SPATIAL PATTERNS OF DROUGHT VULNERABILITY IN RICE-PRODUCING DISTRICTS OF INDIA

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ABSTRACT

Climate variability is perhaps the greatest challenge facing the smallholder farmer. Abnormal temperatures and inconsistent rainfall can destroy a season's harvest despite optimal farm management and market opportunities. Yet the effects of such variability are not constant across a landscape. This paper provides an investigation into the spatial distribution of drought vulnerability across rice-growing districts in India. We show which regions were exposed to drought from 1999-2008 and determine that rice yields in central and eastern India were most sensitive to the effects of moisture deficit. We explore the effect of certain adaptation strategies in times of drought, finding that irrigation, fertilizer use, and cropping diversity all have a positive relationship with rice yields. The spatial methods employed in this study suggest that there are clear geographic patterns in how districts respond to drought, as well as outliers that seem to be more resilient than their neighbors.

BIOGRAPHICAL SKETCH

Hilary Byerly grew up in the Rocky Mountains of Colorado. She received a B.A. in International Affairs and Environmental Studies from the University of Colorado, Boulder. She came to Cornell after working for an organization that supports grassroots environmental projects abroad and living in India.

To Michael, Dhirendrabhai, Koojan, Dr. Ashok, and the woman who picked fresh pigeon peas from her trees and shared them with me, for showing me India.

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Chapter 1 Introduction

1.1 Drought, vulnerability and spatial patterns

Drought is a pervasive natural hazard that can have devastating and far-reaching effects on society and the environment (Wilhite, 2005; Wilhite, Svoboda, & Hayes, 2007). Given the breadth and nuance of its impacts there is no universal definition for drought. It is generally perceived as a shortage in precipitation from 'normal' that is inadequate to meet the water requirements of nature and human activities (Wilhite, 2005). It can cover extensive areas and last for years, imposing economic costs that make it one of the most damaging natural hazards (Sheffield & Wood, 2012). Yet it is hardly a rare or unexpected phenomenon. Contrary to common perceptions, drought is part of the normal climate in every region (Glantz, 2003). It is the way drought affects a particular region and how society is able to cope that determine whether a drought is a natural event or a natural disaster.

Drought is known to be a significant and direct cause of crop failure and income loss on the farm (Hyman et al., 2008). The Intergovernmental Panel on Climate Change (2007) projects that the area affected by drought and its frequency are likely to increase in the coming years and this will negatively affect local crop production. These impacts are expected to be disproportionately worse in regions where adaptive capacity is low (IPCC, 2007).

Following the conceptual approach of McCarthy et al (2001) and others, vulnerability to drought and other natural hazards is defined as a function of exposure to the event, sensitivity to its effects, and adaptive capacity to mitigate losses. In the case of agriculture, this translates to yield

loss as a result of drought intensity, the importance of rainfall to yields, and the ability of farmers to mitigate the impacts of climatic moisture deficit.

More than 68% of the agricultural land in India is vulnerable to drought (S. Pandey, Bhandari, & Hardy, 2007). In 2002 a widespread drought in India caused a 3.2% decline in GDP, $9-billion loss in agricultural income and loss of 1.3 billion person-days in rural employment due to shrinkage of agricultural operations (Samui & Kamble, 2011). Yet these country-level numbers do not capture the distribution of impacts across the Indian landscape.

Agricultural development in India is regionally disparate. The Green Revolution era of the 1960s to the 1980s saw significant yield growth in cereals in the northern states, where climate, soils, and economic development were favorable to the adoption of new high-yield seed varieties and inputs. The poorer, rainfed parts of central and eastern India, however, did not have the endowments to benefit from these advances in technology. In turn, regional inequalities within Indian agriculture widened significantly (Hazell, 2010; Pingali, 2012).

The vulnerability of agriculture to drought is likely to be dependent on the natural, social and economic resources in a given area (Marshall, Aillery, Malcolm, & Williams, 2015). The inequalities in agricultural development across India suggest that the impact of drought will not be evenly distributed. Determining which regions are more sensitive to drought can enable policymakers to target areas that are more high-risk, where investment in adaptive capacity can have the highest returns to benefit the most marginalized.

1.2 Objectives

In the following pages we conduct a spatially explicit, countrywide investigation of drought vulnerability in India. First, we determine exposure to drought at the district level using the

Standard Precipitation Evapotranspiration Index (SPEI). Next, we evaluate the sensitivity of rice yields to drought in Indian districts over a ten-year period based on correlation with the drought predictor. Local spatial autocorrelation indicates which regions are significantly more or less sensitive to drought, as well as outlier districts that contradict the trend of their neighbors. Lastly, we include adaptive capacity in our model to determine the role of different strategies in maintaining yields and the spatial patterns that remain after accounting for them. We finish with a critical evaluation of the data used in the analysis and suggest avenues for future research.

The goal of this study is to employ a newly developed drought index, seasonal data and spatial techniques to gain insights into the relationship between drought and agriculture in India.

Chapter 2 Background

Despite the structural transformation of the Indian economy over the past 50 years, the majority of the country remains heavily reliant on agriculture. Of India's 1.2 billion people, 70% live in rural areas and more than half of the economically active population is engaged in agriculture (Gillespie, Harris, & Kadiyala, 2012). Although investments in irrigation and new seed technologies have reduced dependence on natural conditions in some parts of the country, still more than half of cultivated land remains rainfed and underdeveloped (Venkateswarlu, Raju, Rao, & Rama Rao, 2014). These areas are tremendously susceptible to changes in climate.

2.1 Vulnerability assessments in India

A number of studies have evaluated the vulnerability of Indian agriculture to climatic changes. O'Brien et al. (2004) matched agricultural and socioeconomic data from 1991 with rainfall patterns to develop an India-wide district-level vulnerability profile. Similar regional assessments have been done for the Indo-Gangetic Plains (Seghal, Singh, Jain, & Pathak, 2013), Andhra Pradesh (Murthy, Laxman, & Sesha Sai, 2015), Andhra Pradesh and Maharashtra (Singh, Bantilan, & Byjesh, 2014), and Uttarakhand (Rajesh, Jain, Sharma, & Bhahuguna, 2014). Each of these papers generated a 'vulnerability index' – a composite value of exposure, sensitivity and adaptive capacity – to determine which areas are more or less susceptible to impacts from climate change and/or drought. Regions with high exposure and sensitivity but low adaptive capacity are found to be more vulnerable. Similar approaches are widespread in the literature (for example: Ahsan & Warner, 2014; Luers, Lobell, Sklar, Addams, & Matson, 2003; Monterroso, Conde, Gay, Gómez, & López, 2014; Nelson, Kokic, Crimp, Meinke, & Howden, 2010). In many of these studies each category (exposure, sensitivity, adaptive capacity) is

broadly defined and measured as a composite of values determined to be relevant. The geographic distribution of findings is discussed from a policy perspective, but rarely are spatial tools employed to explore the patterns of vulnerability.

The following analysis builds on the conceptual approach of such studies but leverages more specific indicators (a newly-developed drought index and seasonal rice harvest variability) and spatial techniques to evaluate the patterns in drought vulnerability of Indian agriculture.

2.2 Rice and drought

Rice is a mainstay in India. Its significance reaches from the national level, where it makes up 36% of gross cropped area and 42% of food grain production, to the rural household, where it is a chief source of food and income for millions (Sushil Pandey et al., 2010).

Rice production in India has fallen short of expectations 14 times since the start of the Green Revolution in 1965, 11 of which can be attributed to drought (A. Kumar et al., 2012). The crop's drought vulnerability is primarily due to its high sensitivity to water stress, especially during flowering (Bouman, Humphreys, Tuong, & Barker, 2007; Tuong & Bouman, 2003). However, yields are reduced by water deficit at any growth stage (Lilley & Fukai, 1994). Across the rainfed rice-producing areas of South Asia drought is the most significant yield-reducing influence (A. Kumar et al., 2012).

Rice was chosen for this study because of its importance at all levels of Indian society, the broad geographic reach of its cultivation, and its sensitivity to moisture deficit. Tuong and Bouman (2003) estimate that 15-20 million hectares of rice will be under water scarcity by 2025. Higher temperatures and drought incidence could reduce global rice yields by 12–14% by 2050 (Pandey et al 2010). Understanding where the most drought-sensitive rice-producing districts are and

which strategies are most likely to maintain yields is critical to targeting the most vulnerable regions.

2.3 Measuring drought

Ray et al. (2015) show a third of crop yield variability worldwide is explained by climate variation. Evaluating crop yield with respect to precipitation and temperature is a well-documented approach to measuring the impacts of climate variability on agriculture. Auffhamer, Ramanathan, and Vincent (2012) showed that rice harvests in the *kharif* season are lower when rainfall during that period is lower. While raw values of temperature and precipitation are sometimes used to tease apart their individual effects on yields (for example, Lobell, Cahill, & Field, 2007), often a single drought index is used to focus in on the explicit effect of drought events.

A drought index is a value that indicates water availability relative to a norm for a particular region during a specified time frame. It is useful for marking the onset of a drought, measuring its severity, and evaluating its spatial and temporal characteristics across regions.

Studies on drought and yield in India have tended to use the Standardized Precipitation Index (SPI) (see Pai, Sridhar, Guhathakurta, & Hatwar, 2011; R. P. Pandey, Pandey, Galkate, Byun, & Mal, 2010; Patel, Chopra, & Dadhwal, 2007). This index measures a precipitation deficit at different timescales through a standardized transformation of the probability of the observed precipitation. It is relatively straightforward to calculate, has minimum data requirements (just precipitation), and can be expressed over different timescales (Guttman, 1998).

However, the exclusive focus on precipitation as a measure of drought is problematic. As temperatures rise so do water evaporation from the earth's surface and transpiration from plants.

These evaporative processes can consume up to 80% of rainfall (Vicente-Serrano, Beguería, & López-Moreno, 2010). Because warmer temperatures increase water demand, and thus exacerbate precipitation deficits, temperature is an important consideration in the severity of droughts. This is especially true when evaluating the effects of drought on agriculture, where soil moisture and plant conditions are directly affected by heat.

