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LETTER

El Niño and positive Indian Ocean Dipole conditions simultaneously reduce the production of multiple cereals across India

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Abstract

Natural climate phenomena like El Niño Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD) influence the Indian monsoon and thereby the region's agricultural systems. Understanding their influence can provide seasonal predictability of agricultural production metrics to inform decision-making and mitigate potential food security challenges. Here, we analyze the effects of ENSO and IOD on four agricultural production metrics (production, harvested area, irrigated area, and yields) for rice, maize, sorghum, pearl millet, and finger millet across India from 1968 to 2015. El Niños and positive-IODs are associated with simultaneous reductions in the production and yields of multiple crops. Impacts vary considerably by crop and geography. Maize and pearl millet experience large declines in both production and yields when compared to other grains in districts located in the northwest and southern peninsular regions. Associated with warmer and drier conditions during El Niño, >70% of all crop districts experience lower production and yields. Impacts of positive-IODs exhibit relatively more spatial variability. La Niña and negative-IODs are associated with simultaneous increases in all production metrics across the crops, particularly benefiting traditional grains. Variations in impacts of ENSO and IOD on different cereals depend on where they are grown and differences in their sensitivity to climate conditions. We compare production metrics for each crop relative to rice in overlapping rainfed districts to isolate the influence of climate conditions. Maize production and yields experience larger reductions relative to rice, while pearl millet production and yields also experience reductions relative to rice during El Niños and positive-IODs. However, sorghum experiences enhanced production and harvested areas, and finger millet experiences enhanced production and yields. These findings suggest that transitioning from maize and rice to these traditional cereals could lower interannual production variability associated with natural climate variations.

1. Introduction

Oscillations in tropical sea-surface temperatures drive variations in global rainfall and temperature patterns that affect food production and livelihoods worldwide [1, 2]. India is particularly vulnerable to such natural climate variations, as the country's agricultural activities and water availability closely depend on the Indian summer monsoon rainfall (ISMR). Agriculture is crucial to the Indian economy, contributing substantially to employment, food security, and economic growth. According to the Indian Economic Association [3], agriculture employed about 46.5% of the workforce in 2020–21 and constituted one-fifth of India's economy (Gross Value Added). Fluctuations in temperature and monsoonal rainfall can impact food production, food prices, agricultural activities, and socioeconomic stability of the agricultural workforce [4], thereby affecting food security within India and beyond [5–8].

El Niño Southern Oscillation (ENSO) is a primary mode of natural variability in Earth's climate system and a major driver of ISMR variability [9]. The Indian Ocean Dipole (IOD) also influences the ISMR and modulates monsoon-ENSO teleconnections [10–13]. Typically, the Indian monsoon experiences below average rainfall during El Niño [9] and excess rainfall during La Niña [14]. Positive IOD events typically enhance the monsoon but are associated with delayed monsoon onset over southwestern India [15]. Strong El Niño events often co-occur with positive IOD (IOD^{+}) events, and recent research suggests these co-occurrences have become more frequent in recent decades [16]. However, the impacts of their co-occurrences are not well understood due to the relatively short instrumental record. Understanding how ENSO and IOD influence the summer monsoon and grains typically grown during the monsoon season (referred to locally as kharif grains) can inform the seasonal predictability of agricultural production and development of early warning systems to manage food security impacts.

Previous studies have quantified the impact of ENSO and IOD on the yields and production of cereal grains such as rice, wheat, maize, and soybean in several regions including Africa, Philippines, and globally [17–21]. Climate variability explains over 60% of yield variability in major global breadbaskets [21]. However, a comprehensive evaluation of ENSO and IOD impacts on grain yields and production at finer spatial scales in India has not yet been conducted. Previous studies have examined their influence on national-level yields of rice, maize, wheat, soybean and sorghum [17, 22–24], but studies over India are limited to certain sub-regions. For instance, Bhatla *et al* [25] show that El Niño negatively affects rice, maize, pulse, and sugarcane production over the Indo-Gangetic basin. Nageswararao *et al* [26], found that ENSO had a positive influence on wheat in the Himalayan region, gram in Uttarakhand, rapeseed–mustard and oilseeds in Uttar Pradesh, Chhattisgarh, and Rajasthan during October–April. Moreover, the impacts of climate variability modes on traditional grains such as sorghum (∼1.3% of total Indian production of five major cereals in 2015) and pearl and finger millets (∼7.3% of total Indian production of five major cereals in 2015), have not been assessed. The combined influence of ENSO and IOD on grains at the sub-regional scale has also not been quantified. There is a need to better understand the individual and combined impacts of ENSO and IOD on India's agricultural production—including traditional staples like sorghum and millets—at the sub-regional scale for advancing agricultural predictions and planning.

Our study investigates how these two natural climate variability modes—ENSO and IOD—influence production metrics of rice (Paddy), maize (Corn), sorghum (Jowar), pearl millet (Bajra), and finger millet (Ragi) during the Indian summer monsoon season. India is the second-largest producer of rice and the largest producer of millets in the world. There is growing recognition of the benefits of traditional cereals [27] that are highly nutritious, less resource-intensive and more climate resilient than rice [28, 29]. In 2017, National Institution for Transforming India Aayog, the apex public policy think tank of the Government of India, released the National Nutrition Strategy for 'Nourishing India', and the Indian Government has implemented initiatives such as declaring millets as 'Nutri-cereals' and celebrating 2018 as the National Year of Millets to boost millet production and promote its increased inclusion in diets. The United Nations declared 2023 as the 'International Year of Millets' to raise awareness about its health benefits.

This study specifically aims to (a) quantify the impact of ENSO and IOD on the production, harvested area, irrigated area, and yields of rice, maize, sorghum, and millets, (b) understand the spatial variations in these impacts across India in the context of rainfall and temperature variations, and (c) evaluate the sensitivity of maize and traditional grains relative to rice. Examining multiple production metrics provides a more comprehensive perspective, as most previous literature has focused predominantly on yields. Further, considering harvested areas alongside yields better captures the overall production dynamics by accounting for changes in the spatial extent of crop cultivation in response to climate fluctuations. Our findings are relevant for assessing the resiliency of agriculture to natural climate fluctuations, informing seasonal predictability of crop production, and understanding cascading risks to other allied sectors such as public health and food security.

2. Data and methods

2.1. Summer monsoon grain and soil data

District-level crop production metrics (production, harvested area, irrigated areas, and yields) for 1966–2017 are obtained from the International Crops Research Institute for the Semi-Arid Tropics Village Dynamics of South Asia (ICRISAT-VDSA) dataset (http://data.icrisat.org/dld/src/crops.html) [30]. Our study focuses on the production metrics of five grains during the summer monsoon (or kharif) season (June–September, JJAS): rice, maize, sorghum, pearl

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millet, and finger millet. While exact planting and harvest dates vary across districts and crop varieties within India, June–September broadly captures the primary growing season for all five crops [31, 32]. Yields in the VDSA data are reported as the ratio of production to harvested area. In some districts and years, reported irrigated areas exceeded harvested areas, indicating that harvested areas could be smaller than planted areas for which data is unavailable.

