

Agricultural Hotspots in India: Evidence from Paddy, Wheat, and Millets

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Abstract

We analyze district-level seasonal yields of paddy, wheat, and millets across India (2010–2019) to identify yield hotspots (consistently high or rising) and coldspots (significant declines) using spatial clustering and regression. Coldspots yield roughly half of hotspots, driven by lower irrigation, fertilizer use, and access to crop-specific information via call centers. Hotspots cluster in northern and southern India; coldspots dominate western, eastern, and northeastern regions. Yield gaps average 2.0 t ha⁻¹ (paddy), 2.4 t ha⁻¹ (wheat), and 1.0 t ha⁻¹ (millets). Regressions link a 1% rise in irrigation coverage or call center queries, and 1 kg ha⁻¹ fertilizer, to yield gains of 7, 6, and 0.5 kg ha⁻¹, respectively. For instance, closing the gap in Darbhanga district (Bihar) could boost household revenues by 148% (paddy) and 79% (wheat).

Keywords: Agricultural inputs, Digital agriculture, Food Grains, Seasonal crop yields, Weather deviations, Yield hotspots

JEL codes: O13, O47, R11, Q18

1. Introduction

Spatial clusters favorable to crop cultivation drive agrarian intensification and economic development (Zimmerer, 2013; Zabel et al., 2019). As a spatial industry (Marasteanu and Jaenicke, 2016), agriculture exhibits regional yield disparities shaped by weather patterns and input applications (Sesmero et al., 2019; Niyogi et al., 2010). Farm management hinges on technology adoption and information (Krishnan and Patnam, 2014; Maertens, 2017; Gupta et al., 2024; Pramanik, 2026), alongside agroclimatic factors, cropping practices, policies, and knowledge networks (Foster and Rosenzweig, 1995; Binswanger-Mkhize and Savastano, 2017).

In India, crop yields vary by season and region. We examine district-level seasonal yields for major food grains—paddy, wheat, and millets (Sorghum, Pearl millet, Finger millet, Little millet) (Nagaraj et al., 2013; Gowri and Shivakumar, 2020)—from 2010–2019. Spatial yield clusters differ by crop and season, with hotspots economically vital for small holder-driven rural growth and food security, where yield gains boost farm income and non-farm sectors.

Policymakers need hotspot (top-20th percentile in 2010–14 or 2015–19, or significant gains vs. national averages) and coldspot (significant declines vs. national averages) locations, plus influencing factors. We address: (1) Where are district-level seasonal yield hot/coldspots? (2) How do weather and inputs shape them?

We hypothesize hotspots form in high-input systems. Analysis maps spatial-temporal patterns against rainfall (and deviations), irrigation, fertilizer use, and farmers' (*Kisan*) call center (KCC) queries (Kalirajan, 1981; Goyari, 2014; Letta et al., 2022). Hotspot–coldspot gaps average 2.0 t

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ha⁻¹ (paddy), 2.4 t ha⁻¹ (wheat), and 1.0 t ha⁻¹ (millets). Hotspots cluster in Punjab, Haryana (north), Telangana, Andhra Pradesh, Karnataka, Tamil Nadu (south), and are emerging in Madhya Pradesh. Fixed-effects regressions confirm inputs and KCC engagement drive performance (Dayal, 1984). Bihar's districts lag despite inputs due to low KCC use, while Madhya Pradesh and Odisha improve via synergies. For instance, closing gaps in Darbhanga (Bihar) could raise revenues 148% (paddy) and 79% (wheat).

We highlight differences in cropping practices beyond agroclimatic conditions, stressing judicious use of information and inputs to improve productivity. This district-scale analysis of India's food grains offers unique insights for policy.

The paper proceeds as follows: Section 2 covers the literature and methods; Section 3, the data; Section 4, the results; Section 5, robustness; Section 6, the conclusion.

2. Literature Review and Empirical Methodology

In this section, we review literature on yield gaps and hotspot methods, positioning our study. We then outline our empirical strategy for identifying crop yield hot/coldspots and their drivers.

