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RESEARCH ARTICLE

Does choice of drought index influence estimates of drought-induced rice losses in India?

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Abstract
Drought events have critical impacts on agricultural production yet there is little consensus on how these should be measured and defined, with implications for drought research and policy. We develop a flexible rainfall-temperature drought index that captures all dry events and we classify these as Type 1 (above-average cooling degree days) and Type 2 droughts (below-average cooling degree days). Applied to a panel dataset of Indian districts over 1966–2009, Type 2 droughts are found to have negative marginal impacts comparable to those of Type 1 droughts. Irrigation more effectively reduces Type 2 drought-induced yield losses than Type 1 yield losses. Over time, Type 1 drought losses have declined while Type 2 losses have risen. Estimates of average yield losses due to Type 1 droughts are reduced by up to 27 per cent when Type 2 droughts are omitted. The associated *ex-post* economic costs in terms of rice production are underestimated by up to 124 per cent.

Keywords: agriculture; climate; drought; India; rainfall; rice; temperature

JEL classification: Q10; Q19; Q54; Q56

1. Introduction

Extended periods of low rainfall that reduce the availability of moisture relative to normal climate conditions constitute drought events (Mishra and Singh, 2010), with the severity of these events being aggravated by climatic factors such as temperature (Wilhite, 2000*a*). Since 1900, two billion people have been affected by drought and annual economic costs are estimated at US$6–8 billion (Food and Agriculture Organization, 2013). A number of low- and middle-income countries, including those located in Sub-Saharan Africa and the Indian subcontinent, are particularly vulnerable to the impacts of drought. In India, the setting for our paper, severe drought lowered annual GDP by two to 5 per cent between 1951 and 2003 (Gadgil and Gadgil, 2006); among drought-affected households, drought led to a 12–33 per cent increase in the poverty headcount ratio and a 25–60 per cent decline in household income (Pandey *et al.*, 2007). The onset of drought in India has also been empirically linked to conflict, rural wages and human capital accumulation (Jayachandran, 2006; Sarsons, 2015; Shah and Steinberg, 2017).

Against a backdrop of rising temperatures and drier conditions, droughts are projected to become more common, with critical implications for agricultural production (IPCC, 2012). How *meteorological* drought is defined plays a central role in policymakers' responses, not only in the agricultural sector but also in the water sector and in early-warning systems. Yet, there is presently little consensus on how droughts might be measured and hence, defined. Indeed, there is no universal definition of the conditions constituting a drought (Wilhite, 2000*b*). A range of indices attempt to quantify the severity of a drought, ranging from simple rainfall measures to complex indices that account for rainfall, temperature and estimates of potential evapotranspiration[1] (Mishra and Singh, 2010). Different criteria of what constitutes a 'drought' therefore imply that a drought in one index may not constitute a drought in another. The implication is that, depending on the index used, there are classes of dry events which may be overlooked both in empirical analyses and by policymakers.

In this article, we develop a simple rainfall-temperature index that allows for a flexible characterization of drought events. It captures every dry event in which cumulative rainfall over the growing season is below average relative to the average long-term cumulative rainfall for the growing season, while accounting for temperature. The novelty of our index is to include both the type of dry events typically captured by indices that account for temperature, i.e., characterized by above-average values of cooling degree days (CDD),[2] which we term 'Type 1' droughts, as well as ones characterized by *below-average* values of CDD. To our knowledge, the latter, which we term 'Type 2' droughts, have not been explicitly studied before.

Type 2 droughts are likely to have impacts that differ from those driven by Type 1 droughts. First, rainfall deficiency drives water stress thus negatively impacting on crop yields but the combined effects of heat and rainfall are likely to be greater than their individual impacts (Lamaoui *et al.*, 2018). This implies that Type 1 droughts have higher potential impacts than Type 2 droughts. Second, for a Type 2 drought, a lower value of CDD over the growing season does not imply an absence of hot days. Heat stress, even for short periods of time, can cause permanent harm to plant growth (see, e.g., Luo, 2011). Third, some of the largest deviations in rainfall in India have occurred in years that were not considered particularly hot. In these years, impacts are likely to have been large and as such should not be overlooked.

Our index is applied to a panel dataset of Indian districts over the period 1966–2009 in order to estimate the marginal and total effects of each drought type on rice productivity. Rice is a principal food crop that is mainly grown in the *kharif* season (June to September). We also consider how, conditional on drought type, the marginal effects change over time, as well as the extent to which they are mitigated by irrigation. Our base estimates are then used to calculate yield changes and associated *ex-post* economic impacts, which are likely to be underestimates, given unobserved behavioral responses of farmers, e.g., if they engage in lower-risk, lower-return activities because they anticipate

[1] Evapotranspiration is the combined process of water evaporated from land surfaces and plants.

[2] 'Degree days' is a unit of temperature degree deviation from a benchmark during a 24-h period. A 'cooling' degree day is a measure of heat, traditionally used to calculate the energy used to cool homes during a hot day.

the possibility of a drought (Elbers *et al*., 2007; Oviedo and Moroz, 2014). In a country where over two-thirds of total land area is vulnerable to drought (GoI, Ministry of Agriculture, 2009), and rain-fed agriculture covers approximately 60 per cent of cropped area (Sharma, 2011), our analysis contributes to an important body of research on the impacts of droughts on Indian agriculture (e.g., Pandey *et al*., 2007; Sarkar, 2011).

After presenting background to our analysis in section 2, we present Indian weather data underlying Type 1 and Type 2 droughts and propose an extension to a multiplicative index, developed by Yu and Babcock (2010), in section 3. This extension allows for a more flexible characterization of drought events while retaining a key strength of their index, namely the inclusion of temperature and the capacity to capture the interaction between rainfall and temperature. Applied to our panel dataset of Indian districts, in section 4, we find that Type 2 droughts consistently display large negative marginal and total effects, comparable to those of Type 1 droughts. The omission of Type 2 droughts leads to a large underestimation of total drought impact. Irrigation appears to be more effective at reducing Type 2 drought-induced yield losses than those attributed to Type 1 droughts. Over time, Type 1 drought losses, as a proportion of yield, have become smaller while Type 2 losses have risen. Yield and *ex-post* economic losses are shown in section 5 to be underestimated by up to 27 and 124 per cent, respectively. We also test the forecasting accuracy of our index and we find that, while it outperforms the other indices considered, the improvements in terms of forecasting accuracy are marginal and statistically insignificant. Section 6 discusses the results and their implications for public policy.

2. Defining ‘drought’

Simple drought indices often rely solely on rainfall measures and are typically preferred by policymakers, including the Indian Meteorological Department (IMD), over more complex indices. Until 2016, the IMD recorded a ‘drought event’ when seasonal rainfall was below 75 per cent of its long-term average (between 1950 and 2000), and a ‘severe drought’ when rainfall was below 50 per cent (Indian Meteorological Department, Government of India, undated). Simple metrics of precipitation deficiency, which have the advantage of being easily interpretable, are also used to evaluate drought impacts on agricultural production (e.g., Pandey *et al*., 2007; Auffhammer *et al*., 2012).

