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Research Article

GEOSPATIAL ANALYSIS OF CLIMATE VARIABILITY AND ITS INFLUENCE ON AGRICULTURAL LAND-USE TRANSFORMATION

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Abstract

The feasibility of multiple cropping, irrigation demand, sowing decisions, and fallowing can all be influenced by climate variability, which can result in a significant transformation of agricultural land use. This study assesses those relationships for India by utilising a national annual panel from 2010–11 to 2019–20 and endpoint observations for 14 agriculturally significant states. The India Meteorological Department's monsoon and annual rainfall departures were compared to the official land-use statistics. The analysis was conducted using a three-nearest-neighbor state-centroid matrix and included descriptive change accounting, Mann–Kendall tests, Sen slope estimates, Pearson and Spearman correlations, heteroskedasticity-consistent time-adjusted regressions, and global Moran's I. The mean deviation from the monsoon rainfall was -3.25% (standard deviation 7.96 percentage points). The total cropped area increased by 13.231 million ha, and the cultivation intensity increased from 140.15% to 151.08%. At the same time, the net area sown decreased by 1.468 million ha and agricultural land by 1.923 million ha. The total cropped area and cropping intensity increased substantially, while the net area seeded exhibited a significant negative monotonic trend. A one-percentage-point wetter monsoon was associated with 68.7 thousand ha less current fallow and 83.2 thousand ha more net planted area after adjustment for time. The current fallow land was strongly inversely correlated with monsoon departure ($r = -0.914$, $p < .001$). The state changes were heterogeneous and did not exhibit any significant global spatial clustering at the 5% level. The evidence suggests that rainfall disruptions have an impact on the annual land-use margins, and intensification has partially compensated for the contraction of the cultivated land base. The policy should incorporate irrigation efficiency, soil-moisture conservation, and state-specific land protection, in addition to rainfall-responsive fallow monitoring.

Keywords: Climate variability, Agricultural land use, Current fallow, Cropping intensity, Mann–Kendall trend, Spatial autocorrelation.

INTRODUCTION

Agricultural land use is a socio-economic decision and a biophysical response to climate. In the face of uncertainty regarding rainfall, temperature, prices, labour, and water, farmers must determine whether to sow, leave land fallow, irrigate, diversify crops, or cultivate land more than once. Consequently, climate variability has an impact on more than just crop yields; it can also alter the quantity, timing, and intensity of land use. The matter is of particular significance in India, where the monsoon rainfall continues to be the primary seasonal water source for extensive rainfed regions and where agricultural land is in competition with the expansion of urban, industrial, and infrastructure. The national assessment of climate change documents substantial regional hydro-climatic variability and rising temperatures, while the Sixth Assessment Report identifies South Asia as highly exposed to warming, heavy precipitation, drought, and compound climate risks (IPCC, 2021, 2022; Krishnan *et al.,* 2020). These pressures have the potential to shift land between the current fallow, net sown, repeatedly cropped, and non-agricultural categories. Land allocation is influenced by climate through crop profitability, water availability, and adaptation, as demonstrated by recent research conducted in India. The distribution of agricultural land use is influenced by climatic changes, as discovered by Birthal et al. (2021). Datta et al. (2022) underscore the importance of producers combining incremental adaptation such as altered sowing dates, irrigation, and crop substitution with more transformative responses.

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However, land-use transformation is not a straightforward meteorological consequence. Public irrigation, groundwater access, minimum support prices, road connectivity, farm size, and urban growth can either reinforce or counteract climate signals. A moist year may result in the reactivation of marginal land for cultivation, while sustained water insecurity may promote fallowing or a transition to less water-intensive crops. In contrast, the total cropped area can be increased by increased multiple cropping, even when the net sown area decreases. The observation of cropland extent, vegetation condition, and land-cover conversion has been significantly enhanced by remote sensing. Recent syntheses have underscored the significance of integrating administrative statistics with global products, which now provide frequent 10–30 m classifications and lengthy time series (Brown *et al.,* 2022; Potapov *et al.,* 2022; Zhu *et al.,* 2022). Nevertheless, an official land-use category is not equivalent to a satellite pixel that is classified as cropland. Current fallow, other fallow, net area seeded, and area sown more than once are the categories that administrative statistics distinguish. These categories capture management decisions that a single-date image may overlook. Consequently, the integration of climatic records with official land-use accounts and a spatial description of state-level change is advantageous for a policy-oriented assessment. Three enquiries are addressed in this paper. Initially, were there substantial changes in national agricultural land-use indicators and monsoon conditions from 2010–11 to 2019–20? Secondly, how strongly were annual rainfall departures correlated with current fallow, net sown area, total cropped area, and cropping intensity after accounting for a linear time trend? Third, were the changes in state-level endpoints spatially clustered? The analysis is auditable and is based on published values, robust small-sample diagnostics, and explicit limits on inference. The study evaluates the null hypotheses that rainfall departure is not correlated with annual land-use outcomes, that the land-use series lack a monotonic trend, and that state endpoint changes are spatially random.