2.1. Related Literature on Yield Gaps and Hotspots

Identification India's diverse agriculture offers policy-relevant insights for developing nations (Fabregas et al., 2022). Southeast Asia and sub-Saharan Africa must boost grain yields for food security, reducing import reliance (Pasuquin et al., 2024; Yuan et al., 2022). Efficient nitrogen use cuts maize productivity in Indonesia, Philippines, and Vietnam, while rice yield gaps average 48% regionally. As a frontier economy, India can lead South/Southeast Asia via yield gains and tech sharing (Liu et al., 2020); Africa needs intensification and extensions (Corbeels et al., 2020; Jayne and Sanchez, 2021). Our India hotspots provide a baseline for data-scarce regions.

Hotspot analysis reveals spatial variations, identifying high/low zones via GIS and Local Moran's I (Shackelford et al., 2015; Marasteanu and Jaenicke, 2019). Applications span conservation, organics, yields (Karimi et al., 2015; Asseng et al., 2017), and crime/accidents (Mohler et al., 2020). Socio-economic studies add temporal ranking (Cheng and Washington, 2008; Gao et al., 2024; Van Wart et al., 2013).

Unlike prior work, we integrate spatial-temporal dimensions, percentile ranking, and significance tests to pinpoint sustained high-productivity or improving districts—plus coldspots/low-performers via yield changes. Using observed temporal data, we distinguish from GIS-only methods and add causal evidence via weather/inputs.

2.2. Hotspot identification

We identify hotspots (high-yield districts) via a two-criterion approach. Districts qualify if yields ≥ 80 th percentile in Period 1 (2010–14) or Period 2 (2015–19), or show significant gains vs. national averages (Period 1 to 2). Historical high-yielders have limited upside, so either criterion suffices. Coldspots show significant declines vs. national averages. Average yield difference vs. national average:

Average crop yield differences-

$$\overline{YieldDiff}_{(ds)crp_i} = \frac{1}{5} \sum_{y_{p_i}=1}^5 (Yield_{(ds)crp_i} - \frac{1}{5} \sum_{y_{p_i}=1}^5 \sum_{(ds)=1}^n Yield_{(ds)crp_i})$$

(1)

where,

$\overline{YieldDiff}$: Average yield difference; (ds) : District-State; c : crop; r : seasons; p_i : i^{th} period; y : Year sequence in a period (p_i); n : total number of districts (732, total number of districts in the analysis)

Two-sample Student's t-test- The test to compare district-level yield differences between periods p_1 (2010-2014) and p_2 (2015-2019) based on seasonal crop yield averages.

$$t_{(ds)cr} = \frac{\overline{YieldDiff}_{(ds)crp_1} - \overline{YieldDiff}_{(ds)crp_2}}{\sqrt{s_{(ds)cr}^2 \left(\frac{1}{m_1} + \frac{1}{m_2} \right)}} \quad (2)$$

$$s_{(ds)cr}^2 = \frac{\sum_{i=1}^{m_1} (YieldDiff_{(ds)crp_1} - \overline{YieldDiff}_{(ds)crp_1})^2 + \sum_{j=1}^{m_2} (YieldDiff_{(ds)crp_2} - \overline{YieldDiff}_{(ds)crp_2})^2}{m_1 + m_2 - 2}$$

where,

t : Student's t-statistic; s : Standard deviation; m_i : number of observations for crop yields in respective districts and corresponding period (p_i)

The weather deviation variables designed for the analysis include minimum temperature deviation ($minTD_{(ds)ry}$), maximum temperature deviation ($maxTD_{(ds)ry}$), and rainfall deviation ($RD_{(ds)ry}$). The equations are as follows.

$$minTD_{(ds)ry} = \begin{cases} 0 & \text{if } \frac{1}{20} \sum_{y=2000}^{2019} minT_{(ds)r} - 2\sigma(minT_{(ds)r}) \leq minT_{(ds)ry} \leq \frac{1}{20} \sum_{y=2000}^{2019} minT_{(ds)r} + 2\sigma(minT_{(ds)r}) \\ 1 & \text{otherwise} \end{cases}$$

$$maxTD_{(ds)ry} = \begin{cases} 0 & \text{if } \frac{1}{20} \sum_{y=2000}^{2019} maxT_{(ds)r} - 2\sigma(maxT_{(ds)r}) \leq maxT_{(ds)ry} \leq \frac{1}{20} \sum_{y=2000}^{2019} maxT_{(ds)r} + 2\sigma(maxT_{(ds)r}) \\ 1 & \text{otherwise} \end{cases}$$

$$RD_{(ds)ry} = \begin{cases} 0 & \text{if } \frac{1}{20} \sum_{y=2000}^{2019} R_{(ds)r} - 2\sigma(R_{(ds)r}) \leq R_{(ds)ry} \leq \frac{1}{20} \sum_{y=2000}^{2019} R_{(ds)r} + 2\sigma(R_{(ds)r}) \\ 1 & \text{otherwise} \end{cases}$$

where, $\sigma(minT_{(ds)r})$, $\sigma(maxT_{(ds)r})$ and $\sigma(R_{(ds)r})$ denote the standard deviations of minimum temperature, maximum temperature, and rainfall, respectively.

