Paradigm shift in irrigation sector of Andhra Pradesh (united) and its impact on irrigation efficiency and drought induced loss of crop productivity

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Andhra Pradesh observed a sustained paradigm shift in its irrigation sector in terms of medium of irrigation from surface sources to groundwater sources during the last 30 years. Increasing groundwater use is expected to increase irrigation efficiency and bring critical adaptation benefits against climate change; however, these hypotheses are not validated empirically and demand detailed examination. This study uses district level panel data from Andhra Pradesh to examine the effect of increasing irrigation quality on irrigation efficiency and drought induced yield losses for two major food crops i.e. rice and groundnut. A balanced sample consisting data for all districts of undivided Andhra Pradesh from 1970 to 2007 is constructed using databases provided by ICRISAT and NICRA.

Results exhibited that increasing groundwater use not only augmented contribution of irrigation in explaining crop yields but also reduced drought induced yield losses. Most importantly, findings suggest that adaptive and efficiency effects of groundwater boom in the state were increasing over time contributing to increase yield risk. However these dynamics between drought, irrigation and yield was limited to moderately arid region in the case of rice and to semiarid region in the case of groundnut. Findings indicate that paradigm shift in irrigation sector contributed to increase yield risk of rice and groundnut in major producing regions.

Key words: Drought, Adaptation, Groundwater, Climate Change, Yield

1. Introduction

Historically, irrigation played a critical role in agricultural growth and development in India and elsewhere due to its direct as well as indirect favorable impact on economy (Dhawan 1988; Narayanmoorthy 2006; Narayanmoorthy et al. 2013). Irrigation augments effective land supply by increasing cropping intensity and its spillover effect include increasing use of complementary inputs (Dhawan 1988). Among others, Fan et al. (2000) found strong evidences regarding favorable impact of public infrastructure including irrigation on agricultural output (revenue) growth. However, distribution of irrigation benefits were found to be heterogeneously distributed across agro-climatic regions in India (Binswanger, Khandker, Rosenzweig 1993; Fan et al., 2000b). A major factor explaining differential impact of irrigation on agricultural output growth has been the historical difference among regions in terms of irrigation infrastructure (Dutt and Ravallion 1998). Geographical, financial and managerial constraints associated with irrigation development also played an important role in explaining heterogeneous distribution of irrigation benefits across regions (Binswanger, Khandker, Rosenzweig 1993; Fan and Hazell, 2000).

In comparison to canals, tube-well irrigation is a recent phenomenon in peninsular India (Shah 2012). Considering constrains associated with expanding surface irrigation; peninsular states in India began subsidizing groundwater use and electricity supply to reduce regional disparities in agriculture sector. In particular, development of groundwater sources has been more critical from agricultural growth perspective in historically low irrigated semiarid regions of India (Srivastava et al. 2014; Shah 2012). Andhra Pradesh is a major agricultural state located in peninsular India. Since independence, Andhra Pradesh invested heavily in its irrigation sector to double its irrigation potential in 2011 from what it was in 1970 (figure 1). While canal based irrigation flourished in the state during centralized planning era; limitations of gravity based irrigation forced state to subsidize groundwater based well irrigation (figure 1).

Incentive driven groundwater exploitation brought a boom in well irrigation to shift irrigation paradigm in the state towards groundwater based micro irrigation during 1987 to 1991 (figure 1). However, injudicious use and excessive reliance on groundwater due to lack of access to surface based irrigation also endangered the sustainability of groundwater sources in hard rock regions of Andhra Pradesh (see, figure 2). Direct consequences of groundwater overexploitation in Andhra Pradesh include declining groundwater table, rising irrigation cost, increasing inequality in access and reduced profitability (Ratna Reddy 2003; 2006). These emerging fault lines have increased the uncertainty associated with the agriculture water supply in Andhra Pradesh (Kumar et al. 2011).

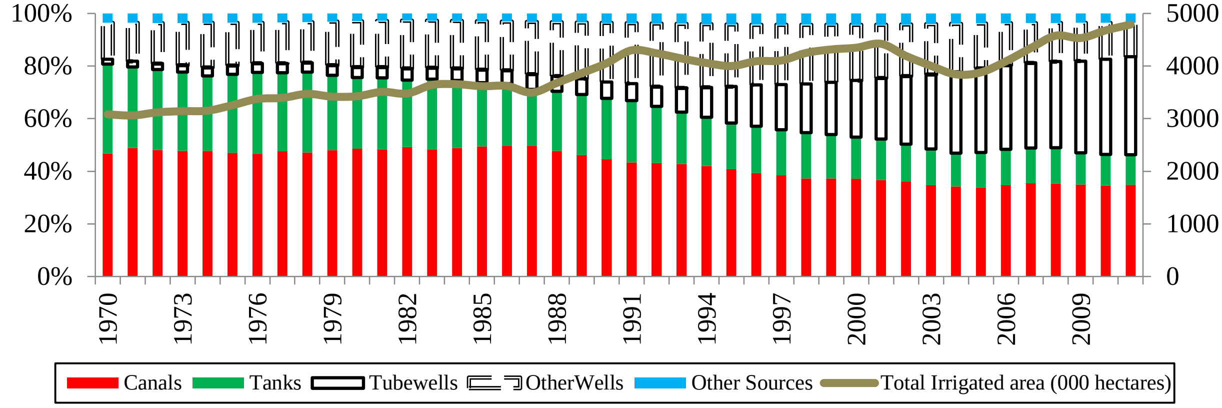

Figure 1: Irrigation development in Andhra Pradesh

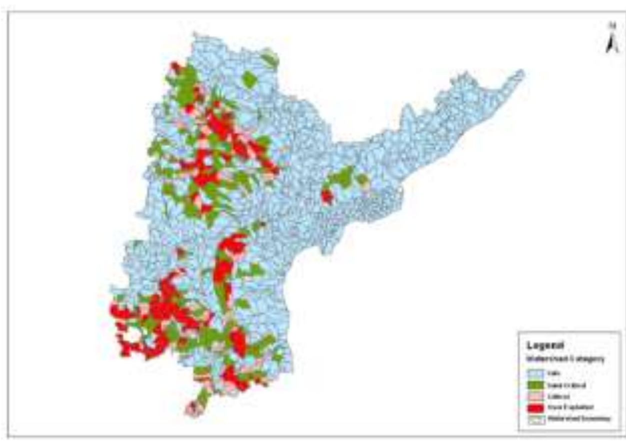

Figure 2: Groundwater status in Andhra Pradesh
Source: Government of Andhra Pradesh, groundwater department (2008)

Land augmenting and productivity enhancing roles of groundwater are well documented in India and elsewhere (see, Shah 2007; 2009; 2012). A critical difference between groundwater and surface irrigation can be described in terms of *flexibility of use* which comes with "*atomic groundwater irrigation*" (Shah 2007; 2009; 2012). Flexibility associated with groundwater use is hypothesized to be critical for climate change adaptation. Groundwater use is also expected to augment efficiency of irrigation sector by stabilizing agricultural water supply (see, Shah 2007; 2009; 2012). In climate change context also, it is argued that ignoring irrigation causes overestimation of climate change impacts on agriculture sector. Schlenker et al. (2005) explicitly demonstrated that impact of climate change was heterogeneous across irrigated and non-irrigated counties of US. In the case of India, Birthal et al. (2014) demonstrated that inclusion of irrigation in climate response function significantly reduced the magnitude of climate change impact on major crops' yields.

