)
Jul Temp Squared	-0.38 (7.85)	0.34 (13.86)	...
Oct Temp Squared	0.41 (9.80)	-0.53 (16.97)	0.76 (2.30)
April Interannual Temp Variance	35.7 (4.12)	0.56 (6.65)	...
July Interannual Temp Variance	-11.0 (3.31)	…	...
October Interannual Temp Variance	24.2 (3.31)	3.63 (8.92)	…
April Temp Variance Squared	3.84 (4.80)	…	…
July Temp Variance Squared	1.28 (3.78)	0.034 (4.90)	...
October Temp	-1.84	-0.37	…

Table 3 (continued)

	United States	Brazil	India
Variance Squared	(2.45)	(8.59)	
July Surface Wetness	8.56	-1.22	...
	(9.94)	(3.57)	
October Surface Wetness	-7.22	1.02	...
	(10.77)	(2.74)	
Apr Surface Wetness	0.158	…	…
Squared	(5.73)		
Jul Surface Wetness	…	0.024	...
Squared		(1.98)	
Oct Surface Wetness	-0.224	-0.024	…
Squared	(5.77)	(1.92)	
April Interannual	2.14	…	...
S. W. Variance	(5.28)		
July Interannual	4.04	-0.21	…
S. W. Variance	(4.09)	(2.18)	
October Interannual	…	-0.29	...
S. W. Variance		(3.09)	
July S. W.	-0.396	0.0014	…
Variance Squared	(4.09)	(2.23)	
October S. W.	…	-0.0018	…
Variance Squared		(2.82)	
Population density	...	0.010	...
		(8.97)	
Slope Length	2.56	…	…
	(10.57)		
Permeability	0.0011	...	...
	(13.22)		
Population change	-0.059	…	…
	(2.89)		
Altitude	-3.51	…	…
	(6.67)		

% Flooding	-11.8	…	...
	(8.23)		
Soil erosion	54.1	…	…
	(8.74)		
Salinity	-45.9	...	…
	(4.94)		
% Clay	6.16	...	…
	(7.11)		
Wetland	-33.6	…	…
	(6.85)		
Soils 522	…	3.27	…
		(10.99)	
Soils 523	…	0.82	…
		(2.52)	
R^2	.807	.374	.844
Number of Observations	1580	2747	218

Table 4 Climate Influence on Percent Cropland

Variable	United States	Brazil	India
Annual Temp	-0.061	0.0014	-0.192
	(-0.019)	(0.00092)	(-0.087)
Annual T Var	0.091	0.034	…
	(0.016)	(0.022)	
Annual S. W.	0.039	-0.0097	…
	(0.014)	(-0.000018)	
Annual S. W. Var	0.071	0.014	…
	(0.036)	(0.0026)	

Results reflect one standard deviation change of set of variables evaluated from country mean. Numbers in parenthesis are marginal impacts.

4. CLIMATE AND RURAL INCOME

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ABSTRACT

This paper tests whether climate has an impact on per capita rural income. The study finds that rural income in counties and *municipios* in the United States and Brazil, respectively, are affected by climate. Climate explains a large fraction of the variation in income across rural areas in both countries. This climate impact is shown to be directly connected to net farm revenues in Brazil and farmland values in the United States. Climate normals explain a large fraction of this variation. Locations with adverse climates for agriculture consequently have lower per capita incomes. Adverse climates clearly contribute to rural poverty. Global warming will not only affect some countries more than others, but it will also affect some regions within countries more than others.

INTRODUCTION

Scientists are increasingly convinced that continued emissions of greenhouse gases into the atmosphere will lead to global warming over the next century (Houghton et al 2001). Mild climate scenarios may lead to small net global effects but more severe warming will cause damages, across the globe (McCarthy et al., 2001). Although our understanding of impacts is growing, climate impacts remain shrouded in uncertainty and even mystery.

This paper attempts to draw a link between climate and an impact not yet studied, rural income. Although it is well known that climate will have an impact on agricultural productivity, the link between rural income and climate has not yet been made. We hypothesize that the impact of climate on agriculture will affect rural income as well. Specifically, we anticipate that regions that suffer reduced agricultural productivity because of climate change will more likely become poorer.

