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Analysis

Climatic impacts across agricultural crop yield distributions: An application of quantile regression on rice crops in Andhra Pradesh, India

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ABSTRACT

Climatic impact on agricultural production is a serious concern, as it is directly linked to food security and poverty. Whereas there are empirical studies that examine this issue with parametric approaches focusing on the "mean" level of variables, few studies have addressed climatic impacts in general settings. Given this paucity, we characterize the impacts on crop yield distributions with a non-parametric approach. We examine the case of rice yield in Andhra Pradesh, India, an important state producing rice as a main crop but reported to be vulnerable to climate change. Employing 34 years of data, we apply quantile regressions to untangle the climatic impacts across the quantiles of rice yield, finding three main results. First, substantial heterogeneity in the impacts of climatic variables can be found across the yield distribution. Second, the direction of the climatic impacts on rice yield highly depends on agro-climatic zones. Third, seasonal climatic impacts on rice yield are significant. More specifically, a monsoon-dependent crop is more sensitive to temperature and precipitation, whereas a winter crop remains largely resilient to changes in the levels of climate variables. These findings clarify the idiosyncratic climatic impacts on agriculture in India, and call for location- and season-specific adaptation policies.

1. Introduction

Though the causes and extent of climate change remain unsettled, the issue of its occurrence is largely settled. Evidences of the changes in temperature, precipitation, and extreme weather events have been found on a scientific basis (IPCC, 2007a). These changes are likely to affect global socio-economic and environmental systems in various ways. Because climatic factors such as temperature and precipitation serve as direct inputs to agriculture, any change in these variables is bound to have a significant impact on crop yield and its variability. Therefore, this topic has drawn the attention of researchers, as evident by the growing number of studies (see, e.g., Dinar et al., 1998; Mall et al., 2006; Cline, 2007; Seo and Mendelsohn, 2008; Lobell et al., 2011).

In the context of developing countries, the issue of "climatic impacts" becomes more serious not only for food security but also for poverty and inequality concerns. From a policy maker's point of view, understanding climatic impacts is essential to making countermeasures against such issues because there are ambiguity and uncertainty with respect to the direction and degree of climatic impacts on crop production. Despite its importance, only a few attempts have been made to map the climatic impacts on agriculture especially in the context of developing countries. Therefore, we seek to address this issue by examining a case in India.

In the last two decades, researchers have conducted a number of studies on climatic impacts. There are two major methodologies: (i) agronomic models and (ii) observational studies including Ricardian models, feasible generalized least square and panel data models. Agronomic models simulate a laboratory-type setup and provide data on climatic factors and crop growth (see, e.g., Mearns et al., 1997). The advantage is that they can generate a hypothetical situation and the corresponding crop growth by applying controlled and randomized climatic conditions. On the one hand, the disadvantage is that they do not take into account adaptive behaviors of an optimizing farmer.

Ricardian models measure the impact of climatic factors through their contribution to farmland prices and have been used for incorporating farm level adaptation (see, e.g., Mendelsohn and Rosenberg, 1994; Mendelsohn et al., 1996). However, a major shortcoming in a Ricardian-type model is the omitted variable bias because it does not take into account time-independent location-specific factors such as the unobservable skills of farmers and soil quality. Application of panel data methods to overcome issues related to Ricardian models is relatively new (see, e.g., Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009), but it also does not properly account for long term adaptation and crop diversification measures taken by farmers.

Recent works have tended to employ a feasible generalized least square approach developed by Just and Pope (1978), because it helps

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in challenging the usual assumption of stationarity (see, e.g., McCarl et al., 2008). In particular, McCarl et al. (2008) and Chen et al. (2004) are pioneering works that examine the climatic impacts on agriculture in this vein of research, and characterize how climatic variables affect crop yields and their variability. The authors find heterogeneous climatic impacts across crop types. With the same approach, several other works also confirm the same qualitative results from other cases and regions (see, e.g., Isik and Devodas, 2006; McCarl et al., 2008; Carew et al., 2009; Cabas et al., 2010; Poudel and Kotani, 2013).

Irrespective of the methodologies employed in the literature, previous works generally establish some potential heterogeneous impacts, even showing some positive impact of climate change in certain regions of the world. For instance, Deschenes and Greenstone (2007) show that climate change will increase annual profits of agriculture in the United States by 4%.[1] In an agronomic model for India, Mohandass et al. (1995) find an increase in rice production under general circulation model scenarios. Lal et al. (1998) also find a positive impact of marginal temperature on rice yield. Rathore et al. (2002) confirm these results by showing particular gains in rice production in South India under predicted climate change models. Comparing the two most popular agronomic models, Aggarwal and Mall (2002) have shown a 1% to 18.8% increase in rice yield even in the most pessimistic climate scenarios. These studies suggest that a favorable shift in weather conditions and carbon fertilization are the main factors behind the positive impact on yields.[2]

On the contrary, there is another group of studies that show negative impacts. For example, India is predicted to experience one of the highest agricultural productivity losses in the world when considering the climate change patterns observed and scenarios projected in several studies. For instance, the projected agricultural productivity loss for India by 2080 is approximately 30% even after accounting for the expected positive effect of carbon fertilization on yield (Cline, 2007). Another study finds that projected agriculture production loss in India by 2100 lies between 10% and 40% even with carbon fertilization (Aggarwal, 2008). Auffhammer et al. (2006) show that the adverse climate change due to brown clouds and greenhouse gases has already caused a slowdown in rice yield growth during the past two decades.[3]

Although each of these results may be sensitive to specific thresholds of phenology and photosynthesis as well as the climatic scenarios used in these models, they present some plausible evidence that climatic impacts on agriculture could be heterogeneous and ambiguous (Knox et al., 2012). They also illustrate importance of identifying the factors that characterize the heterogeneity and its magnitude. Most previous studies have mainly focused on the impact of climate change on the "mean" or "variance" of crop yield, implicitly assuming that climatic impacts follow some parametric family of probability distributions. However, in fact, the heterogeneous impacts could be realized in more complex manners, and there is a possibility that such climatic impacts may not be fully represented within a parametric form. Thus, further detailed analysis on characterizing possible heterogeneous impacts in more general settings is of great value.

One approach to this problem is the quantile regression that enables us to untangle the possible asymmetry in impacts across each quantile of conditional crop yields over some key variables. In this analytical framework, we pose a hypothesis that agro-climatic zones and growing seasons are important factors that differentiate the climatic impacts on rice crop yield distribution in India. Regarding agro-climatic zones, it is believed that the effect of climate change on crops is likely to be heterogeneous across agro-climatic zones. However, there is no regionally focused work that considers this factor explicitly with a systematic and non-parametric empirical framework in the context of India or other developing countries.

Regarding growing seasons, it is well known that rice crops can be grown and harvested twice a year during Kharif and Rabi months in India. To capture these seasonal effects on crop yields, this study uses climate variables derived from daily precipitation and daily temperature in the corresponding crop growing season. Furthermore, standard deviations in daily precipitation and daily temperature of each growing season are included to capture the effect of variation in seasonal temperature and rainfall on conditional distributions of crop yields, in a similar fashion to Cabas et al. (2010). We control these climate variables in empirical analysis to clarify the seasonal effects on crop yield, employing the other factor input variables (fertilizers and irrigation) and weather extremes such as drought and intensity of rain as covariates.

More specifically, in this paper, we address the climatic impacts on distributions of crop yields with quantile regressions in a case of rice yield in Andhra Pradesh, India (see Fig. 1).[4] The novelty lies in clarifying potential heterogeneous climatic impacts on conditional crop yield under a non-parametric setting across agro-climatic zones and seasonal growing variables with a relatively less utilized gridded daily weather data set for India. Heterogeneity in the impact of climate change across the conditional yield quantiles is the main result of this study, which also supports the importance of agro-climatic zones and crop seasons on the nature of climatic impacts. For an illustration of our heterogeneous results, we also carry out a forecasting exercise to analyze the statewide impact on conditional crop yield under expected climate change scenarios.

This paper is organized as follows. In the next section, climate and agriculture conditions in Andhra Pradesh are discussed. Section 3 describes the data set and gives information about the sources and variables. Methodology and technical aspects of the model are discussed in Section 4 which is followed by a discussion on estimated parameters in Section 5 and a graphical analysis of agro-climatic zone yield sensitivity to climate. The next section presents forecasting exercises under various scenarios to understand the net impact on yield in the future. We conclude and summarize the findings in the final section and discuss the policy implications.

2. Climate and Rice Production in Andhra Pradesh

The coastal states of India have been determined to be the most vulnerable regions to climate change (Malone and Brenkert, 2008). Having the second longest coastline, Andhra Pradesh is one of the top seven most vulnerable states in India (see Fig. 1, Kumar et al., 2006; Malone and Brenkert, 2008). Moreover, the agricultural sector in the state is doubly exposed to climate change and globalization and hence, is seen at a much higher risk than most of the other states in India (O'Brien et al., 2004). In fact, a recent report by World Bank (2008) corroborates this assessment based on their evaluation that the adverse effect of climate change may lead to a significant decline in farm income in Andhra Pradesh. Recently, this region has also been characterized by a high frequency of droughts and severe cases of farmer suicides, which makes this study important for policy makers (Tada, 2004).

Rice constitutes approximately 77% of the total food grain production in Andhra Pradesh which amounts to approximately 7% of total state GDP (The Directorate of Economics and Statistics, 2003). Known as the "Rice Bowl of India," Andhra Pradesh produces 12% of total rice output of

[1] See Fisher et al. (2012) for a major criticism of Deschenes and Greenstone (2007).

[2] In the plant biology literature, Poorter (1993) shows that approximately 95% of all plant species operate at sub-optimal efficiency because of CO_2 deficiency, and a recent increase in CO_2 has been helpful in subsequent plant growth simulations. Also, Ainsworth et al. (2002) find a significant positive impact of an increase in CO_2 on plant growth in soybean.

[3] Brown clouds constitute black carbon and other aerosols expelled into the atmosphere mainly through the burning of fossil fuels and biomass (Auffhammer et al., 2006). Through the absorption and subsequent scattering of solar radiation in the lower atmosphere, these clouds reduce the amount of radiation reaching the surface of the earth.

[4] This area is an important agricultural state-producing rice as a main crop but is reported to be vulnerable to climate change (Malone and Brenkert, 2008; O'Brien et al., 2004).

Fig. 1. Map of India showing Andhra Pradesh.
Source: http://www.indiandhra.com/ (accessed on April 2, 2010).

