Climate Sensitivity of Indian Agriculture
Do Spatial Effects Matter?

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Abstract

Climate change impact studies on agriculture can be broadly divided into those that employ agro-economic approaches and those that employ the Ricardian approach. This study uses the Ricardian approach to examine the impact of climate change on Indian agriculture. Using panel data over a twenty year period and on 271 districts, we estimate the impact of climate change on farm level net revenue. The paper contributes to current knowledge on agricultural impacts by accounting for spatial features that may influence the climate sensitivity of agriculture. The key findings reveal that there is a significant positive spatial autocorrelation – both in the dependent variable, farm level net revenue, and in the error term – and that accounting for this can improve the accuracy of climate impact studies. Climate change results in a 9% decline in agricultural revenues in the base model but incorporating spatial effects lowers this effect to 3%. The available evidence suggests that better dissemination of knowledge among farmers through both market forces and local leadership will help popularize effective adaptation strategies to address climate change impacts.

Key Words: Climate change; Indian agriculture; Environmental valuation; Spatial panel data analysis; Adaptation

JEL Codes: Q54, Q1, R1

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1. Introduction

Over the past two decades the debate on global climate change has moved from scientific circles to policy circles with nation-states more serious now than before in exploring a range of response strategies to deal with this complex phenomenon that is threatening to have significant and far reaching impacts on human society. The Intergovernmental Panel on Climate Change (IPCC) in its fourth assessment report observed that, 'the warming of the climate system is now unequivocal, as is now evident from observations of increases in global average air and ocean temperatures, widespread melting of snow and ice, and rising global sea levels' (Solomon *et al.*, 2007). Policy responses to climate change include mitigation of greenhouse gases (GHGs) that contribute to the expected changes in the earth's climate and adaptation to the potential impacts caused by the changing climate. While the first is seen largely as a *reactive* response to climate change, the second one is a *proactive* response. Though GHG mitigation policies have dominated overall climate policy so far, adaptation strategies are now coming to the fore in order to formulate a more comprehensive policy response to climate change.

One of the crucial inputs needed for policy formulation on mitigation and adaptation is information on the potential impacts of climate change on various climate sensitive sectors. Impacts on agriculture due to climate change have received considerable attention in India as they are closely linked to the food security and poverty status of a vast majority of the population. The studies have used two basic methods to estimate the economic impact of climate change on agriculture[1]: i) an agronomic-economic approach that focuses on the structural modeling of crop and farmer responses, combining the agronomic response of plants with the economic/management decisions of farmers. Some refer to this approach as the Crop Modeling Approach and the Production Function Approach. Among the studies that have followed this approach are Rosenzweig and Parry (1994), Adams *et al*. (1999), Kumar and Parikh (2001a), and Fischer *et al*. (2002); ii) a spatial analogue approach that exploits observed differences in agricultural production and climate among different regions to estimate a climate response function. Some call this approach the Ricardian approach, which is similar in spirit to the hedonic pricing technique of environmental valuation. Among the studies that have used the spatial analogue approach are Mendelsohn *et al*. (1994), Kumar and Parikh (2001b), Niggol Seo *et al*. (2005), and Sanghi and Mendelsohn (2008).

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[1] *A few studies have used a third approach based on the agro-ecological zones (AEZ) methodology of the Food and Agricultural Organization. This approach assesses crop suitability to agro-ecological zones under present and changed climatic conditions in order to estimate the change in production potential and consequently their economics implications (see Kumar, 1998, and Darwin et al., 1995, for details).*

The Ricardian approach has received widespread attention due to its elegance and the strong assumptions it makes although a few scholars have questioned both the assumptions and the approach (Cline, 1996; Darwin, 1999; Quiggin and Horowitz, 1999). Several studies in India have followed this approach in the past to assess the climate sensitivity of Indian agriculture (Kumar and Parikh, 2001b; Mendelsohn *et al*., 2001; Kumar, 2003; and Sanghi and Mendelsohn, 2008). This paper contributes to existing knowledge on this field in India by addressing the importance of accounting for spatial features in the assessment of climate sensitivity. In conventional Ricardian studies the units of analysis (say, districts) are implicitly assumed to be perfectly substitutable across space. However, in reality, the values of variables in districts are defined not only by local conditions but also by the conditions in the neighbouring districts. This is what we refer to in this study as spatial autocorrelation of the dependent variable. Alternatively, the spatial distribution of agricultural land within and across districts could affect the error term structure. Ignoring the spatial correlation of error terms can lead to an under-estimation of the true variance-covariance matrix and hence to an over-estimation of the *t*-statistic. We refer to it in this study as the spatial autocorrelation of error terms. The study specifically assesses the evidence for spatial autocorrelation of variables (and errors) and attempts to correct for the same. The paper uses spatial panel data analysis in order to estimate the climate response function under various spatial econometric specifications and uses the estimated climate coefficients to predict the impacts due to climate change on Indian agriculture.

We adopt the following empirical strategy for the study: we use regression analyses and farm-level net revenue to understand the impact of climate change on agriculture. We construct and use a panel data consisting of cross-sectional and time-series data for the analysis. In the dataset, the dependent variable (net revenue) varies from year to year, as do a number of control variables. However, the climate variables (along with variables depicting soil characteristics) vary only across the cross-section. Notably, climate is not expected to change annually although the weather may. Since the inclusion of dummies for cross-sectional units will knock out the climate variables, we include only dummies for time points in the pooled regression analysis. Because it is important to control for spatial correlation, we apply a spatial econometric analysis with both spatial-lag and spatial-error model specification to estimate the climate response of Indian agriculture. Both the regular and spatial panel data analyses follow identical model specifications.

The rest of the paper adopts the following structure: the next section provides a brief review of the literature on the Ricardian approach and climate change impact studies on Indian agriculture. The third section explains the model structure and data used. The fourth section presents results and discusses the distributional issues of climate change impacts on Indian agriculture. The last section discusses the policy implications of the findings of this research.

2. Climate Change and Agriculture

Climate change projections for India for the 2050s suggest an increase in temperature by 2-4^{o}C for the region south of 25^{o}N and by more than 4^{o}C for the northern region. While there is likely to be little change in the average amount of monsoon rainfall, climatologists expect the number of rainfall days to decrease over a major part of the country. The expected changes in climate, especially rainfall, are also marked by significant regional variation, with the western and central parts witnessing a greater decrease in rainfall days compared to the other parts of the country. Climatologists have also projected an increase in the intensity and frequency of extreme events such as droughts, floods and cyclones (NATCOM, 2004).

Mall *et al.* (2006) provide an excellent review of the climate change impact studies on Indian agriculture mainly from a physical impacts point of view. The available evidence shows a significant drop in the yields of important cereal crops like rice and wheat under the changed climate conditions. However, the studies on the biophysical impacts on some important crops like sugarcane, cotton and sunflower are not adequate.

As mentioned above, scholars assess the economic impacts of climate change either through the agronomic-economic approach or through the Ricardian approach. The first approach introduces the physical impacts (in the form of yield changes and/or area changes estimated through crop simulation models) into an economic model exogenously as Hicks neutral technical changes. In the Indian context, Kumar and Parikh (2001a) have estimated the macro level impacts of climate change using such an approach. They estimate yield changes of rice and wheat crops using one of the widely used crop simulation models (Erosion, Productivity and Impact Calculator – EPIC, Stockle *et al*., 1992) at various sites across India. Aggregating the site-specific estimates, the study introduces the yield changes as supply shocks into an applied general equilibrium model of the Indian economy (the Agriculture, Growth and Redistribution of Income Model – AGRIM, Narayana *et al*., 1991) to assess the economy-wide impacts and welfare implications. They show that under doubled carbon dioxide concentration levels in the latter half of the 21st century the gross domestic product would decline by 1.4 to 3 percentage points under various climate change scenarios, with adverse poverty effects. While this approach can account for the so-called carbon fertilization effects[2], one of the major limitations is its treatment of adaptation. Since the physical impacts of agriculture are to be re-estimated under each adaptation strategy, the researchers can analyze only a limited number of strategies. It must be noted however that this approach can easily incorporate other adaptation strategies that are triggered by market signals.

