Agriculture and Food

AIMS Agriculture and Food, 2(2): 165-182
DOI: 10.3934/agrfood.2017.2.165
Received 18 November 2016,
Accepted 18 April 2017,
Published 27 April 2017

http://www.aimspress.com/journal/agriculture

Research article

Observing adaptive capacity in Indian rice production systems

J.M.A. Duncan[1,*], J. Dash[2], and E.L. Tompkins[2]

[1] UWA School of Agriculture and Environment, University of Western Australia, Perth, WA, 6009, Australia
[2] Geography and Environment, University of Southampton, Southampton, Hants, UK, SO171BJ

* **Correspondence:** Email: jmad1v07@gmail.com.

Abstract: Theoretically we understand the dimensions of both generic and specific adaptive capacity, however, there are few studies which document actual observed adaptive capacity. This study aims to address this gap by documenting the adaptive capacity of Indian rice production systems, an agro-socio-ecological system. We explore how Indian rice production systems have responded to historical climate shocks in order to assess their likely capacity to respond to current and future climate changes. Using a panel dataset of both Indian rice crop yield and extreme heat and drought shocks measured at the district level from 1980 to 2009, we sought to detect evidence of farmers: (i) adapting through reduced rice crop yield sensitivity to climate shocks over time, and (ii) responding to climate shocks by altering farming practices. We found that changes in average climate shock exposure over time was not linked to changes in average rice crop yields over time at a location. We also observed that rice crop yield sensitivity to year-to-year fluctuations in climate shocks has not decreased over time; this implies that over time the Indian rice production system has not increased its capacity to buffer inter-annual variation in shock exposure. We did not detect the presence of learning from exposure to climate shocks; in fact, greater exposure to extreme heat shocks eroded farmers' capacity to respond to current heat events. There was no clear pattern of farmers in districts that experienced worsening average climate shock exposure responding with the uptake of plausible adaptive practices. In summary, there was not a clear signal of adaptive capacity being present in Indian rice production systems.

Keywords: adaptive capacity; extreme heat; drought; rice; agriculture

1. Introduction

Rice, the predominant crop in the Indian food system, is important for food security, livelihoods, and the functioning of the economy. In recent decades Indian agricultural growth has been a driver of poverty reduction [1,2]. For a large proportion of the Indian population agriculture constitutes an important component of their livelihood mix. Since the 1960's agricultural productivity at the national level has increased, largely due to the adoption of Green Revolution technologies such as irrigation, fertilizer, and high-yielding crop varieties (HYV) [3-5]. This increase in rice productivity in recent decades is depicted in Figure 1. While there has been a clear trend of increased rice productivity in India, over the same time period rice systems have shown sensitivity to climatic fluctuations. Temperature and precipitation variability [6-9], drought [10], and flooding [11] have negative impacts on rice yield in India. Holding other variables at average levels, Birthal et al. [12] showed that a 1 °C increase in maximum temperatures results in a 11.9% decrease in Indian rice crop yield.

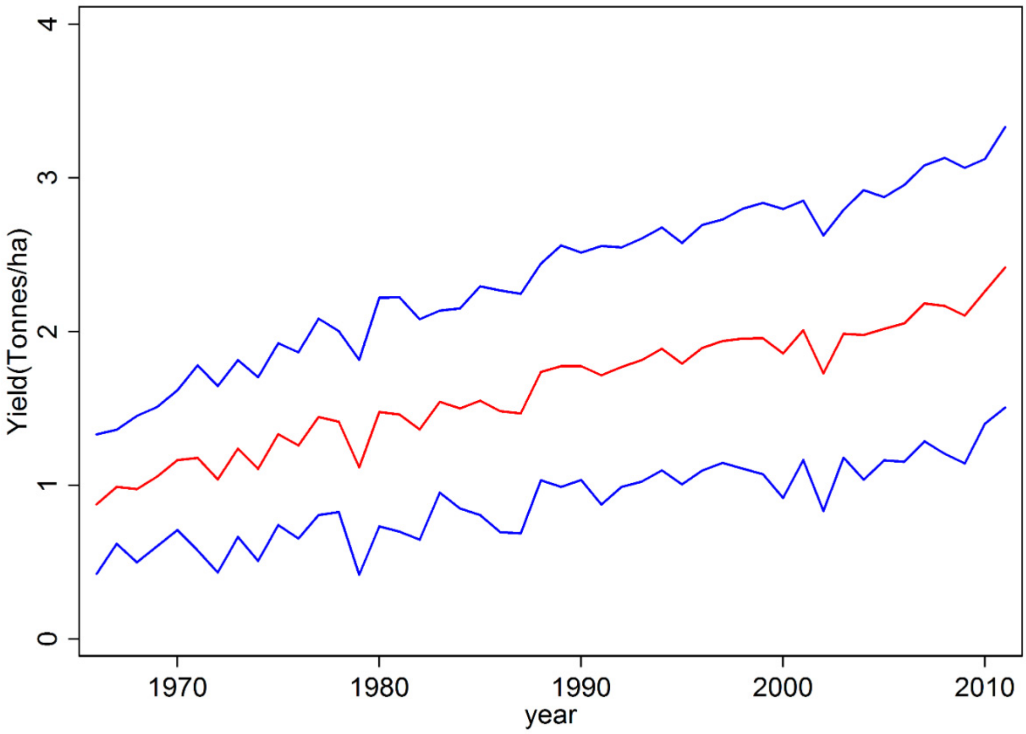

Figure 1. District average rice yield in India computed using the ICRISAT Village Dynamics in South Asia (VDSA) dataset. Blue lines correspond to one standard deviation above and below the average rice crop yield in India for each year (Source: ICRISAT VDSA).

