

RESEARCH ARTICLE

Rainfall shocks and fertilizer use: a district level study of India

Kaushik Bora 

Economic Analysis Unit, Indian Statistical Institute, Bangalore Centre, Bangalore, India
Corresponding author. E-mail: kaushikbora1991@gmail.com

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Abstract

In the context of climate change and increasing occurrences of extreme events, it is essential to understand farmers' responses to weather shocks and adaptations. This paper uses a panel dataset of 311 selected Indian districts ranging from 1966 to 2009 to investigate how application of chemical fertilizers varies in response to rainfall shocks. Two rainfall shock measures are constructed based on deviation in rainfall from the normal, a categorical measure of rainfall shock; and another, a continuous index of negative rainfall deviation. Based on a panel fixed effect regression, the study finds no apparent reduction in the level of fertilizer use in negative rainfall shock years. However, with a one-year lagged rainfall shock, a reduction in fertilizer application rate is observed for the continuous drought index. Further, exposure to higher intensity droughts in the previous year leads to an increase in the amount of fertilizer application in the current year.

Keywords: climate adaptation; droughts; fertilizer; irrigation; rainfall shocks

JEL classification: Q10; Q15; Q25; Q54

1. Introduction

Globally, Agriculture is facing increased challenges due to climate change. Vulnerability to climate change in the form of climate extremes is likely to increase in the future (World Bank, 2013). Crop cultivation has become more vulnerable under changing global climate (Kumar and Parikh, 2001), especially in developing countries that face frequent exposure to climate extremes. The economic impact of climate change varies around the world, and the ability to adapt differs across various regions (Taraz, 2018). Compared to other extreme events, droughts account for the majority of agricultural production risk in India (Cole *et al.*, 2013; Birthal *et al.*, 2019). Prolonged and frequent droughts significantly impact crop productivity in the country (Pandey *et al.*, 2007; Auffhammer *et al.*, 2012; Birthal *et al.*, 2015; Fontes *et al.*, 2020).

A sizable yield gap exists in several crops across the world (Lobell *et al.*, 2009). Global yield variability is mainly a result of nutrient management, water management, and

climatic factors (Mueller *et al.*, 2012). The impact of the first two factors on agricultural productivity is magnified in the presence of climatic shocks because it can influence the adoption of soil and water management practices (Birthal and Hazrana, 2019). Numerous studies on nutrient management have provided evidence that fertilizer is one of the critical inputs to increase crop yield across the world (McArthur and McCord, 2017). Further, fertilizer use can play an essential role in adapting to changing climate and weather variability (Kumar and Parikh, 2001).

Thus, the application of chemical fertilizer can affect agricultural production in two ways: first, through the pathway of nutrient management to bridge the yield gap; and second, it can act as a coping or production optimisation mechanism to counter risks posed by climatic extremes. Concerning changes in rainfall patterns, existing studies have shown both positive and negative associations of fertilizer adoption under rainfall variability (Alem *et al.*, 2010; Dercon and Christiaensen, 2011; Heisse and Morimoto, 2019).

Linkages between climatic shocks and chemical fertilizer use in India is not well studied. To the best of our knowledge, only studies by Selvaraj and Ramasamy (2006) and Pandey *et al.* (2007) have investigated this aspect and compared the effect of chemical fertilizer on crop yields in normal and drought years. Selvaraj and Ramasamy (2006) observed that fertilizer inputs did not significantly impact crop yield in drought-affected years in the Indian State of Tamil Nadu. However, in a normal year, application levels of chemical fertilizer positively impacted crop productivity. Very few prior empirical studies investigate how fertilizer use is affected by climatic shocks (notable exceptions are Kusunose *et al.* (2020) and Jagnani *et al.* (2021)).

Against this backdrop, our paper attempts to assess the relationship between fertilizer use and water availability (measured through rainfall and irrigation) in the context of existing research gap. The study empirically analyses the impact of rainfall shocks on fertilizer use in India. An econometric investigation is carried out to provide estimates of changes in the levels of fertilizer use due to rainfall shocks. The first and primary objective of this paper is to analyse how intensity of fertilizer use varies with climate-related shocks. The second objective is to understand the impact of drought intensity (adverse shocks) on the amount of fertilizer application. This work adds to the knowledge pool that deals with formulating strategies to insulate agricultural productivity and income from climate variability and extremes. We contribute to the emerging climate-economy literature by evaluating how climatic extremes can affect productive farm investments such as fertilizer using long-term district-level panel data.

The paper presents three key findings. First, a greater area under irrigation and good annual rainfall positively contribute to the levels of fertilizer use. Secondly, fertilizer application rates are not significantly different for contemporaneous positive or negative rainfall shocks in India. Lastly, exposure to drought in the previous year is likely to result in lower usage of fertilizers in the current year. However, more intense droughts during the previous year can increase the amount of fertilizer consumption at the district level in the current year.

The remainder of this paper is organized as follows. Section 2 provides background about chemical fertilizer application in India. This section also reviews the literature focusing on the role of weather and climatic extremes in determining fertilizer consumption. Data and empirical approaches are outlined in section 3. Section 4 presents the results and robustness checks. Section 5 summarises and discusses the results, and section 6 provides concluding remarks.

2. Background and analytical framework

2.1 Chemical fertilizer use in Indian agriculture

In 2015–16, India consumed 25,576 thousand tonnes of chemical fertilizers, averaging 128 kg per hectare of crop area (Government of India, 2017). The consumption of fertilizer has increased substantially, from 69 thousand tonnes during 1950–51. Fertilizer consumption increased rapidly after the start of green revolution in the late 1960s (Chand and Pandey, 2009; Sharma and Thaker, 2011). However, it became sluggish during the mid-1970s due to the crude oil crisis. Nevertheless, the growth in fertilizer consumption recovered and increased till 1990–91 (Sharma and Thaker, 2011). After 1991, a progressive slowdown in the growth of fertilizer consumption occurred, but signs of renewed consumption were observed from 2003–04 (Chand and Pandey, 2009; Chand and Parappurathu, 2012).

Higher consumption rates of fertilizer are skewed towards some regions within India characterised by improved irrigation and intensive cultivation practices (Chand and Pandey, 2009; Sharma and Thaker, 2011; Ghosh and Dey, 2014). These regions include several districts of Punjab, Haryana, Western Uttar Pradesh, and Andhra Pradesh (Raghavan, 2008). On the contrary, total chemical fertilizer consumption is relatively low in several parts of eastern India, namely the States of Assam, West Bengal and Odisha (Venugopal, 2004; Birner *et al.*, 2011). Figure A1 in the online appendix illustrates the difference in fertilizer consumption per hectare across various regions of India. We have observed a gradual increase in consumption rates of chemical fertilizer across all the areas since 1966. Still, region-wise heterogeneity continued to remain over the years.

In terms of the cost of cultivation, fertilizer cost is an important component of total input cost. Srivastava *et al.* (2017) show that the share of fertilizer cost in total paid-out cost hovered around 11–12 per cent from 1990–91 to 2014–15. Although the cost-share remains constant, fertilizer cost per hectare has risen since 1970–71 (Raghavan, 2008). Fertilizer prices are connected to the price policy of particular chemical fertilizers. Different subsidies can lead to changes in relative prices of different types of fertilizers. For example, the divergence between nitrogenous fertilizers and other macro-nutrients (phosphorus and potassium) has widened after the decontrol of fertilizer prices in India in 1992 (Venugopal, 2004; Chand and Pandey, 2009). India introduced a nutrient-based subsidy scheme in 2010. Although it aims to promote balanced use of nutrients, the price disparity between nitrogenous fertilizer and other macro-nutrients widened sharply after its implementation (Gulati and Banerjee, 2015).

Higher yields and profitability due to mineral fertilizer application have been demonstrated in past studies (FAO, 2005). However, fertilizer consumption in India is highly varied across regions. India has witnessed an overall increase in fertilizer consumption over the last six decades. Hence, it would be worthwhile to analyse how fertilizer application varies in response to weather anomalies that impact crop productivity.

2.2 Weather, climate extremes and fertilizer use

The literature on the impact of droughts on crop productivity is still emerging. These studies highlight the adverse effects of droughts on crop productivity in India (for example, Auffhammer *et al.*, 2012; Kumar *et al.*, 2014; Birthal *et al.*, 2015; Fontes *et al.*, 2020). Some recent studies checked the effectiveness of adaptation pathways against climatic shocks. Birthal *et al.* (2015) and Zaveri and Lobell (2019) have demonstrated gainful impacts of irrigation against droughts and heat stress in India, respectively. Similarly,

Birthal and Hazrana (2019) find long-run benefits of crop diversification as an adaptation strategy for climatic shocks. Several empirical studies have explored the relationship between crop yield and inputs, such as rainfall (Gupta *et al.*, 2014; Pattanayak and Kumar, 2014; Powell and Reinhard, 2016; Murari *et al.*, 2018), irrigation (Birthal *et al.*, 2015), fertilizer (McArthur and McCord, 2017), and labour and wages (Mahajan, 2017; Emerick, 2018).