For these reasons, the Standardized Precipitation Evapotranspiration Index (SPEI) was selected as the drought indicator for this study. The SPEI measures the combination of water supply and demand changes in in moisture availability:

Climatic water balance = Precipitation (P) – Potential Evapotranspiration (PET)

SPEI values are calculated much in the same manner as the SPI, and expressed as standardized probabilities of observing a particular climatic water balance. Interpretation of the SPEI is straightforward: negative values denote drier than average conditions; positive values denote wetter than average conditions (Cook, Smerdon, Seager, & Coats, 2014).

2.4 Seasonality

Agriculture's susceptibility to climatic changes is no more evident than the way it oscillates with the seasons. In India 80% of rice is grown during the monsoon (*kharif*) season, which stretches from May-June to October-November, depending on the region (Ministry of Agriculture, 2011).

As discussed in Chapter 2.3, drought indices are useful for indicating the temporal parameters of a drought event. The SPEI is also flexible across different timescales, allowing us to specifically focus on the incidence of drought during the *kharif* season.

Following the recommendations of the World Meteorological Institute (2012) a 6-month timescale was chosen to study the monsoon drought across India. The 6-month timescale is

effective for showing variation over distinct seasons. Additionally, Niranjan Kumar et al. (2013) showed that the 6-month time scale of the SPEI reflects the all-India monsoon season rainfall variations.

Chapter 3 Data, Variables, and Descriptive Statistics

3.1 Overview

In order to examine drought in India generally as well as the disparity between regions the following analysis was conducted on the country scale. District-level data was acquired for all variables, allowing a more refined look at trends within regions and states. Lack of data required the omission of Goa, the northeastern states, and union territories. Analysis of drought exposure and sensitivity (Chapters 4.1 & 4.2) included 412 districts; the investigation into adaptive capacity (Chapter 4.3) included 361 districts due to missing data for irrigation and fertilizer.

The analysis stretches 10 years, from 1999 to 2008, due to the constraints of available seasonal rice and irrigation data.

All analysis was conducted using the R software environment via RStudio.

3.2 Drought

Drought was measured using the Standardized Precipitation and Evapotranspiration Index (SPEI). See Chapter 2.3 for a full description on how the index is calculated and its significance.

A global gridded (0.5˚) dataset for SPEI was downloaded from the SPEIbase v2.3 (https://digital.csic.es/handle/10261/104742). The SPEI values were generated by Vicente-Serrano et al. (2010) using monthly precipitation and temperature data from the Climatic Research Unit, University of East Anglia. The long-term 'normal' water balance for the SPEI was defined over the course of January 1901 to December 2013.

The SPEI is available for download at different timescales (1 to 48 months) to be applied on any calendar day of the year. The timescale determines the length of drought under consideration.

For example, a 3-month SPEI captures the normal water balance for the same 90 days across the historical record and the observed variation in those three months for each year of interest. For this study a 6-month timescale was selected, ending on November 16th. This SPEI value captures the long-term normal and variation in water balance from mid-May to mid-November for 1999-2008.

3.3 Rice yield

Data for annual area and production of rice by season was downloaded from the Crop Production Statistics Information System (http://apy.dacnet.nic.in/), a site owned by the Ministry of Agriculture, Government of India. When available, missing years of data were acquired from "Rice in India - A Handbook of Statistics" (Directorate of Rice Development, 2007). When necessary, seasonality was adjusted using the proportions of area and production in different seasons in the original dataset for that district.

Yield was calculated by dividing production (in tons) by area (in hectares), giving units of tons of rice per hectare of land for each district in each year. In order to exclude areas with negligible rice production, the study was limited to districts that had at least 1000 hectares under rice on average over the sample period.

3.4 Adaptive strategies

Certain farming inputs and strategies can help mitigate the impacts of drought on rice yields by increasing the water or nutrients available to the plant. These adaptive management techniques are important tools to cope with water shortage and maintain yields despite the weather.

Irrigation

Irrigation reduces the dependency of plant growth on precipitation on the farm (Schlenker, Hanemann, & Fisher, 2005). More than 75% of the global rice supply is produced under irrigated conditions (Tuong & Bouman, 2003). Depending on the source, irrigation can provide much-needed water to maintain yields in times of water scarcity.

Annual crop-wise seasonal area under irrigation was obtained from the Web Based Land Use Statistics Information System (http://lus.dacnet.nic.in/dt_lus.aspx), a site owned by the Ministry of Agriculture, Government of India. The irrigation data for the kharif season was divided by the area under kharif rice for each district for that same year, yielding a proportion of kharif rice area under irrigation. A value of zero meant no kharif rice was irrigated; a value of 1 meant all kharif rice was irrigated. No data was available for West Bengal.

Fertilizer

Fertilizer plays a similar role by reducing the nutrient stress on rice induced during drought (Sushil Pandey et al., 2010). Appropriate application of nitrogen and phosphate fertilizer can replace missing nutrients from arid soils and mitigate potential yield loss.

Total annual amount of nitrogen, phosphate, and potassium fertilizer applied by district (in tons) was acquired from the Unapportioned Meso Dataset of the International Crops Research Institute of the Semi-Arid Tropics (ICRISAT). Since these statistics were not given by crop or season, the value was divided by gross cropped area (also from ICRISAT) for that district-year. This generated a value of tons of NPK fertilizer per hectare of land under cultivation.

Cropping diversity

Cropping diversity can improve soil structure and health, as well as reduce vulnerability to pests (Pretty, Morison, & Hine, 2003). These traits can improve agricultural resilience during drought by improving the water-holding capacity of the soil and reducing the exposure of crops to stress.

District-wise area under various crops was obtained from ICRISAT and used to calculate Simpson's Index of Diversity (SID) for each year. The index captures the dispersion of activities in a geographic region (Joshi, Gulati, Birthal, & Tewari, 2004). It was calculated as:

$$SID = 1 - \sum_{i=1}^{n} P_i^2$$

where P is the proportion of gross cropped area under cereals, pulses, oilseeds, sugarcane, cotton, and horticulture for each district i. The index moves towards 1 with a greater number of crops and a more even crop distribution, indicating higher cropping diversity.

3.5 Data summaries

Summary statistics of the variables used in this study are listed in Table 3.1. As mentioned the number of observations for irrigation, fertilizer and cropping diversity is fewer, as a result of missing data. In order to create a balanced panel and avoid bias from uneven observations in each district, only districts that had data for all variables for all years were included.

Table 3.1 Summary statistics of variables

Descriptive Statistics

	N	Mean	St. Dev.	Min	Max
Standardized Precipitation Evapotranspiration Index (SPEI)	4,120	-0.29	0.95	-3.14	2.46
Area (hectares)	4,120	87,669	85,528	320	554,471
Production (tons)	4,120	174,305	207,649	150	1,710,000
Yield (tons/hectare)	4,120	1.90	0.96	0.05	5
Irrigation (% of rice area)	3,610	56	38	0	100
Simpson's Index of Diversity (SID)	3,610	0.45	0.19	0.01	0.79
Fertilizer (tons/hectare)	3,610	0.14	0.12	0	1.19

The geographic spread of rice yield, irrigation, fertilizer, and cropping diversity can be seen in Figure 3.1. The mean values for each district are shown.

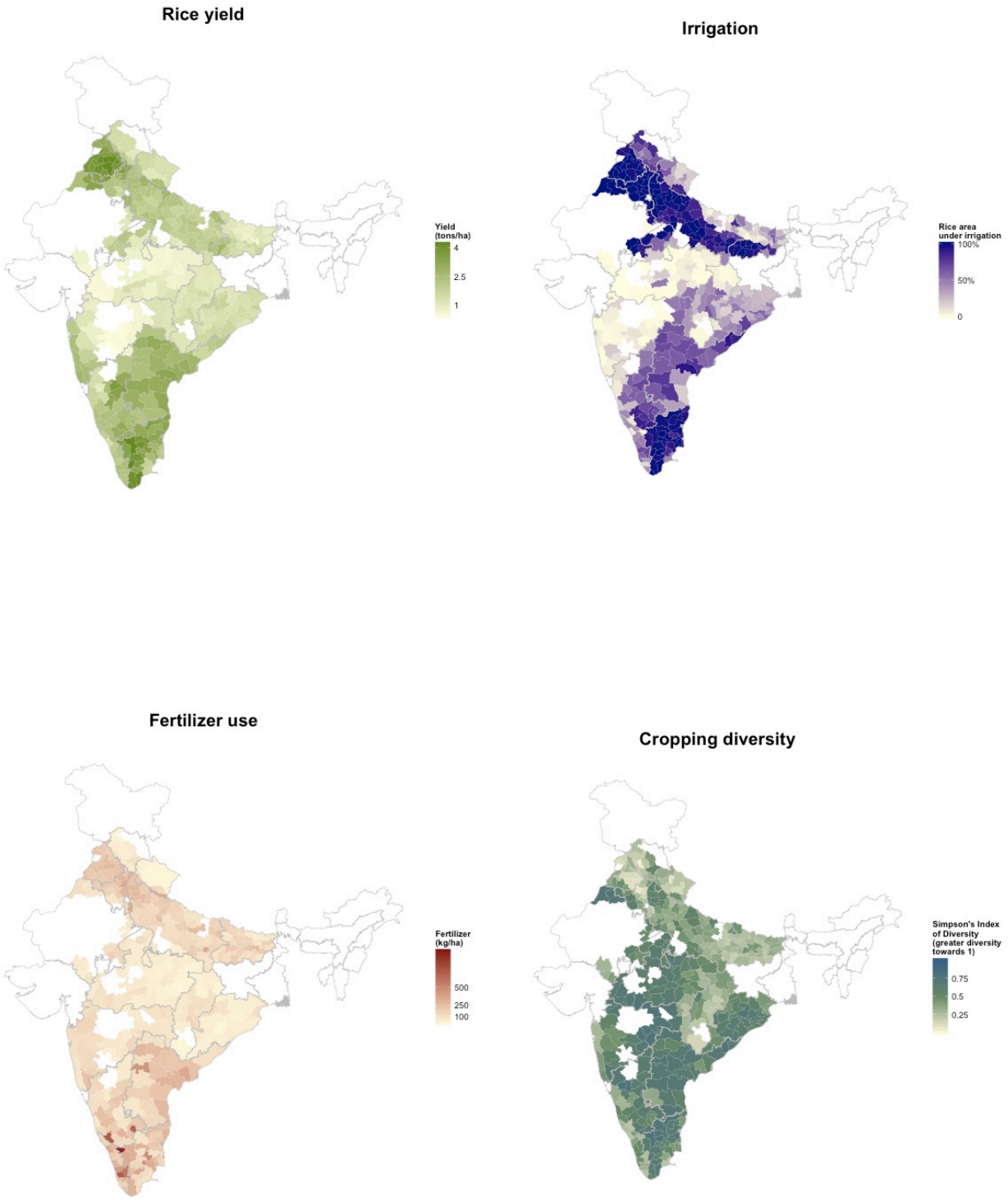

Figure 3.1 Spatial distribution of select variables, shown by the mean over the 10-year sample