India with 9% of the total rice cultivated area (Ministry of Agriculture, Government of India, 2002). About 70% of the households in the state are dependent on income from rice farming and it is the major staple food for about 70 million people. Since more than 54% of the area under total food grains is used for rice farming, rice is a very important factor in the state's agriculture and economy too. Irrigation facilities in the state have seen a continuous development and about 95% of rice fields have been covered under irrigation so far (The Directorate of Economics and Statistics, 2003).

The two main rice growing seasons in the country are Kharif and Rabi, which represent the monsoon and winter crops, respectively. The average rice yield in Andhra Pradesh is approximately 2000 kg/ha. Kharif rice production is approximately 55% of total rice output, whereas the yield has been consistently higher for Rabi rice in the last 40 years (see Figs. 2 and 3). Depending upon soil and climate, Andhra Pradesh is divided into eight major agro-climatic zones. The details of the geographical distribution of the zones and the districts within each zone are given in Table 1 and Fig. 4.

3. Data Set and Sources

Data used in this study come from two sources. Seasonal agriculture yields, area and input data are taken from the harvest data compiled by the Center for Monitoring Indian Economy (CMIE) which uses government records to compile district-level agricultural data.[5] The climate data are synthesized from high-resolution daily gridded rainfall and temperature data provided by the National Climate Centre, Indian Meteorological Department (hereafter, IMD). Although some of these data sets are available for longer periods, we consider the longest consistent time span from 1971 to 2004 (34 years). We closely examine the delimitation of districts. More than half of current Andhra Pradesh districts have not undergone any boundary changes since 1971. Out of 23 current districts, there are 13 such districts with no boundary changes: East Godavari, Guntur, Karimnagar, Khammam, Krishna, Kurnool, Mahbubnagar, Medak, Nalgonda, Nizamabad, Prakasam, Warangal and West Godavari.

After ignoring minor changes of less than 1% area, five districts have observed major changes in area. In 1978, Hyderabad was subdivided into Hyderabad and Rangareddy and in 1979, Vizianagram was carved out of Srikakulam and Visakhapatnam. Hence, post-division Hyderabad, Srikakulam and Visakhapatnam are considered new districts.[6] Furthermore, changes in latitude and longitude of delimited districts are duly taken into account for synthesis of climate data from a high resolution gridded data set. It should be noted that even after rearrangement, there is no change in the distribution of districts in different agro-climatic zones.[7]

5 Accessed in August 2011.

6 This redistricting leaves us with an insufficient number of observations for these districts before delimitation, so they are not included in our analysis. Also, post-division Hyderabad has seen a gradual reduction in agriculture because of rapid urbanization and no rice-sown area has been reported there in the last years. Hence, we have completely excluded Hyderabad from our analysis.

7 For more details about changes in district boundaries over time, see Kumar and Somanathan (2009).

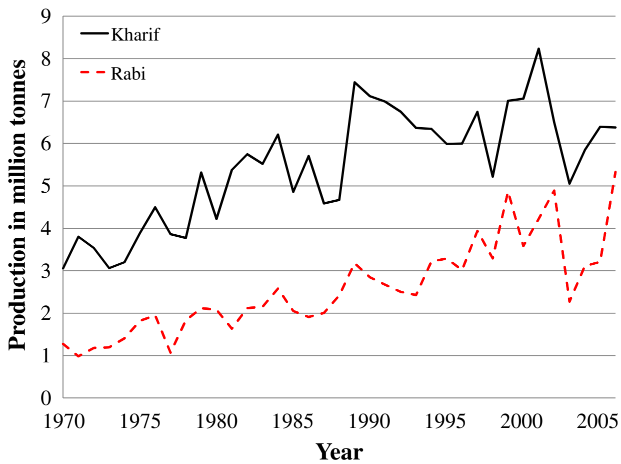

Fig. 2. Kharif and Rabi rice productions in Andhra Pradesh.

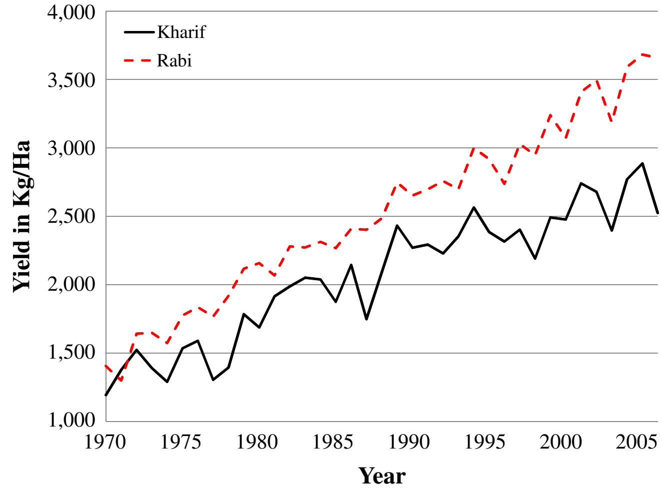

Fig. 3. Kharif and Rabi rice yield in Andhra Pradesh.

There are two main features of data used in this research. First, we use high-resolution daily gridded temperature and climate data for India, which have not been exploited much in climate change and agriculture research. Mearns et al. (1996) show the importance of using variability in daily data in a similar context, though they use simulated and not historical values of daily temperature and precipitation. A recent study by Schlenker and Roberts (2009) use historical fine scale daily temperature data for the United States. However, it has been difficult to find such high-resolution daily weather data in the context of developing countries such as India until recently (Guiteras, 2009). Second, we include district-level seasonal yields and agro-climatic zones in our analysis to facilitate a more useful examination of both intra- & inter-temporal and inter-spatial variances in the yield. The descriptive statistics of the data used in the analysis are provided in Table 2. In the next subsection, we explain the details of compiling the climate and agricultural data.

3.1. Climate Data

Daily temperature data are available in a $1°\times 1°$ latitude–longitude grid form. The gridded temperature data are synthesized using a Shepard's angular distance weighting method on historical data from 395 quality-controlled stations for the period (1969–2005) (Srivastava et al., 2008). Similarly, daily rainfall data from 1803 stations across India are used to develop a high-resolution gridded precipitation data set for the period of 1951–2003 (Rajeevan et al., 2006). IMD claims to have ensured consistency and spatial homogeneity in the selection of temperature and rain gauge stations. Also, both data sets have been rigorously checked for standard quality control and robustness.

For temperature and precipitation data, we use the geographical center of each district and employ a modified Shepard's inverse weighting method to derive associated daily mean rainfall and temperature. We consider all the grids within 100 km of the district center and apply an inverse square root of corresponding distances as the weight.[8] The daily values are used to calculate average temperature, total precipitation and corresponding standard deviation of temperature and precipitation in each district. With limited rainfall during the Rabi season, monsoon rainfall provides the required soil moisture and irrigation water for Rabi crops in India. Therefore, we include the total of Kharif and Rabi rainfall in the analysis of the Rabi crop (Mall et al., 2006).

Using satellite remote sensing data for Andhra Pradesh, Manjunath and Panigrahy (2009) find the Kharif season is from late June to November, whereas the Rabi season starts in early December and ends in first week of April. To take weather pre-conditions into account, we include the whole of June and November in the Kharif and Rabi crop seasons, respectively. The government of India's National Food Security Mission's (hereafter, NFSM) crop calendar suggests October and March as the first months of rice harvesting in Andhra Pradesh.[9] Hence, June to October is considered the Kharif season and November to March is considered the Rabi season. Further, standard deviations of the daily temperature and precipitation values over the corresponding months in each crop season are calculated. To take into account the extremes in precipitation, we also prepare a precipitation intensity and drought index.

Precipitation intensity is the ratio of maximum total monthly rainfall over the total annual rainfall. This figure may vary from 1/12 to 1, i.e., a given district getting uniform rainfall throughout the year to one particular month receiving all of the rainfall. A drought dummy variable is based on a Percent of Normal (hereafter, PN) drought index. The dummy is assigned a value of 1 for each location if the total rainfall in that crop season is less than 33% of normal rainfall over the 33-year period. The climate variables over a crop season are aligned with the corresponding yield data, taking account of differences in reporting year formats between the two data bases. As we have climate data for the calendar year 2003, we can also include Kharif crops for the years 2003–2004. Hence, we carry out the analysis with 34 years of Kharif data and 33 years of Rabi data.

3.2. Agricultural Data

Rice yield data from 1971 to 2004 are obtained from the CMIE database and are denoted in kilograms per hectare (kg/ha). The yield time series data cover all 23 districts of Andhra Pradesh. All agricultural values are adjusted for district delimitation as described earlier in this section. Rice yield and sown area data are available for both the Kharif and Rabi seasons. The yield for both crop seasons is reported in one financial year starting from March and ending in April of the subsequent year. For simplicity, we denote the yield in a given financial year under the second calendar year. For example, rice yield data in 1980–81 is counted as the yield for the year 1981.

Other input variables in this model include irrigation percentage and fertilizer consumed. Although area covered under irrigation is given on an annual basis, rain-fed rice cropping is possible only during the Kharif season; all of the Rabi rice-sown area must be irrigated. Hence, we subtract the Rabi-sown area from the total irrigated area and allocate it to the Kharif season. Fertilizer input data is available as total consumption in each crop season for each district. Although available records do not separate them by crop, fertilizer consumption

[8] As a robustness check, we also carried out this exercise for 75 km and 125 km range and found very similar descriptive statistics of climate data.

[9] NFSM crop calendar portal — http://nfsm.gov.in/NfsmMIS/rpt/CalenderReport.aspx, accessed August 2011.

Table 1
Agro-climatic zones in Andhra Pradesh, India.
Source: Department of Agriculture, Government of Andhra Pradesh.

No.	Name of the zone	Districts	Area ('00,000 ha)
1	North Coastal Zone	Srikakulam, Vizianagaram, Visakhapatnam	18.5
2	Godavari Zone	East Godavari, West Godavari	17.5
3	Krishna Zone	Krishna, Guntur, Prakasam	37.7
4	Southern Zone	Chittoor, Kadapa, Nellore	41.7
5	Northern Telangana Zone	Karimnagar, Nizamabad, Adilabad	35.5
6	Central Telangana Zone	Warangal, Khammam, Medak	30.6
7	Southern Telangana Zone	Mahbubnagar, Nalgonda, Rangareddy, Hyderabad	39.3
8	Scarce Rainfall zone	Kurnool, Anantapur	36.2
9	High Altitude & Tribal Areas Zone	High Altitude & Tribal Areas of Srikakulam, Visakhapatnam, East Godavari, Khammam and Adilabad districts	18.0
		Total	275.0

Note: In this study, agro-climatic zone 9, i.e. High altitude & tribal areas, which includes part of five districts is not considered separately.

data by district may be safely assumed to be representing proportional variations in fertilizer input in rice production.