Recent research strongly indicates that agricultural productivity or net revenue ($/ha) is tied to climate (Mendelsohn et al 1994; 1999; 2001; Mendelsohn and Dinar 2003). If climate conditions are not favorable, agricultural productivity will be low. Since agricultural returns are likely to be a significant fraction of rural income ($/person), we anticipate that rural poverty will be linked with adverse climate conditions. Of course, other factors, such as adverse soils and economic conditions will also play a part in agricultural productivity. Further, there are more economic activities in rural areas than just agriculture. The importance of climate in determining per capita rural income ultimately is an empirical question.

In this paper, we test the relationship between per capita income and climate in the United States and Brazil. We are interested in whether this model applies to rural areas in both developed and developing countries. We test several models. First, we test for direct correlation. Is there an observable relationship between income per capita in rural areas and climate? Second, we explore whether agricultural productivity plays a role in determining rural per capita income. We regress land value or net revenue per hectare on climate and other control variables and test whether climate affects the amount of land used for cropland. We then test whether the predicted values from these regressions explain income per capita. This second test explores whether agriculture is the key, but it does not isolate the effects of climate alone since the predicted values reflect climate, soils and economic conditions. Third, we use only climate normals to explain agricultural land values (net revenues) and cropland share. The predicted climate-only land values and cropland are then regressed on per capita income controlling for soils and economic variables. This last test isolates the link between climate and agriculture as the source of the income effects. The methodology of these three tests is laid out in the next section.

The data used to make these tests are described in the third section and the results of the empirical work for rural counties in the United States and rural municipios in Brazil are presented in the fourth section . All three empirical approaches indicate that climate has an important role to play in explaining rural income in both countries. The implications of this research for immediate development policy and for climate change policy are discussed in the concluding section.

METHODOLOGY

The foundation of this research lies in Ricardian models (Mendelsohn, Nordhaus and Shaw 1994). Ricardian models completed in the United States, Brazil, and India, all indicate that agricultural productivity depends upon climate, soils, and economic conditions (Mendelsohn et al 1994; 1999; 2001). Explicitly, farmland value (H) reflects the present value of future net productivity:

$$H = \int P_{LE}\, e^{-\varphi t}\, dt = \int [\Sigma\, P_i\, Q_i\, (X, F, Z, G) - \Sigma\, RX]\, e^{-\varphi t}\, dt \qquad [1]$$

P_{LE}, the net revenue per hectare, in turn, depends upon P_i, the market price of crop i, Q_i, the output of crop i, F, a vector of climate variables, Z, a set of soil variables, G, a set of economic variables such as market access, X, a vector of purchased inputs (other than land), R, a vector of input prices, t, time, and φ, the discount rate. The farmer is assumed to choose X to maximize net revenues given the characteristics of the farm and market prices. The Ricardian model is a reduced form model that examines how sets of exogenous variables, F, Z, G, and R affect farm value.

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

$$H = B_0 + B_1F + B_2\, F^2 + B_3\, Z + B_4\, G + u_1 \qquad [2]$$

where B_i are estimated coefficients, u_1 is an error term. Both a linear and a quadratic term for temperature and precipitation or soil moisture are used to capture climate normals. Climate normals reflect long-term weather patterns (the average of weather from 1960 through 1990), not annual weather. We rely on seasonal measures of each climate variable.

In addition to explaining the value per hectare of land, climate, soils, and economic conditions also explain the fraction of land devoted to cropland. Because cropland is often the highest valued use of rural land, it is reasonable to expect that the fraction of land used for cropland, Cr, will hinge on the same exogenous variables as cropland value per hectare. The more productive is cropland, the more likely that it will be used for crops:

$$Cr = C_0 + C_1F + C_2\, F^2 + C_3\, Z + C_4\, G + u_2 \qquad [3]$$

where C_i are estimated coefficients, u_2 is an error term. Of course, as a reduced form regression, the model is also revealing the relative value of alternative uses. For example, if dry land is more productive for grazing, then dry land is less likely to be used for crops.