REVIEW OF THE LITERATURE AND RESEARCH GAP

There are numerous pathways through which the land–climate relationship operates. The feasibility of rainfed sowing, reservoir recharge, and soil moisture are all influenced by rainfall. Evapotranspiration, phenology, and irrigation requirements are all influenced by temperature. Standing crops may be damaged and the decision to replant land in the subsequent season may be influenced by extreme events. At a larger scale, producers and institutions adjust by investing in irrigation, diversifying their crops, obtaining insurance, adopting drought-tolerant cultivars, and retiring land. The IPCC (2022) differentiates between incremental adjustments and transformational adaptation, whereas recent Indian assessments have discovered that the efficacy of adaptation is contingent upon agroecology, agricultural resources, and institutional access (Datta *et al.,* 2022; Vij *et al.,* 2025). As a result, national aggregates can identify common temporal shocks; however, they must be supplemented by sub national comparison.

Two forms of evidence are augmented by geospatial analysis. Initially, earth observation is used to determine the locations of cropland that are expanding, contracting, or experiencing a change in intensity. Potapov et al. (2022) reported that the global cropland expansion is accelerating, while Dynamic World and other contemporary products enhance the temporal frequency of land-cover monitoring (Brown *et al.,* 2022). Secondly, spatial statistics evaluate whether neighbouring regions undergo comparable transformations, which may suggest that they share policies, markets, river basins, or climate regimes. Indian case studies demonstrate a robust local coupling between land cover, vegetation, and climate. However, they frequently concentrate on a single district or metropolitan periphery and employ classifications that are not directly comparable to official agricultural categories (Masroor *et al.,* 2022). Although uncertainty and scale mismatch necessitate meticulous management, reanalysis products like ERA5-Land and digital soil products like SoilGrids are advantageous for future multivariable modelling (Muñoz-Sabater *et al.,* 2021; Poggio *et al.,* 2021).

Consequently, a practical gap persists between transparent national evidence and fine-resolution case studies. Many studies infer land transformation from two or three satellite dates, while others model yield rather than land-use decisions. Fewer studies investigate the correlation between annual rainfall deviations and the present dormant period, as well as the distinction between net sown and total cropped area. In order to address this lacuna, the current study employs two linked scales: a ten-year national time series that depicts yearly climatic variability and a 14-state endpoint dataset that characterises geographic heterogeneity. Pixel-level analysis is not substituted by the design. Rather, it establishes a statistically reproducible baseline that can be used to verify remote-sensing results and to generate more detailed hypotheses.

STUDY AREA, DATA, AND VARIABLES

The study area encompasses India, with a national annual series and a state comparison that includes Bihar, Chhattisgarh, Gujarat, Haryana, Jharkhand, Karnataka, Madhya Pradesh, Maharashtra, Odisha, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh, and West Bengal. These states encompass arid, semi-arid, sub-humid, and humid regimes and are home to significant cereal, oilseed, cotton, pulse, and rice systems. The set was chosen due to the availability of comparable endpoint values for all necessary land-use variables. It is an analytical sample rather than a comprehensive census of each state and union territory.