District-level soil type data are also obtained from ICRISAT-VDSA (http://data.icrisat.org/dld/src/crops.html) [30]. Each district is characterized by at least one of three soil types: a primary, secondary, and tertiary, representing the highest to lowest percentage in that district. We focus on seven soil types categorized according to the USDA soil taxonomy—Alfisols, Alfisols-Mollisols-Mix, Alfisols-Inceptisols-Mix, Vertisols, Aridisols, Inceptisols, and Entisols.

2.2. Climate data

For ENSO, we use the Niño3.4 index that captures sea surface temperatures (SST) in the central equatorial Pacific. Niño3.4 SSTs are closely related to Indian monsoon variability [26]. For IOD, we use the Dipole Mode Index (DMI), a measure of the difference in SSTs between the western and eastern Indian Ocean regions [33]. Niño3.4 index and DMI timeseries are obtained from NOAA Earth System Research Laboratory Physical Sciences Division (https://psl.noaa.gov/gcos_wgsp/Timeseries/) [34–37].

Daily gridded rainfall dataset is from the Indian Meteorological Department (0.25° × 0.25°; 1968–2015) (https://www.imdpune.gov.in/cmpg/Griddata/Rainfall_25_NetCDF.html) [38, 39] and monthly maximum temperature dataset is from Climatic Research Unit, CRU TS4.06 (0.5° × 0.5°; 1968–2015) (https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.06/cruts.2205201912.v4.06/) [40]. We select these datasets for their high spatial resolution and the length of the record overlapping with agricultural data (1968–2015).

2.3. Calculating anomalies

Following Iizumi *et al* [41], we remove the 5-year moving averages from the seasonal values of each production metric at the district-level to account for long-term trends driven by advances in technology, management, and other external factors. The choice of the moving average window influences the trend estimate and the number of datapoints in our timeseries; a longer window would reduce the number of years for analysis [41]. These detrended values, referred to as absolute seasonal anomalies, represent interannual variations likely associated with interannual climate variations rather than long-term trends. Percent anomalies of production metrics are calculated as the ratio of seasonal anomalies to their respective 5-year moving averages. We limit our analysis to districts with at least 40 years of data to avoid spurious anomalies due to small sample sizes.

We linearly detrend and standardize the JJAS Niño3.4 Index, DMI, and the total seasonal rainfall and average seasonal maximum temperature by subtracting the climatological (1981–2010) mean and dividing by the standard deviation [42, 43]. We define El Niño/La Niña and IOD$^+$/IOD$^-$ years based on the standardized indices exceeding ± 0.5 standard deviations (σ) (table S1 in the supplementary material).

2.4. Quantifying the influence of climate modes on crop production metrics and climate anomalies

To compare the influence of ENSO and IOD phases at the national-aggregate level, we calculate weighted averages of anomalies of each production metric across all districts growing each crop. This approach ensures that districts with more cropland or higher production contribute proportionally more to the overall national-average anomalies. We also examine the spatial patterns of crop production metric anomalies and climate anomalies using composite maps during six conditions: (a) El Niño, (b) La Niña, (c) IOD$^+$, (d) IOD$^-$, (e) co-occurring El Niño and IOD$^+$, and (f) co-occurring La Niña and IOD$^-$. Co-occurrences of El Niño and IOD$^-$ (2004) and La Niña and IOD$^+$ (2008 and 2011) are rare and excluded from the analysis. The fraction of districts experiencing local deficits (anomalies <0) or excesses (anomalies >0) in each production metric are calculated.

Production impacts aggregated to the national-level reflect multiple factors, including different climate conditions across various districts in India and their relative sensitivity to climate anomalies. To evaluate the relative sensitivity of different pairs of crops, we compare production metrics under similar climate conditions and only in overlapping rainfed districts growing both crops. We only consider rainfed districts for this comparison as irrigation can buffer climate impacts. Rainfed districts are identified based on the proportion of irrigated to harvested areas being below 0.5 for each crop. Rice is the most irrigated crop across districts, while other crops are mostly rainfed (figure S1). This threshold of 0.5 is somewhat arbitrary but ensures a sufficiently large number of rainfed districts growing both rice and alternative grains. We note that production metrics are available at the district-level. Within-district variations in climate conditions, soil types, and topographic effects could also affect the relative sensitivity that we are unable to assess here.

3. Results

3.1. Historical trends in production metrics

The Indian agricultural landscape has changed since the start of the Green revolution in the 1960s. Figure 1 shows trends in production, harvested area, irrigated area, and overall yield for the five grains grown during the Indian monsoon season, India's primary growing

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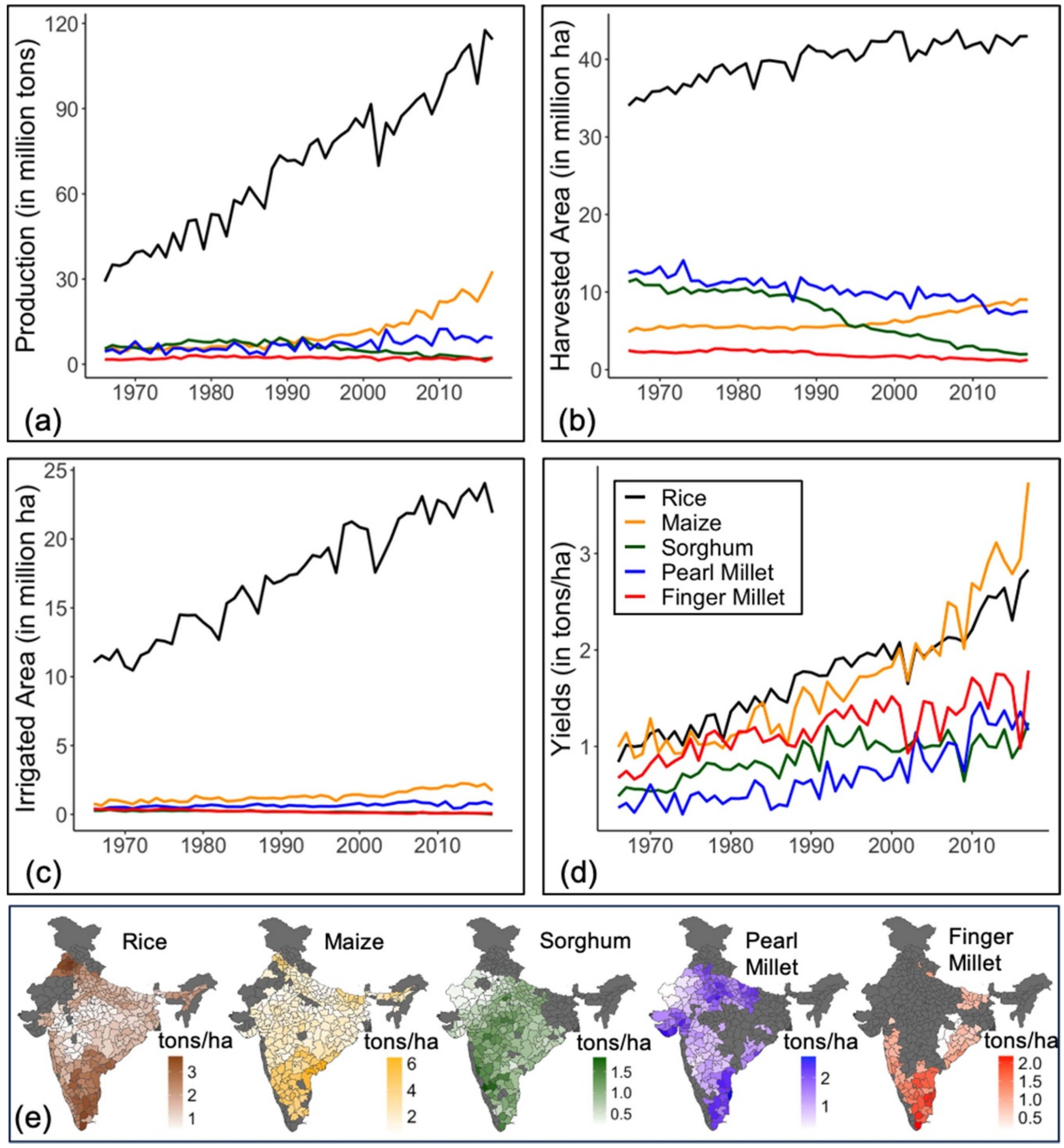