In this study, we are interested in exploring the relationship between rural income and climate. Our first analysis examines this directly by regressing income (Y) on climate and a set of control variables for soils and economic conditions:

$$Y = D_0 + D_1F + D_2\, F^2 + D_3\, Z + D_4\, G + u_3 \qquad [4]$$

where D_i are estimated coefficients, u_3 is an error term. The analysis explores whether climate and soils can explain variations in income across counties. Of course, this approach simply reveals correlations. This direct measure does not prove that climate is important because if its impact on agriculture.

In order to explore whether agriculture is the key link between climate and income, we explore an indirect method of analysis. First we estimate the Ricardian model (2) and the cropland model (3). We then use the predicted values of agriculture, $\hat{H}$, from the Ricardian model and the predicted fraction of cropland, $\hat{C}r$, to explain income:

$$Y= E_0 + E_1\hat{H}+ E_2\hat{H}^2 + E_1\hat{C}r+ E_2\hat{C}r^2 + u_4 \qquad [5]$$

where E_i are estimated coefficients, u_4 is an error term. A quadratic equation is explored for both the predicted agricultural value per hectare and the fraction of land used for cropland. What we expect is that the more productive the cropland and the more land that is used for crops, the higher will be rural income. In converse, rural poverty will increase the less productive the land and the less land available for crops.

This analysis pinpoints a link between income and climate though agriculture. However, it does not isolate the contribution of climate alone. The analysis relies on all the available explanations of agricultural productivity. In our third analysis, we isolate the contribution of climate through agriculture. We begin with a limited Ricardian and cropland regression that only includes climate normals as explanatory variables:

$$H = B_0 + B_1F + B_2 F^2 + u_5 \qquad [6]$$

$$Cr = C_0 + C_1F + C_2 F^2 + u_6 \qquad [7]$$

We then use the predicted value from models 6 and 7, $\hat{H}$ and $\hat{C}r$, in a model of income along with the soils and economic control variables:

$$Y= E_0 + E_1\hat{H}+ E_2\hat{H}^2 + E_3\hat{C}r+ E_4\hat{C}r^2 + E_5 Z + E_6 G + u_7 \qquad [8]$$

This third procedure isolates the contribution of climate through agriculture. Soils and other economic variables enter directly as controls in this regression.

DATA

We test the empirical models described above using data from counties in the United States and municipios in Brazil. We perform the analysis solely on rural locations since only rural economies are dependent on agriculture. We define rural areas as locations with population densities below 500 people/km^2. Data concerning land values for the US are available from the US Census of Agriculture for 1997. These data were supplemented with data on soils (Mendelsohn et al 1994) and economic data from the US Census of Population in 1990. Data on net revenues per hectare were available from Brazil for 1990, 1995, and 2000 from the Instituto Brasiliero de Geografia e Estatica

(IBGE). Soil data in Brazil come from Sanghi (1998). Economic data for Brazil was available for 1996 from Census data (IBGE).

We rely on satellite data for our climate measures. We use channel measurements from the SSM/I sensors on three separate Defense Meteorological Satellite Program (DMSP) polar orbiting satellites (F08, F11, and F13) from 1987 to 2002. These DMSP satellites provide sun synchronized overpasses at 6 A.M. and 6 P.M everywhere on earth. These twice- daily satellite overpasses are processed into 1/3 x 1/3 degree "pixels" by NESDIS and archived at the National Climatic Data Center (NCDC). The data was then matched with the centroids of each county and municipio.

It is not a trivial matter to translate the direct measurements of the satellite to the desired climate variables. A major difficulty in deriving surface temperature from the passive microwave measurements of the satellite is the variable emissivity (reflections) 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 (the temperature measurement from the brightness of the reflection) 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 currently 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 the emissivity adjustment associated with water in the radiating surface (Basist et al 1998; 2001). Surface wetness has strong correspondence with the upper level soil moisture at many locations. Wetness originates from multiple sources (precipitation, snow melt, and irrigation). 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. January observations for the United States had to be dropped because the satellite could not measure values accurately on frozen ground.