Climate events that have negative impacts on rice crop yield are projected to increase over the coming century [13]. Based on the IPCC 5th Assessment report (AR5) climate projections Birthal et al. [12] predicted that rice crop yield will decrease by 5.9 to 15.4% in 2100 depending on the magnitude of temperature and precipitation changes. This suggests that climate change will have a negative impact on Indian agriculture, and as a consequence harm the livelihoods of those engaged in agriculture and potentially the wider population through, for example, price effects on net food buyers [14]. However, studies that estimate a relationship between climate variability and rice crop yield under current conditions and then apply the same relationship in the future to predict longer-run climate change impacts often omit the potential for adaptation. That is, activities undertaken by actors within the rice system to alter the relationship between climate exposure and rice crop yield. In order to assess how vulnerable the Indian rice crop system is to climate change it is important to identify the presence of adaptive capacity.

The IPCC AR5 define adaptation as "The process of adjustment to actual or expected climate and its effects. In human systems, adaptation seeks to moderate or avoid harm or exploit beneficial opportunities. In some natural systems, human intervention may facilitate adjustment to expected climate and its effects" [15]. At the same time that rice productivity in India has increased (Figure 1) the climate in India has worsened (from the perspective of rice production). Figure 2 shows the change in average rice crop yield (a), experience of drought shocks (c), and extreme heat exposure (d) in districts in India between 1980–1994 and 1995–2009. While rice crop yield has increased, this has co-occurred with an increase in drought shocks and extreme heat exposure. These trends are confirmed elsewhere, using Indian Meteorological Department data Birthal et al. [12] demonstrated a statistically significant increasing trend in minimum and maximum temperature in India from 1969 to 2005. Since 1951 large portions of India have experienced an increasing frequency of monsoon drought years and increasing variability in monsoon precipitation [16,17].

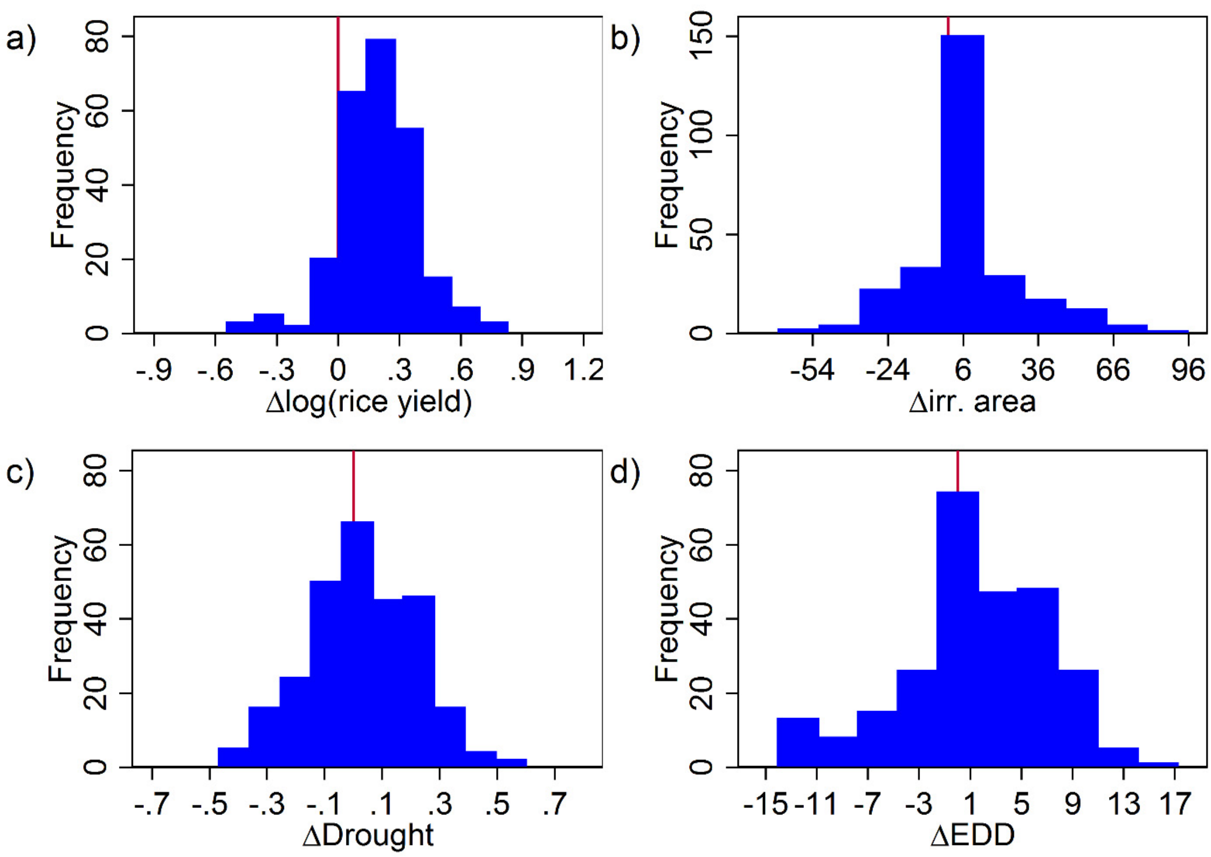

Figure 2. Change in (a) district rice crop yield, (b) irrigated rice area per district, (c) drought shocks, and (d) extreme heat exposure between 1980–1994 and 1995–2009. In each district the average for each variable was taken over each time-slice; these averages were then differenced and the distributions of differences plotted. The red line corresponds to no change in a given variable in a given district over time (Source: ICRISAT VDSA).