In fact, whether groundwater use played any adaptive role is not clear in Indian case due to lack of empirical evidences. In this connection, Shah et al. (2009) argued that groundwater plays a risk stabilizing role which is distinct from the production role of irrigation water while discussing the impact of 2002 drought. To support their argument, they argued that production loss was lesser in 1987-88 drought compared to loss in production in 1965-66 droughts. Dinesh Kumar et al. (2009), on the contrary, argued that difference in losses between two droughts occurred in 1965-66 and 1987-88 were not only because of the productive and stabilizing effect of groundwater but other factors e.g. technology, infrastructure etc. also contributed to lower losses in 1987-88. In a recent study, Birthal et al. (2015) examined whether irrigation increased drought resilience of rice yields in the case of Indian agriculture. Predictions in this study showed that irrigation increased rice yield resilience against drought; however, adaptive benefits of irrigation were found to be decreasing over the years. Study by Birthal et al. (2015) provided insight regarding modelling adaptive role of irrigation and provokes to examine similar hypotheses in the case of groundwater irrigation. Additionally, studies, examining the impact of irrigation on agricultural output, often ignore the effect of existing uncertainties in irrigation sector on agriculture performance. While discussing agriculture growth, one cannot ignore production risk which, to a large extent, depends on quality as well as quality of inputs e.g. irrigation.

Despite these developments in agricultural environment, we have not seen any study conducting a thorough examination into consequences of groundwater boom for agricultural productivity of major crops. To address this research gap, present study analyses the impact of groundwater boom on agricultural yields in Andhra Pradesh. In this regard, we assumed crop yields to be a nonlinear function of a drought index, crop irrigated area, an index of irrigation quality and district specific technology trend. Using a flexible econometric specification, we also analyze the adaptive and efficiency related effects of groundwater use for climatic regions where groundwater boom happened and which are facing serious issues related with the sustainability of groundwater in the state (see, figure 1). Two crops, examined in this study, are rice (paddy) and groundnut.[1] Contribution of both crops in agriculture production in Andhra Pradesh is significant. These two crops together hold more than 40 percent of total cropped area in the state.

[1] Henceforth, we will use paddy and rice interchangeably.

While rice is a water intensive crop; groundnut is known for its drought tolerance. Major groundnut producing districts in the state are located in Rayalseema region; however, rice cultivation is more homogenously distributed among all the districts.

Rest of the paper is organized as follows. Section 2 describes data sources, variables and methodology. Section 3 explores relationship between drought and crop yield using sample information. Section 4 presents results of the econometric exercise. Section 5 presents concluding remarks.

2. Data Sources, Variables and Methodology

2.1. Data

For conducting this study, we borrowed data from secondary sources. Major data sources include NICRA which provides district level daily information on rainfall and temperature and Village Dynamics in South Asia (ICRISAT) which provides compiled data on agricultural and various socio-economic parameters. Sample period in NICRA climate dataset was from 1971 to 2007; however, time period covered in VDSA dataset was from 1966 to 2011.

Due to discrepancy in time span between two datasets, time period considered in econometric study was confined to the period for which weather data was available i.e. 1971 to 2007. A balanced panel consisting data of 20 districts (as per 1965-66 boundaries) covering period from 1971 to 2007 was used for data analysis.[2]

2.2. Variables

a. Climate Region Dummy

For climate classification, we used relative aridity index of De Mortonne (1926). De Mortonne index measures moisture adequacy as:

[2] We assumed that weather of mother district in climate data set was representative despite reorganization of district boundaries in the state.

$$A_M = \frac{P}{T+10}$$

In which, A_M is the index of soil moisture adequacy, P is the total precipitation of the year and T is the annual mean temperature. Based on relative aridity index, a climatic classification of the state was performed, results of which are given in table 1.

Table 1: Climate Classification of Andhra Pradesh

A_M	Climate classification[3]	Districts
I<10	Dry or arid	-
15≤I≤24	Semiarid	Anantpur, Kurnool, Mahbubnagar Nalgonda, Kadapa, Hyderabad Guntur
24<I≤30	Moderately arid	Medak, Chittoor, Nizamabad Warangal, Nellore, Krishna Karimnagar, West Godavari, Adilabad
30<I≤35	Slightly humid	Khammam, East Godavari Srikakulam, Visakhapatnam

Source: Hydrological Observatory of Athens

We used relative aridity index for constructing climate region variable for examining regional adaptation and efficiency effects of groundwater boom. Details of other explanatory variables included in the yield-weather model is explained in following sections.

b. Drought Index

Major indices used for measuring severity of droughts include *Palmer drought severity index*, *rainfall deciles*, and *standardized precipitation index*. In a recent study, Birthal et al. (2015) used an index which defines drought as the product of standardized deviations from rainfall being below the normal and standardized temperature deviations above the normal. McCarl et al. (2008) used Palmer drought severity index (PDSI) which is widely used for measuring droughts in the US. The PDSI intends to 'measure the cumulative departure of moisture supply' and takes a dimensionless value typically ranging between 4 and -4, with negative values showing a shortage of moisture of moderate to extreme kind.

[3] climate classification based on De Mortonne aridity index was conducted using table provided by Hydrological Observatory of Athens,

While PDSI is widely applied in research; it didn't satisfactorily represent duration of rainfall abundance/deficiency. PDSI (Palmer 1965) shows difference in the severity of drought when occurrence of wet months was interchanged by the dry months within a rainfall season (Bhalme and Mooley 1980) i.e. severity of drought will change if we interchange the occurrences of a dry and a wet month while holding the magnitude of wetness and dryness of respective months constant. Bhalme and Moole (1980) argued that *drought intensity must be considered on an incremental basis such that each successive month is evaluated in terms of its contribution to the intensity of the drought* and proposed a new index to measure drought intensity.

Another issue is related with using standardized drought indices in a panel setting. *Standardized indices ignore context i.e. mean rainfall*; therefore, are not useful in a panel setting where cross sectional units exhibit heterogeneous rainfall endowment. Districts with identical drought index may, in real experience, exhibit different absolute and/or relative yield gain/loss due to difference in their rainfall endowment i.e. climate which directly affects land quality and, thus, yield. It is more obvious that *droughts of same intensity cause more damage in better rainfall endowed regions as productivity in these regions is often high*. Additionally, *giving higher weights to droughts in high rainfall regions is also important from food security perspective as these regions contribute more to aggregate production*. In conclusion, damage to agriculture yields due to drought is underestimated in a panel data model which uses standardized drought index as an explanatory variable.[4] Our argument relies on the assumption that while regions with lower mean rainfall are more vulnerable to climate change; yield losses due to droughts of similar magnitude should be relatively higher in regions of relatively more benign climate as these regions often show high land productivity but historically lack responsive behavior due to favorable climatic endowment.