Figure 1. Varying trends in production and harvested area of rice, maize and traditional grains despite increases in yields: timeseries (1966–2017) of (a) production (million tons), (b) harvested area (million hectares), (c) irrigated area (million hectares), (d) area-weighted yields (tons/hectare) for five cereals grown in India during the monsoon season, and (e) district maps of average crop yields from 1966–2017. Grey districts indicate districts with <40 years of yield data.

season. Rice has remained the dominant grain and its production quadrupled, harvested area increased, and irrigated area more than doubled since the 1960s (figures 1(a)–(c)). Rice yields more than doubled (figure 1(d)) through increased fertilizer use and irrigation expansion during the Green Revolution. Maize yields also doubled over this period, surpassing rice yields in the early 2000s, through improvements in technology and agronomic practices to meet the growing demand as food and feed for livestock [44]. Yields of millets and sorghum are substantially lower than that of rice and maize and have increased at a substantially slower pace, reflecting a shift towards prioritization of the cultivation of rice and maize and a shift in diets away from traditional, nutrient-dense grains (figure 1(d)). This is also reflected in the decline in production and harvested area of sorghum and finger millet production since the 1960s (figures 1(a) and (b)). Rice yields are typically highest in the Indian breadbasket region of Punjab, while maize yields are the highest in southeastern India (figure 1(e)). Sorghum yields are highest in the arid and semi-arid parts of central and peninsular India (figure 1(e)). The highest pearl millet yields are found in western and southeastern India and the Indo-Gangetic plains, while finger millets thrive in the southern peninsular regions (figure 1(e)).

3.2. Influence of ENSO and IOD on nationally-aggregated production metrics of kharif grains

Interannual variability in total kharif production, harvested area, irrigated area, and yields of all five grains are associated with ENSO and IOD-driven

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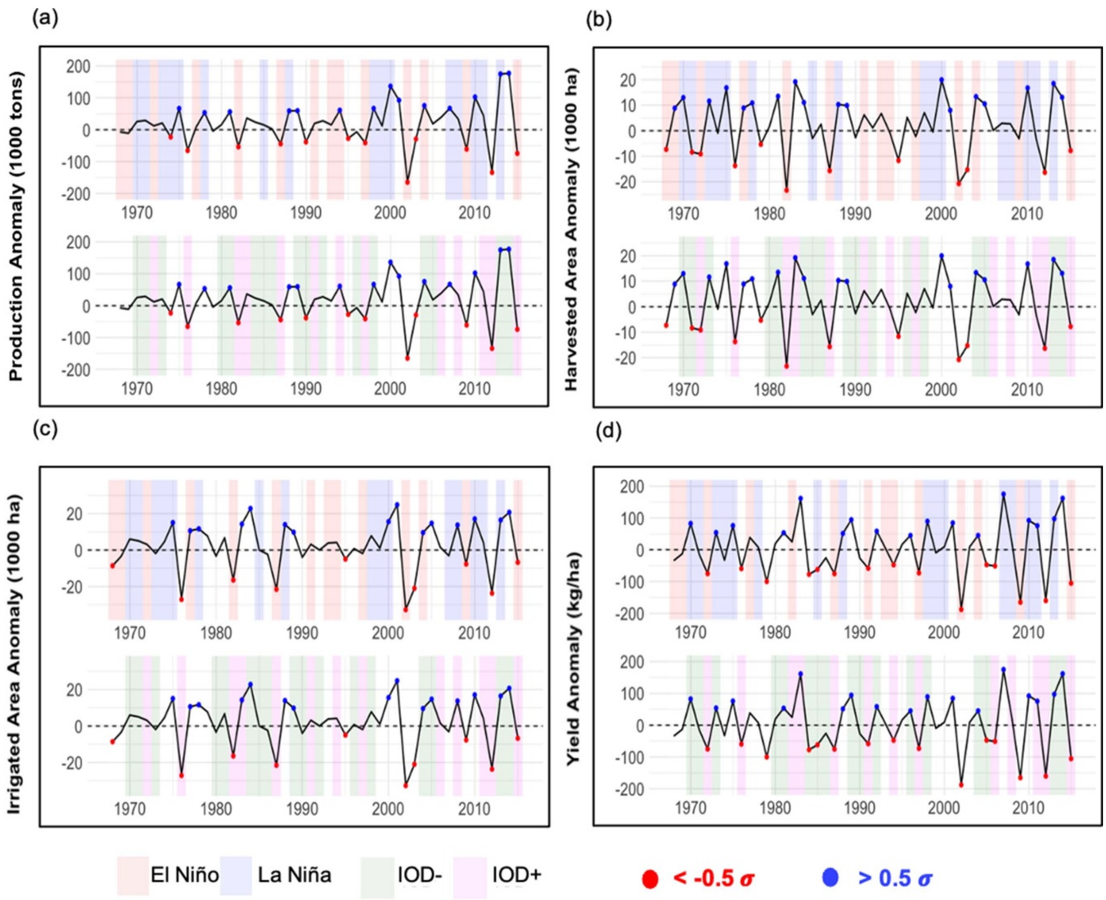

(e) Mode Phase (number of years)	Production decline/increase	Harvested Area decline/increase	Irrigated Area decline/increase	Yield decline/increase
El Niño (14)	6/2	6/3	6/2	8/1
La Niña (16)	1/8	1/8	0/7	1/9
IOD$^+$ (13)	6/1	6/1	5/2	9/2
IOD$^-$ (17)	1/6	1/9	0/6	3/10

Figure 2. El Niño decreases national-average crop yields: Weighted average district-level anomalies of kharif (a) production (1000 tons), (b) harvested area (1000 ha), (c) irrigated area (1000 ha), and (d) yields (kg/hectares) during opposite phases of each mode. The red (blue) dots indicate declines (increases) of $<-0.5\sigma$ ($>0.5\sigma$) in each characteristic. (e) Number of years with declines ($<-0.5\sigma$) in red (increases $>0.5\sigma$ in blue) during each mode phase. Numbers in brackets in the first column indicate numbers of years with each phase.

climate fluctuations (figure 2). We use standardized anomalies to evaluate the extent of interannual variations in these production metrics [45]. We find that El Niños are most strongly associated with declines in harvested area, irrigated area, and yield (figures 2(b)–(d)). For instance, 8 of the 14 El Niño years between 1966 and 2017 coincide with negative yield anomalies exceeding -0.5σ. A majority of years with reduced ($<-0.5\sigma$) production (6 of 12), harvested area (6 of 12), irrigated area (6 of 10), and yields (8 of 15) occur during El Niño years. Alternatively, La Niñas are typically associated with average or higher than average production, harvested area, irrigated area, and yields (figure 2(e)). Notably, half of the La Niña years have higher than average ($>0.5\sigma$) total production.