The sensitivity of the crop yields to climate rely on one or more inputs limiting physical production under climatic stress. Agronomic and soil science literature provide a firm scientific insight on the subject. Among bio-physical inputs, water and nutrient availability are crucial for crop growth. A synergetic relationship is involved between soil-nutrient uptake and water availability. Water-use efficiency can be enhanced by the availability of macronutrients such as nitrogen and phosphorus through crop root development. Similarly, nutrient-use efficiency is dependent on soil moisture availability.¹ Under drought conditions, these intricate relationships become more complicated, and crop systems can simultaneously turn deficient in water and soil nutrients (Karim and Rahman, 2015; Plett *et al.*, 2020).

These broad agronomic relationships hold in several socio-economic studies done around the world. Conventionally, rainfall is used as an indicator of moisture availability. Precipitation favours a higher quantity of fertilizer application (Kaliba *et al.*, 2000; Alem *et al.*, 2010; Haider *et al.*, 2018). The decision to use fertilizer is positively associated with a higher amount of precipitation received in the previous years (Heisse and Morimoto, 2019). In contrast, Nyssen *et al.* (2017) find a negative correlation of average annual rainfall with the quantity of fertilizer purchased in northern Ethiopia. In Nigeria, low rainfall has encouraged the adoption of fertilizer and application in higher doses (Takeshima and Nkonya, 2014). Past studies on India show lower fertilizer application in deficient rainfall years (Nagaraj, 1983; Mohanam, 2002).

Risk-coping literature provides an analytical understanding of fertilizer use responses to climate extremes. Pandey *et al.* (2007) have given a detailed summary of drought-coping mechanisms by farmers. They have classified coping strategies into two broader groups: (i) *ex-ante* (income smoothing) and (ii) *ex-post* (consumption smoothing).

Ex-ante mechanisms target risk reduction through portfolio diversification and production decision-making changes. Altering fertilizer doses might be regarded as such change under flexible decision making. Risk and uncertainty related to weather are among the reasons for the high-intensity application of inorganic fertilizer (Babcock, 1992; Lamb, 2003; Paulson and Babcock, 2010; Sheahan and Barrett, 2014). Past studies opine that nitrogen is perceived as risk-reducing input, even by risk-neutral farmers (SriRamaratnam *et al.*, 1987; Babcock, 1992). A few studies have evaluated rainfall risks and uncertainties from farm/household datasets and measured the risk by variability in rainfall received. Rainfall variability can negatively impact the decision to use fertilizers and lower fertilizer use in Ethiopia (Alem *et al.*, 2010). However, Heisse and Morimoto (2019) find a positive association between the adoption of chemical fertilizer and rainfall variability among Tanzanian maize farmers.

Crop insurance is an effective risk-reducing mechanism. The adoption of crop insurance in India is substantially low (Aditya *et al.*, 2018). In the absence of formal channels of crop insurance, higher application rates can serve as a partial risk insuring mechanism.

¹ A detailed summary of the scientific understanding of water and fertilizer relationships for crop growth is available in Drechsel *et al.* (2015).

Below and Brandau (2001) document the application of higher doses of fertilizer as a cheap form of insurance. Crop insurance literature also provides insights into how farmers can change input use when crop insurance is available. Yu and Hendricks (2020) reviewed the existing studies and suggested that crop insurance can positively and negatively affect input use. Babcock and Hennessy (1996) and Mishra *et al.* (2005) find evidence of reducing fertilizer use if farmers adopt revenue insurance. A recent study by Yu and Hendricks (2020) links input use decisions with information on growing conditions or forecasts. They show that farmers apply more inputs when the forecast predicts a good crop harvest but reduce the input application if the weather forecast is bad.

Several perception-based studies also highlight the increase in fertilizer rate as one of the coping strategies in response to climate change as reported by farmers (Wood *et al.*, 2014; Khanal *et al.*, 2018). Chen and Gong (2021) show that extreme heat reduces the quantity of fertilizer use in both the short and long run. Disease incidence due to unfavourable climate may accentuate plant protection costs. Jagnani *et al.* (2021) find evidence of lowering fertilizer investment because of the increased plant protection cost. However, it is tough to single out coping strategies as they are adopted in bundles.

Ex-post strategies deal with the losses due to shocks after the event. Reduction in production and income due to droughts can lead to lower investment in agriculture in the following years. Lowering the quantity of fertilizer in the subsequent years after a drought can be an *ex-post* response. Dercon and Christiaensen (2011) explain that low rainfall can be perceived as a consumption risk in the absence of insurance, resulting in lower fertilizer adoption decisions in Ethiopia. Given the high cost of chemical fertilizer, farmers can amend fertilizer consumption due to shocks. Nevertheless, the expected direction of change in fertilizer use is not clear from the literature. A reduction in fertilizer consumption due to negative climatic shock seems more plausible under existing economic explanations.

In addition, several other factors can be associated with fertilizer adoption and application rates. Irrigation can safeguard yield in a moisture shortage period. As yield response is a function of the interaction between fertilizer and water availability, irrigation complements nutrient management (Nagaraj, 1983; Kurosaki and Wada, 2015). Similarly, other biophysical and technological factors such as soil type, cropping intensity and high-yielding varieties can influence fertilizer application (Parikh, 1978; Nagaraj, 1983). The ratio of output price of crop to the price of fertilizer required to produce one unit is an essential economic factor in determining per unit consumption (Sharma and Thaker, 2011). Institutional factors such as tenancy (Bharadwaj, 1974; Vaidyanathan, 2010), credit availability (Nagaraj, 1983; Croppenstedt *et al.*, 2003), and extension services (McArthur and McCord, 2017) are other associated factors driving the level of fertilizer use. Nonetheless, the list of factors is not exhaustive, and there might be several other factors.² Moreover, there can be several interactions among the factors, which are not mutually exclusive.

This study focuses on technological and physical factors that determine fertilizer application in India, with a particular focus on rainfall shocks. We confine this study to evaluating changes in fertilizer application under water stress conditions. Following the standard climate impact on agriculture literature (Auffhammer *et al.*, 2012; BIRTHAL *et al.*, 2015; Fontes *et al.*, 2020), we assess the changes in the quantity of fertilizer when exposed to different intensities of rainfall shocks with varying levels of irrigation.

²Wakeyo and Gardebreek (2013) provide a detailed account of factors affecting fertilizer use.

3. Data and methodology

3.1 Data source

The study uses district-level panel data on the agricultural and climatic (rainfall) variables from 1966 to 2009. The dataset, compiled by the International Crops Research Institute on Semi-Arid Tropics (ICRISAT) and Tata-Cornell Institute (TCI), is known as the District Level Database for India (DLD-India) (ICRISAT-TCI, 2015). As several districts are bifurcated into smaller districts during the period of the study, district boundaries are apportioned to the original 1966 district boundaries. The States whose data are used for analysis are Andhra Pradesh, Assam, Bihar, Chhattisgarh, Gujarat, Haryana, Himachal Pradesh, Jharkhand, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Orissa, Punjab, Rajasthan, Tamil Nadu, Telangana, Uttar Pradesh, Uttarakhand and West Bengal.³ The data are available for these 20 States of India from 1966 to 2015. However, our analysis is restricted to 311 districts over 44 years.⁴ Our study period ends in 2009 because India introduced a nutrient-based subsidy scheme in 2010.

The first part of the investigation uses DLD-India data on fertilizer consumption (measured in tonnes of nitrogenous, phosphorous and potassic fertilizer) and information on other variables such as gross cropped area (in hectares), gross irrigated area (in hectares), the area under high-yielding varieties (HYV) (in hectares), and cropping intensity (in per cent). We use weather variables such as annual rainfall (in millimetres) and monsoon rainfall (in millimetres) in the study. Data on all the agricultural and climatic variables are recorded for all crops at the district level. Lack of crop-disaggregated data, especially for fertilizer consumption, is an essential limitation of the study.

3.2 Variable construction

Using agricultural variables, we construct two variables related to the total consumption of fertilizer and irrigation intensity for the district. First, we compute the total consumption of chemical fertilizer (in kg per hectare) by aggregating the consumption of nitrogenous (N), phosphorous (P), and potassic (K) fertilizers and then dividing it by the gross cultivated area (GCA). Secondly, the extent of irrigation is measured as a share of gross irrigated area in the GCA, and we express it in percentage. Table 1 provides summary statistics of key variables of interest.

