Climatic Change (2021) 165: 26
https://doi.org/10.1007/s10584-021-03051-x

Threshold effects of extreme weather events on cereal yields in India

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Received: 5 November 2020 / Accepted: 25 February 2021 / Published online: 20 March 2021

Abstract
Climate change is driving a rise in the intensity and frequency of extreme weather events. Such events are characterised as thresholds beyond which cereal yields significantly change. We apply a threshold model to district-level data collected in India over 1966–2011 and objectively identify thresholds, measured by the Standardised Precipitation-Evapotranspiration Index, before estimating their yield effects, for rice, wheat, maize, millet, sorghum and barley. Heterogeneous, crop-specific thresholds are identified for all crops except wheat. Thresholds are identified at normal climatic conditions but have smaller negative marginal effects than those of thresholds identified at dry conditions. The extent to which agro-ecological conditions and irrigation influence the location of thresholds and the size of their marginal effects varies by crop. Thresholds identified at dry climatic conditions severely reduce yield yet are rarely crossed; those at normal conditions moderately affect yield but are frequently crossed. A threshold's total impact on production is found to be inverse to the severity of its marginal effect. Severe-effect thresholds have been crossed with increasing frequency over time, contributing to growth in the size of total impacts. Our results have welfare implications and have the potential to inform predictions about the impacts of extreme weather events.

Keywords Agriculture · Cereals · Climate change · Drought · India · Thresholds

JEL classification Q10 · Q54 · Q56 · O13

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1 Introduction

Climate change is driving a rise in the intensity and frequency of extreme weather events, specifically droughts and floods, with critical implications for climate-vulnerable sectors (IPCC 2012; Easterling et al. 2000). Of particular concern is agriculture in drought- and flood-prone regions, such as in the Indian subcontinent, where it remains an important source of income and livelihoods (De et al. 2005). India is particularly vulnerable to changes in the intensity and frequency of extreme weather events due to climate change. Key to understanding how extreme weather events translate into impacts on agriculture is our ability to estimate these impacts given the existence of nonlinearities in social-ecological systems (Liu et al. 2007).

Previous research suggests evidence of nonlinearities in the relationship between the conditions underlying extreme weather events and their impacts on agricultural outcomes. Absent universally agreed definitions of such events, especially droughts, nonlinearities are typically characterised as thresholds along the range of one or more weather variables, sometimes combined in the form of an index. Temperature thresholds, often crop-specific and objectively determined, define the temperature beyond which yields are severely affected (e.g. Tack et al. 2017a; Schlenker and Roberts 2009; Lobell et al. 2011a). Although these thresholds have the capacity to capture both heat stress and intra-seasonal extreme weather, they do not capture rainfall. Indeed, temperature is considered less relevant than evapotranspiration for measuring meteorological drought (Benami et al. 2021), defined as the atmospheric conditions resulting in a moisture deficit over a given time period (Hao et al. 2017), and altogether inadequate for identifying excessive rainfall or floods (Benami et al. 2021).

Temperature variables are not used as drought triggers unlike rainfall thresholds. Rainfall shortages, along with higher evapotranspiration and soil moisture deficits, have critical effects on crop growth and development. Yet, rainfall thresholds do not capture heat stress—also critical for crop growth—caused by rising temperatures. Despite this shortcoming, rainfall thresholds are applied widely in research and policy. The former adopts rainfall thresholds typically based on deviations from climatic norms (e.g. Auffhammer et al. 2012; Li et al. 2019; Pandey et al. 2007). In practice, rainfall thresholds and indices, applied in many countries, are often arbitrarily defined with little or no scientific justification (Hao et al. 2017, WMO 2018; Steinemann and Cavalcanti 2006; Steinemann 2003). Threshold values are thus not determined by their empirical relationship with agricultural outcomes. Potential crop-specific heterogeneity is also disregarded.

Indices that measure evapotranspiration, capturing both rainfall and heat stress, are well-suited for analysing drought impacts on agricultural production (e.g. Vicente-Serrano et al. 2012; Zipper et al. 2016). In this paper, we adopt the Standardised Precipitation-Evapotranspiration Index (SPEI), which measures the impact of higher temperatures on water demand (Vicente-Serrano et al. 2010), and identify thresholds in the relationship between seasonal SPEI values and cereal yield in India. A panel threshold regression approach (Hansen 1999) is applied to district-level data collected annually over 1966–2011. The advantage of our approach is that, in contrast to previous work using rainfall or evapotranspiration indices (Chen et al. 2016; Udmale et al. 2020; Leng and Hall 2019), it enables a data-driven search for thresholds beyond which progressively drier conditions drive significant changes in yield. It provides estimates of where thresholds lie in the relationship between climatic conditions and yield but without imposing a priori assumptions on this relationship.

With increasingly dry climatic conditions, as measured by a marginal decline in the SPEI, our methodological approach can detect yield shocks. Thresholds are identified at observed

SPEI values where significant changes in the SPEI-yield relationship occur. Conditional on the thresholds identified and coefficients estimated, we calculate the impacts of the SPEI on yield for rice, wheat, barley, maize, sorghum and millet, which in India collectively account for 70% and 60% of the total caloric intake of rural and urban households, respectively (Deaton and Drèze 2009). Cereal production is dependent on rainfall during the *kharif* season (June–September) (Revadekar and Preethi 2012), when much rice, maize and millet are cultivated, whereas crops grown in the *rabi* season (October–March), such as wheat and barley, are predominantly grown under irrigated conditions. Irrigation compensates for rainfall deficiency and potentially mitigates some of the negative effects of heat stress (Zaveri and Lobell 2019; Tack et al. 2017b).

We first identify thresholds for each crop before examining the extent to which these thresholds vary depending on agro-ecological zone and the extent of irrigation. Millet and sorghum grow in areas where other crops fail and are, to varying degrees, considered drought tolerant and resistant to hotter temperatures (Assefa et al. 2010; Maman et al. 2003; Serba and Yadav 2016; Tack et al. 2017a). We would therefore expect critical thresholds for these crops to occur at lower SPEI values than rice, which has much higher water requirements (Singh et al. 2017; De Datta 1981). For maize, both positive and negative deviations from climatic norms have been shown to affect yields, so we might expect thresholds to occur in both wet (positive) and dry (negative) ranges of the SPEI (Zipper et al. 2016; Li et al. 2019). Despite critical soil moisture provided by rainfall at the end of the *kharif* season, thresholds for wheat and barley are more likely to emerge in the *rabi* rather than the *kharif* season because the post-monsoon months (October and November) are included in the *rabi* season SPEI (Prasanna 2014).

Our empirical approach, applicable to other outcome measures as well as other types of extreme weather event, demonstrates how crossing thresholds identified in the data translate into predicted, average yield losses. To illustrate how the existence of thresholds affects welfare, we compare the average revenue loss per hectare and total revenue losses against several different counterfactuals. We thus distinguish between the additional revenue loss per hectare associated with crossing a particular threshold and its total revenue loss, which depends both on the per hectare effect and the frequency of districts crossing a particular threshold in a given year. In the remainder of the paper, we first discuss the measures used to analyse the impacts of extreme weather events, in Section 2, before detailing our data and methods in Section 3. Our results are presented in Section 4, which are then discussed in Section 5. Section 6 concludes.

2 Measuring the impacts of extreme weather events

There is no universal definition of what constitutes an extreme weather event. Temperatures and rainfall below and above certain thresholds are known to harm crop yields. Yet, temperature thresholds aside (e.g. Schlenker and Roberts 2009), a lot of ambiguity remains regarding the measures used to define extreme weather events and their effects on agricultural outcomes. This is illustrated by more than 150 definitions of ‘drought’ proposed in the literature (Wilhite and Glantz 1985). A key issue is defining how deficient weather conditions need to be to be considered ‘extreme’. Consequently, a wide range of indices and metrics have been used to analyse the impacts of extreme weather events. These range from simple weather-based indices, favoured by policymakers, to very data-intensive multidimensional measures (Mishra and Singh 2010). When researchers and policymakers consider the impacts on agricultural outcomes, the most commonly used are measures of temperature or rainfall, or measures that account for both temperature and rainfall.

Research on temperature thresholds shows that, beyond a certain point, high temperatures have acute effects on crop growth. Temperatures thresholds estimated at 29 and 30 degrees reduced county-level maize yields in the USA and Africa, respectively (Schlenker and Roberts 2009). Higher still are temperatures above 34 degrees, which were found to be harmful for wheat yield (Aiqing et al. 2018; Lobell et al. 2012; Tack et al. 2017b; Tack et al. 2015), with changes in sowing times (Lobell et al. 2013) and irrigation (Tack et al. 2017b) critical for offsetting the effects of extreme heat. Research on rice indicates that temperatures in the 30–35-degree range negatively affected yields (Wang et al. 2014; Zhang et al. 2016; Bheemanahalli et al. 2016) and that rice is sensitive to both minimum and maximum temperatures (Welch et al. 2010; Peng et al. 2004). Similarly, research on sorghum suggests thresholds of around 33 degrees (Tack et al. 2017a; Miller et al. 2020).