In an alternative approach, known as the Ricardian approach, Mendelsohn *et al*. (1994) have attempted to link land values to climate through reduced-form econometric models using cross-sectional evidence. This approach is similar to the Hedonic pricing approach of environmental valuation. The approach is based on the argument that, 'by examining two agricultural areas that are similar in all respects except that one has a climate on average (say) 3°C warmer than the other, one would be able to infer the *willingness to pay* in agriculture to avoid a 3°C temperature rise' (Kolstad, 2000). Since this approach is based on the observed evidence of farmer behavior, it could *in principle* include all adaptation possibilities. In fact, this approach treats farmers as though they have 'perfect foresight' and hence better placed to implement all adaptation options[3]. The literature on the agronomic-economic and Ricardian approaches refers to farmers as 'typical' and clairvoyant', respectively, based on the manner in which they address the adaptation issues. However, if the predicted climate change is much larger than the observed climatic differences across the cross-sectional units, the Ricardian approach cannot (even in principle) fully account for the adaptation. While the Ricardian approach has the potential to address the adaptation satisfactorily, it does not completely address the issues concerning the cost of adaptation. One

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[2] *Higher carbon dioxide concentrations in the atmosphere under the climate change conditions could act like aerial fertilizers and boost crop growth. This phenomenon is called the carbon fertilization effect.*

[3] *Note that the non-implementation of the adaptation options is detrimental to the farmers, and hence rational farmers would implement the adaptation options.*

of the main concerns of this approach is that it may confound climate with other unobserved factors. Recently, Deschenes and Greenstone (2007) and Schlenker and Roberts (2008) among others have addressed this issue. Further, the constant relative prices assumption used in this approach could bias the estimates (see Cline, 1996, Darwin, 1999, and Quiggin and Horowitz, 1999, for a critique of this approach).

In the case of India, Kumar and Parikh (2001b) have used a variant of this approach and showed that a 2^{o}C temperature rise and a seven percent increase in rainfall would lead to almost a 8.4 percent loss in farm level net revenue (1990 net revenue expressed in 1980s prices). The regional differences are significantly large with northern and central Indian districts along with the coastal districts bearing a relatively large impact. Mendelsohn *et al*. (2001) have compared the climate sensitivity of US, Brazilian and Indian agriculture using estimates based on the Ricardian approach and have argued that using the US estimates for assessing climate change impacts on Indian agriculture would lead to an under-estimation of impacts. More recently, Sanghi and Mendelsohn (2008) have compared the climate change impacts on Indian and Brazilian agriculture based on estimates provided by the Ricardian approach. This study follows similar methodology and data as Kumar and Parikh (2001b) and Mendelsohn *et al*. (2001) and reports annual losses varying between 4% and 26% for India under various climate change scenarios (the losses are expressed as a percentage of farm-level net revenue). The climate change scenarios considered cover a temperature increase of 1 to 3.5^{o}C and a precipitation change of -8% to +14%. Under the middle scenario of a 2^{o}C increase in temperature and a 7% increase in precipitation, Sanghi and Mendelsohn (2008) report an annual loss of 12 percent of farm-level net revenue in India. In comparison, our study, which uses more accurate base climate data, estimates the annual loss as 9 percent for a similar climate change scenario.

In addition to these impact studies, a number of studies in the Indian context have looked at the vulnerability of Indian agriculture to climate risks. O'Brien *et al*. (2004) attempted to identify the so-called 'double exposed' districts in India – i.e., the districts that are vulnerable to climate change as well as globalization – with a focus on the agricultural systems. Kumar (2007) provides an overview of these studies in an attempt to put together the available evidence on: (a) the extent of the adverse impacts of climate change on Indian agriculture; (b) the characteristics of relatively more vulnerable regions; and (c) effective adaptation strategies that help to ameliorate the present and future vulnerability of agriculture. More recently, the World Bank (2008) analyzed the climate change impacts in the drought- and flood- affected areas of India. Arguing that present day development strategies must incorporate elements of climate risk management, the authors identify a number of adaptation strategies that seamlessly merge with the overall development agenda.

The use of cross-sectional units for assessing climate change impacts in the Ricardian approach implies that regional fixed-effects cannot be introduced for improving model specification as inclusion of such fixed-effects will knock out the climate coefficients, thus defeating the very purpose of the analysis[4]. Hence, the Ricardian model specification assumes that all heterogeneity

[4] *As discussed in the next section, some recent studies (Deschenes and Greenstone, 2007) have attempted to include regional fixed-effects in the analysis using cross-sectional data. However, as we argue later, such analyses may estimate the impact of weather shock and not necessarily the impact of climate and its change.*

across cross-sectional units is controlled for by the observed explanatory variables including the climate variables. Thus it is very important that the model specification is accurate so that climate coefficients capture only the influence of climate. Further, since there is scope for learning across spatial units through communication and information diffusion, it is important to account for spatial correlation in the Ricardian analysis using cross-sectional data. It is this latter issue that the present study focuses on. Depending on how the spatial correlation would enter into the Ricardian analysis using cross-sectional data, some recent studies assessing climate change impacts on agriculture in the USA have either assumed that the dependent variable is spatially lagged (Polsky, 2004) or the error term is spatially correlated (Schlenker *et al*., 2006). Either way, these studies have argued for the need to account for spatial correlation in the Ricardian analysis. The results from these studies have suggested significant deviations between the climate change impacts of models that account for spatial correlation and those that do not. The present study aims to bridge the knowledge gap in the Indian context by attempting to get accurate estimates on the climate sensitivity of Indian agriculture through specifically accounting for spatial correlation of the cross-sectional units in the Ricardian analysis.

3. Model Specification and Data

As changes in climate would influence crop growth, the behaviour of the producers of agricultural goods would also alter with a changing climate. From the producers' point of view, changes in climate can be considered as a change in the input structure. Consider k purchased inputs and l climate inputs that a production function F relates to the output. Let P_i and Y_i be the output price and quantity of the i^{th} good respectively, X_{ij} the quantity of the j^{th} purchased input used in the production of the i^{th} good, and q_j the price of the j^{th} purchased input. The profit-maximizing behavior of the producer can be represented as,

$$Max \quad P_i \, Y_i - \sum_j q_j \, X_{ij} \tag{1}$$

subject to a production function,

$$Y_i \quad \leq \quad F \; (X_{i1}, X_{i2}, ..., X_{ik}, E_1, E_2, ..., E_l) \tag{2}$$

The inclusion of environmental/climate inputs (variables E in the above equation) makes this specification different from the conventional one. Theoretically, profits, input demands and output supply can be expressed as functions of measured market inputs and climate variables even though there is no market for climate inputs. However, researchers consider an associated econometric analysis in order to obtain the functional relationship between output and changes in climate inputs difficult and hence they often partition the production function represented in equation (2). In the case of agriculture, for example, researchers first estimate yield changes and then introduce them into economic models as measures of supply shifts. While scholars commonly use such neutral technology change assumptions in the literature on climate change impacts, it is not necessary to make such an assumption. Thus, equation (2) becomes,

$$Y_i \quad \leq \quad F_1 \, (X_{i1}, X_{i2}, ..., X_{ik}) * F_2 \; (E_1, E_2, ..., E_l) \tag{3}$$

Such partitioning would allow fairly complex technical relationships among market inputs as described by econometrically related production relationships and among climate inputs as described by crop simulation models. Researchers often integrate the crop responses to climate parameters, estimated using crop simulation models, with either a partial or general equilibrium framework in order to assess the economic and welfare implications.

The Ricardian approach, on the other hand, combines the climate response curves of various crops to arrive at the overall crop response curve recognizing that different crops have different climatic requirements. Though the farmer would voluntarily switch from one crop to another, as not switching over would result in losses, the transition between crops would involve costs. Thus, to take into account the costs and benefits of adaptation, the relevant dependent variable should be net revenue or land values (that is, capitalized net revenues), and not yields[5]. Thus, the Ricardian approach estimates a variant of equation (2). Scholars measure the climate change impacts as changes in net revenue or land value as shown in Mendelsohn *et al.* (1994) and explained below.

Consider a crop with the aggregate demand Y_i and let the production function be as shown in equation (2). Associated with Q (which represents the set of prices of the inputs used in the production), E and Y_i, there will be a cost function (obtained through cost minimization) given by equation (4)

$$C_i = C_i (Y_i, Q, E) \qquad (4)$$

where, C_i is the cost of production of good i. Separating 'land' out of the vector of inputs X and taking its annual rent as p_l, we can write the profit maximization equation as,

$$Max \;\; P_i Y_i - C_i (Y_i, Q, E) - q_l L_i \qquad (5)$$

where, L_i is the amount of land used for producing Y_i. Under perfect competition for land, we can write the rent of land as:

$$q_l = \frac{[P_i Y_i - C_i (Y_i, Q, E)]}{L_i} \qquad (6)$$

If 'i' is the best use for the land, given the environment E and factor prices Q, the observed market rent on the land will be equal to net profits from the production of good 'i'. We can write land value, which is the present value of the stream of revenue over time, as,

$$V_l = \int_0^\infty q_l \, e^{-\rho t} \, dt \qquad (7)$$

The Ricardian approach examines the relationship between land rent (equation 6) or land value (equation 7) and the exogenous variables, P, Q, and E.