$$\overline{z - ScoreWD}_{(ds)} = \frac{1}{3} \sum_{w=1}^3 \frac{WD_{(ds)w} - \mu WD_{(ds)w}}{\sigma WD_{(ds)w}}$$

(3)

where (ds) is the district-state observation, w represents weather variables (maximum temperature, minimum temperature, and rainfall), WD denotes the number of deviations for each

weather variable for each district, μWD is the mean of weather deviation comprising all the districts, and σWD represents the standard deviation of weather deviation comprising all the districts.

2.3. Model determining factors influencing crop yield hotspots

Subsequently, we conduct a detailed empirical analysis to elucidate the determinants of the emergence of hotspots or positive yield deviations. We explore these relationships using a fixed-effect regression model. Rainfall is considered a vital biophysical factor among weather variables. First, we evaluate the relationships between the percentage of the gross irrigated area (GIA) and both observed rainfall and rainfall deviations (RD). Following this, we investigate the relationship between seasonal crop yield deviations and a set of influencing factors, including weather factors (observed and deviations), irrigation coverage, crop-specific KCC queries, and fertilizer consumption.

$$GIA_{(ds)cp} = \alpha + \beta_1 Rain_{(ds)rp} + \beta_2 RD_{(ds)rp} + \lambda_a + \eta_{ds} + \psi_r + \eta_{ds} \times \psi_r + \omega_c + \phi_p + \epsilon_{a(ds)cp} \quad (4)$$

$$\begin{aligned} YieldDiff_{(ds)cp} = & \\ & \alpha + \beta_1 Rain_{(ds)rp} + \beta_2 RD_{(ds)rp} + \beta_3 GIA_{(ds)cp} + \beta_4 NPK_{(ds)p} \\ & + \beta_5 Queries_{(ds)crp} + \gamma_1 X_{(ds)rp} + \gamma_2 Y_{(ds)rp} + \lambda_a + \eta_{ds} + \psi_r + \eta_{ds} \times \psi_r + \omega_c \\ & + \phi_p + \epsilon_{a(ds)cp} \end{aligned} \quad (5)$$

In equation (4), $GIA_{(ds)cp}$ represents the average percentage gross irrigated area in the district d , State s , crop c , and period p . The coefficients β_1 and β_2 capture the effect of changes in the percentage gross irrigated area related to average rainfall and total rainfall deviations.

Next, in equation (5), $YieldDiff_{(ds)cp}$ ($t\ ha^{-1}$) represents the seasonal yields of paddy in the district d , State s , crop c , and period p . The coefficients β_1 , β_2 , β_3 , β_4 and β_5 , capture the effect of changes in the average rainfall (mm.), total rainfall deviation (i.e., dummy variable, 0 or 1), gross irrigated area (%), fertilizer consumptions ($kg\ ha^{-1}$), and queries related to specific crops and seasons at KCC (%).

The variable $X_{(ds)rp}$ is a vector of other observed weather controls that capture average maximum and minimum temperatures ($^{\circ}C$) in the districts. The variable $Y_{(ds)rp}$ is a vector of other weather deviation controls for the district's maximum and minimum temperatures (i.e., dummy variables, 0 or 1). In both the regression equations above, the fixed effects of the region (λ_a), district-State (η_{ds}), season (ψ_r), crop (ω_c), and period (ϕ_p) are included in the analysis to account for the unobserved heterogeneity at these levels. These fixed effects are implemented as sets of indicator (dummy) variables. No observation weights are applied, and estimation proceeds without further transformations such as a within estimator. These categorical fixed effects absorb all time-invariant heterogeneity across regions, district-State, season, crop types, and periods. Consequently, any additional regressor constant within these dimensions (e.g., time-invariant soil characteristics varying only by district-State and region) is perfectly collinear with the dummies, automatically excluded from identification, and not reported in the results. Standard errors are clustered at the state-district level to address the potential correlation within the same district-State.