Drought Index (Bhalme and Moole 1980), used in this study, is based on a moisture anomaly index (*M*) which is defined as the deviation of rainfall from long run average rainfall in a month weighted by the inverse of *coefficient of variation* of rainfall in the corresponding month. Bhalme and Moole (1980), then, defined *rainfall anomaly intensity* for a given month as:

[4] This problem; however, can be taken care of in fixed effects model to some extent. A better option is include mean rainfall as an explanatory variable in a fixed effects model while assessing impact of drought/floods.

$$I_k = 0.50 I_{k-1} + \frac{M_k}{48.55}$$

Equation 2 is the *drought index equation*, in which I represent *drought index* for month k and M is the moisture anomaly index.[5] By introducing past month's rainfall anomaly intensity, I_k for any month indirectly includes the effect of duration of wetness/dryness during entire monsoon. In other words, continuation of drought situations contributes to increase (decrease) intensity of droughts (floods) in next months. Additionally, weighing by inverse of coefficient of variation of rainfall instead of standard deviation of rainfall is equivalent to weighing standardized rainfall anomalies with long run average rainfall in the region. Such weighting, in our view, reduces bias in panel data estimate of drought impact parameter. We used rainfall data of months from June to December to construct drought index.[6]

c. Crop Irrigated Area and Irrigation Quality Index

We employed crop wise irrigated area (thousand hectares) as independent variable as a proxy for irrigation access. Similarly, *ratio of area irrigated by groundwater sources and area irrigated by surface sources* was taken as a proxy for irrigation quality (see, subrahmaniam and Satya Shekhar 2003). The ratio acts as an *indicator of irrigation quality* which changed due to embodied technological change in irrigation sector. Groundwater boom changed the manner in which irrigation used to happen under large gravity based canal irrigation.

[5] Past month rainfall anomaly index for first month is considered zero (see, Bhalme and Moole, 1980).

[6] Andhra Pradesh not only receives rainfall from southwest monsoon but also attains significant amount of rainfall in northeast monsoon.

Summary of variables used in the analysis and details of construction is provided in table 2.

Table 2: Variables and Their Construction

Independent Variable	Symbol	Construction	Unit of measurement
Yield	YLD	Total production of crop/Total area under crop	Kilogram per hectare
Drought index	DI	$I_k = 0.50 I_{k-1} + \frac{M_k}{48.55}$; in which I represent severity of rainfall for month k and M is the moisture anomaly index defined as the *weighted deviation in rainfall in which inverse of coefficient of variation in rainfall* was used as weight. *DI* is defined as the mean of I_k from June to December.	Millimeter
Groundwater dominance	GWD	$GWD = \frac{Area\ irrigated\ by\ wells}{Area\ irrigated\ by\ other\ sources}$	Ratio
Crop area irrigated	IA		Thousand hectares

3. Drought Index and Yield

While hypotheses which we seek to test were drawn from literature; it is useful to examine relationship between drought index and crop yield before model construction. Such cross tabulation is critical as there exists almost no theoretical insight regarding functional relationship between droughts and crop yield. In this connection, figure 3 presents frequency diagram of drought index. Since the index was weighted by average district rainfall, range of drought index distribution was big. However, it can be observed that incidence of rainfall anomalies was tilted towards deficient instead of surplus rainfall. Outlier flooding events also occurred in few districts as the frequency distribution of drought index indicates.

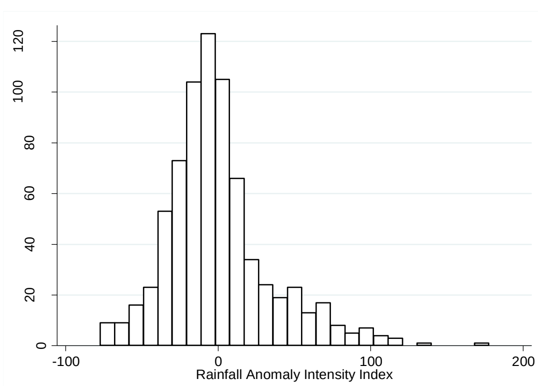

Figure 3: Frequency distribution of drought index

Figure 4 plots relative yield loss, defined as *trend deviation of yield divided by observed yield*, and drought index using sample data.[7] While it is a naïve way to examine the impact of drought index on agricultural yield, it is useful in understanding drought-yield relationship. It can be observed that relationship between drought index and crop yield was stronger in the case of rice yields.

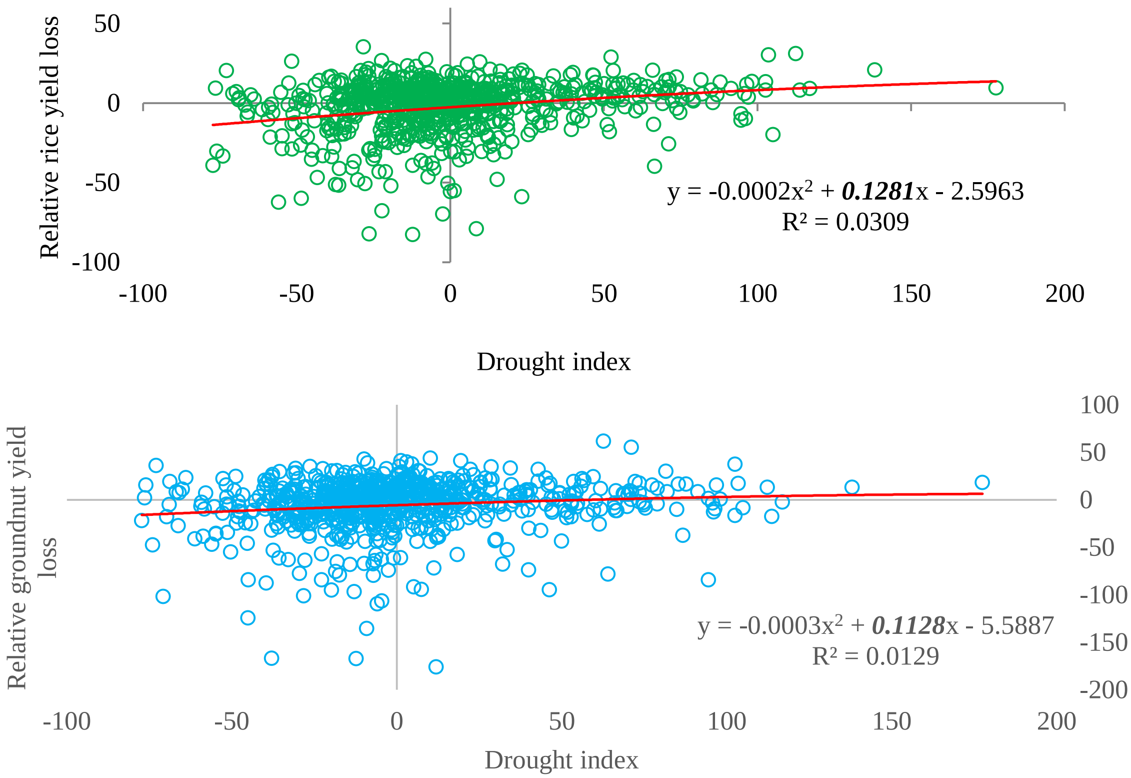

Figure 4: Relative yield loss due to floods and droughts. Relative yield loss, defined as the trend deviation in yield divided by realized yield in a year, was plotted against drought index.