4. Methodology

The core design of this study employs a quantile regression approach proposed by Koenker and Bassett (1978) to analyze the effect of historical variation in temperature and precipitation across rice yield distribution. This approach facilitates a thorough analysis of the differential impact of climate change across the yield distribution. The mean-based regression strategies provide an estimate of the effect of explanatory variables mainly on the "mean" of a dependent variable, implicitly assuming that the variable follows some parametric form of distributions such as normality or other functional forms of heteroskedasticity. However, in the context of studying climate impacts on agricultural yield, it may be more appropriate to analyze the impact of changes in temperature and precipitation across the conditional distribution of yield under more general settings.[10]

Quantile regressions are known to properly take heteroskedasticity into account by allowing for different coefficients at different quantiles. At the same time, the distortion from outliers and extreme values is also minimized.[11] This implies that, in a case of skewed distributions in error terms, quantile regression helps preserve efficiency (Buchinsky, 1998). Furthermore, as pointed out by Chen et al. (2004), stationarity is debatable in the context of climate change and agricultural yield. In other words, it is quite possible that the effects of covariates do not shift the entire conditional distribution by a fixed amount, and a quantile regression approach is useful in such situations and for considering asymmetry and heterogeneity in climatic impacts. Due to the aforementioned advantages, a quantile regression approach has received much attention recently and is employed in this paper. Despite its clear benefits in analyzing the differential impacts of changes in climate across yield distribution, there has not been much application of quantile regression in this area and, to the best of our knowledge, this is the first study to employ quantile regression to analyze the climatic impact on agriculture.[12]

The main specification of our quantile regression analysis is given below:

$$\begin{aligned} Yield = f(&Trend,\ Area,\ Irrigation,\ Fertilizer,\ Drought,\ Intensity, \\ &Temperature,\ SD\ \ Temperature, ACZone, Temp \times ACZone, \\ &Precipitation, SD\ \ Precipitation, Ppt \times ACzone). \end{aligned} \tag{1}$$

Here, *Trend* denotes the corresponding year of observation, *Area* is an annual and seasonal crop area in each district (in hectares), *Irrigation* is the percentage of total crop area under irrigation in each district, *Fertilizer* denotes the consumption of fertilizers in each district (in kg/ha), *Temperature* denotes the mean of daily average temperature in a district over each crop season, *Precipitation* represents a district's sums of the total daily rainfall over each crop season, and *SD temperature* and *SD precipitation* are standard deviations of corresponding daily climatic variables over the crop season in each district. *ACZone* is a dummy variable with the base group of agro-climatic zone 1, which becomes 1 if a district belongs to some specific agro-climatic zone.[13] These dummy variables take into account zone specific soil and climate effects.[14] Finally, *Temp×ACZone* and *Ppt×ACZone* are the sets of interaction variables between agro-climatic zone dummies and climatic variables. The interaction terms are added to clarify heterogeneous climatic impacts across agro-climatic zones. We also include two derived climatic variables to capture extreme rainfall or drought incidence, *Intensity* and *Drought*, respectively.[15] The definition of each aforementioned variable used in the model is summarized in Table 3.

In our analysis, we estimate a vector of coefficients, β_θ, for each of five quantiles, i.e., θ = 25th, 33th, 50th, 67th and 75th for the same model of Eq. (1), which can be mathematically expressed as:

$$y_i = X_i\beta_\theta + u_{\theta i} \text{ with } \mathrm{Quant}_\theta(y_i|X_i) = X_i\beta_\theta \tag{2}$$

[10] We implemented major non-normality tests of residuals such as Shapiro–Wilk by running least squares-type analyses of several different specifications and find the result of non-normality.

[11] This is the main conceptual difference in estimation between quantile regression and OLS types of regressions. The former is based on *least absolute distance deviation* while the latter is based on *least square distance deviation*.

[12] There are a couple of studies that apply quantile regression in the agriculture field. Evenson and Mwabu (2001) examine the effect of agriculture extension on crop yields in Kenya using quantile regression and compare the results with OLS. In another study, Makowski et al. (2007) analyze the relationship between different yield components using quantile regression and find that the quantile regression gives more accurate parameter estimators than the methods currently used by agronomists. Finally, Ph.D. dissertation by Krishnamurthy (2011) applies quantile regressions to look into the impact of climate change on Indian agriculture. His work focuses more on the aggregate impact at the national level.

[13] As mentioned earlier, there are nine agro-climatic zones and the details are summarized in Table 1.

[14] It should be noted that these are zone dummies and they serve different purpose than district dummies. Quantile of difference is, in general, not equivalent to difference in quantiles as we see in usual mean-based panel data models. Following Koenker (2004), when the number of observations on each individual district is not large, it can only be meaningful to take into account the group (here, agro-climatic zone) specific source of unobserved heterogeneity.

[15] Note that this *Drought* dummy is included, because Andhra Pradesh is also known as drought prone districts. For instance, Indian Agricultural Statistics Research Institute publishes the data and statistics that classify Andhra Pradesh as drought prone districts (The data and statistics are sourced from http://www.iasri.res.in/agridata/09data/chapter1/db2009tb1_10.pdf and were accessed on October 17th, 2012). Note also that a flood dummy was included in our initial analysis in the same way. However, it was insignificant both practically and statistically. Therefore, we removed that dummy variable from the regression analysis.

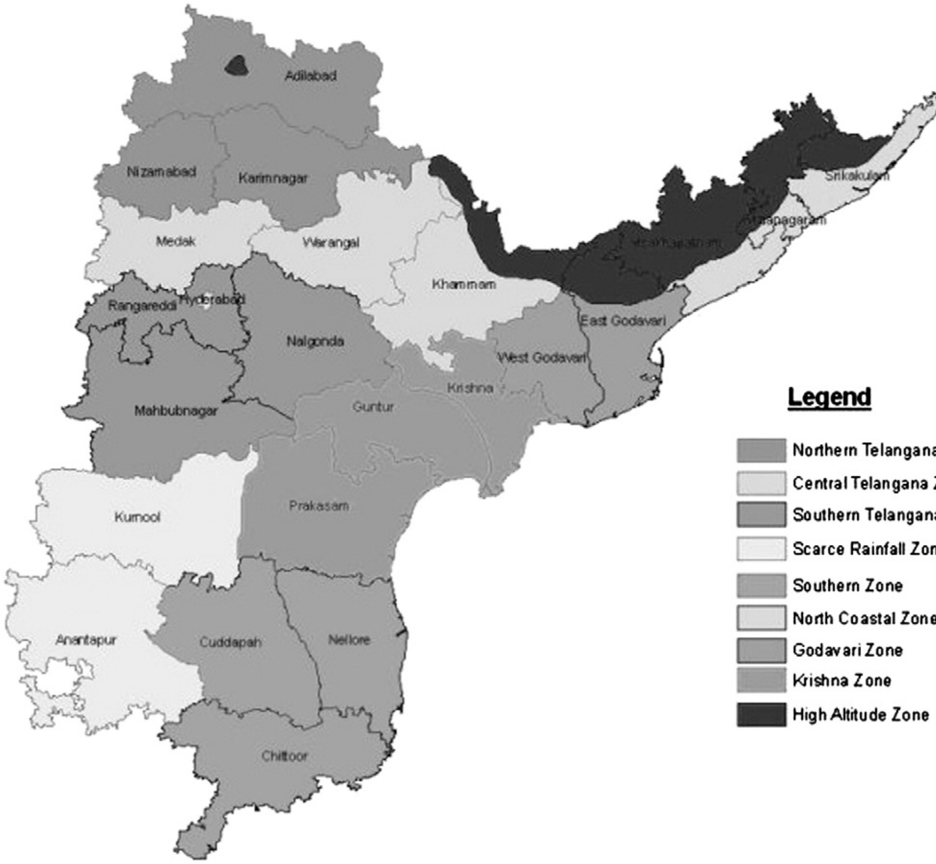

Fig. 4. Map of Andhra Pradesh showing agro-climatic zones.

where $\text{Quant}_\theta(y_i|X_i)$ represents the θth conditional quantile of rice yield y, X denotes the set of independent variables described before, and subscript $i=1, 2, 3, \ldots, N$ represents individual districts.[16] As the quantile regression is non-parametric, the distribution of the error term $u_{\theta i}$ is left unspecified in quantile regression models (Koenker and Bassett, 1978).[17]

We hypothesize the technology trend and fertilizer input to have a positive effect on the yield. Various factors such as expected market prices of rice and input cost are known to farmers ex-ante and they are likely to affect total sown area. Therefore, any increase in total area sown may reflect favorable conditions and prices for rice production. Also, an increase in area is likely to bring an economy of scale and may be an outcome of more information sharing among farmers. Hence, sown area should be positively correlated with the yield. The importance of irrigation depends on the crop season. There is no rice harvest possible in Rabi season unless full irrigation is provided; hence, the Rabi rice must be limited to areas having sufficient surface or groundwater irrigation resources. On the other hand, monsoon season rainfall plays an important role in Kharif rice. Thus, we hypothesize a positive correlation between irrigation and Kharif yield.[18] Finally, drought and excessive rainfall both are expected

[16] Although our quantile regression analysis assumes a linear relationship between rice yield and covariates, we have made some robustness checks by supposing some other alternative specifications of the model. More specifically, we tested possibilities of non-linear relationship by taking the logarithm of the data or including the square terms of the key covariates (see, e.g., Tables 7 and 8 for a result of robustness checks). The results of our robustness check were in line with those generated by a linear model. Therefore, we mainly present the regression results of the linear form in this manuscript.

[17] We employ bootstrapping to compute standard errors, which is considered the most efficient way to estimate the standard errors in this set up (Hao and Naiman, 2007).

[18] For Rabi rice, actual availability of surface water and ground water is more important because Rabi rice is not possible in non-irrigated areas. Therefore, we include rainfall in current and previous Kharif crop seasons in the model.

Table 2
Descriptive statistics.