3.6 Data challenges

3.6.1 Non-stationary district boundaries

One of the greatest challenges in conducting a longitudinal analysis on India is tracking and accounting for the changes in district boundaries over time. Three states were formed during 1999-2008 (Chhattisgarh, Jharkhand, and Uttarakhand in 2002), as well as a number of districts that were split from existing districts. The formation of a new district during a longitudinal analysis makes the panel unbalanced (unequal number of observations for each district), creates an abrupt drop in the raw values of its parent district (area under rice, for example), and complicates spatial analysis without static neighboring districts.

In order to minimize these effects, districts formed during the study period were combined with their parent district. This was done both through polygon merge in the shapefile (which is based on 2011 district census boundaries) and by aggregating observations in the datasets.

3.6.2 Inconsistencies in district and season names

Remarkably, there is no consistent name index for Indian districts across government documents or those of Indian research institutions. There were numerous discrepancies between district names in the census boundary shapefile, agriculture dataset, irrigation dataset, and ICRISAT-provided datasets. These inconsistencies ranged from simple spelling variations to entirely different names altogether. The misspellings were mostly rectified using the 'stringdist' package in R, while the more complicated incongruities required significant labor to manually match districts across datasets. Seasonality in rice and irrigation data was also inconsistently labeled, both within and across states, and required manual correction.

3.6.3 Data errors in rice area and production

There were a number of clerical errors in the rice area and production dataset. For example, the area and production numbers for Maharashtra in 2007 were two orders of magnitude lower than all other years, perhaps recorded as ’00 hectares’ instead of ‘hectares.’ Duplicate observations were also recurrent.

Chapter 4 Methods

First, we determine exposure to drought using the Standardized Precipitation Evapotranspiration Index (SPEI) to define district-level drought incidence from 1999-2008. Second, we estimate the sensitivity of rice yields to drought based on correlation with the SPEI value and map the results. Last, we model the impacts of drought with different farm management strategies to explore the relationship between drought, yields and adaptive capacity.

4.1 Exposure of Indian districts to drought

Drought exposure was defined by values of the Standardized Precipitation Evapotranspiration Index (SPEI). The data was provided in a gridded form, with raster cells holding SPEI values for every 0.5˚ of latitude and longitude. The goal was to define district-level values for SPEI to indicate the exposure of a given district to drought during the study period.

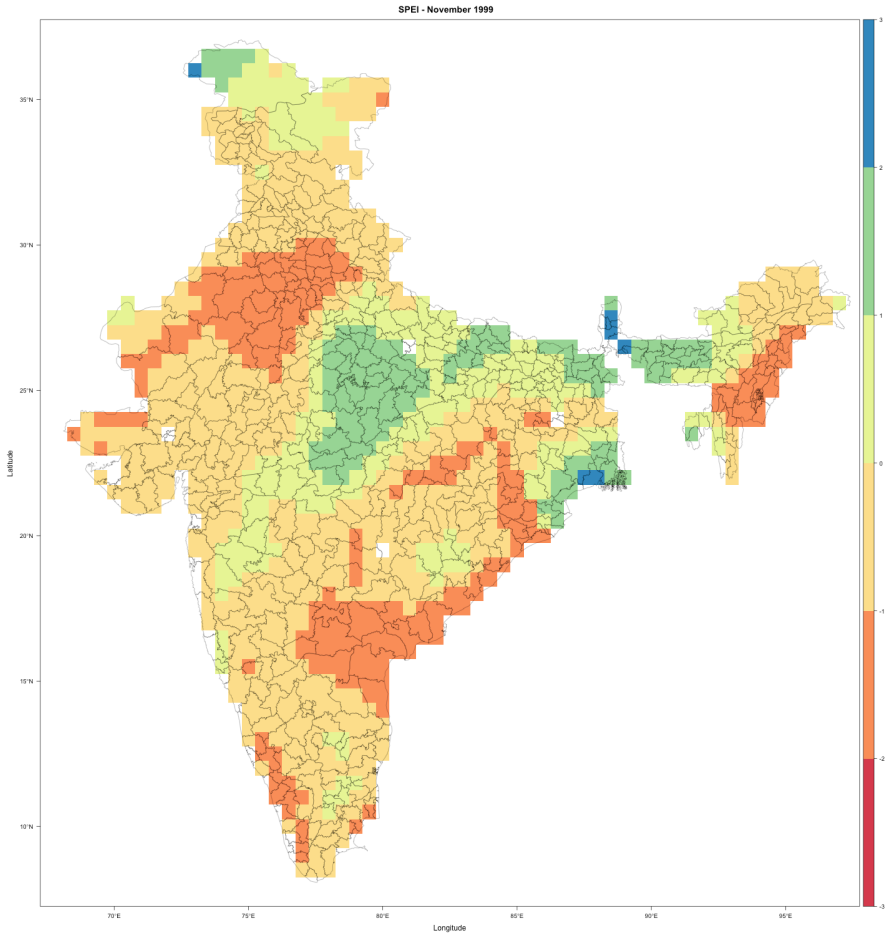

Figure 4.1 Rasterized SPEI values for 1999 with district boundaries overlaid

Global SPEI data was downloaded and imported into R as a netCDF file. First, dates of interest were extracted, and then the geographic extent was subsetted to that of India. This data was rasterized and clipped to the boundaries of India using the revised 2011 administrative boundaries shapefile (Figure 4.1). The centroids of each district in the shapefile were used in inverse distance weighting interpolation to generate district values based on the weighted average of surrounding SPEI values. The power parameter was set at two (neither accelerated nor slower distance decay in weighting the influence of neighbors) and a maximum number of four neighbors were considered. This method is similarly used to generate district-level temperature and precipitation values by Barnwal and Kotani (2013).

Drought exposure was further illuminated by categorizing SPEI values for each district. Following the defined levels of drought intensity from McKee et al. (1993), the following breaks were set:

Table 4.1 Drought intensity levels

SPEI Values	Drought Category
$>$ -1	None
-1 to -1.49	Moderate
-1.5 to -1.99	Severe
$\leq$ -2	Extreme

4.2 Sensitivity of rice yields to drought

The relationship between rice yields and SPEI was explored to determine yield-sensitivity to drought. This was first conducted on an aggregated scale (all districts and years), and then evaluated at the district level using a 'harvest loss' index.

4.2.1 Harvest loss index (HLI) and drought correlation

In order to determine the annual variation in yield, a "harvest loss" index (HLI) was generated to capture relative difference in observed yield from expected yield. This approach was similarly used in vulnerability analyses for China (Simelton, Fraser, Termansen, Forster, & Dougill, 2009) and Ghana (Antwi-Agyei, Fraser, Dougill, Stringer, & Simelton, 2012).

First, expected yield values were adjusted to minimize the influence of time-variant factors, such as crop management and technology adoption. Although the time series stretches only 10 years, a state-level look at yield change over time (Figure 4.2) shows slightly increasing trends in several states, particularly in Punjab.

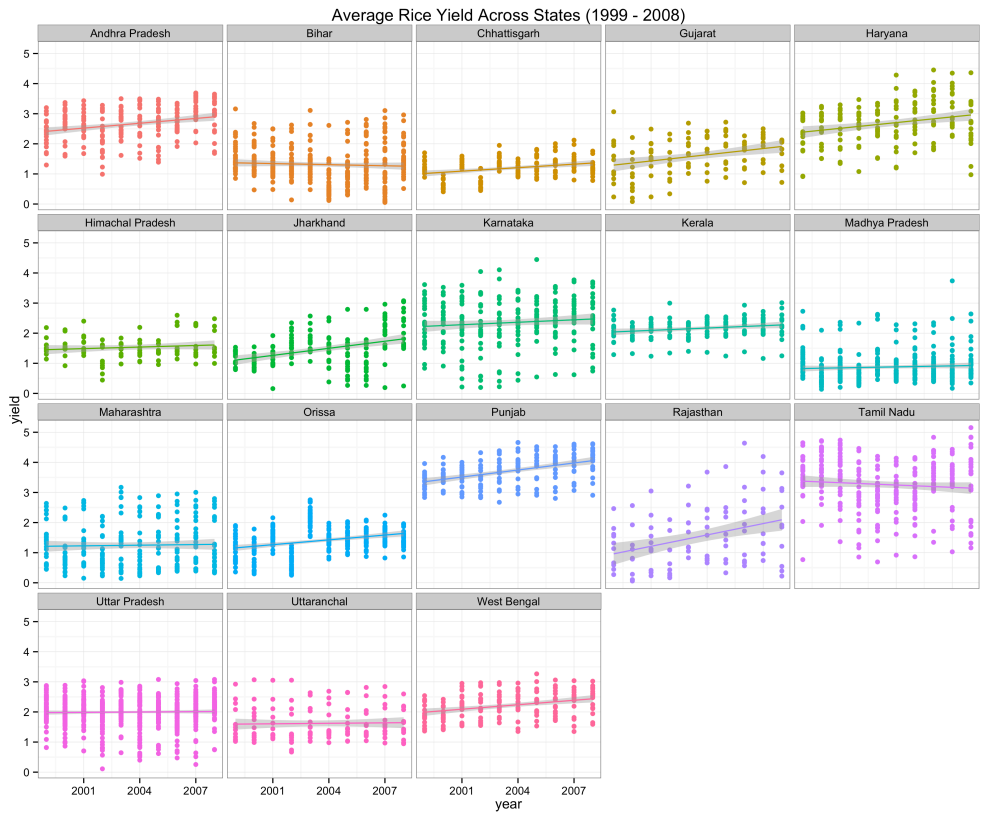

Figure 4.2 Rice yield trends by state, 1999-2008

Thus, following the approach of Shi & Tao (2014), yields were detrended by linear regression against year for each district *i*:

$$yield_{it} = \alpha_i + \beta_i year_t \quad (1)$$

Fitted values $\hat{y}_{it}$ are interpreted as the expected yield in $year_t$. The harvest loss index is then calculated as the ratio of the expected yield to the observed yield for each district-year.

$$HLI_{it} = \frac{\hat{y}_{it}}{y_{it}} \quad (2)$$

An *HLI* value of 1 indicates years when actual rice yield was equal to expected; a value greater than 1 indicates when actual harvests were below expected.