Rainfall shocks are captured in two ways. First, we create a categorical variable for rainfall shocks by following Yu and Babcock (2010). Our study does not include the temperature component as in the original article. We denote the discrete measure as Rainfall Shock 1 (RS1) and construct it using equation (1). We compute the standardized deviation of total rainfall from its long-term normal and express it as total rainfall deviation (TRD)⁵:

$$RS1 = TRD_{it} = \frac{(TR_{it} - TR_i^{\text{normal}})}{sd(TR)_i}, \quad (1)$$

where subscripts i and t denote district and time, respectively. TR is the total rainfall, and $sd(TR)$ is the standard deviation of annual rainfall. To categorise RS1 as a negative and positive shock, we use the following criterion: (i) positive rainfall shock if

³The ICRISAT-TCI (2015) DLD-India is not available for North-Eastern States (except Assam), Jammu and Kashmir and other Union Territories.

⁴The district of Chennai, Tamil Nadu is omitted because of lack of data availability from 1966.

⁵Long-term normal is calculated as average of annual rainfall over 44 years (1966–2009) for each district.

Table 1. Summary statistics and definition of variables, 1966–2009

Variables	Definition	No. of observations	Mean	Standard deviation	Minimum	Maximum
NPK fertilizer (kg/ha)	Sum of nitrogen (N), phosphorus (P) and potassium (K) fertilizers divided by GCA	13,136	58.77	61.34	0	614.49
Irrigated area (%)	Share of gross area irrigated over gross cropped area	12,349	33.65	25.88	0	100
Drought index	Defined in eq. (2)	12,507	0.39	0.53	0	3.77

Notes: Unit of analysis is district. Full set of descriptive statistics is available in table A1 (online appendix).

Source: Author's calculations.

TRD > 0; and (ii) negative rainfall shock if TRD < 0. Secondly, we construct a continuous precipitation-based measure for negative shocks, also denoted as drought index (DI). This variable can quantify the intensity of drought. We create it by separating negative shock years from TRD, as outlined in equation (2):

$$DI = \text{Drought}_{it} = \{-\min(0, \text{TRD}_{it})\}. \quad (2)$$

A similar precipitation-based drought measure was used by earlier studies such as Auffhammer *et al.* (2012) and Amare *et al.* (2018). Our DI ranges from 0 to 3.77 (table 1). The main limitation in quantifying drought by this category of indices is the non-inclusion of temperature because the results of any analysis can be sensitive to the definition of drought (Fontes *et al.*, 2020). However, the advantage of this measure lies in the simplicity of construction and its representativeness of meteorological drought. Since water availability is a key factor for nutrient uptake from the soil, the research is confined to examining water and fertilizer response.

4. Effect of rainfall shocks on fertilizer

4.1 Effect of rainfall shocks

Before investigating the impact of rainfall shocks on fertilizer use, we examine the relationship between water availability and fertilizer use. The amount of available soil moisture is not directly obtained; irrigation and annual rainfall are used as proxies. As per prior studies, a positive relationship between water availability and fertilizer use is expected. We reconfirm a similar association, irrigation and annual rainfall emerge as positive contributors to fertilizer use (table A2, online appendix). Given the sensitivity of fertilizer consumption to moisture availability, we anticipate a similar change in fertilizer consumption in response to rainfall shocks.

The analysis to evaluate the effect of rainfall shock on fertilizer consumption is carried out in two ways. First, we compare the average amount of fertilizer consumed in each rainfall shock category of RS1 measure. Table 2 highlights the occurrence of different types of rainfall shocks and relative fertilizer consumption. Nearly 47 per cent of observations are excess rainfall years, and 53 per cent are negative shock years. Table 2 shows that in comparison to positive shock years, fertilizer consumption is 3 kg per hectare

Table 2. Distribution of different levels of rainfall shocks and average fertilizer use, 1966–2009

Rainfall status	No. of observations	Proportion in total (%)	Mean NPK consumption (kg/ha)
Positive deviation	5,615	47	57.22
Negative deviation	6,417	53	60.30
All	12,032	100	58.86

Note: Rainfall shock status corresponds to RS1 measure.
 Source: Author’s calculations.

more during rainfall deficit years. However, we could not visually find any glaring differences in the distribution between the categories from the density plot (figure A2, online appendix).

Secondly, we empirically investigate how rainfall shock affects the quantum of chemical fertilizer application. Equation (3) specifies the model to investigate the heterogeneous effect of rainfall status on fertilizer consumption:

$$\ln(\text{NPK}_{it}) = \beta_0 + \beta_1 \text{IRR}_{it} + \beta_2 \text{RS1}_{it} + \beta_3 \text{RS1}_{it-1} + \beta_4 (\text{RS1}_{it} \times \text{IRR}_{it}) + \beta_5 (\text{RS1}_{it-1} \times \text{IRR}_{it}) + \beta_6 \text{HYV}_{it} + \beta_7 \text{CI}_{it} + \beta_s \text{Trend} + d_{i+t} + \varepsilon_{it}, \tag{3}$$

where NPK_{it} is fertilizer consumption (NPK) in kg/ha; IRR_{it} is irrigation intensity defined as the proportion of gross irrigated area over the gross cropped area; i denotes districts; t denotes time; and d and δ are the district and time fixed effects, respectively. Trend variable is the linear state-specific trend, where s denotes States. We also use two additional controls for HYV area (HYV) and cropping intensity (CI).

In a rainfall-deficient year, farmers are more likely to get a bad harvest, resulting in a low ability to reinvest in successive seasons. So, a one-year lag of rainfall shock is included in this model. Dercon and Christiaensen (2011) and Heisse and Morimoto (2019) also used a similar specification for Ethiopia and Tanzania, respectively. As the unit root is not a problem in this panel for any of the concerned variables, we proceed with modelling the effects (table A3, online appendix). We use a Fisher-type unit root test because the panel is unbalanced. Since our fixed effect regression estimates suffer from the problem of heteroskedasticity and serial correlation, we compute two-way clustered standard errors for all the estimations. First, to allow for heteroskedasticity and serial correlation, clustering is done within districts across years. Second, within a State (region) by year clustering is followed to account for spatial auto-correlation. Fishman (2016) followed a similar strategy of two-way clustering.

Table 3 shows the coefficients and standard errors of the model as specified in equation (3) for the log-level specification. Presence of irrigation positively and significantly influences fertilizer consumption. We do not find any significant change in fertilizer consumption due to a change in the current year rainfall shock from excess to negative. However, change in the previous year rainfall status from positive to negative shock significantly changes the level of fertilizer consumption. A deficient previous year rainfall reduces fertilizer consumption by 4.1 per cent⁶ compared to a positive previous

⁶Since the dependent variable is log-transformed, we use Halvorsen and Palmquist’s (1980) formula to calculate the change given as $100 \times [\exp^\beta - 1]$. However, Kennedy (1981) shows that it can be a biased estimator. Even if we use Kennedy’s bias-corrected formula, we get approximately the same result for column 3 (−4.12%).

Table 3. Estimated regression coefficients for effects of irrigation and different levels of rainfall shock (RS1) on the rate of fertilizer consumption, 1966–2009

Explanatory variable	Dependent variable = ln (NPK consumption)				
	(1)	(2)	(3)	(4)	(5)
Current year rainfall					
Excess (Positive deviation)	Base		Base	Base	Base
Deficit (Negative deviation)	−0.020 (−0.0190)		−0.022 (−0.0198)	−0.026 (−0.0210)	−0.027 (−0.0212)
Previous year rainfall status					
Excess (Positive deviation)		Base	Base	Base	Base
Deficit (Negative deviation)		−0.041** (−0.0201)	−0.042** (−0.0202)	−0.043** (−0.0213)	−0.042** (−0.0213)
Irrigation share	0.010*** (−0.0018)	0.009*** (−0.0018)	0.010*** (−0.0019)	0.012*** (−0.0023)	0.013*** (−0.0023)
HYV Area (%)				−0.0020* (−0.0011)	−0.0021* (−0.0011)
Cropping intensity (%)					−0.0014 (−0.0015)
District and time fixed effects	Yes	Yes	Yes	Yes	Yes
State specific trend	Yes	Yes	Yes	Yes	Yes
Observations	11,098	10,852	10,488	8,526	8,526
Adjusted R ²	0.934	0.935	0.935	0.936	0.936
Marginal effects at mean					
Negative shock	−0.034*** (−0.011)		−0.033*** (−0.011)	−0.029** (−0.013)	−0.030** (−0.013)
Negative shock (Lag = 1)		−0.042*** (−0.010)	−0.042*** (−0.010)	−0.041*** (−0.011)	−0.041*** (−0.011)
Irrigation share	0.010*** (−0.002)	0.009*** (−0.002)	0.009*** (−0.002)	0.012*** (−0.002)	0.013*** (−0.002)

Notes: ***, **, and * indicate levels of significance at 1, 5 and 10%, respectively. Two-way clustered standard errors (district and state × year) are reported in the parenthesis. Full results are available in table A4 (online appendix).
Source: Author’s calculations.

year rainfall shock (column 3). The magnitude of the effect persists at a similar level even after the inclusion of two control variables, HYV area (column 4) and cropping intensity (column 5).⁷ The sign of the coefficient of the interaction term with irrigation and current rainfall status is non-significant (table A4, online appendix). In terms of average marginal effects, negative shocks in the present and the preceding year can lower fertilizer consumption by 3 and 4 per cent, respectively (column 5).

