Economics & Management Series *EMS-2010-17*

Impact of variation in climatic factors on crop yield: A case of rice crop in Andhra Pradesh, India

Prabhat Barnwal
Graduate Student, Ph.D. Program in Sustainable Development, Columbia University, USA

Koji Kotani
International University of Japan

November 2010

IUJ Research Institute
International University of Japan

Impact of variation in climatic factors on crop yield: A case of rice crop in Andhra Pradesh, India

Prabhat Barnwal* Koji Kotani†

November 25, 2010

Abstract

This study examines the effects of temperature and precipitation on the mean and variance of seasonal rice yield in Andhra Pradesh, India, over a period of 33 years (1969-2002). For this purpose, two distinct approaches are employed: (i) panel data analysis using Just and Pope stochastic production function and (ii) quantile regression approach. The first approach suggests that, in general, an increase in temperature as well as inter-annual variance of temperature and rainfall adversely affect the mean crop yield, while the effect of increase in precipitation highly depends on the cropping season. Furthermore, an increase in average temperature, rainfall and their respective inter-annual variance are likely to increase inter-annual variability in crop yield. Second, the quantile regression reveals that rice yield's sensitivity to climate change differs significantly across the quantiles of yield distribution. In particular, the adverse effect of climate change is found to be more profound for the crop yields in lower quantiles. In addition, evidences in support of heterogeneity in the impact of climate change across the agro-climatic zones are also found. Overall, these findings call for a more location specific adaptation policies to address heterogeneity and an integrated policy framework covering the downside risk to build resilience in the food security system.

Key Words: *Agriculture, Yield, Yield Variability, Rice, Climate Change, Stochastic production function, Quantile regression, Andhra Pradesh, India*

*Graduate Student, Ph.D. Program in Sustainable Development, Columbia University, USA.

†Associate Professor, International Development Program, Graduate School of International Relations, International University of Japan, 777 Kokusai-cho, Minami-Uonuma, Niigata 949-7277, Japan (e-mail: kkotani@iuj.ac.jp).

1 Introduction

Though the extent of climate change may still remain debatable, the issue of its occurrence is almost settled now. Evidences of changes in temperature, precipitation, and extreme weather events have been found on a scientific basis (IPCC (2007)). These changes and their effects are likely to affect global socio-economic and environmental systems in various ways. Since climatic factors serve as direct inputs to agriculture, any change in climatic factors is bound to have a significant impact on crop yield and production. This area has caught attention of researchers in the recent times as evident by the growing number of studies on the impact of climate change on agriculture. Previous studies have shown a significant effect of change in climatic factors on average crop yield (See, e.g., Dinar et al. (1998), Seo and Mendelsohn (2008), Mall et al. (2006) and Cline (2007)).

While many studies have examined the impact of climatic factors on mean crop yield, how climate affects its variability has not been investigated much especially in agriculture-based developing economies where there would likely be more serious repercussions in terms of food security, inequality and economic growth. Furthermore, the downside risks of the impact of climate change (Tol (2008)), which is a critical concern in agriculture (Kingwell (2006)), have not been incorporated in previous studies estimating its impact across output distribution. This study aims to answer these questions in the context of the coastal state of Andhra Pradesh, India.

The way climate change will affect agricultural productivity is expected to vary depending upon various factors including geography and technology levels.[1] While an overall significant damage of 3.2% is expected in the global agriculture production by the 2080s under business as usual scenario, it is found that the losses may even go up to 15.9% if the carbon fertilization effect is not realized.[2] Industrial countries are likely to observe a loss of 6.3% in agricultural

[1] We examine effect of climatic variables, i.e., temperature and precipitation (both mean and variability), rather the effect of climate change on crop yield. Of course, this will have direct implications for climate change. The latter involves forecasting the future changes in crop yield under the projected climate change scenarios, which is beyond the scope of this study.

[2] Increased concentration in carbon dioxide may increase growth rate of certain plant species and this

Table 1: Summary estimates for impact on global agricultural output potential by 2080

	Without carbon fertlization	With carbon fertlization
Global	-15.9	-3.2
Industrial countries	-6.3	7.7
Developing countries	-21.0	-9.1

Source: Table 7.1, Cline(2007)

output. However, developing countries, predominantly located near the lower altitude, are likely to incur a much greater loss quantified at 21% (Cline (2007)). A summary estimate for impact of climate change on world agricultural output potential by the 2080s is presented in Table 1.

Many previous studies have shown that India is likely to witness one of the highest agricultural productivity losses in the world in accordance with the climate change pattern observed and scenarios projected. The projected agricultural productivity loss for India by 2080 is about 30% even after taking the expected positive effect of carbon fertilization on yield into consideration (Cline (2007)). Another study finds that projected agriculture production loss in India by 2100 lies between 10% to 40% after taking carbon fertilization effect into account (Aggarwal (2008)). It has also been shown 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 (Auffhammer et al. (2006)).

Two major methodologies employed in previous studies to examine the impact of climate on agriculture[3] are: Agronomic models (Mearns et al. (1997)) and Ricardian models

phenomenon is termed as carbon fertilization effect.

[3]It should be noted here that there is significant difference between weather and climate. *Weather* is what we observe over days or weeks and *Climate* is how the atmosphere behaves over relatively long periods of time (National Aeronautics and Space Administration (2005)). A number of studies have investigated weather related effect on crop yield. For example, Schlenker and Roberts (2009) find a non linear and asymmetric relationship between crop yield and weather variables using a fine-scale weather data set. In another study, Staggenbors et al. (2008) discuss the effect of rainfall and temperature stress on grain sorghum and corn. This study, however, does not consider variables like daily temperatures, growing days or daily precipitation. We use an average of temperature and rainfall data for two different cropping seasons here which extends over a period of more than 30 years, since this study intends to analyze the impact of climate (or variation in climatic variables) on crop yield.

(Mendelsohn and Rosenberg (1994)). The agronomic models simulate a laboratory-type set up and provide data on climatic factors and crop growth. Although the agronomic models provide a controlled and randomized application of environmental conditions, it does not take adaptive behavior of an optimizing farmer into account. On the other hand, Ricardian models measure the impact of climatic factors through their contribution to farmland-prices and have been extensively used for incorporating farm level adaptation (Mendelsohn et al. (1996)). Since availability of land prices as well as non-existence of efficient land markets are two major obstacles in applying the Ricardian method to most of the developing countries, Semi-Ricardian models using data on average profits instead of land prices are used in two major studies on India and Brazil (Seo and Mendelsohn (2007) and Dinar et al. (1998)).

One of the major shortcomings of a Ricardian model is the omitted variable problem because it does not take time-independent location-specific factors such as unobservable skills of farmers and soil quality into account. Additionally, yield variability has been found significant in many other studies but a Ricardian model is not capable of capturing the effect of changes in climatic factors on it (Mearns et al. (1997)). Schlenker and Roberts (2009) show that a panel data approach can take care of the omitted variable problem by including district dummies in the model, though the issue of effect on yield variability still remains unattended in simple panel data models.

Both of the shortcomings of a Ricardian model are duly addressed with the stochastic production function model approach employed by Chen et al. (2004). Using a county-level panel data for 24 years, they reveal evidences of the negative effect of change in mean and intra-annual variances of the U.S. climate on the mean as well as variability of crop yield in a crop specific manner. Estimating a similar stochastic production function, McCarl et al. (2008) investigate the yield of five major crops in the US with a richer specification that also includes variance in climatic variables and interactional terms of temperature with regional dummies as independent variables while Cabas et al. (2010) examine the effects of climatic as well as non-climatic factors on crop yield in a Canadian province.

None of the previous studies investigate the impact of climate on yield variability in India. Although two recent studies on Indian agriculture use panel data models, these do not allow variance of output to be affected (Auffhammer et al. (2006); Sanghi and Mendelsohn (2008)). Specifically, this paper aims to answer the following open questions based on the methodologies applied. First, how does the change in temperature and rainfall affect seasonal mean yield and its variability across the state? Based on previous literatures, we hypothesize that an increase in the average temperature and total precipitation should increase inter-annual yield variability. Second, how does an increase in the intra-seasonal variability in temperature and precipitation affect the seasonal mean yield and its variability? Various global climate models have predicted an increase in the variability in temperature and rainfall with time and it is likely to have an adverse effect on mean yield and an escalating effect on the yield variability. Lastly, how does the effect of change in climatic factors on crop yield vary across different quantiles of yield distribution? We hypothesize that the lower levels of yield are likely to be more sensitive to any change in climatic factors.

In order to examine the last hypothesis above, this study additionally employs quantile regression method to analyze the effect of the change in mean and variance of climatic factors on crop yield across the quantiles of yield distribution. Introduced by Koenker and Bassett (1978), this method is particularly important in models having a non-normally distributed dependent variable. Furthermore, quantile regression is more useful in our case because it can correct for heteroskedasticity in the error terms of crop yield as well as remove the impact of outliers. We expect that lower yield levels are more sensitive to any change in climatic factors and the results of quantile regression should be helpful in answering the third question above. In summary, two methodologies are applied in this study to address the above three research questions: Three stage Feasible Generalized Least Squares (FGLS) using a stochastic production function approach and then quantile regression to further explore the effect of climate on crop yield.

Andhra Pradesh, a state at the Southeast coast of India, is selected as a study area for this analysis. Rice is the main crop in the state, which produces about 13% of total national rice output. Agriculture in Andhra Pradesh has been found to be highly vulnerable to climate change (Malone and A. L. Brenkert (2008); O'Brien et al. (2004)). Recently, this region is being characterized by a high frequency of droughts and severe cases of farmer's suicide, which makes this study more important for policy makers (Tada (2004)). The data set used consists of seasonal rice yield and monthly average temperature and precipitation, which could be found from various sources as mentioned in Section 3.

Although the empirical model used in this study is developed on the basis of models analyzed by McCarl et al. (2008) and Chen et al. (2004)), significant modifications have been made to test our hypotheses. While McCarl et al. (2008) use annual precipitation to capture the effect of rainfall on winter wheat and other crops, this study uses total precipitation in the corresponding crop growing season to capture the effect of changes in rainfall and so our model includes the sum of the monthly precipitation over Kharif and Rabi months. Also, standard deviation in monthly precipitation over the months in the growing season is included to capture the effect of variance in rainfall on the mean and variance of rice yield in the way similar to Cabas et al. (2010). Furthermore, we use agro-climatic zones instead of regional dummies to take care of local soil conditions as well as weather specific effects.

To the best of our knowledge, this paper introduces several novel features in the analysis and is the first systematic attempt to study the effect of climate on yield variability in Indian agriculture. Furthermore, none of the previous studies have focuses on the effect of climate on rice yield by considering the average and variance of season-wise climate variables as well as the corresponding yields with the stochastic production approach. Finally, the application of quantile regression is a novel approach to gain further insight on the effect of climate over yield distributions. Especially, it is one of the most effecitve approaches to clarify the potential downside risk of agricultural production.

Three important results are found using the above approaches. First, in most of the cases, an increase in average temperature, rainfall and their respective intra-seasonal variance are likely to increase inter-annual variability in crop yield. This finding provides further basis to the concerns of increasing fluctuation in agricultural output with time under the effect of climate change. In addition, an increase in temperature and intra-seasonal variance is found to be adversely affecting the mean crop yield. Second, results of quantile regression reveal a difference in the sensitivity of rice crop yield towards climatic factors as per quantiles of yield distribution suggesting an increasing downside risk. It is found that farms with lower yield levels are likely to suffer more with unfavorable changes in climatic variables. Finally, the estimated effects vary significantly across agro-climatic zones which advocates for a differentiated and customized approach in climate change adaptation policies.