3. Data

In our empirical study, we draw on multiple district-level data sources from 2010 to 2019. First, we extract data on seasonal crop yields and gross cropped area for paddy, wheat, and millets. Second, we collect crop-specific and gross irrigated area data, as well as total fertilizer consumption data. These datasets are sourced from the government database Directorate of Economics and Statistics, Ministry of Agriculture and Farmers Welfare, Government of India, as well as ICRISAT's district-level database. ICRISAT's District-level Database (DLD) provides extensive longitudinal datasets on agriculture. Third, we obtain twenty years (2000 to 2019) of monthly climatological observations from the TerraClimate database, which are used to quantify seasonal weather variations over the study period 2010 to 2019. Fourth, our analysis involves data collated from farmers' (*Kisan*) call centers (KCC), a digital agriculture service provided by the government. This dataset provides insights into the reach and efficacy of agricultural extension services via mobile phones, particularly for crops such as paddy, wheat, and millets, across all districts in India. We conducted an extensive analysis of farmers' conversations using text-analysis protocols and developed an agricultural data dictionary to classify the conversations into three crop types (i.e., three dummy variables per crop).

Indian crop production follows a seasonal cropping pattern aligned with monsoon rains (the *Kharif* season), winter (the *Rabi* season), and summer. The monthly distribution of these cropping seasons varies according to agroclimatic regions, geographic regions, and States. Typically, the monsoon season begins in July or August and lasts until October or November. Winter spans three months from December to February, while summer generally commences in March or April and continues until June or July.

While analyzing the seasonal crop yield data, we divide it into two consecutive five-year periods for comparative analysis. The first period (2010-2014), with the start year matching the 2010-11 agricultural census. The second period covers 2015-2019, beginning with the 2015-16 agricultural census year. Comparing district-level yields between these two periods allows us to assess yield changes over time, indicating hot/coldspots.

On the other hand, we have weather data from 2000 to 2019, including average monthly minimum and maximum temperatures and total monthly rainfall. The seasonal weather deviations are estimated for each district for the period (2010 to 2019). In addition to weather data, we have the average percentage of gross irrigated area by crop type, as well as the average percentage of seasonal KCC queries for each crop type and district over the study period. We integrate these datasets, along with the fertilizer dataset, by crop, season, and period for our empirical analysis. We compare the influence of these agro-climatic factors on the formation of crop yield hotspots or coldspots across the country. We hypothesize that the distributions of input consumptions (i.e., irrigation, fertilizer consumption, and information access through KCC) have positive effects on hotspot cluster formation. In contrast, weather deviations (in particular, rainfall deviations) negatively affect the formation of positive yield deviations or hotspot clusters.

4. Results

The results show distinct regional patterns of crop yield hotspots and coldspots across seasons, with the north (Punjab, Haryana, Uttar Pradesh) and south (Tamil Nadu, Andhra Pradesh,

Telangana, Karnataka) emerging as consistent high-yield zones for paddy, wheat, and millets, while central and eastern regions (Maharashtra, Chhattisgarh, Bihar, Odisha, Jharkhand, and the northeast) mostly fall into low-yield clusters (Figure 1 to Figure 3). The magnitude of yield gaps between hotspots and coldspots is largest for wheat (about 2.4 t ha⁻¹), followed by monsoon paddy (2 t ha⁻¹), winter paddy (1.34 t ha⁻¹), and summer paddy (0.77 t ha⁻¹), indicating that wheat-growing regions exhibit the strongest spatial polarization in performance.

4.1. Weather and crop yield patterns

Weather deviations are highest in the northwest, central, and southern peninsula, with relatively stable conditions in the north, West Bengal, and the northeast. Rainfall deviation hotspots are scattered but more common in the north, while observed rainfall hotspots concentrate in the northeast, eastern India, and parts of the south. Interestingly, crop-yield coldspot districts often receive more rainfall than hotspots in monsoon and summer, yet still underperform, suggesting that deviations rather than absolute rainfall matter more for yield.