RESULTS

We use weighted least squares for the crop value regressions, weighting by the hectares of cropland. This places greater emphasis on counties and municipios with more cropland. For the fraction of cropland and income regressions, we use ordinary least square regressions.

In Table 1, climate, soil, and economic variables are regressed on income per capita. The results reveal that both seasonal temperature and soil moisture affect income in rural counties of both countries. The effect is quadratic as both linear and squared terms are significant. Summing the effects across seasons and evaluating the result at the mean for each country, the marginal impact of higher temperatures reduce income in both the US and Brazil[i]. The marginal value of annual temperature in the US is -\$59/°C where as the marginal value in Brazil is -\$77/°C. The marginal value of soil moisture in the US is \$51/unit whereas the marginal value is \$-8/unit in Brazil. None of these annual effects are statistically significant from zero. The slightly higher negative value of warming in

Brazil may be due to the higher average temperatures there. It is less clear why soil moisture is beneficial in the US but has almost no effect in Brazil.

Table 1 reveals that other factors also contribute to rural income. The more urban the counties, the higher were people's income. Development leads to urbanization and higher income. Areas with growing populations tend to have higher income. Whether growth leads to income or vice versa is not clear. More productive agricultural land also contributes to income. Better soils lead to more productive farms and higher income.

The results in Table 1 show that climate and income are clearly correlated across space. They reveal that in places that are conducive to growing crops, incomes are higher. Table 1, however, does not prove that agriculture is the cause of the observed relationship. In the next analysis, we first determine how crop productivity variables affect land value and cropland and then use predicted values from these regressions to examine income. The first and second columns in Table 2 are traditional Ricardian analyses of net revenue for Brazil and land value for the United States. Climate, soils and economic variables are regressed on cropland value per acre. It is clear from the results that both temperature and soil moisture are very important. Both the linear and quadratic terms are significant. Evaluated at the mean, higher temperature reduced net revenues by \$120 per ˚C and more soil moisture reduced net revenues by \$12 per unit in Brazil. The annual marginal impact of higher temperature reduced cropland values by \$100 per ˚C and more soil moisture reduced land values by \$25 per unit in the US. Given that land values are over ten times net revenues, the climate effects in Brazil are much larger proportional changes. Both economic and soil variables are also significant in both regressions. Increased flooding, altitude, soil erosion, sand, and wetlands all reduce land values in the US but salinity, longer slope length, and water capacity all increase land values. Increased percent urban, population density, and population growth also have positive effects on land value.

The third and fourth columns in Table 2 present the parallel results for the percent of cropland. The fraction of land used for cropland is regressed on climate, economic variables, and soils. The relationship between temperature and percent cropland is quadratic in Brazil but linear in the US. In contrast, soil moisture has a quadratic relationship with cropland in both countries. Evaluated at the Brazilian mean, higher temperature and soil moisture both slightly increase the fraction of cropland in municipios. Higher temperatures and soil moistures have a much larger positive effect on the fraction of cropland in the US. Population density has a positive but declining effect on cropland in the US and a positive and linear effect in Brazil. Population growth reduces the fraction of land in cropland in the US. Soils also have a role to play in determining cropland in both countries. Increased clay, soil erosion, sand, and slope length are all associated with more cropland in the US. Increased flooding, wetlands and water capacity, however, are associated with lower fractions of cropland.

Table 3 presents the results of regressing the predicted values from Table 2 for cropland and land value upon income for the United States and Brazil. Both linear and squared terms of the predicted farm value and predicted percent cropland are significant in both countries (with the exception of net revenue squared in Brazil). An urban variable is also introduced to control for the effect of cities. The marginal impact of higher farm value or net revenue is positive and significant in both countries. A one dollar increase in net revenue in Brazil is predicted to increase income by $0.52. A one dollar increase in land value in the US increases income by $0.76. The basic underlying hypothesis of this paper is confirmed: higher farm productivity does lead to higher rural income. The marginal impact of more cropland reduces income in the United States. Counties with more cropland have lower incomes in the US. In contrast, the marginal impact of more cropland is positive and larger in Brazil. Municipios with more cropland have higher incomes in Brazil.