The analysis presented in this study has direct implications for policy makers. First, the effect of climate change on yield variability should be given due focus in policy design in order to make our food production systems more resilient to climate change. Second, policy makers need to consider the heterogeneity in the impact of climate change to tackle the issues related to food security and rural poverty eradication more efficiently. This confirms the existence about a location and crop dependent effect and it calls for more localized adaptation policy frameworks instead of common state level policies. Third, farms with yield lying on the lower side of yield distribution should be given special attention and facilities like microfinance and crop insurance since they are likely to incur more losses in productivity.

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 discussion on estimated parameters in Section 5. We conclude and summarize the findings in the final section.

2 Climate and rice production in Andhra Pradesh

The coastal states in India are found to be the most vulnerable regions to climate change (Malone and A. L. Brenkert (2008)). Having the second longest coastline (Sanil Kumar et al. (2006)), Andhra Pradesh features into one of the top seven most vulnerable states in India (Malone and A. L. Brenkert (2008) and see figure 1). Moreover, the agriculture sector in the state has been found to be doubly exposed to the 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 the 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 and particularly for small farms in Andhra Pradesh, it may go down by 20% under projected climate scenario.

Rice contributes about 77% of the total food grain production in Andhra Pradesh which amounts to about 7% of total state GDP (The Directorate of Economics and Statistics (2003)). Famous as the 'Rice Bowl of India,' Andhra Pradesh produces 12.24% of total rice output in India with 8.57% 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. Furthermore, Andhra Pradesh has been a pioneer in introducing modern rice varieties and a major part of its increase in rice output has come from yield enhancement since the late 1960s. Also, 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)).

Two main rice growing seasons in the country are Kharif and Rabi. Details of the sowing and harvesting months according to the cropping season are given in Table 2 (The Directorate of Rice Development, Government of India (2002)). The average rice yield in Andhra Pradesh is about 2000 Kg/ha. Kharif rice production is about 55% of total rice output, whereas yield has been consistently higher for Rabi rice in the last 40 years (See Figure 3 and Figure 4). Depending upon soil and climate, Andhra Pradesh is divided in to nine agro-climatic zones. The details of the geographical distribution of the zones and the districts coming under each zone are given in Figure 2 and Table 3.

3 Data set and sources

Data used in this study come from two sources. Season wise crop yield data are taken from Centre for Monitoring Indian Economy (CMIE) reports.[4] CMIE is the leading and most authentic economic data provider in India. The yield data are compiled by CMIE from government reports. Data on climatic variables are downloaded from India Water Portal. The dataset available at the portal is developed using the publicly available Climate Research Unit (CRU) TS2.1 dataset, out of the Tyndall Centre for Climate Change Research, School of Environmental Sciences, University of East Anglia in Norwich, UK.[5] A major strength of this study comes from the use of district level climate and season wise yield data across the Andhra Pradesh, which allows for the examination of both inter-temporal and inter-spatial variances in the data with district level characteristics and technology trend controlled.

3.1 Climate data

India Water Portal provides datasets for various indicators such as rainfall, temperature, humidity etc from 1901 to 2002, for any part of India. For this study, we consider district wise monthly average temperature and monthly total precipitation as the basic climate data and which is further used to calculate average temperature and total monthly precipitation over the corresponding months in Kharif and Rabi seasons. As shown in Table 2, June to November months are considered the Kharif season and December to April are considered

[4] accessed from the Library, National Council of Applied Economics Research, New Delhi (September 2009).

[5] Further details can be obtained from http://indiawaterportal.org/metdata

the Rabi season (The Directorate of Rice Development, Government of India (2002)).

3.2 Rice yield data

Rice yield data from 1969-70 to 2002-03 are obtained from CMIE database and are denoted in Kilograms per hectare (Kg/ Ha). CMIE collates the statistics on Indian agriculture from a comprehensive range of sources including government reports. The yield time series data cover all 23 districts of Andhra Pradesh. From 1969 to 2003, there have been changes in the boundaries of 10 out of current 23 districts and two new districts have been formed since the 1971 census (Kumar and Somanathan (2009)). However, since we are considering yield data in this study, our results would not be affected by any changes in district boundaries over time.

Rice yield data cover both Kharif and Rabi seasons. The yield for both cropping season is reported in one financial year starting from March and ending in April in the subsequent year. For simplicity, we denoted 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. In addition, the climate variables i.e. average temperature and precipitation over a cropping season are aligned with the yield data accordingly.

4 Methodology

The study uses panel data across all 23 districts of Andhra Pradesh in investigating the impact of variability in climatic factors: temperature and rainfall on seasonal rice yield from 1969-70 to 2002-03. First, the feasible generalized least square (FGLS) with Just-Pope stochastic production function approach is employed to analyze the panel data. In exploring further the effect of variation in mean and variance of climatic variable across the quantiles of rice yield distribution, quantile regression is applied. In the following sections, details about the empirical model, data used and methods of analysis are provided.

4.1 Panel data model specification

We summarize our fixed effect panel data yield model as given in the equation (1) below:

$$\begin{aligned} Yield = f(&Trend, Temperature, SDTemperature, Precipitation, \\ &SDPrecipitation, Temp\ X\ ACZone, Ppt\ X\ ACzone) \end{aligned} \tag{1}$$

Here, *Temperature* denotes average temperature in a district over each cropping season, *Precipitation* represents total rainfall in a district over each cropping season, *SD Temperature* and *SD Precipitation* are standard deviation of corresponding climatic variables over the months. *Temp X ACZone* and *Ppt X ACzone* are the sets of interaction variables between agro-climatic zone dummies and climatic variables. A summary of the variables used in the model is presented in Table 5.

To estimate the effects of climatic variables on mean yield and yield variability under heteroskedastic disturbances,[6] the Just and Pope stochastic production function[7] is applied as given in Equation (2) below.

$$y = f(X, \beta) + \mu \doteq f(X, \beta) + h(X, \alpha)^{0.5}\epsilon \tag{2}$$

Here, y is the output or yield, X is a vector of explanatory variables, $f(\cdot)$ denotes the deterministic component (mean function) of yield and relates X to average yield with β representing the set of estimated coefficients, μ is the heteroskedastic disturbance term with a zero mean, $h(\cdot)$ is the stochastic component (variance function) of yield and relates X to the standard deviation of yield with α representing the corresponding set of estimated coefficients, and ϵ is a random error term with a mean of zero and variance of σ^2. Thus,

[6] There is no need of conducting a separate test to check the presence of heteroskedasticity because the same will be reflected by the estimated F-value in the second stage Log yield variance regression. Cabas et al. (2010) and McCarl et al. (2008) also do not perform any test to check heteroskedasticity.

[7] Taking care of heteroskedasticity is not the main strength of of stochastic production function approach because it is equally possible with the robust estimation techniques. The main utility of this method is in exploring the effect of independent variables on the variance of dependent variable.

this specification shows mean yield and yield variance as two separate components being explained by change in input variables i.e. temperature, rainfall and other derived variables (Just and Pope (1978); Chen et al. (2004)).

Although yield and climatic data used here covers 23 districts in Andhra Pradesh over a time period of 33 years, unobservable effects of omitted variables may lead to a biased estimate of relationship between dependent and explanatory variables. For instance, rice farming in a given district may depend on some or all of the following factors: local soil condition, labor and fertilizer availability, infrastructure and access to major markets. Panel data estimation models provide a way to take care of such omitted variables. Two models are normally used to estimate panel data: Fixed Effect (FE) and Random Effect (RE).[8]

This study will use FE model because of two main reasons. First, FE model allows estimating a district-specific effect. Second, there is a possibility of correlation between unobserved time-invariant characteristics and included covariates. For instance, districts with relatively more suitable climate may have developed better irrigation facility or more fertile soil over a period of time. Since RE model strictly requires the assumption of no correlation between unobserved time-invariant characteristics and independent variables, FE model can provide a better estimate. In other words, if the above assumption is violated, FE will give unbiased estimates while RE will not. Hence, Fixed Effect model is employed here. The choice of FE is also consistent with McCarl et al. (2008) and Cabas et al. (2010).

In similar models, unit specific time varying unobserved effects are also likely to cause an omitted variable bias. All input variables other than climate such as fertilizer, pesticide, labor etc. may come in this category. However, following McCarl et al. (2008), Chen et al. (2004) and Weersink et al. (2010), we assume that there is no significant correlation between time varying input factors and climatic factors. Furthermore, included time trend variable is supposed to incorporate time-varying determinants to crop yield such as technology

[8]Hausman specification test is not used here to determine which model to use since the choice of fixed effect model to estimate the panel is well supported by previous studies and it also addresses concerns pertaining to district specific effects.

improvements.

4.2 Panel data model estimation

4.2.1 Panel unit root test

The Just and Pope production function as specified above may incur issues related to spurious correlation between included variables (Chen et al. (2004)). These spurious correlations between variables are likely to be caused by deterministic and stochastic trends in the series (Granger and Newbold (1974)) and thus, correlations can be detected between variables which are increasing for different reasons (McCarl et al. (2008)). As Chen et al. (2004) point it out; even including a deterministic time trend in the model may not completely solve the issue of spurious correlation. So, before proceeding with three stage FGLS procedure to estimate the panel parameters, it is necessary to test for the presence of unit root for each variable. The variables which are found to have an $I(1)$ series must be differenced before panel estimation (McCarl et al. (2008)).

Although traditional panel unit root tests work only with one time series at a time, recently developed methods for panel unit root testing allow the test for unit roots across all cross-sections using the panel structure as a whole. Previous studies with similar panel data set have used unit root tests proposed by Im et al. (2003) (IPS) and Levin et al. (2002) (LLC). As a pooled test, LLC is found to be useful with a panel of moderate size ($10 < N < 250$ *and* $25 < T < 250$). IPS is an averaged t-test and is found to be more powerful. Given this, Maddala and Wu (1999) propose the use of Fisher test for testing unit roots in panel variables which is based on combining the p-values of the unit root test statistics in each cross-sectional unit more and they show that Fisher test achieves more accurate size and high power relative to the LLC test. However, the biggest strength of Fisher test comes from the fact that it does not require panel to be balanced (Barbierie (2009)). IPS and LLC both require panel structure to be balanced and for the same reason, and thus McCarl et al. (2008) delete all the observations with missing variables while applying the IPS test. In the same way, this study employs Fisher test to carry out panel unit root testing in our analysis.[9] This test combines the P-values of the unit root test statistics of N independent Augmented Dickey-Fuller regressions, where N represents the number of districts.[10]

4.2.2 Estimation

Three stage FGLS procedure is applied to estimate the parameters of equation (1). In the first stage, y is regressed on $f(X, \beta)$ and we calculate the resulting least square residuals as $\hat{\mu}$ as $\hat{\mu}=y - f(X, \beta)$, where $\hat{\mu}$ is a consistent estimate of μ, a heteroskedastic disturbance term with zero mean. The second stage regresses square of least square residual ($\hat{\mu}$) on its asymptotic expectation $h(X, \alpha)$ where $h(\cdot)$ is assumed to be in exponential form. Using the predicted error terms from the previous stage as inverse of weights, third stage produces FGLS estimates for the mean yield equation. It results in a consistent and asymptomatically efficient estimator of β under the usual conditions for stochastic production functions. The final stage results are corrected for the heteroskedastic disturbance term with this procedure (Just and Pope (1978); Cabas et al. (2010)). In all three stages, district dummies are included to take fixed effects into account.

To summarize, the estimated set of parameters β and α provides information about the effect of climatic variables on mean and variability of rice crop yield respectively. In other words, α is estimated with Log yield variance regression in the second stage and it provides an estimate of effect of climatic factors on the yield variability. On the other hand, β is estimated with Yield mean regression in the third stage and it gives an estimate of effect of climatic factors on the mean yield.