4.2. Role of irrigation, fertilizer, and information

Hotspot districts receive significantly more irrigation than coldspots (paddy: +57 %, wheat: +69 %, millets: +20 %) and apply about 86.5 kg ha⁻¹ more fertilizer per gross cropped area on average. They also show higher crop-specific queries via KCC (paddy: about 7, 5, 3 percentage points more in monsoon, winter, and summer; wheat: 22 percentage points more; millets: 0.17 percentage points more). Fixed-effect models show that each 1 percentage point increase in crop-specific irrigation and KCC queries raises yield by roughly 7 and 6 kg ha⁻¹, respectively, while an extra 1 kg ha⁻¹ of fertilizer adds about 0.5 kg ha⁻¹ to yield, conditional on controls (Table 1).

4.3. Interpretation and implications

These patterns highlight that hotspots combine favorable weather, high irrigation coverage, intense fertilizer use, and better access to crop-specific information, whereas coldspots lag on multiple inputs despite sometimes receiving more rainfall. The findings suggest that bridging the gap would require roughly doubling current yields in coldspots, which is feasible through targeted expansion of irrigation, fertilizer support, and digital extension (e.g., KCC-style mobile services). For policymakers, this points to a dual strategy: short-term scaling of information-based interventions and medium- to long-term investments in irrigation infrastructure and soil-specific nutrient management, especially in drought-prone and lagging regions. To illustrate, consider the district of Darbhanga in northern Bihar, which persistently exhibits low-performing crop yield clusters. Should the yields of paddy and wheat be elevated to match those characteristic of hotspot districts, the revenue could potentially escalate from Rs. 18,600 to Rs. 41,416 ha⁻¹ for paddy, and from Rs. 35,376 to Rs. 62,645 ha⁻¹ for wheat. Consequently, this improvement in yields is projected to enhance the revenue per household engaged in paddy cultivation from Rs. 2,757 to Rs. 6,850 and for those cultivating wheat from Rs. 5,038 to Rs. 9,003.

5. Conclusion

The study demonstrates that high- and low-performing district clusters for seasonal food grains emerge from the interplay of agro-climatic location, weather variability, and uneven access to irrigation, fertilizer, and agricultural information. Northern districts, with relatively stable weather and extensive irrigation, form dominant yield hotspots, whereas many western, central, and eastern districts remain low-performing despite higher rainfall. Southern and Madhya Pradesh districts

achieve high yields by combining strong irrigation, intensive fertilizer use, and active engagement with KCC-based information, underscoring the importance of integrated input and knowledge systems. To shift coldspots into hotspots, lagging regions—such as Bihar, Odisha, Chhattisgarh, and Jharkhand—must expand irrigation infrastructure, optimize fertilizer use, and intensify demand-driven information access via platforms like KCC, which together can substantially raise yields and farm-level incomes under varying climatic conditions.