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[5] *However, even net revenue cannot fully account for the costs of the transition incurred by the farmer while moving from one crop to another in response to the changes in the climatic conditions.*

Under the assumption that environmental changes will leave market prices unchanged, we can write the welfare value of a change in the environment as,

$$W(E_A - E_B) \;=\; [PY_B - \sum C_i\,(Y_i, Q, E_B)] \;-\; [PY_A - \sum C_i(Y_i, Q, E_A)] \quad (8)$$

plugging equation (6) in equation (8), we can show that,

$$W(E_A - E_B) \;=\; \sum (q_{lB}\,L_{EB} - q_{lA}\,L_{EA}) \quad (9)$$

where q_{lA} and q_{lB} are land prices under different environmental conditions. Alternatively, we give the present value of this welfare change by,

$$\int_0^{\infty} W(E_A - E_B)\,e^{-\rho t}\,dt \;=\; \sum (V_{lB} - V_{lA}) \quad (10)$$

Equations (9) and (10) are the definitions of the Ricardian estimate of the value of environmental changes. If the output prices do not change under changed climate conditions, the change in aggregate land values or the change in the present value of net revenues captures exactly the value of the change in the climate.

The empirical strategy of the study is to estimate a functional relationship between land value, or net revenue, and climate variables using cross-sectional data while controlling for variables that could cause variability in the dependent variable. We could then use the estimated functional relationship to assess the climate change impacts.

Scholars have used a variant of the Ricardian approach due to the non-existence of well functioning land markets in the developing countries (see, Dinar *et al.*, 1998). In place of land values, in the earlier Indian studies scholars have used farm level net revenue as a welfare indicator while they have assessed the value of the change in the environment/climate through a change in farm level net revenue. They control for variability in the dependent variable caused by factors other than climate through: (a) soil characteristics (both soil quality and top-soil depth could differ significantly across the cross-section leading to variability in the farm-level net revenue); (b) the level of technology penetration (wide divergence across the cross-sectional units in terms of draught force utilization, mechanization, and penetration of new growing technologies could lead to variability in the dependent variable); (c) the extent of development (opportunity cost of land and market access and alternative livelihood opportunities could differ across the cross-sectional units and hence contribute to the variability in the dependent variable). Differences across cross-sectional units in physical characteristics such as the extent of the day length could also contribute to variability in the farm-level net revenue.

It is possible that some of these control variables are endogenous in nature and hence do not qualify as exogenous variables. However, we have included them as exogenous variables in line with the existing literature on climate change impacts (Kumar and Parikh, 2001b; Sanghi and Mendelsohn, 2008) in order to facilitate comparability of results.

We thus specify the Ricardian model as follows:

$$\begin{aligned} NR \quad = \quad & f(T_j, T_j^2, R_j, R_j^2, T_j R_j,\ SOIL, BULLOCK, TRACTOR, \\ & \qquad POPDEN, LITPROP, CULTIV, HYV, IRR, ALT) \end{aligned} \tag{11}$$

where, *NR* represents farm level net revenue per hectare in constant rupees and *T* and *R* represent temperature and rainfall respectively. It is noteworthy that based on the existing literature we adopt a quadratic functional specification along with climate interaction terms. The control variables include soil (captured through dummies representing several soil texture classes and top-soil depth classes), the extent of mechanization (captured through the number of bullocks and tractors per hectare), the percentage of literate population, population density, altitude (to account for solar radiation received), the number of cultivators (since we could not account for the cost of labour while calculating the dependent variable), the fraction of area under irrigation and the fraction of area under high-yielding variety seeds. We do not include the prices – output as well as input – in the model. This is because an earlier study by Kumar and Parikh (2001b) has shown that the climate coefficients have not significantly changed when they include the prices of major cereal crops in the model specification. However, no evidence exists from previous studies about the influence of input prices. We therefore assume their cross-sectional variation to be not significant here.

We use pooled cross-sectional and time-series data to estimate the above model. Districts are the lowest administrative unit at which reliable agricultural data is available. We use a comprehensive district level dataset for the period 1966 to 1986 for the purpose of the analysis. We assemble agricultural data at district level in the dataset along with the relevant demographic and macro economic data. The dataset covers districts defined according to the 1961 census across thirteen major states of India (Andhra Pradesh, Haryana, Madhya Pradesh, Maharashtra, Karnataka, Punjab, Tamil Nadu, Uttar Pradesh, Bihar, Gujarat, Rajasthan, Orissa and West Bengal). The dataset includes 271 districts in all.

The variables covered in the dataset include the gross and net cropped area; the gross and net irrigated area; the cultivators; the agricultural labourers; the cropped area under high-yielding variety seeds; the total cropped area under five major crops (rice, wheat, maize, *bajra* and j*owar*) and fifteen minor crops (barley, gram, *ragi*, *tur*, potato, ground nut, tobacco, *sesamum*, *ramseed*, sugarcane, cotton, other pulses, jute, soybean, and sunflower); bullocks; tractors; literacy rate; population density; fertilizer consumption (N, P, K) and prices; agricultural wages; crop produce; farm harvest prices; soil texture and top soil depth. For purposes of analysis, we define farm level net revenue per hectare as follows:

$$Net\ \mathrm{Re}venue\ per\ ha \quad = \quad \frac{\left((Gross\ \mathrm{Re}venue) - (Fertilizer\ and\ Labor\ Costs)\right)}{Total\ Area} \tag{12}$$

where, we calculate gross revenue over the twenty crops mentioned above and where the total area is the cropped area under the twenty crops, the fertilizer costs are the total yearly costs incurred towards the use of fertilizer for all the crops and the labour costs are the yearly expenses towards hiring agricultural labour. It is noteworthy that we do not include costs attributable to cultivators, irrigation, bullocks and tractors in the net revenue calculations because appropriate prices are difficult to identify. However, we use these variables as control variables in the model as specified in equation (11).

Unfortunately, there is no 'clean' climate data available for the analysis. Meteorological stations typically collect meteorological data and any district may have one or many stations within its boundary. Since all other data is attributable to a hypothetical centre of the district, it is necessary to work out the climate data too at the centre of the district. For this purpose, it is customary to interpolate meteorological station data to arrive at a district specific climate (see Kumar and Parikh, 2001b, and Dinar *et al*., 1998, for more details on the surface interpolation employed to generate district level climate data). We use climate data corresponding to about 391 meteorological stations spread across India for the purpose of developing the district level climate. The data on climate – at the meteorological stations and hence at the districts – correspond to the average observed weather over the period 1951-1980 as documented in a recent publication of the India Meteorological Department. We represent all the climate variables through four months, January, April, July and October, corresponding to the four seasons. The climate variables include average daily temperature and monthly total rainfall in the four months mentioned above. The average temperature and rainfall for each of these four months over the period 1951-1980 for each of the 271 districts represent the climate variables used in this study. Thus, these data points do not vary over time but instead vary across districts.

We measure the dependent variable (namely, net revenue) in equation (11) and some of the explanatory variables (such as population density, tractors, bullocks, etc.) for every single year of the entire time period. If annual weather data for each district were available for a continuous period of time, then we could have used the rolling averages of 30 year weather data as 'climate' for each year. That is, for the year 1966, the average weather over the period 1937 to 1966 would serve as climate, whereas for the year 1970, the average weather over the period 1941 to 1970 would serve as climate. This would ensure that the farmer in each year responds to the climate that she experiences. However, reliable annual weather data for a long period of time is not available in India. Hence, climate data in the analysis corresponds to the average weather over the period 1951 to 1980. However, we work under the assumption that the climate has not changed significantly over the study period and that the average weather over the 30 year period is highly correlated[6].

Given the scope for the presence of unobserved variables that could confound with climate variables, it is possible to employ the district fixed effects specification for efficient estimation. Such a specification would knock out the climate coefficients which are invariant over time. Deschenes and Greenstone (2007) in a recent study on US agriculture have used county fixed-effects specification and have assessed the value of weather shocks to the farmer as against the climate change impacts. The present study with its focus on climate change impacts attempts to address this issue by including state fixed-effects. The year effects are captured through year fixed effects after the Hausman test rejected the null hypothesis, implying that the random effects model produces biased estimates. Further, since the units of analysis (i.e., districts) differ

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[6] *Sanghi and Mendelsohn (2008) in their analysis of the climate change impacts on Indian agriculture use climate data corresponding to the period 1930-1960 and report almost similar results as in this study. This is seen as justification for the above claim that the climate has remained stable over the study period.*

significantly in size and agricultural activities, the measurement errors might also substantially differ across districts. Hence, we weigh the data for each unit of analysis by the total area under the twenty crops in order to adjust for heteroscedasticity.