Since we have included interactional terms, the zone-wise effect of changes in temperature

[9] Researchers have found different results for panel unit root test in similar type of studies. Chen et al. (2004) find some variables to be non-stationary using IPS test and they difference these variables before proceeding with the panel estimation procedure. McCarl et al. (2008) do not find unit roots in any of their variables. Cabas et al. (2010) do not carry out any unit root test on their panel.

[10] See Barbierie (2009) for more details.

and rainfall can be easily estimated. However, results obtained via the three stage FGLS cannot be used to examine how farmers in an extreme distribution of the rice yield residuals would be affected by changes in climatic variables. The next section describes an application of quantile regression to tackle this problem.

4.3 Quantile regression

Quantile regression provides a powerful and effective method to generate useful insight for policy makers by estimating the linear relationship between independent variables and the median or other specified quantiles of the dependent variable. First introduced by Koenker and Bassett (1978), in the estimated conditional quantile functions, quantiles of the conditional distribution of the dependent variable are expressed as a function of observed covariates.[11] Thus, quantile regression provides a flexible way to explain how a given quantile ρ $(0 < \rho < 1)$ of the rice yield changes as a result of changes in one or more climatic variables.

In quantile regression, an estimated coefficient vector is not much sensitive to outlier observations on the dependent value because the function is a weighted sum of absolute deviation.[12] Furthermore, when error term is non-normal, quantile regression estimators may be more efficient than least squares estimators (Buchinsky (1998)).[13] Both of these issues are highly likely in the case of rice crop yield. For instance, high yield varieties and other favorable factors may lead to higher yield in certain areas in a given district and for similar reasons; a relatively lower level of rice yield is also possible at the same location. In such cases, generalizing the effect of change in climatic variables over the whole spectrum of crop yield may not be very helpful and resorting to an objective function that identifies a

[11] Recently some related studies have used quantile regression. Evenson and Mwabu (2001) examine 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 relation 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

[12] This is the main conceptual difference in estimation between quantile regression and OLS. Former is based on *least absolute distance deviation* while later is based on *least square distance deviation*.

[13] Non-normality in error term does not cause any biasedness in OLS estimates, though it does affect the efficiency.

conditional quantile would be a better alternative.

In this study, to empirically test our assumption of the non-normal distribution of rice yield, Shapiro-Wilk and Shapiro-Francia normality tests are employed. Quantile regression provides valuable new information by estimating the whole spectrum of coefficients on climatic variables corresponding to different rice yield levels. Here, the spectrum is divided into five divisions i.e. 10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} quantiles for the analysis purpose.

$$\begin{aligned} Yield = f(&Trend, Temperature, SDTemperature, Precipitation, \\ &SDPrecipitation, ACzonedummies) \end{aligned} \tag{3}$$

Equation (3) above summarizes the model used for analysis using quantile regression method. Although district dummies and interactional variables are not included, the results still give a useful qualitative measure of the effect of climatic variables across the range of yield in various agro-climatic zones. The quantile regression function is given as:

$$y_i = X_i\beta_\theta + u_{\theta i} \ with \ Quant_\theta(y_i|X_i) = X_i\beta_\theta \tag{4}$$

where $Quant_\theta(y_i|X_i)$ represents the θ^{th} conditional quantile of rice yield y and X denotes the set of independent variables and subscript $i = 1, 2, 3, \ldots, N$ represents individual districts. Relevant climatic variables included in the model are: seasonal average monthly temperature, seasonal mean total monthly precipitation and their standard deviations. To capture the change in technology trend, year variable is also included. Finally, in order to control for fixed effects by agro-climatic zones, zone dummies are also included. The distribution of error term $u_{\theta i}$ is left unspecified in quantile regression models (Koenker and Bassett (1978)).

The most useful feature of quantile regression is that the estimated parameters differ over quantiles of yield distribution. For example, the magnitude of increase in average temperature may be relatively higher for lower levels of yield located in the 10^{th} quantile. Similarly, the effect of change in temperature and rainfall is expected to be different for yield in the 90^{th} quantile than yield in the 10^{th} quantile. In particular, this exercise explores how climatic variables affect the crop yield on the median as well as extreme quantiles of the yield distribution.

The quantile regression method requires a special treatment for heteroskedasticity. Bootstrapping methodology is the most frequent application in the literature to obtain robust standard errors. This method allows drawing samples of size n with replacement from the actual observed data set. In this study, number of resamples is set at 400. The bootstrap method helps in estimating the standard error as well as confidence interval for an individual quantile regression parameter and ensures robust estimates are obtained (Hao and Naiman (2007)).

The quantile regression model includes zone specific time invariant characteristics using zone dummies instead of fixed effects of time invariant district specific factors. We intend to capture agro-climatic zone wise heterogeneity with this model assuming that within an agro-climatic zone, effect of omitted variables does not vary significantly. Further, the data set consists of only 23 or less observations per district and so, it may not be very useful in analyzing the effect of climatic factors across the five quantiles of rice crop yield distribution in a true Fixed effect panel model. Finally, quantile regression model already takes care of unobserved heterogeneity and heterogeneous effects to a great extent. Hence, in place of district dummies, agro-climatic zone dummies are included in the quantile regression model.

5 Results and discussions

5.1 Panel unit root test results

Results of the Fisher panel unit root test applied on the data on seasonal yield and climatic variables are presented in Table 6. The estimated test statistics clearly suggest that the null hypothesis of unit root can be rejected for all included variables at the 99% confidence interval. Moreover, seasonal yields as well as climatic variables show the same results with or without trend.[14] Since the panel unit root results clearly reject the null hypothesis of non-stationarity, there is no need to difference the data before the three-stage FGLS estimation.[15]

5.2 Panel estimation results

Three stage FGLS procedure is applied to estimate the parameters of equation (2). Log yield variance regression, in the second stage, adjusts standard errors appropriately taking first stage yield variation into account. F-value is less than 0.1 in Log yield variance regression for Kharif as well as Rabi, which suggests existence of heteroskedasticity (See $Prob > F$-values of Log yield variance regression in table 7). The final stage FGLS estimates parameters for Yield mean regression using the square root of variance predictions from the second stage as inverse of weights. Variance equation takes a non-linear (logarithmic) form and assures positive predicted variances, whereas Yield mean regression is linear in all dependent and independent variables. The final estimates of the stochastic function parameters with Kharif and Rabi rice yield as dependent variable are shown in Table 7.

Table 7 shows the estimated value of coefficients for Log yield variance (second stage) and Yield mean (third stage) regressions. Log yield variance takes Log of variance of the residuals from the first stage as dependent variable and corresponding part of the table provides information about effect of climatic factors on the yield variability. Here, the interpretation of positive coefficient will imply that a higher yield variance is expected with an increase in the corresponding explanatory variable, keeping all other factors constant. Furthermore, joint significance test result (F-test) for Kharif as well as Rabi, given at the bottom of the Table 7 shows that effect of all the climatic variables on the yield variance is not null and it validates our assumption about heteroskedasticity in the model.

[14] Adding a time trend usually improves the test statistic in favor of alternate hypothesis in this case (Wooldridge (2001)). Here, the results are positive even without including the time trend. However, specified model includes time trend to take technology effect into account.

[15] These findings are in consistent with (McCarl et al. (2008)). However, earlier study by Chen et al. (2004) did find unit root in the panel and so, followed the differencing procedure before estimation.

The outcome in the mean regressions of Table 7 suggests that mean yield significantly varies with both mean and variance of temperature and rainfall variables. In particular, irrespective of season, any increase in mean temperature is likely to cause a reduction in mean yield. The effect of increase in precipitation is advantageous for Kharif rice. Overall, the effects of change in the mean of climatic variables are apparently more significant in the Kharif season than in the Rabi season. Yield variability is likely to increase with an increase in the variance of climatic variables, though some of the coefficients are not significant. A detailed discussion on Log yield variance and Yield mean regression for each season is presented below.

Furthermore, the coefficient on variable Temperature denotes the effect of temperature on the base agro-climatic zone i.e. agro-climatic zone 1 in our case.[16] The coefficients on the terms *Temp X ACZone* 'n' show the difference between estimate for the effect of Temperature for agro-climatic zone 'n,' where $n = 2, 3, \ldots, 8$ with respect the base zone i.e. agro-climatic zone 1.[17] Finally note again that the joint significance test results (F-test), given at the bottom, reflect that the model is able to explain the variation in the mean rice yield adequately.

5.2.1 Kharif rice yield

First, we focus on explaining the results of Kharif rice yield shown in Table 7. Most of the estimated parameters in the Yield mean regression show a significant effect on the yield. As expected, an increase in the average temperature in Kharif months is associated with a decrease in the rice yield whereas yield is likely to increase with an increase in the total rainfall for most of the agro-climatic zones. The Log yield variance regression suggests an increase in yield variability with increase in mean as well as intra-seasonal variance of

[16] To analyze zone wise effect from the coefficient of interaction terms, agro-climatic zone 1 is taken as the base zone.

[17] Additional statistical tools to compute point estimate and standard errors for a linear combination of coefficients can be employed here. However, we follow the way McCarl et al. (2008) estimated and interpreted the coefficients.

climatic variables.

Technology trend is showing a significant positive correlation with the Kharif rice yield. The dataset used in the analysis covers the post-green revolution period in India and it is expected that technology consistently improves the yield. The effect of change in average temperature over Kharif months is showing a negative and significant effect on the yield. The adverse effect of increase in average temperature on the mean yield is the highest for agro-climatic zone 1 and it remains negative and significant for all other zones except agro-climatic zone 3. The high and significant inverse effect of average temperature rise on rice yield is in line with the previous studies on tropical regions in India and other countries (Seo et al. (2005); Cline (2007)). The effect of change in total precipitation is mostly positive for all agro-climatic zones except Godavari (zone 2) and Krishna (zone 3). These two zones are coastal regions and are likely to receive high rainfall. The results suggest that an increase in precipitation in these regions may not have any positive effect on yield. All other zones observe a positive impact of any increase in rainfall with the Central Telangana zone garnering the highest estimated coefficient.

The variability in average monthly temperature and total monthly rainfall, as denoted by SD Temperature and SD precipitation in Table 7, is found to be negatively correlated with the mean rice yield. Since climate variability is predicted to increase in the future, this finding is important for the region. This finding is also consistent with Mendelsohn et al. (2007) who reported the negative impact of an increase in intra-seasonal variance in temperature and rainfall on the farm value, which acts as a proxy for the productivity of farms.

Although the estimated coefficients for Agro-climatic zones 2, 3, 4 and 7 suggest that increase in mean temperature may decrease the yield variability, the effect of change in the mean climatic variables, i.e., temperature and precipitation on yield variability is positive in general for most of the zones (Log yield variance regression results, Table 7). Further, the positive signs on *SD Temperature* and *SD Precipitation* suggest that yield variability is likely to rise with an increase in intra-seasonal variance in temperature and rainfall.

All together, any increase in average temperature tends to decrease the mean yield of rice in Andhra Pradesh, whereas an increase in total precipitation is likely to increase the mean yield. Overall, rice yield in Andhra Pradesh is likely to suffer from any increase in the average temperature and a decrease in the total precipitation. Results suggest that increasing intra-seasonal variance in temperature and rainfall may lower down the mean yield while increasing the variability in the rice yield. Kharif rice yield variability is also likely to increase with increase in total precipitation for most of the zones, whereas effect of temperature on yield variability is zone specific.

5.2.2 Rabi rice yield

Next, we focus on presenting the regression results of Rabi rice yield again shown in Table 7. As per the coefficient on year variable, technology trend shows a significant and positive effect on Rabi rice yield. It should be noted that the estimate of trend for Rabi rice is about 10% higher than the same for Kharif rice and it may partially explain why the average Rabi rice yield is higher than the average Kharif rice yield (Figure 4). The estimated coefficients for Rabi rice yield suggest a negative impact of increase in average temperature and intra-seasonal variance in average monthly temperature and total monthly precipitation over the Rabi months. However, the effect of precipitation over mean yield is ambiguous and varies across agro-climatic zones. Results from the Log yield variance regression suggest an increase in yield variability with increase in average temperature and intra-seasonal variance in both climatic variables. Many of the estimated coefficients are not found to be significant, so interpretation presented here is more of qualitative in nature.