The indirect method presented in Tables 2 and 3 suggests that higher farmland values do result in higher income. However, the method does not isolate the contribution of climate to land value. In a second indirect method, only climate normals are used to predict land value or net revenue. These climate-only predictions of farm value and cropland are then used to explain income. Table 4 presents the results of regressing only climate normals on land value (net revenue) and percent cropland. The results of Table 4 strongly resemble what was presented in Table 2. Climate normals explain over 60% of the variation in land values in the United States and 15% of the variation in net revenue in Brazil. They also explain over 50% of the variation in percent cropland in the US and over 25% of the percent cropland in Brazil.

Table 5 shows the impact of introducing the climate-only predicted values of farm value and percent cropland from Table 4. Control variables for soils and economic factors are also included. The marginal impact of higher land values in the United States is positive and significant, adding $0.51 for every dollar of land value. The marginal impact of adding cropland is also positive and significant. The marginal impact of higher net revenues in Brazil is also positive and significant, adding $0.49 for every dollar of net revenue. Adding cropland is also positive and significant in Brazil. The analysis shows that areas with more productive climates for crops have higher incomes. The marginal impact of the urban coefficients is also positive implying that urban areas tend to have higher incomes.

CONCLUSION AND POLICY RECOMMENDATIONS

This analysis explores the hypothesis that climate affects agricultural productivity, which in turn affects rural per capita income. Three analyses are conducted in rural regions in Brazil (municipios) and the United States (counties) that test the hypothesis. All three analyses confirm that climate has an effect on rural income and that this effect is likely due to changes in agricultural productivity. Specifically, the analyses show that higher temperatures reduce per capita income in the United States and especially in Brazil. Increases in soil moisture further increase rural incomes in the United States but the effect is muted in Brazil. The analyses further show that increases in land value and net revenue per hectare are closely associated with higher per capita incomes. Increases in the percent of cropland, however, have positive impact on income only in Brazil. In the United Ststes, areas with more cropland have lower incomes.

Changes in climate variables that increase agricultural value increase per capita income. It therefore follows that less productive climates lead to increased poverty. Climate clearly plays a role in determining rural poverty. It is simply more difficult to make a living in rural places that are less productive. This is evident even in the United States, which has plenty of access to capital and modern technology.

The results have important policy implications. The results suggest that people are poor in hostile climates because they live in a low productive location. This implies that providing new technology and capital may be an ineffective strategy in these places unless the technology counterbalances the climatic handicap of the location. For example, irrigation may successfully turn around an area that is too dry. In general though, low productive locations will have low marginal productivity with respect to capital. Sending more capital into agriculture in these locations may not be an economically sustainable policy. For example, Mendelsohn and Dinar (2003) show that capital-intensive irrigation technology such as drip irrigation can be an effective way to adapt to high temperatures and low rainfall. However, drip irrigation is very costly and it must yield high returns to be economically feasible. If capital-intensive projects such as drip irrigation yield poor results in an area, the investment will still leave local people in poverty. In low-productivity locations, climat-neutral development strategies such as urban development may be more effective than traditional rural development. By giving people an alternative to move to cities that are less climate sensitive, urban development is likely an effective policy to relieve current rural poverty.

The results also suggest that some policy adaptations should be regionally specific. Since each region is likely to face completely different threats from climate change, each region must determine the optimal response. For example, some regions may become too dry but they have access to runoff. They can move to irrigation. Another region may find that its runoff has been curtailed. It may want to move from gravity to drip irrigation. Another region may find it is too warm for its original crops. It may want to consider the set of crops best suited for its new climate. All of these responses are regionally specific.