Simple definitions of drought based on rainfall are, however, problematic for our understanding of drought impact. Variables in addition to rainfall, in particular temperature, help determine the physical severity of a drought. A growing literature suggests critical turning points at which higher temperatures cease to have positive impacts on agricultural yield (e.g., Guiteras, 2009; Schlenker and Roberts, 2009; Lobell *et al*., 2012; Burgess *et al*., 2014). High temperatures have particularly acute effects on crop growth during periods of low precipitation since the rate of evapotranspiration increases as temperatures rise (Prasad *et al*., 2008; Lobell and Gourdji, 2012). In general, this increases a plant’s demand for water at a time when water availability is already low due to deficient precipitation. Drought is documented to increase in severity as mean temperatures have risen. Higher temperatures, rather than the increased intensity of low rainfall events, have been held responsible for these drying trends (Vicente-Serrano *et al*., 2014; Diffenbaugh *et al*., 2015). As such, neglecting the effect of temperature on the severity of a drought event could underestimate drought impact.

More complex indices tend to rely on data that are often not readily available in most economic datasets, e.g., for soil moisture levels. The lack of data needed to derive such measures, which can depend on factors such as wind, radiation and humidity, limits their applicability in empirical analysis of drought impacts. Bridging the gap between simple and complex indices, Yu and Babcock (2010) propose a drought index that neatly captures the interaction between temperature and rainfall, thus giving it the potential to capture the combined effect of cumulative heat and water stress on yield. Applied to the study of drought tolerance of soybean and corn yields in the US, it takes a non-zero value for years of below-average rainfall and above-average values of CDD:

$$\mathrm{DI}_{it} = [-\max(0, \mathrm{CDD}_{it}^{\mathrm{stand}})] \times [\min(0, \mathrm{TR}_{it}^{\mathrm{stand}})], \tag{1}$$

where DI_{it} denotes the drought index for geographical unit i in year t; $\mathrm{TR}_{it}^{\mathrm{stand}}$ is standardized total monthly rainfall over the growing season; and $\mathrm{CDD}_{it}^{\mathrm{stand}}$ is standardized, cumulative CDD above 18°C.

The index described in (1) gives a value of zero whenever either $\mathrm{CDD}_{it}^{\mathrm{stand}}$ is below or $\mathrm{TR}_{it}^{\mathrm{stand}}$ is above their respective long-term averages. Thus, a drought 'event' or 'year' is defined when $\mathrm{CDD}_{it}^{\mathrm{stand}}$ is higher and $\mathrm{TR}_{it}^{\mathrm{stand}}$ is lower than their respective long-term averages. A strength of this index lies in its capacity to capture the potential of high temperatures to exacerbate the effects of low rainfall on crop production. Birthal *et al.* (2015) adopt the index to study the tolerance of rice yields to drought in India.

While Yu and Babcock's (2010) approach has the advantage of being a relatively simple way to account for both temperature and precipitation, the index restricts the definition of drought to events characterized by below-average $\mathrm{TR}_{it}^{\mathrm{stand}}$ accompanied by above-average values of $\mathrm{CDD}_{it}^{\mathrm{stand}}$, that is, our Type 1 drought. It does not consider events characterized by below-average values of $\mathrm{CDD}_{it}^{\mathrm{stand}}$ as well as below-average $\mathrm{TR}_{it}^{\mathrm{stand}}$, that is, our Type 2 drought. Despite being common in many settings, the impacts of such events on agricultural production remain unknown, due to either being omitted altogether (as in Birthal *et al.*, 2015) or joined with Type 1 droughts in arbitrarily-defined rainfall indices.

Type 2 droughts should not be omitted *a priori* because, as explained in the introduction, focusing only on years with an above-average value of $\mathrm{CDD}_{it}^{\mathrm{stand}}$ (Type 1 drought) ignores the possibility that, in years with a below-average value of $\mathrm{CDD}_{it}^{\mathrm{stand}}$, there may still be a number of very hot days sufficient to negatively impact agricultural productivity.[3] Thus, a class of potentially destructive dry events would not be defined as 'drought' per equation (1), which may underestimate the aggregate impact of all dry events. The classification of these events as non-droughts could lead to biased estimates of drought impact. Thus, if Type 2 droughts do have a significant negative impact on productivity, then the application of Yu and Babcock's index potentially underestimates drought impacts due to the inclusion of Type 2 drought events in the 'no drought' control group. Finally, since we expect crops to respond differently to increasing deviations from mean rainfall, depending on whether the value of $\mathrm{CDD}_{it}^{\mathrm{stand}}$ is below- or above-average, Type 2 droughts ought not only to be included but also to be modelled separately from Type 1 droughts.

[3]In Yu and Babcock (2010), a below-average value of $\mathrm{CDD}_{it}^{\mathrm{stand}}$ means that the cumulative sum of degree-days above 18°C over a given period is lower than its long-term average. While this suggests lower cumulative heat during the season, it does not imply an absence of hot days and/or temperature spikes during the growing season.

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Our definitions of drought – Type 1 and Type 2 – are important for understanding and predicting crop yields. We argue that they are an improvement on measures and indices used in earlier research. Table 1 lists previous studies that have adopted both simple and more complex nonlinear functions of temperature and rainfall as predictors for crop yields. In general, these measures focus on either heat or rainfall, thus neglecting the combined impact on yield from cumulative heat and water stress. One possible reason is that the temperature bins approach is often used and requires a very large number of coefficients to estimate the combined effect of heat and rainfall. Previous work on drought impacts also typically adopts a single binary definition to estimate the impact of drought on yields. However, the use of a binary definition makes it difficult to assess the relationship between drought and yield.

3. A new index to define drought in India

Weather data on daily rainfall and daily average temperature at the district level are sourced from the IMD for figures 1 and 2.[4] We define our growing season as June-September[5] and both long-term average rainfall and CDD are defined vis-à-vis their 1956–2009 averages.[6]

Panel (a) of figure 1 shows the proportion of districts, by year, limited to events characterized by both below-average rainfall and above-average values of CDD (Type 1). The vertical lines indicate All-India Drought Years.[7] Panel (b) of figure 1 shows the proportion of districts in years characterized by below-average rainfall and below-average values of CDD (Type 2).

Figure 2 shows why the omission of Type 2 droughts is likely to be problematic. For each year, we estimate the number of districts affected by Type 1 droughts net of the number of those affected by Type 2 droughts, with a positive number (in darker grey) denoting a year in which the former exceeds the latter. A negative number (in lighter grey) indicates a year in which the latter exceeds the former. Overall, Type 1 droughts are slightly more prevalent (55 per cent) than Type 2 droughts (45 per cent). In the 1990s, most of the drought-affected districts were affected by Type 1 droughts. Since 1999, Type 2 droughts have increased, with the number of districts affected by Type 2

[4]The weather data were obtained under license from IMD for a fee. The rainfall data are available in gridded format at a resolution of 0.25° × 0.25° (Pai *et al*., 2014). Gridded temperature data are at a resolution of 1° × 1° (Srivastava *et al*., 2009). District-level weather data are then obtained by taking a weighted average of gridded weather observations from grid cells that fall within a district's boundary, based on the proportion of the grid cell that falls in each district.

[5]The majority of India's rice production is cultivated in the *kharif* season, between June and September, and the majority of total yearly rainfall (approximately 80 per cent) also falls between these months (Jain and Kumar, 2012).

[6]The reference temperature for the CDD is the average June-September daily temperature for the district between 1956 and 2009. The CDD variable is calculated as $\mathrm{CDD}_{it} = \sum_{m=1}^{M} \sum_{d=1}^{D} (\mathrm{DT}_{\mathrm{imd}} - \mathrm{DTA}_i)$, where we subtract the average daily temperature over the growing season observed from 1956–2009 (DTA_i) from the observed daily temperature ($\mathrm{DT}_{\mathrm{imd}}$). We then sum all the positive deviations over the growing period and give a value of 0 to negative deviations. See online appendix A.