Estimated coefficient for *Temperature* in Yield mean regression is consistently negative for most of the agro-climatic zones suggesting an inverse effect of an increase in average temperature on the mean Rabi rice yield (Yield mean regression, Table 7). Only for Godavari and Krishna agro-climatic zones (zones 2 and 3), the estimated parameter is positive and it seems that local soil and other conditions may lead to an increase in yield with a rise in average temperature. Results suggest that the zone specific effect of an increase in precipitation would likely increase mean yield for four out of eight agro-climatic zones. These four zones namely- Krishna, Southern, Northern Telangana and Central Telangana are likely to get benefitted from any increase in rainfall in Rabi season. The coefficient on *SD Temperature* and *SD Precipitation* are negative and significant[18] and so, in a way similar to Kharif rice, mean Rabi rice yield is likely to decline with an increase in intra-seasonal variance in climatic variables.

Log yield variance regression results (Table 7, left side) suggest that the yield variability is likely to increase with increase in intra-seasonal variance in temperature and precipitation. The effect of changes in average temperature on yield variability is generally positive; whereas increase in total precipitation is seem to be reducing the yield variability for most of the agro-climatic zones. Particularly, for agro-climatic zones 2, 3 and 4, these effects are significant and negative. Since Rabi rice is mostly dependent on irrigation and so it is possible that a year with a good amount of rainfall in Rabi months may observe less uncertainty in the rice yield.

The overall effect of increase in temperature is negative on the mean Rabi rice yield, whereas the effect of increase in precipitation is dependent on specific agro-climatic zones. Increase in intra-seasonal variance in climatic variable is likely to decrease the mean yield while increasing the yield variability. The effect of increase in average temperature on yield variability is positive in general, while an increase in total precipitation is associated with a decrease in yield variability for about 50% of agro-climatic zones.

5.2.3 Yield across Kharif and Rabi cropping season

The most consistent finding is the negative impact of increase in intra-seasonal variance in climatic variables on the mean rice yield irrespective of cropping season. From the Log

[18] P-value for the estimated coefficient of *SD Precipitation* is close to 10%.

yield variance regression results (Table 7), it is evident that the effect of increase in intra-seasonal variance in temperature and rainfall is likely to increase the yield variability in both seasons. Furthermore, an increase in average temperature and total precipitation is expected to increase the inter-annual yield variability for rice in most of the agro-climatic zones.

Both cropping seasons are likely to witness a decrease in mean rice yield with an increase in average temperature and a decrease in total precipitation for most of the agro-climatic zones. Yield variability is found to be increasing with time for the Kharif as well as the Rabi season. However, the estimated coefficient for the technology trend for Rabi rice is more than Kharif rice's, which may be showing the increasing irrigation facilities[19] and development of winter season compatible yield varieties over time. The positive sign on the coefficient for trend is consistent with previous studies (Chen et al. (2004); McCarl et al. (2008); Cabas et al. (2010)).

5.3 Quantile regression results

This section further explores the effect of climatic variables on Kharif and Rabi rice yield across the quantiles of rice crop yield distribution. A graphical presentation of the quantile of Kharif and Rabi rice yield is shown in Figure 5. These quantile plots facilitate a quick comparison of ordered values of a seasonal yield data with quantiles of the normal distribution (shown as a straight line). A significant level of deviation from the normal distribution is clearly evident here. Furthermore, Shapiro-Wilk and Shapiro-Francia[20] normality tests are conducted for both dependent variables, i.e., Kharif and Rabi rice yield. Table 8 shows that the null hypothesis of normality can be rejected for both yield variables at 99% confidence level. The estimates by quantile regression are more efficient than the least square regression when error terms are non-normal (Buchinsky (1998)) and the above results formally justify

[19] Irrigation is likely to be more important for Rabi rice than the Kharif rice since the latter receive adequate rainfall with the Southwest summer monsoons.

[20] Shapiro-Wilk and Shapiro-Francia are two numerical methods to test normality in data. The Shapiro-Wilk test gives the ratio of the best estimator of the variance to the usual corrected sum of squares estimator of the variance. The value of ratio varies from 0 to 1, where 1 denotes a perfect normality. Shapiro-Francia is a modified form of Shapiro-Wilk (Park (2008)).

the use of this method. In order to take care of heteroskedasticity which is an already known issue in this study, bootstrapping is used to estimate robust standard errors.

The parameters for quantile regression are estimated for five levels of quantiles: 0.10, 0.25, 0.50, 0.75 and 0.90 and the results are presented in Table 9 and Table 10 for Kharif and Rabi rice yields respectively. Here, column q50 i.e. results for the 50^{th} quantile corresponds to regression through the median. The interpretation of the estimated coefficients is conditional to the specific quantile and so would remain valid within the quantile. The estimates indicate the likely effect of an increase in one unit of the corresponding independent variable on the yield variable within the quantile in consideration. Moreover, for the variables specified in the form of interaction terms in the model, interpretation should remain confined to the corresponding zones. For instance, in agro-climatic zone 1, holding all other factors constant, an increase of 1 cm in rainfall is associated with an increase of 0.893 Kg/hectare in the Kharif rice yield at 10% quantile level (Table 9). Since the estimated coefficients provide extensive detail about the impact of climatic variable across the quantiles of yield distribution for each agro-climatic zone, the following discussion is intended to capture the most interesting points. However, using an approximation method to visualize the zone wise effect of climatic variables, similar to the one applied by Conley and Galenson (1994), the findings are presented qualitatively.

5.3.1 Kharif rice yield

The estimated coefficients for Temperature show interesting results across different quantiles and agro-climatic zones (Table 9). For base zone i.e. agro-climatic zone 1, the effect of average temperature on Kharif rice yield is consistently negative and significant. Moreover, the degree of inverse impact is significantly higher for the lowest quantile (q10) than the same for the higher quantile (q90) of rice yield. The results clearly suggest that farms at the lower tail of yield distribution are likely to witness greater loss in Kharif rice yield with an increase in average temperature in agro-climatic zone 1. The estimates support similar effect for rice yield in agro-climatic zone 2, 5, 7 and 8 too. For rest of the zones, estimated coefficients suggest either non-significant or a positive correlation between average temperature and rice yield. However, in general, the coefficients on the lower quantiles consistently suggest a negative and higher impact of an increasing average temperature on the Kharif rice.

The effect of change in Precipitation is found to vary significantly across various agro-climatic zones. Zones 1, 5, 6 and 7 consistently show a positive impact of an increase in total precipitation on the yield suggesting an increase in rainfall may be beneficial for Kharif yield, though estimated coefficients are not significant for all of the quantiles. Out of the remaining zones, agro-climatic zone 2 is likely to observe a decrease in rice yield with an increase in precipitation for all the quantiles. Higher absolute values of corresponding estimated coefficients for lower quantiles clearly imply that the farms with rice yield on the lower side of yield distribution are more sensitive to changes in seasonal precipitation.

The estimated coefficients for intra-seasonal variance in climatic variables are not significant for any of the quantiles. However, their signs imply that an increase in the variances in either monthly average temperature or total precipitation is likely to reduce the rice yield for lower quantiles. In other words, the farms with rice yield lower than the median are expected to observe an adverse impact of increase in the intra-seasonal variability in climatic variables. Overall, the farms at the lower side of the Kharif rice yield distribution are likely to suffer more with any increase in average temperature, a decrease in total precipitation, or an increase in the intra-seasonal variability in climatic variables.

5.3.2 Rabi rice yield

The effect of change in climate variables on Rabi rice yield differs across the agro-climatic zones and in some cases, it even varies significantly within a zone across the rice yield quantiles (Table 10). The estimated coefficients for average temperature suggest a negative impact of any increase in the average temperature on the rice yield for almost all the zones except zone 1 and 2. Although the estimated parameters are positive for these two zones, the values are not significant. In a way similar to the Kharif rice case, the results reflect a high degree of the inverse effect on the yield for lower quantiles.

Although some of the zones are found to be benefitting from an increase in precipitation in terms of Rabi rice yield, in most of the cases the estimates are negative across the quantiles. Estimated coefficients for Agro-climatic zones 1, 2, 6, 7 and 8 are consistently negative across the quantiles and some of the values are significant at the 1% level. Agro-climatic zones 3, 4 and 5 are showing the positive impact of an increase in total precipitation on the Rabi rice yield for lower quantiles, but the effect becomes negative as we proceed towards the higher quantiles of yield distribution.

The intra-seasonal variation in climatic variables tends to influence rice yield in the expected manner. Most of the estimated coefficients are negative which suggests that an increase in the variance in monthly average temperature or monthly total precipitation is likely to decrease the Rabi rice yield. Furthermore, the higher absolute values of the estimated coefficients for lower quantiles imply a more severe inverse effect on the farms with rice yield on the lower side of the yield distribution.

In summary, an increase in average temperature, total precipitation and their respective intra-seasonal variances is likely to decrease the yield in Rabi season. Although the degree of effect on crop yield varies across the zones, in general, these effects are found to be more intense for lower levels of yield.

5.3.3 Yield across Kharif and Rabi season

Overall, both cropping seasons are likely to suffer from an increase in the average temperature. It is evident that the lower quantiles of rice yield are more sensitive towards any change in average temperature irrespective of the cropping season. Effect of change in precipitation on rice yield varies across the zones, quantiles and cropping seasons. While a Kharif crop is likely to get benefitted for most of the agro-climatic zones, a Rabi crop may witness a significant loss in yield with an increase in precipitation. Intra-seasonal variance in climatic variables exhibits a negative correlation with the yield and again, sensitivity is more on the lower side of yield distribution for both of the cropping seasons.

Why lower unit yields are more sensitive to climate? Lower yield levels may be more sensitive because of poor farm management practices such as irrigation, soil fertility maintenance etc. It also includes not having proper adaptation strategies in place and so such farms are likely to suffer more with any adverse change in climate.

5.3.4 Zone wise graphical analysis of yield sensitivity to climate

Tables 9 and 10 reflect a significant level of variation in the magnitude as well as the sign of the estimated coefficient across eight agro-climatic zones, which make it difficult to filter the local and yield level specific effects. Furthermore, understanding the location specific characteristics of the effect of climate on crop yield is very important for designing effective adaptation policies (Mall et al. (2006)). Hence, an effort to show the individual effect of change in temperature and precipitation on seasonal rice yield is made here.

The graphs shown in Figure 6 to Figure 9, plot predicted values of rice yield for Kharif and Rabi against corresponding seasonal average temperature and total precipitation. The coefficients estimated with quantile regression are used to predict the yield level. All the independent variables except the one shown on the X- axis are kept at their mean levels. These plots are similar to the return to education vs. experience plots by Buchinsky (1994) and predicted wealth vs. age plots by Conley and Galenson (1994).

$$\hat{y_k} = f(trend, temperature, \beta_i, mean\ of\ other\ independent\ variables) \tag{5}$$

where β_i represents the parameters estimated in equation (4).

Figures 6-9 provide a qualitative understanding of the inter-relationship between climatic factors and rice yield by plotting the function summarized above (equation (5)). For example,

Figure 6: Graphical display of agro-climatic zone wise relationship between Kharif rice yield and Temperature provides a quick observation that the lower quantiles are more sensitive to change in the average temperatures than the upper quantiles, especially in agro-climatic zone 1, 3 and 5. These plots are not much helpful in extracting any quantitative information.