3.1 Climate Sensitivity and Spatial Autocorrelation

We can introduce spatial features into the Ricardian approach based on two arguments: (i) theory-driven and (ii) data-driven. In the theory-driven arguments, the focus is on interacting agents and social interactions (Anselin, 2002). This means that agents across space communicate with each other in order to learn about farm management practices and response strategies in order to handle climate and other risks. The assumption is that such interaction results in a spatially correlated dependent variable (and, sometimes, independent variables also). The resultant econometric specification then involves including a spatially lagged dependent variable as an additional independent variable.

In the data-driven specification, the focus is on accounting for the inefficiency being created by the possible presence of spatial correlation in the error terms of the linear regression models. Two immediate examples of these two types of specification can be seen in the climate change context. While Polsky (2004) introduces spatial econometric specification of the Ricardian model mainly to account for social interactions, Schlenker *et al.* (2006) bring in spatial features to arrive at *efficient* estimates of regression coefficients. In most Ricardian studies of climate change impacts (including those carried out in the Indian context), the *t*-statistic values are very high reflecting a possible spatial correlation of the error terms. In fact, Schlenker *et al.* (2006) argue that the *t*-values in models that do not account for spatial heteroskedasticity of error terms are likely to be 9 times larger than those in models that account for spatial correlation of the error terms. Either way, the estimation procedure involves specifying the spatial weight matrix, which provides a structure to the assumed spatial relationships.

Thus, the presence of spatial autocorrelation necessitates re-specification of the model as either spatial-lag or spatial-error model as shown below:

Spatial-error model: $\boldsymbol{y} = \boldsymbol{X}\beta + \eta$, where $\eta = \boldsymbol{\rho} \mathbf{W}\eta + \varepsilon$ (13a)

Spatial-lag model: $\boldsymbol{y} = \boldsymbol{\rho}\boldsymbol{W}\boldsymbol{y} + \boldsymbol{X}\beta + \varepsilon$ (13b)

where, $\boldsymbol{y}$ is (nx1) the vector of dependent variable observations, $\boldsymbol{X}$ is (nxm) the matrix of observations on independent variables including the climate and other control variables, β is (mx1) the regression coefficient vector, η is (nx1) the vector of spatially correlated error terms, $\boldsymbol{\rho}$ is (1x1) the spatial autoregressive parameter, $\boldsymbol{W}$ is (nxn) the spatial weights matrix, and $\boldsymbol{e}$ is (nx1) the vector of random error terms. Note that $\boldsymbol{y}$ and $\boldsymbol{X}$ are respectively the left hand and right hand side variables specified in equation (11) above.

One of the crucial inputs that spatial analysis needs is the weight matrix ***W***. We use three weight matrices – rook-based contiguity, queen-based contiguity, and distance-based contiguity – in the present analysis. We generate these weight matrices for the Indian districts in GeoDa software[7]. We carry out a spatial econometric analysis in GeoDa and STATA software for single cross-

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[7] *We use the spatial econometric software developed by Prof. Luc Anselin of the University of Illinois (version 0.9.5).*

sections. However, since it is not feasible to estimate the spatial fixed-effects model in GeoDa (and also in STATA for computational limitations), we transfer the weight matrices via R-software to ASCII data format. We estimate the spatial panel models – spatial-lag and spatial-error – using MATLAB software[8] as it provides scope for reading sparse matrices.

3.2 Climate Change Projections for India

For the analysis, we use the climate change projections for India reported in Cline (2007). The climate change projections are the average of predictions of six general circulation models including HadCM3, CSIRO-Mk2, CGCM2, GFDL-R30, CCSR/NIES, and ECHAM4/OPYC3. Table 1 shows the region-wise and season-wise temperature and rainfall changes for the period 2070-2099 with reference to the base period 1960-1990. From these regional projections, we assess the state-wise climate change predictions by comparing the latitude-longitude ranges of the regions with those of the states. In addition to this India-specific climate change scenario, we also assess the impacts for two illustrative uniform climate change scenarios (a +2^{o}C temperature change along with a +7 percent precipitation change; and a +3.5^{o}C temperature change along with a +14 percent precipitation change) that embrace the aggregate changes outlined in the fourth assessment report of IPCC (Solomon, 2007).

4. Results and Discussions

The results are reported in three sub-sections: in the first sub-section, we present the estimates of the classic Ricardian approach, which is followed by a discussion on spatial diagnostics with different weight matrices; the last sub-section reports the estimates of the panel data analysis under spatial-lag and spatial-error specifications and presents the estimates of climate change impacts on Indian agriculture.

4.1 Climate Response Function – Averaged Regression

For purposes of comparison and carrying out spatial diagnostic tests, we average the data over the entire period of analysis to create a single cross-sectional dataset. We use this single cross-sectional dataset for estimating equation (11) using the weighted least squares approach, with area under cropland in each district serving as the weight. Table 2 reports the estimated regression coefficients. We use the reported coefficients as the basis for interpreting the rest of the analyses.

The estimated climate response function for the average data over the period 1966-1986 has several expected features with about 66 percent goodness of fit. A large number of climate variables are significant. Since soils tend to differ across districts, we include the soil variables mainly to control for the influence of cross-sectional variability of soil quality on the dependent variable. The other control variables include cultivators per hectare, bullocks per hectare and tractors per hectare. Both cultivators and bullocks have a mixed expected influence on the farm-level net revenue. On the one hand, the higher values of these variables reduce the

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[8] *J. Paul Elhorst (www.spatial-econometrics.com) has written the MATLAB codes for spatial panel analysis.*

cost to the farmer, but on the other hand high values also represent a low technological base. Tractors per hectare clearly have a high significant positive influence on farm-level net revenue. Literacy and population density have a positive effect as expected. The percentage of land under irrigation clearly increases farm-level net revenue. Some studies have argued against the use of irrigation as one of the explanatory variables due to the potential endogeneity problem and have suggested instead the use of area under high-yielding variety cultivation. However, since most of the irrigated land also cultivates high-yielding variety crops, these two variables could be largely collinear.

The climate variables are largely significant and the estimated response function appears to be non-linear, in line with available evidence in the literature. The temperature effects are far higher than the precipitation effects. The temperature coefficients are all negative in January (Winter), April (Spring), and July (Summer) but positive in October (Autumn). While higher temperatures during the hot spring and summer days would adversely influence crop growth, warmer autumns could lead to an enhanced growing season. Higher temperature during winter could favourably influence pest growth and hence could have an adverse impact on crop growth. Higher precipitation as expected is beneficial in the winter and autumn seasons, but harmful during spring and summer.

The temperature response functions exhibit mixed curvature properties, with the winter and autumn temperatures showing a concave nature, and the spring temperature showing a convex nature. The precipitation response functions on the other hand are convex for the spring and summer, but concave for the winter precipitation. The autumn precipitation is almost linear with a small square coefficient.

For purposes of comparison with the spatial models, we carry out a pooled regression analysis covering all the years of the study period with exactly similar specification as the averaged regression discussed here. In addition to all the variables discussed above, we include the year fixed effects in the panel data analysis. All the coefficients retained the sign and magnitude in the pooled regression and have improved statistical significance. Almost all the climate coefficients were statistically significant in the pooled regression. We report these results in Table 4 along with spatial panel data analyses results.

As discussed above, a valid criticism of the Ricardian approach is unobserved cross-sectional variables confounding with climate variables. And including district fixed effects in the pooled data analysis is not feasible given the non-varying nature of some of the independent variables, including the climate variables, over the years. In an attempt to improve the model specification, we added regional fixed effects to the equation (11) in the form of state dummies. We report the estimated coefficients in Table A1 in the appendix. Almost 70 percent of the climate variables remained significant in the model with state dummies, confirming that regional fixed effects have not nullified the influence of climate on farm-level net revenue. Barring a few exceptions, the direction of influence also remained similar between models without and with regional fixed effects. The magnitude of individual coefficients however has changed as was to be expected. But, we did not include the regional dummies for the rest of the analysis.

4.2 Diagnostics for Spatial Dependence

We analyze the spatial clustering of the dependent variable (i.e., net revenue per hectare) and the residual of the ordinary least squares regression by constructing Moran scatter plots for several

time points in the period 1966-1986. Figure 1 shows the scatter plots along with the Moran's I value for the years 1970, 1975, 1980 and 1985. The top panel shows the Moran scatter plot for the dependent variable while the bottom panel shows that for the error. The scatter plot is graph of *Wy* versus *y*, where *W* is a row-standardized spatial weight matrix and *y* = [(variable value – mean of variable)/standard deviation of variable]. We use a rook-contiguity based weight matrix for constructing the Moran scatter plots. The clustering of values in the upper right quadrant and lower left quadrant represents a significant positive spatial autocorrelation. As seen in Figure 1, for all the four periods for which we report scatter plots, the dependent variable and the error te
The indication of significant spatial clustering given by the spatial autocorrelation statistic represents only the first step in the analysis of spatial data. We carry out spatial diagnostic tests on the averaged regression reported in the previous section to statistically assess the extent of spatial dependence in the data and to identify the appropriate correction for removing the spatial dependence in the data. Table 3 reports various test statistics under different weight matrix specifications. The weight matrices considered include rook-contiguity based, queen-contiguity based, and distance-based weight matrices.

