WORKING PAPER 183/2019

Assessment of Climate Change Impacts and Adaptation:

A Methodological Review and Application to Indian Agriculture

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July 2019

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WORKING PAPER 183/2019

July 2019

Price : Rs. 35

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Abstract

In the context of agriculture both crop modelling as well as statistical modelling approaches are used to assess climate change impacts. Studies comparing both approaches across developed as well as developing countries have argued that there is little or no difference in their estimates, resulting in further proliferation of statistical approaches. This paper presents a methodological review of the statistical approaches that broadly use cross-sectional and panel datasets to quantitatively assess the climate change impacts on agriculture. Arguing that adaptation is modelled differently in different models, the paper provides an estimate of the extent to which impacts could be moderated through long-term adaptation in the context of Indian agriculture. In addition, the paper provides a brief review of the vast parallel literature that exclusively uses time-series data for assessment of the impacts of climate/weather trends.

Key words: *Climate change impacts; Indian agriculture; Statistical models; Adaptation*

JEL Codes: *Q54; Q10; C10*

Acknowledgement

This paper was earlier presented at the two-day national workshop on 'Economic Costs of Climate Change in Rural India', organized during 12-13 July 2018 by the Madras School of Economics, Chennai in collaboration with GIZ, New Delhi. The authors would like to thank the participants for their valuable comments.

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INTRODUCTION

The climate change impact assessment literature has gone through a metamorphosis in the recent decades. The policy objectives of these assessments as well as the various approaches adopted to carry out the assessments have evolved. While several of these approaches evolved as improvements over already existing approaches, other new methods have also emerged in the main strand of this literature. Most of these methods have been developed through application in the context of climate change impacts on agriculture, which remains a key study area.

Early on the aim of assessing the impacts of climate change was to inform mitigation actions. With increasing evidence of global changes already occurring in human and natural systems however the objective has tilted more towards averting or adjusting to the imminent impacts, i.e., towards adaptation actions. The linkages between climate change impacts and climate change adaptation are understood only conceptually, and vaguely so. The impact assessment studies provide a broad platform to examine the nature, and in a rather limited manner, the extent of climate change adaptation. With different approaches the inferences drawn regarding adaptation also could be different. More exclusive and broad-based assessment of the nature and extent of adaptation remain unavailable in the literature.

In the context of agriculture both crop modelling as well as statistical modelling approaches are used to assess climate change impacts. Studies comparing both approaches across developed as well as developing country context find little or no difference in their estimates (see Liu et al., 2016; Lobell and Asseng, 2017). This paper presents a methodological review of the statistical approaches that broadly use cross-sectional and panel datasets to quantitatively assess the climate change impacts on agriculture. Arguing that adaptation is modelled differently in different models, the paper provides an estimate of the extent to which impacts could be moderated through long-term adaptation in the context of Indian agriculture. In addition, the paper provides a brief review of the vast parallel literature that exclusively uses time-series data for assessment of the impacts of climate/weather trends.

The rest of the paper is structured as follows: The following section provides brief review of cross-sectional, panel, and long-difference models used in climate change impact assessment literature. This section also discusses the way in which intensive and extensive adaptation can be understood across different impact assessment approaches. The third section presents climate change impact estimates on Indian agriculture under different methods and provides an estimate of the extent to which adaptation can moderate climate change impacts. The fourth section briefly describes a parallel strand of literature that uses times-series data for impact assessment. The last section concludes the paper.