For Kharif rice yield, the effects of temperature across all the zones are not uniform (Figure 6). For agro-climatic zones 1 and 5, these are clearly negative, whereas the sensitivities to temperature are relatively low in zones 2, 4, 6 and 8. Interestingly, agro-climatic zones 3 and 7 reveal that quantile wise predicted yield may diverge or converge with increasing temperature and it shows a clear case of heteroskedasticity. As evident from Figure 7, Kharif rice yield increases with an increase in total precipitation for agro-climatic zones 1, 5, 6 and 7. The plots for zones 2 and 3 reveal a decreasing trend in yield with a rise in total precipitation. Agro-climatic zones 1, 4 and 5 show the heteroskedastic behavior of yield against changes in precipitation. In all of the plots, the slope of the lines representing the upper quantile is flatter suggesting a higher sensitivity towards average temperature and total precipitation in lower quantiles.

Similarly, plots of predicted values of Rabi rice against average temperature show a diminishing trend in the yield with increasing temperature (Figure 8). Agro-climatic zones 2, 3, 6 and 7 observe a higher degree of inter-quantile variation in estimates, which calls for a cautious interpretation of the results. A lack of sufficient number of observations may be one possible reason. However, further research is required to study these patterns. In line with our discussion in the previous section, Rabi rice yield show a decreasing trend with total precipitation for all agro-climatic zones except zone 3, 4 and 5 (Figure 9). Heteroskedastic behavior of yield is clearly evident from both figures.

The quantile regression analysis presented above confirms the major findings of the stochastic production function approach as discussed in previous section. It further provides detailed insight about the inter-relation between yield and climatic variables across the quantiles of seasonal rice yield distribution. Two main points are revealed by the quantile regression model. First, the degree of effect of climatic variables on yield clearly differs according to agro-climatic zones. Second, even in the same agro-climatic zone, the sensitivity to change in temperature and rainfall varies across the quantiles of rice yield distribution and farms with yield on the lower side of yield distribution are likely to incur more loss in the productivity with unfavorable changes in temperature. Thus, this analysis provides evidences in favor of heterogeneity and intensified downside risk due to changes in climate factors.

6 Conclusion

The objective of this work is to study the effect of climate on the rice crop yield in Andhra Pradesh, India. Three main research questions addressed here are: First, how does the change in temperature and rainfall affect seasonal rice yield across the agro-climatic zones in the state? Second, how does an increase in intra-seasonal variability in temperature and precipitation affect the seasonal rice yield? Lastly, how do these effects vary across the quantiles of yield distribution? Two methodologies are employed here: (i) Three stage FGLS using a stochastic production function approach and (ii) quantile regression.

There are strong evidences that an increase in the average temperature will inversely affect the crop yield irrespective of the cropping season. A rise in precipitation is found to be advantageous for most of the districts in the Kharif season. Both of these findings are in line with our expectations and previous studies for a tropical region (Cline (2007); Mendelsohn et al. (2007); Seo and Mendelsohn (2008)). However, for Rabi rice crop, the effect of change in precipitation varies across the agro-climatic zones. The yield variability, in general, is likely to increase with a rise in the average temperature and total precipitation. The change in inter-annual variance in temperature and rainfall is found to have an inverse effect on the mean yield and a proportional effect on the yield variability. This finding provides further basis to the concerns of productivity loss with increasing fluctuations in climate.

The results reveal that the sensitivity or rice crop yield to change in temperature and rainfall varies across the quantiles of yield distribution even in the same agro-climatic zones. It is clearly evident that farms with lower yield levels are likely to observe greater loss in their crop productivity, which further implies that rice farms are facing a downside risk because of changes in climatic factors. As mentioned before in the corresponding section, poor farm management practices may be responsible for such an effect. Finally, the findings confirm that a high degree of aggregation at the province or country level may overlook critical information required for adaptation at the local level. There are strong evidences showing various agro-climatic zones face different kinds of threats to the crop productivity suggesting heterogeneity in the effect of climate across agro-climatic zones. Thus, this study presses the case for a more location specific approach in further research in the climate and agriculture area.

As a limitation, this study does not take long term adaptations like crop-switching into account, though it still reflect the farm level adaptation with changes made by farmers to maximize the crop yield. Second, the variation in yield cannot be related to production directly because changes in crop area are not included in the model. This study can be further extended to yield forecasting for various climate scenarios, which will be useful for an assessment of future risk and trend in crop yield.

The analysis presented in this study is vital for policies related to food security, rural poverty and crop insurance. Under a combination of major projected climate scenarios, Southeast India is likely to observe a 3.05 degree Celsius increase in the average temperature and a 3.42 mm per day rise in the average precipitation by 2070-90 (Cline (2007)), which translates into a high degree of loss in crop productivity. The severity of the impact of climate varies across the zones and so will be the effect on the crop productivity. It renders common nation or state level adaptation policies irrelevant and ineffective. Hence, the policy makers need to take the heterogeneity in the impact of climate into account in order to plan and utilize available resources in the most effective way.

Local and state level policies for ensuring food security and alleviating rural poverty should also integrate the risk of crop yield loss into their design. Proper irrigation facilities, microfinance and regionally-relevant research and development projects may play an important role in mitigating the adverse impact of climate variability and hence, these must be prioritized for the most vulnerable districts in order to make the food production systems resilient to climate change. High downside risk which comes from an increase in the variability of crop yield distribution suggests a thorough risk analysis. Particularly, because of the increasing pace of climate change (IPCC (2007)), the findings of this study are very relevant to the risk modelers in crop insurance companies as well as government regulators. Finally, in order to ensure optimal utilization of land resources in the light of expected changes in mean and variance of crop productivity with changes in climatic factors, land planning should be integrated with climate change adaptation policy framework.

References

Aggarwal, P. K. (2008). Global climate change and Indian agriculture: Impacts, adaptation and mitigation. *Indian Journal of Agricultural Sciences*, 78(11):911–919.

Auffhammer, M., Ramanathan, V., and Vincent, J. (2006). Integrated model shows that atmospheric brown clouds and greenhouse gases have reduced rice harvests in India. *Proceedings of the National Academy of Sciences of the United States of America*, 103(52):19668–19672.

Barbierie, L. (2009). Panel unit root tests under cross-sectional dependence: An overview. *Journal of Statistics: Advances in Theory and Applications*, 1(2):117–158.

Buchinsky, M. (1994). Changes in the U.S. wage structure 1963-1987: Application of quantile regression. *Econometrica*, 62(2):405–58.

Buchinsky, M. (1998). Recent advances in quantile regression models: A practical guideline for empirical research. *Journal of Human Resources*, 33(1):88–126.

Cabas, J., Weersink, A., and Olale, E. (2010). Crop yield response to economic, site and climatic variables. *Climatic Change*, Forthcoming.

Chen, C. C., McCarl, B. A., and Schimmelpfennig, D. E. (2004). Yield variability as influenced by climate: A statistical investigation. *Climatic Change*, 66(1-2):239–261.

Cline, W. R. (2007). *Global Warming and Agriculture: Impact estimates by country*. Peterson Institute of International Economics.

Conley, T. and Galenson, D. W. (1994). Quantile regression analysis of censored wealth data. *Historical Methods*, 27(4):149–165.

Dinar, A., Mendelsohn, R., Evenson, R., Parikh, J., Sanghi, A., Kumar, K., McKinsey, J., and Lonergen, S. (1998). Measuring the impact of climate change on Indian agriculture. Technical report, The World Bank.

Evenson, R. E. and Mwabu, G. (2001). The effect of agricultural extension on farm yields in Kenya. *African Development Review*, 13(1):1–23.

Granger, C. W. J. and Newbold, P. (1974). Spurious regressions in econometrics. *Journal of Econometrics*, 2(2):111–120.

Hao, L. and Naiman, D. Q. (2007). *Quantile Regression*. Sage Publication.

Im, K. S., Pesaran, M. H., and Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics*, 115(1):53–74.

IPCC (2007). Climate change-a synthesis report of the IPCC. Technical report, Intergovernmental Panel on Climate Change.

Just, R. E. and Pope, R. D. (1978). Stochastic specification of production functions and economic implications. *Journal of Econometrics*, 7(1):67–86.

Kingwell, R. (2006). Climate change in Australia: agricultural impacts and adaptation. *Australasian Agribusiness Review*, 14:Paper 1.

Koenker, R. W. and Bassett, G. (1978). Regression quantiles. *Econometrica*, 46(1):33–50.

Kumar, H. and Somanathan, R. (2009). Mapping Indian districts across census years, 1971-200. *Economic and Political Weekly*, 44(41-42):69.

Levin, A., Lin, C. F., and Chu, C. S. J. (2002). Unit root tests in panel data: Asymptotic and finite-sample properties. *Journal of Econometrics*, 108(1):1–24.

Maddala, G. S. and Wu, S. (1999). A comparative study of unit root tests with panel data and a new simple test. *Oxford Bulletin of Economics and Statistics*, 61(0):631–52.

Makowski, D., Dore, T., and Monod, H. (2007). A new method to analyse relationships between yield components with boundary lines. *Agronomy for Sustainable Development*, 27(2):119–128.

Mall, R. K., Singh, R., Gupta, A., Srinivasan, G., and Rathore, L. S. (2006). Impact of climate change on Indian agriculture: A review. *Climatic Change*, 78(2-4):445–478.

Malone, E. L. and A. L. Brenkert, A. (2008). Uncertainty in resilience to climate change in India and Indian states. *Climatic Change*, 91(3-4):451–476.

McCarl, B. A., Villavicencio, X., and Wu, X. (2008). Climate change and future analysis: Is stationarity dying? *American Journal of Agricultural Economics*, 90(5):1241–1247.

Mearns, L. O., Rosenzweig, C., and Goldberg, R. (1997). Mean and variance change in climate scenarios: Methods, agricultural applications, and measures of uncertainty. *Climatic Change*, 35(4):367–396.

Mendelsohn, R., Basist, A., Dinar, A., Kurukulasuriya, P., and Williams, C. (2007). What explains agricultural performance: Climate normals or climate variance? *Climatic Change*, 81(1):85–99.

Mendelsohn, R., Nordhaus, W., and Shaw, D. (1996). Climate impacts on aggregate farm value: Accounting for adaptation. *Agricultural and Forest Meteorology*, 80(1):55–66.

Mendelsohn, R. and Rosenberg, N. J. (1994). Framework for integrated assessments of global warming impacts. *Climatic Change*, 28(1-2):15–44.

Ministry of Agriculture, Government of India (2002). Department of Agriculture and Cooperation.

National Aeronautics and Space Administration (2005). What's the difference between weather and climate? urlhttp://www.nasa.gov//.

O'Brien, K., Leichenko, R., Kelkar, U., Venema, H., Aandahl, G., Tompkins, H., Javed, A., Bhadwal, S., Barg, S., Nygaard, L., and West, J. (2004). Mapping vulnerability to multiple stressors: Climate change and globalization in India. *Global Environmental Change*, 14(4):303–313.

Park, H. (2008). Univariate analysis and normality test using SAS, Stata, and SPSS. Working Paper, The University Information Technology Services (UITS), Center for Statistical and Mathematical Computing, Indiana University.

Sanghi, A. and Mendelsohn, R. (2008). The impacts of global warming on farmers in Brazil and India. *Global Environmental Change*, 18(4):655–665.

Sanil Kumar, V., Pathak, K., Pednekar, P., Raju, N., and Gowthaman, R. (2006). Coastal processes along the Indian coastline. *Current Science*, 91(4):530–536.

Schlenker, W. and Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences of the United States of America*, 106(37):15594–15598.

Seo, N. and Mendelsohn, R. (2007). A Ricardian analysis of the impact of climate change on Latin American farms. Technical report, The World Bank.

Seo, N. and Mendelsohn, R. (2008). A Ricardian analysis of the impact of climate change on South American farms. *Chilean Journal of Agricultural Research*, 68(1):69–79.