[7]According to the IMD, 13 'All-India Drought Years' have been recorded since 1966 (Birthal *et al*., 2015). Such 'Drought Years' were recorded when the total area affected by a moderate or severe drought covered 20–40 per cent of the total land area of the country and rainfall during the monsoon season fell 10 per cent below average seasonal rainfall recorded between 1950 and 2000. When more than 40 per cent of the total land area was affected by drought, this was termed an 'All India Severe Drought Year'.

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Table 1. List of previous studies

Author(s)	Context	Variable used	Inclusion of drought in model	Empirical model	Crop(s)
Auffhammer *et al.* (2012)	India	Drought dummy	Dummy variable. 1 if 15% below state mean annual rainfall, 0 otherwise.	Fixed effects	Rice
Birthal *et al.* (2015)	India	Drought index	Continuous drought index variable (linear and quadratic). Drought index is the interaction between the S.D. seasonal rainfall and S.D. mean monthly temperature.	Fixed effects	Rice
Burgess *et al.* (2014)	India	Daily temperature and Annual rainfall	Seven 'bins' of 2°C capturing number of days each year spent in bin	Rainfall terciles	Fixed effects multiple (composite index)
Lobell *et al.* (2012)	India	Degree days (>34°C)	Continuous variable (number of days above 34°C)	Linear regression	Wheat yields
Sarsons (2015)	India	Drought dummy	Dummy variable. 1 if Annual rainfall below 20th percentile of normal	Fixed effects	Multiple (composite index)
Schlenker and Roberts (2009)	US	Daily temperature	Temperature and precipitation included additively as: (i) A step function for 3°C temperature interval; (ii) Eighth order Chebychev polynomial; and (iii) Piecewise linear function. Precipitation and squared precipitation are included separately.	Fixed effects	Soy, corn, cotton
Yu and Babcock (2010)	US	Drought index	Continuous drought variable (linear and quadratic). Drought index is the interaction between the S.D. seasonal rainfall and S.D. mean monthly temperature.	Fixed effects	Corn, soy
Deschênes and Greenstone (2007)	US	Degree days. Annual precipitation	Separate temperature (growing season degree days) and rainfall variables (linear and quadratic)	Fixed effects	Multiple (profits per hectare)
Lobell *et al.* (2014)	US	Daytime vapor deficit pressure	Multivariate adaptive regression splines to account for nonlinearities	Regression splines	Maize, soybean

(*continued*)

Table 1. Continued

Author(s)	Context	Variable used	Inclusion of drought in model	Empirical model	Crop(s)
Gammans *et al*. (2017)	France	Daily temperature and Seasonal rainfall	Separate regressions of stepwise 2°C temperature bins and flexible polynomial over 1°C bins. Rainfall is included separately in all regressions.	Fixed effects	Wheat, barley
Schlenker and Lobell (2010)	Sub-Saharan Africa	Temperature and rainfall	Temperature and rainfall included as follows: (i) Linear in the average growing season temperature and total precipitation for growing season; (ii) Quadratic specification for mean temperature and total precipitation; (iii) Piecewise-linear function captured by two variables (degree days 10–30°C and above 30°C); and (iv) Degree days categories: piecewiselinear functions within 5°C intervals.	Fixed effects	Maize, sorghum, millet, groundnuts and cassava
Chen *et al*. (2016)	China	Degree days and annual rainfall	Climate effects on crop yields are cumulative and additively substitutable over time. Temperature is captured by degree days above 34°C and rainfall is included separately using annual rainfall.	Fixed effects	Corn, soy

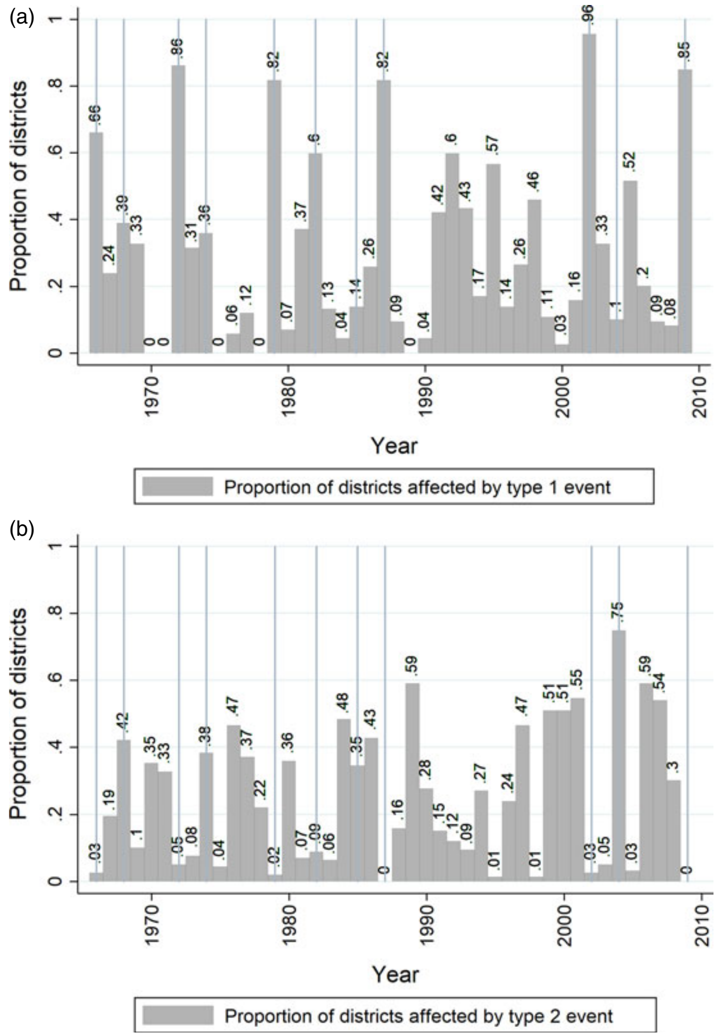

Figure 1. Proportion of affected districts, by drought type. (a) Proportion affected (Type 1); (b) Proportion affected (Type 2).
Notes: The numbers above the bars represent the proportion of districts (rounded to two decimal places) that were affected by a given drought type in a given year.
Source: Authors' own calculations.

droughts outnumbering the number of districts affected by Type 1 droughts in seven out of 11 years.

Formally shown in online appendix A, the first step of our index involves the calculation of the deviation of CDD over the growing season (June–September) from average long-run (1956–2009) CDD over the growing season, a variable we define as DCDD. Positive values of DCDD indicate above-average CDD while negative values indicate below-average CDD. A similar procedure is followed for rainfall in that we create a variable, DTR, which is defined as the deviation of district-specific, cumulative rainfall from

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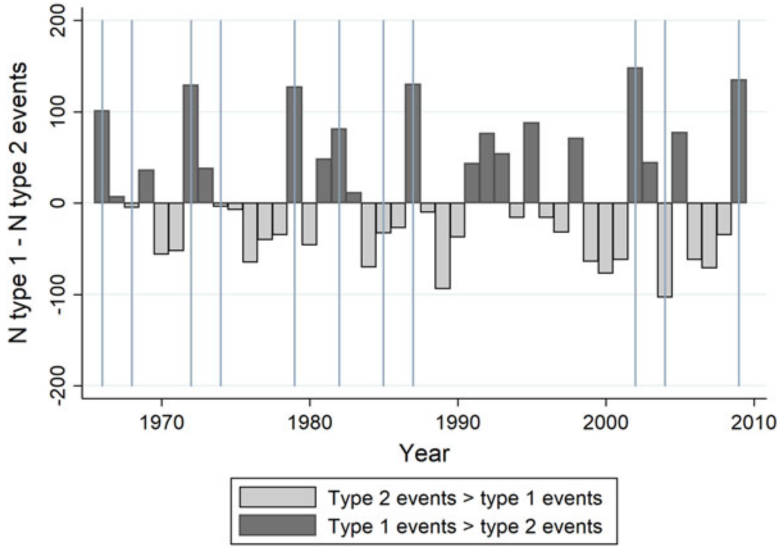

Figure 2. Type 1 droughts in excess of Type 2 droughts (June-September only).
Notes: Bar graphs show the number of districts affected by Type 1 droughts in excess of the number affected by Type 2 droughts. As a result, a value of 50 would mean that there were 50 more districts affected by a Type 1 drought than affected by a Type 2 drought in a given year. The converse applies to a negative number, which highlights a higher number of districts affected by type 2 droughts in a given year. The solid vertical lines represent the years considered by the Indian Government as All-India drought years.
Source: Authors' own calculations.

long-term, mean cumulative rainfall between 1956 and 2009. Negative values of DTR represent below-average cumulative rainfall while positive values indicate above-average rainfall.