The Directorate of Economics and Statistics, Ministry of Agriculture and Farmers Welfare, (Government of India, 2023), issued Land Use Statistics at a Glance, 2010–11 to 2019–20, which provided the land-use values. All of the data in the national panel is expressed in thousand hectares, including current fallow, fallow other than current fallow, net area sown, total cropped area, area sown more than once, and agricultural land. The Agricultural Statistics at a Glance 2024, which replicates the India Meteorological Department series (Government of India, 2024), was used to obtain rainfall totals and deviations from the norm. The monsoon departure is the percentage difference between the official normal for the corresponding reporting framework and the rainfall observed between June and September. Only the first and last land-use years are employed in the state analysis. Cropping intensity was determined by dividing the total cropped area by the net area sown and multiplying the result by 100. The endpoint percentage change was determined in relation to the 2010–11 value. The nearest-neighbor spatial weights matrix and a schematic locator were constructed exclusively using approximate state-centroid coordinates; they are not official boundaries. The government's land-use framework is the basis for the interpretation of agricultural land, rather than as a cropland subdivision that is remotely sensed. This distinction is crucial because official categories are based on annual utilisation and can include numerous cropping, whereas many land-cover maps are characterised by prevalent surface cover.

ANALYTICAL FRAMEWORK

Five stages were implemented during the examination. Initially, the national series was summarised using endpoint differences, annual means, standard deviations, and time graphs. Secondly, Kendall's rank-based statistic was employed to assess monotonic change, and the Theil–Sen median slope was employed to quantify it. These techniques are suitable for brief environmental series because they are resistant to outliers and do not necessitate normally distributed residuals. The sample contains only ten observations, so exact p-values and 95% slope intervals are reported, despite the fact that a two-sided significance level of.05 was employed.

The third step involved the examination of bivariate association using Pearson correlation for linear co-variation and Spearman correlation for rank consistency. Monsoon rainfall departure was the primary exposure, as the June–September season directly influences *kharif* sowing and water storage. The annual departure was maintained as a sensitivity indicator. A correlation was not considered to be causal evidence.

Table 1. Data sources, analytical variables and scale

Dataset	Period / unit	Variables used	Analytical role
Land Use Statistics at a Glance	2010–11 to 2019–20; 000 ha	Current fallow, other fallow, net sown, total cropped, area sown more than once, agricultural land	National panel and 14-state endpoints
Agricultural Statistics at a Glance 2024 / IMD	2010–11 to 2019–20; mm and %	Monsoon rainfall, annual rainfall and departure from normal	Climate variability indicators
Derived indicators	Annual and endpoint	Cropping intensity, absolute change, percentage change	Land-use transformation metrics
Approximate state centroids	Single location per state; decimal degrees	Latitude and longitude	Three-nearest-neighbour weights and schematic map

Note. *Official agricultural and rainfall publications are the source of all raw values. Derived variables were recomputed in Python. "000 ha" denotes thousand hectares.*

Table 2. National rainfall and agricultural land-use panel

Year	Monsoon departure (%)	Current fallow (Mha)	Net sown (Mha)	Total cropped (Mha)	Cropping intensity (%)	Agricultural land (Mha)
2010-11	2.2	14.38	141.37	198.13	140.15	181.92
2011-12	1.4	14.66	140.79	195.55	138.89	181.92
2012-13	-7.6	15.44	139.75	194.46	139.15	182.05
2013-14	5.6	14.30	141.24	201.30	142.53	181.81
2014-15	-12.3	15.07	139.44	198.28	142.20	181.27
2015-16	-14.3	15.71	138.97	198.12	142.56	181.37
2016-17	-2.9	15.30	139.00	201.16	144.72	180.92
2017-18	-5.2	14.99	138.77	200.88	144.75	180.82
2018-19	-9.4	15.21	138.44	201.18	145.32	180.62
2019-20	10.0	13.77	139.90	211.36	151.08	179.99

Note. *Mha = million hectares. Values were converted from the official thousand-hectare series; cropping intensity is derived.*

A high coefficient may be indicative of a common response to extreme years, unmeasured irrigation conditions, or the influence of a high-leverage endpoint. Fourthly, separate ordinary least-squares models were estimated for current fallow, net sowed area, total cropped area, and cropping intensity. Each model involved a centred linear year term and a monsoon rainfall departure. Heteroskedasticity-consistent HC3 covariance estimates were implemented due to the potential for conventional standard errors to be unreliable in small samples. The formula was as follows: $Y\_t = β0 + β1$ Rain Departure + $β2$ Time_t + ε_t. The coefficient β1 approximates the conditional change in the outcome that is associated with a one-percentage-point change in rainfall departure, while maintaining the linear time trend constant. The report includes robust p-values, confidence intervals, and model fit.