Definitions of extreme weather events using rainfall measures, however, vary. One approach defines a specific threshold with respect to the long-term average. In India, studies of drought impacts on rice yields defined droughts as departures of 15%–20% below the long-term mean, finding negative impacts (Auffhammer et al. 2012; Pandey et al. 2007). Auffhammer et al. (2012) also found that excess rainfall negatively impacted rice yields. In the USA, both extreme rainfall and extreme drought, defined as −2 and + 2.5 standard deviations from the mean, respectively, had comparable effects on maize yields (Li et al. 2019). Leng and Hall (2019) analysed the effects of drought on wheat, rice and maize crop failure in various countries, using the Standardised Precipitation Index (SPI). Their results suggest that drought, at and below a SPI value of −0.8, nonlinearly increased the probability of crop failure. Rainfall thresholds and indices are also used in drought monitoring systems. In India, for example, negative deviations of 20% from the long-term monsoon rainfall represented the threshold for declaring a drought at the district level (Gupta et al. 2011). According to the World Meteorological Organization, the SPI index has been used in research, or in operational situations, in more than 70 countries (WMO 2012).

Recognising the importance of temperature and its increasing role in drying trends worldwide (Vicente-Serrano et al. 2014), an increasing number of indices that incorporate both rainfall and temperature have been proposed (Vicente-Serrano et al. 2012; Yu and Babcock 2010; Fontes et al. 2020). Of these, researchers have been turning to the Standard Precipitation Evapotranspiration Index (SPEI), which captures both precipitation and temperature (Vicente-Serrano et al. 2012; Zipper et al. 2016). Much of the literature using the SPEI has, so far, used sharp cut-off values to define a drought event, often around a value of −1 (Chen et al. 2016; Udmale et al. 2020).

Our study adopts the SPEI over alternative measures, although all measures have advantages and disadvantages depending on application. Compared to precipitation and evapotranspiration indices, temperature variables better capture both heat stress and intra-seasonal extreme weather (when using degree-day variables). Thus, temperature variables are particularly relevant for climate change projections because climate change-induced changes in rainfall are less certain, more geographically heterogeneous and possibly smaller than temperature increases associated with global warming (Fishman 2016; Lobell et al. 2011b; Lobell and Burke 2008). However, temperature variables do not account for excessive rainfall and are a less adequate proxy than evapotranspiration for measuring meteorological drought (Benami et al. 2021). The inability to detect potential excessive rainfall thresholds has been shown to be important in crops such as maize (Li et al. 2019; Zipper et al. 2016).

Although favoured by policymakers, rainfall indices fail to capture heat stress, a crucial determinant of crop yields. This is especially problematic because increases in temperature, rather than the increased intensity of low rainfall events, seem to account for observed drying trends (Vicente-Serrano et al. 2014). As such, indices that measure evapotranspiration, capturing both precipitation and heat stress, are critical for analysis of the impacts of extreme weather events on agricultural production (Mishra and Singh 2010; Vicente-Serrano et al. 2012). Recent research has also shown that the SPEI has typically outperformed rainfall indices, such as the SPI, when examining impacts on yields (Chen et al. 2016; Vicente-Serrano et al. 2012).

3 Data and methods

3.1 Data

The SPEI is a multi-scalar index that relies on the concept of a climatic water balance. It is calculated as the difference between precipitation and evapotranspiration over a given period of time (see SI - 1). Following the calculation of the water balance, its value is then standardised using a log-logistic distribution and computed at different timescales. The SPEI therefore captures both precipitation and temperature and is comparable across time and space. Negative (positive) SPEI values denote dry (wet) climatic conditions and are used to categorise extreme weather events (Labudová et al. 2017). SPEI values between −0.99 and 0.99 denote normal climatic conditions, while values in excess of −1 (1), −1.5 (1.5) and − 2 (2) denote moderate, severe and extreme drought (wet) conditions, respectively. Our SPEI data are sourced from Vicente-Serrano et al. (2010).

Our empirical model, described below, is only capable of detecting a threshold for a single, continuous variable.[1] Aggregation is therefore necessary. Specifically, we condense the seasonal information into one index, and adopt the SPEI with a 4-month lag in September for the *kharif* season and with a 6-month lag in March for the *rabi* season, thus capturing the cumulative climatic water balance over each of these two periods. Although we are unable to identify the months during the season when deviations in the climatic norms are most likely to affect yields, our SPEI lags are consistent with widely used definitions of both the *kharif* and *rabi* seasons, e.g. Mall et al. (2006), Revadekar and Preethi (2012), Auffhammer et al. (2012), Rao et al. (2014), Prasanna (2014), Gumma et al. (2019) and Mahto and Mishra (2020). The SPEI measures are compiled at district scale for each year between 1966 and 2011, the values of which are shown in Fig. S.1. Ideally, we would create a more granular district-crop specific lag. This, however, requires information about the growing periods of different crop varieties and the share of the crop sown or harvested in a given month, all of which are likely to have changed over our 46-year sample period. To our knowledge, such granular information is unavailable.

Our agricultural data are drawn from the ICRISAT Meso-level Database, which contains information on a range of agricultural and socioeconomic variables at the district level (ICRISAT 2012). We use data for the years 1966–2011. Since 1966, several districts have

[1] According to Hansen (2000), there is no known distributional theory for models that use multiple threshold variables. To our knowledge, no threshold models for multiple threshold variables have been developed for a panel data setting.

split into smaller districts. To maintain spatial consistency over time, district splits are addressed by returning split districts to their parent districts in 1966. Out of the 311 available in the database, 242 districts are used to create a balanced panel for generating our main results. Data are available on annual crop production and area, which we use to construct crop yield variables for rice, wheat, maize, barley, sorghum and millet. These crops are produced across the country (Fig. S.2), although there has been a shift away from the cultivation of sorghum, barley and millet towards rice, wheat and maize over our study period (Fig. S.3). For each crop sample, we create additional sub-samples according to agro-ecological zone and the extent of irrigation. The former is defined as either arid or humid (see SI – 1 and Fig. S.4). The latter defines 'low irrigation' ('high irrigation') as districts where the average share of irrigated area for a given crop is below (above) the median. Table S.1 provides summary statistics of some of our key variables.

3.2 Empirical approach

To estimate the impact of the SPEI on yield, we employ a threshold regression estimation strategy with fixed effects (Hansen 1999). Our empirical approach is broadly applicable, both to other types of extreme weather events as well as other outcome variables, assuming that (i) the outcome variable is stationary, (ii) the threshold variable is continuous and (iii) the expected threshold is not in the trimmed section. The threshold model augments the standard linear fixed effects model by estimating how the effect of the SPEI on crop yield differs for different ranges of the SPEI. It is estimated by utilising Stata code described in Wang (2015).

Equation (1) formalises the model in the case of a single threshold q_{it} of the SPEI for district i in year t: $SPEI_{it}$ is the SPEI value; $\ln(y_{it})$ is the natural logarithm of crop yield; α_i is a district-level fixed effect; $\boldsymbol{\lambda}_i \mathrm{t}$ and $\boldsymbol{\mu}_i \mathrm{t}^2$ are, respectively, district-specific linear and quadratic trend variables; and e_{it} is the error term.[2] In several specifications, as a robustness check (see below), we also include a set of control variables ($\boldsymbol{X}_{it}$,).

$$\ln y_{it} = \alpha_i + SPEI_{it}^j (q_{it} < \gamma)\beta_1 + SPEI_{it}^j (q_{it} \geq \gamma)\beta_2 + \boldsymbol{X_{it}}\delta + \boldsymbol{\lambda}_i \mathrm{t} + \boldsymbol{\mu}_i \mathrm{t}^2 + e_{it} \tag{1}$$

where:

$$\ln y_{it} = \begin{cases} \alpha_i + SPEI_{it}^j \beta_1 + \boldsymbol{X_{it}}\delta + \boldsymbol{\lambda}_i \mathrm{t} + \boldsymbol{\mu}_i \mathrm{t}^2 + e_{it} & \text{if } q_{it} < \gamma \\ \alpha_i + SPEI_{it}^j \beta_2 + \boldsymbol{X_{it}}\delta + \boldsymbol{\lambda}_i \mathrm{t} + \boldsymbol{\mu}_i \mathrm{t}^2 + e_{it} & \text{if } q_{it} \geq \gamma \end{cases} \tag{2}$$

Rather than the effect of changes in the SPEI being constant across all values of the threshold variable (ranges of the SPEI, q_{it}), the threshold model estimates the value of one or more thresholds ($q_{it} = \gamma$), for which the marginal effect of changes in the SPEI has a different effect on yields (see also SI – 2). This method allows us to test whether such a threshold exists and if so, enables us to estimate threshold values and compute different coefficients for different ranges of the SPEI.