Next, we normalize DCDD and the negative of DTR, which we define as NCDD_{it} and NTR_{it}, respectively. Normalizing the negative of rainfall, rather than rainfall directly, allows us to generate a variable bounded between 0 and 1, with higher values signaling more severe rainfall deficiency. Thus, NCDD_{it} is increasing in temperature and NTR_{it} is increasing in rainfall deficiency. Using the normalized negative of rainfall enables us to construct an index without running into the problem of negative values that emerges from the interaction of the standardized variables. Finally, a multiplicative relationship is generated between the two normalized variables, resulting in two drought indices. Type 1 droughts are denoted $\mathrm{DI1}_{it}$ and Type 2 are denoted $\mathrm{DI2}_{it}$:

$$\text{Drought} = \begin{cases} \mathrm{DI1}_{it} = \mathrm{NTR}_{it} \times \mathrm{NCDD}_{it} & \text{if } \mathrm{DTR}_{it} < 0 \text{ and } \mathrm{DCDD}_{it} > 0; \;\; 0 \text{ otherwise} \\ \mathrm{DI2}_{it} = \mathrm{NTR}_{it} \times \mathrm{NCDD}_{it} & \text{if } \mathrm{DTR}_{it} < 0 \text{ and } \mathrm{DCDD}_{it} < 0; \;\; 0 \text{ otherwise} \end{cases}. \quad (2)$$

As such, $\mathrm{DI1}_{it}$ can be interpreted as a normalized version of Yu and Babcock's (2010) index. It takes a strictly positive value for all events characterized by below-average rainfall and above-average $\mathrm{CDD}_{it}^{\mathrm{stand}}$. The second index, $\mathrm{DI2}_{it}$, only takes non-zero values for events with below-average rainfall and below-average $\mathrm{CDD}_{it}^{\mathrm{stand}}$, the category that Yu and Babcock omit. Constructing these two indices separately allows us to test their respective statistical significance in the yield regressions.

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Table 2. Summary statistics of observations in the sample

Variables	*N*	Mean	S.D	Min	Max
Rice area (1,000 ha)	6,996	122.49	141.65	0.09	956.63
Rice irrigated area (1,000 ha)	6,996	74.97	103.22	0.00	663.70
Rice yield (t/ha)	6,996	1.63	0.95	0.01	4.78
Proportion of cereal area under rice production	6,996	0.36	0.29	0.00	1.00
Rural population density (by gross cereal area)	6,995	3.40	1.67	0.62	13.68
Fertilizer (t/ha)	6,996	71.45	67.50	0.00	614.49
Cumulative rainfall (mm) (June-September)	6,996	755.38	417.48	28.89	4, 557.98
Cooling degree days (CDD, June-September)	6,996	100.36	48.07	2.70	274.88
Babcock-Yu index, June-September	6,996	0.25	0.66	0.00	8.53
DI1 (Drought index-type 1 events)	6,996	0.15	0.25	0.00	1.00
DI2 (Drought index-type 2 events)	6,996	0.05	0.10	0.00	0.54

Notes: Rural population density is calculated by dividing total rural population by gross cropped area. Our cooling degree-days measure is calculated based on average daily district temperature in the months of June-September for the period 1956–2009.

Our indices are increasing in temperature but decreasing in rainfall and reflect that both higher temperatures and lower rainfall are expected to contribute to drought severity. A maximum value of one is obtained for the most severe droughts, and is only possible for the restricted set of drought events considered by Yu and Babcock. The similarity of their index to our own is illustrated in online appendix table A1, which shows the correlation coefficients and the Spearman correlation coefficient. As expected, our index DI1 is highly correlated with Yu-Babcock, displaying a correlation coefficient of 0.787 and a Spearman correlation coefficient in excess of 0.99. Our second index DI2, on the other hand, has a negative correlation coefficient with a correlation coefficient of −0.189 and a Spearman coefficient of −0.363. Since Yu-Babcock is invariant with a value of zero for these events, this result is also as anticipated. In addition, these two indices differ in terms of their maximum values. While the maximum value for Type 1 droughts is one (which occurs when the hottest year is also the year with the lowest rainfall), the maximum value of events in which both rainfall and CDD are below-average is 0.54 (see table 2). These two maximum values capture the fact that a combination of above-average CDD with below-average rainfall is likely to lead to a more severe drought than below-average CDD combined with below-average rainfall.

Figure 3 shows how our index values change over time for all districts. There are clear spikes in the values of the index for a number of All-India Drought Years. The years 2002 and 2009 are associated with the largest deviations in rainfall. Similarly, 1972, 1979 and 1987 are also considered years with particularly high deviations and our index rises in these years. Throughout the 1990s, however, it is striking that, despite relatively modest deviations of rainfall from trend, our index still records high values. One possible explanation for this could be rising land-surface air temperatures over time (Pai *et al.*, 2013).

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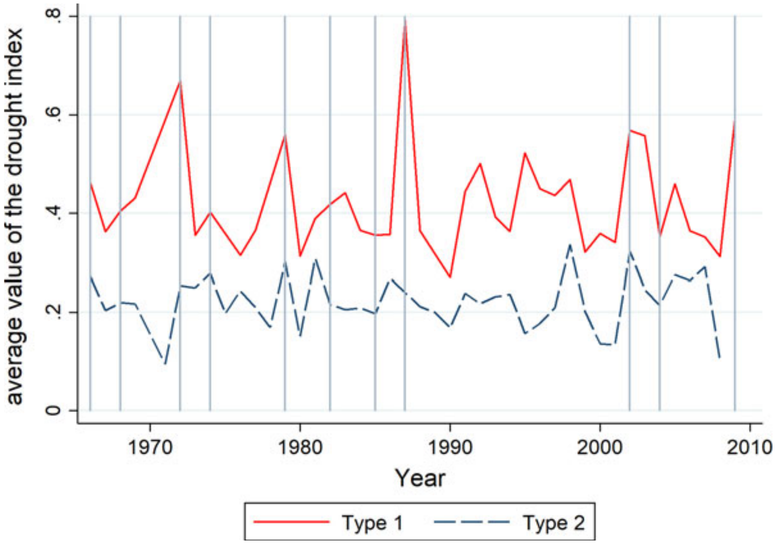

Figure 3. Average drought index value.