Similarly, IOD also influences national-level production metrics (figure 2). IOD$^+$ years are more often associated with below average harvested area, irrigated area, and yields. However, there are an equal number of years with declines and increases in production. In contrast, IOD$^-$ years are largely associated with increases in all production metrics. It is also notable that the magnitude and frequency of yield declines during El Niño and IOD$^+$ years are higher than the increases during La Niña or IOD$^-$. For instance, yield declines during three recent El Niño years—2002, 2009, and 2015—exceeded 100 kg ha^{-1} whereas yield increases during only one La Niña year—2007 exceeded 100 kg ha^{-1} (figure 2(d)). Declines in these production metrics during El Niño or IOD$^+$ years highlight the risk of

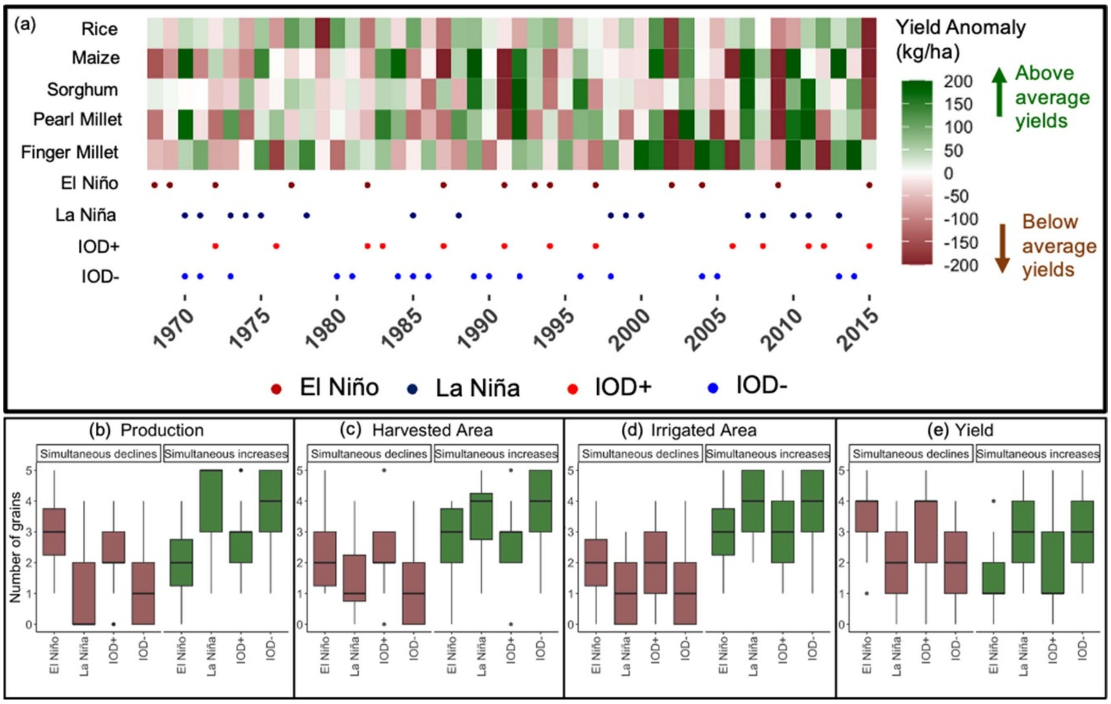

Figure 3. Simultaneous declines in multiple crops and grains likely to reduce during El Niño and positive IOD events: (a) weighted seasonal yield anomalies for each crop. Dots in panel (a) indicate occurrences of each mode phase. Number of grains with simultaneous declines (anomalies <0; brown) and increases (anomalies >0; green) in absolute (b) production, (c) harvested area, (d) irrigated area, and (e) yield during ENSO and IOD phases.

food shortages and insecurity, while increases during La Niña or IOD$^-$ years might not effectively compensate for shortages.

El Niño or IOD$^+$ conditions reduce the yields of multiple grains simultaneously (figures 3 and S2). For instance, 10 of 14 El Niño years and 9 of 13 IOD$^+$ years experience simultaneous reductions in the yields of three or more grains (figure 3(a)). During El Niño or IOD$^+$ years, a median of four grains experience simultaneously reduced yields, whereas a median of two grains experience reduced yields during La Niña or IOD$^-$ years (figure 3(e)). For instance, rice, maize, sorghum and pearl millets experienced markedly reduced yields during the strong 2015 El Niño. Conversely, during La Niña or IOD$^-$ years, a median of three grains experience simultaneously higher yields (figure 3(e)). These results indicate that El Niño or IOD$^+$ events have a relatively stronger and consistent negative impact on the yields of multiple grains than La Niña or IOD$^-$ events. In contrast, La Niña or IOD$^-$ events are more consistently associated with higher production, harvested, and irrigated area of multiple crops than the corresponding declines during El Niño or IOD$^+$ years (figures 3(b)–(d)).

Compared to yields, production, harvested area, and irrigated area (figures 3(b)–(d)) are more likely to experience simultaneous increases than declines during ENSO and IOD events. This suggests that adverse climate conditions are less likely to negatively affect these production characteristics of multiple crops simultaneously and that farmers might adopt strategies to minimize production losses during conditions that are likely to negatively impact yields of multiple crops. For instance, during El Niño years, there is a higher likelihood of simultaneous declines in yields and production than increases but more crops are likely to experience simultaneous increases in harvested and irrigated area. This could indicate that farmers increase the area they plant and irrigate in anticipation of El Niño. Since El Niños often bode weaker monsoons in India, early warnings and interventions are often in place to help farmers mitigate these impacts [46]. Farmers might employ strategies to mitigate the negative impacts of weaker monsoonal rains, such as adjusting sowing times and spacing, adopting new sowing techniques, implementing soil conservation measures, and improving pest, water, and livestock management. They also shift to climate-ready crop varieties, change crop systems, relocate agricultural fields, and modify policy structures [46]. During La Niña and IOD$^-$ conditions, a combination of higher yields and more harvested and irrigated area for multiple crops likely contributes to greater increases in overall production of multiple crops (figure 3). This explains why we see more simultaneous increases in production than in yields (figures (b) and (e)). It is also possible that yields are more directly sensitive to climate conditions, while anticipated production losses can be mitigated by adjusting planted or irrigated area.