Fifth, a cross-sectional regression and global Moran's I were employed to investigate variations in state endpoints. The regression coefficient that relates the percentage change in total cropped area to the percentage variations in net sown and current fallow. In Moran's I, the weights were row-standardized, and each state was connected to its three nearest centroid neighbors. Statistical significance was assessed using a two-sided pseudo-p value and 999 random permutations. The spatial results are interpreted as exploratory rather than definitive due to the fact that geographic centroids simplify state geometry and connectivity.

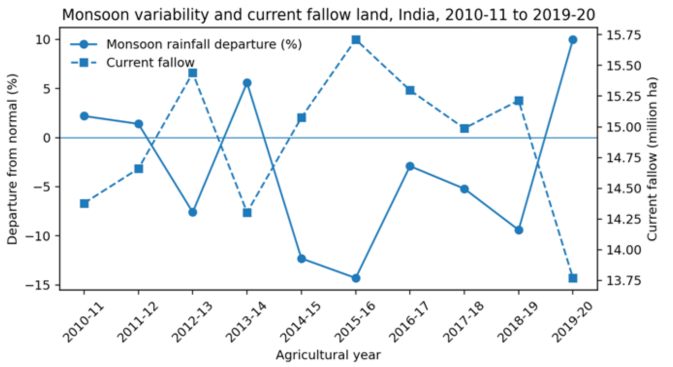
Cropping intensity (%) = (Total cropped area / Net area sown) × 100 (1)

$$I = (n / S_0) [\Sigma_i \Sigma_j w_{ij}(z_i z_j) / \Sigma_i z_i^2] \quad (2)$$

Decision rule. The rainfall-association null was rejected when the HC3 rainfall coefficient had p < .05. Trend nulls were evaluated with Mann–Kendall p-values, and the spatial-randomness null was evaluated with permutation p-values for Moran's I.

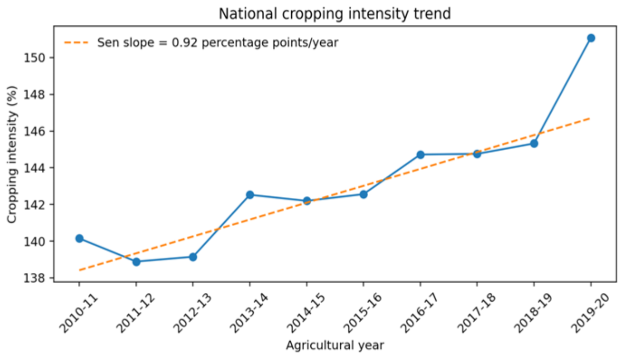
RESULTS

The monsoon conditions were characterised by a sharp alternation in contrast to a seamless progression. The standard deviation was 7.96 percentage points, and the average deviation from the mean was -3.25%. The monsoon that was the most deficient in the panel was 2015–16 (-14.3%), followed by 2014–15 (-12.3%). The wettest relative year was 2019–20 (+10.0%). The Sen Estimate was −0.85 percentage points per year with an interval spanning zero, and the Mann–Kendall test did not identify a monotonic monsoon trend (τ = −0.111, p =.727). The absence of monotonic change was observed in the annual rainfall departure. Therefore, the climatic exposure utilised in this analysis is inter-annual variability, rather than a statistically established decade-long rainfall decline. Different orientations were observed in national land-use indicators. The net area sown decreased from 141.370 to 139.902 million ha, resulting in a loss of 1.468 million ha (−1.04%), and agricultural land decreased by 1.923 million ha. In contrast, the total cropped area increased from 198.128 to 211.359 million ha, representing a 13.231 million ha (6.68%) increase. Consequently, the intensity of cropping increased by 10.93 percentage points, from 140.15% to 151.08%. The current fallow ended 0.609 million ha below its initial value; however, its trajectory was non-monotonic and reached its zenith at 15.711 million ha in 2015–16, the monsoon year with the least rainfall. Structural change was distinguished from annual fluctuation by trend tests. The net area sown experienced a substantial decline (τ = −0.600, p =.0167; Sen slope −251.5 thousand ha per year). The negative trend in agricultural land was even more pronounced (τ = −0.822, p <.001; −216.3 thousand ha per year). Intensity of cultivation increased significantly (τ = 0.867, p <.001; +0.92 percentage points per year), and the total cropped area increased (τ = 0.511, p =.0466; +913.0 thousand ha per year;). The current fallow did not exhibit a monotonic trend (τ = 0.022, p = 1.000), and the positive trend in the cumulative fallow did not meet the 5% threshold. These findings suggest that the extensive land base is contracting, while the land that is already under cultivation is being intensified. The most robust bivariate correlation was seen between monsoon departure and present fallow (Pearson r = −0.914, p < .001; Spearman ρ = −0.855). Unusually wet monsoons corresponded with a reduction in uncultivated land for the present year. The exit of the monsoon had a good correlation with the net sown area (r = 0.665) and the total cropped area (r = 0.549), however the unrefined coefficients lacked precision.