4. Impact of drought on rice productivity

To investigate drought impacts on aggregate rice productivity at the district level, we obtain agricultural data from the ICRISAT Meso-level Database.[8] For the period 1966–2009, this dataset contains detailed agricultural and socioeconomic information (ICRISAT, 2012). Data are available for annual crop production and area under crop production for a range of crops, for most districts. Focusing on rice, we create a balanced panel, which implies that, of the 311 districts available in the dataset only 159 are used in our empirical analysis due to missing data for irrigated rice area (see map in online appendix figure A1). Rice yield is estimated by dividing total rice production by total rice area. Table 2 summarizes the variables used in our analysis.

To model the relationship between rice yield and our drought index, we estimate the following fixed-effects model[9]:

$$\ln(y_{it}) = \alpha_i + \gamma_t + \delta_{i1} \times t + \delta_{i2} \times t^2 + \beta_{1q}\mathrm{DI}_{itq} + \beta_{2q}\mathrm{DI}^2_{itq} + \beta_{3q}\mathrm{DI}_{itq} \times t$$
$$+ \beta_{4q}\mathrm{DI}^2_{itq} \times t + \beta_{5q}\mathrm{DI}_{itq} \times \mathrm{propirri}_{it} + \beta_{6q}\mathrm{DI}^2_{itq} \times \mathrm{propirri}_{it} + \epsilon_{it}, \qquad (3)$$

where for district i in year t: In(y_{it}) denotes the natural logarithm of rice yield; α_i and γ_t represent the district and year fixed effects, respectively; and δ_{i1} and δ_{i2} are the coefficients on the district-specific linear and quadratic trends, respectively. Quadratic terms are also included for the following variables, to account for potential nonlinearities in the relationship between drought type and yield. First, the coefficients associated with a type q (i.e., Type 1 – above-average CDD, or Type 2 – below-average CDD)

[8]Since 1966, a number of districts have split into smaller districts. To maintain spatial consistency over time, district splits are dealt with by returning split districts to their 'parent' districts as of 1966.

[9]We prefer a fixed-effects model over a pooled ordinary least squares because it captures time-invariant heterogeneity. Also, a Hausman test rejected a random-effects model in favor of a fixed-effects model.

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drought index, which captures the marginal impact of a type q drought, are denoted β_{1q} and β_{2q}. Coefficients β_{3q} and β_{4q} capture the interaction between drought type and time, t, while the coefficients β_{5q} and β_{6q} capture the interaction between drought type and the proportion of rice area under irrigation. Finally, ϵ_{it} represents the error term. Consistent with Yu and Babcock (2010) and Birthal *et al.* (2015), we do not include additional controls in our main specifications. This is also the norm in the climate impacts literature.

4.1 Regression results

We run a regression of the natural logarithm of yield on a set of district-specific quadratic trends and the drought indices. Specifically, we estimate the model in (3), in both log-levels and levels. First, we include only Type 1 drought events (columns 1 and 3 in table 3). Second, we estimate separate coefficients for Type 1 and Type 2 drought events (columns 2 and 4 in table 3).

Table 3 highlights two results.[10] First, at mean drought intensity (the average for all events with non-zero index values), both drought types have significant and negative effects when considered separately. Thus, Type 2 events have large and statistically significant, negative impacts on rice yield. Second, we find that at means of all variables, Type 2 droughts have a higher marginal effect on yield. However, as will be shown in the next section, the overall effects on yield and associated economic costs are higher for Type 1 droughts. This is because the index value of Type 2 droughts is typically around half of the index value of Type 1 droughts.[11] Although both excess heat and reduced moisture have negative impacts on production, reduced rainfall carries greater weight in the Type 2 index than in the Type 1 index, explaining the greater marginal effect. Values of CDD are, by definition, higher in the latter than in the former. As a result, yields are likely to respond (more) negatively to changes in the Type 2 index than in the Type 1 index.

The differences in impacts between Type 1 and Type 2 are tested into two ways. First, the confidence intervals of the marginal effects at means for the two drought types are shown in table 3 (see rows '95 per cent CI'). The DI2 marginal effect (evaluated at means of all variables) is outside the 95 per cent CI of the DI1 marginal effect (again at means of all variables) for the levels specification and it is just marginally inside the 90 per cent CI for the log-levels specification. Second, we tested whether all the DI1 coefficients (and interactions) are jointly different from all the DI2 coefficients (and their interactions) (see online appendix table A3). For the log-levels specification, the F-test was rejected at the 10 per cent level. For the levels specification, the hypothesis that the coefficients are equal could not be rejected. This may be due to the large number of interactions included in the model.

[10]The R^2 (within, between and overall) are estimated for three different regressions and are shown in online appendix table A2: district and year fixed effects; district and year fixed effects plus a district-specific quadratic trend; and all the variables included in table 3. These results suggest that trends have a high explanatory power (overall R^2 increases from 0.168 to 0.645 (levels) and 0.164 to 0.22 (log-levels) following their inclusion). The results also suggest that adding the remaining variables (irrigation, drought indices and their interactions) leads to an improvement in the explanatory power of the model (overall R^2 increases from 0.645 to 0.775 (levels) and from 0.22 to 0.446 (log-levels)).

[11]A value of 0.5 in our Type 2 index represents approximately the same rainfall deficiency as a value of one in our Type 1 index, which helps explain larger marginal impacts.

Table 3. Full sample results

	Levels		Log-levels	
	1	2	3	4
Variables	Type 1 only	Type 1 and 2	Type 1 only	Type 1 and 2
Drought index (type 1)	−0.352*** (0.114)	−0.450*** (0.118)	−0.656*** (0.189)	−0.828*** (0.200)
Drought index (type 1)^2	0.119 (0.172)	0.201 (0.175)	0.09 (0.296)	0.234 (0.299)
Drought index (type 1) × time	0.009** (0.004)	0.009** (0.004)	0.007* (0.004)	0.006 (0.004)
Drought index (type 1)^2 × time	−0.013** (0.007)	−0.012* (0.006)	−0.003 (0.006)	−0.002 (0.006)
Drought index (type 1) × Irrigation	0.079 (0.125)	0.088 (0.132)	0.552*** (0.190)	0.698*** (0.202)
Drought index (type 1)^2 × irrigation	−0.028 (0.169)	−0.044 (0.173)	−0.203 (0.256)	−0.322 (0.261)
Drought index (type 2)		−0.750** (0.342)		−1.185*** (0.336)
Drought index (type 2)^2		1.314 (1.166)		1.912 (1.204)
Drought index (type 2) × time		0.007 (0.011)		0.016 (0.010)
Drought index (type 2)^2 × time		−0.033 (0.034)		−0.073** (0.035)
Drought index (type 2) × Irrigation		0.43 (0.327)		0.602* (0.316)
Drought index (type 2)^2 × irrigation		−1.461 (1.117)		0.047 (1.155)
Irrigation (prop)	0.735*** (0.162)	0.757*** (0.161)	0.428*** (0.125)	0.451*** (0.124)
Irrigation (prop)^2	−0.256** (0.100)	−0.266*** (0.100)	−0.158** (0.076)	−0.194** (0.077)
Constant	0.786*** (0.064)	0.810*** (0.063)	−0.293*** (0.047)	−0.254*** (0.047)
Marginal elasticity DI1 (at DI1 = 0.493)	−0.293***	−0.305***	−0.283***	−0.294***
95% CI	(−0.37, −0.22)	(−0.38, −0.23)	(−0.38, −0.18)	(−0.39, −0.20)
Marginal elasticity DI2 (at DI2 = 0.207)		−0.462***		−0.375***
95% CI		(−0.65, −0.28)		(−0.54, −0.21)
Time trends	X	X	X	X
District fixed effects	X	X	X	X
Year fixed effects	X	X	X	X

(*continued*)

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Table 3. Continued

	Levels		Log-levels	
	1	2	3	4
Variables	Type 1 only	Type 1 and 2	Type 1 only	Type 1 and 2
N	6,996	6,996	6,996	6,996
Number of districts	159	159	159	159
R^2 a	0.725	0.729	0.600	0.611
R^2 w	0.739	0.744	0.621	0.632

Notes: Values in parentheses denote clustered standard errors at the district level. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively. Time trends denote quadratic district-specific trends.