The coincident increase in rice crop yield and climatic conditions challenging for rice cropping offers an opportunity to assess if the productivity increases are evidence of adaptation. If there is evidence of Indian rice systems adapting to recent changes in the climate to maintain or increase output then it suggests the presence of adaptive capacity within the system. Assuming future changes do not overwhelm this capacity then we might expect the Indian rice system to continue adapting to climate change, all else held equal. However, it might be that the increase in rice crop yield we observe is due to adoption of technologies that have increased output in "good" years but not reduced the sensitivity of rice cropping to adverse climatic conditions. In other croplands around the world increased yields have been associated with increasing sensitivity to climatic conditions. Farm simulation studies in Burkina Faso showed that increasing farm inputs raises productivity, but under a changing climate increased farm inputs led to increased gains in "good" years but larger losses in "bad" years [18]. Seeking to clarify the concept of adaptation within the context of agriculture Lobell [19] proposed that a change in behavior or technology is considered an adaptation if it is "impact reducing" as opposed to productivity enhancing. In particular, Lobell [19] emphasized the importance of not conflating a technology that increases crop productivity by the same amount under different climatic conditions with an adaptation; an adaptation specifically reduces the magnitude of loss as the climate changes.

Here, we seek to test for the presence of adaptive capacity in Indian rice production systems as distinct from observing a correlation between productivity and a change in climate. We employ two approaches to detect adaptive capacity. First, we seek to identify the presence of adaptation occurring; that is evidence of reduced sensitivity of rice crop yields to climate shocks over time. Second, we seek to observe the presence of adaptive processes; that is directly observing changes in behavior or farming practices that can be plausibly associated with lessening climate impacts. Jointly observing evidence of adaptation occurring and observing climate driven change in behavior and farming practice to lessen future impacts would provide a strong indication of the presence of adaptive capacity in the Indian rice production system. We do this by using a panel dataset of rice crop yield and climate shock exposure at the district level in India spanning 30 years from 1980 to 2009. This dataset allowed us to track change in the sensitivity of rice crop yield to climate shocks over time, and to see how trends in climate shock exposure are associated with trends in rice system characteristics.

2. Detecting adaptive capacity

This study aimed to detect the presence of adaptive capacity within Indian rice production systems. We define adaptive capacity as the capacity to respond to a change in climatic conditions to maintain or increase productivity. As outlined above we posit that adaptive capacity can be detected in two ways; the first through observing reduced sensitivity of rice crop yield to climate shock over time, and the second through observing a change in behavior or activities that can be plausibly attributed to trends in climate shock exposure. Detecting adaptive capacity through both approaches would provide confidence in a conclusion that rice farmers in India have the capacity to respond to changes in the climate.

2.1. Observing the occurrence of adaptation

Carleton et al. [20] outlined two approaches to detecting the occurrence adaptation. The first is to estimate models that identify the causal effect of a climate variable on an outcome of interest (here rice crop yield) for different time-slices. A change in the coefficient for the climate variable across time-slices indicates sensitivity to climate shocks is changing over time. Evidence of reduced sensitivity between time-slices suggests the presence of adaptive capacity. The regression model to operationalize this approach is:

$$y_{it}^{p} = \beta \mathrm{CS}_{it}^{p} + \theta t + c_i + \varepsilon_{it} \quad (1)$$

Where y_{it} is the outcome variable of interest (e.g. rice yield) in a given location (i) and time (t); c_i is a location fixed effect to capture location-specific factors that determine levels of rice productivity, θ is a time-trend to account for change in rice productivity over time associated with economic and agricultural development. $\mathrm{CS}_{\mathrm{it}}$ is a location and time specific climate shock. A change in β between time-slices p would indicate the presence of adaptive capacity. The second approach outlined by Carleton et al. [20] is to estimate long-differences regression models following the approach of Burke and Emerick [21]. This approach identifies how trends in average climate shock exposure are correlated with trends in average crop productivity over longer time periods [21]. The long-differences model takes the form:

$$y_{ip2} - y_{ip1} = \beta(\mathrm{CS}_{\mathrm{ip2}} - \mathrm{CS}_{\mathrm{ip1}}) + \varepsilon_{p2} - \varepsilon_{p1} \quad (2)$$

Where $p1$ and $p2$ represent time-slices over which average climate shock exposure and average rice crop yield is computed. The regression coefficient β identifies how change in average rice crop yield over time is correlated with longer-run trends in average climate shock exposure. A comparison of the regression coefficient in equation 2 with the regression coefficient from a model that identifies the effect of short-run (e.g. year-to-year) variation in climate shock exposure will determine the presence of adaptation [20,21]. A model that identifies the effect of short-run variations in climate shocks on rice crop yield is the equivalent of equation 1 (but pooling all years rather than segmenting the dataset into time-slices). The logic here is that if adaptive capacity is present the effect of long-term trends in a climate shock will be smaller than the effect of year-to-year variation in climate shock exposure. Farmers may not have the capacity to adjust quickly to inter-annual variability in climate shock exposure, but if over time the prevalence of climate shocks changes farmers will adjust if they have the capacity to do so.

2.2. Observing the process of adaptation

A second approach to detect the presence of adaptive capacity is to observe if experience of climate shocks causes a change in farming practices that can be plausibly attributed to behavior to lessen the impact of future climate shocks. Skjelflo and Westberg [22] identified if the magnitude of historical exposure to climate shocks moderates the impact of contemporaneous shocks on smallholder farm productivity in Tanzania. If historical climate shock exposure increases the negative impact of contemporaneous shocks then it suggests that past climate shocks erode response capacity to future climate shocks. However, if historical climate shock exposure reduces the negative impact of contemporaneous shocks it suggests the presence of learning and adaptive capacity. In Tanzania, Skjelflo and Westberg [22] found that past exposure to moderate drought events increases smallholder farmers' capacity to respond to future drought, but this adaptive effect does not hold for severe droughts. The regression model to operationalize this approach is:

$$y_{it} = \beta_1 \mathrm{CS}_{it} + \beta_2 \mathrm{HCS}_{it} + \beta_3 \mathrm{CS}_{it} * \mathrm{HCS}_{\mathrm{it}} + \theta t + c_i + \varepsilon_{it} \quad (3)$$