Source: *Author's calculations from Government of India (2023, 2024) and IMD series.*

Figure 1. Monsoon rainfall departure and current fallow land in India, 2010–11 to 2019–20



Source: *Author's calculations from Government of India (2023).*

Figure 2. National cropping-intensity trajectory with the Sen median trend

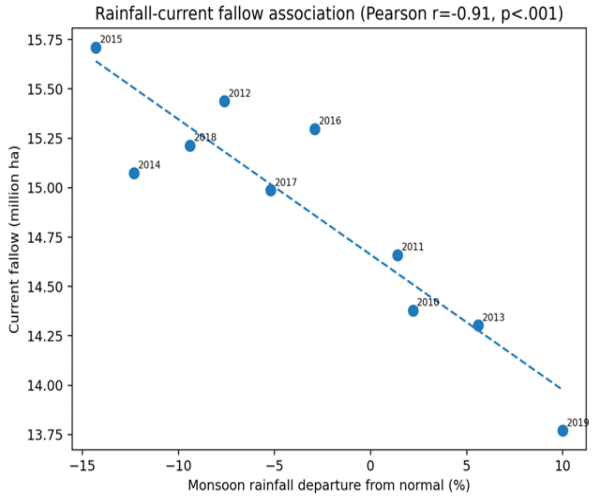
Table 3. Mann–Kendall trend tests and Sen slopes

Variable	Kendall τ	p	Sen slope / year	95% interval
Monsoon departure (%)	-0.111	0.7275	-0.85	[-2.83, 2.10]
Annual departure (%)	-0.067	0.8618	-0.37	[-2.65, 1.57]
Current fallow (000 ha)	0.022	1.0000	34.75	[-178.00, 174.00]
Total fallow (000 ha)	0.422	0.1083	175.00	[-51.00, 366.00]
Net area sown (000 ha)	-0.600	0.0167	-251.50	[-454.50, -111.25]
Total cropped area (000 ha)	0.511	0.0466	913.00	[10.50, 1,676.50]
Cropping intensity (%)	0.867	0.0001	0.92	[0.56, 1.43]
Agricultural land (000 ha)	-0.822	0.0004	-216.33	[-277.00, -157.00]

Note. *Theil–Sen intervals are based on the ten annual observations. Slopes retain each variable's original units.*