Climate change will likely have its most dramatic impacts on regions that are already stressed by high temperatures and low precipitation. Changes that exacerbate these conditions will only worsen the outcomes. If climates become more hostile, this analysis suggests that they will further reduce rural incomes. Low-income rural households in marginal climates may be one of the most vulnerable populations to global warming. Lower farm productivity may leave many of these households deeper in poverty. Even if aggregate agricultural production in many countries survives global warming, it is very likely that selected populations in certain regions in many low-latitude countries will be seriously at risk. Rather than trying to keep people engaged in agriculture in these marginal locations, it may be far more effective to entice them toward other more productive farming locations. An alternative route is to attract marginalized rural populations to the cities. Economic development may be a very effective long-term adaptation to climate change for the most vulnerable rural people in the low-latitude countries.

REFERENCES

Basist, A., Williams Jr., C., Grody, N., Ross, T.E., Shen, S., Chang, A., Ferraro, R., Menne, M. J.: 2001. "Using the Special Sensor Microwave Imager to monitor surface wetness". *J. of Hydrometeorology,* **2,** 297-308.

Basist, A., Peterson, N., Peterson, T., and Williams, C.: 1998. "Using the Special Sensor Microwave Imager to monitor land surface temperature, wetness, and snow cover". *J. Appl. Meteor.,* **37**, 888-911.

Houghton, J., Ding, Y., Griggs, D., Noguer, M., van der Linden, P., Dai, X., Maskell, K., and Johnson, C. (eds.): 2001. *Climate Change 2001: The Scientific Basis*. Third Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge.

McCarthy, J., Canziani, O., Leary, N., Dokken, D., and White, K. (eds.): 2001. *Climate Change 2001: Impacts. Adaptation, and Vulnerability*. Third Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge.

Mendelsohn, R., Nordhaus, W., and Shaw, D.: 1994. "The Impact of Global Warming on Agriculture: A Ricardian Analysis" *American Economic Review* **84**: 753-771.

Mendelsohn, R. and Neumann, J.: (eds) The Impact of Climate Change on the United States Economy. Cambridge University Press, Cambridge, UK, 1999.

Mendelsohn, R., Dinar, A., Sanghi, A.: 2001. "The Effect of Development on the Climate Sensitivity of Agriculture", *Environment and Development Economics* **6,** 85-101.

Mendelsohn, R. and Dinar, A.: 2003. "Climate, Water, and Agriculture", *Land Economics* **79,** 328-341.

Sanghi, A.: 1998. "Global Warming and Climate Sensitivity: Brazilian & Indian Agriculture." Ph.D. dissertation, Department of Economics, University of Chicago, Chicago.

Table 1 Direct Rural Income Regressions

Independent Variables	United States Income	Brazil Income
Constant	21100	1760
	(12.31)	(2.01)
January Temp	…	272.
		(2.16)
April Temp	103.	-355.
	(0.72)	(2.31)
July Temp	-1210	-410.
	(6.97)	(6.87)
October Temp	13.	416.
	(0.07)	(5.34)
January Temp Squared	…	-6.90
		(2.44)
Apr Temp Squared	-30.3	9.20
	(4.96)	(2.59)
Jul Temp Squared	32.5	10.6
	(8.30)	(6.56)
Oct Temp Squared	14.0	-10.3
	(1.95)	(5.60)
January Soil Moisture	…	-84.3
		(3.10)
April Soil Moisture	113.	83.6
	(1.99)	(3.12)
July Soil Moisture	167.	-67.2
	(1.99)	(2.79)
October Soil Moisture	-233.	60.4
	(2.58)	(2.20)
January Soil Moisture Squared	…	1.08
		(1.74)

Table 1-continued

	United States	Brazil
Apr Soil Moisture	0.2	-2.09
Squared	(0.05)	(1.87)
Jul Soil Moisture	-16.8	2.74
Squared	(2.18)	(3.17)
Oct Soil Moisture	14.6	-1.79
Squared	(2.05)	(2.36)
Population density	13.5	…
	(12.99)	
% Urban	668.	-1570
	(6.65)	(6.74)
% Urban Squared	…	2410
		(12.23)
Population change	32.2	…
	(14.00)	
% Flooding	-668.	…
	(4.34)	
Soil erosion	-1320	...
	(2.24)	
Salinity	-2690	...
	(3.01)	
%Wetland	-1140	...
	(2.47)	
Water capacity	-277.	...
	(1.65)	
Slope Length	105.	…
	(3.99)	
Soils 524	…	205.
		(2.65)
R^2	.481	.606
N	1942	2326