The relationship between yields and drought was then explored by calculating the correlation coefficients between HLI and SPEI for each district. Because the harvest loss index was right-skewed (not normally distributed) and the relationship is not linear, Spearman's rank-order correlation was used.

4.2.2 Local Indicators of Spatial Autocorrelation

To explore the spatial patterns in drought sensitivity, this study uses Local Indicators of Spatial Autocorrelation (LISA). LISA estimates spatial dependence where there is coincidence of value similarity with locational similarity (Anselin, 1995). It identifies spatial clusters of positive local autocorrelation, where districts with high (low) values are surrounded by other districts with high (low) values. Negative local autocorrelation is determined by neighbors with significantly dissimilar values.

In order to define neighboring districts, a spatial weights matrix must be generated. This is an $N \times N$ matrix, where N is the number of cross-sectional observations (districts), that represents the strength of influence between districts.

The method for determining district neighbors was rook contiguity, as the spatial processes driving yield variability could be a function of infrastructure and population movement that follow borders. Kumar (2011) show that the choice of spatial weights matrix, however, may not have a significant influence on district-level yield responses to climate. Figure 4.3 depicts the neighbor contiguities between districts in the study area. The number of neighbors was then row-standardized, which reduced weighting of observations with few neighbors.

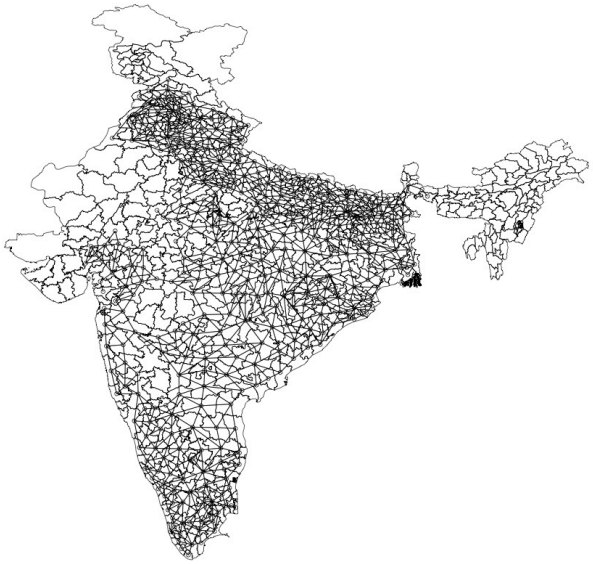

Figure 4.3 District neighbors sharing boundaries (rook-style contiguity)

Two methods of evaluating and visualizing local autocorrelation in this study are the Moran scatterplot and the LISA cluster map.

4.3 Adaptive capacity of Indian districts

After exploring the exposure and sensitivity of Indian districts to drought we consider the role of different management strategies that could affect the ability of a district to adapt to drought, thereby mitigating vulnerability.

Since the data is structured in district-years, a panel data model is appropriate to account for individual differences between districts and inter-temporal trends. This approach helps control for the influence of unobserved or missing variables.

To test the validity of the approach, the model is first run as a simple ordinary least squares regression:

$$y_{it} = \alpha + \beta spei_{it} * \boldsymbol{X_{it}} + \varepsilon_{it} \quad (1)$$

where $\boldsymbol{X}$ is a vector of farm management strategies that could mitigate the impacts of drought (irrigation, fertilizer, and cropping diversity). These variables are interacted with SPEI to explore whether their effect changes in times of drought.

Next, fixed effects for district were included to control for dependence across observations of the same district and to capture time-invariant characteristics such as soil quality (Blanc, 2012; Schlenker et al., 2005; Ward, Florax, & Flores-Lagunes, 2014):

$$y_{it} = \alpha_i + \beta spei_{it} * \boldsymbol{X_{it}} + \varepsilon_{it} \quad (2)$$

Finally, year fixed effects were included. This method allows us to control for omitted variables that vary over time but not over districts. These could include changes in national government spending or price-support policies.

$$y_{it} = \alpha_i + \beta spei_{it} * \boldsymbol{X_{it}} + \delta_t + \varepsilon_{it} \quad (3)$$

Chapter 5 Results and Discussion

5.1 Exposure of Indian districts to drought

The drought occurrence across India was mapped for rice-producing districts from 1999-2008 (Figure 5.1).

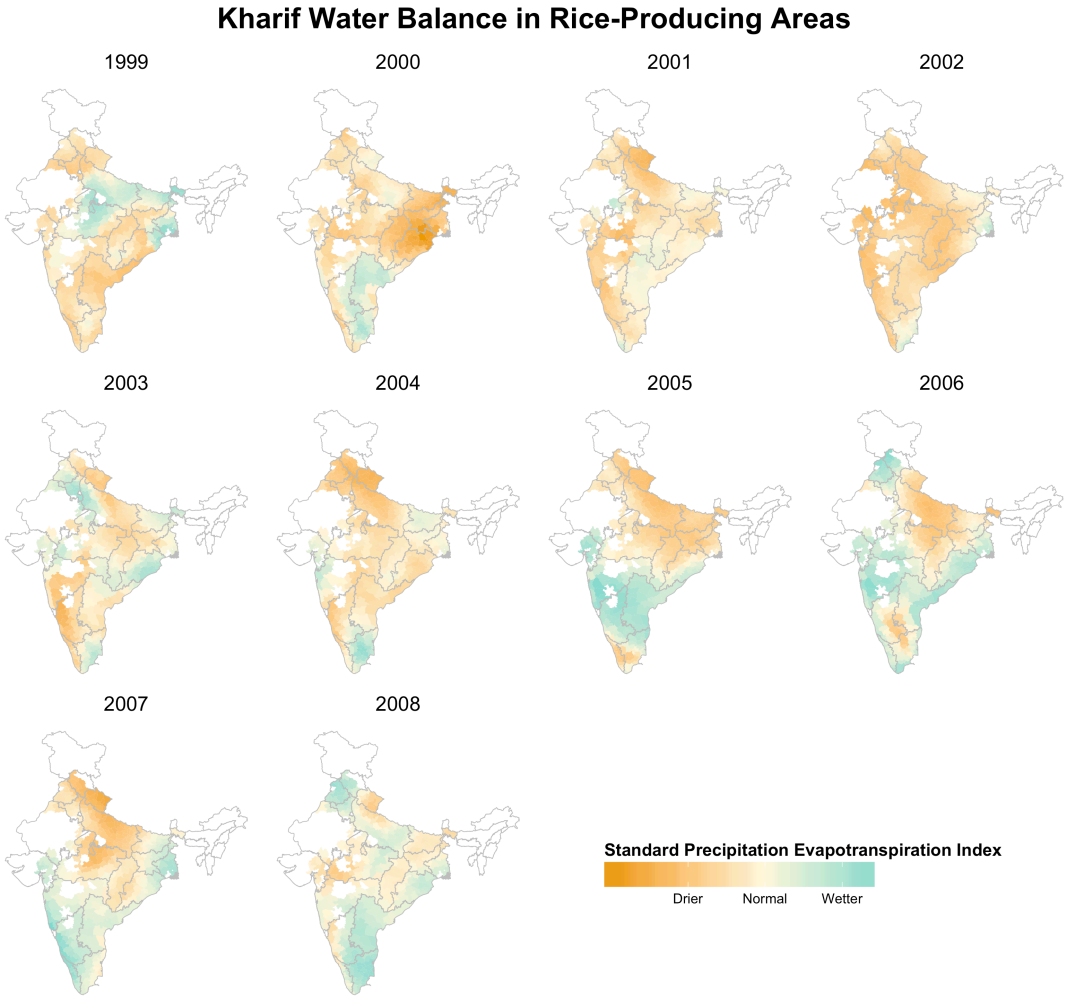

Figure 5.1 District-level SPEI values, 1999-2008

The SPEI values for the period range from -3.140 to 2.460, with the most extreme droughts occurring in eastern India in 2000 and northern India in 2004 and 2007 (Figure 5.1). The most

widespread drought during the time frame was in 2002, when 218 districts experienced at least moderate drought (SPEI ≤ -1). The geography of drought varies over time, although the northern states tended to see drier than normal monsoon seasons between 1999 and 2008.

Although the 10-year time series is shorter than many climate-yield evaluations, this annual map of SPEI values shows that most every region in India experiences a range of dryness (or wetness) over the time period. This in-sample drought variation is important to estimate the relationship between drought and yields.

Drought intensity was also mapped to bring exposure into clearer relief (Figure 5.2). Parts of the Indo-Gangetic plains of northern India experienced drought in almost every year between 1999-2008. However, it is important to consider this classification in the context of Figure 5.1, which illustrates the gradient of moisture conditions. Categorizing drought is useful for conceptualizing where and when a drought occurs, but the boundaries between 'drought-affected' and 'no drought' are much more ambiguous.