It could be erroneous to assume all deviations from the long-term normal are shocks and classify them as weather anomalies. We redefine rainfall anomalies under a three-way classification by adding a normal category to test for sensitivity. We outline two

⁷ A sizable change in the number of observations in models 4 and 5 from the rest is because of the unavailability of information about area under HYV seeds, particularly in the initial years of study.

methods to classify normal rainfall years along with rainfall shock years. First, we define a new rainfall shock variable RS2 under the following classification: (i) positive rainfall shock if $TRD \geq +1$; (ii) normal if TRD is between -1 and $+1$; and (iii) negative rainfall shock if $TRD \leq -1$.⁸ Secondly, we use the definition provided by the Indian Meteorological Department (IMD) for rainfall anomalies to construct our rainfall shock ‘RS3’ variable. According to the IMD, annual rainfall deviation (ARD) is expressed as:

$$RS3 = ARD_{it} = \left\{ \frac{(TR_{it} - TR_i^{normal})}{TR_i^{normal}} \right\} \times 100. \tag{4}$$

Similar to equation (1), TR is the annual rainfall, and TR (normal) is the long-term rainfall in the district. Anomalies are characterised based on the following cut-off: (i) normal year if ARD is between -20% to $+20\%$; (ii) positive rainfall shock if $ARD \geq +20\%$; and (iii) negative rainfall shock if $ARD \leq -20\%$. Pandey *et al.* (2007) used a similar definition of drought in their analysis.

Table A5 (online appendix) presents the results of the new classifications. Columns 1 and 2 correspond to the results of RS2, and we reconfirm the adverse effects of the previous year rainfall shock. The IMD-based rainfall shock (RS3) definition also yields similar results (columns 3 and 4). The reduction effect is found to be more extensive compared to the previous two definitions. The use of the same cut-off across all the districts to define negative shock could be the reason for the higher effect.

The results from the above analysis do not provide sufficient evidence to predict the direction of the relationship between the level of fertilizer use and the current year rainfall status. No change in concurrent fertilizer use signifies that fertilizer is less likely to be used for *ex-ante* production risk management in our sample. Nonetheless, we find a robust negative effect of rainfall shock in the previous year on fertilizer application per hectare. The importance of irrigation as a determinant is certain. However, we do not find any significant effect of an increase in irrigated area impacting the level of fertilizer use when a district is exposed to rainfall shocks. A further analysis is required to investigate the differential impact of the intensity of droughts (negative deviation) on investment in fertilizer.

4.2 Effect of droughts

Equation (5) provides a basic specification to model the effect of drought on fertilizer use:

$$\ln(NPK_{it}) = \beta_0 + \beta_1 DI_{it} + \beta_2 DI_{it}^2 + \beta_3 IRR_{it} + \beta_4 (DI_{it} \times IRR_{it}) + \beta_5 (DI_{it-1} \times IRR_{it}) + \beta_6 HYV_{it} + \beta_7 CI_{it} + \beta_8 Trend + d_{i+t} + \varepsilon_{it}. \tag{5}$$

here, the DI is a continuous variable defined in equation (2). A continuous variable gives more flexibility than the earlier categorical variable of rainfall shock. The coefficient of the squared term can be interpreted as the impact of high-intensity droughts. We compute a panel fixed effects model for linear and log-linear specifications. Our specifications continue to include HYV area and cropping intensity as controls.

⁸ $A \pm 1$ TRD cut-off has been followed in earlier studies (Zaveri *et al.*, 2020) and it is consistent with the standardized precipitation index (SPI) cut-off.

Table 4. Estimated regression coefficients for effects of irrigation and drought intensity (DI) on the rate of fertilizer consumption, 1966–2009

Explanatory variable	Linear		Log-Linear	
	(1)	(2)	(3)	(4)
Drought	−1.532 (−1.2628)	−1.649 (−1.2943)	−0.066* (−0.0342)	−0.070** (−0.0352)
Drought ²	1.108* (−0.6641)	1.177* (−0.6939)	0.016 (−0.0176)	0.015 (−0.0184)
Drought (lag = 1)		−3.172*** (−1.1202)		−0.099*** (−0.0326)
Drought ² (lag = 1)		1.788*** (−0.601)		0.026* (−0.0151)
Irrigation share	0.764*** (−0.1345)	0.759*** (−0.1367)	0.013*** (−0.0023)	0.012*** (−0.0023)
State-specific trend	Yes	Yes	Yes	Yes
District and time fixed effects	Yes	Yes	Yes	Yes
Observations	8,954	8,563	8,915	8,526
Within R ²	0.057	0.055	0.034	0.037
Marginal effects (at mean DI = 0.73, DI (lag = 1) = 0.72, Irrigation share = 33.64)				
Drought	−1.319** (−2.358)	−1.233** (−2.242)	−0.032** (−2.520)	−0.036*** (−2.956)
Drought (lag = 1)		−1.090** (−2.130)		−0.041*** (−3.828)
Irrigation share	0.733*** (−5.630)	0.720*** (−5.465)	0.013*** (−5.805)	0.013*** (−5.539)

Notes: ***, ** and * indicate levels of significance at 1, 5 and 10%, respectively. Two-way clustered standard errors (district and state × year) are reported in the parentheses. Full results are available in table A6 (online appendix).

Source: Author's calculations.

The following are highlights of the results shown in table 4. First, the reduction in the quantity of fertilizer applied is not conclusive for contemporaneous drought shock; coefficients are only significant for log-linear specification in column 4.⁹ Secondly, previous year drought shocks significantly lower fertilizer consumption. A one unit increase in past drought intensity can reduce per hectare NPK consumption by 10 per cent (column 4). Thirdly, this relationship turns positive at a higher level of drought exposure. Finally, the magnitude of reduction in fertilizer is higher in response to the previous year than the current-year drought.

The average marginal effects show that the negative effect of past drought shock on fertilizer application is 1.3 percentage points more than the current (see estimates of log-linear specification of marginal effects in table 4). We obtain similar results even after changing state-specific trend variables by district-specific linear time trend (table A7, online appendix). As irrigation is perceived as the best-adapting strategy against droughts, we use the interaction of irrigation with drought to study the effect

⁹Changes in the number of observations in the linear and log-linear model are because districts with zero fertilizer use are dropped in the log-linear specification.

Linear prediction with 95% CI

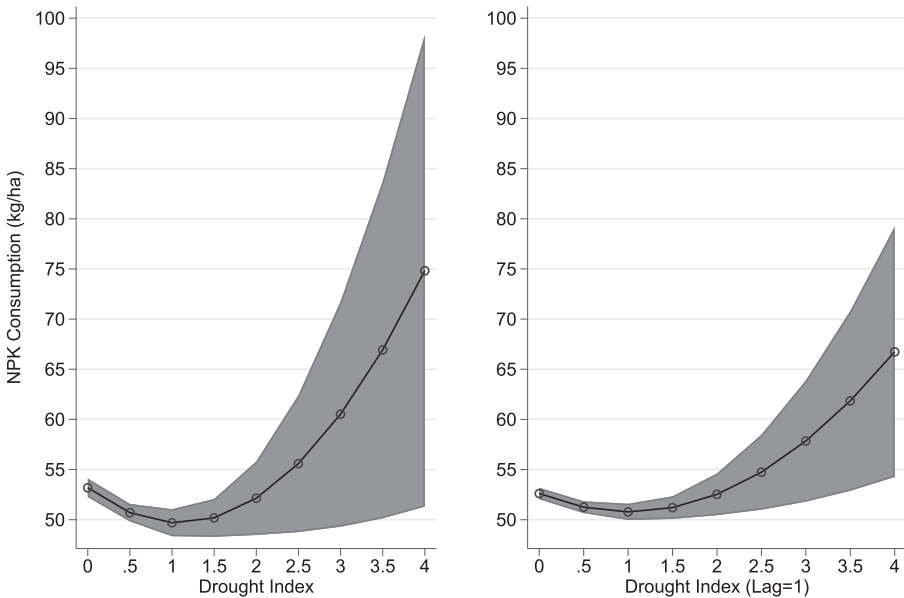


Figure 1. Predicted level of NPK fertilizer consumption by changing levels of drought (current and previous year)
 Source: Author’s calculations.

in different levels of irrigation. Similar to section 4.1, we find a significant effect of the area under irrigation for NPK consumption (online appendix table A6). We fail to ascertain any positive effect of irrigation in lowering the impact of droughts on fertilizer consumption.

We find a significant negative relationship between previous droughts at the district level on the current year fertilizer application rates. Figure 1 represents the predicted relationship between NPK consumption and drought levels (current and previous year) at a 95 per cent confidence interval (based on column 2 of table 4). On both occasions, the curve is convex. The curves are negative sloping at the beginning until $DI = 1$, then a reversal of the relationship occurs. Following the SPI classification, we can categorise DI less than one as low-intensity droughts. Our results exhibit a negative response to low-intensity past droughts. However, moderate and severe droughts in the past induce higher application of fertilizer. In total, we find that incremental addition of NPK becomes higher with the severity of droughts.