Variable	Observation	Mean	Std. dev.	Min	Max
Annual					
Rice yield (kg/ha)	647	2105.76	590.10	308.00	5338.00
Sown area ('00,000 ha)	647	170.68	114.12	23.70	491.70
Production ('00,000 metric tons)	647	386.74	327.66	15.20	1680.00
Percentage of irrigated area	627	93.38	8.30	59.15	100.00
Drought dummy	705	0.06	0.23	0.00	1.00
Intensity	705	0.30	0.07	0.16	0.58
Total precipitation (cm)	705	852.94	260.70	251.76	2124.10
Kharif					
Rice yield (kg/ha)	647	2053.66	584.00	181.00	3504.00
Sown area ('00,000 ha)	647	123.40	84.71	15.00	327.83
Production ('00,000 metric tons)	647	263.93	216.04	8.65	987.00
Percentage of irrigated area	627	91.59	9.37	40.08	100.00
Fertilizer input ('000 kg)	582	28.75	22.86	0.61	138.87
Average temperature (°C)	705	28.25	0.89	25.95	30.77
Total precipitation (cm)	705	748.69	258.55	219.63	2096.90
Std. dev. (daily temperature)	705	1.84	0.40	0.84	3.13
Std. dev. (daily precipitation)	705	10.11	3.45	4.05	29.94
Rabi					
Rice yield (kg/ha)	605	2339.67	660.12	857.00	4691.00
Sown area ('00,000 ha)	605	47.94	50.66	0.10	203.01
Production ('00,000 metric tons)	605	124.19	163.57	0.10	896.00
Percentage of irrigated area	605	100.00	0.00	100.00	100.00
Fertilizer input ('000 kg)	560	29.31	24.48	1.11	123.71
Average temperature (°C)	683	25.02	0.83	22.70	27.52
Total precipitation (cm)	683	106.17	111.72	0.00	668.78
Std. dev. (daily temperature)	683	2.52	0.43	1.60	4.04
Std. dev. (daily precipitation)	683	3.56	3.38	0.00	22.124

Table 3
Definition of variables used in the empirical model.

Variable	Description
Year	Representing technology trend
Yield	Rice yield in kg/ha
Area	Rice sown area in '00,000 ha
Irrigation	Percentage sown area covered under irrigation
Fertilizer	Fertilizer consumption (for all crops)
Drought	equals 1 for the year with total annual precipitation 33% less than normal, 0 otherwise
Intensity	equals the proportion of maximum monthly rain to annual rain (varies between 1/12 and 1)
Temperature	Mean of daily average temperature in the corresponding cropping season
Precipitation	Sum of total daily precipitation in the corresponding cropping season (or annual)
SD temperature	Standard deviation in daily temperature in the corresponding cropping season
SD precipitation	Standard deviation in daily precipitation in the corresponding cropping season
ACZone 'n'	Agro-climatic zone dummy for zone 'n'
Temp × ACZone 'n'	Interaction term with *Temperature* and agroclimatic zone dummy 'n'
Ppt × ACZone 'n'	Interaction term with *Precipitation* and agroclimatic zone dummy 'n'

to hamper the rice harvest, leaving a negative expected correlation with the rice yield. Finally, according to our core hypotheses, we expect substantial heterogeneity in the effect of changes in the level and variation in climatic variables on the yield depending on agro-climatic zones and growing seasons.

5. Results

5.1. Quantile Regression Results

A vector of coefficients is estimated for each quantile of {0.25, 0.33, 0.50, 0.67, 0.75}, and the results are presented in Tables 4 and 5, respectively, for Kharif and Rabi. Here, column q50—the estimation results for the 50th quantile—corresponds to the median regression. Accordingly, each of columns q25, q33, …, q75 present a vector of estimated coefficients in the regression for the corresponding quantile of crop yield distribution. Agro-climatic zone dummies are found to have significant coefficients. Estimated coefficients on control variables are generally significant and in line with our discussions in the previous section, although heterogeneity in significance and magnitude of estimated effects may be seen across the quantiles and seasons.

To observe heterogeneous climatic impacts across agro-climatic zones, the variables specified in the form of interaction terms in the model must be examined. The interpretation of the interaction terms

Table 4
Quantile regression results for Kharif rice.

Variables	q25		q33		q50		q67		q75	
	Coef	Se	Coef	Se	Coef	Se	Coef	Se	Coef	Se
Year	32.777***	4.677	31.711***	4.341	36.026***	4.005	33.593***	3.946	36.211***	3.917
Irrigation	20.290***	3.681	21.688***	2.923	23.347***	2.645	26.294***	3.083	27.807***	3.242
Fertilizer	2.924	2.310	3.462	2.159	1.638	1.893	2.284	1.939	1.376	1.908
Area	1.776**	0.719	1.574**	0.661	1.690**	0.679	1.258	0.786	0.982	0.754
Drought	−224.957**	109.971	−245.884**	115.311	−126.605	114.252	−149.367	112.117	−208.551	128.088
Intensity	−52.119	353.550	−134.747	322.043	−84.279	290.689	−43.118	358.777	−288.592	375.721
Temperature	−183.282*	104.451	−160.029*	91.586	−106.888	119.574	−178.898	124.594	−215.527*	130.054
Temp × ACZone2	225.880	230.999	196.791	180.302	208.819	178.229	193.165	171.044	275.810	179.137
Temp × ACZone3	−219.043	204.310	−75.455	168.433	−126.501	169.422	94.599	191.078	40.581	199.926
Temp × ACZone4	371.908***	135.377	316.882***	115.238	221.887*	132.683	256.144*	136.722	308.295**	141.039
Temp × ACZone5	244.595*	144.826	257.327**	118.744	244.976*	141.037	303.305*	159.374	307.118*	158.396
Temp × ACZone6	286.724**	125.449	270.081**	119.384	283.542*	145.581	409.610***	154.451	448.807***	156.000
Temp × ACZone7	484.586***	143.026	398.364***	124.312	422.384***	135.491	535.869***	156.483	615.615***	162.416
Temp × ACZone8	187.606	137.479	216.259*	122.174	181.366	145.161	212.132	151.982	211.300	152.000
SD temperature	−35.810	92.564	−55.101	82.357	−103.340	69.864	−39.674	80.992	−6.515	77.610
Precipitation	0.898***	0.279	0.742***	0.284	0.833**	0.343	0.866	0.535	1.433**	0.624
Ppt × ACZone2	−2.465***	0.712	−1.578**	0.703	−0.931*	0.511	−1.290**	0.544	−1.731***	0.648
Ppt × ACZone3	−1.429***	0.489	−1.190***	0.432	−1.329***	0.454	−1.244*	0.646	−1.591**	0.688
Ppt × ACZone4	−0.178	0.367	−0.170	0.363	−0.434	0.395	−0.729	0.606	−1.334*	0.681
Ppt × ACZone5	−0.434	0.319	−0.350	0.314	−0.432	0.345	−0.659	0.521	−1.290**	0.622
Ppt × ACZone6	−0.082	0.302	0.118	0.300	−0.089	0.385	−0.076	0.549	−0.544	0.634
Ppt × ACZone7	−0.216	0.459	−0.036	0.433	0.094	0.504	0.226	0.616	−0.155	0.685
Ppt × ACZone8	−0.672	0.486	−0.551	0.474	−0.632	0.484	−0.384	0.651	−0.829	0.723
SD precipitation	−15.617	12.016	−14.430	11.488	−10.532	10.308	−4.664	10.020	−9.870	9.802
Observations	562									
Pseudo R2	0.42		0.43		0.45		0.47		0.47	

Note:
1. Dependent variable is Kharif rice yield in kg/ha.
2. Standard errors are obtained using bootstrapping.
3. Kharif regression covers 1971–2004.
4. Districts with less than 15 years of data are not included. These are pre-partition Hyderabad, Srikakulam, Visakapatnam and post-partition Hyderabad.
5. Agro-climatic zone dummies are included.

*** Significant at 1%.
** Significant at 5%.
* Significant at 10%.

Table 5
Quantile regression results for Rabi rice.

Variable	q25		q33		q50		q67		q75	
	Coef	Se	Coef	Se	Coef	Se	Coef	Se	Coef	Se
Year	25.697***	4.350	28.472***	4.006	33.890***	4.678	33.921***	4.768	37.144***	4.838
Irrigation	−1.068	3.317	−0.765	3.143	−5.593	3.784	−5.053	3.675	−5.186	3.932
Fertilizer	9.302***	2.046	9.949***	1.989	7.588***	2.314	7.802***	2.089	5.937**	2.318
Area	2.211**	1.068	2.048**	0.974	2.804***	0.960	1.920**	0.974	1.812*	1.075
Drought	−138.323	141.334	−110.036	134.856	−214.064	141.388	−157.568	147.622	−68.284	155.193
Intensity	−117.746	353.255	404.493	333.683	378.964	318.779	9.589	327.689	57.650	364.188
Temperature	−39.101	156.248	−46.451	112.569	−48.778	90.958	−73.142	89.197	−56.505	84.921
Temp × ACZone2	3.048	213.360	−113.588	172.021	−113.675	166.889	−66.967	161.547	−23.844	175.158
Temp × ACZone3	118.278	216.604	122.228	185.485	16.829	184.591	112.159	169.938	29.597	176.906
Temp × ACZone4	−85.853	198.782	−170.551	151.967	−249.458*	130.824	−32.882	132.652	30.406	123.464
Temp × ACZone5	212.614	167.383	241.595*	126.467	150.147	118.508	267.279**	123.202	314.932***	122.003
Temp × ACZone6	171.171	184.803	121.164	137.192	135.905	120.748	112.669	128.669	122.913	130.459
Temp × ACZone7	−20.447	207.432	−30.094	166.402	−31.616	125.697	84.484	114.653	105.843	124.753
Temp × ACZone8	−42.575	185.938	−2.758	148.781	89.940	125.246	87.229	127.943	71.669	127.905
SD temperature	22.552	91.821	63.368	77.676	40.167	86.518	70.255	86.907	62.617	84.582
Precipitation	0.717	0.547	0.542	0.514	0.482	0.437	0.769*	0.447	0.469	0.435
Ppt × ACZone2	−0.765	0.653	−0.830	0.644	−0.884*	0.526	−1.086**	0.517	−0.706	0.554
Ppt × ACZone3	0.534	0.649	0.712	0.611	0.717	0.615	0.398	0.639	0.508	0.658
Ppt × ACZone4	−0.563	0.607	−0.539	0.577	−0.605	0.496	−0.816	0.513	−0.566	0.533
Ppt × ACZone5	−0.348	0.621	−0.210	0.573	−0.272	0.464	−0.348	0.471	−0.091	0.495
Ppt × ACZone6	−0.135	0.568	−0.074	0.530	0.008	0.466	−0.433	0.473	−0.178	0.464
Ppt × ACZone7	−0.511	0.686	−0.314	0.642	−0.352	0.549	−0.455	0.630	0.226	0.655
Ppt × ACZone8	−0.947	0.693	−0.736	0.661	−0.903	0.557	−0.933	0.575	−0.456	0.591
SD precipitation	−7.982	8.952	−8.962	7.352	−10.897	7.684	−18.141**	8.249	−18.473*	9.938
Observations	542									
Pseudo R2	0.41		0.43		0.45		0.49		0.51	

Note:
1. Dependent variable is Rabi rice yield in kg/ha.
2. Standard errors are obtained using bootstrapping.
3. Rabi regression covers 1971–2003.
4. Districts with less than 15 years of data are not included. These are pre-partition Hyderabad, Srikakulam, Visakapatnam and post-partition Hyderabad.
5. Agro-climatic zone dummies are included.
*** Significant at 1%.
** Significant at 5%.
* Significant at 10%.

should remain confined to the corresponding zones relative to agro-climatic zone 1 of the base group. For instance, in agro-climatic zone 4, holding all other factors constant, a one degree increase in the average of daily temperature over Kharif months is associated with an increase of 188($\approx -183.282+371.908$) kg/ha in the Kharif rice yield at the 25th quantile level. The net effect is positive. Notice that −183.282 is an estimated coefficient for temperature when we take *ACZone1* as a base group, and 371.908 is an estimated coefficient for *Temp × ACZone4* for Kharif rice q25 regression. With this method of interpreting the coefficients in the interaction terms, we describe the details of regression analysis, focusing on possible heterogeneity across crop seasons and agro-climatic zones.