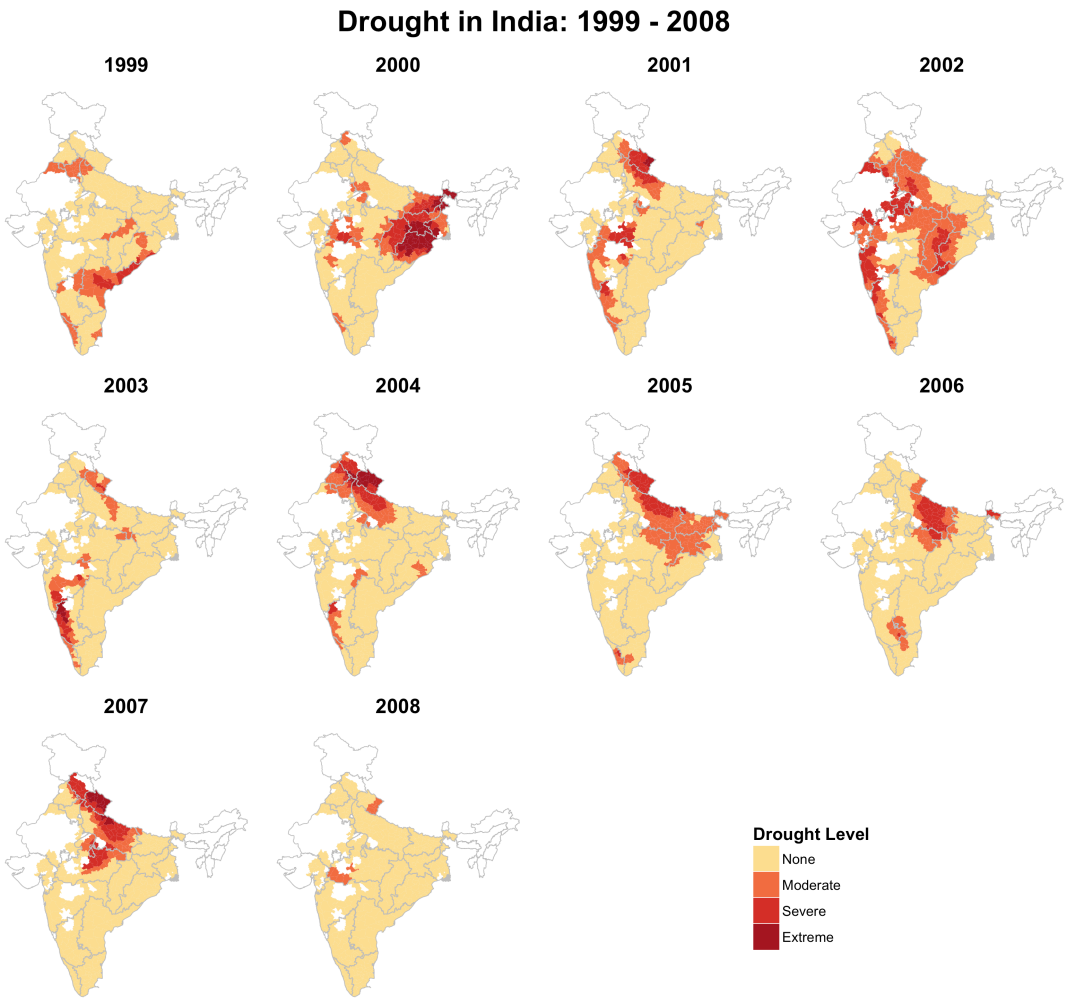

Figure 5.2 District-level drought intensity, 1999-2009

5.2 Sensitivity of rice yields to drought

A first look at the relationship between rice yield and drought at the India level shows a very faint relationship (Figure 5.3, left). Deconstructing the relationship into drought categories illustrates a more apparent trend (Figure 5.3, right) although the dispersion of yield values remains broad (especially at the low end). These plots are unsurprising, as we anticipated that the relationship between yield and drought would vary by district.

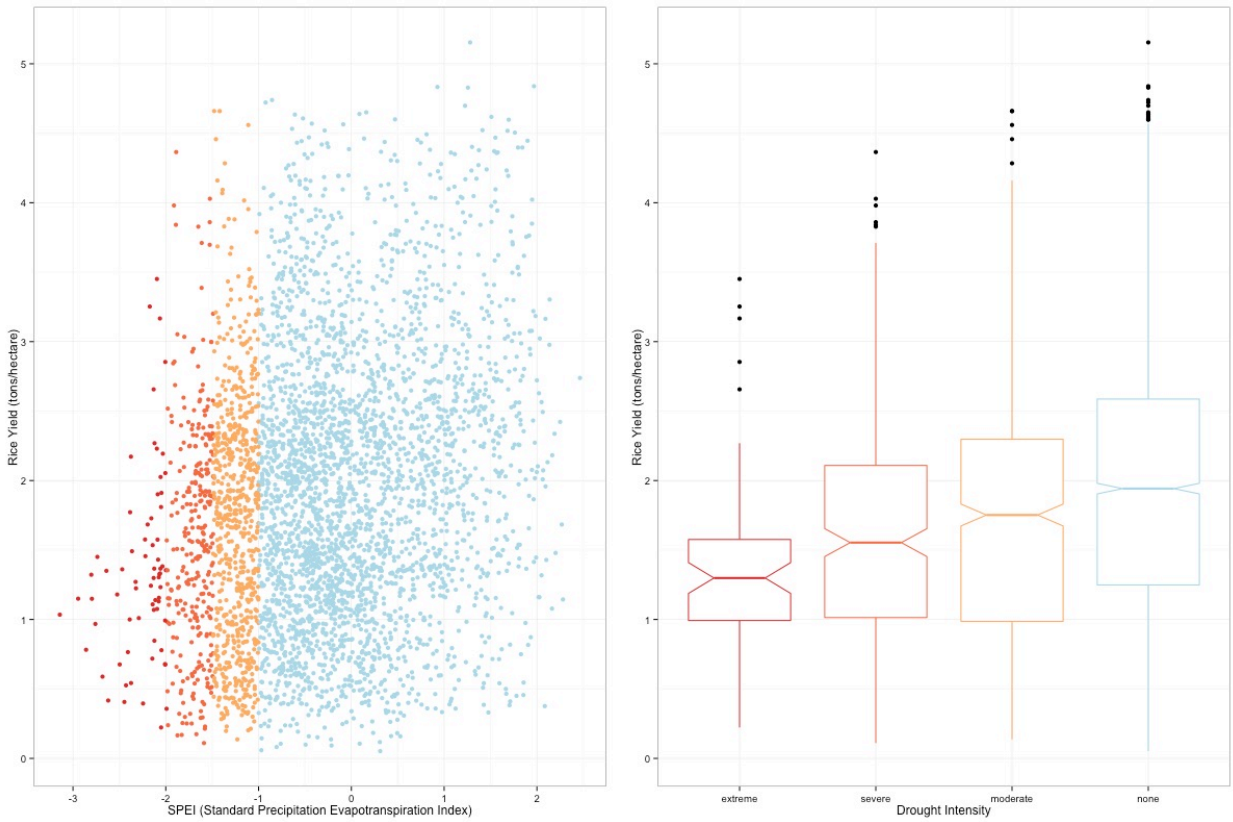

Figure 5.3 Rice yield by SPEI (left) and drought intensity (right); includes all years for all districts

5.2.1 Drought, harvest loss, and spatial patterns

After calculating the district-level correlation coefficient between the Harvest Loss Index (HLI) and the Standard Precipitation Evapotranspiration Index (SPEI) we found significant correlation between harvest loss and drought for 32 districts ($p < 0.05$). This amounts to about 8% of districts in the sample. Mapping the district correlation coefficients shows a visible spatial pattern in the correlation between yield variation and drought (Figure 5.4).

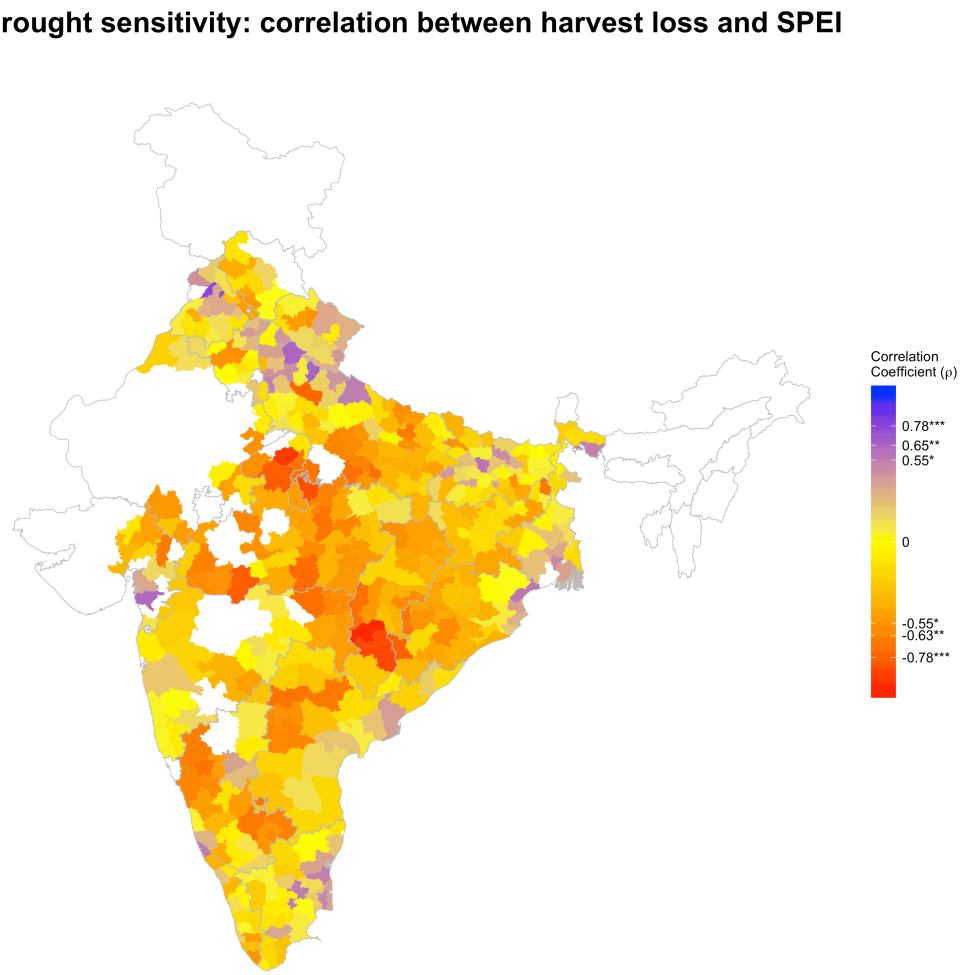

Figure 5.4 District-level correlation coefficients (*ρ*) between harvest loss index (HLI) and drought (SPEI); negative value (red) indicates increasing harvest loss with drought (*p<0.1; **p<0.05; ***p<0.01)