4.3 Robustness checks

We check the robustness of our main results to alternative specifications and definitional change of drought variable. We test the robustness of our categorical rainfall shock variable to a few definitional changes in the latter part of section 4.1. Here, we focus on checking the robustness of fertilizer response to drought intensity results.

We begin by checking to see that changes in fertilizer use are not driven by changes in district gross cropped area. Iizumi and Ramankutty (2015) point out that weather

Table 5. Estimated regression coefficients for effects of gross cropped area and drought intensity on rate of fertilizer consumption, 1966–2009

Explanatory variable	Dependent variable			
	Gross cropped area ('000 ha) (1)	Ln (Gross cropped area in '000 ha) (2)	NPK consumption ('000 tons) (3)	Ln (NPK consumption in '000 tons) (4)
Gross cropped area (1,000 ha)			0.071*** (−0.0171)	0.001*** (−0.0002)
Drought	−27.332*** (−5.6629)	−0.045*** (−0.0086)	0.227 (−1.0240)	−0.081** (−0.0345)
Drought ²	1.208 (−3.8045)	0.003 (−0.0062)	0.798 (−0.5594)	0.011 (−0.0173)
Drought (lag = 1)	−3.726 (−4.2356)	−0.007 (−0.0072)	−1.988** (−0.8705)	−0.101*** (−0.0328)
Drought ² (lag = 1)	1.484 (−2.2973)	0.003 (−0.0038)	0.984** (−0.3819)	0.029* (−0.0151)
Observations	11,592	11,592	8,563	8,526
Within R ²	0.034	0.033	0.109	0.056

Notes: ***, ** and * indicate levels of significance at 1, 5 and 10%, respectively. Two-way clustered standard errors (district and state × year) are reported in the parentheses. Full results are available in table A8 (online appendix).

Source: Author's calculations.

and climatic factors can influence all spheres of crop production, including crop area. Zaveri *et al.* (2020) find 9 per cent of cropland expansion on account of dry anomalies around the globe. Since our dependent variable is fertilizer consumption per hectare of gross cropped area, drought-induced cropland adjustment might be causing the change in our dependent variable. We find a reduction in the cultivated area if a district experiences drought in any given year (columns 1 and 2 in table 5). However, our estimates do not show any changes in the cultivated area on account of previous year exposure to droughts. We believe that climatic shocks can alter the extent of the planting area in a district. However, changes to fertilizer consumption cannot be entirely attributed to such changes.

We change our dependent variable to NPK consumption (tonnes) and include the gross cropped area as a covariate in the specification of equation (5). For the concurrent year drought effect, the reduction in total consumption of fertilizer is valid only for the log-linear specification. The negative effect of previous year drought shock is still persistent (table 5). Reversal of the relationship at higher levels of past drought is equally significant. The magnitude of reduction remains at a similar level of about 10 per cent (column 4, table 5).

The second set of evidence of the robustness of our results is related to consumption of nitrogenous fertilizer. In terms of cost, the price of nitrogenous fertilizer (e.g., urea) is the lowest among the three macronutrients as a result of subsidies. Because of the subsidised price of nitrogenous fertilizers, only a small increase in their prices occurred in the study period. We do not expect changes in price because of any climatic adversities. Since nitrogen is consumed in higher quantities, we expect a possible change in the amount of N-fertilizer application to reduce the overall cost of cultivation. Columns 1 and 2 of table A9 (online appendix) present the estimated coefficients of previous year

drought shocks on nitrogen consumption. Our earlier assessment about the reduction in NPK fertilizer application remains valid for nitrogenous fertilizer as the dependent variable. The negative effect is slightly less for nitrogenous fertilizer (about 8 per cent) than the overall results from the baseline specification. A higher application of nitrogenous fertilizer is also observed for high-intensity droughts but it is non-significant in the log-linear specification. An increase in irrigation share contributes to about a 1.2 per cent increase in nitrogenous fertilizer (similar to earlier estimates in the main specification).

Thirdly, we change our assumption that any shortfall in annual rainfall is driving the relationship. The productivity of several crops is dependent on the sufficiency of monsoon rainfall, so we modify the DI to be based on monsoon rainfall. We define monsoon rainfall as the total of rainfall in June, July, August, and September. Table A9 (columns 3 and 4) presents regression results based on our new monsoon DI. A similar response to a one-year lag monsoon drought shock is observed on fertilizer application (about 10.6 per cent reduction). The relationship continues to be convex. In comparison to annual drought, we find a slightly higher effect of monsoon drought in reducing the fertilizer application. The current year monsoon drought shock produces inconsistent findings for linear and log-linear specification, and we fail to assert any effect conclusively.

4.4 Estimates based on agro-ecological regions

Previous assessments of climatic impacts on agricultural productivity show differential magnitude of adverse effects by agro-climatic regions (Mall *et al.*, 2006; Barnwal and Kotani, 2013; Murari *et al.*, 2018). Aggarwal and Mall (2002) demonstrate that yield sensitivity to climate change varies over agro-environments for irrigated rice in India. Based on the crop simulation model, the study highlights that climate sensitivity would be higher for the southern and eastern regions of India. However, the same research finds that the magnitude of sensitivity varies with nitrogen management levels. Keeping heterogeneity of climate in mind, we further disaggregate our analysis by agro-ecological regions (AERs). This exercise aids us in delineating our national-level results by agro-climatic regions.

DLD-India database classifies Indian districts into four AERs based on length of growing period (LGP) and temperature.¹⁰ We can evaluate the differences in mean drought exposure and its ranges from table A10 (online appendix). Although the mean DI over the years looks very similar, the range of drought intensity differs considerably across the regions. The average fertilizer application is distinctively dissimilar by region, and we expect a differential response to drought exposure within each region. The highly input-intensive part of northern India falls into the semi-arid temperate region classification. From the climate sensitivity point of view, semi-arid tropics and arid areas are very important as these regions experience long-lasting exposure to drought conditions.

Our split-sample analysis for different agro-climatic regions produces mixed results. For consistency, we focus only on the effect of past droughts on fertilizer consumption. Previous year drought exposure in the districts of semi-arid temperate and semi-arid tropics negatively affect current year fertilizer consumption (table A11 and figure 2). The effect is highest in the semi-arid temperate region compared to other areas. We find a reduction of about 8 kg per hectare for a unit increase in drought exposure. At the

¹⁰These categories are: (i) Humid (LGP > 180 days); (ii) Semi-Arid Temperate (LGP = 75–179 days, Temperature ≤ 18°C); (iii) Semi-Arid Tropic (LGP = 75–179 days, Temp ≥ 18°C); and (iv) Arid (LGP = 0–74 days).

Linear prediction with 95% CI

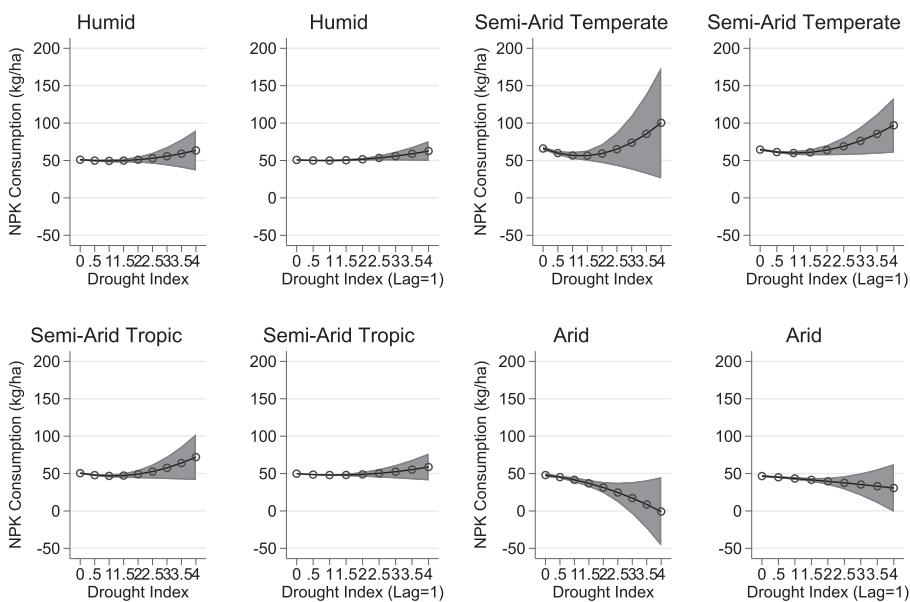


Figure 2. Predicted level of NPK fertilizer consumption, by levels of drought (current and previous year), by AER
 Source: Author's calculations.

mean level of DI (excluding $DI = 0$), our estimate shows a 4.7 and 3.4 per cent reduction for a 1 per cent increase in current and previous year DI, respectively (see marginal elasticity rows of column 2 of table A11). It is worth noting that the reduction is highest in the region where the intensity of chemical fertilizer application is highest. A much smaller but significant decrease of 2.7 kg per hectare is observed for semi-arid tropics. **Figure 2** shows the predicted values of NPK consumption for different AERs. The arid region shows an exceptional pattern in contrast to all other regions. This region maintains a negative relationship throughout the range of drought intensity. The marginal elasticity (at mean) for lag DI is about -5.5 per cent. The difference in behaviour may be because frequent exposure to droughts reduces the capacity of farmers to reinvest in any productive inputs in arid districts.