When searching for a threshold, we need to eliminate (trim) the largest and smallest n% of the threshold variable (Hansen 1999). As in Hansen (1999), we trim the top and bottom 1%, and the remaining values of the threshold variable constitute the searchable

[2] We also test for stationarity of the dependent variable and apply several panel unit root tests (Table S.2). In all cases, the null of a unit root is rejected at the 1% level.

range of values for a threshold.[3] To test for the statistical significance of a threshold, this method implements a likelihood ratio test of whether the coefficients are equal on both sides of the threshold (i.e. $H_0 : \beta_1 = \beta_2$). A bootstrap procedure ran over 1000 iterations is used to construct the *p*-values for this test. If we fail to reject H_0, the model is equivalent to the linear fixed effects model. The method also allows us to compute multiple thresholds, with Stata allowing for a maximum of three.[4]

A benefit of using panel data to measure impacts of deviations in the SPEI is that it allows us to control for the influence of time-invariant district-specific factors that could influence yields, such as different soil types, altitude or institutional differences that have persisted over the sample period. District-specific quadratic time trends are included to account for different trends in yields across districts. Standard errors are clustered at the district level. The number of districts, in excess of 50, is sufficient to ensure that the asymptotic assumptions for clustering are satisfied (Cameron and Miller 2015). Compared to other methods, the threshold model has several advantages. First, it does not impose a global linear relationship between the independent variable and the dependent variable as in the case of a linear regression. Second, it does not impose symmetry in the functional relationship between the SPEI and yield as in a quadratic model,[5] nor does it impose a strict functional form as is the norm in the case of higher-order polynomial regressions (see also SI – 2).

3.3 Robustness checks

We undertake several robustness checks on our results. First, we test the sensitivity of our results to changes in the trimming cut-off point (at 0.5, 1.5 and 2.5%). Second, to test the sensitivity of our standard errors, we re-run all of the regressions using different clustering variables (by year and state-year) and estimate Conley (1999) standard errors, which account for spatial and temporal correlation, using the code provided by Hsiang (2010). Third, we test the sensitivity of our results to changes in the SPEI lag for the *kharif* season. While most of India's rainfall falls in June–September, climatic conditions in other months (e.g. October and November) have also been shown to be important for crop yields (Auffhammer et al. 2012). We therefore adopt alternative lag specifications of the SPEI, using a 5-month (June–October) and a 6-month (June–November) lag. Fourth, we test the sensitivity of our results to the inclusion of control variables (cropped area, rural population per hectare, fertiliser used and proportion of land under irrigation). However, given that our method requires a balanced panel, we lose many districts.

Estimated yield losses from our threshold model are also compared to estimates from a model using dummy variables to capture the effects of the SPEI on our yield variables at different percentiles or increments of the SPEI index ('bins' approach). Our preference is to use the percentiles approach (see SI - 3) but we also test the sensitivity of our results by using coarser bins (increments of 0.25 and 0.5 of the SPEI), to alleviate concerns related to imprecise

[3] A 1% cut-off was selected because there is a trade-off in allowing the identification of thresholds as close as possible to the extremes (requiring a low trimming cut-off) and having a sufficient number of observations to allow for identification (requiring a higher cut-off). A similar cut-off was used by Hansen (1999) with a dataset of a similar size to our dataset.

[4] In our case, we identify a maximum of two threshold values in all samples, with the model always rejecting the possibility of a third threshold.

[5] In the case of yields, there is a good reason to believe that impacts of the SPEI may be asymmetric. Thus, a model that does not impose symmetry in the SPEI-yield relationship is desirable.

estimates of more granular bins.[6] The bins approach is a suitable robustness check because it also does not, a priori, impose a shape on the SPEI-yield relationship and, with small bins, allows us to visually identify whether the 'jumps' and thresholds identified by the threshold model are reflected in the data. Thus, unlike a quadratic functional form, it allows the relationship to be asymmetrical around a given turning point.

However, to address our research question, we prefer the threshold model over the bins approach for several reasons (see also SI – 3). First, the bins approach is more subjective than the threshold model. The results and the ability to identify thresholds hinge on both the choice of baseline category and the coarseness of the bins. Second, identifying the location of the SPEI at which the yield-SPEI relationship is likely to change is problematic using bins. Granular bins, which allow us to visualise 'jumps', are estimated more imprecisely, whereas coarser bins, although estimated more precisely, may render the range of the identified threshold too large to be meaningful.[7] Third, the baseline category could prevent a threshold from being identified if the threshold falls within this category, thus potentially generating underestimates in the costs of extreme events.[8] Fourth, near the extremes, where there are typically fewer observations but where extreme event thresholds are most likely to be located, it would be very difficult to identify thresholds using a bins approach. Too few observations imply noisier estimates. The threshold model improves on the bins approach because it is both more objective and allows for the identification of thresholds near the extremes. That said, the confidence intervals will typically be larger for such thresholds.

3.4 Estimating the per ha and total revenue losses

Our yield loss estimates are multiplied by national-level crop prices reported in 2005 to obtain the average revenue loss per hectare.[9] The predicted revenue loss associated with a 0.1 decrease in the SPEI value at each identified threshold is estimated using different specifications, specifically a log-linear and a quadratic model for the negative range of the SPEI, as alternative counterfactuals against our threshold model (see SI - 4). To obtain total revenue losses, we multiply estimates of district- and year-specific yield losses by cultivated area and crop prices for all observations with a negative SPEI. The procedure for calculating the marginal and total revenue losses is detailed in the SI (4). Finally, we compare our estimates with those generated from a number of plausible counterfactuals, starting with the quadratic and log-linear specifications, where for each the SPEI threshold is set first at 0 and then at −1. Two more counterfactuals are generated, using the bins approach (increments of 0.5) and from a rainfall dummy consistent with India's district-level drought declaration threshold, that is, a 20% rainfall deviation from long-term average rainfall (Gupta et al. 2011).

[6] Note, however, that using coarser bins results in a loss of granularity which makes it more difficult to assess whether our linear relationship changes at the identified SPEI value.

[7] For example, the difference in return periods between a SPEI value of −1 and − 2 is very large (in the range of 4–6 years and 50–60 years, respectively, in our samples). Therefore, knowing that the threshold lies somewhere between −1 and − 1.5 or between −1 and − 2 may not be very useful for policy-makers.

[8] Here we note that it is possible to avoid this by changing the range of the SPEI used as the baseline category.

[9] We choose 2005 because it is a recent year with relatively few drought-affected districts, so national prices were less likely to be affected by drought. A fixed year was chosen to ensure comparability of costs over space and time (see also SI – 4).

4 Results

Figure 1 shows the number of events per district below (above) a SPEI threshold of −1 (1) and − 1.5 (1.5). Over the sample period, northern and eastern India, where districts tend to cultivate rice, wheat, barley and, to a certain extent, maize, have experienced a higher number of events in which the SPEI has been below −1 or − 1.5. Wet years, events in which the SPEI has been above 1 or 1.5, have occurred more frequently in southern and north-western India, where more millet, sorghum and, to a certain extent, rice are produced. We estimate the impacts of a marginal decline in the SPEI on yield. A SPEI-yield threshold is identified (at a SPEI value) when the marginal effect has a significantly different impact on yield either side of the threshold. For all results, we report the percentage yield changes associated with a 0.1-unit fall in the seasonal SPEI value, on either side of each identified threshold. Figures 2 and 3 present the crop-specific threshold results (from Table S.3).[10] Crop-specific results by irrigation extent and agro-ecological zone are presented in Tables S.6–S.10 (see also SI – 3). Vertical lines indicate the location of the thresholds: when two are identified, the one with the lowest SPEI value is denoted T1 (solid red line), followed by T2 (dashed red line). No threshold implies a linear relationship between the SPEI and log-yield. All estimated coefficients are statistically significant at the 1% level unless stated otherwise.

Starting with rice, we identify two thresholds during the *kharif* season: −1.348 (T1) and 0.339 (T2) (Fig. 2a). Above T2, a 0.429% yield loss is observed. Between T2 and T1, yield loss jumps almost threefold to 1.331%, increasing to 2.032% below T1. In the *rabi* season, one threshold is identified: 0.890. Above, yield declines by 0.192% (Fig. 2b); below, yield loss almost trebles to 0.544%. By irrigation extent (Table S.6), we find thresholds at lower SPEI values in districts with higher levels of irrigation and smaller marginal effects. Across agro-ecological zones, thresholds occur at lower values of the SPEI index and marginal effects are more severe in arid areas, a result that holds for both *kharif* and *rabi* rice.