Similar to the findings of O'Brien et al. (2004), the rainfed regions of central and western India appear to be the most sensitive to drought. Districts in Chhattisgarh and Madhya Pradesh have the most significant negative correlation, meaning as the SPEI becomes more negative—and drought more intense—rice harvest losses become greater. Parts of the north and southeast have harvest loss that is positively correlated with SPEI. These areas are likely to have access to irrigation, making them much less dependent on rainfall. Rice yields in these regions could increase in time of drought if farmers invest more into their crops because of increased prices due to shortage from yield-reducing drought in other parts of India. Or, if rain is less (meaning fewer cloudy days), there could be a physiological explanation for higher yields: areas with irrigation would have more control over water management, while extra sunshine would also increase photosynthesis. Alternately, these areas could be suffering yield losses from extreme wetness (floods).

A Moran scatterplot confirms the finding of local differences in yield sensitivity (Figure 5.5). While the linear trend in the plot expresses the slight countrywide pattern of spatial association, the lack of fit indicates local pockets of non-stationarity (Anselin, 1993). The lower left (Low-Low) and upper right (High-High) quadrants hold observations with positive spatial association, while the districts in the upper left (Low-High) and lower right (High-Low) quadrants have negative association with their neighbors.

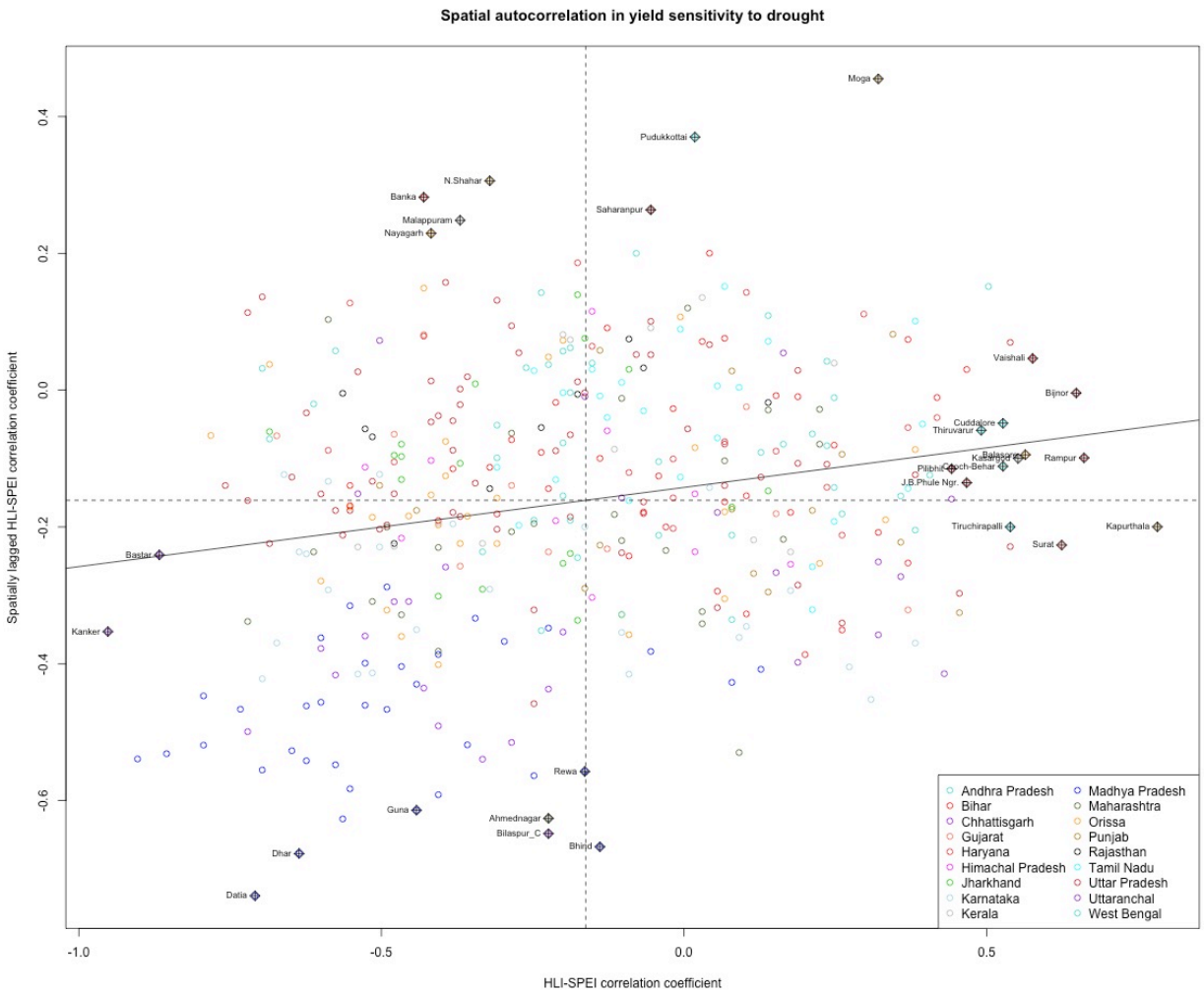

Figure 5.5 Moran scatterplot of significant clusters and outliers in drought yield-sensitivity; moving from top left clockwise these quadrants are 'Low-High', 'High-High', 'High-Low' and 'Low-Low'

The policy application of this methodological tool is significant: the different quadrants can help to identify regions that are overwhelmingly vulnerable or resilient to drought, as well as districts that are much better or worse off than their neighbors. The lower left quadrant (Low-Low), for example, contains districts where low values of ρ (increasing harvest loss with greater drought intensity) neighbor districts that also have low values of ρ. These are clusters of districts that are

highly sensitive to drought, such as those in Madhya Pradesh and Chhattisgarh that were identified in the drought sensitivity map (bright red in Figure 5.4). These areas should be targeted for policies and investment in building resilience because they are most likely to suffer significant yield losses in times of severe drought.

In contrast, the lower right quadrant (High-Low) contains districts that have high values of ρ in regions where most other districts have low values. These districts are much less sensitive to drought than their neighbors, and there may be something about them—certain policies, infrastructure, or socioeconomic characteristics—that suggests an important means of coping with drought. The High-Low quadrant can point researchers to districts that may have promising strategies to improve drought vulnerability.

The relative densities of the diagonal quadrants (lower left and upper right; upper left and lower right) specifies which of the two patterns dominates in the data (Anselin, 1993). Visual assessment of the scatterplot indicates that Low-Low is prevailing, which is supported by the drought sensitivity map (Figure 5.4). This means that, overall, rice-producing districts in India are sensitive to drought. However the wide dispersion of districts across the four quadrants indicates that the relationship does not hold for all parts of the country.

A LISA cluster map (Figure 5.6) allows us to connect the patterns in the Moran scatterplot with those observed in the initial drought sensitivity map. Here we see the significant ($p < 0.05$) Low-Low clustering in the same regions we identified in the scatterplot. This confirms a local pattern of drought sensitivity across districts in central India. We are also able to look more closely at outliers that contradict the trend of their neighbors. The light red district in the middle of India (colored 'High-Low') does not have the same strong yield sensitivity to drought as most of its neighbors. A closer look at the data shows that this district (Amravati, Maharashtra) had higher

than average yield in 2001 despite suffering severe drought. The dark blue district to its left, Khandwa, had a rice yield that was almost one standard deviation below normal for that same severe drought.

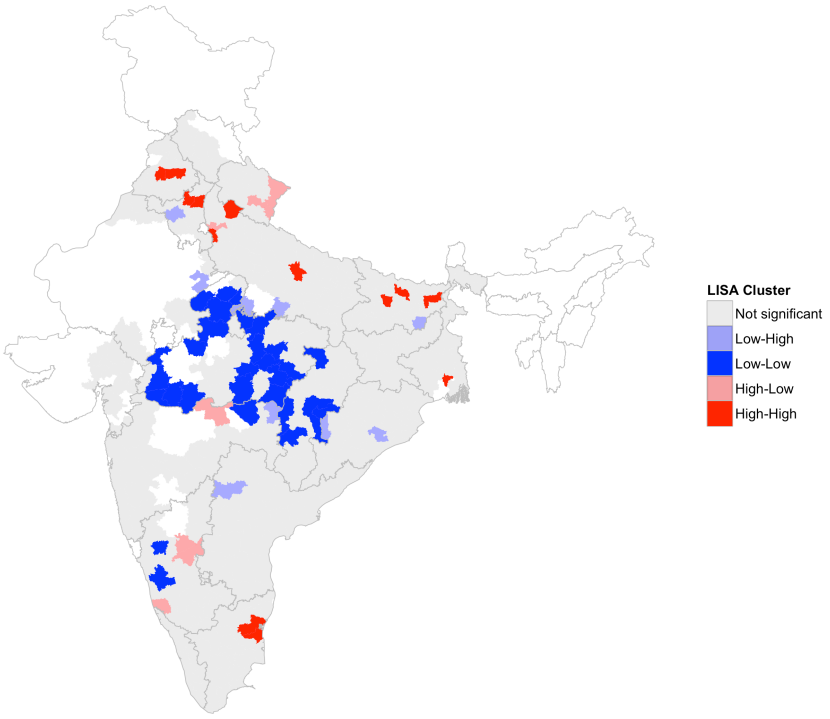

Figure 5.6 LISA clusters and outliers in yield sensitivity to drought

5.3 Adaptive capacity of Indian districts

Results from the three regression models in Chapter 4.3 can be seen in Table 5.1. The inclusion of individual and year fixed effects absorbs a considerable amount of explanatory power of the model and each coefficient, but we suspect that the estimators of the pooled OLS are biased due to the presence of unobservable individual heterogeneity across districts. Indeed, the F-test comparing the pooled OLS with the fixed effects rejects the null hypothesis that all of the district intercepts are zero ($p < 0.000$). An F-test of the individual fixed effects against the two-way (including year) also rejects the null ($p < 0.000$). Thus, the model that includes both district and year fixed effects (3) is chosen.