The first row in Table 3 shows the Moran I statistic of the error along with the associated probability. It shows the statistic to be highly significant indicating the problem of spatial dependence in the data. The value of Moran I statistic is close to 0.2 across the different weight matrix specifications indicating that alternative weight matrices may not have a significant influence on the analysis.

We use the Lagrange Multiplier test to determine which spatial model should be used for spatial correction (spatial-lag or spatial-error). The sequence of the search is as follows: if both Lagrange Multiplier (lag and error) statistics are significant, then we consider the robust versions of these tests to be significant and we choose the model specification with the higher significance for the spatial analysis. In all cases reported in Table 3, the Lagrange Multiplier (lag and error) statistics are highly significant, necessitating the need for examining the robust Lagrange Multiplier test statistic. In rook-contiguity and queen-contiguity based weight matrix specifications, the robust Lagrange Multiplier statistics for both lag and error are significant, with the latter highly significant compared to the former. In the case of distance-based weight matrix specification, however, the robust Lagrange Multiplier tests suggest the spatial-error model as the preferred model for spatial correction.

Based on these results, we attempt spatial correction using both spatial-lag and spatial-error model specifications. We discuss these results in the next section.

4.3 Effect of Spatial Autocorrelation on Climate Sensitivity

The evidence presented above based on averaged regression makes it clear that: (a) the choice of the weight matrix may not have a significant influence on the analysis, and (b) the choice between the model for spatial correction – namely, spatial-lag and spatial-error – is not obvious, with the robust Lagrange Multiplier test statistic remaining significant under lag as well as error specifications. Hence, we use both these models for spatial correction and re-estimate equation (11) with the modifications specified in equations (13a) and (13b) using the panel data over the period 1966 to 1986. We base all the estimates on fixed (year) effects specification in the pooled data and the observations are weighted by the total area under all the crops considered in the analysis. Thus, we attempt two kinds of heteroscedasticity corrections in the spatial analysis:

the first is through the crop area in each district in order to account for differences in the size of the districts and hence the difference in the measurement error; and the second is through the weight matrix in order to account for spatial dependence in the data. We use the rook-contiguity based weight matrix to estimate the spatial models.

Table 4 shows the climate response functions estimated with and without consideration of spatial autocorrelation. Though the adjusted R-square value is higher under both the spatial models, it is what is known as the pseudo R-square and hence not exactly comparable with that in OLS. The climate coefficients in both the spatial-lag and spatial-error models are largely significant and have a similar influence as the base model without the spatial correction. Barring a few exceptions, the climate coefficients in the models that account for spatial autocorrelation (either through spatial-lag or spatial-error models) are uniformly lower than that which ignores the presence of spatial autocorrelation. This implies that the explanatory power of the climate variables that we attributed to their within district value in the base model was partly due to the influence of neighbouring districts.

With regard to the choice between the two spatial models, the diagnostic tests were inconclusive as discussed in the previous section. The coefficient of the spatially lagged farm-level net revenue in the spatial-lag model and the coefficient of spatially correlated errors in the spatial-error model are both positive and highly significant. The model performance parameters, the higher adjusted R-square value (0.72 *vs.* 0.65) and the higher log-likelihood value (-127406 *vs.* -127861), indicate that the spatial-error model is preferred over the spatial-lag model.

In order to gain insight into the influence of various climate change scenarios on Indian agriculture, we assess the impacts based on the estimated climate response functions. We consider two climate scenarios: a) one illustrative scenario with a +2^{o}C uniform change in temperature and a +7 percent uniform change in precipitation; b) one India-specific scenario with the expected regional changes in temperature and precipitation as reported in Table 1. We measure the climate change induced impacts through changes in the net revenue triggered by the changes in the climate variables. We estimate the impacts for each year at the individual district level, which we then aggregate to derive the national level impacts. We report the average impacts over all the years in Table 5. The Table reports the all India level impacts estimated in each time period as a percentage of the 1990 all India net revenue expressed in 1999-2000 prices. We consider the 1990 net revenue mainly to accommodate a comparison with previous results reported in the literature. We interpret the impacts as a change in 1990 net revenue if future climate changes were to be imposed on the 1990 economy and are annual impacts. We estimate that the overall impacts (for the same climate change scenario) using climate coefficients obtained from the model that accounts for spatial autocorrelation (either through spatial-lag or through spatial-error specification) are significantly lower than those obtained from the model that ignores the spatial effects.

Since the aggregate impacts mask significant regional differences, Figures 2 and 3 compare the distribution of climate change impacts at the state and district levels between the models that account for spatial autocorrelation and those that do not. For these figures, we use the India specific climate change scenario that incorporates non-uniform changes in temperature and precipitation across regions. The results show that climate change is likely to adversely affect agriculture in almost all the regions in India with the exception of the eastern states of Bihar and

West Bengal along with the inland region of Karnataka. Severe impacts are borne by the high-value agricultural regions of Haryana, Punjab and Uttar Pradesh, along with the dry regions of Gujarat and Rajasthan. Coastal states like Andhra Pradesh and Tamil Nadu also lose out under changed climatic conditions. Between the models that do not incorporate spatial correction and the models that do, we predict significant changes in Andhra Pradesh, Tamil Nadu, Rajasthan, Madhya Pradesh and to some extent in Uttar Pradesh. This means that in the case of these states the model without spatial correction overestimated the climate change impacts.

5. Conclusions and Policy Recommendations

This paper contributes to existing knowledge on the impacts of climate change on Indian agriculture by accounting for spatial issues in a Ricardian framework. Using approximately 20 years of district level agricultural data coupled with climate and soil data, the analysis employs spatial panel data models to explore these issues. Besides estimating the climate response function for Indian agriculture, the paper estimates the expected impacts due to climate change on Indian agriculture.

The evidence presented in this paper suggests that, (a) accounting for spatial autocorrelation is important due to the presence of significant spatial clustering of the data; and (b) the climate change impacts are significantly lower after incorporating spatial correction either through spatial-lag or through spatial-error model specifications. The choice between spatial-lag and spatial-error model specifications for spatial correction is largely inconclusive. However, purely from a model performance perspective, the spatial-error model has a slight edge over the spatial-lag model.

An illustrative climate change scenario that envisages a +2^{o}C temperature change and a +7 percent precipitation change uniformly across India would result in an estimated 9 percent decline in farm-level net revenue annually. This decline is estimated to be 3 percent once we account for spatial effects using the spatial-error model.

The results from this paper are lower than the range of results obtained from other climate change agricultural impact studies in India. Relative to the annual decline of 3 percent in farm-level net revenue estimated here, Kumar and Parikh (2001b) estimate a 8.4 percent decline while Sanghi and Mendelsohn (2008) conclude that climate impacts will result in a 12 percent decline annually in farm-level net revenue in India. The impacts on the GDP estimated by Kumar and Parikh (2001a) are not strictly comparable with those reported in the above studies due to the partial equilibrium approach adopted in the Ricardian framework. However, yield losses estimated by Kumar and Parikh (2001a) and others reported in Mall *et al.* (2006) are relatively higher than the losses in net revenue estimated by the Ricardian studies. In sum, the estimates of climate change impacts on Indian agriculture from this paper are lower than the reported estimates in the existing literature.

Since uniform changes in climate considered in the illustrative scenario would mask the expected regional variation in the climate change, we also estimate the impacts due to an India-specific climate change scenario along with the regional distribution of impacts. With the exception of the eastern states of Bihar and West Bengal and the inland region of Karnataka, in all other regions of India climate change is likely to have an adverse impact on agriculture. While the high-value agricultural regions of Haryana, Punjab and Uttar Pradesh together with the dry regions of Gujarat and Rajasthan bear significant impacts, coastal states like Andhra Pradesh and Tamil Nadu also suffer to some extent in a consideration of overall impacts.

In the case of Andhra Pradesh, Tamil Nadu, Rajasthan, Madhya Pradesh and, to some extent, Uttar Pradesh, incorporating the spatial effects results in a lowering of the climate change impacts on agriculture. This suggests that in these states, a strong flow of information amongst farmers may contribute to better adaptation and thereby lower the impact of climate change on agriculture. The assessment of climate change impacts on Indian agriculture through a careful consideration of spatial issues in the Ricardian framework that this study has carried out would be useful in providing a more accurate picture of the potential impacts of climate change on Indian agriculture. However, from a policy perspective, it would be helpful to identify factors that contribute to the observed spatial correlation of variables across districts. Such knowledge would be useful in designing policies that contribute to enhancing the facilitating factors.