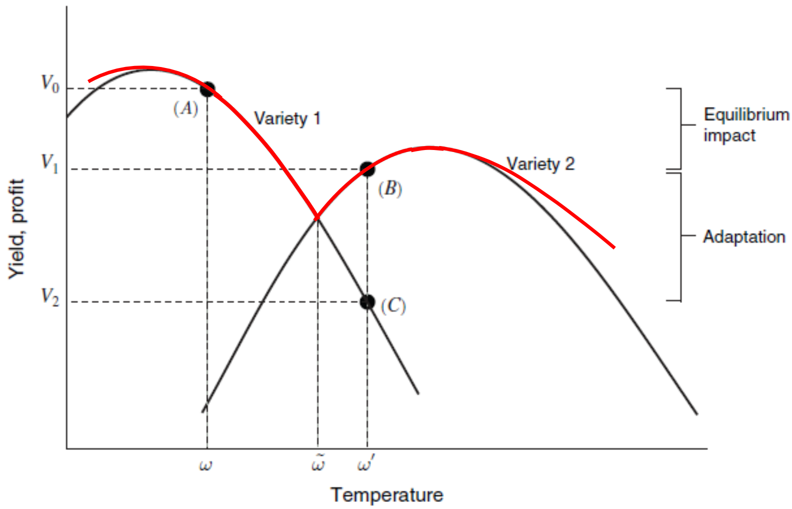
CLIMATE CHANGE IMPACT ASSESSMENT – STATISTICAL MODELS

Cross-sectional Impact Assessment Models

The statistical impact assessment literature has gained prominence with the seminal study by Mendelsohn, Nordhaus and Shaw (1994) (henceforth, MNS) that examines the cross-sectional relationship between land values and climatic parameters. The study follows the hedonic approach of environmental valuation to examine the economic impacts due to climate change. It is based on the proposition that observed outcome (say, crop yield) across geography are long-run equilibrium responses by agents to their local climate incorporating all potential adaptation possibilities. In brief, farmers have adapted to the current range of climates across regions. The unknown functional relationship between vectors of climatic variables (C), outcome (y) and other control variables (X) (y = f(C, X)) can be examined through a cross-sectional information using eq (1):

$$y_i = \alpha + \beta \mathbf{C}_i + \gamma \mathbf{X}_i + \varepsilon_i \quad (1)$$

In terms of Figure 1, the equilibrium response of farmers across locations can be captured through a movement from point (A) to point (B) (along the red curve) which represent two crop varieties adapted to their respective climate in two different locations. That is, the estimated cross-sectional relationship states that if farmers in one location (with given climatic conditions) growing crop variety 1 gets to face climate of any other given location where crop variety 2 is already grown, by instantaneously switching over to variety 2, the farmer could adapt to the altered environmental conditions.



Source: Adapted from Burke and Emerick (2016).

Figure 1: Conceptualizing Various Approaches to Impact Assessment

Weather Versus Climate[1]: Emergence of the Panel Models

The cross-sectional approach has been widely applied to a large number geographical setting. Although theoretically appealing, in methodological implementation the approach faces a major challenge: in the absence of appropriate control variables could confound the true relationship between outcome and climatic variables and potentially estimate a biased relationship. Deschenes and Greenstone (2007) (henceforth DG) along with others have critiqued the cross-sectional studies on these grounds and have employed weather variability within a given geography, rather than climatic variation across geographies to identify the key parameters of interest. The approach adopted by DG based on long panel data can be specified as in eq (2):

$$y_{it} = \alpha + \beta \mathbf{W}_{it} + \gamma \mathbf{Z}_{it} + \lambda_i + \phi_t + \varepsilon_{it} \qquad (2)$$

Here, W is the vector of `weather' parameters, Z is the vector of time-varying control variables, λ is the time-invariant unobserved factors affecting yield and ϕ is the time varying unobserved factors which affecting all regions alike at any given time.

The fact that year-to-year variations in weather in a given location are random allows for identification of the effects of weather parameters on the outcome variable of interest. Further, this approach addresses the possibilities of omitting variables bias by allowing unobserved heterogeneity through the introduction of fixed effects. These models are more robust in their statistical properties compared to cross-sectional models and have gained prominence in the impact assessment literature in the past decade.[2] By virtue of its construction,

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[1] Climate scientists consider weather as what occurs at a particular point in time. Due to natural variability, weather fluctuates on an hourly, daily, monthly, and year-to-year basis representing itself as a transitory or short-term phenomenon. The term climate may simply be used to imply the distribution of weather outcomes, or simply averaged weather over a long (30 years or so) period of time. Thus, changes in climate is considered longer-term in nature.