5. Discussion

The results of the above sections can be summarised in several findings. First, fertilizer application levels are determined by rainfall and the area under irrigation in any particular year. Secondly, we do not find sufficient evidence of contemporaneous change in chemical fertilizer use due to negative rainfall shocks. Thirdly, with specific reference to droughts, the analysis finds a new pattern of fertilizer consumption. A low level of drought in the preceding year would lower the application rates, but higher levels of droughts contribute positively. Finally, previous year drought can exhibit a differential effect on fertilizer use by agro-climatic conditions.

As the central hypothesis is to check whether adverse shocks decrease fertilizer application, the results from the study are mixed. Insignificant reduction in chemical fertilizer application levels under negative shocks could be because farmers perceive fertilizer as a risk-reducing input and do not change their current investment portfolio. The results support the observation of Auffhammer *et al.* (2012) who find that the non-weather variables (such as fertilizer and labour) are not sensitive to the weather conditions in India. In a different setting, Jagnani *et al.* (2021) find a reduction in fertilizer use with warmer growing season temperatures for maize farmers in Kenya. In this case, the authors argue that farmers are diverting investment from productivity-enhancing technology, like fertilizer, to more defensive inputs such as pesticide and weeding. Katengeza *et al.* (2019) find inconsistent effects for organic manure use in response to dry spells of the previous three years in Malawi for maize crop.

Our study finds a negative relationship between fertilizer use and previous year drought exposure. This pattern would probably mean a reduction in current year fertilizer expenditure because of the lower profitability caused by droughts in the last year. Dercon and Christiaensen (2011) also find that crop failure discourages the application of fertilizer in Ethiopia. Alem *et al.* (2010) explain that favourable-rainfall years could relax the liquidity constraints for the next year, and farmers can afford fertilizer accordingly. Our findings can also be understood through these mechanisms, and productive investments appear to have been affected by bad harvests.

In the absence of district-level fertilizer price data, we could not convert our estimates to economic value terms. However, based on estimates of FAO (2005), we get a rough sense of the economic implications of our findings. For 2004–05, FAO (2005) estimates show an increase of 12 kg (or Rs 66 in value terms) of rice for an additional kilogram of nitrogen. Our estimated average marginal effect of the previous year drought shock is about 1.2 kg/ha of N. Certainly the mentioned estimates will differ widely across the regions, crops and year. A reduction in fertilizer application would reduce land productivity and farmers' income.

The phenomenon of increasing the amount of fertilizer usage when the district is exposed to severe drought conditions in the previous year is challenging to explain. With severe droughts resulting in higher yield loss in the previous year, farms might alter fertilizer application towards the higher side to safeguard production or in anticipation of higher yield in the subsequent period. The total number of moderate and high-intensity droughts is only about 14 per cent in our sample (table A12, online appendix), and low-intensity droughts ($DI < 1$) account for most shocks (figure A3, online appendix). We could not corroborate the exact reasons from district-level analysis because of limitations of data availability.

A probable reason could be the higher application of fertilizer as a cheap form of insurance (as documented by Below and Brandau (2001)). We believe the increase in fertilizer application at high-intensity droughts is linked to the inability of smallholders to invest in irrigation infrastructure. Lack of ability to invest in fixed inputs by smallholders, particularly in irrigation, is a reason for the existence of an inverse (negative) relationship between farm size and inorganic fertilizer application rates in China (Wu *et al.*, 2018; Ren *et al.*, 2021). The inverse relation also holds for Indian conditions, and fertilizer application rates are highest among smallholders compared to large farmers (Murari and Jayaraman, 2017). Past research in India indicates better access to irrigation by large landowning classes compared to smaller ones (Sarkar, 2011; Srinivasan and Nuthalapati, 2019). Therefore, we made a possible connection that the convex relationship could be because of the behaviour of small and marginal

farmers. Small farmers may try to compensate for costly inputs related to climatic adaptation (irrigation) with increased fertilizer application even after drought exposure. We select a sub-sample of Punjab and Haryana to test this hypothesis and check the drought-fertilizer application relationship (table A13, online appendix). The average size of operational area in these two States is among the highest across the States of India. The coverage of irrigation has been gradually increasing since the green revolution in this region. These two States have more than 85 per cent area under irrigation in the total cultivated area (figure A4, online appendix). The convex relationship does not hold for these two states. The absence of a convex relationship in this region with better irrigation infrastructure makes a probable case for fertilizer being used as a cheaper form of insurance against weather risks. Alem *et al.* (2010) show a similar convex relationship and find higher chemical fertilizer use when rainfall variability or risk is very high.

The results of this study have implications for agricultural productivity, profitability, and environmental sustainability. Sustaining agricultural productivity under unfavourable climatic extremes has a broader impact on the poverty trap in a developing country like India. As observed by several other studies such as Birthal *et al.* (2015) and Amare *et al.* (2018), a negative association between crop yields and rainfall shocks is a reality in agriculture. However, crop yields are not substantially higher even when water is not a limiting factor in excess rainfall years in India (Gadgil and Gadgil, 2006). Past studies find a higher negative effect of low rainfall on crop productivity in farmers' fields as compared to an agricultural research station. In contrast, the gain in crop yields by farmers is less in good monsoon years compared to the research stations in semi-arid tropics of India (Sivakumar *et al.*, 1983). This asymmetry may be attributed to differences in input management between research stations and farmers' fields (mainly in terms of applying productive inputs like fertilizer and pesticides). Our study does not find any difference in application levels of fertilizer during adequate and deficient rainfall years. This finding points towards the inability of farmers to adequately invest in productivity-enhancing mechanisms to reap the benefit of a good monsoon.

Our region-disaggregated results show a pattern of increase in fertilizer application in the semi-arid temperate zone following any moderate and high-intensity drought. Given that some areas of this country are already using high levels of chemical fertilizer, any additional increase is not encouraging for the environment. On the contrary, in the arid region, where consumption of chemical fertilizer is at a lower level, any further reduction induced by climatic shock can have a negative consequence on soil fertility. As Kurosaki and Wada (2015) document the prevalence of low gross value crops (e.g., pearl millet, sorghum, and other millets) in arid ecosystems, we can expect drought-coping mechanisms to be different in this region. Moreover, these crops are less responsive to fertilizers than rice and wheat. In harsh environments, weather shocks contribute to persistent poverty, and even affluent households are vulnerable (Gaiha and Imai, 2004). However, the ability to cope with rainfall shock is contingent on wealth status, as demonstrated for semi-arid tropics of India (Rosenzweig and Binswanger, 1993). Palmer-Jones and Sen (2003) effectively demonstrate the need for irrigation development to foster agricultural growth in less favourable agricultural regions. Our study makes an argument for effective nutrient-management strategies to maintain soil health in these areas. We believe a further reduction in fertilizer application in areas of low crop yields and less intensive input use (semi-arid tropics and arid regions) can have a far-reaching consequence on poverty.

6. Concluding remarks

Nutrient management through fertilizer application can be a vital mechanism for adjusting to climatic variability because of its potential to reduce the yield gap. Although the benefits of fertilizer use have been widely acknowledged, the environmental implications of excessive fertilizer application are also a matter of concern. A range of negative externalities, such as nitrate leaching and runoff, are associated with chemical fertilizers (Abrol and Raghuram, 2007; Vitousek *et al.*, 2009). In the Indian context, indiscriminately higher use of chemical fertilizers, mainly nitrogen, is already prevalent in some parts of the country. Globally, the safe operating space or planetary boundaries for biogeochemical flows (nitrogen and phosphorus cycle) has already been exceeded (Steffen *et al.*, 2015). However, given the intensive nature of cultivation and widespread soil-nutrient deficiencies worldwide, it is not possible to ban the use of chemical fertilizers (Singh and Wanjari, 2013).

Droughts are expected to increase in future and coping, or production optimisation processes, may increase fertilizer demand. It has to be noted that it is tough to ascertain any management practice as an adaptation against climate variability. It is tough to disentangle the sole climatic adaptation aspect of agricultural management practices, such as fertilizer, from the regular input optimisation behaviour of farmers. In the context of the increase in the frequency of climate extremes due to climate change, the focus should be therefore on integrated soil fertility management to safeguard farmers against productivity losses. Further research is required, particularly at the crop-disaggregated level, to better understand farmers' responses toward different nutrient-management practices under climatic risks.