$\mathrm{HCS}_{\mathrm{it}}$ is a measure of historical climate shock exposure; for example, the sum of extreme heat events over the past 10 years in a district. A complement to this approach is to identify if climate shock exposure causes a change in farming practice. For example, in Mozambique, Salazar-Espinoza et al. [23] identified the effect of past drought and flood exposure on future allocation of land to different crops on smallholder farms. They found that after a flood or drought farmers devote less land to cash crops, but two years after a flood or drought they devote less land to staples suggesting behavior consistent with a desire to maintain buffer food stocks. In the Nile Basin of Ethiopia, along with a range of socio-economic and institutional factors, increased temperature increases smallholder farmer adoption of adaptive practices including soil conservation, irrigation, crop switching, and a change in planting date [24]. Again in Ethiopia, Di Falco et al. [25] showed that rainfall during the previous season is negatively correlated with crop diversity. Crop diversity is associated with spreading risk, and, thus, implies if farmers experience a negative climate shock they respond to reduce future crop loss. In Eastern India Bahinipati [26] showed that flood- and cyclone-affected farmers are more likely to adopt farming practices associated with adaptation. We can estimate models analogous to equation 2, but instead of the dependent variable being average rice crop yield it is the average level of a characteristic of the rice cropping system that is a plausible adaptive practice (e.g. percentage of rice area irrigated). Such a model would inform on whether locations that experienced trends of increased average climate shock exposure over time also experienced increases in average levels of an adaptive practice:

$$\mathrm{adap}_{\mathrm{ip2}} - \mathrm{adap}_{\mathrm{ip1}} = \beta(\mathrm{CS}_{\mathrm{ip2}} - \mathrm{CS}_{\mathrm{p1}}) + \varepsilon_{ip2} - \varepsilon_{ip1} \quad (4)$$

Where $\mathrm{adap}_{\mathrm{ip}}$ is the average level of an adaptive practice within a given time slice specified by p_n. Here, β captures the effect of trends in average climate shock exposure on trends in the average levels of an adaptive practice at a location.

3. Data

3.1. Rice production system variables

We used the ICRISAT VDSA district level database that compiles numerous variables of relevance to agriculture in India for each district (when available) from 1966 to 2011, we used the data from 1980 to 2009 which has greater coverage. The dataset is available to download at: http://vdsa.icrisat.ac.in/vdsa-database.aspx. In particular, we used the variables of annual district rice production and annual district rice cultivated area to estimate rice crop yield, and annual district rice crop area that was irrigated. Summary statistics for these variables for rice crops are presented in Table 1.

Table 1. Summary statistics for district-wise rice yield, rice area cultivated, rice production, and percentage of district area cultivated with rice that was irrigated (Source: ICRISAT VDSA).

		Rice Yield (Tonnes/ha)	Rice Area ('000 ha)	Rice Production ('000 Tons)	% Rice area irrigated
1980–1994	mean	1.62	130.78	220.36	73.41
	SD	0.76	149.64	279.89	36.15
1995–2009	mean	1.97	144.67	304.08	78.56
	SD	0.88	167.71	385.35	34.11
1980–2009	mean	1.80	137.74	262.32	76.00
	SD	0.84	159.09	339.47	35.23

3.2. Climate variables

In our analysis we estimate regression models that detect the impact of two measures of climate shocks: drought shocks and extreme heat exposure. To compute a measure of drought shocks we obtained district-wise monsoon precipitation (June-September; the monsoon is the predominant rice growing season in India and is often termed the *kharif* season) from the ICRISAT VDSA database, and for each district and each year we computed the standardized precipitation anomaly (SPA):

$$\mathrm{SPA_{it}} = \frac{(P_{it} - \pi_i)}{\sigma_i} \quad (5)$$

Where $\mathrm{SPA_{it}}$ is the standardized precipitation anomaly for a given district i and year t; π_i is mean district-wise monsoon precipitation from 1980–2009 and σ_i is the standard deviation of monsoon precipitation over the same time period. We created a binary drought indicator if SPA was less than −0.5. This meant that drought was defined by deviations in monsoon precipitation below district-specific normals. Lacking an appropriate physical threshold (in terms of levels of precipitation) to define drought studies have used deviations from local averages to define drought events in India [16] and across smallholder croplands globally [22,23,27]. A secondary advantage of binary drought shock measures is that when accumulating past shock exposures years with above average rainfall do not cancel out the effect of droughts, this would happen with a continuous measure of precipitation [22].

We measured extreme degree days (EDD) during the rice growing season to capture extreme heat shocks; EDD measures accumulated exposure to temperature above a certain threshold. Here, we measured district-wise exposure to temperatures greater than 33 °C through the months of June to September. A review of climate impacts on crop production suggested that 33 °C was the optimum temperature for rice crop vegetative and reproductive development [28]. However, for other crops in different contexts similar temperatures have been used as thresholds (often ranging from 30 to 34 °C) for computing EDD [29-32]. EDD is a more suitable measure of crop exposure to extreme heat than average growing season daily maximum temperature, this is because EDD directly measures the magnitude of exposure to warm temperatures which are known to be damaging to crops [32,33]. We computed EDD following Lobell et al. [30] whereby we fitted a cosine curve to daily minimum and maximum temperatures to interpolate temperature to an hourly temporal resolution. Then, for each day we computed the number of hours of exposure above 33 °C and generated a measure of EDD exposure using:

$$\mathrm{EDD} = \sum_{d=1}^{N} D_d \quad D = \begin{cases} 0 & if \;\; T \leq 33 \\ T - 33 & if \;\; T > 33 \end{cases} \quad (6)$$

Where, N is the number of hours from June 1st through till the end of September and d is hour. EDD estimation requires daily temperature which is not contained in most available gridded monthly datasets such as the CRU TS v 3.23 dataset. Therefore, we used the Berkeley Earth Daily Land Temperature (BEST) experimental dataset which measures daily temperature at a 1° spatial resolution [34]. Table 2 presents the summary statistics for our climate variables. Over time, we see an increase in the occurrence of drought shocks and an increase in extreme heat shocks. This increase in climate shock exposure is clear in Figure 2c and d which displays histograms depicting distributions of district differences in average drought and EDD exposure over these two time-slices.