In another check, we classified drought index into three categories to examine how drought effects were different from flood effects. Results of this exercise are plotted in figure 5. Three such categories of drought index considered were below 30th percentile (droughts), between 30th and 70th percentiles (normal), and above 70th percentile (floods) of drought index. This categorization was chosen to separate flood effects from drought effects.[8] It can be observed

[7] In this section, we used relative yield loss instead of absolute yield losses due to ease of interpretation. However, we used absolute yield as dependent variable in econometric model. Linear specification was consistent with our argument that droughts of equal magnitude in terms of standardized drought index create more yield damage in absolute terms in more productive regions which also possess benign rainfall regime.

[8] Bottom 30 percent observations in drought index distribution represent droughts and top 30 percent observations represent flood.

that mean relative yield loss in drought percentiles was marginally higher for groundnut. Range of drought index percentiles considered as normal indicated that mean relative yield loss in this range of drought index distribution was substantially bigger for groundnut in comparison to rice. Most of the important droughts in semiarid regions may also fall in this range due to lower mean rainfall in semiarid districts. Since semiarid region of the state has been the dominant producer of groundnut in the state, results do not surprise. While average relative rice yield loss was less in middle category of droughts; standard deviation of relative yield loss was high. Mean relative deviation in rice yield was positive for rice; however, it remained negative for groundnut in higher percentiles which represent normal to surplus rainfall.

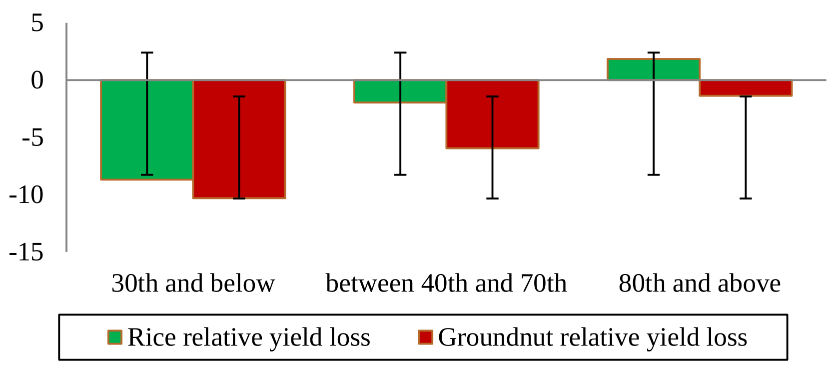

Figure 5: Relative yield loss due to floods and droughts. Relative yield loss is defined as the trend deviation in yield divided by realized yield in a year. In each category, mean and variance of yield anomaly was estimated for comparing the difference between drought and flood effects.

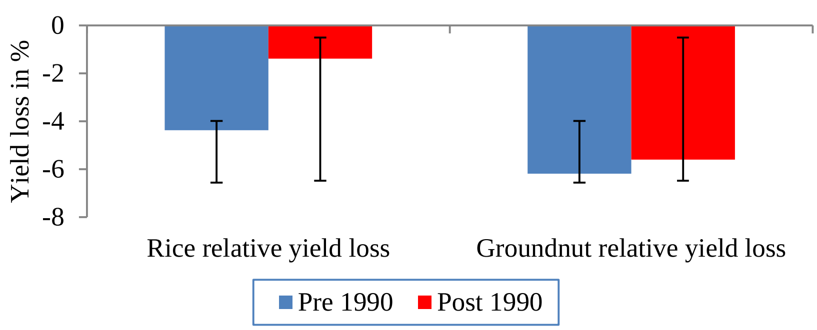

Figure 6: Relative yield loss due to floods and droughts. Relative yield loss is defined as the trend deviation in yield divided by realized yield in a year. Year 1990 was included in the definition of post 1990. Mean and variance of yield anomalies was estimated for comparing the difference between periods.

To examine presence of any temporal change in drought induced yield losses as hypothesized; we plotted mean and standard deviation of relative yield losses of rice and groundnut in figure 6 in pre and post 1990 period. It can be seen that relative yield loss was significantly lower in post liberalization period in the case of rice. It can also be observed that reduction in mean yield loss was marginal between pre and post 1990 period in the case of groundnut.

In following section, econometric scheme is explained which was used to understand effect of groundwater boom on drought adaptation and irrigation efficiency.

4. Econometric Model

Fixed effects (FE) or least squares dummy variable (LSDV) model is an ideal choice to examine impact of drought and irrigation on crop yields. Fixed effects model allows controlling time invariant effects which may be correlated with the independent variables. Similarly, FE/LSDV model, unlike random effects model, doesn't impose restrictive assumption regarding unobserved time invariant effects. Model specifications for hypotheses testing are as follows:

$$YLD_{it}^{rc,gn} = \alpha_i + \delta_i D_i T + \theta_1 DI_{it} + \theta_2 IA_{it}^{rc,gn} + \theta_3 GWD_{it} + \varepsilon_{it} \quad (1)$$

$$\begin{aligned} YLD_{it}^{rc,gn} = {} & \alpha_i + \delta_i D_i T + \theta_1 DI_{it} + \theta_2 IA_{it}^{rc,gn} + \theta_3 GWD_{it} + \\ & \phi_1 (DI_{it} \times GWD_{it}) + \phi_2 (IA_{it} \times GWD_{it}) + \varepsilon_{it} \end{aligned} \quad (2)$$

$$YLD_{it}^{rc,gn} = \alpha_i + \delta_i D_i T + (\theta_1 DI_{it} + \theta_2 IA_{it}^{rc,gn} + \theta_3 GWD_{it}) \times (1 + D_{HARID} + D_{MARID}) + \varepsilon_{it} \quad (3)$$

$$YLD_{it}^{rc,gn} = \alpha_i + \delta_i D_i T + (\theta_1 DI_{it} + \theta_2 IA_{it}^{rc,gn} + \theta_3 GWD_{it}) \times (1 + D_{HARID} + D_{MARID}) \times T + \varepsilon_{it} \quad (4)$$

$$\begin{aligned} YLD_{it}^{rc,gn} = {} & \alpha_i + \delta_i D_i T + \theta_1 DI_{it} + \theta_2 IA_{it}^{rc,gn} + \theta_3 GWD_{it} + \\ & (\phi_1 DI_{it} \times GWD_{it} + \phi_2 IA_{it}^{rc,gn} \times GWD_{it}) \times (D_{HARID} + D_{MARID}) + \varepsilon_{it} \end{aligned} \quad (5)$$

$$\begin{aligned} YLD_{it}^{rc,gn} = {} & \alpha_i + \delta_i D_i T + \theta_1 DI_{it} + \theta_2 IA_{it}^{rc,gn} + \theta_3 GWD_{it} + \\ & (\phi_1 DI_{it} \times GWD_{it} + \phi_2 IA_{it}^{rc,gn} \times GWD_{it}) \times (D_{HARID} + D_{MARID}) \times T + \varepsilon_{it} \end{aligned} \quad (6)$$

In equation 1 to 6, y stands for crop yield; super-scripts *rc* and *gn* stand for rice and groundnut respectively.[9] Subscripts i and t denote district and year, respectively. α_i stands for district specific intercept in fixed effects model. D_iT denotes interaction of district dummy with time trend *(T)* to allow heterogeneous technological change in districts. ε_{it} is *identically and independently* distributed error term.

Equation 1 depicts a production function in which drought index (*DI*), irrigated area (*IA*) and irrigation quality index (*GWD*) as inputs to determine crop yield. Description and definition of other explanatory variables is provided in table 2.