Millet also has two thresholds during the *kharif* season (Fig. 2c): −1.724 (T1) and 0.689 (T2). A 0.050% yield loss is observed above T2, although this impact is not significantly different from zero. Between T2 and T1, yield loss is 1.677%. Below T1, yield loss grows to 2.892%. We do not find large differences depending on irrigation extent (Table S.7). Although impacts are slightly smaller in districts with higher shares of irrigated millet, this is expected due to the very low share of irrigated area for millet in both high- and low-irrigation subsamples. We find much higher marginal effects in arid areas as opposed to humid areas. Only a small proportion of millet is grown during the *rabi* season, and hence, the model is not estimated. For a similar reason, the model is not estimated for maize during the *rabi* season.

In contrast to rice and millet, the marginal effect at higher SPEI values is associated with yield increases of maize and sorghum in the *kharif* season; at lower values, the marginal effect is negative. Maize has two thresholds: −1.746 (T1) and − 0.358 (T2) (Fig. 2d). We observe a 0.769% yield increase above T2. Between T2 and T1, this becomes a 0.672% yield loss. Below T1, yield loss more than doubles to 1.688%. This is a pattern we observe across all irrigation and agro-ecological sub-samples (Table S.8). Interestingly, whereas in arid areas maize yields are affected by both high and low values of the SPEI, in humid areas, wet conditions seem to have larger negative impacts on maize yields.

Sorghum also has two *kharif* thresholds: −1.702 (T1) and − 0.205 (T2) (Fig. 2e). Above T2, we report a 0.657% yield increase. Between T2 and T1, this becomes a yield loss of 1.653%,

[10] Threshold tests and the confidence intervals of thresholds are presented in Tables S.4 and S.5.

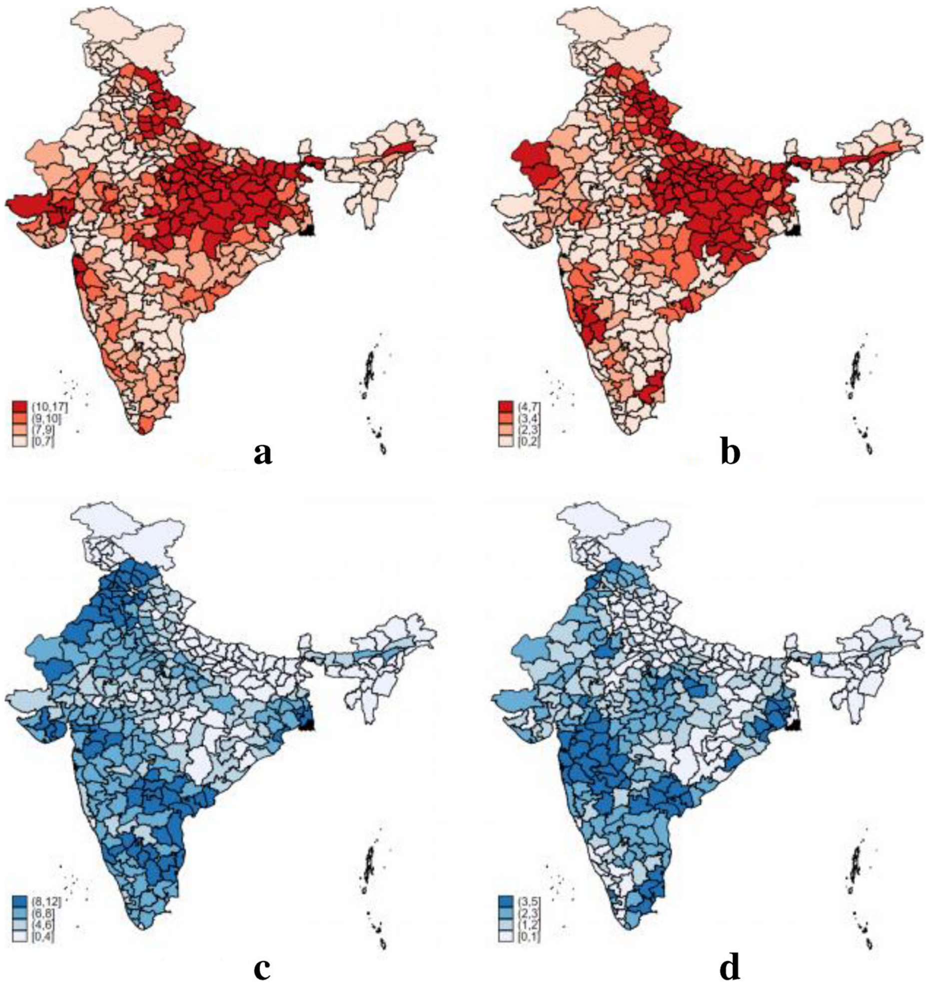

Fig. 1 The number of events per district with a SPEI below or equal to (above or equal to) − 1 (1) and − 1 (1.5), 1966–2011. Note: Figure 1 maps the district frequency of events with a SPEI value: below -1 (panel **a**), below -1.5 (panel **b**), above 1 (panel **c**), and above 1.5 (panel **d**)

rising to 2.561% below T1. We also find two thresholds in arid areas but only one in humid areas (Table S.9). While low SPEI values seem to have the largest negative effects on yields in arid areas, the coefficients in humid areas suggest that high SPEI values are likely to be equally problematic in humid areas. No threshold for sorghum is identified in the *rabi* season (Fig. 2f).

No thresholds are identified for wheat in either season (Fig. 3a–b), except for the low-irrigation and humid sub-samples in the *rabi* season (Table S.10). Both sub-samples indicate that wet years are likely to lead to larger impacts than dry years. For barley, we find no threshold during the *kharif* season (Fig. 3c) but identify two thresholds in the *rabi* season: −0.674 (T1) and 0.600 (T2) (Fig. 3d). Above T2, we report a 0.040% increase in yield, although this impact is not significantly different from zero. Between T2 and T1, yield loss is 0.997% and below T1, 0.419%. We do not compute barley results by sub-sample because the samples are too small.