Supplementary material. The supplementary material for this article can be found at <https://doi.org/10.1017/S1355770X21000413>.

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References

- Abrol YP and Raghuram N (2007) *Agricultural Nitrogen Use and Its Environmental Implications*. New Delhi: IK International Pvt Ltd.
- Aditya KS, Kahan T and Kishore A (2018) Adoption of crop insurance and impact: insights from India. *Agricultural Economics Research Review* 31, 163–174.
- Aggarwal PK and Mall RK (2002) Climate change and rice yields in diverse agro-environments of India. II. Effect of uncertainties in scenarios and crop models on impact assessment. *Climatic Change* 52, 331–343.
- Alem Y, Bezabih M, Kassie M and Zikhali P (2010) Does fertilizer use respond to rainfall variability? Panel data evidence from Ethiopia. *Agricultural Economics* 41, 165–175.
- Amare M, Jensen ND, Shiferaw B and Cissé JD (2018) Rainfall shocks and agricultural productivity: implication for rural household consumption. *Agricultural Systems* 166, 79–89.
- Auffhammer M, Ramanathan V and Vincent JR (2012) Climate change, the monsoon, and rice yield in India. *Climatic Change* 111, 411–424.
- Babcock BA (1992) The effects of uncertainty on optimal nitrogen applications. *Review of Agricultural Economics* 14, 271–280.
- Babcock BA and Hennessy DA (1996) Input demand under yield and revenue insurance. *American Journal of Agricultural Economics* 78, 416–427.
- Barnwal P and Kotani K (2013) Climatic impacts across agricultural crop yield distributions: an application of quantile regression on rice crops in Andhra Pradesh, India. *Ecological Economics* 87, 95–109.

- Below F and Brandau P** (2001) How much nitrogen does corn need? Paper presented at 2001 *Agronomy Field Day*, University of Illinois Extension, University of Illinois Urbana-Champaign.
- Bharadwaj K** (1974) *Production Conditions in Indian Agriculture: A Study Based on Farm Management Surveys*. Cambridge, UK: Cambridge University Press.
- Birner R, Gupta S and Sharma N** (2011) *The Political Economy of Agricultural Policy Reform in India: Fertilizers and Electricity for Irrigation*. Washington, D.C, USA: International Food Policy Research Institute.
- Birthal PS and Hazrana J** (2019) Crop diversification and resilience of agriculture to climatic shocks: evidence from India. *Agricultural Systems* **173**, 345–354.
- Birthal PS, Negi DS, Khan MT and Agarwal S** (2015) Is Indian agriculture becoming resilient to droughts? Evidence from rice production systems. *Food Policy* **56**, 1–12.
- Birthal PS, Negi DS and Hazrana J** (2019) Trade-off between risk and returns in farmers' choice of crops? Evidence from India. *Agricultural Economics Research Review* **32**, 11–23.
- Chand R and Pandey LM** (2009) Fertiliser growth, imbalances and subsidies: trends and implications. *Margin: The Journal of Applied Economic Research* **3**, 409–432.
- Chand R and Parappurathu S** (2012) Temporal and spatial variations in agricultural growth and its determinants. *Economic and Political Weekly* **47**, 55–64.
- Chen S and Gong B** (2021) Response and adaptation of agriculture to climate change: evidence from China. *Journal of Development Economics* **148**, 102557.
- Cole S, Giné X, Tobacman J, Topalova P, Townsend R and Vickery J** (2013). Barriers to household risk management: evidence from India. *American Economic Journal: Applied Economics* **5**, 104–135.
- Croppenstedt A, Demeke M and Meschi MM** (2003) Technology adoption in the presence of constraints: the case of fertilizer demand in Ethiopia. *Review of Development Economics* **7**, 58–70.
- Dercon S and Christiaensen L** (2011) Consumption risk, technology adoption and poverty traps: evidence from Ethiopia. *Journal of Development Economics* **96**, 159–173.
- Drechsel P, Heffer P, Magen H, Mikkelsen R and Wichelns D** (eds) (2015) *Managing Water and Fertilizer for Sustainable Agricultural Intensification*. International Fertilizer Industry Association (IFA), International Water Management Institute (IWMI), International Plant Nutrition Institute (IPNI), and International Potash Institute (IPI).
- Emerick K** (2018) Agricultural productivity and the sectoral reallocation of labor in rural India. *Journal of Development Economics* **135**, 488–503.
- FAO** (2005) *Fertilizer Use by Crop in India*. Land and Water Development Division, Food and Agriculture Organization, Rome.
- Fishman R** (2016) More uneven distributions overturn benefits of higher precipitation for crop yields. *Environmental Research Letters* **11**, 024004.
- Fontes F, Palmer C and Gorst A** (2020) Does choice of drought index influence estimates of drought-induced rice losses in India? *Environment and Development Economics* **25**, 1–25.
- Gadgil S and Gadgil S** (2006) The Indian monsoon, GDP and agriculture. *Economic and Political Weekly* **41**, 4887–4895.
- Gaiha R and Imai K** (2004) Vulnerability, shocks and persistence of poverty: estimates for semi-arid rural South India. *Oxford Development Studies* **32**, 261–281.
- Ghosh A and Dey SK** (2014) How efficiently is chemical fertilizer used in Indian agriculture? Challenges and alternatives. *Agrarian South: Journal of Political Economy* **3**, 403–426.
- Government of India** (2017) *Agricultural statistics at a glance 2016*. Directorate of Economics and Statistics, Department of Agriculture, Cooperation and Farmers Welfare, Ministry of Agriculture and Farmers Welfare, Government of India.
- Gulati A and Banerjee P** (2015) Rationalising fertiliser subsidy in India: key issues and policy options. Working Paper no 307, Indian Council for Research on International Economic Relations (ICRIER), New Delhi.
- Gupta S, Sen P and Srinivasan S** (2014) Impact of climate change on the Indian economy: evidence from food grain yields. *Climate Change Economics* **5**, 1450001-1-29.
- Haider H, Smale M and Theriault V** (2018). Intensification and intrahousehold decisions: fertilizer adoption in Burkina Faso. *World Development* **105**, 310–320.
- Halvorsen R and Palmquist R** (1980) The interpretation of dummy variables in semilogarithmic equations. *American Economic Review* **70**, 474–475.

- Heisse C and Morimoto R** (2019) Climate change, chemical fertilizers, and sustainable development: panel evidence from Tanzanian maize farmers. SOAS Department of Economics Working Paper No. 217, SOAS University of London, London.
- ICRISAT-TCI** (2015) The district level database (DLD) for Indian agriculture (apportioned data). International Crops Research Institute for the Semi-Arid Tropics, Hyderabad and Tata-Cornell Institute for Agriculture and Nutrition (TCI), New Delhi. Available at <http://data.icrisat.org/dld/src/crops.html>.
- Izumi T and Ramankutty N** (2015) How do weather and climate influence cropping area and intensity? *Global Food Security* 4, 46–50.
- Jagnani M, Barrett CB, Liu Y and You L** (2021) Within-season producer response to warmer temperatures: defensive investments by Kenyan farmers. *The Economic Journal* 131, 392–419.
- Kaliba AR, Verkuil H and Mwangi W** (2000) Factors affecting adoption of improved maize seeds and use of inorganic fertilizer for maize production in the intermediate and lowland zones of Tanzania. *Journal of Agricultural and Applied Economics* 32, 35–47.
- Karim MR and Rahman MA** (2015) Drought risk management for increased cereal production in Asian least developed countries. *Weather and Climate Extremes* 7, 24–35.
- Katengeza SP, Holden ST and Fisher M** (2019) Use of integrated soil fertility management technologies in Malawi: impact of dry spells exposure. *Ecological Economics* 156, 134–152.
- Kennedy PE** (1981) Estimation with correctly interpreted dummy variables in semilogarithmic equations. *American Economic Review* 71, 801.
- Khanal U, Wilson C, Hoang VN and Lee B** (2018) Farmers' adaptation to climate change, its determinants and impacts on rice yield in Nepal. *Ecological Economics* 144, 39–47.
- Kumar KSK and Parikh J** (2001) Indian Agriculture and climate sensitivity. *Global Environmental Change* 11, 147–154.
- Kumar P, Joshi PK and Aggarwal P** (2014) Projected effect of droughts on supply, demand, and prices of crops in India. *Economic and Political Weekly* 49, 54–63.
- Kurosaki T and Wada K** (2015) Spatial characteristics of long-term changes in Indian agricultural production: district-level analysis, 1965–2007. *Review of Agrarian Studies* 5, 1–37.
- Kusunose Y, Mason-Wardell N and Tembo S** (2020) The role of liquidity in preventing dis-investment in crop inputs: evidence from Zambia. *Journal of African Economies* 29, 375–396.
- Lamb RL** (2003) Fertilizer use, risk, and off-farm labor markets in the semi-arid tropics of India. *American Journal of Agricultural Economics* 85, 359–371.
- Lobell DB, Cassman KG and Field CB** (2009) Crop yield gaps: their importance, magnitudes, and causes. *Annual Review of Environment and Resources* 34, 179–204.
- Mahajan K** (2017) Rainfall shocks and gender wage gap: evidence from Indian agriculture. *World Development* 91, 156–172.
- Mall RK, Singh R, Gupta, A, Srinivasan G and Rathore LS** (2006) Impact of climate change on Indian agriculture: a review. *Climatic Change* 78, 445–478.
- McArthur JW and McCord GC** (2017) Fertilizing growth: agricultural inputs and their effects in economic development. *Journal of Development Economics* 127, 133–152.
- Mishra AK, Nimon RW and El-Osta HS** (2005) Is moral hazard good for the environment? Revenue insurance and chemical input use. *Journal of Environmental Management* 74, 11–20.
- Mohanam TC** (2002) *The Determinants of Fertilizer Consumption and Its Growth*. New Delhi: Northern Book Centre.
- Mueller N-D, Gerber JS, Johnston M, Ray DK, Ramankutty N and Foley JA** (2012) Closing yield gaps through nutrient and water management. *Nature* 490, 254–257.
- Murari KK and Jayaraman T** (2017) Fertilizer use and the small-scale farms. In Swaminathan M and Baksi S (eds), *How Do Small Farmers Fare?* New Delhi: Tulika Books, pp. 201–229.
- Murari KK, Mahato S, Jayaraman T and Swaminathan M** (2018) Extreme temperatures and crop yields in Karnataka, India. *Review of Agrarian Studies* 8, Available at <http://ras.org.in/91036314fb4c1338277b3da6a01a6a36>.
- Nagaraj R** (1983) Determinants of fertilizer use in Indian agriculture. *Economic and Political Weekly* 18, A2–15.
- Nyssen J, Biruk B, Tesfamariam Z, Frankl A, Demissie B, Ghebreyohannes T, Meaza H, Poesen J, Van Eetvelde V, Zenebe A and Deckers J** (2017) Geographical determinants of inorganic fertilizer sales and of resale prices in north Ethiopia. *Agriculture, Ecosystems and Environment* 249, 256–268.