Equation 2 examines adaptation and irrigation efficiency hypothesis related with groundwater boom. Measuring adaptation in this manner assumes that *GWD* is a measure of exogenous technical change which interacts with rainfall anomalies (bad input) and irrigation (good input) to shift yield frontier. Differentiating equation 2 w.r.t. *DI*/*IA*, first and, then w.r.t. *GWD* gives adaptive and efficiency gains due to increasing groundwater use.

$$\begin{aligned} &Adaptative\, gain = \frac{\partial}{\partial GWD_{it}}\left(\frac{\partial y_{it}}{\partial DI_{it}}\right) = \phi_1; \\ &Efficiency\, gain = \frac{\partial}{\partial GWD_{it}}\left(\frac{\partial y_{it}}{\partial IA_{it}}\right) = \phi_2 \end{aligned} \qquad (7)$$

Equation 3 is meant to examine the regional differences in the relative contribution of independent variables in explaining crop yields. Equation 4 further extended equation 1 to access whether relative contribution of drought index, irrigation and irrigation quality index in explaining variations in crop yield increased/decreased or remained constant over time in different climatic regions. Differentiating equation 4 w.r.t. independent variables first and then w.r.t time trend (*T*) variable gives;

$$\textit{Temporal change in drought impact:}\ \frac{\partial}{\partial T}\left(\frac{\partial y_{it}}{\partial DI_{it}}\right) = \theta_1\left(1 + D_{HARID} + D_{MARID}\right) \quad (8)$$

[9] While using interaction of variables, original variables were kept as regressors in regression model (see, Balli and Sorensen 2013). Linear specification was chosen over a logarithmic specification as it was less restrictive.

Similarly, temporal change in relative contribution of irrigation (*AI*, *GWD*) variables in explaining annual crop yield can be estimated across different climatic regions. Equation 5 is an extension of equation 2 and was meant to access the regional heterogeneity in adaptive and efficiency gains due to increasing groundwater use. Equation 6 further extends equation 2 to examine whether adaptive and efficiency gains of groundwater use changed over time.

5. Groundwater Boom, Droughts and Crop Yield

Sample summary of variables is provided in table 3 and table 4 reports correlation matrix of explanatory variables used in the regression analysis. It can be seen from table 2 that drought variance was highest in slightly humid region followed by moderately arid region. Similarly, groundwater boom was mostly confined to districts falling in semiarid climate followed by moderately arid region. Mean groundnut irrigated area was lower and standard deviation in groundnut irrigated area was higher.

Table 3: Sample Summary of Variables

	Full sample		Slightly humid region		Moderately arid region		Semiarid region	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
RCYLD	2165.75	644.14	1869.76	603.83	2224.16	654.33	2259.78	605.16
GNYLD	1053.78	418.72	954.54	261.37	1176.16	463.13	953.14	390.02
DI	0.00	34.32	0.00	40.84	0.00	37.17	0.00	25.39
GWD	1.42	2.56	0.70	1.29	1.49	2.49	1.73	3.07
RCAI	93.85	9.43	87.55	8.81	93.87	10.58	97.40	5.60
GNAI	36.12	28.14	19.96	19.87	48.93	30.38	28.88	21.01

Table 4: Correlation among Independent Variables

	DI	GWD	RCAI	GNAI
DI	1.00			
GWD	-0.06	1.00		
RCAI	0.01	0.17	1.000	
GNAI	-0.01	0.31	0.11	1.00

Regression results for all models depicted in equation 1-6 are reported in table 5 and table 7 for rice and groundnut, respectively. Important diagnosis and regression performance tests for all models are reported in table 6 and table 8 respectively for rice and groundnut. Dependent variable in all models was crop yield measured in kilogram per hectare. We tested model errors for heteroscedasticity and cross sectional dependence. Significant test statistics rejected null of homoscedasticity and no cross section dependence, justifying the choice of FGLS technique. For efficient estimation of standard errors, we applied Driscoll-Kraay (1998) estimator which provides robust standard error of model estimates in presence of heteroscedastic, temporally and spatially correlated errors (also see, Hoechle, 2007).

In the case of rice, coefficient associated with drought index (*DI*) turned statistically significant (table 5) implying that any increase in drought intensity in districts will reduce rice yield. One unit increase in drought intensity reduced rice yield by 1.14 kilogram per hectare to 1.58 kilogram per hectare depending on the model specification. However, droughts effect on rice was distributed homogenously across climatic regions as coefficients associated with interaction of drought and region dummies didn't turn statistically significant. Contrary to droughts, we failed to confirm any significant impact of irrigated area on rice yield. However, coefficient associated with interaction of irrigated area and moderately arid region dummy turned statistically significant at 10 percent level implying that irrigation significantly contributed to explain variation in rice yield in moderately arid region of the state (see, column 3; table 5). Results are not surprising considering that most of the gain in irrigated area and a corresponding gain in rice cultivated area in the state was experienced in this region.

As far as temporal change in impact of drought on rice yield is concerned, results failed to reject null hypothesis of no significant change in both moderately and semiarid regions (column 4, table 5). As far as temporal growth in impact of irrigation on rice yield is concerned, results were not statistically significant in this case too for any of the regions (column 4, table 5). Impact of irrigation quality index (*GWD*) on rice yield was significantly negative in few climatic regions but this effect was decreasing over time. Twofold justification can be provided to explain negative relationship between *GWD* and crop yield. First, groundwater boom brought marginal lands into cultivation as well as permitted intensive cultivation which lowered the mean annual yield. Secondly, results indicate that regions where area irrigated by surface irrigation sources was low, yields were also low in those regions. Statistically significant negative effect of increasing groundwater dominance on rice yield was observed in both climatic regions which probably hint that cropland expansion effect of groundwater was decreasing over time.[10]

[10] Similar explanation can be given in the case of groundnut yields too.

Table 5: Drought, Irrigation and Rice Yield

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
DI	**1.585** (0.593)**	**1.144* (0.574)**	**1.340* (0.796)**	**1.369** (0.534)**	**1.201** (0.584)**	**1.258** (0.569)**
DI*HARID			0.375 (0.818)			
DI*MARID			0.112 (0.710)			
RCAI	8.041 (4.894)	8.965 (5.853)	3.615 (3.881)	2.158 (3.506)	7.181 (5.127)	7.627 (5.008)
RCAI*HARID			-4.587 (5.391)			
RCAI*MARID			**15.07* (9.072)**			
GWD	-24.30 (14.64)	34.72 (182.9)	**-98.23** (42.17)**	**-62.57*** (19.62)**	**-92.89*** (29.54)**	**-51.06** (21.07)**
GWD*HARID			**79.00** (38.19)**			
GWD*MARID			73.69 (47.26)			
DI*GWD		**0.343*** (0.0515)**				
RCAI*GWD		-0.545 (1.867)				
DI*HARID*T				0.00171 (0.00173)		
DI*MARID*T				0.000322 (0.00119)		
RCAI*HARID*T				-0.0102 (0.0155)		
RCAI*MARID*T				0.0514 (0.0387)		
GWD*HARID*T				**0.123*** (0.0337)**		
GWD*MARID*T				**0.0997** (0.0456)**		
DI*GWD*HARID					-0.00650 (0.165)	
DI*GWD*MARID					**0.388*** (0.0572)**	
RCAI*GWD*HARID					**0.776*** (0.250)**	
RCAI*GWD*MARID					**0.757** (0.307)**	
DI*GWD*HARID*T						0.000200 (0.000648)
DI*GWD*MARID*T						**0.000743*** (0.000147)**
RCAI*GWD*HARID*T						**0.000921* (0.000496)**
RCAI*GWD*MARID*T						**0.000781* (0.000418)**
Constant	669.9 (447.2)	583.9 (538.1)	614.3 (407.0)	431.2 (606.0)	750.2 (469.0)	710.4 (457.8)
Observations	740	740	740	740	740	740
District wise trend	yes	yes	yes	yes	yes	Yes

Note: *, **, *** indicate statistical significance at 10 percent, 5 percent and 1 percent level, respectively. Standard errors reported in parentheses were estimated using Driscoll-Kraay (1998) estimator.