[2] See Dell et al. (2014) for a review of this vast literature and its limitations.

these models essentially capture the effects of weather shocks and not necessarily changes in climate. Moreover, being random in nature weather shocks are difficult to anticipate a priori and therefore limits the possibility of any adaptive responses by farmers. Thus, their ability to inform about the effect of changes in climate and potential adaptation remain limited. In terms of Figure 1, panel models would identify yield movements along either of the two curves (say from point A to point C), representing a greater yield decline.

Extension to Long Difference Models

Long difference (henceforth LD) models are a recent extension of the impact assessment literature. In the context of US agriculture Burke and Emerick (2016) have employed this novel approach with the objective of estimating the effects of climate change and comparing these with the panel estimates to infer about the potential magnitude of adaptation. The authors argue that since panel model, exploiting short-run (e.g., year-to-year) variations in weather, do not convey about effects of climate change, using longer-term variations (e.g., decadal averages in temperature and precipitation across geography could represent future climate changes better. A simple LD models can be specified as in eq (3) below:

$$\Delta y_i = \alpha + \beta \Delta \mathbf{W}_i + \gamma \Delta \mathbf{Z}_i + \Delta \varepsilon_i \tag{3}$$

where, Δy_i represents the change in yield in district i between two periods (say, each period spanning a decade). The first period could be an early period and the second being a later period in the dataset. District yield and other covariates are averaged (smoothed) over each period. Changes in the smoothed weather variables between the two far-off periods enable the identification of more longer-run impacts and thus could more effectively capture the effects due to climate changes. Equation (3) essentially regresses the changes (long differences) between the smoothed yields of both periods on the corresponding differences in smoothed temperature and rainfall variables and other control variables.[3] Identification of parameters is possible under the more reasonable assumption that longer-run changes in unobserved factors are uncorrelated with the changes in the covariates of the model. If agents can adjust in the long run in ways that are unavailable to them in the short-run, then impact estimates derived from these LD models may reasonably capture the damages from longer run changes in climate.

By comparing longer-term realizations of the cross-sectional units these models combine the advantages of the cross-sectional models and the panel models; these models reduce the possibilities of bias due to omitted variables while retaining the adaptation possibilities. These estimates are expected to lie somewhere between the panel estimates (encompassing no adaptation possibilities) and the cross-sectional estimates (capturing all possible adaptation). Thus, in terms of Figure 1, the yield losses suggested by the LD models may not be as high as projected under the panel models ($V_0 - V_2$) nor as low as projected under the cross-sectional models ($V_0 - V_1$). Burke and Emerick (2016) compare the LD model estimates for extreme heat with those from the panel models and find that ~22-23 percent of the short-run effects are outweighed through longer-run adaptive responses.