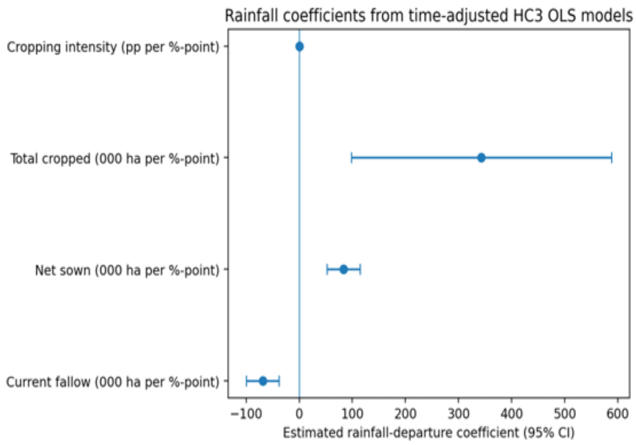
The correlation with cropping intensity was less robust (r = 0.309), aligning with the notion that multiple cropping relies not just on present rainfall but also on irrigation, water reserves, technology, and policy. Time-modified HC3 models enhanced the differentiation between short-term rainfall responsiveness and long-term change. A one-percentage-point rise in monsoon departure correlated with a reduction of 68.7 thousand hectares in present fallow land (95% CI −99.6 to −37.8; p < .001). The relevant coefficients were +83.2 thousand hectares for net sown area (95% CI 52.0 to 114.3; p < .001), +342.9 thousand hectares for total cropped area (95% CI 98.2 to 587.7; p = .006), and +0.161 percentage points for cropping intensity (95% CI 0.012 to 0.309; p = .034).

The temporal coefficient was insignificant for present fallow, although it exhibited a pronounced negative correlation for net sown area and a positive correlation for total cropped area and intensity. Model R^2 values varied between .839 and .946. These regression magnitudes need to be interpreted as conditional correlations within a decade-long national dataset. The 2019–20 analysis integrates a +10.0% monsoon deviation with an exceptionally large total cultivated area and little present fallow, providing it significant influence. Nonetheless, the rank correlation, the visually consistent scatter, and the strong confidence interval all support the assertion that rainfall variability influences the yearly cultivation margin. The models do not demonstrate that precipitation only caused the alterations.



Source: *Author's calculations from Government of India (2023, 2024).*

Figure 3. Association between monsoon rainfall departure and current fallow land



Source: *Author's calculations; bars show 95% robust confidence intervals.*

Figure 4. *Rainfall-departure coefficients from time-adjusted HC3 regressions*

Table 4. Time-adjusted OLS models with HC3 robust inference

Outcome	Rainfall coefficient	95% CI	p	Time coefficient / year	p	R^2
Current fallow (000 ha)	-68.72	[-99.62, -37.82]	<.001	-10.16	0.775	0.839
Net area sown (000 ha)	83.15	[51.96, 114.35]	<.001	-242.49	<.001	0.932
Total cropped area (000 ha)	342.92	[98.18, 587.66]	0.006	1,195.11	<.001	0.905
Cropping intensity (%)	0.16	[0.01, 0.31]	0.034	1.10	<.001	0.946

Note. *n = 10 in every model. Rainfall is monsoon departure in percentage points. Time is centred at 2010–11. Coefficients use the outcome units shown.*

Table 5. State-level land-use transformation, 2010–11 to 2019–20

State	Net sown change (%)	Current fallow change (%)	Total cropped change (%)	Cropping-intensity change (pp)
Odisha	-12.39	20.30	-13.98	-2.11
Tamil Nadu	-4.36	-9.36	3.29	9.28
Maharashtra	-3.93	5.71	2.94	9.52
Bihar	-3.46	16.20	1.43	6.93
Gujarat	-3.19	37.84	8.76	15.51
Rajasthan	-1.73	25.91	5.82	10.88
Uttar Pradesh	-1.36	-18.35	5.83	11.25
Chhattisgarh	-1.32	15.02	1.13	3.00
Punjab	-0.75	166.67	-0.57	0.33
Haryana	0.97	-22.13	1.72	1.38
Madhya Pradesh	2.60	-25.65	28.26	36.47
Karnataka	2.67	-22.85	5.89	3.89
West Bengal	5.40	-48.63	14.36	15.07
Jharkhand	18.99	-16.77	40.91	21.21

Note. *pp = percentage points. Very large percentage changes may arise from small baseline values; Punjab's current-fallow increase is one example.*