Focus group interviews from the field indicate that the main sources of information to farmers are the more affluent farmers in the neighbourhood, fertilizer and pesticide dealers, seed providers, and the better informed family members. Contrary to the general belief that agricultural extension centres operate as the primary source of information, the evidence from the field suggests that, in reality, farmers benefit very little from these government outfits. While market sources seem to have the appropriate self-regulated checks against the provision of wrong information, it is important to ensure that incorrect information does not reach the farmers even inadvertently.

The field studies also reveal that policy makers should explore and experiment with new sources of information diffusion. Given the fragmented nature of Indian agricultural lands, the large scale participation of the corporate sector in providing agricultural extension services would be difficult, thereby necessitating the exploration of other options. Among other options, the farmers favoured in particular the participation of agricultural cooperatives, NGOs, and dealers of inputs and fertilizers in information diffusion. In this context, it might be worthwhile to carefully study other country experiences in order to identify the routes through which the State can provide agricultural extension services to the farmers in India. For instance, in Ecuador, the agricultural extension workers operate in tandem with the farmers through share cropping in order to ensure proper information diffusion. On the other hand, Chile finances the costs of private sector firms which transfer technology know-how and information on new agricultural practices to small-scale farmers.

The Ricardian approach we used in this study deals largely with private adaptation measures undertaken by farmers for whom not adapting (that is, through changes in crop-mix and crop management practices) would be sub-optimal. However, climate change also requires large-scale public adaptation alongside the afore-mentioned private adaptation practices. Future research in this field could focus on the nature of such adaptation as well as assessment of cost-effective adaptation strategies in order to ameliorate the adverse impacts of climate change on Indian agriculture.

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References

Adams, R.M., B.A. McCarl, K. Seerson, C. Rosenzweig, K.J. Bryant, B.L. Dixon, R. Conner, R.E. Evenson and D. Ojima (1999), 'The economic effects of climate change on U.S. agriculture', in R. Mendelsohn and J. Neumann (eds.), *Impacts of Climate Change on the U.S. Economy*, Cambridge, U.K.: Cambridge University Press, pp. 55-74.

Cline, W. (2007), *Global Warming and Agriculture: Impact Estimates by Country*, Washington, D.C.: Peterson Institute.

Cline, W.R. (1996), 'The impact of global warming on agriculture: comment', *American Economic Review* 86(5): 1309-11.

Darwin, R. (1999), 'The impact of global warming on agriculture: a Ricardian analysis: Comment', *American Economic Review* 89(4): 1049-52.

Darwin, R., M. Tsigas, J. Lewandrowski and A. Raneses (1995), 'World agriculture and climate change: economic adaptations', Report No. 703, Economic Research Service, U.S. Department of Agriculture, Washington, D.C.

Deschenes, O. and M. Greenstone (2007), 'The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather', *American Economic Review* 97(1): 354-385.

Dinar, A., R. Mendelsohn, R. Evenson, J. Parikh, A. Sanghi, K. Kumar, J. McKinsey, and S. Lonergan (1998), 'Measuring the impact of climate change on Indian agriculture', Technical Paper 402, World Bank, Washington, D.C.

Fischer, G., M. Shah and H.V. Velthuizen (2002), *Climate Change and Agricultural Vulnerability,* Laxenburg, Austria: IIASA.

Kolstad, C. (2000), *Environmental Economics*, New Delhi: Oxford University Press.

Kumar, K.S. Kavi (1998), *Modeling and Analysis of Climate Change Impacts on Indian Agriculture*, Unpublished Ph.D. Thesis, Indira Gandhi Institute of Development Research, Mumbai.

Kumar, K S Kavi (2003), 'Vulnerability of agriculture and coastal resources in India to climate change', Report submitted to the Ministry of Environment and Forests, Government of India, New Delhi.

Kumar, K.S. Kavi (2007), 'Climate change studies in Indian agriculture', *Economic and Political Weekly* November 17: 13-18.

Kumar, K.S. Kavi and J. Parikh (2001a), 'Socio-economic impacts of climate change on Indian agriculture', *International Review of Environmental Strategies* 2(2): 277-293.

Kumar, K.S. Kavi and J. Parikh (2001b), 'Indian agriculture and climate sensitivity', *Global Environmental Change* 11(2): 147-154.

Mall, R.K., R. Singh, A. Gupta, G. Srinivasan and L.S. Rathore (2006), 'Impact of climate change on Indian agriculture: A review', *Climatic Change* 78: 445-478.

Mendelsohn, R., A. Dinar and A. Sanghi (2001), 'The effect of development on the climate sensitivity of agriculture', *Environment and Development Economics* 6(1): 85-101.

Mendelsohn, R., W. Nordhaus and D. Shaw (1994), 'The impact of global warming on agriculture: a Ricardian analysis', *American Economic Review* 84(4): 753-71.

Narayana, N.S.S., K.S. Parikh and T.N. Srinivasan (1991), *Agriculture, Growth and Redistribution of Income*, New Delhi: North-Holland/Allied Publishers.

NATCOM (2004), *India's Initial National Communication to the UNFCCC*, report, Ministry of Environment and Forests, Government of India, New Delhi.

Niggol Seo, Sung-No, Robert Mendelsohn and Mohan Munasinghe (2005), 'Climate change and agriculture in Sri Lanka: a Ricardian valuation', *Environment and Development Economics* 10 (5): 581-596.

O'Brien, K., R. Leichenko, U. Kelkar, H. Venema, G. Aandahl, H. Tompkins, A. Javed, S Bhadwal, S. Barg, L. Nygaard and J. West (2004), 'Mapping vulnerability to multiple stressors: climate change and globalization in India', *Global Environmental Change* 14: 303-313.

Polsky, C. (2004), 'Putting space and time in Ricardian climate change impact studies: agriculture in the US Great Plains, 1969-1992', *Annals of the Association of American Geographers* 94(3): 549-564.

Quiggin, J. and J. K. Horowitz. (1999), 'The impact of global warming on agriculture: a Ricardian analysis: comment', *American Economic Review* 89(4): 1044-45.

Rosenzweig, C. and M.L. Parry (1994), 'Potential impact of climate change on world food supply', *Nature* 367: 133-138.

Sanghi, A. and R. Mendelsohn (2008), 'The impacts of global warming on farmers in Brazil and India', *Global Environmental Change* 18: 655-665.

Schlenker, W. and M. Roberts (2008), 'Estimating the impact of climate change on crop yields: the importance of non-linear temperature effects', Working Paper 13799, National Bureau of Economic Research, Cambridge.

Schlenker, W., W.M. Hanemann and A.C. Fisher (2006), 'The impact of global warming on U.S. agriculture: an econometric analysis of optimal growing conditions', *Review of Economics and Statistics* 88(1): 113-125.

Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor and H.L. Miller (eds.) (2007), *Climate Change 2007: The Physical Science Basis,* Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge: Cambridge University Press, 996 pp.

Stockle, C.O., P.T. Dyke, J.R. Williams, C.A. Jones and N.J. Rosenberg (1992), 'A method for estimating the direct and climatic effects of rising atmospheric Carbon Dioxide on growth and yield of crops: modification of the EPIC model for climate change analysis', *Agricultural Systems* 38: 225-238.

World Bank (2008), 'Climate change impacts in drought and flood affected areas: case studies in India', Report No. 43946-IN, Social, Environment and Water Resources Management Unit, India Country Management Unit (South Asia Region), New Delhi.