Table 2 Cropland Value and Percent Cropland Regressions

All Control Variables Included

:Independent Variables	Cropland Net Revenue Brazil	Cropland Value US	%Cropland Brazil	%Cropland US
Constant	10560	7050	-115.	-432.
	(6.90)	(11.18)	(3.56)	(2.36)
April Temp	-1360	434.	- 0.5	-48.1
	(6.34)	(8.89)	(0.11)	(3.22)
July Temp	546.	-558.	-36.9	37.6
	(5.02)	(9.42)	(14.91)	(2.05)
October Temp	37.	-80.5	41.2	45.2
	(0.25)	(1.41)	(11.75)	(2.56)
Apr Temp Squared	31.3	-19.5	0.07	0.03
	(6.14)	(9.31)	(0.66)	(0.05)
Jul Temp Squared	-9.4	8.33	0.85	-0.43
	(3.22)	(6.24)	(12.62)	(1.03)
Oct Temp Squared	-5.9	8.59	-0.84	-0.18
	(1.72)	(3.45)	(10.38)	(0.24)
April Soil	-100.	17.8	1.19	86.4
Moisture	(2.26)	(0.87)	(1.19)	(14.53)
July Soil	142.	-63.0	-6.07	79.6
Moisture	(3.07)	(2.04)	(5.96)	(8.92)
October Soil	-54.	1.6	5.93	-110.
Moisture	(1.28)	(0.05)	(6.41)	(11.58)
Apr Soil Moisture	1.8	3.8	-0.09	-1.82
Squared	(0.96)	(2.91)	(2.03)	(4.94)
Jul Prec Moisture	-0.5	6.5	0.14	-1.72
Squared	(0.31)	(1.93)	(3.80)	(2.15)
Oct Prec Moisture	-1.3	-7.7	-0.10	1.29
Squared	(0.98)	(2.92)	(3.23)	(1.73)
Population density	…	5.07	4.1	0.99

		(13.02)	(10.56)	(3.13)
Density Squared	…	…		-0.006
				(3.20)
% Urban	518.	116.	…	...
	(5.68)	(3.41)		
Population change	…	6.88	…	-1.35
		(8.02)		(5.69)
Soils 511	…	…	-4.94	…
			(4.90)	
Soils512	…	…	-7.79	…
			(7.48)	
Soils 513	-259.	…	-5.55	…
	(3.67)		(3.12)	
Soils 522	-104.	…	9.66	…
	(2.77)		(11.49)	
Soils 524	1450	…	-12.4	…
	(9.25)		(4.30)	
Erosion 5	231.	…	…	…
	(4.26)			
Permeability	…	…	…	14.8
				(16.16)
Altitude	...	-189.	…	…
		(10.29)		
% Clay	...		...	71.6
				(7.32)
% Flooding	...	-291.	...	-162.
		(4.61)		(9.97)
Soil erosion	...	-1700.	...	788.
		(6.94)		(11.33)
Salinity	...	904.	…	-331.
		(4.01)		(3.58)
% Sand	...	-215.	…	29.9
		(3.21)		(1.81)

Table 2 (continued)

	Cropland Brazil	Cropland US	%Cropland Brazil	%Cropland US
%Wetland	...	-971.	...	-412.
		(5.03)		(8.41)
Water capacity	...	505.	…	-98.5
		(8.56)		(5.65)
Slope Length	…	20.5	...	30.5
		(2.79)		(10.91)
R^2	.201	.765	.345	.705
N	2327	1942	2752	1942

The coefficients in columns 3 and 4 have been multiplied by 1000.