5.1.1. Kharif

Table 4 shows the Kharif regression results for each quantile. The estimated coefficients for the technology trend and irrigation are higher in magnitude for higher quantiles, which confirms our intuition that greater technology application leads to higher yields. On the other hand, fertilizer inputs to yield elasticity do not come out to be significant, although it remains positive for all of the yield quantiles.[19] Average temperature over Kharif months has significant effects across quantiles in many agro-climatic zones. First, agro-climatic zone 1 observes a significant and negative effect of an increase in temperature in some yield quantiles. Next, in zones 4, 5, 6 and 7, an increase in temperature has a significant and positive net effect across the conditional quantile distribution.[20] We also observe positive coefficients for all of the quantiles in zone 8, but the effect is significant for the 33th quantile only. Thus, five of eight zones are likely to gain from an increase in temperature. These results validate similar results obtained with crop simulation models, as discussed earlier.

Precipitation in a Kharif month is likely to affect most of the yield quantiles in three zones and the extreme quantiles in specific zones. The net effect of an increase in precipitation is negative in zones 2 and 3, while it is likely to increase Kharif yield across the yield distribution in zone 1. The same effect is identified for higher yield quantiles in zones 4 and 5. This type of heterogeneous effects of precipitation across agro-climatic zones is clearly demonstrated by quantile regressions. Together with the results associated with temperature, the quantile regressions suggest how heterogeneity in the impacts of temperature and precipitation can arise in each quantile of the conditional distribution and in each climatic zone. We also see significant and negative impacts of drought in lower quantiles. Estimated coefficients for intensity and standard deviations in intra-seasonal daily temperature and precipitation are not significant. Overall, we could say that substantial heterogeneity in the effects of covariates across the conditional yield quantiles is clearly evident.

5.1.2. Rabi

Table 5 shows the Rabi regression results for each quantile. Control variables show the expected effects. The technology trend is significantly associated with the Rabi yield and, similar to the Kharif, the magnitude is larger for higher yield quantiles. Non-significance in the effect of irrigation is not surprising because Rabi rice production is known to be relatively well-irrigated. Area and fertilizer input have significant effects on yield across the yield distribution. The estimated results on these covariates basically follow our intuition.

[19] Apparently, the result comes from a known weakness in the fertilizer data available to us, which does not segregate fertilizer application for rice separately.
[20] "Positive impact" indicates that the net effect of a one unit increase in temperature is positive in zones 4, 5, 6 and 7.

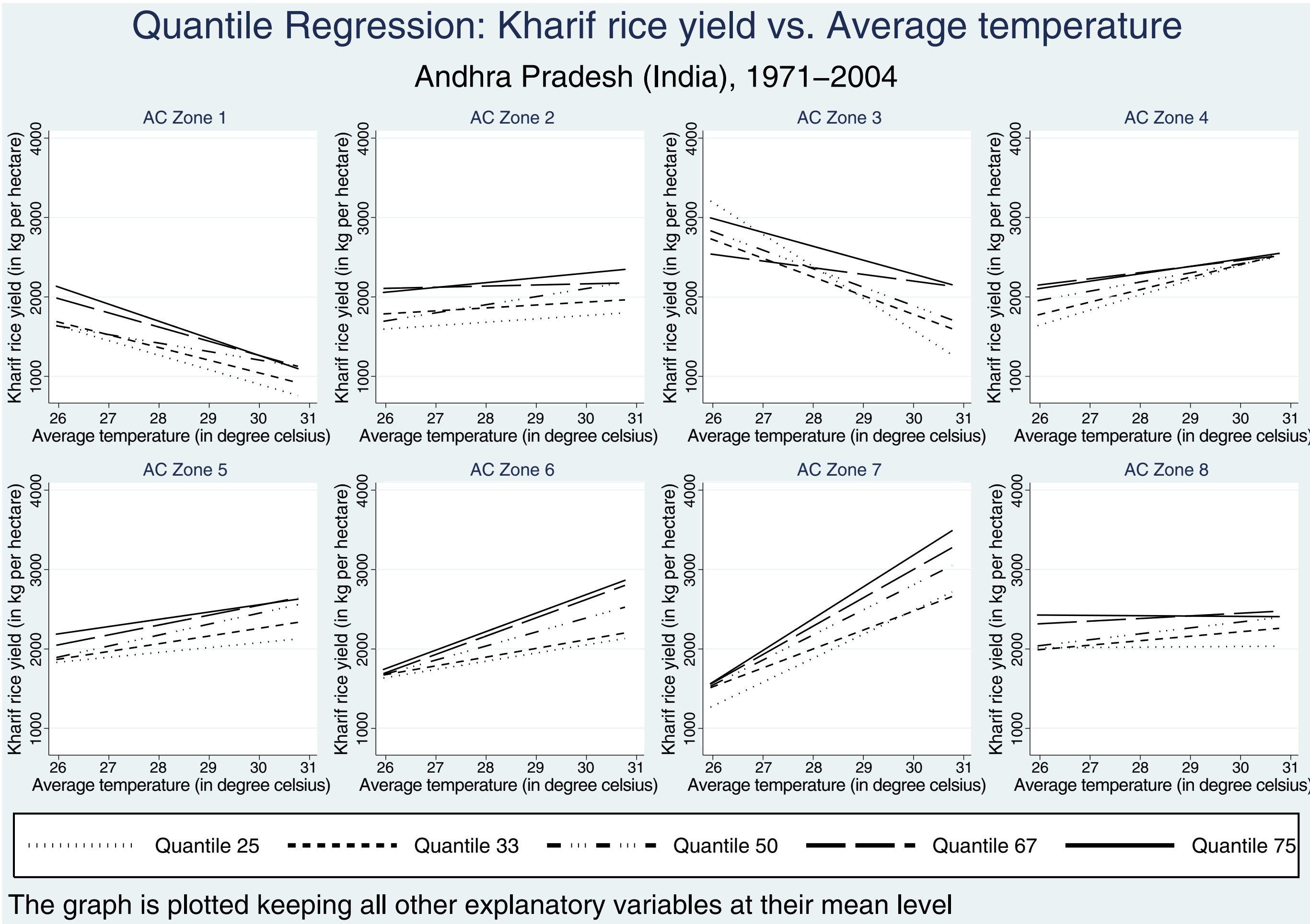

Fig. 5. Agro-climatic zonal relationship between Kharif rice yield and average temperature.

Overall, the Rabi crop is identified to be mostly resilient to changes in temperature and precipitation compared to the Kharif crop (see Table 5 and note that many estimated coefficients associated with climate variables are insignificant). However, it must be noted that an increase in intra-seasonal variability of precipitation represented by *SD precipitation* exhibits some statistically significant and negative effects on higher quantiles of the Rabi crop. Furthermore, the result also shows a gain potential in zone 5 and a possible loss in yield in zone 4 with an increase in temperature. Similarly, for precipitation, particular yield quantiles in zones 1 and 2 may see an impact on yield. Estimated coefficients for drought and the variability of temperature and rainfall show consistently negative values, though it is significant only in the case of standard deviations of precipitation in higher yield quantiles. Overall, the Rabi rice crop seems to be more resilient to changes in climate variables.

5.2. Agro-climatic Zone Wise Graphical Analysis of Yield Sensitivity to Climate

In this subsection, we visualize the heterogeneity of agro-climatic zone effects in a more useful manner. The graphs shown in Figs. 5 to 8 plot predicted values of rice yield for Kharif and Rabi against the corresponding seasonal average temperature and the total precipitation in each zone. The coefficients estimated with quantile regressions are used to predict the yield level. We are interested in the pattern of changes in yield with the variable on the *X*-axis, i.e., temperature or precipitation. Assuming all other variables are kept at their sample mean levels,[21] predicted values are computed as follows:

$$\hat{y}_k = f(\textit{temperature} \text{ or } \textit{precipitation}, \beta_i, \text{sample averages of all other covariates}) \quad (3)$$

where β_i represents the parameters estimated in Eq. (2). Figs. 5 to 8 provide a qualitative understanding of the effect of climate change on rice yield by plotting the function of the predicted values in Eq. (3). In other words, these are basically plots of the predicted value over the long term range observed for particular climate variables.

Again note that our focus is on clarifying the heterogeneity in the effect of an increase in climate variables across the quantiles and across the agro-climatic zones. In Fig. 5, which shows the agro-climatic zonal relationship between Kharif rice yield and temperature, zones 2, 4, 5, 6 and 7 undergo a gain in yield with temperature, while zones 1 and 3 show a decrease in yield with temperature. On the other hand, for Rabi rice (Fig. 7), zones 1 and 2 experience a reduction in yield, while zones 5 and 6 may have an increase in yield with an increase in temperature. No clear trend is found for zones 3, 4, 7 and 8. With an increase in precipitation, most of the zones are likely to undergo an increase in yield or remain stable in both the seasons, though we do find specific instances of a negative slope (see zone 2 in Figs. 6 and 8).

[21] These plots are similar to return to education vs. experience plots by Buchinsky (1994) and predicted wealth vs. age plots by Conley and Galenson (1994).