Table 5.1 Results from regression model of rice yield on drought and adaptive capacity, 1999-2008

	Dependent variable:		
	yield		
	OLS	*panel linear*	
	No FE	District FE	Dist+Year FE
	(1)	(2)	(3)
spei	−0.056	0.105***	0.076***
	(0.039)	(0.024)	(0.024)
irr_prop	1.424***	0.264***	0.209**
	(0.033)	(0.090)	(0.089)
sid	0.301***	0.270*	0.279**
	(0.064)	(0.144)	(0.140)
fert_t.ha	2.642***	0.637***	0.317**
	(0.100)	(0.140)	(0.148)
spei:irr_prop	0.156***	−0.042**	−0.045**
	(0.034)	(0.020)	(0.020)
spei:sid	0.332***	0.088**	0.078**
	(0.064)	(0.038)	(0.038)
spei:fert_t.ha	−0.226**	−0.187***	−0.167***
	(0.096)	(0.057)	(0.055)
Constant	0.660***		
	(0.040)		
Observations	3,610	3,610	3,610
R^2	0.531	0.075	0.032
Adjusted R^2	0.531	0.068	0.029
Residual Std. Error	0.679 (df = 3602)		
F Statistic	583.770*** (df = 7; 3602)	37.790*** (df = 7; 3242)	15.503*** (df = 7; 3233)
Note:			*p<0.1; **p<0.05; ***p<0.01

As expected, SPEI and yield have a positive and significant relationship, suggesting that yields are higher when there is more climatic moisture. The relationship holds for irrigation, which has similar implications. The interaction term for irrigation and SPEI, however, is negative, indicating that the effect of irrigation is not necessarily additive. This is logical, as larger SPEI

values signify wetter than normal years, when irrigation may not be needed to meet crop water needs. Or, as postulated in Chapter 5.2.1, irrigated areas may even see higher yields in times of drought due to more controlled water management and more sunlight for photosynthesis. If we consider the districts shown to have the highest sensitivity to drought (Figure 5.4) we see remarkable overlap with the part of India that has very little rice under irrigation (Figure 3.1).

Cropping diversity is also positive and significant ($p < 0.05$), both on its own and when interacted with SPEI. While this could partly be the result of healthier soil and more resilient crops, as mentioned in Chapter 3.4, it could also be a function of the choices available to farmers. Some areas with low cropping diversity may be more marginalized, where rice is the only crop suited for the puddled or flood-prone (deepwater) fields of the wet season. Even in times of relative drought, the climate and soil or infrastructure in these areas may not be conducive to alternate cropping patterns.

Fertilizer, like irrigation, has a positive relationship with rice yields, but is negative when interacted with drought. Since fertilizer use is most concentrated in the heavily irrigated areas of northern and southern India (Figure 3.1), its yield benefits may be higher in times of less climatic moisture, when farmers can better manage the water on their fields.

Although we have controlled for individual heterogeneity through fixed effects, it is important to consider the likelihood of spatial autocorrelation. Plotting the model residuals against the fitted values shows greater dispersion of residuals with increasing fitted values, indicating the presence of heteroskedasticity. To explore the spatial distribution of the residuals, we mapped them for each year in the panel (Figure 5.7).

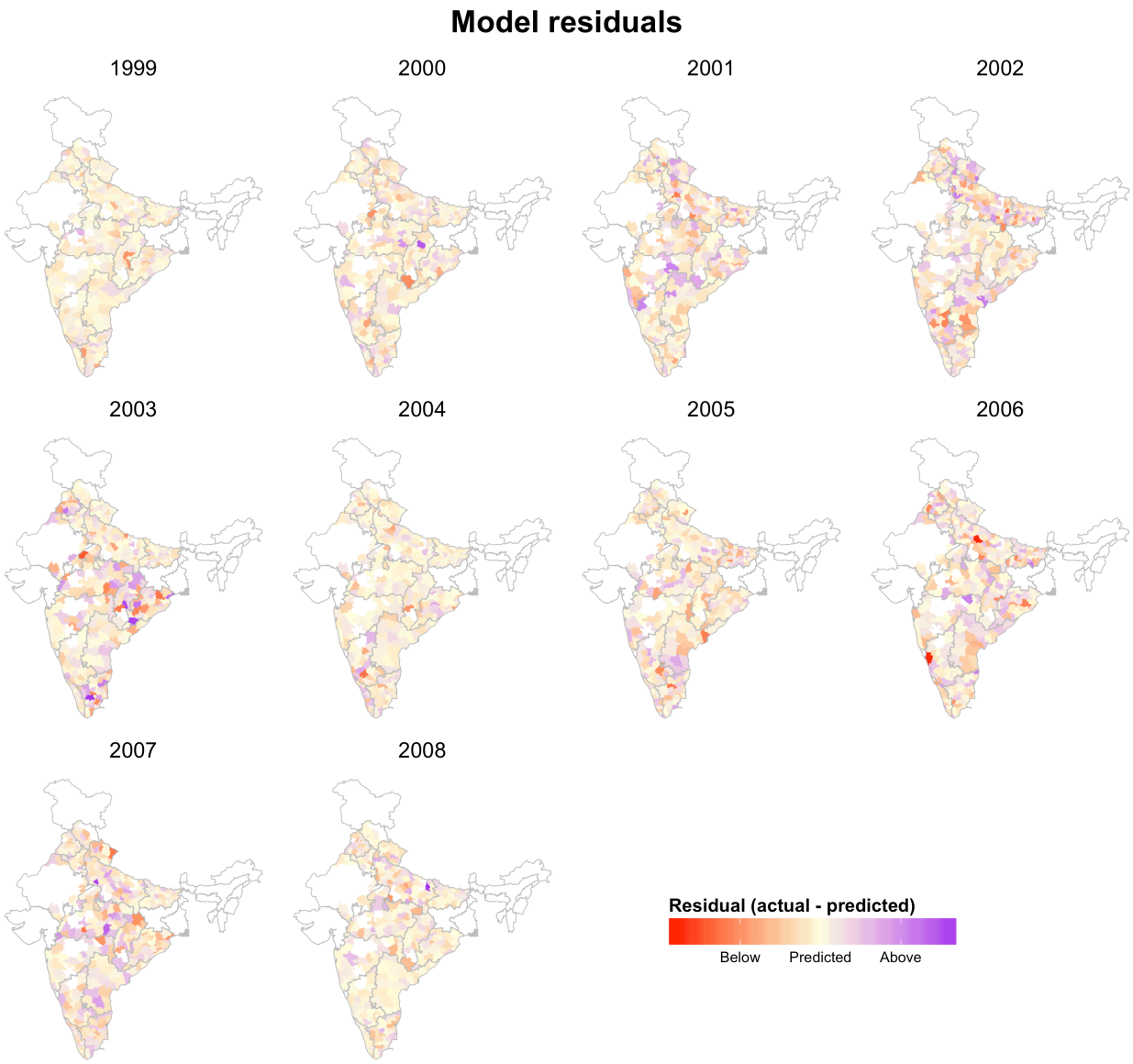

Figure 5.7 Residuals for the regression of rice yield on drought and adaptive capacity, 1999-2008

The maps in Figure 5.7 do not show an overt grouping of over- or under-predicted values, however there may be some clustering (see Andhra Pradesh in 2005 and 2006). It could be that certain spatially correlated unobservable factors remain, such as technology spillovers that are not included in the model or changes in regional agricultural policies or population structure.

Chapter 6 Conclusion

In this paper we have provided an investigation into the spatial distribution of drought vulnerability across rice-growing areas in India. We showed which regions were exposed to monsoon drought from 1999-2008 and determined that central and eastern India were most sensitive to the impacts of moisture deficit during the wet season. We explored the effect of certain adaptation strategies in times of drought, finding that irrigation, fertilizer use, and cropping diversity all have a positive relationship with rice yields.

Drought is a pervasive natural hazard that can have devastating impacts on agriculture, but not all regions are affected equally. For this reason it is critical to identify areas that are the most susceptible to the effects of drought to ensure that limited resources reach the communities that need them most. The Drought Prone Areas Program (DPAP) is an initiative of the Government of India to support regions that suffer frequent droughts. The program covers 183 districts in 17 states that have met minimum criteria of annual average moisture inadequacy and insufficient area under irrigation, based on climate and irrigation data from 1990 (Venkateswarlu et al., 2014).

Although many of the districts covered by DPAP overlap with the same part of central India identified in the present study (Figure 6.1), the program's criteria of exposure and adaptive capacity does not consider which districts are actually sensitive to drought. The map in Figure 6.1 or a simple list of the districts covered by the DPAP gives no indication which areas are most vulnerable to the effects of drought and which are performing relatively well, considering their lack of moisture and irrigation.