Table 4. Levels specification: marginal elasticities (irrigation) proportion of area irrigated

		Type 1 only	Types 1 and 2 (sep.)	
Variable	Value	Type 1	Type 1	Type 2
Irrigated area (%)	0	−0.32***	−0.33***	−0.36***
Irrigated area (%)	20	−0.31***	−0.32***	−0.40***
Irrigated area (%)	40	−0.30***	−0.31***	−0.43***
Irrigated area (%)	60	−0.29***	−0.30***	−0.47***
Irrigated area (%)	80	−0.28***	−0.30***	−0.50***
Irrigated area (%)	100	−0.27***	−0.29***	−0.54***

Notes: *** denotes statistical significance at the 1% level. For both types of events, marginal effects are computed at the mean value when affected (DI1 = 0.493 and DI2 = 0.207).

The estimated change in marginal effects by irrigation and over time are presented, respectively, in tables 4 and 5 for the levels specifications. The marginal effects for the log-levels specifications are shown in online appendix tables A4 and A5.

From table 4, the levels specification results suggest that absolute drought impacts either remain fairly constant (Type 1) or increase (Type 2) as the proportion of rice area under irrigation rises. Yet, as a proportion of total yield, the log-levels specification suggests that marginal impacts decrease substantially as the proportion of rice area under irrigation increases (see online appendix table A4). This can be explained by the fact that yields in irrigated areas tend to be higher and, even if losses remain constant or increase moderately in absolute terms, yield increases from improved irrigation imply a fall in losses as a proportion of the total. Our results also suggest that, as a proportion of the total, increases in the proportion of rice area under irrigation reduce the marginal impact more when considering Type 2 droughts compared with Type 1 droughts. With increasing proportion of rice area under irrigation (above 95 per cent irrigated), impacts of Type 2 droughts (at mean intensity) are not significantly different from zero (at the 5 per cent level). The same does not apply for Type 1 droughts: even when the proportion of rice area under irrigation is very high, we still find statistically significant effects on yields. This suggests that irrigation seems to be an effective strategy at substituting for water deficiency, but less effective at mitigating the combined effects of heat and water deficiency.

Table 5. Levels specification: marginal elasticities (time)

		Type 1 only	Types 1 and 2 (sep.)	
Variable	Value	Type 1	Type 1	Type 2
Year	1966	−0.21***	−0.23***	−0.31*
Year	1970	−0.22***	−0.24***	−0.34**
Year	1974	−0.24***	−0.26***	−0.37***
Year	1978	−0.26***	−0.27***	−0.40***
Year	1982	−0.27***	−0.29***	−0.42***
Year	1986	−0.29***	−0.30***	−0.45***
Year	1990	−0.30***	−0.31***	−0.48***
Year	1994	−0.32***	−0.33***	−0.51***
Year	1998	−0.33***	−0.34***	−0.53***
Year	2002	−0.35***	−0.36***	−0.56***
Year	2006	−0.36***	−0.37***	−0.59***
Year	2010	−0.38***	−0.38***	−0.62***

Notes: *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively. For both types of events, marginal effects are computed at the mean value when affected (DI1 = 0.493 and DI2 = 0.207).

From table 5, the results over time suggest that absolute yield losses attributed to drought have increased. As a proportion of total production, the log-levels specification in online appendix table A5 shows that losses follow a different pattern depending on the type of drought.[12] Type 1 drought impacts as a proportion of the total have fallen over time whereas Type 2 impacts have increased. Two potential explanations for this result can be derived from our data and are summarized in figure 4.

First, our results could be driven by trends in the composition of Type 1 and Type 2 events, with the former increasingly driven by cumulative heat over the growing season and the latter by rainfall deficiency. Figure 4a shows the ratio of normalized CDD to normalized rainfall deficiency. A higher value indicates a higher contribution of CDD relative to rainfall in our index. The plotted linear trend in figure 4a suggests that the composition of the two types of drought has followed different patterns over time, with Type 1 droughts increasingly driven by CDD and Type 2 droughts increasingly driven by rainfall deficiency. As shown in figure 4b, this change in composition is not captured by the index value, which has followed very similar trends. However, should rainfall deficiency and CDD increases be associated with different impacts, the change in composition could partially explain the increase in impacts over time for Type 2 droughts.

Second, Type 2 droughts seem to be increasingly preceded by dry years, which could increase the impact of this type of drought, turning what we have defined in this study

[12] An F-test, of differences in the DI1 and DI2 trends shows that, for the log-level estimation, equality of the trend coefficients was rejected at the 5 per cent level, which is not the case for the levels specification (see online appendix table A3). However, in the case of the levels specifications, the marginal effect of Type 2 droughts evaluated at the mean of the drought index (and all other covariates) at different points in time is often outside the 95 per cent confidence interval of the marginal effect for the Type 1 drought evaluated at its mean and at the same point in time.

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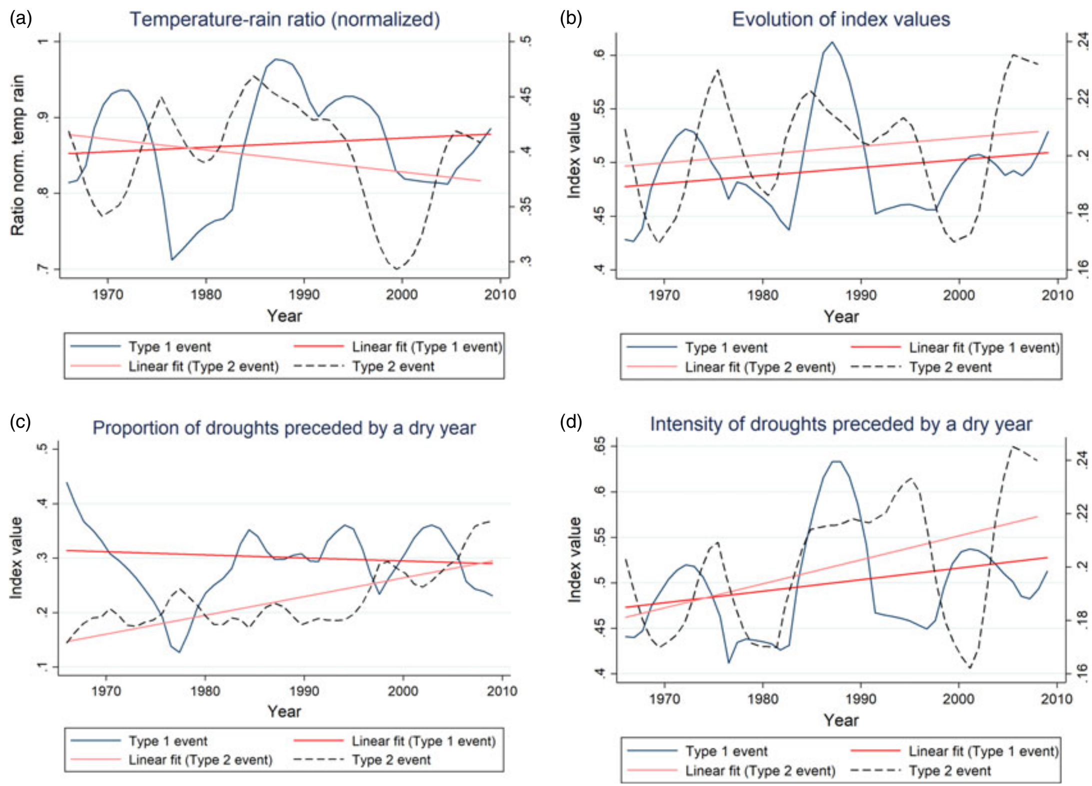

Figure 4. Ratio of temperature to rainfall and drought intensity following dry years. (a) Ratio of temperature to rainfall over time; (b) Drought intensity over time (affected only); (c) Average proportion of dry events following a dry year, by type; (d) Average index value following a dry year, by type (affected only).