Table 6. Global spatial-autocorrelation results

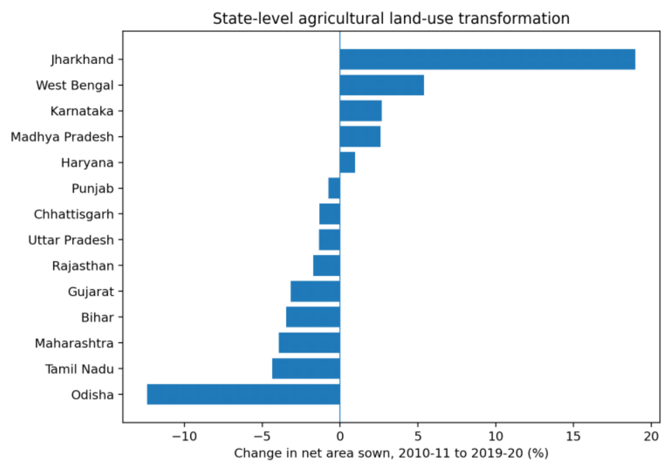
Variable	Moran's I	Permutation mean I	Two-sided p	k neighbours
Net sown change (%)	-0.316	-0.068	0.060	3
Current fallow change (%)	-0.066	-0.083	0.680	3
Total cropped change (%)	-0.285	-0.075	0.102	3
Cropping-intensity change (pp)	-0.103	-0.078	0.599	3

Note. *Weights were row-standardized from three nearest approximate state centroids. Significance used 999 permutations with a fixed seed.*

The comparison of state endpoints showed very divergent trajectories. Odisha saw the most significant net-sown reduction (−12.39%) with a 13.98% decrease in overall cultivated area. Tamil Nadu (−4.36%), Maharashtra (−3.93%), Bihar (−3.46%), and Gujarat (−3.19%) had a reduction in net sown area; nevertheless, all regions except Odisha expanded their total cropped area, indicating that continuous cultivation somewhat mitigated land loss. Madhya Pradesh had a 2.60% growth in net sown area, with a 28.26% augmentation in total cropped area and a 36.47-percentage-point escalation in cropping intensity. Jharkhand and West Bengal also indicated significant increases in net sown and overall cultivated area. These statistics are to administrative land use and therefore not be construed as direct indicators of ecological status or productivity.

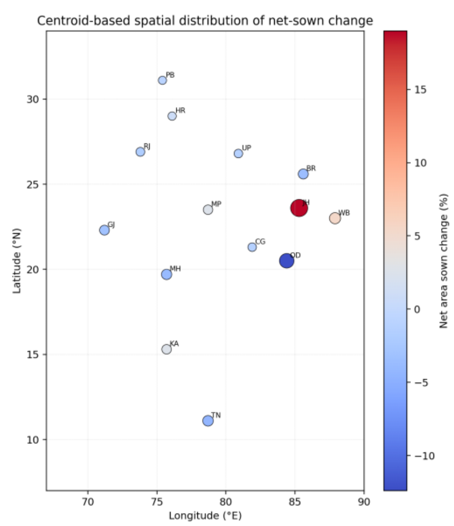
The exploratory state regression accounted for 79.9% of the variation in the percentage change in total cropped area. The net-sown change exhibited a favourable coefficient of 1.631 (HC3 $p < .001$), whereas the current-fallow change was minimal and statistically insignificant (−0.032, $p = .647$). This cross-sectional pattern indicates that the enlargement or safeguarding of the net cultivated area is intricately linked to overall crop yield, although the outcome is susceptible to the limited sample size and the impact of high-growth states. It does not segregate irrigation, agricultural pricing, or statistical amendments.

The Global Moran's I did not indicate statistically significant positive aggregation. The net-sown change was $I = -0.316$ (permutation $p = .060$), suggesting a little inclination towards spatial dispersion instead of clustering. The changes in current-fallow ($I = -0.066$, $p = .680$), total-cropped ($I = -0.285$, $p = .102$), and cropping-intensity ($I = -0.103$, $p = .599$) were not statistically significant. The hypothesis of spatial randomisation was hence not dismissed. Diverse pathways across adjacent states may indicate variations in irrigation practices, agroecological conditions, legislative frameworks, and reporting methods, but centroid-based weights diminish geographic accuracy.