Role of Adaptation in Climate Change Impact

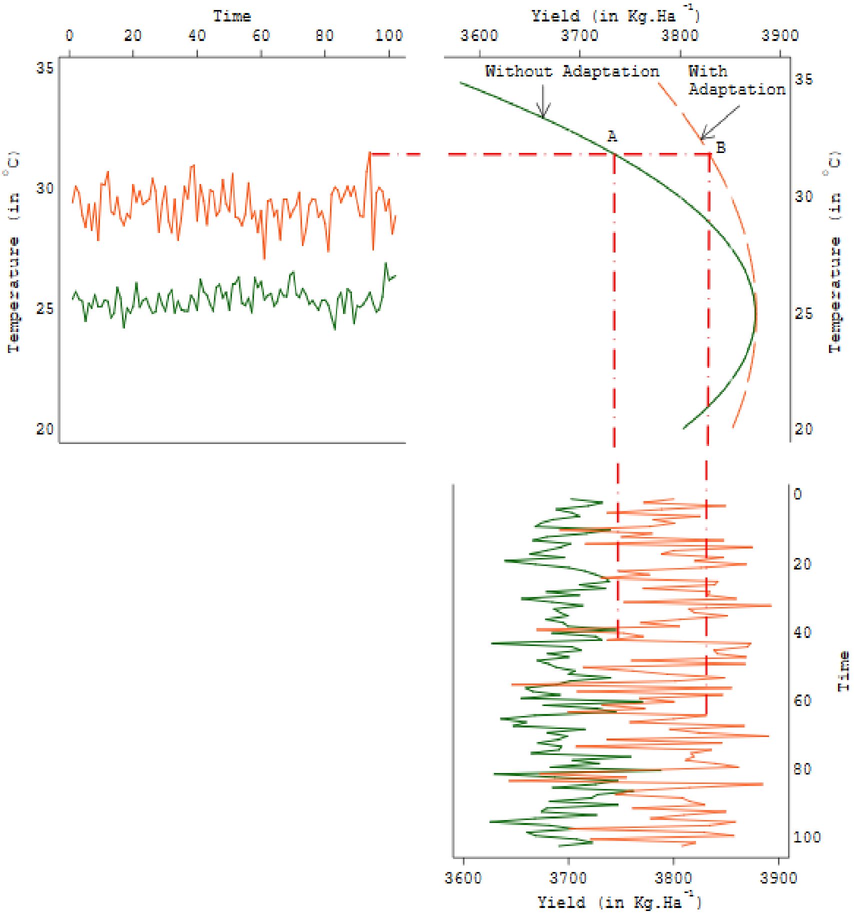
As discussed so far the realized impacts of climate variability and climate change will crucially depend on both planned and unplanned adaptation measures undertaken. Extensive literature has evolved that tried to characterize the nature and extent of adaptation in various climate sensitive sectors. Within economics literature two margins of adaptation are identified – intensive and extensive margin of adaptation (Auffhammer, 2018). While intensive margin of adaptation refers to use

[3] So long as the variability in long-differenced climatic (weather) parameters observed within the data mimics the longer-run changes in climate, the long differences models could claim to capture the changes in climate.

of existing devices/techniques more intensively to offset the adverse impacts of changes in climate variables, the extensive margin of adaptation additionally makes use of new techniques/cultivars to counteract the negative effects of climate change.

Figure 2 below illustrates the intensive and extensive margins of adaptation in the context of climate change impacts on agricultural sector. The top-left panel shows possible variation of temperature over time under pre (green) and post (red) climate change regimes. The top-right panel represents the yield-temperature response function. The green line in the top-right panel shows the yield response function with intensive margin of adaptation that may involve adjustments in sowing dates and irrigation schedules, and use of new cultivars. The red line on the other hand depicts the yield response function that incorporates extensive margin of adaptation also. The extensive margin of adaptation may include changes in irrigation technologies used and changes in crops cultivated by the farmers following the changes in climate. It is expected that accounting for extensive margin of adaptation will reduce the adverse impacts of climate change. The bottom-right panel in the figure shows the realized output (crop yield or production) over time with (green) and without (red) consideration of extensive margin of adaptation.

In terms of different statistical models discussed in the above sub-sections, it can be argued that the panel models account for intensive margin of adaptation and miss out incorporating the extensive margin of adaptation in impact estimation. As a result these models may overestimate the climate change impacts or underestimate the benefits of adaptation. The panel data used for the analysis in these models represents climate variability rather than climate change and hence miss out providing appropriate signal to the agents to undertake wide spread adaptation measures (referred as extensive margin of adaptation). The cross sectional models on the other hand in principle can account for both intensive and extensive margins of adaptation. The long-difference models would be able to provide an estimate of benefits of accounting for intensive margin of adaptation while assessing climate change impacts.