Table 2. Summary statistics for climate shock variables.

		Drought	EDD
1980–1994	mean	0.214991	43.64253
	SD	0.410855	49.16584
1995–2009	mean	0.253444	44.32732
	SD	0.435024	47.57284
1980–2009	mean	0.23427	43.98843
	SD	0.423562	48.36655

4. Methods

In order to identify the presence of adaptive capacity in Indian rice production systems we estimated regression models similar to those presented in section 2.

4.1. Observing the occurrence of adaptation

To detect the occurrence of adaptation in Indian rice production systems between 1980 and 2009 we operationalized the regression models presented in section 2.1 using the panel dataset of district rice crop yield and climate shock variables presented in section 3. For all models the dependent variable was the natural logarithm of district rice crop yield, and the models were estimated separately for both climate shock treatments (drought and EDD).

First, we estimated a model similar to equation 1 but for a single time-slice with all years pooled in one dataset. This identified the average effect of a climate shock on district rice crop yield over the period 1980 to 2009. Here, we identified the impact of climate shocks on rice crop yields off year-to-year fluctuations in shock exposure. Second, we estimated equation 1 for two time-slices: 1980–1994 and 1995–2009. A comparison of coefficients for the models estimated in different time-slices revealed if adaptation had occurred.

Next we estimated a long-differences model as in equation 2; this model identified the effect of a change in average climate shock exposure over time on average rice crop yield. Average climate shock exposure and rice crop yield were computed over two time-slices 1980–1994 and 1995–2009 and then differenced prior to estimating the regression model. When estimating this model location fixed effects differenced out, but we included a constant in the model which controlled for change over time in average rice crop yield not explained by a change in climate shock exposure. A comparison of the coefficient on the climate shock in the long-differences model to the coefficient on the climate shock using the pooled panel dataset informed on whether rice farmers in India are able to adapt to longer-run trends in climate shock exposure as compared to their capacity to buffer year-to-year variation in climate shocks.

All regression models were estimated with district fixed effects that controlled for time-invariant unobserved factors that might bias our coefficient estimates. This is important as there is considerable spatial heterogeneity in agro-ecological and socio-economic conditions across India. We also needed to account for time-varying omitted variables; this is important in India where there has been a noted increase in agricultural productivity over recent decades (Figures 1 and 2). In part this increase in productivity is associated with the uptake of Green Revolution technologies [3,4]. Approaches to account for time-varying omitted variables include using year fixed effects or time-trends as variables in regression models. This avoids conflating the effect of changes in climate on rice cropping with other forms of agricultural development. We estimated regression models with year fixed effects (supplementary) and time trends (main results). The results for drought shocks were robust to the use of year fixed effects or time-trends. However, when year fixed effects were used the coefficient on extreme heat shocks was not statistically significant. Together year fixed effects and district fixed effects explained over 92% of the variation in EDD suggesting there is little residual variation left to identify temperature impacts. Similarly, Guiteras [6] found too little residual temperature variation when including year fixed effects in rice crop yield-temperature regression models in India and resort to using time-trends to remove confounding factors. To retain sufficient variation in the climate variables while accounting for rice yield changes due to agricultural development we estimate all panel models with linear time-trends. Finally, in all regression models standard errors were clustered at the district level.

4.2. Observing the process of adaptation

To observe the processes of adaptation we operationalized the regression models introduced in section 2.2. All regression models estimated to detect processes of adaptation included district fixed effects and time-trends with standard errors clustered at the district level. First, we estimated the regression model in equation 3 with the natural logarithm of district rice crop yield as the dependent variable separately for both drought shocks and extreme heat shocks. To measure historical climate shock exposure, we computed the sum of five and 10 years of lags of drought shocks and EDD separately. We estimated the regression model in equation 3 separately for both five and 10 years of lags of historical climate shock exposure to assess if the length of "shock memory" (as it is termed by Skjelflo and Westberg [22]) influenced the results. A positive regression coefficient on the interaction term between historical climate shock exposure and contemporaneous climate shocks indicates the presence of learning from past climate shock exposure.

Aside from observing the presence of learning (in the short-run as determined in equation 3) we can also directly observe if long-run changes in farming practice or behavior that are plausibly associated with lessening the impact of future climate shocks are associated with long-run shifts in average climate shock exposure. Here, we tested if long-run shifts in climate shock exposure during the *kharif* rice growing season were associated with long-run shifts in adaptive farming practices. The adaptive farming practices we monitored were:

i. The percentage of rice area under irrigation (average levels in 1980–1994 and 1995–2009).
ii. Percentage of rice area cultivated with high yielding varieties (HYVs) (average levels in 1980–1994 and 1995–2009).
iii. Average area of non-rice *kharif* season crops (maize, sorghum, groundnut, and pigeon pea [12]).
iv. Average area of *rabi* season crops that occurs after the *kharif* rice growing season (wheat, barley, chickpea, and rapeseed-mustard [12]).

We estimated equation 4 separately for each of these dependent variables; we obtained these variables at the district level from the ICRISAT VDSA dataset.