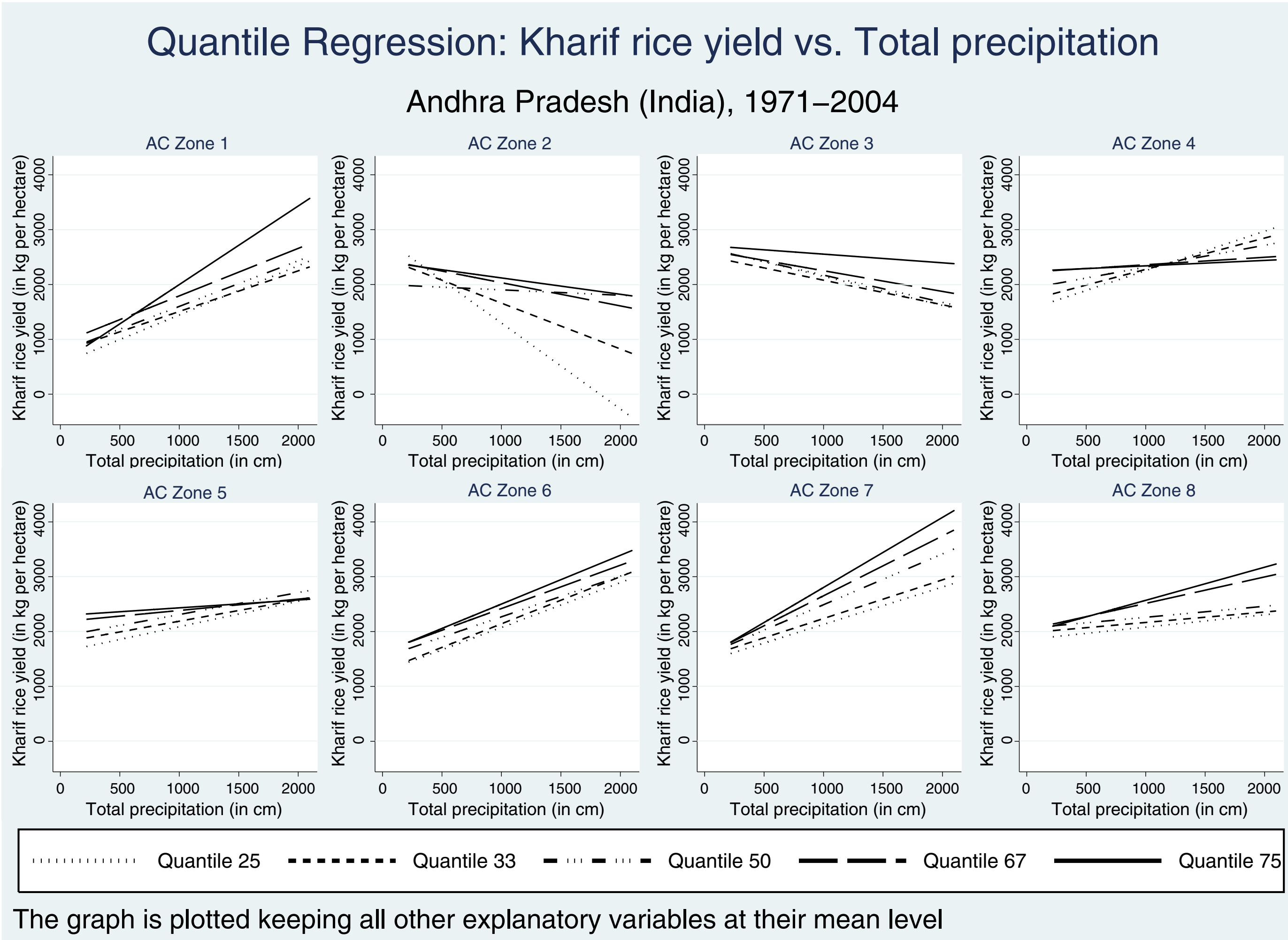

Fig. 6. Agro-climatic zonal relationship between Kharif rice yield and total precipitation.

Heterogeneous trends across the quantiles are also evident by looking at convergence or divergence in slopes across the yield quantiles, which indicates a possible heterogeneity in the impact of climate change on yield. Agro-climatic zones 6 and 7 (zone 3) in Fig. 5 show that lower quantiles are likely to observe less gain (more loss) in yield with favorable changes in climate compared to higher quantiles. On the other hand, higher yield quantiles are less likely to gain with an increase in rainfall in zones 4 and 5 (see Fig. 6). Similar trends in the quantile divergence or convergence are also exhibited by Rabi rice yields. Hence, we should expect substantial heterogeneity in the effect of climate change on yield as per the location specific soil and climate conditions and crop season across agro-climatic zones. Even in the same agro-climatic zone, the sensitivity to change in temperature and rainfall varies across the conditional yield quantiles. Moreover, the direction of effect of climate change on yield may not align for Kharif and Rabi crops in the same agro-climatic zone.

6. Forecasting

An aggregate impact of future climate change on yield should take the specific effects of the agro-climatic zones and yield quantiles into consideration. Herein, we make an attempt to match changes in Kharif rice yield with a marginal increase in climate variables and their variation. Using the regional averages of temperature and precipitation projections from 21 global models for the *A1B* scenario, IPCC projects the global mean warming and an increase in precipitation for South Asia during 2080–2099 (IPCC, 2007b). They project a 5% decrease in precipitation during the dry season (i.e. December to February), but a significant precipitation increase the rest of the year, led by the summer monsoon, which is likely to raise the median precipitation by 11%. On average, annual temperature is projected to increase by 3.3 °C over the 1980–1999 average (Solomon et al., 2007).

Assessment of future impact of climate change is mainly built on GCM predictions. In the most common set up, a mild scenario with two extreme scenarios on either side is considered. We base our forecast scenario on studies by Sanghi and Mendelsohn (2008) and Cline (2007). Sanghi and Mendelsohn (2008) consider a range over 0 °C to 3.5 °C and a precipitation increase up to 14% uniformly for a whole country. Cline (2007) applies a scenario with 3.05 °C increase in temperature and about 3.43 mm per day rise in precipitation for the period 2070–90. We further fine-tune our forecast scenarios using IPCC's mean projection for 2080–2099 (A1B scenario) and define three categories of forecast, low, medium and high; first, scenario F1 with a 2 degree increase in temperature and no increase in precipitation; next, scenario F2 with a 3 degree increase in temperature and 10% increase in precipitation; and finally, scenario F3 with a 4 degree increase in temperature and 20% increase in precipitation. Our mid-scenario F2 is similar to the one used by Cline (2007) for Southeast India, which is most relevant to our study region.

We represent a percentage change in the Kharif yield under the expected scenarios described above, and the results are summarized

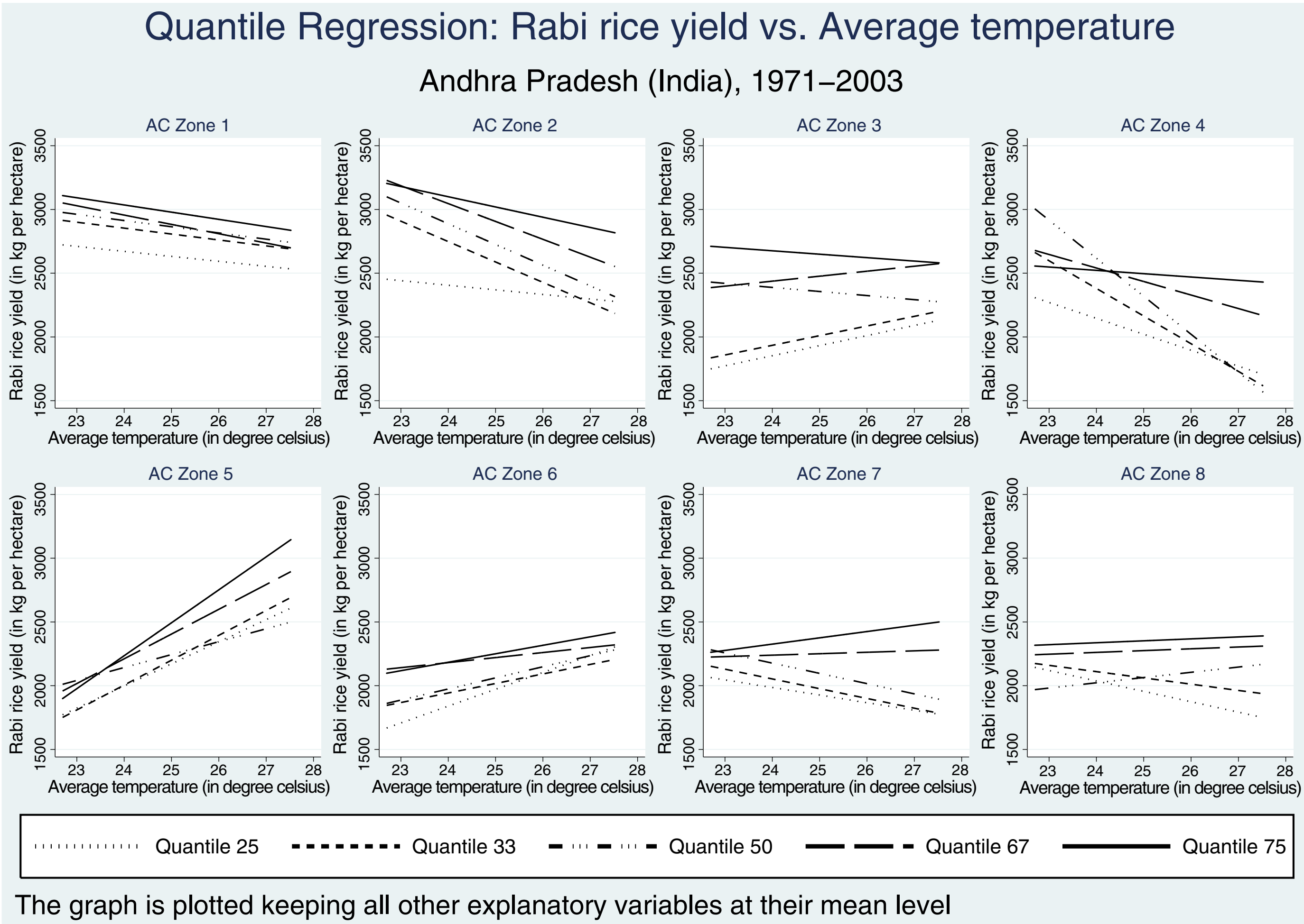

Fig. 7. Agro-climatic zonal relationship between Rabi rice yield and average temperature.

in Table 6.[22] Note that the percentage change in the seasonal yield across the quantiles is calculated for each agro-climatic zone under the three scenarios of F1, F2 and F3. More specifically, the percentage change in yield is calculated by identifying the difference between the predicted yields from the quantile regression model using estimated coefficients under the scenarios and the predicted yield under the observed data of independent variables as a benchmark in each year.