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The magnitude of impacts of ENSO and IOD events vary by crop and also vary depending on whether we evaluate absolute anomalies in various metrics or percent anomalies relative to their averages because of the substantial differences in average production metrics of these crops. In absolute and percent terms, we observe that the median nationally-aggregated production, harvested area, and yield declines are largest for pearl millets and maize during El Niño (figure S3). During La Niña and IOD$^-$ years, pearl millets experience the largest absolute increases in harvested areas while rice experiences the largest increases in production, and finger millets experience the largest increase in yields. We also find that percent anomalies in production metrics of traditional grains during all ENSO and IOD phases experiences larger variations than that of rice and maize.

Overall, the findings suggest that at the nationally-aggregated level, the production metrics of traditional grains such as pearl millet experience larger fluctutations relative to rice in response to ENSO and IOD. Rice is the main irrigated crop across many districts (figure S1) while other grains have limited irrigation (figure S4), highlighting the importance of irrigation in buffering crop production from climate variations. Further, the potential for multiple grains to be negatively impacted simultaneously underscores the agricultural risks posed by natural climate variations.

3.3. Spatial differences in production metrics and climate anomalies during ENSO and IOD events

The impacts of ENSO and IOD exhibit substantial heterogeneity across districts likely associated with differences in soil types, climate conditions, topography, and management practices such as irrigation, pesticide and fertilizer application. To examine these spatial variations, we analyze district-level anomalies in production metrics during El Niño and IOD$^+$ events, as these phases demonstrate the most substantial negative impacts (figures 4, S5–8). An understanding of the geographical variations in impacts can help identify the grains and districts most likely to be affected to inform planning, preparedness, and agricultural decision-making.

Figure 4 shows the spatial variations in yield impacts of all five grains. El Niño events result in the largest and most widespread yield reductions for maize in the climatological drier northwestern, eastern, and semi-arid peninsular regions of India, where several districts experience negative anomalies exceeding 200 kg ha^{-1} (figure 4(d)). Approximately 80.7% of maize-producing districts experience decreases in maize yields during El Niño (table 1). The most substantial yield reductions occur in districts that experience anomalously drier and hotter conditions linked to El Niño events (figure 5(a)–(b)) that can lead to water stress and soil moisture deficits associated with reduced photosynthesis, stunted growth, and lower crop yields [47]. Over 61% of maize-producing districts are associated with hot conditions and dry conditions during El Niño (figure 5(c)). Similarly, 70.4% of the rice-growing districts show declines in rice yields during El Niño conditions (table 1), with the largest reductions in arid and semi-arid districts (figure 4(a)). Most districts in the Indo-Gangetic basin and southeastern India show limited impacts for most crops during El Niño (figure 4), likely because of the high rates of irrigation in those regions that can minimize rainfall deficits.

Previous research suggests that sorghum and millets demonstrate greater tolerance to hot and dry conditions [48]. Our results support this finding — figure 4 shows that the magnitude of absolute yield anomalies for these traditional rainfed grains is similar to or lower than that for irrigated crops like rice and maize in arid and semi-arid regions during El Niños. However, a higher percentage of districts cultivating traditional grains experience yield reductions compared to rice districts during El Niños (table 1). Specifically, 85.6% of sorghum districts, 79.3% of pearl millet districts, and 73.1% of finger millet districts experience yield reductions (table 1). The largest declines in sorghum and finger millet yields occur in districts in peninsular India (figure 4(g) and (m)), while the largest declines in pearl millet yields are in northwestern India (figure 4(j)). The relatively smaller fraction of districts affected for finger millet could be because it is well-suited for cultivation in the cooler, hilly regions of the western and eastern ghats, where it could benefit from anomalously warm conditions (figure 5(b)). In addition, millets in the southernmost part of India experience yield increases rather than declines during El Niños and IOD. Overall, these results suggest that while the magnitude of yield reductions are typically smaller for traditional grains relative to rice and maize, El Niño could adversely affect a larger fraction of districts growing traditional grains.

During El Niño events, maize also sees the largest number of districts with production (79.8% districts), harvested area (69.8% districts), and yield (80.7% districts) declines (table 1). The most substantial absolute reductions in production (>50,000 tons) and harvested area (>20,000 ha) are seen for rice in East India and pearl millet in arid regions (figures S7 and S8), where they are primarily cultivated. The absolute reductions in production and harvested area for sorghum and finger millet are not as substantial as those for other grains. Maize, on the other hand, experiences widespread but relatively small reductions in both production (∼79.8% of districts) and harvested areas (∼69.8% of districts) (table 1, figures S7 and S8).

Relative to El Niño, IOD$^+$ events affect fewer districts. The absolute yield anomalies during IOD$^+$

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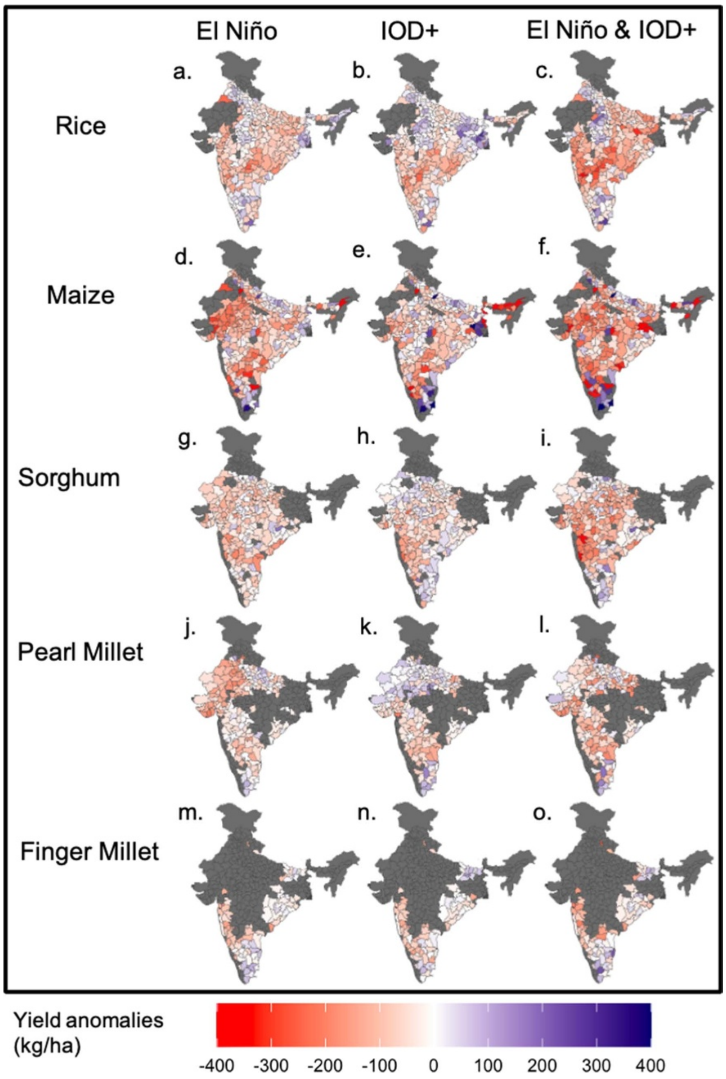

Figure 4. Spatial differences in yield impact anomalies during El Niño and positive IOD+ events: composite maps of yield anomalies for each crop (a–c) rice, (d–f) maize, (g–i) sorghum, (j–l) pearl millet, and (m–o) finger millet during (left) El Niño, (center) positive IOD, and (right) co-occurring El Niño & positive IOD years.