Seo, N. N., Mendelsohn, R., and Munasinghe, M. (2005). Climate change and agriculture in Sri Lanka: A Ricardian valuation. *Environment and Development Economics*, 10(5):581–596.

Staggenbors, S. A., Dhuyvetter, K. C., and Gordon, W. B. (2008). Grain sorghum and corn comparisons: Yield, economic, and environmental responses. *Agronomy Journal*, 100(6):1600–1604.

Tada, P. R. (2004). Distress and the deceased: Farmers suicides in Andhra Pradesh; A plausible solution. *The IUP Journal of Applied Economics*, 3(5):47–59.

The Directorate of Economics and Statistics (2003). *Trends of Rice Production in Andhra Pradesh (1955-56 to 2001-2002)*. Government of Andhra Pradesh, Hyderabad.

The Directorate of Rice Development, Government of India (2002). Rice in India- A status paper. urlhttp://drdpat.bih.nic.in//.

Tol, R. (2008). Why worry about climate change? a research agenda. *Environmental Values*, 17(4):437–470.

Weersink, A., Cabas, J. H., and Olale, E. (2010). Acreage response to weather, yield, and price. *Canadian Journal of Agricultural Economics*, 58(1):57–72.

Wooldridge, J. M. (2001). *Econometric Analysis of Cross Section and Panel Data*, volume 1 of *MIT Press Books*. The MIT Press.

World Bank (2008). Climate change impacts in drought and flood affected areas: Case studies in India. Technical report, The World Bank.

Table 2: Cropping seasons in Andhra Pradesh

	Sowing	Harvesting
Kharif	May-June	Nov-Dec
Rabi	Dec-Jan	April-May

Source:The Directorate of Rice Development (2002)

Table 3: Agro-Climatic Zones in Andhra Pradesh, India

Sr. 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

Source: Department of Agriculture, Government of Andhra Pradesh

Note: In this study, agro-climatic zone 9 i.e. High altitude & tribal areas is not considered.

Table 4: Descriptive statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Annual					
Rice yield (in kgs per hectare)	738	2025.7	610.1	308.0	5338.0
Average Temperature (in deg. Celsius)	805	27.30	0.96	24.32	29.41
Total Precipitation (in cm.)	805	860.63	251.59	78.07	1579.74
Std. Dev. (Monthly Temperature)	805	3.1210	0.4709	2.1033	4.5793
Std. Dev. (Monthly Precipitation)	805	84.0981	24.7868	27.4899	180.4246
Kharif					
Rice yield (in kgs per hectare)	735	1970.0	595.6	181.0	3438.0
Average Temperature (in deg. Celsius)	782	27.30	1.06	24.65	29.60
Total Precipitation (in cm.)	805	770.28	246.11	0.00	1572.71
Std. Dev. (Monthly Temperature)	782	1.8523	0.4521	0.5531	3.4474
Std. Dev. (Monthly Precipitation)	782	81.2499	31.0438	8.3965	200.7648
Rabi					
Rice yield (in kgs per hectare)	714	2265.6	669.5	166.0	4691.0
Average Temperature (in deg. Celsius)	805	26.21	1.19	21.35	28.79
Total Precipitation (in cm.)	805	45.57	34.82	0.00	187.61
Std. Dev. (Monthly Temperature)	782	3.6794	0.6033	2.1049	5.4670
Std. Dev. (Monthly Precipitation)	782	12.2564	10.0625	0.1262	76.6803

Table 5: Summary of variables used in the empirical model

Variable	Description
Year	representing trend
Temperature	Mean of monthly average temperature in the corresponding cropping season
Precipitation	Sum of total monthly precipitation in the corresponding cropping season
SD Temperature	Standard deviation in monthly average temperature in the corresponding cropping season
SD Precipitation	Standard deviation in total monthly precipitation in the corresponding cropping season
ACZone'n'	Agro-climatic zone dummy for zone 'n'
Temp x ACZone'n'	Interaction term with *Temperature* and agroclimatic zone dummy 'n'
Ppt x ACZone'n'	Interaction term with *Precipitation* and agroclimatic zone dummy 'n'

Table 6: Panel unit root test results using Fisher test

Variable name	test statistic for individual effect	test statistic for individual effect with trend
Kharif rice yield	162.633***	380.145***
Rabi rice yield	144.189***	358.149***
Kharif temperature	434.949***	554.413***
Rabi temperature	424.802***	314.610***
Kharif precipitation	1,171.889***	960.293***
Rabi precipitation	470.108***	354.435***

** Null hypothesis of non-stationarity is rejected with 99% confidence.*

Table 7: Panel data analysis for rice yield in Andhra Pradesh, India (1969-2002)

Variables	Log yield variance regression				Yield mean regression			
	Kharif		Rabi		Kharif		Rabi	
	coef	se	coef	se	coef	se	coef	se
Year	0.018*	0.011	0.041***	0.010	40.50**	1.421	48.95**	1.456
Temperature	0.520	0.706	0.150	0.575	-421.04**	97.502	-36.871	80.324
Precipitation	-0.001	0.002	0.008	0.008	0.522**	0.232	-1.328	1.181
SD Temperature	0.196	0.259	0.400	0.324	-64.96**	33.023	-83.26**	45.770
SD Precipitation	0.002	0.004	0.035*	0.020	-0.157	0.574	-4.320	2.745
Temp x ACZone2	-0.928	0.905	0.322	0.795	335.46**	131.017	141.611	108.221
Temp x ACZone3	-0.943	0.867	-0.413	0.731	461.99**	117.405	267.27**	112.082
Temp x ACZone4	-0.715	0.941	0.114	0.779	319.45**	126.434	-144.956	112.719
Temp x ACZone5	0.883	0.860	0.191	0.695	294.62**	119.762	-0.083	97.448
Temp x ACZone6	-0.130	0.864	0.943	0.703	301.73**	112.950	-56.848	96.011
Temp x ACZone7	-0.958	0.863	-0.265	0.678	417.86**	118.281	-84.770	91.604
Temp x ACZone8	-0.449	0.989	0.046	0.813	285.98**	130.393	-81.615	106.031
Ppt x ACZone2	0.004	0.002	-0.032***	0.010	-1.55**	0.352	-0.853	1.344
Ppt x ACZone3	0.001	0.002	-0.024**	0.010	-0.60**	0.304	2.150	1.500
Ppt x ACZone4	-0.001	0.003	-0.020**	0.009	0.157	0.363	3.24**	1.324
Ppt x ACZone5	0.002	0.002	-0.008	0.012	0.267	0.301	1.446	1.786
Ppt x ACZone6	0.000	0.002	0.002	0.013	0.536*	0.285	1.616	1.699
Ppt x ACZone7	0.002	0.002	-0.019	0.012	0.167	0.307	-1.085	1.486
Ppt x ACZone8	0.002	0.003	0.002	0.015	-0.372	0.408	-4.400**	2.020
Constant	-25.72	21.58	-72.39	20.73	-77,860.5**	2,831.13	-93,846.1**	2,918.84
Number of Obs	735		692		735		692	
Prob >F	0.0692		0.0000		0.0000		0.0000	
Adjusted R^2	0.0197		0.0820		0.7355		0.7605	

note:

1. ****significant at 1%, ** significant at 5%, * significant at 10%*
2. *Dependent variable= yearly/seasonal rice yield in Kg per hectare, Independent climate variables*
3. *Yield mean regression shows the Second stage WLS results with predicted SD as weights.*
4. *Estimated coefficients for District dummies are not shown here.*

Table 8: P-values of normality test

Variable name	No. of Observations	Shapiro-Wilk test	Saparo-Francia test
Kharif rice yield	735	0.0017	0.0047
Rabi rice yield	724	0.0000	0.0000

** Null hypothesof normaility is rejected for both varaibles*

Figure 1: Map of India showing Andhra Pradesh (not to scale). *Source*: http://www.indiandhra.com/ (accessed on April 2, 2010)

Table 9: Quantile regression results for Kharif rice

Variables	Quantile regression results for Kharif rice									
	q10		q25		q50		q75		q90	
	coef	se	coef	se	coef	se	coef	se	coef	se
Year	33.927***	3.113	36.696***	2.539	39.874***	2.212	43.151***	2.508	44.728***	2.983
Temperature	-341.345***	70.517	-275.616***	62.784	-252.872***	61.768	-301.513***	59.556	-239.609***	72.234
Precipitation	0.893***	0.343	0.776***	0.281	0.927***	0.310	0.378	0.266	0.396	0.346
SD Temperature	-21.195	72.510	-93.447	68.714	-14.088	62.386	25.326	65.920	0.378	56.692
SD Precipitation	-0.199	1.654	0.052	1.115	-0.399	0.887	0.097	0.873	0.026	0.837
Temp x ACZone2	193.175	307.464	345.004**	135.942	277.702**	131.193	294.401***	98.238	259.920*	143.552
Temp x ACZone3	577.795***	170.103	389.862***	118.802	319.402***	111.071	419.141***	121.842	271.451	168.484
Temp x ACZone4	352.914***	90.539	351.434***	79.777	329.738***	74.857	338.650***	69.296	241.266***	90.238
Temp x ACZone5	-336.942*	181.746	-255.038**	123.772	-105.341	103.853	-19.088	154.971	2.702	156.952
Temp x ACZone6	385.603***	96.270	289.722***	79.048	300.749***	75.243	354.892***	77.301	256.583**	104.627
Temp x ACZone7	337.441**	132.372	250.845*	138.060	291.777**	142.484	526.826***	146.203	579.710***	221.823
Temp x ACZone8	298.284***	99.194	278.476***	87.342	248.755***	70.202	266.573***	68.315	261.381***	101.318
Ppt x ACZone2	-2.590***	0.904	-2.022***	0.632	-1.753***	0.450	-1.206***	0.416	-1.087**	0.490
Ppt x ACZone3	-0.135	0.620	-0.808*	0.431	-1.292***	0.423	-0.657*	0.384	-0.625	0.485
Ppt x ACZone4	0.036	0.636	-0.147	0.444	-0.817*	0.422	-0.579	0.394	-0.364	0.535
Ppt x ACZone5	-0.260	0.528	-0.308	0.497	-0.543	0.411	-0.218	0.508	-0.341	0.645
Ppt x ACZone6	0.284	0.538	0.341	0.383	0.175	0.359	0.718*	0.390	0.191	0.533
Ppt x ACZone7	-0.048	0.468	-0.284	0.511	-0.143	0.482	0.287	0.436	-0.189	0.647
Ppt x ACZone8	-0.697	0.606	-0.942	0.646	-0.943**	0.458	-0.297	0.580	-0.218	0.966
ACZone2	1,332.001***	397.273	1,211.241***	227.379	1,281.558***	199.694	1,109.734***	143.977	990.216***	202.952
ACZone3	915.305***	242.270	1,108.584***	202.398	1,232.207***	158.563	976.702***	156.802	1,075.630***	223.627
ACZone4	1,142.156***	138.287	1,099.420***	124.298	1,126.321***	111.249	932.769***	108.613	896.850***	139.931
ACZone5	291.987*	153.686	485.667***	184.681	684.885***	147.806	738.644***	158.197	750.678***	161.770
ACZone6	742.035***	151.005	737.777***	127.193	741.652***	110.862	541.489***	107.263	545.308***	140.219
ACZone7	849.212***	126.406	779.644***	118.354	889.439***	126.936	821.365***	118.537	923.105***	169.604
ACZone8	1,018.220***	208.907	972.993***	194.067	1,005.007***	144.347	833.958***	198.760	802.883***	283.904
Constant	-66,680.951***	6,253.865	-71,857.661***	5,124.023	-78,119.303***	4,472.170	-84,373.635***	5,024.969	-87,249.451***	5,929.697
Pseudo R2	0.38		0.41		0.43		0.45		0.45	

*note: 1. ***significant at 1% , ** significant at 5% , * significant at 10% 2. Number of observations = 735*