Table 3 Regressions of Predicted Values of Agriculture on Income

From Table 2: All Explanatory Variables

Independent Variables	United States	Brazil
Constant	9190	582.
	(94.96)	(7.64)
Predicted Farm Value	1.02	0.59
	(8.70)	(10.10)
Pred. Farm Value Squared	-1.21e-4	-3.54e-5
	(5.43)	(1.47)
Predicted % Cropland	-2400	1080
	(5.03)	(6.63)
Pred. %Cropland Squared	3190	14600
	(5.17)	(4.90)
Density	9.49	…
	(8.14)	
Urban	1130	-1410
	(9.93)	(5.63)
Urban Squared	…	2060
		(9.69)
R^2	.285	.542
N	1973	2312

Table 4 Cropland Value and Cropland Regressions

Only Climate Normals Included

Independent Variables	Net Revenue Brazil	Land Value US	%Cropland Brazil	%Cropland US
Constant	12800	7310	-42.6	-226.
	(8.53)	(10.29)	(1.26)	(1.09)
April Temp	-1440	693.	-6.7	-72.4
	(6.79)	(11.92)	(1.43)	(4.00)
July Temp	961.	-525.	-35.5	-15.8
	(8.62)	(7.72)	(14.02)	(0.76)
October Temp	-402.	-310.	39.6	102.
	(2.61)	(4.46)	(11.65)	(4.70)
Apr Temp	32.2	-33.0	0.22	1.01
Squared	(6.34)	(13.25)	(1.92)	(1.30)
Jul Temp	-22.2	5.0	0.80	1.25
Squared	(7.30)	(3.28)	(11.61)	(2.71)
Oct Temp	5.6	24.9	-0.80	-3.12
Squared	(1.59)	(8.33)	(10.10)	(3.41)
January Soil	-122.	...	…	…
Moisture	(2.22)			
April Soil	31.	-12.	1.52	128.
Moisture	(0.54)	(0.51)	(1.44)	(18.83)
July Soil	7.	-256.	-5.77	96.3
Moisture	(0.13)	(7.82)	(5.48)	(9.32)
October Soil	130.	206.	4.85	-149.
Moisture	(2.34)	(6.15)	(4.99)	(13.55)
Jan Soil	0.66	…	…	…
Moisture Squared	(0.53)			
Apr Soil	1.92	6.4	-0.11	-2.98
Moisture Squared	(0.78)	(4.22)	(2.38)	(6.76)
Jul Soil	0.31	19.2	0.14	-2.34
Moisture Squared	(0.16)	(4.94)	(3.79)	(2.39)

Table 4 Continued

Only Climate Normals Included

Independent	Net Revenue	Land Value	%Cropland	%Cropland
Oct Soil	-4.10	-20.2	-0.07	2.05
Moisture Squared	(2.47)	(6.43)	(2.11)	(2.24)
R^2	.149	.638	.264	.539
N	2750	1973	2771	1973

Table 5 Regressions of Predicted Values of Agriculture on Income

Climate Only

Independent Variables	United States	Brazil
Constant	8560	588.
	(79.05)	(7.14)
Predicted Farm Value	.703	.408
	(4.88)	(4.22)
Pred. Farm Value Squared	-8.87e-5	3.92e-5
	(2.18)	(0.81)
Predicted % Cropland	1570	11100
	(6.60)	(4.90)
Pred. %Cropland Squared	…	180000
		(4.175)
Density	9.76	…
	(9.48)	
Urban	858.	-1610
	(7.83)	(6.67)
Urban Squared	...	2440
		(11.99)
Population change	32.5	…
	(13.67)	
Flooding	-1040	…
	(6.39)	
Erosion	-2570	…
	(4.24)	
Slope Length	118.	…
	(4.29)	
Wetland	-2600	…
	(5.91)	
Soil 524	…	192
		(2.57)

Table 5 Continued

R^2	.367	.579
N	1942	2317

Predicted values from Table 4.

Endnote

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[i] Annual marginal values were calculated by summing both the linear and squared coefficients from (4) and average climate values (f_j) for each season j: MV= Σ ($d_{1,j} + d_{2,j} f_j$).