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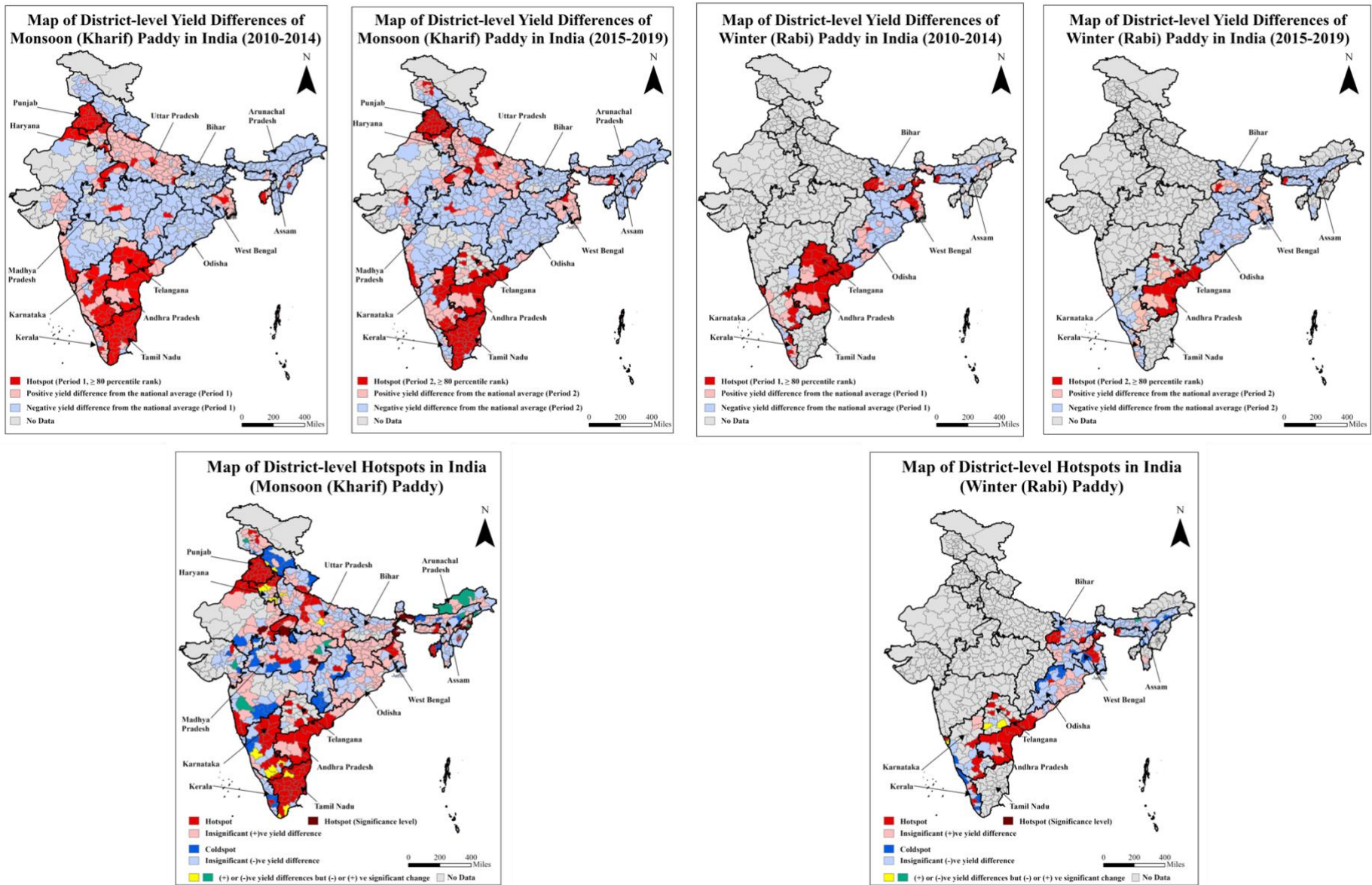


Figure 1: Maps of district-level yield differences for the two periods and hotspots for monsoon (*Kharif*) and winter (*Rabi*) paddy in India