Each of these changes in farming practice represent plausible adaptations to trends in average climate shocks to rice cropping in India. Irrigation reduces the impact of climate shocks on rice cropping in India [7,10]; thus, increasing irrigated area in a district is a plausible adaptive response. Different rice crop varieties have differing sensitivities to climate shocks [11,35], and there is evidence of rice farmers adopting different rice crop varieties in response to cyclone and flood exposure in Eastern India [26]. High yielding rice varieties that have been adopted in India in recent decades often have denser canopies affording greater evapotranspirative cooling effects [5]. Thus, there is a logical reason for farmers to switch rice varieties in response to changes in climate shock exposure, and indeed there is evidence of this occurring [26]. The final two observable adaptation processes that we tested for relate to crop switching or diversifying the crop portfolio. Communities in Jharkand, a state in East India, have responded to monsoon variability by selecting out of rice cropping and planting crops such as maize and pulses [36]. An increase in the area of a district area under *rabi* crops as the *kharif* rice season climate worsens would be indicative of farmers compensating for lost rice production by planting other crops in a different season.

5. Results

5.1. Impact of climate shocks on rice crop yields

Both extreme heat exposure (EDD) and drought had a negative effect on rice crop yield in India between 1980–2009 (Table. 3). An extra extreme degree day caused a 0.12% decline in rice crop yield, holding all else equal. While this seems a small effect, the average district EDD exposure during this period was 43.99 (Table. 2) with a one standard deviation increase in EDD exposure causing a 5.3% reduction in yield, all else held equal. A drought shock caused a 9.39% reduction in rice crop yield, all else held equal. These results represent the average effect of a climate shock across all years and districts in our sample.

Table 3. Regression coefficients for models identifying the effect of climate shocks on rice crop yield between 1980–2009.

	EDD	Drought
EDD	−0.00122***	
	(−6.00)	
Drought		−0.0939***
		(−7.74)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.2. The occurrence of adaptation

There is no evidence of reduced sensitivity of rice crop yields to year-to-year variation in climate shocks between 1980–1994 and 1995–2009 (Table 4). In both time-slices and both EDD and drought had negative impacts on rice crop yield. For example, in the time-slice 1980–1994 a drought shock caused 9.5% reduction in crop yield holding all else equal. In the later time-slice a drought shock caused a 9% reduction in rice crop yield.

The results from the long-differences model indicate that trends in climate shock exposure between 1980–1994 and 1995–2009 did not have a statistically significant impact on change in average rice crop yield over this period (Table 5). The increase in rice crop yields over time, due to factors other than climate shock exposure, is illustrated by the positive and statistically significant constant term (Table 5). We estimated a variant of equation 2 where the dependent variable was the difference in the coefficient of variation in rice crop yield between 1995–2009 and 1980–1994 (as opposed to average yields). This informed on whether an increase in yield variability was associated with long-run shifts in increased climate shock exposure; the results are presented in Table 6. We found that increased average extreme heat exposure caused increased yield variability ($p = 0.052$), and that long-run shifts in drought shocks were not associated with changes in yield variability.

Table 4. Regression results for models identifying the effect of climate shocks on rice crop yield in two time slices (1980–1994 and 1995–2009).

	EDD - early	EDD - late	Drought - early	Drought - late
EDD	−0.00155***	−0.00111***		
	(−0.00222, −0.000888)	(−0.00155, −0.000664)		
Drought			−0.0950***	−0.0900***
			(−0.123, −0.0666)	(−0.119, −0.0614)

95% confidence intervals in brackets; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5. Regression results for long-differences model with EDD, drought shocks, and the natural logarithm of rice yield averaged over the periods 1980–1994 and 1995–2009 before differencing. Only districts with at least 25 observations out of a possible 30 were retained for analysis.

	EDD	Drought
EDD	0.00248	
	(1.12)	
Drought		−0.0637
		(−0.94)
Constant	0.189***	0.197***
	(14.26)	(15.45)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6. Regression results for long-differences model with average EDD, average drought shocks, and the coefficient of variation of rice crop yield computed over the periods 1980–1994 and 1995–2009 before differencing. Only districts with at least 25 observations out of a possible 30 were retained for analysis.

	EDD (CV)	Drought (CV)
EDD	0.00299	
	(1.95)	
Drought		0.00387
		(0.08)
Constant	−0.0412***	−0.0363***
	(−4.50)	(−4.12)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.3. Processes of adaptation

We observed little evidence suggestive actual adaptive processes or practices being adopted (Figure 3, Tables 7 and 8). Figure 3 presents the marginal effect of a climate shock on the natural logarithm of rice crop yield for different levels of historical rice crop exposure. On average, as a district experiences greater historical extreme heat exposure an equivalent contemporaneous extreme heat shock has a larger negative impact (Figure 3a and b). At all levels of historical drought shocks, a contemporaneous drought shock has a negative impact (Figure 3c and d). Increased historical drought shock exposure slightly decreases the negative impact of contemporaneous shocks; however, this effect is very small with wide confidence intervals, and does little to override the harmful effects of present droughts. Table 7 presents the regression results for models identifying the impact of historical climate shock exposure on sensitivity to contemporaneous shocks. The time-period over which historical climate shocks are measured has little impact on the results.

Table 8 presents the regression results that identify if trends in climate shock exposure are associated with trends in the adoption of adaptive practices. An increase in average extreme heat exposure from 1980–1994 to 1995–2009 caused an increase in district area cultivated under crops that were not rice in the *kharif* season and in *rabi* crops (Table 8). This indicates that long-run shifts in extreme heat exposure during the *kharif* season have led to an increase in the cultivation of other crops. We found that an increase in average drought exposure over the same period caused a decrease in average rice area under irrigation and use of rice HYVs (Table 8).