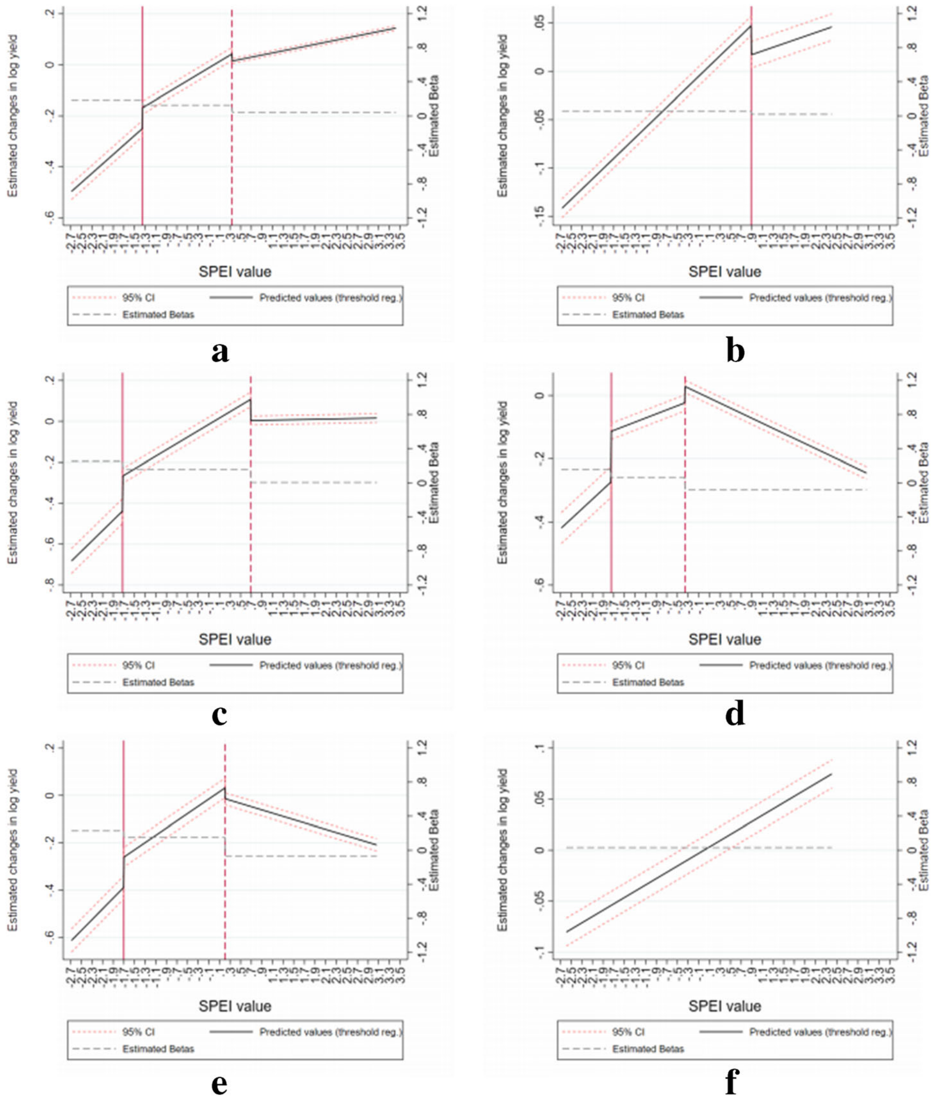

Fig. 2 Threshold regression results for rice, millet, maize and sorghum. Note: The panels in Figure 2 show the following results: Panel (**a**) – Rice (*kharif*), Panel (**b**) – Rice (*rabi*), Panel (**c**) - Millet (kharif), Panel (**d**) - Maize (kharif), Panel (**e**) - Sorghum (*kharif*), and Panel (**f**) - Sorghum (*rabi*). The black line denotes the predicted change in log-yields from the threshold model when compared to a reference SPEI value (set to zero), and corresponds to the left-hand y-axis. The dashed grey line denotes the estimated coefficients (marginal effects) associated with a specific SPEI value over its whole range, and corresponds to the right-hand y-axis. The vertical lines indicate the thresholds' locations. When two thresholds are estimated, the one with the lowest SPEI value is a solid line shaded red denoted T1, followed by T2 (dashed line shaded red). The dotted red lines denote the 95% confidence interval ± 1.96 s.e

4.1 Robustness checks

Our results remain very similar when we change the trimming cut-off points, cluster at different levels, and account for spatial correlation (Tables S.11 and S.12). We test the

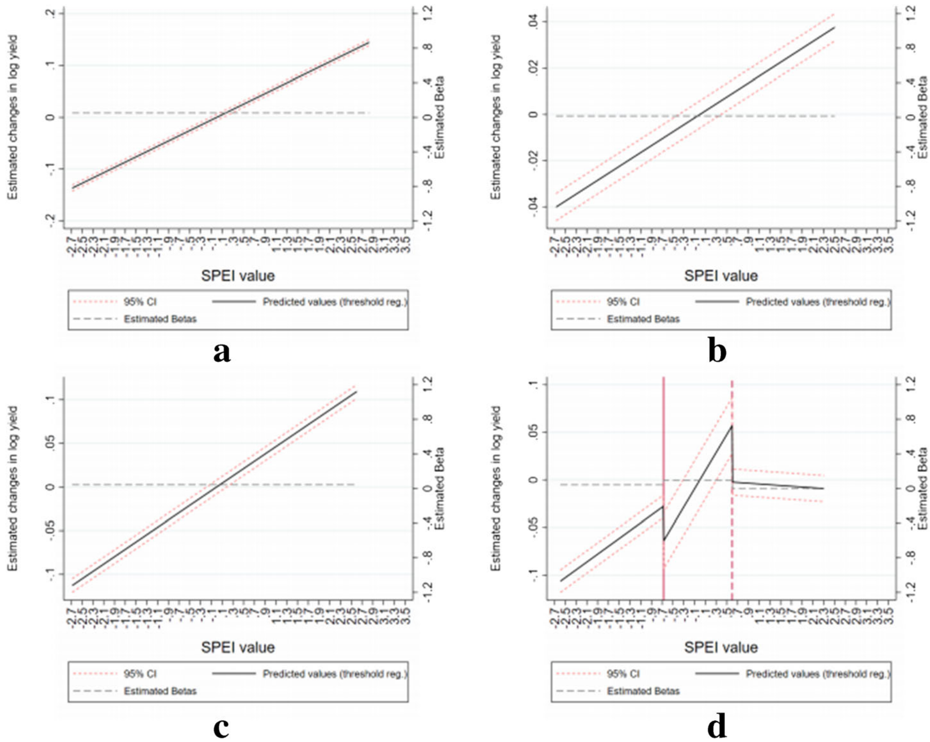

Fig. 3 Threshold regression results for wheat and barley. Note: The panels in Figure 3 show the following results: Panel (**a**) - Wheat (*kharif*), Panel (**b**) - Wheat (*rabi*), Panel (**c**) - Barley (*kharif*), and Panel (**d**) - Barley (*rabi*). The black line denotes the predicted change in log-yields from the threshold model when compared to a reference SPEI value (set to zero), and corresponds to the left-hand y-axis. The dashed grey line denotes the estimated coefficients (marginal effects) associated with a specific SPEI value over its whole range, and corresponds to the right-hand y-axis. The vertical lines indicate the thresholds' locations. When two thresholds are estimated, the one with the lowest SPEI value is a solid line shaded red denoted T1, followed by T2 (dashed line shaded red). The dotted red lines denote the 95% confidence interval ± 1.96 s.e

robustness of the *kharif* results to alternative lag specifications of the SPEI, using a 5-month (June–October) and a 6-month (June–November) lag (Table S.13). Overall, we find no differences in the number of identified crop thresholds for all crops grown mainly in the *kharif* season. For wheat, changing the lag of the SPEI changes the number of estimated thresholds but this is due to the inclusion of post-monsoon months, which is likely to affect wheat yields (Prasanna 2014). Potential omitted variable bias is addressed by including time-varying controls in our threshold models (Table S.14), and the fit of the threshold model is checked by application of a bins approach using different increments (percentiles, 0.25 and 0.5 increments; see Figs. S.5-S.10). The results are consistent with our main results in Figs. 2 and 3. The line depicting the threshold model follows the scatter dots from the coefficients of the different 'bins' specifications very closely. Thus, these two specifications generate similar results.

4.2 Revenue losses: severity versus frequency of threshold effects

Figure 4 shows estimates of the additional revenue loss per hectare (evaluated at the threshold) attributable to thresholds, by comparing the predicted revenue losses generated by the threshold model with estimates from a log-linear model (a) and a quadratic model (b). For all samples, except barley during the *rabi* season, the T1 are associated with the highest increases in the revenue loss per hectare compared to the T2.

Most of the T1 are identified at low SPEI values, −1.3 to −1.8 (moderate to severe drought), which implies that districts rarely cross T1. Return periods (the average frequency that an event, as or more severe, is likely to occur) range between 9.3 and 25.6 years for the *kharif* crop samples (Table S.3). By contrast, most of the T2 are identified at SPEI values characterising normal climatic conditions and are likely to be crossed every 1.3 to 2.3 years (Table S.3). That such ‘crossing events’ often occur at least partially within ranges of the SPEI defining climatic norms implies that they are likely to be overlooked by policymakers. The estimated coefficients from the threshold regression associated with these events are, in most cases, much smaller (barley aside, they are 30–70% lower), but these events occur more frequently. This implies that, although each event might be associated with a low revenue loss, the total revenue loss could be high if events occur frequently.

We illustrate how the frequency of crossing thresholds combine with revenue loss per event to generate total revenue losses in Fig. 5 a and b, which show the additional total revenue losses associated with crossing the T2 (but staying above the T1) and the T1. Despite lower revenue losses per hectare, the much lower return periods for the T2 in comparison to those for the T1 generate higher total revenue losses. Also, total revenue losses due to districts crossing thresholds have risen over our study period, particularly after 2000 (see Figs. S.11 and S.12 using alternative counterfactuals). Rising total revenue losses are due to rising cereal yields over time and an increase in the frequency of districts crossing the T1.

To emphasise the policy relevance of our estimates, Fig. 6 compares the estimated revenue losses from our threshold models not only with those from the quadratic and log-linear models but also with two alternative yet arbitrarily defined thresholds that have been adopted in research and policy, namely, rainfall deviations below 20% of long-term mean (‘rainfall dummy’) and SPEI values below −1. Compared to a SPEI of 0, all of these counterfactuals underestimate revenue losses to some extent, from around 5% (quadratic) to approximately 60% (log-linear using a SPEI threshold of −1).