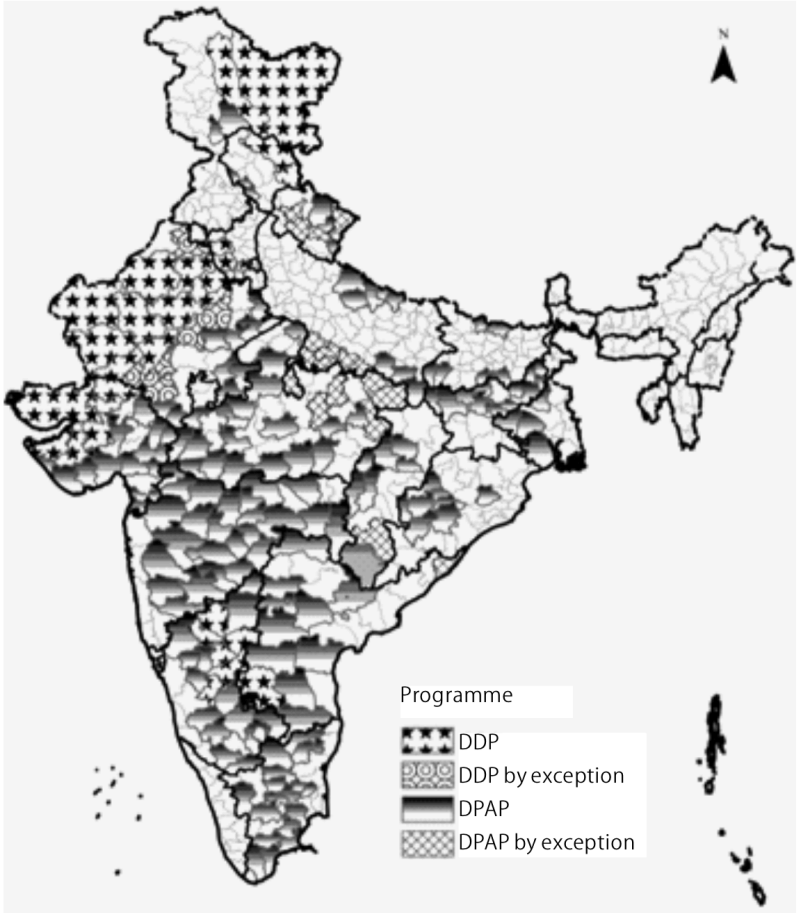

Figure 6.1 Drought Prone Area Program (DPAP) and Desert Development Program (DDP) districts (Venkateswarlu et al., 2014)

For this reason we developed a new index and used local indicators of spatial autocorrelation to gain a more accurate assessment of drought vulnerability. The Low-Low areas of the Moran scatterplot and LISA cluster map highlighted the specific region within central India where rice yields are most sensitive to monsoon drought. These are districts where agriculture could benefit most from investments in adaptation strategies or the watershed development projects of the DPAP, and they should be targeted accordingly. Similarly, the High-Low districts—the outliers that are more resilient to drought relative to their neighbors—can also point policymakers to places where certain strategies are effective in building drought resilience. The characteristics of

these districts should be carefully examined to understand why they are able to maintain yields while others around them suffer losses. This could be a particularly useful approach for prioritizing which adaptive strategy might be most effective in that particular region, since neighboring districts might otherwise not be so different.

The spatial methods employed in this study show clear geographic patterns in how sensitive districts are to drought, as well as outliers that appear more resilient than their neighbors. With limited resources to invest in drought-sensitive regions, government programs and the districts they are mandated to help could benefit from this sort of explicit spatial evaluation of drought vulnerability.

6.1 Data critique

6.1.1 Accuracy

Some of the conclusions drawn from this analysis must be considered in the context of uncertain data quality. Although the methods used to evaluate and locate drought-vulnerable districts could be valuable tools for policymakers to target scarce resources, the usefulness of their results does depend on the accuracy of the data. As mentioned in Chapter 3.6.3, there were a number of glaring errors in the rice area and production data. Even when the statistics were not a clear order of magnitude off, large oscillations in area under rice from year to year generated skepticism about their true values.

There is no information provided with the rice data regarding how it was collected, although a disclaimer on the website indicates that states self-report. Mapping the coefficient of variation (CV) of rice production by district illustrates remarkably defined values along state boundaries (Figure 6.2).

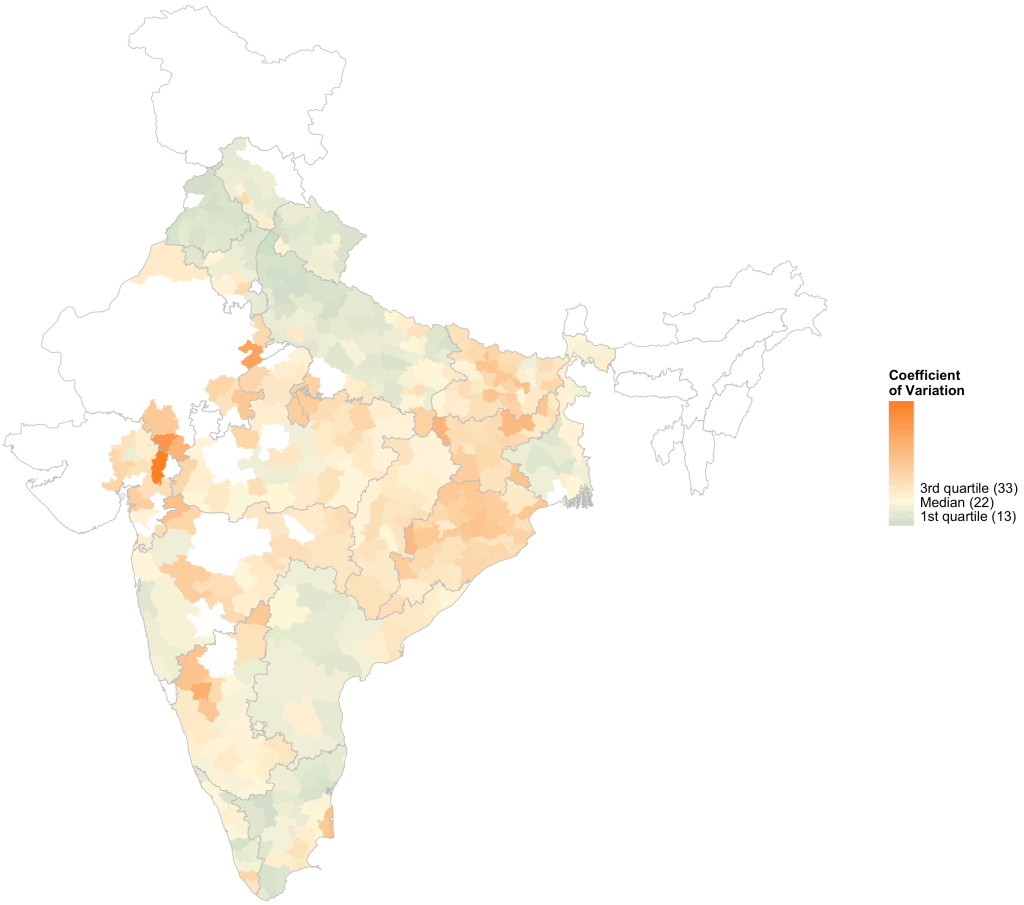

Figure 6.2 Coefficient of variation of rice yield by district (using data from 1999-2008)

Bhalla and Singh (2012) use these same crop-wise area and production statistics and determine their statistical reliability to be "problematic" (p. 18). According to them, area data are gathered from revenue records, while production numbers are estimates based on crop-cutting experiments from sample fields. Their assessment is confirmed by an informal report published on the website of the Ministry of Statistics and Program Implementation (part of the Government of India), which also remarks, "…the [crop production] survey estimates are subject to a variety

of non-sampling errors…The main problem in producing reliable estimates is the poor performance of field operations" (Ministry of Statistics and Program Implementation, 2001).

The irrigation and ICRISAT-sourced datasets are likely subject to comparable errors, demanding caution in evaluating the study's findings.

Additionally, although the datasets for rice and irrigation were published as 'seasonal', the data itself was not always so. For example, Tamil Nadu "seasonal" rice data was only reported for 'kharif' for 1999-2005, then 'whole year' for 2006-2008. Since Tamil Nadu is known to have three rice-producing seasons (Directorate of Rice Development, 2007), it is clear that the naming is incorrect and the data for Tamil Nadu is, in fact, not seasonal. In turn, the effect of seasonal drought in this region is no longer reflected directly in the "seasonal" yields.

These discrepancies in the data are particularly problematic for this type of spatial analysis, where we are looking for localized trends and outliers. Although the LISA techniques are useful for identifying districts that are performing unusually well relative to their neighbors *in theory*, there is concern that some of these anomalies are simply data errors.

6.1.2 Unit of analysis

District-level data was the most disaggregated data available for the agricultural and socio-economic variables of interest in this study. While this scale allowed for a relatively refined spatial investigation (compared to country or state), it subjects us to the modifiable areal unit problem (MAUP). Using administrative boundaries to evaluate environmental factors that are likely to change along a gradient in space creates a false sense of precision, where differences across districts may be more fuzzy than abrupt.

In addition, by omitting state-level analysis from the model we may have missed important factors that affect adaptive capacity. While the district and year fixed effects control for unobservables at those levels, there could be time-variant policies that changed at the state level that were not captured in the model. Subsidies for high-yield seeds, for instance, could have been implemented at the state level, thus increasing yields with increased use of fertilizer. This potential endogeneity should be considered in future research.

6.2 Directions for future research

This study provides a number of avenues for future research.

Methods used for generating district-level drought exposure could be applied to examine the effect of drought at different timescales. This could be particularly useful with a more targeted look at the effect of drought during critical growth periods for rice. More specific crop planting dates could dictate different timeframes for SPEI in different parts of India. Or longer timescales for the SPEI could be used to examine the effects of long-term drought and irrigation sources.

Drought sensitivity analysis could be expanded to look at trends over longer time series. This would allow for more drought incidence to confirm this study's findings. Additionally, it could be worthwhile to determine whether patterns of drought sensitivity change over time and for different crops. Although ICRISAT's area and production data are not currently offered by season, this could be a good starting point.

Lastly, the adaptive capacity regression model should be further refined to correct for spatial autocorrelation or other omitted variables that are reflected in the residuals. There could also be a need to address sample selection bias in the model. As Ward et al. (2014) suggest, observed rice

yields will be low in regions where farmers systematically choose not to plant or invest in rice because they anticipate yields will be low.

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