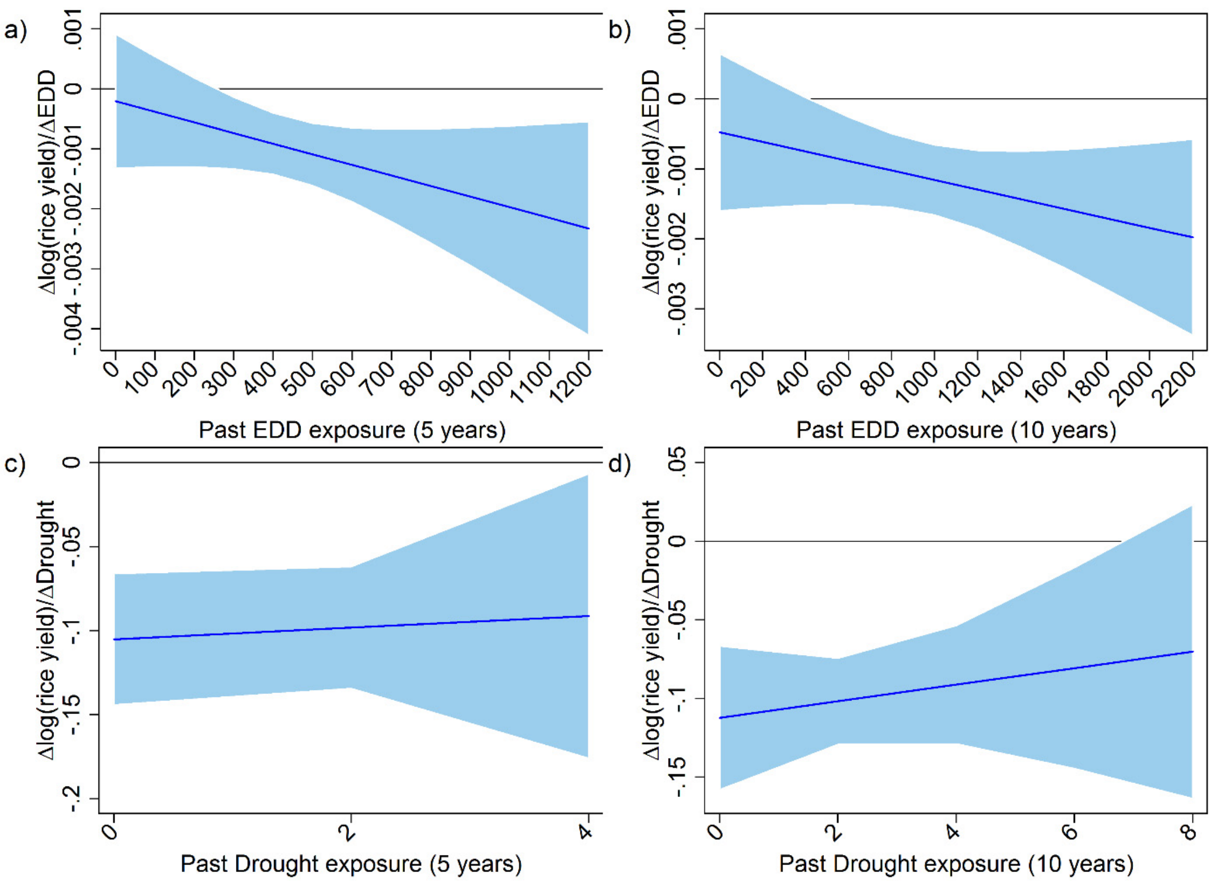

Figure 3. The marginal effect of EDD (a) and (b) and drought (c) and (d) on the natural logarithm of rice crop yield at different levels of historical climate shock exposure. Panels (a) and (c) correspond to accumulated climate shock exposure over the previous five years whereas panels (b) and (d) correspond to accumulated climate shock exposure over the previous 10 years.

Table 7. Regression results for models identifying the effect of historical climate shock exposure on contemporaneous sensitivity to climate shocks.

	EDD (5 years)	EDD (10 years)	Drought (5 years)	Drought (10 years)
EDD	−0.000318 (−0.55)	−0.000592 (−1.03)		
Past EDD exposure (5 years)	0.000796*** (4.89)			
EDD - Past EDD exposure (5 years)	−0.00000131 (−1.10)			
Year	0.00813*** (6.31)	0.00824*** (6.49)	0.00841*** (7.02)	0.00825*** (6.92)
Past EDD exposure (10 years)		0.000221 (1.53)		
EDD - Past EDD exposure (10 years)		−0.000000433 (−0.80)		
Drought			−0.107*** (−5.39)	−0.115*** (−4.93)
Past drought exposure (5 years)			0.00681 (1.11)	
Drought - Past drought exposure (5 years)			0.00529 (0.38)	
Past drought exposure (10 years)				0.00997 (1.77)
Drought - Past drought exposure (10 years)				0.00649 (0.81)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8. Regression results for long-differences model with EDD, drought, and the percentage of irrigated rice area, the natural logarithm of the area under other *kharif* and *rabi* crops, and percentage rice area cultivated with HYVs averaged over the periods 1980–1994 and 1995–2009 before differencing. Only districts with at least 25 observations out of a possible 30 were retained for analysis.

	EDD-Irr	Drought-Irr	EDD-*kharif*	Drought-*kharif*	EDD-*rabi*	Drought-*rabi*	EDD-HYV	Drought-HYV
EDD	−0.0694 (−0.30)		0.0528*** (6.81)		0.0225*** (4.00)		−0.110 (−0.42)	
Drought		−19.37** (−2.79)		−0.494 (−1.93)		0.0958 (0.54)		−20.32** (−2.63)
Constant	6.337*** (4.60)	6.682*** (5.09)	−0.242*** (−5.28)	−0.183*** (−3.75)	0.0896** (2.68)	0.116*** (3.44)	17.87*** (11.57)	18.33*** (12.57)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6. Discussion

While there has been evidence of increased rice crop productivity since 1980 (Figures 1 and 2) there is inconclusive evidence that actual adaptation to trends in climate shock exposure has occurred. Rice crop yields remained sensitive to climate shocks in the later time-slice (1995–2009) despite increases in productivity (Table 4). The results from the long-differences model indicate that long-run shifts in average climate shock exposure are not associated with changes average rice crop yields over time at a location (Table 5). Viewed together these results suggest that intensifying average shock exposure has not precluded the capacity to increase levels of average rice crop productivity over time, but also that there is little evidence to indicate that farmers have increased their capacity to buffer the impacts of year-to-year variation in climate shocks. There is some evidence that locations that experienced an increase in yield variability between 1980–1994 and 1995–2009 also experienced an increase in average extreme heat shock exposure (Table 6; though the result is weakly statistically significant $p = 0.052$). Thus, there is not conclusive evidence that farmers have displayed a capacity to reduce the impacts of climate shocks over time, in other words displayed a clear adaptive capacity as distinct from a productivity enhancing capacity. This lack of apparent adaptive capacity is worrying given that climate shocks are likely to become more intense over much of India in the coming decades [13,37].