Table 1. Percent districts with below average (anomalies <0) production, harvested area, and yield during each phase.

	Production			Harvested area			Yield		
% Districts with loss	El Niño	IOD$^+$	El Niño & IOD$^+$	El Niño	IOD$^+$	El Niño & IOD$^+$	El Niño	IOD$^+$	El Niño & IOD$^+$
Rice	74.5%	71.9%	79.8%	66.7%	70%	70.2%	70.4%	64.4%	78.6%
Maize	79.8%	79.4%	81.9%	69.8%	68.7%	73.3%	80.7%	73.7%	80.2%
Sorghum	75.6%	78.1%	83.6%	60.7%	68.2%	68.2%	85.6%	69.7%	80.1%
Pearl millet	81.1%	67.7%	84.8%	70.1%	71.3%	72%	79.3%	62.8%	76.8%
Finger millet	82.1%	88.5%	85.9%	59%	67.9%	75.6%	73.1%	70.5%	71.8%

events show a dipole pattern across several grains, particularly for rice, sorghum, and pearl millet (figure 4). Districts across the Indo-Gangetic basin observe yield increases due to relatively wetter and cooler conditions (figures 4 and 5), while districts in the southern semi-arid regions that experience drier and hotter conditions observe yield reductions (figures 4 and 5). Over at least 62% of grain-producing districts are affected by negative yields in IOD$^+$ years (table 1). During IOD$^+$, pearl millet has the smallest percent of districts with production (67.7%) and yield (62.8%) declines and finger millet has the smallest percent of districts with harvested area (67.9%) declines compared to other grains (table 1). During IOD$^+$ events, there is an average reduction of ~100,000 tons in the absolute rice production in the eastern districts, which are the primary rice-producing regions (figure S7). IOD$^+$ events are also associated with reduction in the absolute harvested areas of over 10,000 ha for rice in the eastern districts,

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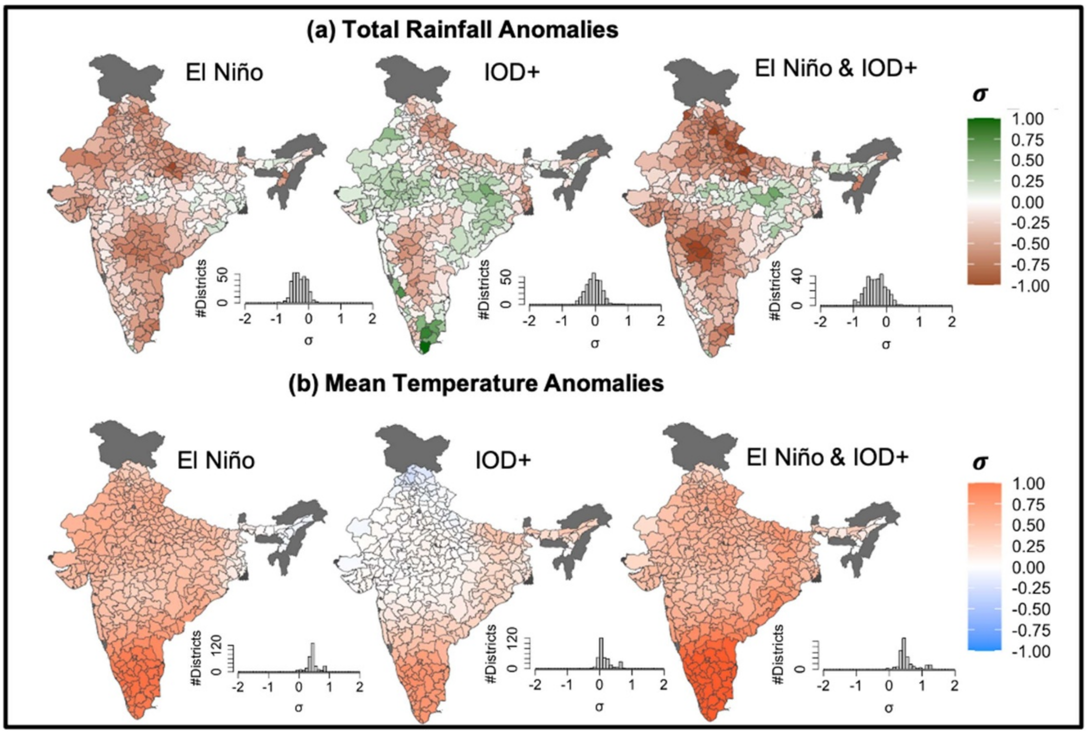

(c) Fraction of districts experiencing Dry and Hot conditions

Phase / Crop	El Niño: Dry conditions (rain anomaly < 0)	El Niño: Hot conditions (tmax anomaly > 0)	IOD+: Dry conditions (rain anomaly < 0)	IOD+: Hot conditions (tmax anomaly > 0)	El Niño & IOD+: Dry conditions (rain anomaly < 0)	El Niño & IOD+: Hot conditions (tmax anomaly > 0)
Rice	85.8%	91.8%	44.2%	55.8%	80.1%	97.7%
Maize	61.6%	62.3%	36.7%	46.9%	74.6%	97.7%
Sorghum	47.4%	83.0%	34.3%	57.1%	4.8%	98.8%
Pearl Millet	73.6%	78.0%	31.7%	65.0%	88.8%	100.0%
Finger Millet	64.9%	91.2%	43.9%	65.9%	74.0%	98.0%

Figure 5. Spatial patterns of climate conditions during El Niño and positive IOD+ events: composite maps of anomalies in (a) total seasonal rainfall, and (b) maximum temperature during El Niño, positive IOD, and co-occurring El Niño & positive IOD years. The inset histograms illustrate the number of districts experiencing dry or wet (panel a) and hot or cool (panel b) conditions. (c) Fraction of districts experiencing dry and hot conditions for each phase and crop.

and pearl millet in the arid regions where pearl millets are primarily cultivated (figure S8).

La Niña conditions are generally linked to wetter and cooler climates (figure S9), leading to a majority of districts experiencing increases in production metrics (table S2). During La Niña, finger millet sees the largest percent of districts with production (>75.6%) and yield (>79.5%) increases, while rice sees the largest percent of districts with harvested area (>63.7%) increases compared to other grains (table S2). Furthermore, while IOD$^-$ conditions tend to be associated with less wet and cool conditions compared to La Niña, they lead to smaller increases in production and yields but a larger percent of districts experience production and yield increases across all grains except finger millet (table S2, figure S5). IOD$^-$ conditions are associated with smaller increases in rice and pearl millet production and harvested area compared to La Niña, in the primary regions growing those grains (figures S7–S8). Yield anomalies during IOD$^-$ show similar spatial patterns to La Niña (figure S5).