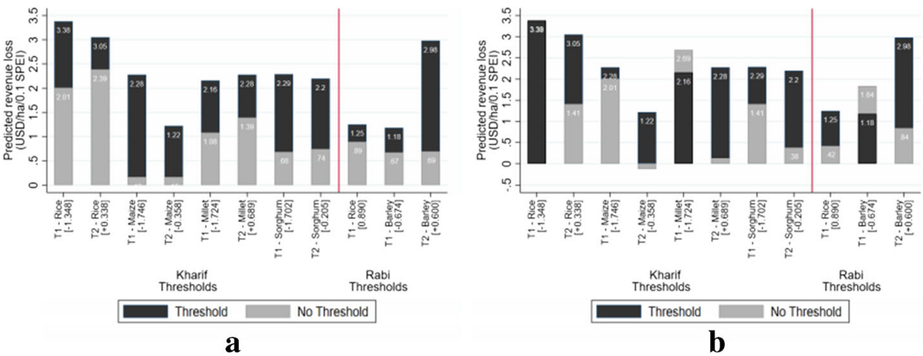

Fig. 4 Revenue loss per hectare by crop and threshold. Note: Figure 4 shows the revenue loss per hectare by crop and threshold against a log-linear counterfactual (panel **a**) and a quadratic counterfactual (panel **b**). Predicted losses to the left of the red vertical line are for kharif season thresholds; those to the right are for rabi season thresholds. For the quadratic counterfactual for T1 rice, the bar is almost completely black because the two specifications give almost the exact same result (3.378 for the threshold model vs. 3.388 for the quadratic model) and as a result the grey bar is “hidden” behind the black bar

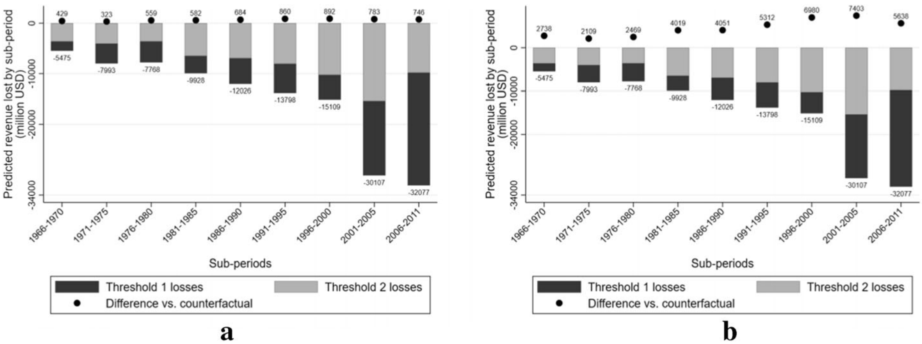

Fig. 5 Total revenue loss per time sub-period. Note: Total costs per sub-period are estimated by summing the predicted yields given the observed SPEI value vs. predicted yields at SPEI equal 0 for each crop for which a threshold is found. The difference implied by the threshold is estimated by comparing the implied yields under the threshold model given observed SPEI values against the implied yields given observed SPEI values using an alternative specification: (**a**) vs. quadratic; (**b**) vs. quadratic (threshold at SPEI = -1)

5 Discussion

Extreme weather events in India, specifically drought, are characterised as thresholds, the crossing of which generate large, asymmetric shocks to the marginal effect on yield. Consistent with previous research using text-based impact reports (Bachmair et al. 2016), we found no evidence for thresholds that could be uniformly applied in heterogeneous agro-ecological conditions and to different crops, except possibly across crop cluster groups (e.g. millet and sorghum) in areas with similar conditions. This implies that the application of a uniform,

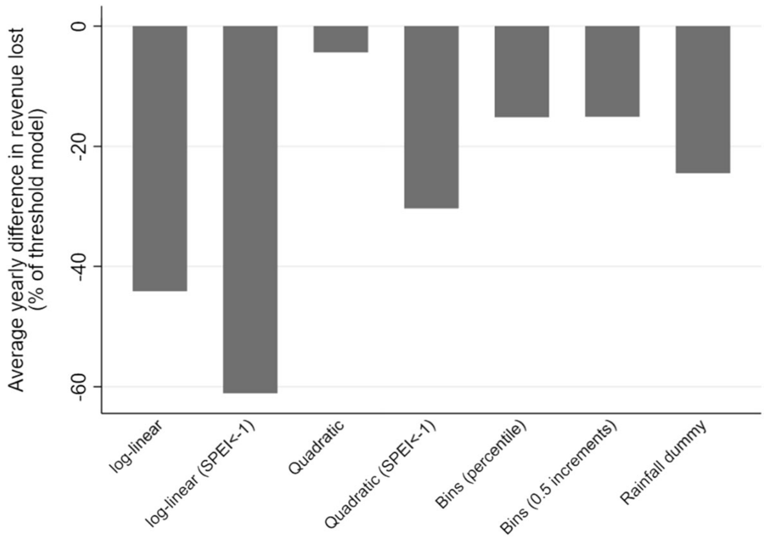

Fig. 6 Comparison of estimated revenue losses across counterfactuals. Note: Total costs per sub-period are estimated by summing the predicted yields given the observed SPEI value vs. predicted yields at SPEI equal 0 for each crop for which a threshold is found. The difference implied by the threshold is estimated by comparing the implied yields under the threshold model given observed SPEI values against the implied yields using different counterfactuals. The comparison across counterfactuals is obtained by dividing the average difference between the threshold model and a given counterfactual by the average predicted revenue loss using the threshold model

arbitrarily defined threshold, as is commonly used in many countries (Hao et al. 2017; WMO 2018), potentially misidentifies the impacts of drought on yield and leads to incorrectly targeted policy responses.

Consistent with rice's substantial water requirements and despite being mostly grown in humid areas, drier conditions reduced yield substantially, even at positive SPEI values. The identification of thresholds within climatic norms can be explained by the fact that most of our districts have seasonal rainfall below the optimal for rice (Ratnasiri et al. 2019; Singh et al. 2017; De Datta 1981). The crops considered best suited to dry conditions, millet and sorghum, are often grown in more arid regions under non-irrigated conditions. We estimated moderate impacts on millet yield at SPEI values characterising normal climatic conditions, a result that is consistent with drought being the major abiotic stress to millet production in India (Murty et al. 2007) and with research in other settings, e.g. China (Chen et al. 2016).

Millet and sorghum, along with maize, had T1 with SPEI values close to −2 (extreme drought), thus generating very severe yield losses. These values indicate a high capacity for drought tolerance but also show where the limits to tolerance lie, which in arid areas suggests a need for new cultivars and innovation in strategies to adapt sorghum (Tack et al. 2017a) and maize to extreme drought conditions. Consistent with previous research on maize and sorghum (Zipper et al. 2016; Assefa et al. 2010; Li et al. 2019; Tack et al. 2017a),[11] we also found a negative effect on sorghum and maize yields along the positive range of the SPEI.

Wheat aside, two thresholds were identified for every crop in at least one season. Although a lower level of rainfall during the previous *kharif* season increased wheat's dependence on rainfall in the *rabi* season (Zaveri et al. 2016), we found no evidence of thresholds in either season. This we attribute to irrigation.

Across the irrigation sub-samples, we only found substantial differences in thresholds and coefficients for those crops, namely, wheat and rice, where there was considerable variation in the share of irrigation. Consistent with research showing that irrigation mitigates both heat and water stress, smaller marginal effects were estimated in districts where irrigation was more prevalent (Tack et al. 2017b; Zaveri and Lobell 2019). Another consistent finding is that thresholds occurred at lower SPEI values in the 'high irrigation' sub-sample, suggesting evidence for the important role of irrigation mitigating the impacts of extreme weather. Yet, the effectiveness of, and potential for, expanding irrigation is likely constrained by rapidly depleting groundwater reserves since groundwater has increasingly been used as a buffer (Zaveri and Lobell 2019; Siegfried et al. 2010). If resilience to crossing thresholds is built upon unsustainable water management practices, this may simply mean that districts are trading current for future resilience. In such cases, to develop resilience to a warming climate, rules are needed that potentially improve water management, to help determine the use rights of surface water in wet years and those of groundwater in dry years (Siegfried et al. 2010).

A consistent finding across agro-ecological zones is that, although thresholds tended to occur at lower values of the SPEI in arid areas, yield impacts in humid districts in both seasons were noticeably smaller for all crops at low values of the SPEI. In arid districts, with harsher growing conditions, we estimated large marginal effects even at SPEI values characterising normal climatic conditions. To some extent, this is consistent with the finding that SPEI impacts are larger at high temperatures (Matiu et al. 2017) and that the impacts of heat stress are amplified by drought conditions (Lobell et al. 2011a). Since arid districts are generally hotter and drier, a low SPEI value is likely to represent both substantial heat and water stress.

[11] The estimated rainfall-yield relationship estimated in Tack et al. (2017) indicates that above 500-600 mm, additional rainfall may decrease crop yields.

In general, lower SPEI values were associated with higher yield losses in the *kharif* than in the *rabi* season, in line with *kharif* being India's main cropping season. In the *rabi* season, for certain crops, our results suggest that wet, rather than dry conditions, had a larger overall effect on yields. Indeed, in the wet range of the SPEI, we observed larger negative impacts on yields in humid districts: the thresholds identified for wheat in the *rabi* season and sorghum in the *kharif* season highlight the threat of excessive wetness for yields.

6 Conclusion

Between 1966 and 2000, SPEI values rarely fell below T1, with a low proportion of revenue losses attributed to crossing T1. Yet, between 2000 and 2011, the likelihood of the SPEI value crossing T1 increased in frequency, as shown by the increased share of revenue losses attributable to events below T1, with critical implications for agricultural production, incomes and livelihoods. Given climate change projections of increasingly erratic rainfall and rising temperatures in India (IPCC 2014), there is a risk of more intense and frequent yield losses potentially inflicting further revenue losses.