- Palmer-Jones R and Sen K** (2003) What has luck got to do with it? A regional analysis of poverty and agricultural growth in rural India. *The Journal of Development Studies* **40**, 1–31.
- Pandey S, Bhandari HS and Hardy B** (2007) *Economic Costs of Drought and Rice Farmers' Coping Mechanisms: A Cross-Country Comparative Analysis*. Manila: International Rice Research Institute.
- Parikh KS** (1978) HYV Fertilizers: synergy or substitution: implications for policy and prospects for agricultural development. *Economic and Political Weekly* **132**, A2–A8.
- Pattanayak A and Kumar KSK** (2014) Weather sensitivity of rice yield: evidence from India. *Climate Change Economics* **5**, 1450011-1-23.
- Paulson ND and Babcock BA** (2010) Readdressing the fertilizer problem. *Journal of Agricultural and Resource Economics* **35**, 368–384.
- Plett DC, Ranathunge K, Melino VJ, Kuya N, Uga Y and Kronzucker HJ** (2020) The intersection of nitrogen nutrition and water use in plants: new paths toward improved crop productivity. *Journal of Experimental Botany* **71**, 4452–4468.
- Powell JP and Reinhard S** (2016) Measuring the effects of extreme weather events on yields. *Weather and Climate Extremes* **12**, 69–79.
- Raghavan M** (2008) Changing pattern of input use and cost of cultivation. *Economic and Political Weekly* **43**, 123–129.
- Ren C, Jin S, Wu Y, Zhang B, Kanter D, Wu B, Xican X, Zhang X, Chen D, Xu J and Gu B** (2021) Fertilizer overuse in Chinese smallholders due to lack of fixed inputs. *Journal of Environmental Management* **293**, 112913.
- Rosenzweig M and Binswanger H** (1993) Wealth, weather risk and the composition and profitability of agricultural investments. *The Economic Journal* **103**, 56–78.
- Sarkar A** (2011) Socio economic implications of depleting groundwater resources in Punjab: a comparative analysis of different irrigation systems. *Economic and Political Weekly* **12**, 59–66.
- Selvaraj KN and Ramasamy C** (2006) Drought, agricultural risk and rural income: case of a water limiting rice production environment in Tamil Nadu. *Economic and Political Weekly* **41**, 2739–2746.
- Sharma VP and Thaker H** (2011) Demand for fertiliser in India: determinants and outlook for 2020. *Indian Journal of Agricultural Economics* **66**, 638–661.
- Sheahan M and Barrett CB** (2014) Understanding the agricultural input landscape in Sub-Saharan Africa: recent plot, household, and community-level evidence. World Bank Policy Research Paper 7014. World Bank, Washington, DC.
- Singh M and Wanjari RH** (2013) All India coordinated research project on long-term fertilizer experiments to study changes in soil quality, crop productivity and sustainability. Annual Report – 2012-13, AICRP – LTFE, Indian Institute of Soil Science (ICAR), Nabibagh, Bhopal, India.
- Sivakumar MVK, Singh P and Williams JS** (1983) Agroclimatic aspects in planning for improved productivity in alfisols. Paper presented at the Alfisols in the Semi-arid Tropics: A Consultant's Workshop, December 1-3, ICRISAT Centre, India.
- Srinivasan JT and Nuthalapati CSR** (2019) Groundwater extraction, agriculture and poverty in Godavari River basin. *Ecology, Economy and Society-the INSEE Journal* **2**, 45–74.
- SriRamaratnam S, Bessler DA, Rister ME, Matocha JE and Novak J** (1987) Fertilization under uncertainty: an analysis based on producer yield expectations. *American Journal of Agricultural Economics* **69**, 349–357.
- Srivastava SK, Chand R and Singh J** (2017) Changing crop production cost in India: input prices, substitution and technological effects. *Agricultural Economics Research Review* **30**, 171–182.
- Steffen W, Richardson K, Rockström J, Cornell SE, Fetzer I, Bennett EM, Biggs R, Carpenter SR, De Vries W, DeWit CA and Folke C** (2015) Planetary boundaries: guiding human development on a changing planet. *Science* **347**, 1259855-1-10.
- Takeshima H and Nkonya E** (2014) Government fertilizer subsidy and commercial sector fertilizer demand: evidence from the Federal Market Stabilization Program (FMSP) in Nigeria. *Food Policy* **47**, 1–12.
- Taraz V** (2018) Can farmers adapt to higher temperatures? Evidence from India. *World Development* **112**, 205–219.
- Vaidyanathan A** (2010) *Agricultural Growth in India: Role of Technology, Incentives and Institutions*. New Delhi: Oxford University Press.
- Venugopal P** (2004). *Input Management, vol. 8: State of the Indian Farmer: A Millennium Study*. New Delhi: Academic Foundation.

- Vitousek PM, Naylor R, Crews T, David MB, Drinkwater LE, Holland, E, Johnes PJ, Katzenberger J, Martinelli LA, Matson PA, Nziuguheba G, Ojima D, Palm CA, Robertson GP, Sanchez PA, Townsend AR and Zhang FS** (2009) Nutrient imbalances in agricultural development. *Science* **324**, 1519–1520.
- Wakeyo MB and Gardebroek C** (2013) Does water harvesting induce fertilizer use among smallholders? Evidence from Ethiopia. *Agricultural Systems* **114**, 54–63.
- Wood SA, Jina AS, Jain M, Kristjanson P and DeFries RS** (2014) Smallholder farmer cropping decisions related to climate variability across multiple regions. *Global Environmental Change* **25**, 163–172.
- World Bank** (2013) Turn down the heat: climate extremes, regional impacts, and the case for resilience. A Report for the World Bank by the Potsdam Institute for Climate Impact Research and Climate Analytics. World Bank, Washington, DC.
- Wu Y, Xi X, Tang X, Luo D, Gu B, Lam SK, Vitousek PM and Chen D** (2018) Policy distortions, farm size, and the overuse of agricultural chemicals in China. *Proceedings of the National Academy of Sciences* **115**, 7010–7015.
- Yu T and Babcock BA** (2010) Are US corn and soybeans becoming more drought tolerant? *American Journal of Agricultural Economics* **92**, 1310–1323.
- Yu J and Hendricks N-P** (2020) Input use decisions with greater information on crop conditions: implications for insurance moral hazard and the environment. *American Journal of Agricultural Economics* **102**, 826–845.
- Zaveri E and Lobell DB** (2019) The role of irrigation in changing wheat yields and heat sensitivity in India. *Nature Communications* **10**, 1–7.
- Zaveri E, Russ J and Damania R** (2020) Rainfall anomalies are a significant driver of cropland expansion. *Proceedings of the National Academy of Sciences* **117**, 10225–10233.

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