In addition to absolute yield anomalies, we also consider percent yield anomalies to compare the relative impact of climate variability on each crop's expected yield, independent of baseline production levels. While the absolute yield declines in traditional grains across their primary growing districts are modest, the relative yield declines are more pronounced in these districts during ENSO and IOD phases (figures 4 and S6). Maize and rice experience the most widespread reductions, with ∼72% of districts seeing percent yield declines during El Niño (figure S6 and table S3). Sorghum and pearl millet percent yield declines are comparable to maize percent yield declines in the northwest, with about 20% reduction during El Niño (figure S6). During IOD$^+$ events, more districts experience percent yield

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declines in pearl millet (∼63.4% of districts) and finger millet (∼79.5% of districts), primarily in the southern peninsular region (table S3). Rice, pearl and finger millet experience the most widespread increases in percent yields, with more than 64% of districts experiencing yield increases during La Niña and IOD^-(table S3). All crops experience declines and increases in percent yield in similar regions and roughly to the same magnitude during ENSO and IOD events (figure S6).

3.4. Influence of co-occurring ENSO and IOD events

Since El Niño and IOD^+ events individually have substantial negative impacts on most production metrics studied here (figure 4), and their co-occurrences are increasing [16], we examine the influence of their co-occurrences on all production metrics. In our study period, there are 7 co-occurring El Niño and IOD^+ years and 6 co-occurring La Niña and IOD^- years (table S1). Most co-occurring El Niño and IOD^+ years are associated with overall yield declines except 1982, with the greatest yield declines (>80 kg ha^{-1}) in 1972, 1987, 1997, and 2015 (figure S10(d)). Most co-occurring El Niño and IOD^+ years are also associated with declines in other production metrics (figure S10(a)–(c)). For instance, overall production declined by 15,000 tons in 1982, 1987, 1997, and 2015 (figure S10(a)) and harvested and irrigated areas declined by 10,000 ha in 1982 and 1987 (figure S10(b)–(c)). In contrast, all co-occurring La Niña and IOD^- years are associated with increases in absolute overall production (>15,000 tons) (figure S10(a)). Most co-occurring La Niña and IOD^- years are also associated with increases in harvested areas and yields (except 1971 and 1985) (figure S10 (b) and (d)).

Co-occurring El Niño and IOD^+ years lead to more severe and widespread reductions in absolute production and harvested area for all grains except finger millet, relative to the impacts during individual events (figures S7–8 and table 1). This is likely because co-occurring El Niño and IOD^+ conditions are associated with stronger drier and hotter conditions in the Indo-Gangetic and peninsular India, and stronger wetter and hotter conditions in central and eastern India than during the occurrences of the individual modes (figure 5(a)–(b)). These intensified conditions result in larger reductions in rice yields and production compared to traditional grains (figures 4 and S7) and also affect the harvested areas of rice and pearl millet (figure S8). During co-occurring El Niño and IOD^+ years, over 71% of districts experience reductions in absolute production and yields for all grains (table 1). However, during co-occurring El Niño and IOD+ years, absolute yield reductions are more severe but less widespread for most grains except rice, while percent yield declines for rice, maize, and pearl millet are more widespread compared to the impacts observed during El Niño alone (figure 4 and table 1). Similarly, co-occurring La Niña and IOD^- years are associated with stronger but less widespread increases in absolute and relative production metrics for most grains corresponding to the stronger wetter and more widespread cooler conditions across India than individual La Niña and IOD^- years (figures S5–9 and tables S2–3). All crops show similar regional patterns and magnitudes of percent yield changes during co-occurring ENSO and IOD events (figure S6).

3.5. Relative sensitivity of grains to ENSO and IOD in rainfed areas

To understand the spatial patterns of crop impacts under similar climate conditions and their relative differences among crops, we analyze the sensitivity of alternative grains to rice, the dominant kharif grain in India, during ENSO and IOD events in predominantly rainfed districts. We find that there is greater yield variability during ENSO and IOD conditions in rainfed districts than irrigated districts (figure S4). This greater variability indicates that rainfed districts are more susceptible to the erratic nature of ENSO and IOD events. Therefore, we compare the sensitivity of maize, sorghum, pearl millet, and finger millet relative to rice, during individual ENSO and IOD phases in overlapping rainfed districts where both rice and the alternative grains are grown (figure 6). This approach allows us to discern the impacts on production metrics of different crops under similar rainfall and temperature conditions. We define sensitivity as the median anomaly in production metrics influenced by natural climate variations associated with ENSO and IOD. We focus the discussion here on the sensitivity to ENSO but figures 6 and S11 also show the sensitivity to IOD.

In predominantly rainfed districts that grow both rice and maize, the median negative production and yield anomalies of maize are larger than rice during El Niño conditions (figure 6). We find similar results comparing the median production and yield anomalies of rice and pearl millets in overlapping districts, suggesting that maize and pearl millets have higher sensitivity than rice. In contrast, comparing the median production and harvested area anomalies of rice and sorghum and rice and finger millets in overlapping districts, suggests that sorghum has lower sensitivity than rice and finger millets are equally or less sensitive than rice (figures 6(a)–(c)). Contrastingly, during La Niñas, the median rice production and yield increases surpass those of other grains. These findings remain consistent even when evaluating sensitivity in terms of percent median anomalies in production and harvested areas. However, median percent production, harvested area, and yields of sorghum and finger millet surpass rice in overlapping rainfed districts during El Niño. This implies that, given the lower climate sensitivity of

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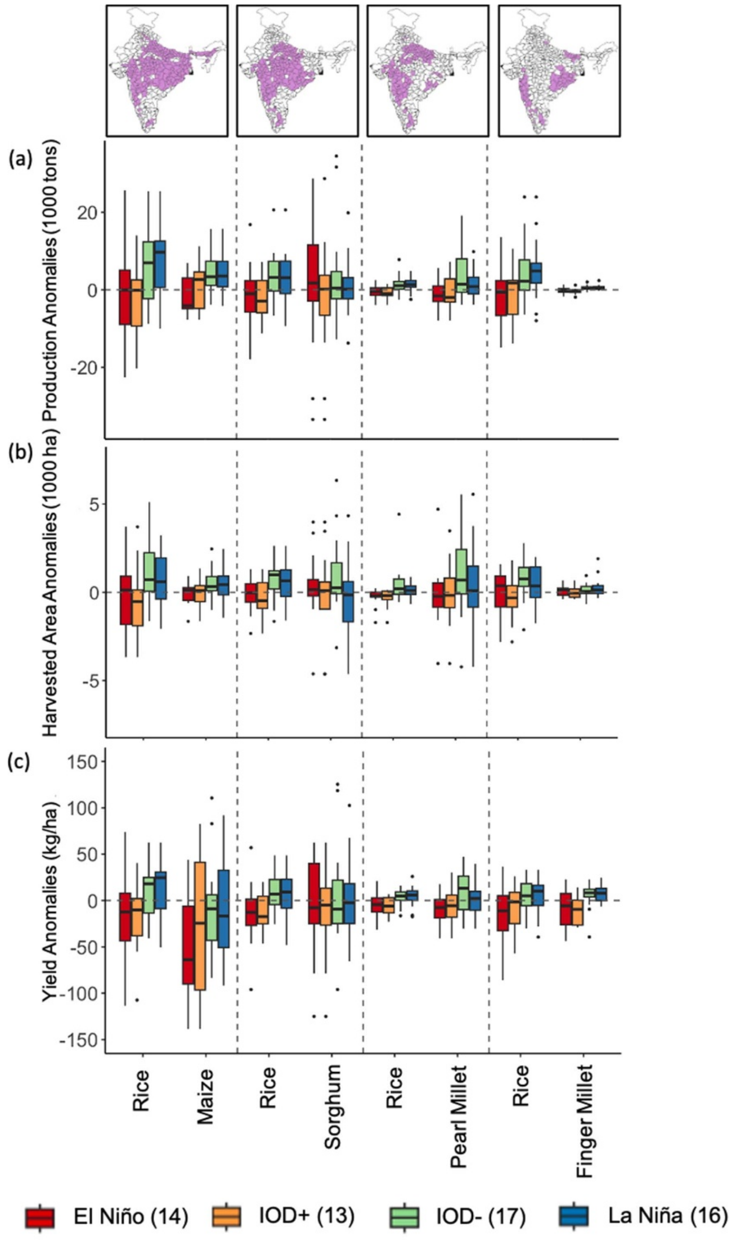