Table 4. Quantile regression results using Kharif rice yield as dependent varaible

Table 10: Quantile regression results for Rabi rice

Variables	Quantile regression results for Rabi rice									
	q10		q25		q50		q75		q90	
	coef	**se**	**coef**	**se**	**coef**	**se**	**coef**	**se**	**coef**	**se**
Year	37.936***	4.510	44.463***	2.233	48.710***	2.289	54.886***	2.364	60.159***	3.623
Temperature	63.388***	102.220	28.701***	38.884	23.611***	28.442	72.833***	44.732	57.313***	50.643
Precipitation	-1.935***	3.139	-2.030***	1.997	0.133***	1.215	-1.896	1.364	-2.185	1.491
SD Temperature	-302.908	79.597	-217.153	59.668	-167.089	52.735	-161.420	60.841	-78.738	93.570
SD Precipitation	-9.556	6.052	-5.479	4.274	-6.749	4.285	3.061	4.183	3.374	4.510
Temp x ACZone2	73.445	196.647	-3.996**	83.757	62.006**	126.704	221.109***	146.484	232.673*	146.705
Temp x ACZone3	-232.008***	134.226	-100.915***	122.399	30.186***	158.301	-131.174***	120.565	-126.971	109.474
Temp x ACZone4	11.091***	176.906	-127.588***	103.307	-137.240***	69.216	-181.414***	73.894	-156.078***	82.054
Temp x ACZone5	-214.451*	136.375	-174.066**	76.163	-180.763	92.139	-165.402	98.996	-120.532	104.553
Temp x ACZone6	-236.263***	167.753	-261.027***	124.485	-60.193***	97.993	-190.337***	95.904	-150.974**	108.653
Temp x ACZone7	-389.484**	137.257	-267.119*	65.987	-183.941**	68.741	-200.944***	84.698	-276.649***	134.607
Temp x ACZone8	-48.908***	132.285	-111.439***	96.042	-29.341***	61.221	-90.018***	58.085	-66.192***	75.911
Ppt x ACZone2	1.642***	3.508	-0.954***	2.231	-2.689***	1.597	-3.279***	1.384	-2.757**	1.896
Ppt x ACZone3	4.465	3.388	3.331*	2.793	1.177***	2.312	1.333*	1.936	3.177	2.253
Ppt x ACZone4	5.502	3.555	3.185	2.247	2.691*	1.728	1.288	1.378	0.662	1.819
Ppt x ACZone5	4.340	4.064	1.989	2.659	-0.594	2.139	1.534	2.884	2.389	3.107
Ppt x ACZone6	-0.965	4.750	-0.005	3.016	-1.645	1.966	0.394*	2.550	1.261	2.812
Ppt x ACZone7	-0.380	3.838	-0.377	2.317	-2.583	1.457	-3.603	1.961	-2.138	3.040
Ppt x ACZone8	-2.022	4.082	-5.027	3.231	-6.941**	2.933	-7.766	2.112	-6.753	2.588
ACZone2	76.903***	253.969	246.831***	100.320	350.072***	96.772	382.200***	107.057	315.711***	125.132
ACZone3	-522.268***	242.970	-461.620***	137.018	-327.352***	155.608	-178.498***	131.076	-116.018***	135.504
ACZone4	-629.163***	279.565	-485.558***	106.736	-477.788***	87.054	-478.643***	112.307	-427.475***	131.752
ACZone5	-175.366*	273.516	-255.043***	124.089	-203.492***	99.982	-228.229***	120.536	-282.312***	150.274
ACZone6	-458.199***	274.662	-379.286***	106.810	-420.996***	86.045	-505.715***	121.127	-501.643***	157.657
ACZone7	-329.055***	257.516	-275.008***	100.553	-385.419***	88.699	-464.968***	124.536	-352.802***	193.245
ACZone8	-456.178***	256.741	-485.209***	92.139	-429.684***	87.099	-531.163***	110.828	-590.022***	123.809
Constant	-71,963.689***	8,971.670	-85,119.368***	4,512.017	-93,556.164***	4,604.595	-105,690.152***	4,768.359	-116,288.513***	7,334.366
Pseudo R2	0.37		0.44		0.48		0.53		0.59	

*note: 1. ***significant at 1% , ** significant at 5% , * significant at 10% 2. Number of observations = 692*

Table 5. Quantile regression results using Rabi rice yield as depdendent varaible

Figure 2: Map of Andhra Pradesh showing agro-climatic zones

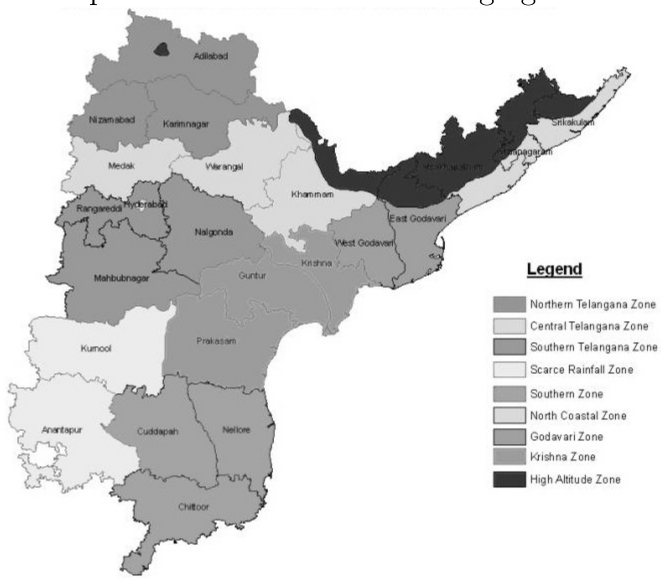

Figure 3: Production of Kharif and Rabi Rice in Andhra Pradesh

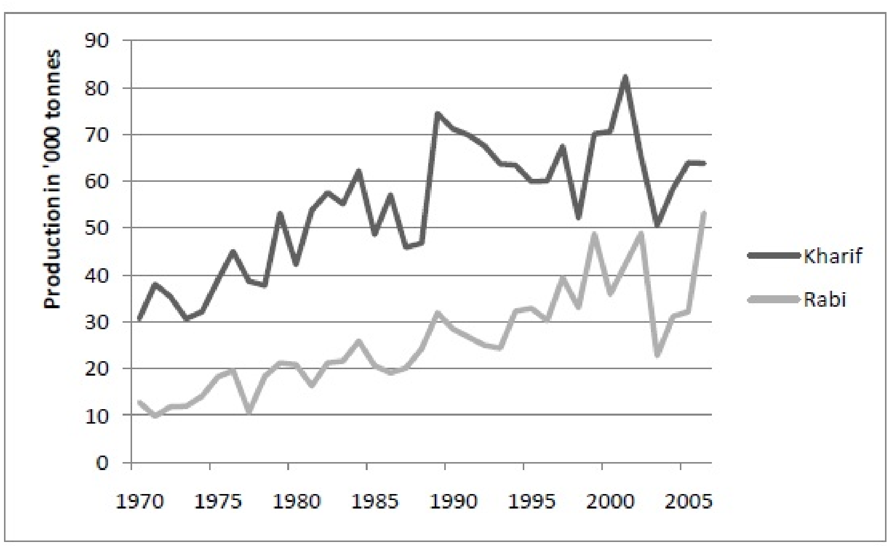

Figure 4: Yield of Kharif and Rabi Rice in Andhra Pradesh

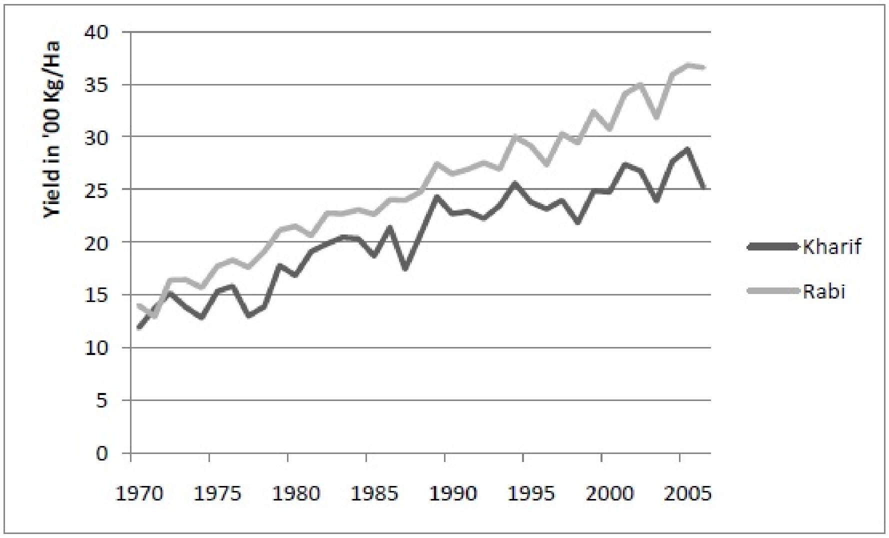

Figure 5: Quantile of Kharif and Rabi rice yield

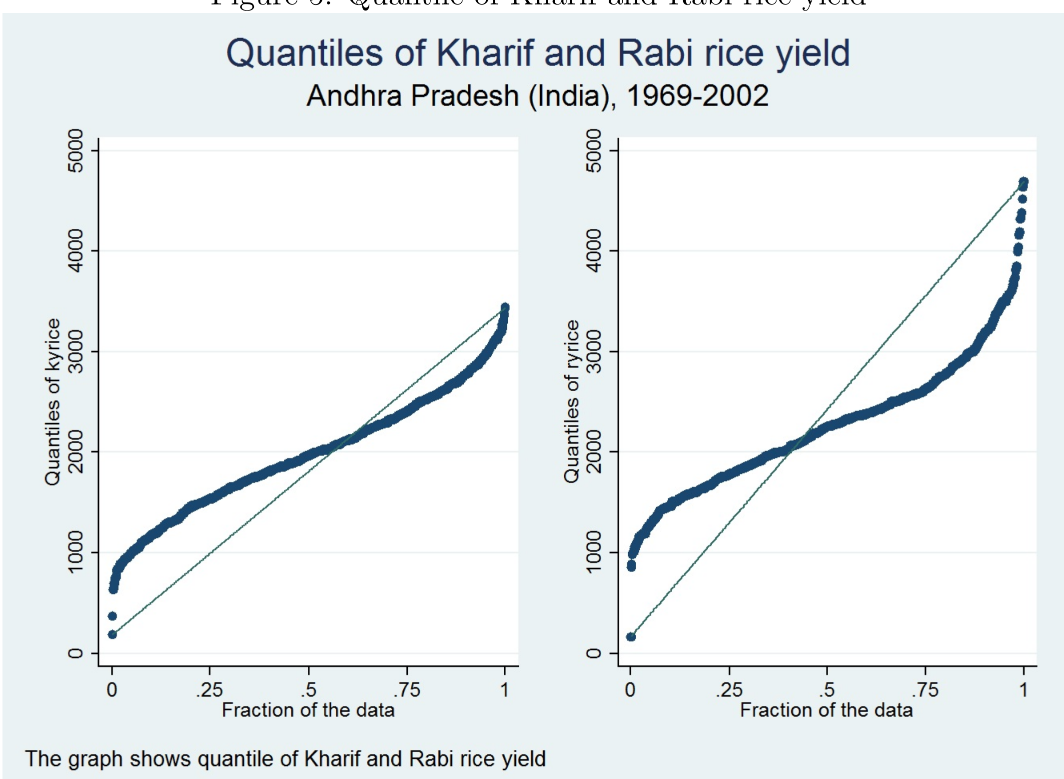

Figure 6: Graphical display of agro-climatic zone wise relationship between Kharif rice yield and Temperature