Source: Adapted and modified from Auffhammer (2018)

Figure 2: Accounting for Adaptation in Impact Assessment – Illustrative

Application of Different Approaches to Indian Agriculture

In the context of Indian agriculture, a limited number of studies have applied the cross-sectional model and the panel models. Some of the studies employing the cross-sectional models include Dinar et al., (1998), Kumar and Parikh (2001), Sanghi and Mendelsohn (2008), Kumar (2011), and Kar and Das (2015). Studies that have applied the panel models to examine effects of weather variation on net revenue as well as crop productivity include Guiteras (2009), Krishnamurthy (2012), Dasgupta et al. (2013), Gupta et al. (2014) Birthal et al. (2014) and Pattanayak and Kumar (2014). However, no study thus far has employed the long-difference models to examine the effects of longer-term variation in climatic (or weather) parameters in the context of Indian agriculture.

This paper focusing on Indian agriculture assesses the effects of climatic parameters on Kharif rice productivity as evident from various modelling approaches. Specifically, panel and the LD models are estimated and the effects of key climatic parameters are compared across these two models to get a sense of possible adaptation to recent changes in climate.

Data and Method

Using district-level data for weather and non-weather variables for the period 1969-2007, Pattanayak and Kumar (2014) estimate panel models assessing the relationship between weather variables and Kharif rice yield.[4] The estimated relationship found daytime-temperature to be the most important of all climatic factor in reducing rice productivity. Using the same dataset and considering the importance of this seasonal climatic parameter, modified versions of eq (2) and eq (3) are used to estimate the panel model and the LD models and compare the respective

[4] Pattanayak and Kumar (2014) estimate their panel model by constructing and using intra-seasonal weather variables to examine their effects on rice yield. The panel model presented in this paper estimates the relationship at the aggregated seasonal level. The intra-seasonal panel model for comparison with corresponding LD model is presented in the appendix.

coefficients. Variations in seasonal (June-November) weather parameters, viz., nighttime temperature (T_{min}), daytime temperature (T_{max}), solar radiation and rainfall are used to identify the respective parameter of interest. These are presented in Table 1.

The panel model uses information available for the entire period under consideration. For estimating the LD model, the two periods under consideration are 1970-1974 and 2003-2007. All the variables in the model are smoothed over both periods and long-differenced. The variables are expressed in their natural logarithms, enabling the interpretation of the estimated coefficients as elasticities. Denote β_{FE} and β_{LD} as the estimates from the panel model and LD model respectively for T_{max}. The value $(1 - \beta_{LD}/\beta_{FE})$ represents the extent of negative short-run effects of T_{max} that is offset in the longer run - a measure of adaptation to daytime temperature.

Table 1: Comparison of Long Differences and Panel Estimates: The Effects of Climatic Parameters on Kharif Rice Yield in India

	(1) LD_M2	(2) Panel_M2	(3) LD_M4	(4) Panel_M4
Jun-Nov: $T_{\min}$	0.5464	0.954***	0.6895	0.834***
	(0.661)	(0.001)	(0.505)	(0.003)
Jun-Nov: $T_{\max}$	-4.5867**	-5.836***	-6.3044***	-5.884***
	(0.016)	(0.000)	(0.001)	(0.000)
Jun-Nov: Sol. Rad.	-0.1718	-0.302***	0.3610	-0.373***
	(0.843)	(0.008)	(0.638)	(0.002)
Jun-Nov: Rainfall	0.0357	0.0692***	0.0632	0.0726***
	(0.358)	(0.001)	(0.123)	(0.000)
Observations	211	8191	211	8191
R squared	0.131	0.778	0.076	0.775
Fixed Effects	None	Dist, Yr	None	Dist, Yr
Econ Controls$	Yes	Yes	No	No

Source: $Economic controls include labor, fertilizer, irrigation and high-yielding-variety *kharif* rice area as in Pattanayak and Kumar (2014). Dependent variable is ln(yield). All covariates expressed in natural logarithm. *p*-values in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Across both models the harmful effects of higher seasonal daytime temperature are observed.[5] These are robust to exclusion of the economic variables (Col. (3) and (4)). The negative effects of $T_{\max}$ from LD models (Col. (1)) are smaller in absolute as compared to panel models (Col. (2)). This suggests that ~21 percent of the short-run