Table 6: diagnosis test for rice yield regression model

Test name/model	1	2	3	4	5	6
F test for model goodness of fit	1027.62 (22, 36)***	1053.00 (24, 36)***	1562.86 (28, 36)***	1331.48 (28, 36)***	777.41 (26, 36)***	986.90 (26, 36)***
Adjusted R square	0.69	0.69	0.69	0.70	0.69	0.69
Hausman test	327.05 (22)***	324.85 (24)***	289.62 (28)***	547.58 (26)***	328.25 (26)***	320.26 (26)***
Panel heteroskedasticity Test	196.14 (20)***	193.86 (20)***	174.79 (20)***	175.13 (20)***	193.24 (20)***	540.98 (190)***
Cross section correlation test	536.012 (190)***	538.244 (190)***	515.799 (190)***	514.576 (190)***	540.334 (190)***	195.02 (190)***
F test for joint significance of district wise trend	577.22 (19, 36)***	637.32 (19, 36)***	505.29 (19, 36)***	163.67 (19, 36)***	534.73 (19, 36)***	505.35 (19, 36)***

Note: *, **, *** indicate statistical significance at 10 percent, 5 percent and 1 percent level, respectively. Rejection of homoscedasticity confirms Just and Pope (1978) postulate. Cross section correlation (Pesaran 2004) justifies the choice of a flexible estimation technique. Null hypothesis for F test (district specific trend)- H_0: all estimated coefficients associated with district specific technological trend were simultaneously equal to zero.

As far as adaptive effect of groundwater use on rice yield is concerned, a statistically significant yield loss mitigating effect of increasing groundwater use was observed (column 2, table 5). However, results failed to confirm any significant impact of increasing groundwater use on marginal productivity of irrigation in the case of rice (column 2, table 5). Further investigation revealed that adaptive effects of groundwater dominance on drought induced yield loss were insignificant in semiarid region; however, reduction in drought induced yield loss was statistically significant in moderately arid districts (column 5, table 5). Considering the low penetration of supportive canal irrigation and low carrying capacity of aquifers in semiarid region, results were not surprising.

Interaction of groundwater dominance (GWD), irrigated area and regional dummies turned statistically significant in rice yield model signifying the heterogeneity in groundwater induced efficiency gains in the case of rice. Nature of irrigation development in different regions could be a factor to explain econometric findings. While semiarid and most of the moderately arid districts are now dominantly irrigated by groundwater sources; canals and tanks are still important sources of irrigation in slightly humid region. Hypothesis regarding temporal change in adaptive and efficiency benefits of increasing groundwater dominance were also examined in the case of rice cultivation by interacting DI/IA, GWD, regional dummies and time trend. Adaptive effect of groundwater grew significantly over time in moderately arid region as statistically significant coefficient associated with the interaction of drought index, GWD and Moderately arid region dummy suggested (column 6 in table 5). Contrary to the adaptive effects, efficiency effects of groundwater use exhibited statistically significant positive growth in both climatic regions.

In the case of groundnut, drought effect on yield was statistically significant; however, hypothesis was rejected only at lower level of statistical significance (10 percent level) (column 1, table 7). Further examination revealed that significant impact of drought on groundnut yield was limited to semiarid region only (column 3, table 7). This result is of special importance considering the concentration of groundnut cultivation in semiarid region. According to results, a unit increase in drought index reduced groundnut yield by 1.5 kilogram per hectare in semiarid region which is large considering the low yield per hectare of groundnut in semiarid region.

Irrigated area, unlike the case of rice, significantly explained variations in groundnut yield (column 1, table 7). Historical difference between proportion of irrigated rice cultivation and irrigated groundnut cultivation might be a reason explaining different behavior of irrigation in the case of two crops. A thousand hectare increase in groundnut irrigated area increased groundnut yield by 7.090 kilogram per hectare (column 1, table 7). Relative contribution of irrigated area in explaining groundnut yield was different across climatic regions (column 3, table 7). Unlike the case of rice, we failed to confirm any significant impact of increasing groundwater dominance on groundnut yield (column 1, table 7). However, statistically significant and negative coefficients associated with the interactions of GWD with climate region dummy highlighted that groundwater boom negatively influenced groundnut yield; however, its impact was heterogeneous across regions (column 3, table 7).

Table 7: Drought, irrigation and groundnut yield

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
DI	**1.011***	0.470	0.702	0.688	0.524	0.575
	(0.592)	(0.497)	(0.568)	(0.443)	(0.482)	(0.469)
DI*HARID			**1.463****			
			(0.628)			
DI*MARID			-0.0568			
			(0.468)			
GNAI	**7.090*****	**6.516*****	**3.116***	**2.406*****	**6.517*****	**6.414*****
	(2.041)	**(1.973)**	**(1.623)**	**(0.590)**	**(1.963)**	**(1.885)**
GNAI*HARID			**7.592*****			
			(1.992)			
GNAI*MARID			**3.508***			
			(1.945)			
GWD	-10.42	**-63.39*****	**-89.67*****	**-49.91*****	**-61.49*****	**-66.08*****
	(8.181)	**(20.60)**	**(28.85)**	**(12.03)**	**(15.02)**	**(16.54)**
GWD*HARID			**84.66*****			
			(29.50)			
GWD*MARID			**83.53****			
			(39.86)			
DI*GWD		**0.342*****				
		(0.0527)				
GNAI*GWD		**0.790*****				
		(0.229)				
DI*HARID*T				**0.00367****		
				(0.00161)		
DI*MARID*T				0.000432		
				(0.000798)		
GNAI*HARID*T				**0.0214*****		
				(0.00440)		
GNAI*MARID*T				**0.0157*****		
				(0.00427)		
GWD*HARID*T				**0.132*****		
				(0.0432)		
GWD*MARID*T				**0.106****		
				(0.0495)		
DI*GWD*HARID					**0.602*****	
					(0.189)	
DI*GWD*MARID					**0.250*****	
					(0.0573)	
GNAI*GWD*HARID					**0.965*****	
					(0.185)	
GNAI*GWD*MARID					**0.691*****	
					(0.197)	
DI*GWD*HARID*T						**0.00174*****
						(0.000554)
DI*GWD*MARID*T						**0.000408****
						(0.000165)
GNAI*GWD*HARID*T						**0.00374*****
						(0.000798)
GNAI*GWD*MARID*T						**0.00173*****
						(0.000478)
Constant	607.9***	638.4***	600.2***	572.0***	640.2***	646.0***
	(52.63)	(49.98)	(47.40)	(54.80)	(48.07)	(45.79)
Observations	740	740	740	740	740	740
District specific trend	Yes	Yes	Yes	Yes	Yes	Yes

Note: *, **, *** indicate statistical significance at 10 percent, 5 percent and 1 percent level, respectively. Standard errors reported in parentheses were estimated using Driscoll Kraay (1998) estimator.