Table 6 shows which zones have a positive or negative effect in each climate scenario. For example, agro-climatic zones 2, 4, 5, 6, 7 and 8 are predicted to see a positive impact on crop yield under all scenarios across each quantile. This case corresponds to a situation where yield gains from an increase in temperature largely offset most of the loss expected with an increase in precipitation. However, there is an opposite situation in which yield gains from an increase in precipitation cannot offset the loss expected with an increase in temperature. This case represents the situation of zone 1, which suffers a net loss under any of the climate scenario. Our regression results also predict a loss in zone 3.

In summary, zones 2, 4, 5, 6, 7 and 8 are likely to experience a positive impact from climate scenarios assumed in the forecasting exercises, although zone 8 may undergo some loss in rice yield for the higher quantiles. Zones 1 and 3 are likely to suffer in all three scenarios. While most of the quantiles in each zone are likely to exhibit the same directional change, the magnitudes depend on the quantiles. Also, the directions and magnitudes of the change are different depending on zones. For example, notice that lower yield quantiles in agro-climatic zone 3 are likely to experience a greater percentage loss even in the mildest climate change scenario. On the other hand, agro-climatic zones 4, 6 and 7 may see a significant increase in rice production, but the degree varies across the quantiles. Given this illustrating example of forecasting exercises, we believe that this type of quantile regression analysis helps in prioritization of climate change adaptation needs, which in turn are very important from food security and poverty reduction perspectives (Lobell et al., 2008).

7. Discussion and Conclusion

The objective of this paper is to explore heterogeneity in the impact of climate change on crop yield across the conditional yield distribution by hypothesizing that crop seasons and agro-climatic zones are key determinants. We focused on a state, Andhra Pradesh in south India, and a major cereal crop in that region, rice. Particular attention is given to the effect of changes in intra-seasonal and inter-seasonal variation in temperature and precipitation across agro-climatic zones. Employing 34 years of data, we apply quantile regression methods to untangle the heterogeneous climatic impacts and find three main results.

[22] Rabi rice has shown resilience to climate variables. Thus, we include only Kharif yields here.

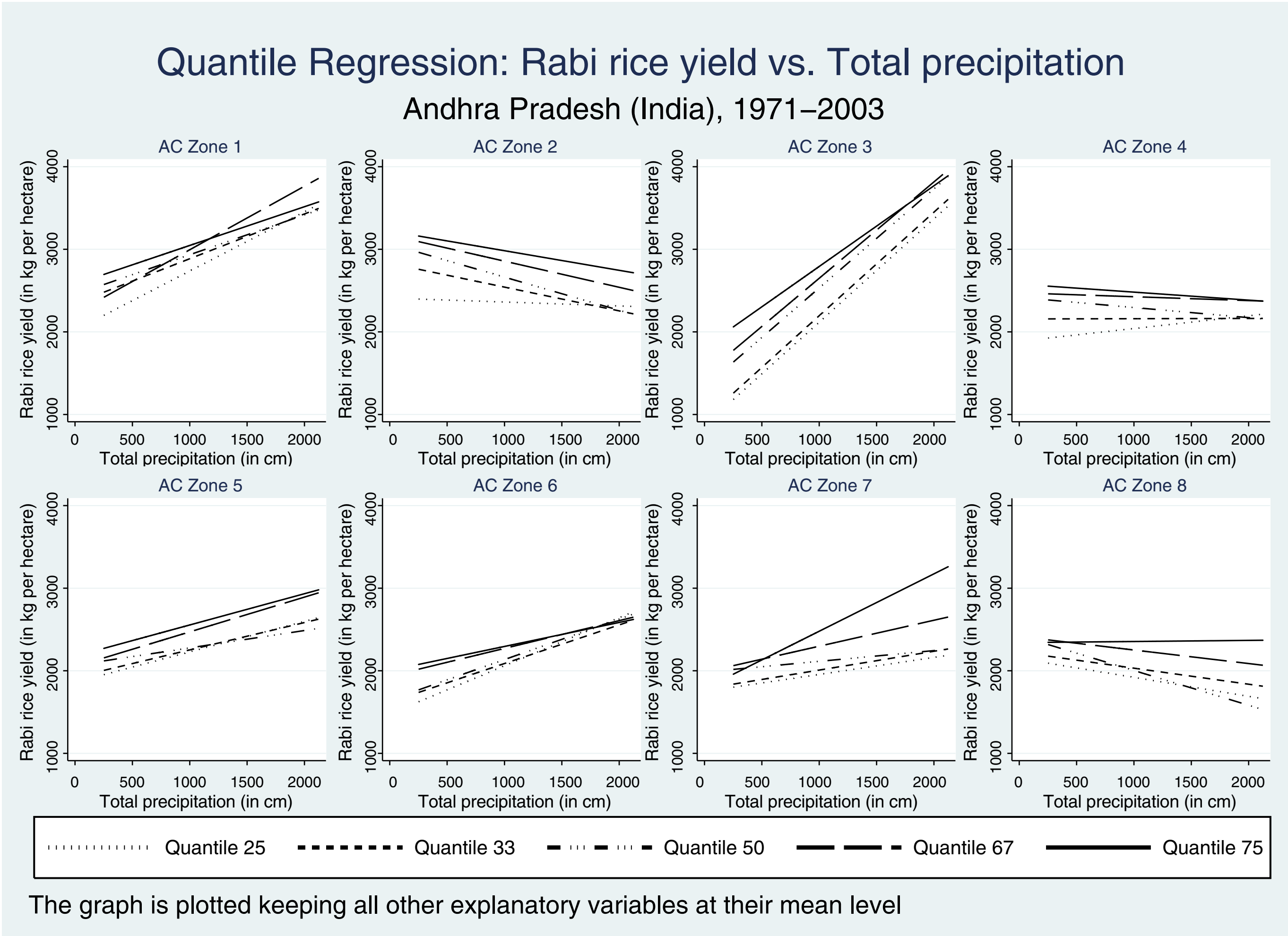

Fig. 8. Agro-climatic zonal relationship between Rabi rice yield and total precipitation.

Table 6
Forecast for percentage change in Kharif rice yield under scenarios F1, F2 and F3.

Agro-climatic zones	Quantiles				
	25	33	50	67	75
(a) Scenario F1: 2 °C increase in temperature					
ACzone1	−22.96	−20.05	−13.39	−22.41	−27.00
ACzone2	3.95	3.41	9.46	1.32	5.60
ACzone3	−34.16	−20.00	−19.82	−7.16	−14.86
ACzone4	17.33	14.41	10.57	7.10	8.52
ACzone5	6.19	9.82	13.94	12.56	9.24
ACzone6	10.74	11.43	18.35	23.96	24.23
ACzone7	29.33	23.20	30.71	34.75	38.94
ACzone8	0.41	5.29	7.00	3.13	−0.40
(b) Scenario F2: 3 °C increase in temperature, 10% increase in precipitation					
ACzone1	−33.69	−29.45	−19.39	−32.89	−39.30
ACzone2	4.73	4.48	14.12	1.66	8.17
ACzone3	−51.09	−29.86	−29.58	−10.63	−22.24
ACzone4	25.42	21.16	15.53	10.54	12.71
ACzone5	9.83	15.19	21.38	19.08	14.03
ACzone6	16.46	17.51	27.83	36.28	36.72
ACzone7	43.63	34.42	45.57	51.54	57.73
ACzone8	0.34	7.71	10.27	4.12	−1.31
(c) Scenario F3: 4 °C increase in temperature, 20% increase in precipitation					
ACzone1	−44.42	−38.86	−25.39	−43.38	−51.61
ACzone2	5.51	5.55	18.77	2.00	10.74
ACzone3	−68.01	−39.73	−39.34	−14.09	−29.62
ACzone4	33.50	27.90	20.49	13.97	16.89
ACzone5	13.47	20.56	28.82	25.60	18.82
ACzone6	22.18	23.59	37.32	48.59	49.21
ACzone7	57.93	45.65	60.43	68.33	76.53
ACzone8	0.28	10.13	13.53	5.11	−2.22

First, substantial heterogeneity in the impacts of climatic variables is found across the yield distribution. Second, the direction of the climatic impacts on rice yield highly depends on agro-climatic zones. Third, seasonal effects of climate change on rice yield are significant. More specifically, the monsoon-dependent crop (Kharif) is more sensitive to temperature and precipitation, while the winter crop (Rabi) stays largely resilient to changes in the levels of climate variables. Overall, these findings clarify the idiosyncratic impacts of climate on yield quantiles with respect to agro-climatic zones and crop seasons in India. These results call for location- and season-specific adaptation policies to attain a more stable food supply and poverty reduction.

The effects of drought, excessive rainfall and other input variables such as irrigation across the conditional yield quantiles are also investigated. Drought is found to have a negative and significant effect on lower yield quantiles in the Kharif season. Surprisingly, yield is not found to be sensitive to excessive rainfall. However, if climate change dramatically affects the likelihood of drought and intense rainfall, conclusions based on observed data may not hold true in the future. Irrigation is identified to positively affect the Kharif crop, but not the Rabi crop, which is consistent with agricultural practices and knowledge in the region.

Many studies have shown a possible positive effect of the increase in temperature on rice yield in India (see, e.g., Mall et al., 2006), whereas other studies have predicted an adverse impact on yield (Cline, 2007). Our results for Kharif rice provide some evidence for gains with an increase in temperature in most agro-climatic zones. Our results also indicate that the effect of an increase in precipitation on Kharif rice is significant. However, overall, our results suggest that the direction or degree of the effect on the Kharif crop can vary in an agro-climatic zonal manner. Conversely, the resilience of the Rabi crop is clarified, which has never been reported in other literature to our knowledge. Thus, this finding may also deserve some attention. In summary, these results appear to establish heterogeneous climatic impacts, but imply that the aggregate effect could be positive or negative depending on how our society responds to the change in climate and how climate will evolve in the future as demonstrated in the forecasting results shown in Table 6.