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Table 1: Projected Changes in Climate in India: 2070-2099

	Jan.-March	April-June	July-Sep.	Oct.-Dec.
Temperature Change (^oC)				
Northeast	4.95	4.11	2.88	4.05
Northwest	4.53	4.25	2.96	4.16
Southeast	4.16	3.21	2.53	3.29
Southwest	3.74	3.07	2.52	3.04
Precipitation Change (%)				
Northeast	-9.3	20.3	21.0	7.5
Northwest	7.2	7.1	27.2	57.0
Southeast	-32.9	29.7	10.9	0.7
Southwest	22.3	32.3	8.8	8.5

Source: Cline (2007)

Table 2: Climate Response Function – Averaged Regression

Variable	Coefficient	*t*-statistic
January temperature	-435.34	-1.84
April temperature	-593.01	-2.31
July temperature	-946.30	-2.05
October temperature	2170.91	3.68
January precipitation	31.67	1.11
April precipitation	-14.19	-1.62
July precipitation	-2.07	-1.06
October precipitation	28.62	2.86
January temperature sq.	-46.11	-1.22
April temperature sq.	127.10	1.89
July temperature sq.	-102.44	-0.75
October temperature sq.	-264.03	-3.39
January precipitation sq.	-2.56	-2.85
April precipitation sq.	0.17	2.26
July precipitation sq.	0.004	1.00
October precipitation sq.	0.03	0.33
January temperature x precipitation	-32.64	-2.99
April temperature x precipitation	15.19	4.34
July temperature x precipitation	-1.21	-0.94
October temperature x precipitation	-2.60	-0.61
Soil type 1	296.94	0.96
Soil type 2	1449.99	3.59
Soil type 3	-907.00	-1.69
Soil type 4	55.70	0.13
Top-soil depth class 1	-535.40	-0.66
Top-soil depth class 2	137.34	0.16
Cultivators per hectare	1125.11	1.63
Bullocks per hectare	-325.89	-0.42
Tractors per hectare	286077.50	3.30
Literacy	1577.35	0.85
Population density	184.36	1.48
Percentage of irrigated land	3786.24	3.25
Altitude	-0.98	-1.00
Intercept	4717.93	3.62
Number of observations	271	
Adjusted R^2	0.668	

Table 3: Spatial Diagnostics – Averaged Regression

Diagnostic Parameter	Weight Matrix		
	Rook-contiguity	Queen-contiguity	Distance-based (50 km)
Moran I (error)	0.19917 (0.000)	0.19394 (0.000)	0.20392 (0.000)
LM (lag)	14.94 (0.000)	14.41 (0.000)	7.33 (0.006)
Robust LM (lag)	3.56 (0.059)	3.41 (0.065)	0.81 (0.267)
LM (error)	26.53 (0.000)	26.05 (0.000)	14.55 (0.000)
Robust LM (error)	15.15 (0.000)	15.05 (0.000)	8.03 (0.004)

Note: Values in the parentheses are p-values

Table 4: Climate Response Function – Pooled Regression with Spatial Correction

Variable	Without Spatial Autocorrelation		With Spatial Autocorrelation			
			Spatial Lag Model		Spatial Error Model	
	Coeff.	*t* -statistic	Coeff.	*t* -statistic	Coeff.	*t* -statistic
Climate Variables						
January temperature	-443.3	-6.5	-394.8	-5.6	-395.3	-5.1
April temperature	-695.5	-9.6	-537.1	-7.5	-668.5	-8.3
July temperature	-817.9	-6.1	-575.3	-4.3	-809.3	-5.4
October temperature	2160.4	12.5	1833.0	10.5	1709.0	9.2
January precipitation	38.5	4.6	13.6	1.6	-7.3	-0.8
April precipitation	-17.2	-6.8	-14.6	-5.5	-7.8	-2.9
July precipitation	-2.2	-3.9	-1.3	-2.2	-2.5	-4.3
October precipitation	29.5	10.1	20.8	7.1	18.4	5.9
January temperature sq.	-43.8	-3.9	-24.1	-2.1	-11.4	-1.0
April temperature sq.	118.4	6.2	101.9	5.2	139.0	6.5
July temperature sq.	-96.9	-2.5	-25.6	-0.6	117.7	2.7
October temperature sq.	-264.0	-11.6	-234.0	-10.1	-236.3	-9.7
January precipitation sq.	-2.8	-10.6	-2.6	-9.5	-1.9	-6.5
April precipitation sq.	0.2	8.0	0.2	6.9	0.097	4.8
July precipitation sq.	0.004	3.4	0.005	4.5	0.002	2.1
October precipitation sq.	0.028	1.2	0.1	3.8	0.057	2.3
January temperature x precipitation	-36.3	-11.4	-38.5	-11.7	-26.8	-7.2
April temperature x precipitation	15.8	15.7	15.2	14.7	10.3	10.5
July temperature x precipitation	-1.5	-4.0	-0.7	-1.8	-0.4	-0.9
October temperature x precipitation	-2.9	-2.3	-4.1	-3.2	1.8	1.3
Control Variables						
Cultivators/ha	382.1	2.3	163.1	1.0	758.5	5.0
Bullocks/ha 91.2	0.4	558.4	2.6	1105.6	5.5	
Tractors/ha 153798	9.6	63282	4.1	67539	4.3	
Literacy 2780.0	5.4	4039.0	8.5	3160.2	6.5	
Pop. Density	128.8	3.9	174.5	4.8	182.0	4.7
Irrigation % 2643.9	9.3	2648.4	9.4	3538.1	13.0	
Spatial Lag/Spat. Auto.			0.0649	4.3	0.57	4.2
No. of Obs.	5691		5691		5691	
Adj. R^2	0.5464		0.6517		0.7233	

Note: The model specification is same as equation (11); soil variables are not reported to save space.

Table 5: Climate Change Impacts – Without and With Spatial Autocorrelation

Scenario (DT/DP)	Without Spatial Auto correlation		With Spatial Autocorrelation			
			Spatial Lag Model		Spatial Error Model	
	Impacts	% of 1990 Net Revenu	Impacts	% of 1990 Net Revenu	Impacts	% of 1990 Net Revenu
+2^{o}C/7%	-81.2	-9.17	14.2	1.6	-22.9	-2.6
India Specific CC Scenario	-195.1	-22.1	43.4	4.9	-2.1	-0.23

Note: Impacts are in billion rupees, 1999-2000 prices. Net revenue in India in 1990 is Rs. 885 billion (1999-2000 prices)

LIST OF FIGURES

Figure 1: Moran's I Scatter Plots for Dependent Variable and Error Terms

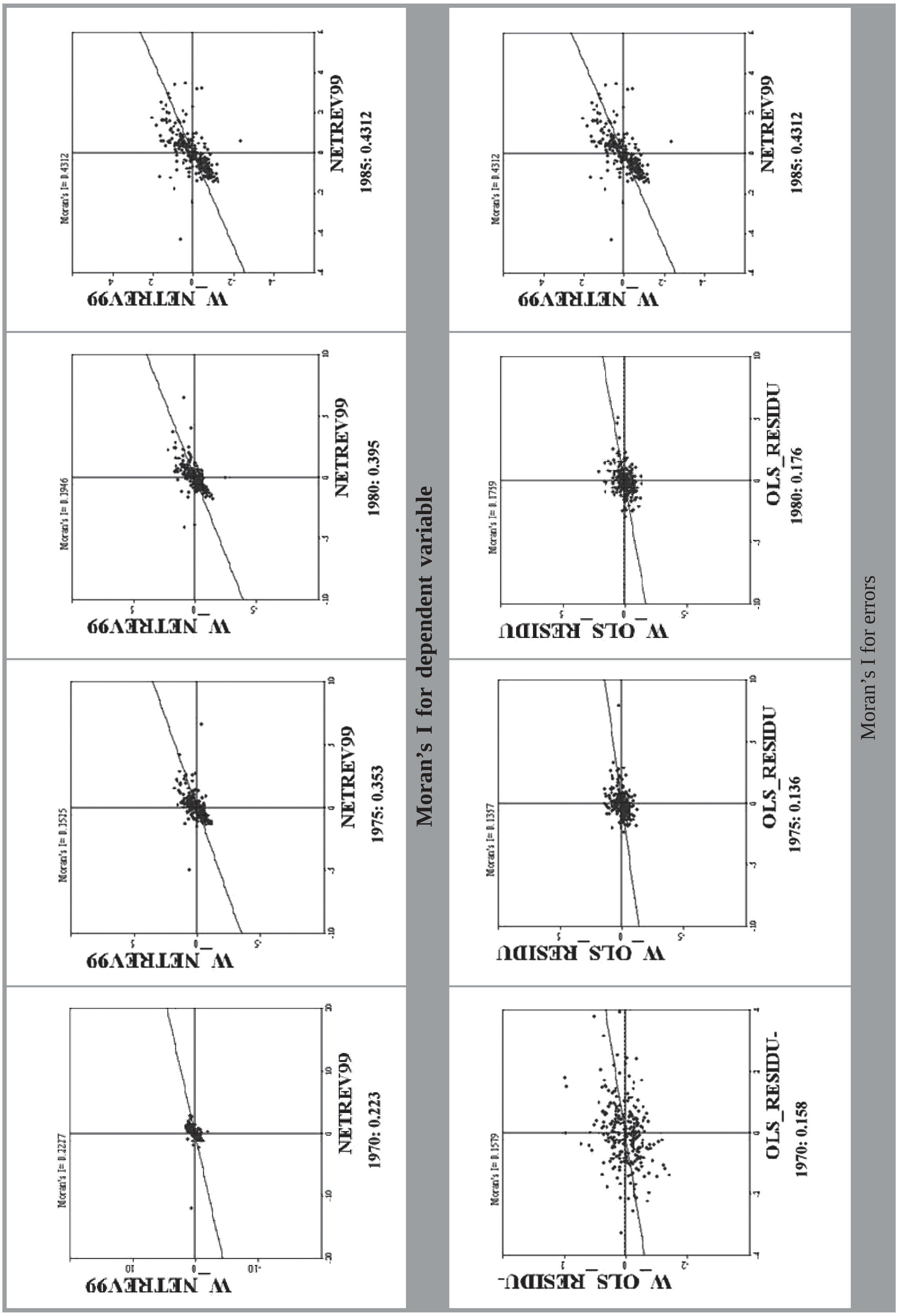


Figure 2: State-wise Distribution of Climate Change Impacts: Without and with Spatial Correction