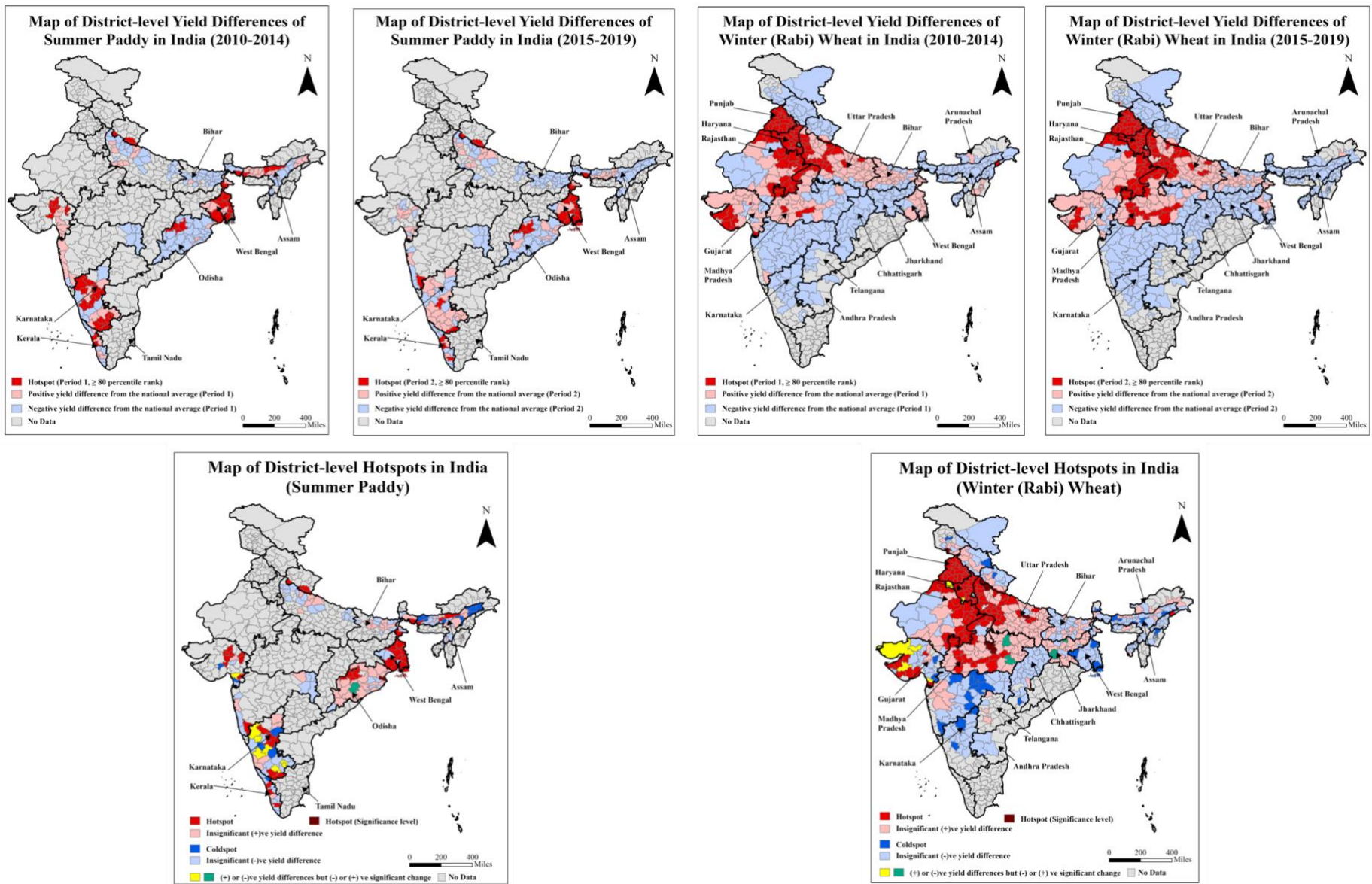


Figure 2: Maps of district-level yield differences for the two periods and hotspots for summer paddy and winter (*Rabi*) wheat in India