Notes: All figure panels use a bandwidth of 2 for the local polynomial. For panels (a), (b) and (d), the left y-axis refers to values for type 1 events whereas the y-axis on the right-hand side shows values for type 2 events. Panel (a) plots the ratio of the normalized cooling-degree days over the normalized negative cumulative rainfall for all events where the index is positive. A lower value of this ratio implies that the contribution of temperature to the drought index is lower. Panel (b) plots the changes in the index values over time for affected districts. Panel (c) plots the proportion of drought-affected districts if either index was positive the preceding year. Finally, panel (d) plots the index value if the preceding year was characterized by a positive index value.

as a meteorological drought into a potential hydrological drought. Figure 4c plots the proportion of affected districts (by drought type) in a given year, conditional on the previous year being drier than average (i.e., either a Type 1 or Type 2 drought). This figure shows contrasting trends for Type 1 and Type 2 events, with the proportion of the former declining slightly while the proportion of the latter follows an increasing trend. Figure 4d, which plots the average intensity of droughts (by type) if preceded by a drier-than-average year, also suggests that the intensity of Type 2 droughts increased at a faster rate than that of Type 1 droughts.[13]

Supporting evidence that lagged dry events might be associated with larger drought impacts is given by Shah and Kishore (2009), who argue that in years of below-average precipitation, more groundwater tends to be extracted to compensate for rainfall deficiency and minimize production losses. However, the extent to which losses can be minimized depends on the availability of groundwater. For example, 2002–2003 was an exceptionally dry period preceded by two moderately dry years, which put additional pressure on groundwater resources. These resources had not sufficiently recovered by 2002–2003, thus limiting their capacity to minimize production losses.

5. Estimating yield and economic losses

We estimate yield impacts and economic costs by running simple simulations using our estimated regressions in table 3 (see appendix B). Column 1 shows the predicted impacts of Type 1 droughts when Type 2 droughts are excluded (i.e., using results from columns 1 and 3 in table 3) and columns 2–4 show the impacts of both types of drought (i.e., using results from columns 2 and 4 in table 3). Specifically, we estimate the: (i) average yield loss for an affected district over the sample period; (ii) average total production loss for an affected district over the sample period; (iii) average value of production loss for an affected district; (iv) average yearly production loss across all the Indian districts in our sample; and (v) the average yearly cost of predicted production losses across sampled districts. A summary of estimates is presented in table 6.

From table 6, we note that, despite a higher estimated coefficient, total yield and economic losses from Type 2 droughts are smaller than those from Type 1 droughts. This is due to the index values for Type 2 droughts being substantially lower (approximately half) in affected districts. Depending on the specification used, we estimate the range of average yield loss per district at 130–155 kg/ha (table 6, column 2) and 84–121 kg/ha (table 6, column 3) for Type 1 and Type 2 droughts, respectively. These smaller impacts on yield translate into lower total economic costs. We estimate that, in a given year, the total economic cost of a Type 1 drought ranges, on average, between US$224–265 million (table 6, column 2),[14] whereas this falls to US$121–185 million for a Type 2 drought (table 6, column 3). We note that the estimated impact of Type 1 droughts increases when Type 2 droughts are included. This is due to the fact that, when Type 2 droughts are excluded, they are part of the 'no drought' counterfactual, which is likely to bias the Type 1 drought impacts downwards.

[13]We also test whether the differences in trends for panels (a)–(d) in figure 4 are statistically different. They are statistically significant (at the 1 per cent levels) for panels (a) and (c), but not for panels (b) and (d).

[14]Crop prices in Indian rupees are converted into US$ using the average monthly exchange rate obtained from http://www.x-rates.com/average/?from=USD\&to=INR\&amount=1\&year=2008. More details on how prices are computed are available in online appendix B.

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Table 6. Cost estimates

	Main			
	1	2	3	4
	Type 1 (only)	Type 1 (sep.)	Type 2 (sep.)	2 types (sep.)
	Log-levels			
Av. yield loss (district) (t/ha)	0.122	0.155	0.121	0.139
Av. production loss (district) (1,000t)	14.328	18.594	15.379	17.122
Av. production cost (district) (mil USD)	4.291	5.568	4.606	5.128
Av. yearly total production loss (1,000 t)	682.218	885.338	618.652	1, 503.990
Av. yearly total cost (mil USD)	204.306	265.135	185.270	450.405
	Levels			
Av. yield loss (district) (t/ha)	0.104	0.130	0.084	0.109
Av. production loss (district) (1,000t)	12.601	15.839	10.128	13.221
Av. production cost (district) (mil USD)	3.774	4.743	3.033	3.959
Av. yearly total production loss (1,000 t)	597.707	749.146	405.792	1, 154.938
Av. yearly total cost (mil USD)	178.997	224.349	121.524	345.873

Notes: Rice prices use the 2008 prices converted into US$ using the average monthly exchange rate for 2008. All numbers were rounded to two decimal places. The results presented in column 4 are simply the aggregation of the results presented in columns 2 and 3.

Omitting Type 2 droughts can lead to a lower estimate of Type 1 drought impacts. These effects are quantifiably large as we illustrate by comparing the first two columns of table 6 for the full sample. Average yield losses are estimated to be approximately 25–27 per cent higher (from 104–122 kg/ha to 130–155 kg/ha) when Type 2 droughts are included. These estimates have a substantial effect on the estimated average annual cost. This ranges from US$179–204 million (table 6, column 1) when Type 2 droughts are omitted compared to US$224–265 million (table 6, column 2) when they are included, which represents a 25–30 per cent increase. Thus, if estimating the economic cost of Type 1 droughts without accounting for Type 2 droughts, the average yearly total costs of drought would approximate US$179–204 million. Including Type 2 droughts raises this total cost by 121–124 per cent to US$402–450 million (table 6, column 4). Overall, both specifications suggest that Type 2 droughts are responsible for about 35–40 per cent of the total *ex-post* economic value of yield losses.

5.1 Forecasting accuracy

To test the forecasting accuracy of our index, an out-of-sample prediction on yield (levels) is undertaken using: (1) the DI1 and DI2 index (separately); (2) the normalized Yu-Babcock index (DI1); (3) the combined DI1 and DI2 index (DI12); (4) a rainfall-only index (proportion of rainfall against the long-term average for years below normal); and (5) a CDD only index. We estimate out-of-sample accuracy by estimating the models up to 2000 and forecasting yield from 2001 to 2006.[15] The year 2000 was chosen as a cut-off period as the 2001–2006 period is notoriously difficult to predict; many districts were

[15]We performed the same exercise for different cut-off years and results do not change substantially.

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affected by drought so the results can be seen as a lower-bound in terms of forecasting accuracy.[16] All the statistics used to evaluate the forecast accuracy are bootstrapped (100 repetitions), which gives an indication of the sensitivity of the results (see also online appendix C).