[5] The LD models considered here differ from the preferred models of Burke and Emerick (2016) which also exploits state-level unobserved heterogeneity beyond to identify the parameters of interest. In a LD model, inclusion of the state fixed effects amounts to including a state-level time-trending variable in the original model with level terms. This however restricts the variations in the already "differenced" climatic (and other) variables only to the individual state, presupposing that any district level variation is observed around a state-level average. However, caution must be taken for including these state-level fixed effects since in the presence of weak influence of state-level unobservables, longer period time-varying factors, this could introduce significant bias in the estimates. Models without such fixed effects were therefore estimated in Table 1.

adverse effects could be mitigated through longer-run farmer adjustments, referred in the previous section as extensive margin of adaptation.[6]

PARALLEL MODELLING APPROACH: TIME-SERIES MODELS

This section briefly discusses the vast literature using time series data that has grown parallel to the statistical approaches discussed above to assess climate change impacts. The time-series approach essentially rests on exploiting variation across time within a given geography to identify the causal relationship between the outcome variable (say, crop yield) and climate. Lobell et al. (2003; 2007; 2008) have been pioneers in applying this approach to examine the influence of climate change on agriculture across the globe as well as at regional levels. The time-series models can be described with eq (4):

$$y_t = \alpha + \beta \mathbf{C}_t + \gamma \mathbf{X}_t + \varepsilon_t \tag{4}$$

However, given that several of the model variables have time trends underlying them, correlation of one variable with another could describe more about the relationship between the underlying trend and may give a biased picture or a spurious relationship. Hence, variables are de-trended and first-differenced data is used as in eq (5):

$$\Delta y_t = \alpha + \beta \Delta \mathbf{C}_t + \gamma \Delta \mathbf{X}_t + \Delta \varepsilon_t \tag{5}$$

In most application with annual information, the first-differencing produces year-to-year variations in the variables which enable identification of the parameters of interest. The objective of climate

[6] Similar comparison between Col. (3) and Col. (4) however suggested that longer-run impacts exert more adverse effects on rice productivity than short-run effects. However, economic variables being absent could have introduced some bias in the estimates suggesting that comparison of the full model (Model 2) would only be appropriate.

impact assessment studies in the agriculture context is to estimate the yield changes due to changes in the climatic parameters, say temperature and precipitation.[7] The term $\beta\Delta C_t$ in essence captures the effect of climate trends on crop yield.

A few points need emphasis that pertains to the time-series models. First, since the models exploit short-run variations in weather, like the panel models these models also exclude extensive margin of adaptation possibilities. In fact, time-series models by their statistical construction focus completely on the study unit (geography) and do not relate in any manner to the relationship that holds in a contiguous region-spatial context. Second, these models using first difference allow removal of trends which may be more deterministic in nature. Thus, the presence of stochastic trends may not be fully ruled out. Third, these models tend to be biased against capturing the true temperature effects as compared to the effects of precipitation in yield (Lobell and Burke, 2010).

CONCLUSIONS

While the impact assessment literature has evolved in many ways through applications of different modelling approaches, few studies have drawn parallels between these approaches. Each approach presents its own advantages and limitations over the other. The comparability of each of the approaches is essential given the common objective of assessment of impacts and role of adaptation. However, there are still large gaps in the literature which do not provide clear inference on the potential for adaptation nor on the nature of adaptation. Long difference approach could provide a middle-ground if objective is to choose between different approaches and thus requires future work to focus on its extensions.

[7] These year-to-year changes in the climatic parameters have come to be known as "climate trends" in the literature.

However if the objective is careful assessment of impacts without having to make a choice between models, an important aim of future research could be to place each of the modelling approaches into the broader continuum of impact and adaptation modelling and assessment to inform policy making effectively.

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