Yet, our current understanding of the impacts of extreme weather events in general, and drought in particular, remains constrained by our limited capacity to identify the point at which the intensity of the impacts of evapotranspiration significantly worsens thus triggering a drought. Knowledge of the differences in sensitivity to deviations in the SPEI would help make drought triggers more objective and improve our understanding of potential climate change-induced drought impacts. While acknowledging that thresholds are likely to change in the future, our results could help identify when the conditions underlying drought might start significantly increasing the magnitude of yield losses. Given evidence of asymmetric impacts, our results also suggest how adaptation policy might be cost-effectively targeted, for example, to reduce the impacts of frequently crossed T2.

Our methodology can be extended to estimate threshold values and yield losses for a given month, although we are yet able to condition a monthly value on the previous month's value. Hence, it can partially but not fully address the intra-annual or -seasonal deviations characterising the response function between the SPEI and yield. Forecasting models also stand to benefit from extensions of our methodology. Threshold values and their coefficients could be combined with forecasted SPEI values to help predict future impacts, with the generated yield-response functions used to simulate the nonlinear impacts of climate change scenarios on yield. Finally, our methodology can be extended to the estimation of impacts on other outcome variables and, assuming a threshold characterised as a plausibly exogenous biophysical process or extreme weather event, it could also be applied to threshold identification in other socio-ecological systems.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10584-021-03051-x.

Acknowledgments We thank Ben Groom, Daniel Osberghaus and three anonymous referees for useful comments. Fontes and Gorst also wish to thank the ESRC for their financial support during this paper as well as the Grantham Research Institute for access to research facilities.

Availability of data and material All the agricultural data is sourced from the ICRISAT meso-level database, which can be accessed using the following URL (http://data.icrisat.org/dld/src/crops.html) and the SPEI data is also freely available from the following website (http://spei.csic.es/). Both datasets are publicly available.

Code availability All the analysis was carried out using Stata 14.

Author contribution FF designed the analysis, carried out most of the statistical analysis, interpreted the results and contributed to the writing of the paper. CP was mainly responsible for writing the paper and contributed to the research design and the interpretation of the results. AG was responsible for the data collection, treatment of spatial data, and contributing to some of the statistical analysis in the early versions of the paper.

Funding Dr. Fontes and Dr. Gorst were recipients of ESRC doctoral grants during the period in which the research was conducted.

Declarations

Ethical approval No ethical approval was required for this study.

Consent to participate Not applicable, as dataset used does not contain data from any individual person.

Consent to publish Not applicable.

Competing interests The authors declare no competing interests.

References

Aiqing S, Somayanda I, Sebastian SV, Singh K, Gill K, Prasad PVV, Jagadish SK (2018) Heat stress during flowering affects time of day of flowering, seed set, and grain quality in spring wheat. Crop Sci 58(1):380–392. https://doi.org/10.2135/cropsci2017.04.0221

Assefa Y, Staggenborg SA, Prasad VP (2010) Grain sorghum water requirement and responses to drought stress: a review. Crop Management 9(1):1–11. https://doi.org/10.1094/CM-2010-1109-01-RV

Auffhammer M, Ramanathan V, Vincent JR (2012) Climate change, the monsoon, and rice yield in India. Clim Chang 111(2):411–424. https://doi.org/10.1007/s10584-011-0208-4

Bachmair S, Svensson C, Hannaford J, Barker LJ, Stahl K (2016) A quantitative analysis to objectively appraise drought indicators and model drought impacts. Hydrol Earth Syst Sci 20(7):2589–2609. https://doi.org/10.5194/hess-20-2589-2016

Benami E, Jin Z, Carter MR, Ghosh A, Hijmans RJ, Hobbs A et al (2021) Uniting remote sensing, crop modelling and economics for agricultural risk management. Nature Reviews Earth & Environment:1–20. https://doi.org/10.1038/s43017-020-00122-y

Bheemanahalli R, Sathishraj R, Tack J, Nalley LL, Muthurajan R, Jagadish KS (2016) Temperature thresholds for spikelet sterility and associated warming impacts for sub-tropical rice. Agric For Meteorol 221:122–130. https://doi.org/10.1016/j.agrformet.2016.02.003

Cameron AC, Miller DL (2015) A practitioner's guide to cluster-robust inference. J Hum Resour 50(2):317–372. https://doi.org/10.3368/jhr.50.2.317

Chen T, Xia G, Liu T, Chen W, Chi D (2016) Assessment of drought impact on main cereal crops using a standardized precipitation evapotranspiration index in Liaoning Province, China. Sustainability 8(10):1069. https://doi.org/10.3390/su8101069

Conley TG (1999) GMM estimation with cross sectional dependence. J Econ 92(1):1–45. https://doi.org/10.1016/S0304-4076(98)00084-0

De Datta SK (1981) Principles and practices of rice production. Int. Rice Res, Inst

De US, Dube RK, Rao GP (2005) Extreme weather events over India in the last 100 years. J Ind Geophys Union 9(3):173–187

Deaton A, Drèze J (2009) Food and nutrition in India: facts and interpretations. Econ Polit Wkly:42–65

Easterling DR, Meehl GA, Parmesan C, Changnon SA, Karl TR, Mearns LO (2000) Climate extremes: observations, modeling, and impacts. Science 289(5487):2068–2074. https://doi.org/10.1126/science.289.5487.2068
Fishman R (2016) More uneven distributions overturn benefits of higher precipitation for crop yields. Environ Res Lett 11(2):024004. https://doi.org/10.1088/1748-9326/11/2/024004
Fontes F, Gorst A, Palmer C (2020) Does choice of drought index influence estimates of drought-induced rice losses in India? Environ Dev Econ 25(5):459–481. https://doi.org/10.1017/S1355770X2000011X
Gumma MK, Nelson A, Yamano T (2019) Mapping drought-induced changes in rice area in India. Int J Remote Sens 40(21):8146–8173
Gupta AK, Tyagi P, Sehgal VK (2011) Drought disaster challenges and mitigation in India: strategic appraisal. Curr Sci:1795–1806
Hansen BE (1999) Threshold effects in non-dynamic panels: estimation, testing, and inference. J Econ 93(2): 345–368. https://doi.org/10.1016/S0304-4076(99)00025-1
Hansen BE (2000) Sample splitting and threshold estimation. Econometrica 68(3):575–603. https://doi.org/10.1111/1468-0262.00124
Hao Z, Yuan X, Xia Y, Hao F, Singh VP (2017) An overview of drought monitoring and prediction systems at regional and global scales. Bull Am Meteorol Soc 98(9):1879–1896. https://doi.org/10.1175/BAMS-D-15-00149.1
Hsiang SM (2010) Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America. Proc Natl Acad Sci 107(35):15367–15372. https://doi.org/10.1073/pnas.1009510107
ICRISAT (2012). “District level database documentation” (technical report, ICRISAT-ICAR-IRRI collaborative research project, 2012)
Intergovernmental Panel on Climate Change (IPCC) (2012) *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation.* A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change [Field, C.B., V. Barros, T.F. Stocker, D. Qin, D.J. Dokken, K.L. Ebi, M.D. Mastrandrea, K.J. Mach, G.-K. Plattner, S.K. Allen, M. Tignor, and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, UK and New York, USA, 582 pp.
IPCC (2014). Impacts, adaptation, and vulnerability. Part B: regional aspects. Contribution of working group II to the fifth assessment report of the intergovernmental panel on climate change. *Climate change*
Labudová L, Labuda M, Takáč J (2017) Comparison of SPI and SPEI applicability for drought impact assessment on crop production in the Danubian Lowland and the East Slovakian Lowland. Theor Appl Climatol 128(1–2):491–506. https://doi.org/10.1007/s00704-016-1870-2
Leng G, Hall J (2019) Crop yield sensitivity of global major agricultural countries to droughts and the projected changes in the future. Sci Total Environ 654:811–821. https://doi.org/10.1016/j.scitotenv.2018.10.434
Li Y, Guan K, Schnitkey GD, DeLucia E, Peng B (2019) Excessive rainfall leads to maize yield loss of a comparable magnitude to extreme drought in the United States. Glob Chang Biol 25(7):2325–2337. https://doi.org/10.1111/gcb.14628
Liu J, Dietz T, Carpenter SR, Alberti M, Folke C, Moran E et al (2007) Complexity of coupled human and natural systems. Science 317(5844):1513–1516. https://doi.org/10.1126/science.1144004
Lobell DB, Burke MB (2008) Why are agricultural impacts of climate change so uncertain? The importance of temperature relative to precipitation. Environ Res Lett 3(3):034007. https://doi.org/10.1088/1748-9326/3/3/034007
Lobell DB, Bänziger M, Magorokosho C, Vivek B (2011a) Nonlinear heat effects on African maize as evidenced by historical yield trials. Nat Clim Chang 1(1):42–45. https://doi.org/10.1038/nclimate1043
Lobell DB, Schlenker W, Costa-Roberts J (2011b) Climate trends and global crop production since 1980. Science 333(6042):616–620
Lobell DB, Sibley A, Ortiz-Monasterio JI (2012) Extreme heat effects on wheat senescence in India. Nat Clim Chang 2(3):186–189. https://doi.org/10.1038/nclimate1356
Lobell DB, Ortiz-Monasterio JI, Sibley AM, Sohu VS (2013) Satellite detection of earlier wheat sowing in India and implications for yield trends. Agric Syst 115:137–143. https://doi.org/10.1016/j.agsy.2012.09.003
Mahto SS, Mishra V (2020) Dominance of summer monsoon flash droughts in India. Environ Res Lett 15(10): 104061. https://doi.org/10.1088/1748-9326/abaf1d
Mall RK, Singh R, Gupta A, Srinivasan G, Rathore LS (2006) Impact of climate change on Indian agriculture: a review. Clim Chang 78(2):445–478
Maman N, Lyon DJ, Mason SC, Galusha TD, Higgins R (2003) Pearl millet and grain sorghum yield response to water supply in Nebraska. Agron J 95(6):1618–1624. https://doi.org/10.2134/agronj2003.1618
Matiu M, Ankerst DP, Menzel A (2017) Interactions between temperature and drought in global and regional crop yield variability during 1961-2014. PLoS One 12(5):e0178339. https://doi.org/10.1371/journal.pone.0178339