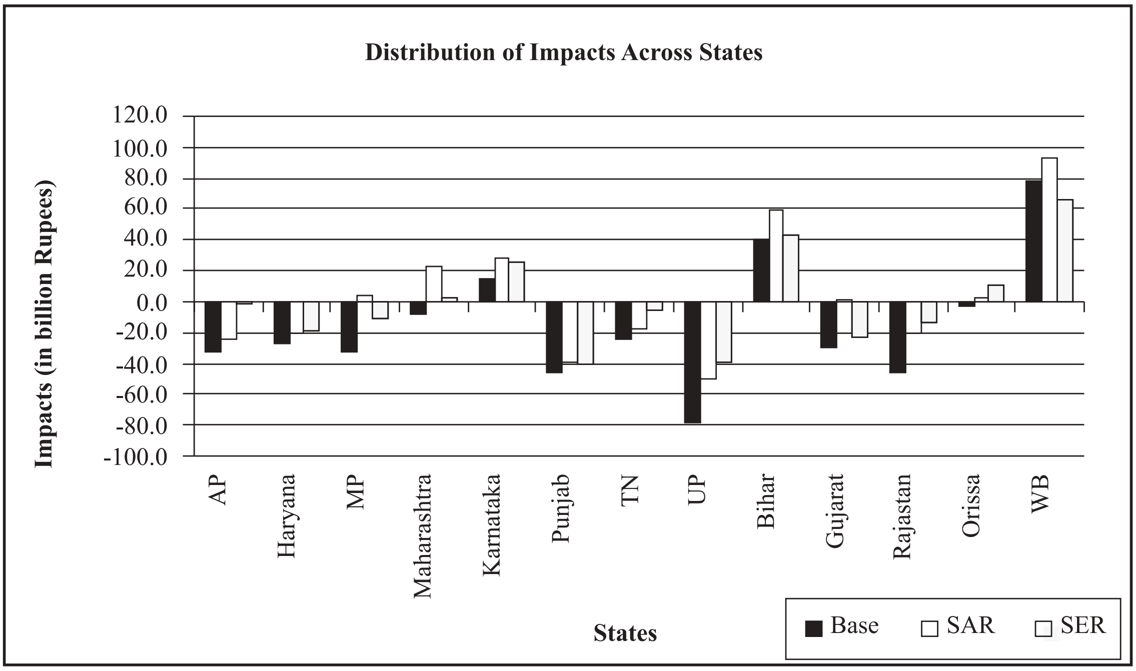
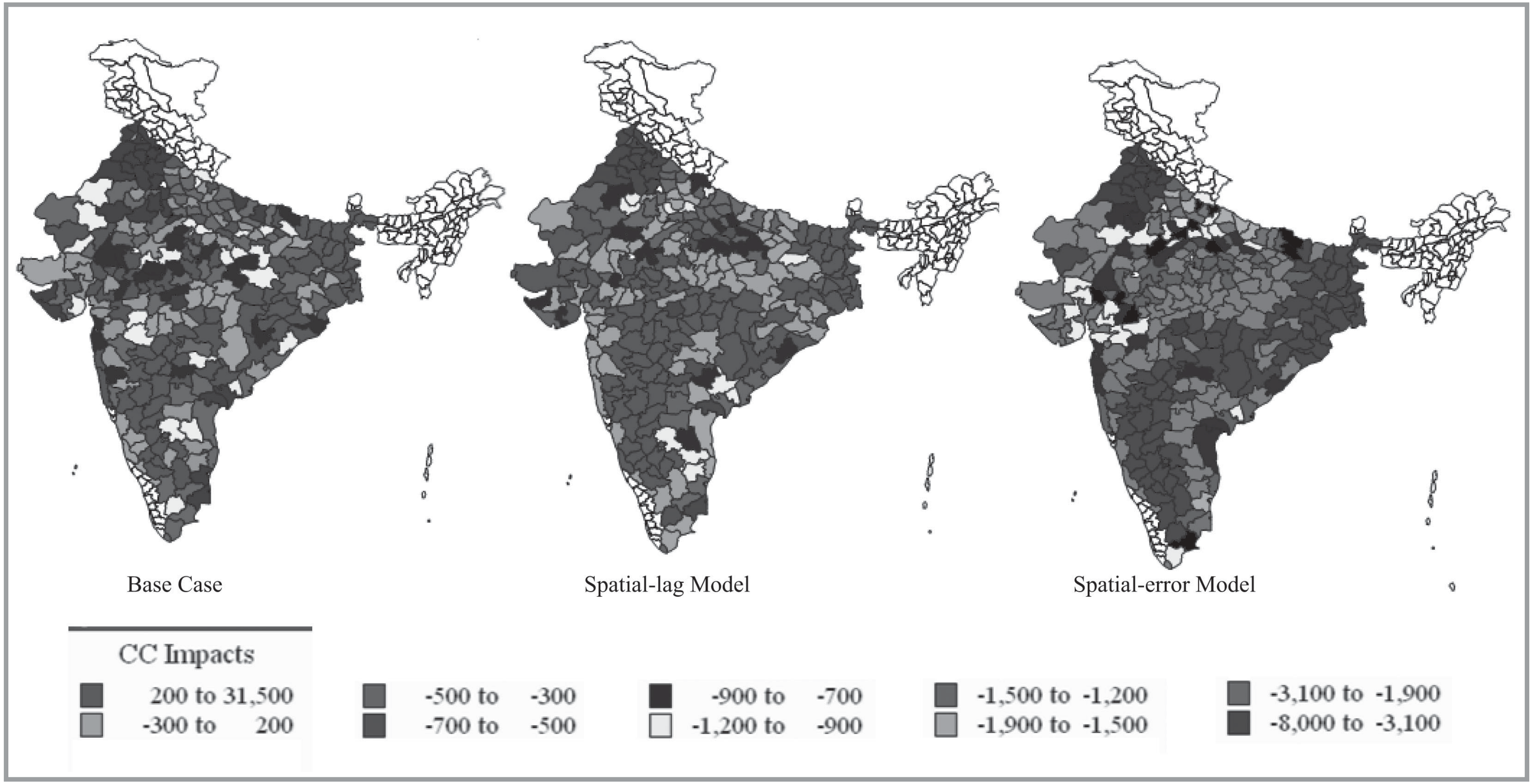


Figure 3: Distribution of Climate Change Impacts across Districts – Without and With Spatial Correction



Note: Base – Model without spatial correction

APPENDIX A

Table A1: Climate Response Function – Pooled Regression with Regional Effects

Variable	Coefficient	t-ratio
January temperature	217.59	2.65
April temperature	-694.19	-7.83
July temperature	-180.75	-1.29
October temperature	247.98	1.26
January precipitation	1.80	0.18
April precipitation	-21.70	-7.94
July precipitation	-0.58	-1.01
October precipitation	12.16	3.8
January temperature sq.	-58.03	-4.94
April temperature sq.	40.23	1.73
July temperature sq.	-84.56	-1.71
October temperature sq.	-56.59	-2.32
January precipitation sq.	-3.45	-11.99
April precipitation sq.	0.10	4.38
July precipitation sq.	0.002	2.11
October precipitation sq.	0.06	2.38
January temperature x precipitation	-45.27	-12.31
April temperature x precipitation	10.21	9.66
July temperature x precipitation	-1.46	-3.59
October temperature x precipitation	-0.63	-0.39
Soil type 1	-108.66	-1.13
Soil type 2	832.74	6.83
Soil type 3	-1274.17	-7.92
Soil type 4	1077.15	6.89
Top-soil depth class 1	-423.05	-1.9
Top-soil depth class 2	147.67	0.6
Cultivators per hectare	633.89	4.04
Bullocks per hectare	459.35	2.32
Tractors per hectare	162153.10	10.75
Literacy	1778.88	3.04
Population density	-50.02	-1.43
Percentage of irrigated land	4325.93	15.74
Altitude	-0.53	-1.83
Intercept	8185.50	16.23
Number of observations	5691	
Adjusted R^2	0.615	

Note: The model specification is same as equation (11).