Figure 6. Comparison of the sensitivity of alternative grains to climate variability relative to rice: boxplots of absolute anomalies for (a) production, (b) harvested area, and (c) yield for rice and each alternative grain during ENSO and IOD phases in overlapping rainfed districts. For instance, the first set of boxplots represent weighted anomalies for rice and maize only in the subset of districts growing both grains. The corresponding inset maps show overlapping rainfed districts for rice and the alternative grain in purple. Vertical lines separate boxplots for each pair of grains. *Note:* rainfed districts are defined as districts with irrigated area fraction of harvested areas below 50%.

sorghum and finger millet compared to rice, shifting investments from rice cultivation to sorghum and finger millet could reduce the sensitivity of grain production to natural climate fluctuations.

4. Discussion

Our analysis examines the influence of ENSO, IOD and their co-occurrences on four production metrics—yields, production, harvested areas, and irrigated areas—for five key monsoon cereals across India and their geographic variations. Our key findings are [1] El Niño and IOD$^+$ are associated with reductions in national-level yield, production, harvested area, and irrigated area of kharif grains, whereas La Niñas and IOD$^-$ are associated with increases; [2] El Niño and IOD$^+$ simultaneously reduce yields for a median of four grains while La Niña and IOD- simultaneously enhance yields for a median of three grains; [3] co-occurring El Niño and IOD$^+$ years are associated with stronger and more widespread reductions in rice yields than alternative grains compared to the impacts of individual El Niño and IOD$^+$ events; and [4] Compared to rice, maize and pearl millet production and yields have higher sensitivity to

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similar climate variations, while sorghum and finger millet have lower sensitivity to El Niños than rice.

Through this analysis, we make several unique contributions to the literature. *First*, we document the effects of ENSO and IOD on relatively understudied characteristics such as harvested and irrigated areas, providing a more comprehensive understanding of grain production dynamics. *Second*, we assess the spatial pattern of production metrics to gain insights into the geographical distribution of impacts and identify specific sub-regions and grains that are the most and least sensitive to ENSO and IOD-driven climate variations. Such spatial information can help agricultural planners and farmers prioritize and tailor interventions to mitigate climate-related risks for specific grains in specific regions. *Third*, we characterize the yield response of the 5 grains to individual and co-occurring ENSO and IOD events, which has not yet been done. *Lastly*, we compare the sensitivity of traditional grains relative to rice to evaluate their resilience to natural climate variations, which can inform recent efforts to incentivize the production and consumption of these nutrious cereals.

Our results are consistent with Bhatla *et al* [25] and Pandey *et al* [49], who found declines in rice and maize production during El Niño events in parts of the Indo-Gangetic basin, and Cherian *et al* [50], who found that El Niño events reduce rice production in Karnataka (peninsular India) due to below-normal rainfall. Our finding that $\sim$81% of maize-producing districts experience yield reductions during El Niño and co-occurring El Niño & IOD$^+$ years helps contextualize the results of Anderson *et al* [17], which shows that ENSO accounts for 25% of maize production variability in India. Consistent with Davis *et al* [28], we find that sorghum and finger millet are less sensitive to climate variations compared to rice. Differences between our studies arise because our analysis examines the average impacts from large-scale climate fluctuations driven by ENSO and IOD while Davis *et al* [28] define sensitivity to the locally hottest and driest years. Furthermore, consistent with our finding, Heino *et al* [23] show that irrigation has reduced the effects of natural climate variability on global yields of several crops.

We note a few caveats of this study. Although we used the longest available dataset of crop data (1966–2017), the relatively short time period limits the sample size of ENSO and IOD events. Additionally, we define predominantly rainfed areas as districts with the proportion of irrigated to harvested areas $<$0.5, which is an arbitrary threshold aiming to capture a sufficient number of rainfed districts growing both rice and alternative grains for the sensitivity analysis. However, the rainfed versus irrigated yields and production of each grain are not explicitly available, limiting our ability to characterize the effect of irrigation. Finally, we use district-level climate and yield data, which may not capture finer-scale variations in temperature and precipitation within a district, limiting the accuracy of climate-crop production relationships.

Overall, our study provides geographically explicit information on how key cereals are affected by two key modes of natural climate variability that are a source of seasonal predictability [51, 52]. This knowledge can inform short-term planting decisions and management interventions to minimize negative impacts on agricultural production and farmer livelihoods when ENSO or IOD events are forecast. Studies have indicated that ENSO events can affect how forecasts influence farmer decision making. For instance, Maggio and Sitko [53] found that seasonal forecast information could influence farmers' adaptive practices in response to forecasted drought. However, Guido *et al* [54] highlighted the challenges farmers face when forming expectations about upcoming seasonal rainfall, particularly when these expectations are disconnected with observed trends in climate data. These studies emphasize the significance of providing local climate information to empower farmers to make well-informed agricultural decisions. Reducing sensitivity of agricultural production to such known climate variations can help better prepare for and minimize food security risks from climate variability and change.

Data and materials availability

The crop and soil data, climate data, and climate variability indices used in this study are available for download at http://data.icrisat.org/dld/src/crops.html; https://www.imdpune.gov.in/cmpg/Griddata/Rainfall_25_NetCDF.html; https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.06/cruts.2205201912.v4.06/, https://psl.noaa.gov/gcos_wgsp/Timeseries/. The source code used to perform the analyses and generate the publication figures can be accessed at a dedicated GitHub repository maintained by the corresponding author: https://github.com/madhulikag/climatevariability_monsooncrops_india. All data necessary to evaluate the conclusions of this study are provided within the paper and/or in the Supplementary Materials. The data supporting the findings of this study are openly available at the following URL/DOI: https://github.com/madhulikag/climatevariability_monsooncrops_india.

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Conflict of interest

The authors declare that they have no competing interests.

Author contributions

All authors contributed to designing the research. M G conducted the analyses. M G and D S drafted the paper with feedback from all coauthors.

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