Miller, N., Tack, J., & Bergtold, J. (2020). The impacts of warming temperatures on US Sorghum yields and the potential for adaptation. Mimeo

Mishra AK, Singh VP (2010) A review of drought concepts. J Hydrol 391(1–2):202–216. https://doi.org/10.1016/j.jhydrol.2010.07.012

Murty, M. V. R., Singh, P., Wani, S. P., Khairwal, I. S., & Srinivas, K. (2007). Yield gap analysis of sorghum and pearl millet in India using simulation modeling (No. 37)

Pandey S, Bhandari HS, Hardy B (2007) Economic costs of drought and rice farmers' coping mechanisms: a cross-country comparative analysis. Int. Rice Res, Inst

Peng S, Huang J, Sheehy JE, Laza RC, Visperas RM, Zhong X et al (2004) Rice yields decline with higher night temperature from global warming. Proc Natl Acad Sci 101(27):9971–9975. https://doi.org/10.1073/pnas.0403720101

Prasanna V (2014) Impact of monsoon rainfall on the total foodgrain yield over India. Journal of Earth System Science 123(5):1129–1145

Rao BB, Chowdary PS, Sandeep VM, Rao VUM, Venkateswarlu B (2014) Rising minimum temperature trends over India in recent decades: implications for agricultural production. Glob Planet Chang 117:1–8. https://doi.org/10.1016/j.gloplacha.2014.03.001

Ratnasiri S, Walisinghe R, Rohde N, Guest R (2019) The effects of climatic variation on rice production in Sri Lanka. Appl Econ 51(43):4700–4710. https://doi.org/10.1080/00036846.2019.1597253

Revadekar JV, Preethi B (2012) Statistical analysis of the relationship between summer monsoon precipitation extremes and foodgrain yield over India. Int J Climatol 32(3):419–429. https://doi.org/10.1002/joc.2282

Schlenker W, Roberts MJ (2009) Nonlinear temperature effects indicate severe damages to US crop yields under climate change. Proc Natl Acad Sci 106(37):15594–15598. https://doi.org/10.1073/pnas.0906865106

Serba DD, Yadav RS (2016) Genomic tools in pearl millet breeding for drought tolerance: status and prospects. Front Plant Sci 7:1724. https://doi.org/10.3389/fpls.2016.01724

Siegfried T, Sobolowski S, Raj P, Fishman R, Vasquez V, Narula K et al (2010) Modeling irrigated area to increase water, energy, and food security in semiarid India. Weather, Climate, and Society 2(4):255–270. https://doi.org/10.1175/2010WCAS1048.1

Singh K, McClean CJ, Büker P, Hartley SE, Hill JK (2017) Mapping regional risks from climate change for rainfed rice cultivation in India. Agric Syst 156:76–84. https://doi.org/10.1016/j.agsy.2017.05.009

Steinemann A (2003) Drought indicators and triggers: a stochastic approach to evaluation 1. JAWRA Journal of the American Water Resources Association 39(5):1217–1233. https://doi.org/10.1111/j.1752-1688.2003.tb03704.x

Steinemann AC, Cavalcanti LF (2006) Developing multiple indicators and triggers for drought plans. J Water Resour Plan Manag 132(3):164–174. https://doi.org/10.1061/(ASCE)0733-9496(2006)132:3(164)

Tack J, Barkley A, Nalley LL (2015) Effect of warming temperatures on US wheat yields. Proc Natl Acad Sci 112(22):6931–6936. https://doi.org/10.1073/pnas.1415181112

Tack J, Lingenfelser J, Jagadish SK (2017a) Disaggregating sorghum yield reductions under warming scenarios exposes narrow genetic diversity in US breeding programs. Proc Natl Acad Sci 114(35):9296–9301. https://doi.org/10.1073/pnas.1706383114

Tack J, Barkley A, Hendricks N (2017b) Irrigation offsets wheat yield reductions from warming temperatures. Environ Res Lett 12(11):114027

Udmale P, Ichikawa Y, Ning S, Shrestha S, Pal I (2020) A statistical approach towards defining national-scale meteorological droughts in India using crop data. Environ Res Lett 15(9):094090. https://doi.org/10.1088/1748-9326/abacfa

Vicente-Serrano SM, Beguería S, López-Moreno JI (2010) A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. J Clim 23(7):1696–1718. https://doi.org/10.1175/2009JCLI2909.1

Vicente-Serrano SM, Beguería S, Lorenzo-Lacruz J, Camarero JJ, López-Moreno JI, Azorin-Molina C et al (2012) Performance of drought indices for ecological, agricultural, and hydrological applications. Earth Interact 16(10):1–27. https://doi.org/10.1175/2012EI000434.1

Vicente-Serrano SM, Lopez-Moreno JI, Beguería S, Lorenzo-Lacruz J, Sanchez-Lorenzo A, García-Ruiz JM et al (2014) Evidence of increasing drought severity caused by temperature rise in southern Europe. Environ Res Lett 9(4):044001. https://doi.org/10.1088/1748-9326/9/4/044001

Wang Q (2015) Fixed-effect panel threshold model using Stata. The Stata Journal 15(1):121–134. https://doi.org/10.1177/2F1536867X1501500108

Wang P, Zhang Z, Song X, Chen Y, Wei X, Shi P, Tao F (2014) Temperature variations and rice yields in China: historical contributions and future trends. Clim Chang 124(4):777–789. https://doi.org/10.1007/s10584-014-1136-x

Welch JR, Vincent JR, Auffhammer M, Moya PF, Dobermann A, Dawe D (2010) Rice yields in tropical/subtropical Asia exhibit large but opposing sensitivities to minimum and maximum temperatures. Proc Natl Acad Sci 107(33):14562–14567. https://doi.org/10.1073/pnas.1001222107

Wilhite DA, Glantz MH (1985) Understanding: the drought phenomenon: the role of definitions. Water Int 10(3): 111–120. https://doi.org/10.1080/02508068508686328

World Meteorological Organisation (WMO) (2018) 'Guidelines on the definition and monitoring of extreme weather events'

World Meteorological Organization (2012) Standardized Precipitation Index User Guide (M. Svoboda, M. Hayes and D. Wood). (WMO-No. 1090), Geneva

Yu T, Babcock BA (2010) Are US corn and soybeans becoming more drought tolerant? Am J Agric Econ 92(5): 1310–1323. https://doi.org/10.1093/ajae/aaq074

Zaveri E, Lobell DB (2019) The role of irrigation in changing wheat yields and heat sensitivity in India. Nat Commun 10(1):1–7. https://doi.org/10.1038/s41467-019-12183-9

Zaveri E, Grogan DS, Fisher-Vanden K, Frolking S, Lammers RB, Wrenn DH et al (2016) Invisible water, visible impact: groundwater use and Indian agriculture under climate change. Environ Res Lett 11(8): 084005. https://doi.org/10.1088/1748-9326/11/8/084005

Zhang S, Tao F, Zhang Z (2016) Changes in extreme temperatures and their impacts on rice yields in southern China from 1981 to 2009. Field Crop Res 189:43–50. https://doi.org/10.1016/j.fcr.2016.02.008

Zipper SC, Qiu J, Kucharik CJ (2016) Drought effects on US maize and soybean production: spatiotemporal patterns and historical changes. Environ Res Lett 11(9):094021. https://doi.org/10.1088/1748-9326/11/9/094021

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