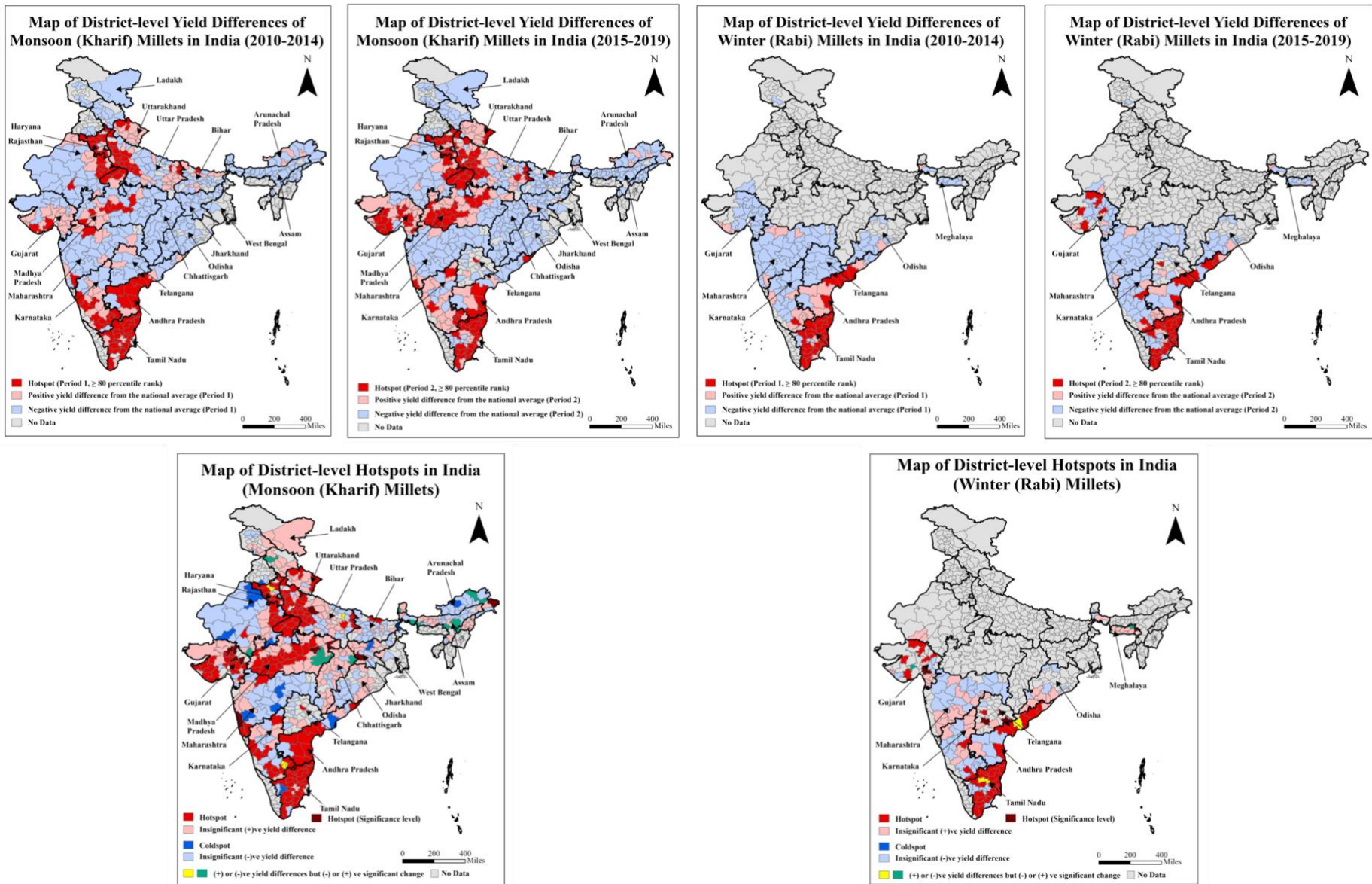


Figure 3: Maps of district-level yield differences for the two periods and hotspots for monsoon (*Kharif*) and winter (*Rabi*) millets in India

Table 1: Factors influencing crop yields in India

	Dependent variable: Yield Deviation						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rainfall	0.0001 (0.0005)		0.0004 (0.001)	0.002** (0.001)	0.002** (0.001)	0.002* (0.001)	0.001 (0.001)
Rainfall Deviation		-0.009 (0.008)	-0.011 (0.009)	-0.032** (0.01)	-0.033** (0.011)	-0.025* (0.012)	
GIA				0.008*** (0.001)	0.007*** (0.001)	0.007*** (0.001)	0.007*** (0.001)
NPK					0.001* (0.0002)	0.0005* (0.0002)	0.0005* (0.0002)
KCC Queries					0.005* (0.002)	0.006* (0.002)	0.006* (0.002)
Maximum Temperature						0.094** (0.030)	0.104*** (0.030)
Minimum Temperature						-0.055 (0.037)	-0.070 (0.036)
Max Temp Deviation						-0.009 (0.010)	-0.014 (0.010)
Min Temp Deviation						-0.015 (0.012)	-0.011 (0.012)
Region f.e.	✓	✓	✓	✓	✓	✓	✓
District × Season f.e.	✓	✓	✓	✓	✓	✓	✓
Period f.e.	✓	✓	✓	✓	✓	✓	✓
Crop f.e.	✓	✓	✓	✓	✓	✓	✓
Observations	4,452	4,532	4,452	3,709	3,652	3,652	3,652
R ²	0.786	0.786	0.786	0.816	0.82	0.82	0.82

Note: All the regressions are based on data at the district-level for two periods (Period 1: 2010-2014 and Period 2: 2015-2019). Columns (1) to (4) display the relation between seasonal crop yield deviations and rainfall, rainfall deviations, and crop-specific percentage gross irrigated area. In column (5), we include other input factors (fertilizer consumption and the percentage of KCC queries). Column (6) includes other weather variables as controls (maximum temperature, minimum temperature, and their average historical deviations). There is no significant change in estimates when comparing column (6) and column (7). All regression equations include district × season, Period, and Region fixed effects. Standard errors are clustered at the district level and are reported in parentheses. GIA: Gross Irrigated Area, NPK: Total Fertilizer consumption (GCA) per Gross Cropped Area (GCA), KCC: Farmers (*Kisan*) call center, d: District, s: State, c: Crop types (Paddy, Wheat, Millets), r: Season, p: Period. Significance level: * p<0.1; ** p<0.05; *** p<0.01.