Table 8: Diagnosis test for groundnut yield regression model

Test name	1	2	3	4	5	6
F test for model goodness of fit	1320.44 (22, 36)***	2038.68 (24, 36)***	2866.00 (28, 36)***	319.37 (26, 36)***	2711.12 (26, 36)***	2250.48 (26, 36)***
Adjusted R sq.	0.58	0.60	0.59	0.61	0.70	0.60
Hausman test	240.50 (22)***	232.61 (24)***	207.58 (28)***	167.08 (26)***	234.45 (26)***	218.10 (26)***
Panel heteroskedasticity Test	678.25 (20)***	545.50 (20)***	695.64 (20)***	583.32 (20)***	544.49 (20)***	573.91 (20)***
Cross section dependence Test	667.551 (190)***	562.245 (190)***	636.162 (190)***	682.218 (190)***	551.521 (190)***	565.944 (190)***
F test for joint significance of district specific technology trend	173.28 (19, 36)***	149.15 (19, 36)***	118.68 (19, 36)***	47.10 (19, 36)***	102.22 (19, 36)***	105.06 (19, 36)***

Note: *, **, *** indicate statistical significance at 10 percent, 5 percent and 1 percent level, respectively. Rejection of homoscedasticity confirms Just and Pope (1978) postulate. Cross section correlation (Pesaran 2004) justifies the choice of a flexible estimation technique. Null hypothesis for F test (district specific trend)- H_0: all estimated coefficients associated with district specific technological trend were simultaneously equal to zero.

Interaction of *DI* with semiarid dummy and time trend turned statistically significant in groundnut yield model with positive sign inferring that negative impact of drought on groundnut yield was decreasing over time in dominant groundnut producing region (see, column 4, table 7). This result indicates the general adaptation behavior of agricultural sector against climate change in semiarid regions; however, results also highlight the existence of other factors which contribute to increase risk associated with groundnut cultivation in this region. Increasing monoculture can be one such factor. Similarly, positive influence of irrigated area on groundnut yield also exhibited positive growth over time in both moderately and semiarid regions (column 4, table 7). Impact of irrigation quality index (GWD) on groundnut yield also experienced statistically significant positive growth over time (column 4, table 3). Adaptive and efficiency effects of increasing groundwater use on groundnut yields were observed to be statistically significant across both climatic regions (column 5, table 7). Null hypothesis stating no significant change in adaptive and efficiency gains of increasing groundwater use was rejected in the case of groundnut in both climate regions (column 6, table 7). Here also, it can be observed that annual growth in adaptive and efficiency effects of groundwater use were relatively higher in semiarid region.

6. Did increasing adaptive effects of groundwater increased yield risk?

Temporal change in influence of explanatory variables on crop yields implies that change in these factors increased yield risk. We present a robustness check for econometric findings by estimating equation 5 using stochastic production function framework proposed by Just and Pope (1978, 1979). Just and Pope (1978) stochastic production function for crop yield (*y*) and associated inputs (*x*) in district *i* at year *t* can be represented as:

$$y_{it} = f(x_{it};\beta) + \omega_{it} h(x_{it};\delta)^{1/2} \qquad (4.2)$$

where ω_{it} is homoscedastic stochastic term with mean zero and β, δ are the parameters of the production function. In this production function, the expected crop yield $E[y_{it}]$ is $f(x_{it};\beta)$; and thus estimation of $f(x_{it};\beta)$ gives the impact of independent variables on mean yield. The variance of crop yields $V(y_{it})$ is given by $h(x_{it};\delta)$ and estimation of $h(x_{it};\delta)$ gives the influence of inputs on the yield variance. In Just and Pope (1978) production function, risk estimation can be interpreted as estimation with heteroskedastic errors using FGLS Methods (see, Harvey 1976). Others argued to estimate parameters of mean and variance function using maximum likelihood (ML) method (Isik and Devadoss 2006). However, efficiency of both FGLS and ML depends on the assumption that chosen functional form for the risk function is correct (Asche and Tveteras 1999; Tveteras 1999). Another reason why FGLS and MLE are not efficient because estimated errors in agricultural models often show high correlation across cross sectional units due to porous agricultural boundaries.

Results of just and Pope (1978) production function model for both crops are reported in table 9. We employed a two-step procedure discussed in Asche and Tveteras (1999) which uses the fact that Just and Pope (1978) exploited heteroskedasticity in mean yield model for identifying yield risk. Building on this argument, Asche and Tveteras (1999) estimated mean function to get errors which are used as dependent variable in risk function. In second step, both models can be estimated using OLS with robust standard errors which is the only requirement to make model estimates efficient as FE model estimates are consistent. Driscoll-Kraay (1998) estimator was used for consistent estimation of standard errors in mean and variance models.

Results of yield risk equations; however, must be taken with caution, as variance equation uses logarithmic value of squared residuals of mean yield equation.[11]

Table 9: Impact of groundwater boom on yield variability (Just and Pope 1978)

	Rice		Groundnut	
Variables	**Mean**	**Variance**	**Mean**	**Variance**
DI	1.201**	-0.00518*	0.524	-0.00210
	(0.592)	(0.00295)	(0.489)	(0.00292)
AI	7.181	0.0171	6.517***	0.0175**
	(5.197)	(0.0138)	(1.990)	(0.00722)
GWD	-92.89***	-0.584***	-61.49***	0.106
	(29.94)	(0.125)	(15.22)	(0.131)
DI*GWD*HARID	-0.00650	0.00114	0.602***	-0.000352
	(0.167)	(0.00116)	(0.191)	(0.00151)
DI*GWD*MARID	0.388***	0.000350	0.250***	-0.000607
	(0.0580)	(0.000610)	(0.0581)	(0.000618)
AI*GWD*HARID	0.776***	0.00776***	0.965***	0.000351
	(0.253)	(0.00164)	(0.188)	(0.00273)
AI*GWD*MARID	0.757**	0.00575***	0.691***	-0.000138
	(0.311)	(0.00163)	(0.200)	(0.00182)
Constant	2,047***	10.06***	1,049***	8.797***
	(543.4)	(1.301)	(111.6)	(0.625)
R-squared	0.778	0.112	0.730	0.114
F test for model goodness of fit	F(45, 36) = 2939.25***	F(45, 36) = 147.18***	F(45, 36) = 13173.27***	F(45, 36) = 592.94***

Note: *, **, *** indicate statistical significance at 10 percent, 5 percent and 1 percent level, respectively. LSDV technique was used for estimating parameters of the mean and variance models. To maintain positive variance, we used logged values of squared residuals of mean yield equation as dependent variable in variance models; therefore, coefficients of variance model give semi-elasticity specific to inputs. Standard errors reported in parentheses were estimated using Driscoll Kraay (1998) estimator.