The results are shown in online appendix table A8 in which we also report four indicators of forecast accuracy, namely the Mean Absolute Error (MAE), the Root Mean Square Error (RMSE) and the proportion of false negatives (FN) and positives (FP). We define false positives as cases where the observed yield was not 10 per cent below normal[17] yield (drought), but our model predicted yields lower than 10 per cent below normal. Conversely, false negatives are defined as cases where observed yields are lower than 10 per cent below normal, but the model predicts yields above this level.

Overall, the separate indices (DI1 and DI2) and the combined index (DI12) perform better than other indices in all metrics (online appendix table A8). The FP and FN rates are approximately 16 and 24 per cent, respectively. Also, while the DI12 model performs better than alternative indices, the difference in performance is not statistically different and the MAE remains large (above 500 kg/ha). This is mainly due to the fact that the estimated model was not primarily conceived for forecasting. In online appendix C, we show how forecasting performance can be improved with some very minor alterations in terms of the chosen specification; online appendix table A10 shows the results of these alternative specifications.

6. Discussion

Overall, three main findings emerge from our analysis. First, we show that two types of dry event, defined according to whether they have an above- or below-average value of CDD, have significant impacts on rice productivity in India. A consideration of the latter type – Type 2 – is shown to be critical, especially in a setting where there has been a clear increase in the number of such events in recent years. If an assessment of economic impacts is performed solely based on Type 1 droughts alone, i.e., those considered by Birthal *et al.* (2015), approximately half of all potential dry events would be overlooked. Our results strongly suggest that Type 2 events have had quite a severe impact on rice yields.

Second, the impacts are ameliorated differently when rice is irrigated. Specifically, absolute losses increase with the proportion of rice area under irrigation as a result of higher yields, although they decline as a proportion of total yield. We also find that irrigation seems to be more effective at reducing drought-induced yield losses from Type 2 droughts than Type 1 droughts. This suggests that the potential effects of irrigation in mitigating drought-induced impacts of climate change hinges on drought typology.

Third, there is some evidence that marginal impacts over time differ depending on drought type. Overall, absolute yield losses have either remained fairly constant or increased over time. As a proportion of yield, Type 1 drought losses have become smaller while Type 2 losses have risen. We attribute this partially to the fact that Type 2 droughts have become increasingly severe over time and have increasingly been preceded by dry years, which may have accentuated the impacts of this type of drought.

The economic value of production losses attributable to Type 2 droughts is calculated to be approximately 70 per cent of the value of losses attributable to Type 1 droughts.

[16] Forecasting performance is better for years other than the cut-off period.

[17] Normal yield is defined as the median yield for the five years preceding the cut-off.

Also, the omission of Type 2 droughts underestimates the economic value of production losses caused by to Type 1 droughts, by around 27 per cent. While we acknowledge that our back-of-the envelope estimates are based on a number of assumptions regarding prices and so forth, they do suggest that we have found sufficient empirical evidence and an economic rationale to justify the inclusion of Type 2 droughts, both in *ex-post* analyses of drought impact and in forecasts of impact.

We acknowledge that our index has a number of technical limitations. First, similar to any index based on relative values, our index may have limited transferability because index values change when the minimum and maximum values change over time. Thus its values might not be easily comparable across different regions, e.g., dry versus humid areas. Second, the normalization process is bounded between 0 and 1. If a given district has a very large outlier in a given year but records lower values in other years, then this would indicate a low value in the drought index thus masking what might have been a severe drought year. The third potential weakness arises from the multiplicative nature of the index. Whenever temperature is close to 0, this can lead to a very low value of the drought index despite very deficient rainfall, an issue that also applies to Yu and Babcock's index. Fourth, similar to their index, our index does not take into account intra-seasonal deficiencies in rainfall, which have been shown to have important impacts on agricultural productivity[18] (e.g., Fishman, 2016). Finally, similar to most drought indices, our index does not take into account (rare) multi-year droughts because this would require an index with 'memory' that takes into account soil moisture conditions. That said, since drought in India is mainly driven by variation in the annual monsoon, we argue that using an annual measure of monsoon rainfall is of greater relevance when estimating drought impact in our setting.

6.1 Behavioral responses to drought

Our empirical analysis precludes a consideration of the *ex-ante* and *ex-post* behavioral responses to drought (Oviedo and Moroz, 2014). Previous research has shown that farmers often engage in lower-risk-lower-return activities as strategies to cope with anticipated weather shocks, e.g., the adoption of less-profitable crop portfolios less sensitive to rainfall deviations (Rosenzweig and Wolpin, 1993), field scattering (Goland, 1993) and the adoption of low-risk-low-return crops (Dercon, 2008). Such strategies have been shown to have large negative impacts on profits and capital stock growth. Similarly, *ex-post* responses to drought have been shown to have negative impacts, e.g., a disinvestment in productive assets (Rosenzweig and Wolpin, 1993), a slowdown in the post-drought asset recovery process (Jodha, 1978), as well as effects on human capital (Shah and Steinberg, 2017).

In our particular context, we might expect a reduction in rice areas in anticipation or as a result of a drought. Higher perceived drought risk may drive higher levels of diversification, and hence potential yield losses from rice specialization. Divesting in productive inputs (seeds, livestock) as a result of a previous drought is another type of behavioral response that is not captured in our data. The implication is that our cost estimates, which are only based on yield losses, are likely to represent an underestimate of the true economic cost of drought's impact on rice yield in India.

[18] However, we show that when we include a monthly index for different months during the cropping season, our main results still hold (see online appendix tables A6 and A7).

6.2 Policy implications

In 2016, the IMD officially stopped using the word 'drought' as part of a policy decision to move away from the use of terms it did not consider to have much scientific precision (Koshy and Vasudeva, 2016). An All India Drought Year was changed to a 'Deficient Year' while an All India Severe Drought Year became a 'Large Deficient Year'. Yet, these events are still defined according to rainfall shortfall and the proportion of area affected, as described in section 3. The declaration of droughts remains the prerogative of India's States and, while a rainfall shortfall combined with area affected allows a State to declare an 'agricultural' and 'meteorological' drought, this gives no indication of the impact on yield.

Our index covers all events defined as 'Deficient Years' by the IMD. Since it incorporates the impact of temperature as well as rainfall shortfalls on productivity, it could complement the existing efforts of Indian policy makers. It could also be adopted in other settings given its simplicity, reproducibility, and flexibility, e.g., it can be broken into 'bins' or adapted to other quadrants of interest. Since our index is based on readily-available, climactic data, it has the potential to be used as an input in the design of weather-based index insurance.

The results derived from application of our index have general implications for policy. We show that different water-stress, heat-stress combinations have different impacts on yield. Thus, the future impacts of rising temperatures driven by climate change may depend not only on the frequency and intensity of drought but also on the composition of drought, in terms of the relative importance of heat and water stress. This is of particular relevance in drought-prone areas.

Shaping the appropriate policy response to drought, particularly with respect to the costs of mitigation as well as climate adaptation in the agricultural sector, often involves the application of cost-benefit analysis (e.g., Mechler *et al.*, 2008). In general, this and other economic modelling approaches, e.g., general equilibrium models, rely upon estimates of drought impacts on production (e.g., Pauw *et al.*, 2011; World Meteorological Organization and Global Water Partnership, 2017). Yet, if such models focus solely on events where the value of CDD is above average, then this is likely to lead to a downward bias in the predicted economic benefits, by both reducing the potential gains from mitigation (since the gains from mitigation depend on the size of the impacts) and adaptation, hence lowering the cost of inaction.

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/S1355770X2000011X.

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