We find evidence that increased exposure to historical extreme heat shocks erodes future capacities to respond to extreme heat rather than providing opportunities for learning (Figure 3; Table 7). The capacity to learn and respond to past disturbances is a key component of resilience in systems facing change and uncertainty in external shock exposure [38,39]. The (apparent) lack of capacity to respond positively to past climate shocks is worrying given uncertainty over future monsoon precipitation [40], projected warming, and projections of intensifying climate shocks [13,37]. In-depth insights based on farmers' experiences of climatic shock events align with the broad pattern of previous shock exposure amplifying future vulnerabilities. In Eastern India Chhotray and Few [41] documented how cyclone and flood events caused vulnerability to persist for farming households for several years.

A logical response to drought shocks is to increase the area under irrigation; Birthal et al. [10] showed that levels of irrigation can change the response of rice yield to droughts (with irrigation reducing sensitivity). Here, we found that locations that experienced an increase in prevalence of drought shocks reduced average levels of irrigated rice area (Table 8). There was also no evidence of increased drought shock exposure causing changes other potential adaptive practices (such as crop diversification or growing crops in other seasons) (Table 8). Viewed in the light of increased uncertainty over future monsoon precipitation [40] and the sensitivity of rice yield to drought shocks (Tables 3 and 4) this lack of observed adaptive capacity to drought is a concern for Indian rice systems. We found that in districts that experienced trends of increasing average extreme heat exposure during the *kharif* rice growing season there had been an increase in the uptake other *kharif* season crops and an increase in growing crops during the *rabi* season (Table 8). Attributing these changes to extreme heat impacts to rice cropping is challenging, but they do indicate that in locations where extreme heat climates are changing so is the portfolio of crops grown. Important avenues for future work are to (i) identify if these changes are adaptive in the sense of reducing farmers' sensitivity to climate shocks (e.g. as in Lobell [19]), and (ii) to assess the costs and benefits of these different adaptations.

This research has sought to identify the presence of adaptive capacity within Indian rice production systems, on average, at the national level. These insights are useful for capturing the broad degree of adaptive capacity and suggesting how vulnerable the nation's food system might be to shifts in the climate in the coming decades. Understanding how vulnerable India's food system is to climate change is important given on-going trends of urbanization; this implies that more individuals will become food buyers and be susceptible to climate driven food shortages or price increases. However, there is considerable spatial variation in agro-ecology, average climate conditions, trends in climatic conditions [16,17,37], uptake of agricultural technologies [3,35], and indicators of development and vulnerability to climate change [42,43]. This indicates that (i) the capacity of rice farmers to adapt to changes in climate shock exposure, (ii) the relationship between rice yields and climate shocks, and (iii) trends in climate shock exposure is likely uneven across India. Further analysis to empirically identify spatial variation in adaptive capacity is important to identify where pockets of vulnerability to the current climate exist, to identify locations where climate change adaptation policy and interventions should focus, and to match appropriate adaptive practices to changes in climate affecting each location.

7. Conclusion

This research assessed whether we could (i) detect the occurrence of Indian rice systems adapting to changes in climate shock exposure, and (ii) detect the processes of adaptation. First, we identified that climate shocks between 1980 and 2009 reduced rice crop yields, all else held equal; rice crop yields were negatively impacted by both drought shocks and extreme heat shocks. We identified that long-run shifts in average climate shock exposure were not associated with long-run changes in average district level rice crop yields. However, we also found that rice crop yield sensitivity to year-to-year fluctuations in climate shock exposure has not decreased over time. Thus, while farmers have been able to increase levels of productivity they have not been able to increase their capacity to buffer production from climate shocks. We did not detect the presence of farmers learning from historical climate shocks; in fact, greater exposure to historical extreme heat shocks eroded farmers' capacity to respond to contemporaneous heat events. There was not a clear pattern of farmers in districts that experienced worsening average climate shock exposure responding with the uptake of plausible adaptive practices. On average, in districts where drought shocks increased over time there was a decrease in the rice area cultivated under irrigation. There was some evidence of crop diversification in districts exposed to trends of increased extreme heat exposure. In summary, these results do not present a clear signal of adaptive capacity within Indian rice production systems either through detecting reduced sensitivity to climate shocks over time or through learning from past shocks and responding with altered farming practices. This lack of a clear adaptive capacity signal is worrying given projected intensification of climate shock exposure over coming decades.

Acknowledgements

The authors would like to acknowledge the Leverhulme Trust who provided funding (RPG-2013-214) for this research through the PREFUS project. The authors would also like to acknowledge ICRISAT for making the Village Dynamics in South Asia (VDSA) data available, and Berkeley Earth (http://berkeleyearth.org/) for making the temperature data available.

Conflict of interest

All authors declare no conflict of interest.

Supplementary

Table S1. Regression coefficients for models identifying the effect of climate shocks on rice crop yield between 1980–2009 with year fixed effects.

	EDD	SPA
EDD	0.000146	
	(0.52)	
SPA		−0.0658***
		(−6.27)
year fixed effects	Yes	Yes

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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