We believe that the quantile regression results and the corresponding forecasting exercises help in identifying the most vulnerable and most promising targets for investments and government support. Adaptation programs may not be effective unless differential impact is properly mapped and understood at the local level. At a finer spatial scale, the analytical approach and framework employed in this study may be considered an illustrative example of finding local hot spots over agro-climatic zones. For example, the forecasting exercises shown in Table 6 clearly identify the order of the priorities in adaptation strategies at local levels under some hypothetical climate scenarios. In our analysis of forecasts, agro-climatic zones 1 and 3 are identified to be hot spots that require adaptation strategies.

In reality, a straightforward effect on the market and rice prices is difficult to draw at the national level because the overall effects of a change in climate are ambiguous or complex. However, our analysis can guide which zones are likely to suffer. In those areas, regional markets should observe a decrease in supply and hence, an increase in prices for consumers. At the same time, in well-connected markets, the price rise because of location specific climate change could be just marginal and eventually, in that case, farmers' incomes likely drop. This type of occurrences implies that the adverse effects on the rice crop in the local areas may further increase already existing inequality in Indian agriculture by deteriorating the income of local farmers in a specific region. Ideally, such adverse climatic impacts must be tackled with proper policies in the targeted local areas. The farmers who are likely to see greater adverse impacts or much lower gains should be properly compensated with insurance or provided with technical knowledge of adaptation practices or alternative crops feasible in the area.

Among the possible strategies, land use planning and alternative crop choice could be an extremely helpful element in adaptation under the heterogeneity observed in the climatic impacts. As demonstrated in the forecasting section, agro-climatic zones 1 and 3 are such spots, and the analysis suggests that something new must be tried, such as a change of land use or crop choice in the targeted areas. For example, the region-specific land plan should be chalked out to relieve land from areas observing significant losses in rice yield from climate change, while rice cropping should be encouraged where we expect further significant gains. Of course, there are opportunity costs of adopting new crops and usage of land resources, so the possible adaptation strategies must be carefully evaluated based on these opportunity costs.

As a limitation of this study, we admit that long-term adaptations like crop-switching are not taken into account, though this study still reflects farm-level adaptation with the changes made by farmers to maximize the rice crop yield. Furthermore, as already discussed, the variability in climate factors may go beyond the historical variability observed in the data set, which definitely calls for further research in this area. However, as is clear from the quantile regression results presented in this paper, heterogeneity in the climatic impacts on agriculture appears to be evident at a local level, and there is a way to identify hot spots in advance. It is our hope that the analytical framework and empirical evidence presented in this paper offer some guidance on future adaptation strategies against possible changes in climate.

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Appendix A. Quantile Regressions of Log–log Forms

Table 7
Quantile regression results for Kharif rice—log–log form.

Variables	q25		q33		q50		q67		q75	
	Coef	Se	Coef	Se	Coef	Se	Coef	Se	Coef	Se
Year	0.024***	0.004	0.024***	0.004	0.019***	0.003	0.019***	0.003	0.017***	0.003
Year square	−0.001**	0.000	−0.001**	0.000	−0.000	0.000	−0.000*	0.000	−0.000*	0.000
Irrigation	1.125***	0.166	1.147***	0.141	1.124***	0.138	1.102***	0.143	1.010***	0.157
Fertilizer	0.001	0.034	−0.018	0.029	0.012	0.025	0.004	0.027	0.021	0.025
Area	0.137***	0.044	0.133***	0.036	0.099***	0.030	0.072**	0.032	0.050	0.030
Drought	−0.057	0.055	−0.068	0.059	−0.051	0.062	−0.013	0.059	−0.012	0.064
Intensity	−0.031	0.189	0.007	0.163	0.094	0.137	0.040	0.149	−0.008	0.149
Temperature	−4.126*	2.427	−3.957*	2.136	−4.655**	2.097	−3.413**	1.694	−3.365**	1.714
Temp × ACZone2	3.827	3.779	5.316*	2.908	5.303*	2.720	4.473**	2.160	4.083*	2.221
Temp × ACZone3	1.408	2.885	0.857	2.510	1.890	2.672	0.492	2.478	3.018	2.453
Temp × ACZone4	6.073**	2.667	6.394***	2.308	5.908***	2.247	4.226**	1.827	4.049**	1.852
Temp × ACZone5	5.412*	2.838	5.330**	2.387	6.589***	2.179	5.081**	2.118	4.466**	2.192
Temp × ACZone6	5.932**	2.695	6.136**	2.384	6.853***	2.401	6.329***	2.032	6.694***	2.024
Temp × ACZone7	8.569***	2.924	7.788***	2.428	8.440***	2.337	7.815***	2.140	7.615***	2.304
Temp × ACZone8	3.623	2.662	4.487*	2.495	4.873**	2.361	3.595*	1.966	2.813	2.011
SD temperature	−0.088	0.080	−0.091	0.066	−0.020	0.062	−0.013	0.059	−0.056	0.062
Precipitation	0.577***	0.181	0.542***	0.167	0.464**	0.202	0.512**	0.221	0.607***	0.224
Ppt × ACZone2	−1.350***	0.368	−0.914***	0.328	−0.568**	0.232	−0.600***	0.219	−0.679***	0.227
Ppt × ACZone3	−0.557***	0.199	−0.560***	0.177	−0.553***	0.208	−0.562**	0.227	−0.600**	0.237
Ppt × ACZone4	−0.394**	0.176	−0.324**	0.164	−0.380**	0.192	−0.501**	0.218	−0.547**	0.227

(continued on next page)

Table 7 (*continued*)

Variables	q25		q33		q50		q67		q75	
	Coef	Se	Coef	Se	Coef	Se	Coef	Se	Coef	Se
Ppt × ACZone5	−0.254	0.210	−0.266	0.188	−0.242	0.206	−0.348	0.232	−0.413*	0.235
Ppt × ACZone6	−0.211	0.166	−0.144	0.160	−0.133	0.201	−0.182	0.219	−0.259	0.224
Ppt × ACZone7	−0.156	0.182	−0.185	0.173	−0.157	0.209	−0.170	0.246	−0.261	0.258
Ppt × ACZone8	−0.423**	0.182	−0.420**	0.180	−0.448**	0.208	−0.405*	0.214	−0.440**	0.218
SD precipitation	−0.093	0.074	−0.114	0.072	−0.041	0.067	−0.025	0.059	−0.061	0.056
Observations	562									
Pseudo R2	0.45		0.45		0.45		0.45		0.45	

Note:
1. All variables, except Year, are in log form.
2. Standard errors are obtained using bootstrapping.
3. Kharif regression covers 1971–2004.
4. Districts with less than 15 years of data are not included. These are pre-partition Hyderabad, Srikakulam, Visakapatnam and post-partition Hyderabad.
5. Agro-climatic zone dummies are included.

*** Significant at 1%.
** Significant at 5%.
* Significant at 10%.

Table 8
Quantile regression results for Rabi rice—log–log form.

Variables	q25		q33		q50		q67		q75	
	Coef	Se	Coef	Se	Coef	Se	Coef	Se	Coef	Se
Year	0.018***	0.002	0.019***	0.002	0.018***	0.002	0.018***	0.002	0.017***	0.002
Year square	−0.001***	0.000	−0.001***	0.000	−0.001***	0.000	−0.000*	0.000	−0.000	0.000
Irrigation	−0.005	0.170	−0.019	0.152	0.009	0.135	−0.111	0.143	−0.067	0.142
Fertilizer	0.076***	0.024	0.065***	0.022	0.050**	0.023	0.022	0.023	0.035	0.023
Area	0.016	0.018	0.016	0.016	0.027**	0.013	0.030**	0.012	0.014	0.012
Drought	−0.052	0.077	−0.083	0.076	−0.071	0.075	−0.067	0.065	−0.048	0.061
Intensity	0.073	0.167	0.075	0.155	0.051	0.137	0.113	0.141	0.023	0.137
Temperature	1.272	1.271	−0.051	1.008	0.351	0.699	−0.517	0.629	−0.789	0.673
Temp × ACZone2	−1.628	1.949	0.304	1.700	−0.229	1.417	0.790	1.149	1.568	1.302
Temp × ACZone3	−1.782	2.118	0.883	1.939	−0.311	1.748	−0.327	1.863	0.426	1.902
Temp × ACZone4	−3.265*	1.841	−2.064	1.580	−1.799	1.133	−0.016	1.097	0.693	1.006
Temp × ACZone5	0.395	1.580	1.796	1.346	2.341**	1.172	2.814**	1.159	3.068**	1.253
Temp × ACZone6	0.906	1.738	2.024	1.429	1.364	1.129	2.179*	1.285	2.639**	1.293
Temp × ACZone7	−0.745	2.181	−0.400	1.819	−0.407	1.243	−0.020	1.112	0.746	1.200
Temp × ACZone8	−1.967	1.517	−0.078	1.300	0.221	1.140	1.706	1.168	1.405	1.222
SD temperature	−0.058	0.097	−0.006	0.098	0.132	0.096	0.060	0.079	0.067	0.077
Precipitation	0.391*	0.223	0.229	0.213	0.152	0.138	0.109	0.126	0.025	0.130
Ppt × ACZone2	−0.290	0.286	−0.146	0.258	−0.206	0.172	−0.147	0.159	0.008	0.172
Ppt × ACZone3	0.209	0.267	0.341	0.245	0.417**	0.187	0.269	0.193	0.376**	0.190
Ppt × ACZone4	−0.275	0.243	−0.182	0.241	−0.167	0.161	−0.120	0.155	0.003	0.160
Ppt × ACZone5	−0.161	0.259	−0.060	0.243	0.037	0.164	0.056	0.154	0.147	0.158
Ppt × ACZone6	−0.115	0.232	0.010	0.227	0.064	0.164	−0.003	0.141	0.089	0.146
Ppt × ACZone7	−0.235	0.265	−0.089	0.245	−0.093	0.184	−0.112	0.179	0.040	0.189
Ppt × ACZone8	−0.382	0.241	−0.221	0.236	−0.186	0.167	−0.139	0.163	0.046	0.170
SD precipitation	−0.006	0.012	−0.005	0.010	−0.006	0.009	−0.005	0.010	−0.006	0.011
Observations	542									
Pseudo R2	0.40		0.41		0.42		0.45		0.47	

Note:
1. All variables, except Year, are in log form.
2. Standard errors are obtained using bootstrapping.
3. Rabi regression covers 1971–2003.
4. Districts with less than 15 years of data are not included. These are pre-partition Hyderabad, Srikakulam, Visakapatnam and post-partition Hyderabad.
5. Agro-climatic zone dummies are included.

*** Significant at 1%.
** Significant at 5%.
* Significant at 10%.

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