Unlike earlier results, drought index showed statistically significant and negative impact on rice yield risk which is more optimistic than earlier results. In case of groundnut; however, coefficient associated with DI turned insignificant possibly because temporal change in drought effects was found significant only in semiarid region. Like mean yield, irrigation didn't show any significant impact on rice yield risk which corroborates regression findings in earlier section. Irrigation, however, significantly improved mean groundnut yield but only at the cost of increasing yield risk. It is noteworthy that rice yield risk fell significantly with increasing groundwater dominance. Regression results in earlier section also confirmed that negative effect of increasing groundwater use on rice yield decreased with time.

[11] A log-linear model was also estimated; however, no major difference in two estimates was found. We have not reported estimates of log-linear specification of yield function.

Impact of *GWD* on drought induced yield risk was not statistically significant in the case of either crop. In earlier results also (see, table 5 and 7), significant adaptation effects of *GWD* were observed only in selected regions. Similarly, coefficients associated with the interaction of *AI* and *GWD* indicated that increasing groundwater use increased irrigation induced rice yield risk in both regions. However, results failed to confirm any significant risk consequences of drought adaptation or irrigation efficiency in the case of groundnut which is different from the results in the earlier section. Therefore, groundwater results must be taken cautiously as far as adaptive and efficiency benefits of groundwater use is concerned.

Discussion

We examined impact of increasing irrigation quality due to groundwater boom on drought adaptation and irrigation efficiency. In this connection, we used a modified drought index to remove bias from impact assessment which incurs into model due to using standardized drought indices in a panel data setting (see, Yu and Babcock 2010; Birthal et al. 2015). We have shown that drought impact on agricultural yields was decreasing over time in the case of groundnut in semiarid region. Groundnut is an important crop in semiarid region of the state. If drought impact on groundnut yield was decreasing in these districts then it had serious implications for recently announced agricultural insurance policy. If insurance premiums are determined under the assumption of constant variance; actuarially fair premium rate determined by the insurance companies may be misleading (see, Yu and Babcock 2010). Inclusion of private players in agricultural insurance market demand better and transparent mechanisms to determine insurance premiums to stop subsidy leakages.

Findings also indicated that there was significant impact of groundwater boom on drought adaptation and irrigation efficiency. Adaptive as well as efficiency effects showed significant annual growth, however, robustness check of findings highlighted that while results were consistent but must be taken with caution as drought and irrigation effects on yield were regional in nature.

Considering the superiority of groundwater irrigation as far as effectiveness of irrigation and climate change adaptation is considered; groundwater sustainability becomes critical for sustainable agricultural growth. In fact, there are various tools which state government has applied to manage negative externalities emanating from groundwater boom. Andhra Pradesh Farmer Managed Irrigation System (APFMIS 1997) and Andhra Pradesh Farmer Managed Groundwater Irrigation Systems (APFMGS 2002) are innovative programs to support community management of irrigation resources. To support community management of groundwater resources, Andhra Pradesh government initiated WALTA Act- 2002 which made registration of well mandatory. Similarly, state promoted special crop programs to divert cropping pattern and increasing proportion of drought tolerant crops in semiarid region signals success in this perspective. While political constraints restrict state from using hard economic measures; it is also true that hard economic measures are useless unless property rights are well defined. In this connection, registration of wells under WALTA is a first step. Considering the fact the drought intensity and frequency may increase due to climate change, effective implementation of WALTA provisions is needed.

Along with it, state is also sensitive regarding availability of surface irrigation; however, lift irrigation schemes currently running in the state are not environmentally benign as they are energy intensive and open to corruption (Ratna Reddy 2003, 2006). In past, government ran a program for converting beleaguered tanks into percolation tank (Sakthivadivel et al. 2004). In recent years, state has also began providing subsidies for farm ponds.[12] Integrating farm pond programs with horticulture, sericulture and fishery can bring environmental benefits in terms of increasing biodiversity and economic benefits in terms of rising income or risk reduction.

[12] http://www.financialexpress.com/india-news/andhra-pradesh-to-launch-water-conservation-programme-tomorrow/628548/; and, http://www.thehindu.com/news/national/andhra-pradesh/1-lakh-pond-programme-launched-in-anantapur/article7973078.ece

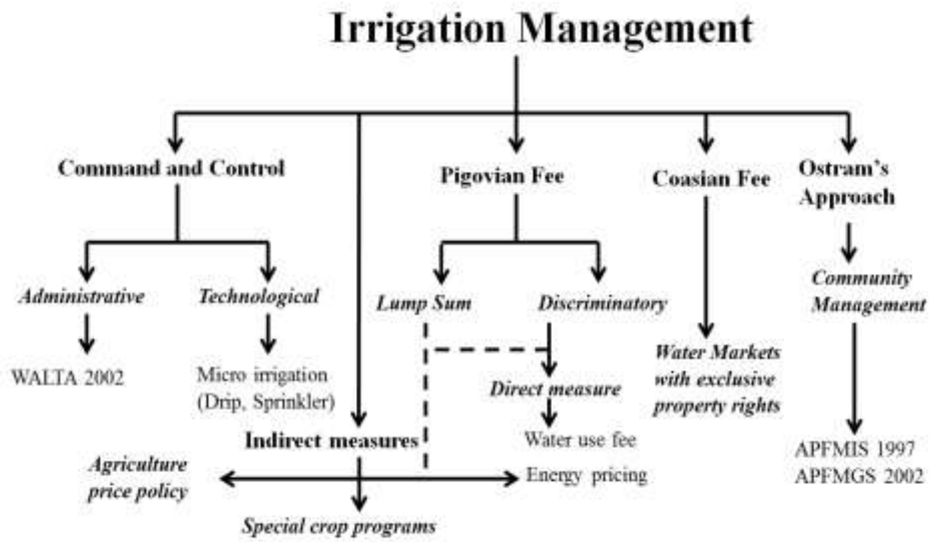

Figure 8: Irrigation Management Policy in Andhra Pradesh

7. Conclusion

We conducted an econometric exercise to understand dynamics between irrigation, drought and agricultural yield to understand certain hypothesis related with drought impact and drought adaptation by promoting groundwater use. In support to our regression results, we also presented a robustness check. Results confirmed that increasing groundwater use increased irrigation efficiency by increasing relative contribution of irrigation in explaining variation in yields of major crops. However, increasing yield risk due to adaptive behavior hinted for increasing conjunctive use of ground and surface water.

Positive growth in adaptive and efficiency effects of groundwater explained the boom in groundwater sector and highlighted imminent danger on the sustainability of groundwater resources and its economic implications. Unsustainable groundwater resource use increased productivity risk and lack of stringent groundwater regulation turned adaptation unsustainable. Sustainable adaptation demands minimizing externalities arising from adaptive activities. In light of the results, it can be said that inter-temporal irrigation budgeting along with effective intra-temporal irrigation budgeting is an impending need of the day. Results, here, indicate that groundwater sector, specifically, and irrigation sector, in general, demand immediate attention in the state.

While there may be other policy implications of results presented here, major objective of the study was to put a few untested but intensely debated hypotheses in Indian agriculture under empirical enquiry. In this connection, we also highlighted few problems associated with using standardized drought indices in a panel setting. Results, in general, confirmed that shift towards groundwater use increased adaptive potential of agriculture in Andhra Pradesh despite increasing drought induce losses.

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