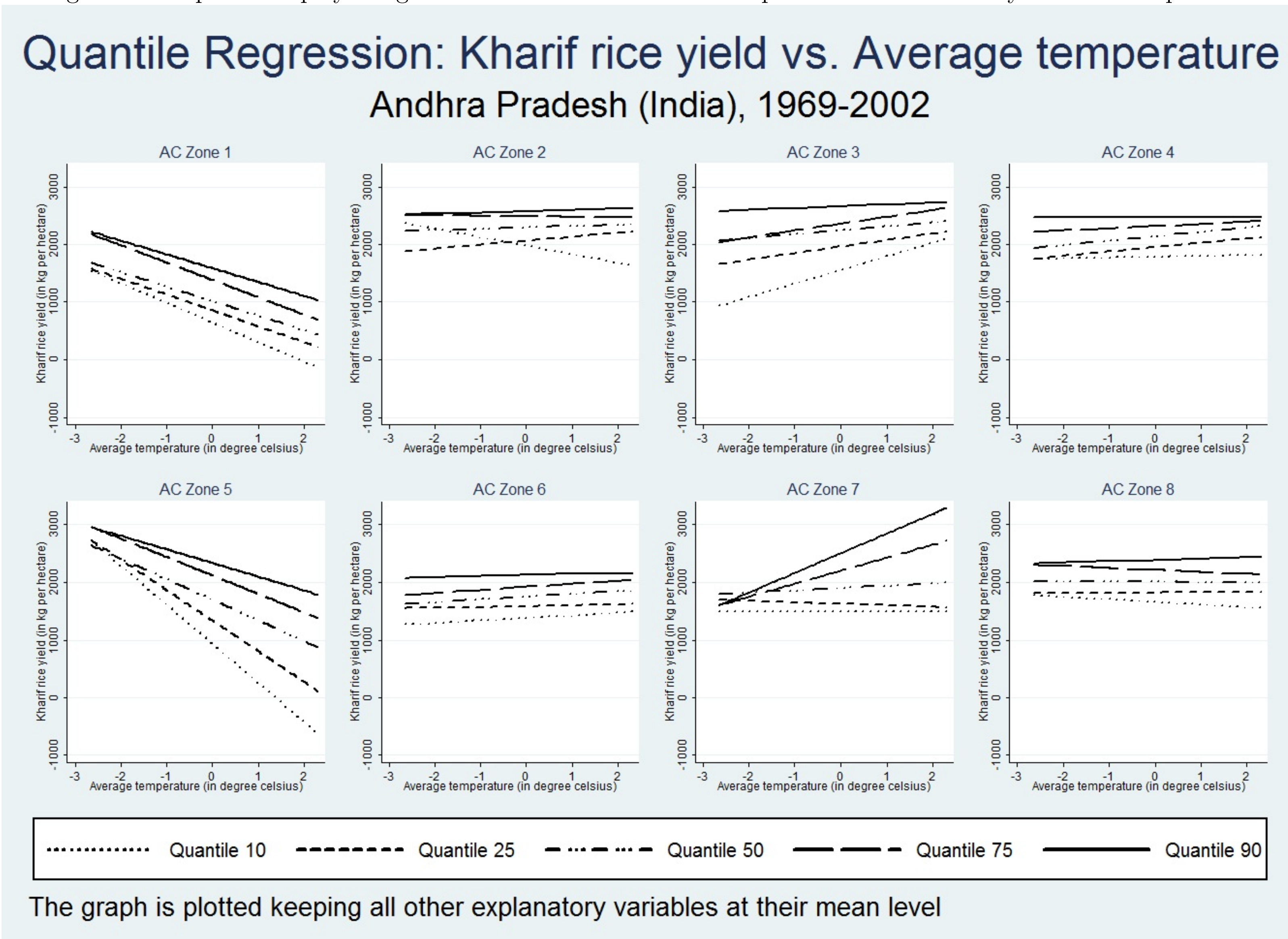

Figure 7: Graphical display of agro-climatic zone wise relationship between Kharif rice yield and Precipitation

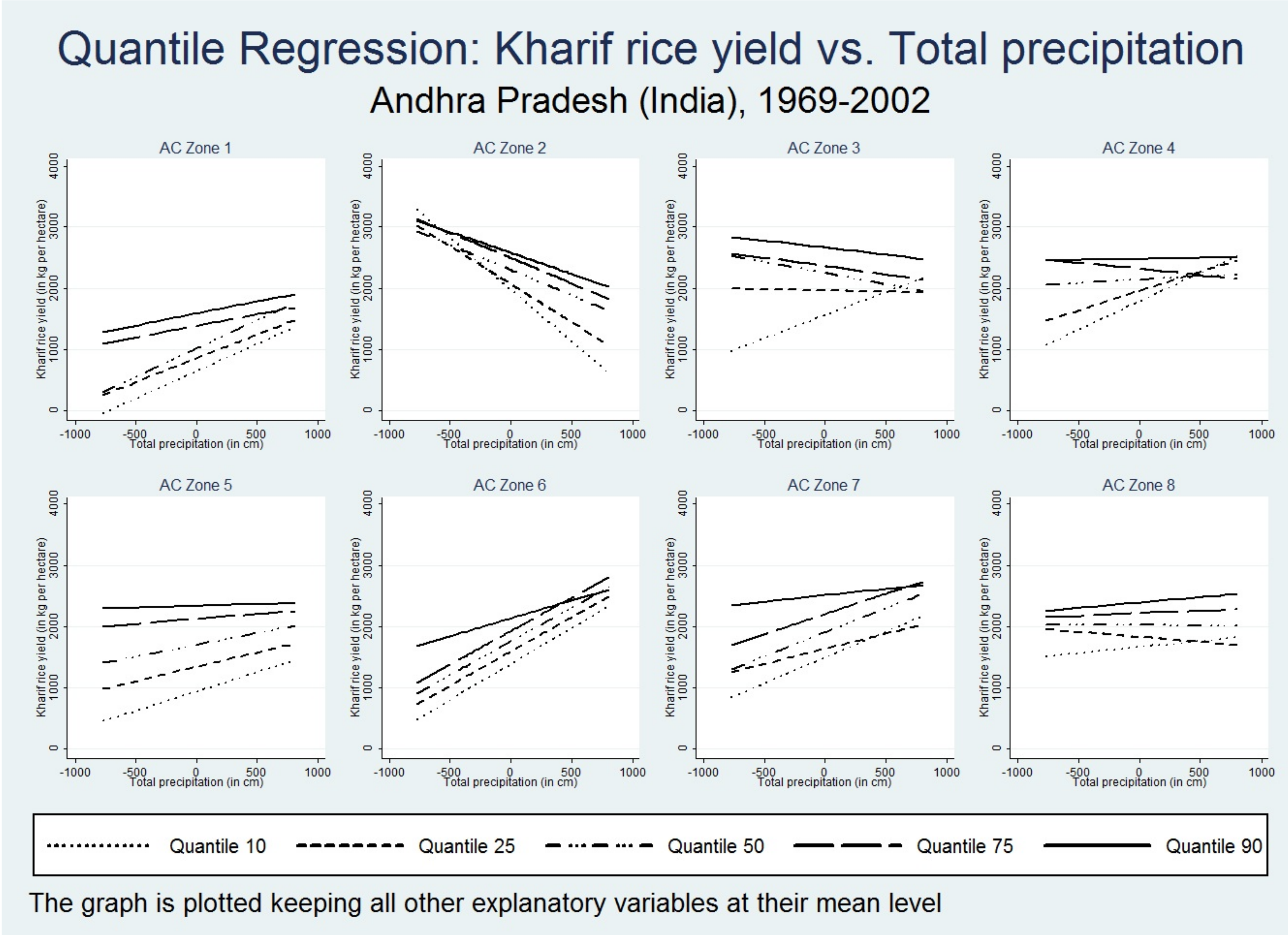

Figure 8: Graphical display of agro-climatic zone wise relationship between Rabi rice yield and Temperature

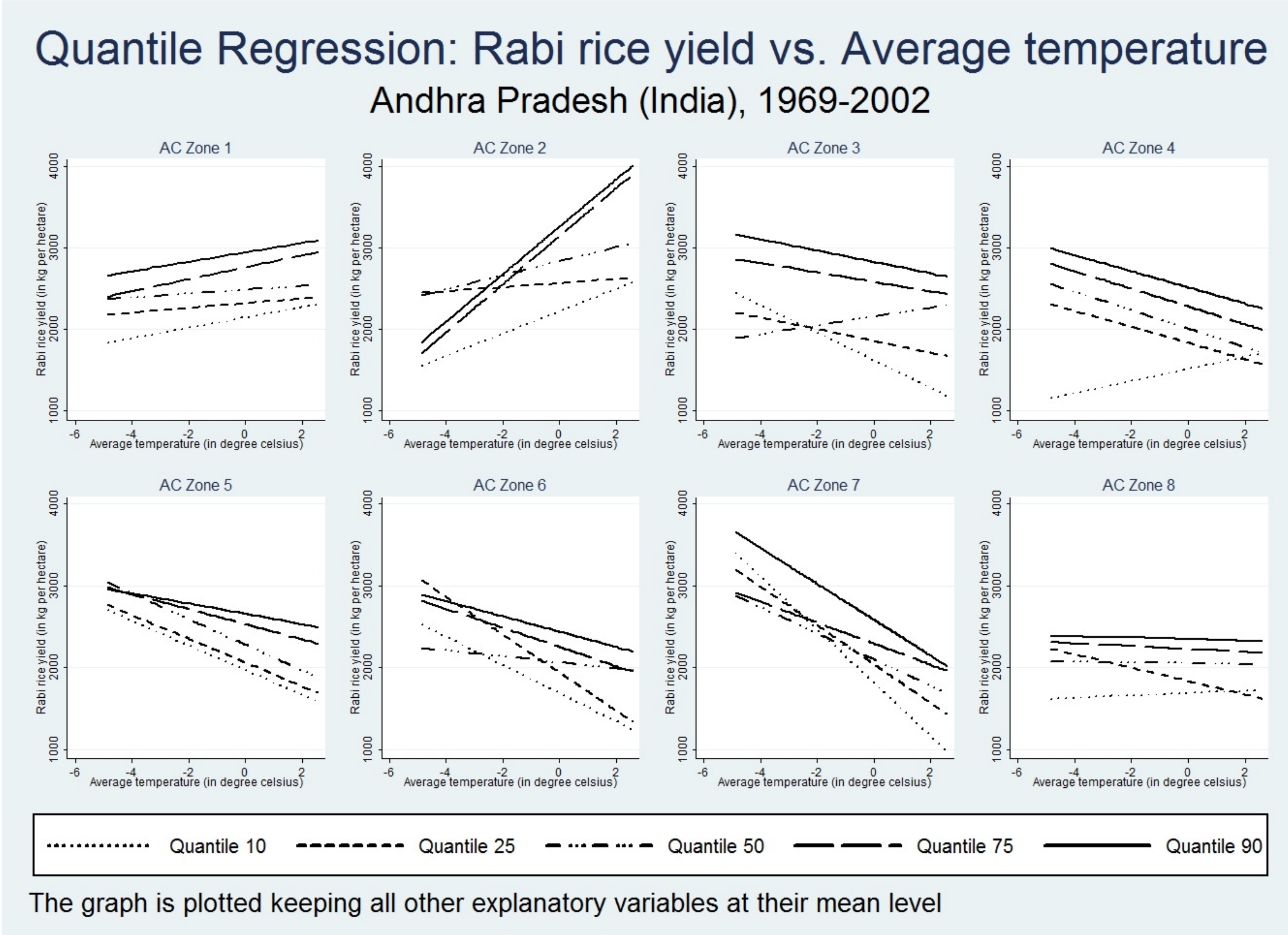

Figure 9: Graphical display of agro-climatic zone wise relationship between Rabi rice yield and Precipitation