Source: *Author's calculations from Government of India (2023).*

Figure 5. State-level percentage change in net area sown between 2010–11 and 2019–20



Source: *Author's schematic using approximate state-centroid coordinates; not an administrative-boundary map.*

Figure 6. Centroid-based spatial distribution of net-sown change in the 14-state sample

DISCUSSION

The findings indicate two concurrent changes: climate-responsive activity at the yearly farming boundary and a prolonged transition from broad land use to increased intensity. The robust negative correlation between rainfall deviation and present fallow is ergonomically credible. Inadequate monsoon precipitation results in postponed planting, unsuccessful seed sprouting, and inadequate water reserves for rainfed farmers, increasing the likelihood of temporary fallowing. When precipitation is advantageous, marginal lands might resume cultivation, and irrigated systems may accommodate an expanded agricultural area. Birthal et al. (2021) contend that changes in climate influence the distribution of agricultural land, while Datta et al. (2022) demonstrate that the availability of irrigation and other resources determines the adaptation strategy.

Simultaneously, fluctuations in precipitation do not account for the significant increase in agricultural intensity. The time-adjusted model exhibited a robust upward trend after the incorporation of rainfall, indicating structural factors such irrigation development, shorter-duration cultivars, mechanization, market incentives, and enhanced access to inputs. This analysis aligns with the discrepancy between net sown area and total cropped area. A nation may forfeit a portion of its arable land while yet achieving increased crop yields on the area that remains. This intensification may safeguard overall output, although it might also elevate groundwater extraction, energy requirements, and soil nutrient strain if water and nutrient management practices are inadequate. The FAO (2021) and UNCCD (2022) assert that enhancements in productivity should be evaluated alongside the deterioration of land and water.

The state data underscores the need of eschewing a singular national narrative. The decline in both net sown and total cropped area in Odisha contrasts with the intensification seen in Madhya Pradesh, Gujarat, or West Bengal. Tamil Nadu and Maharashtra had a reduction in net sown area while simultaneously expanding total cropped area, a trend consistent with irrigation-facilitated intensification or changes in reporting and crop schedules. Jharkhand's substantial percentage increases may partially indicate a poor starting point. These divergent trajectories align with the literature's focus on context-dependent adaptation and varied institutional capabilities (Vij *et al.,* 2025). High-resolution remote sensing can ascertain whether administrative changes signify genuine conversion, seasonal fallow, plantation growth, or enhanced enumeration.

The absence of a substantial positive Moran's I is also revealing. If climatic zones were the only determinants of land alteration, one would anticipate nearby states to undergo similar changes. Conversely, the unfavorable or minimal data suggest a fragmented scenario where local irrigation systems, agricultural specialization, urban development, and governmental regulations disrupt extensive regional uniformity. The outcome should not be exaggerated since it encompasses just 14 states, and centroid neighbours do not reflect common boundaries or river-basin interconnections. A comprehensive geographic panel including district polygons, gridded precipitation, groundwater levels, and remotely sensed seasonal crops might provide more robust conclusions.

The examination aligns with, however does not establish, a causal relationship between rainfall anomalies and changes in fallow land. Precipitation is quantified on a national scale, whereas land-use results compile data from millions of agricultural operations. Concurrent disturbances like pricing fluctuations, government procurement, drought assistance, or cyclonic events can affect both the discerned land-use configuration and the reaction to precipitation. The very high current-fallow coefficient is therefore most accurately understood as a reliable descriptive indicator. The overarching inference is that climatic variability is paramount in determining land cultivation in any given year, although structural economic and technical factors influence the intensity of land usage.

A geographical augmentation of these findings must maintain the differentiation between land cover and agricultural use. A solitary yearly cropland mask could categorise a plot as agricultural while being left uncultivated throughout the assessment year, but a seasonal composite may misinterpret post-harvest bare soil as desolate terrain. The most comprehensive approach would include three data for every agricultural year: a pre-sowing baseline, a peak-growth composite, and a post-harvest depiction. Phenological patterns derived from Sentinel-2 or Landsat may then be aligned with government figures on current fallow and net planted areas. Independent validation need to be categorised according to irrigation regime, crop calendar, and parcel size, since categorisation error is improbable to be geographically consistent. Dynamic World may provide a regular first layer; nonetheless, locally educated classifications and precision-adjusted area assessments are essential prior to interpreting pixel counts as agricultural change.

The noted increase in cropping intensity also generates a policy dilemma. Engaging in multiple cropping may enhance agricultural revenue and provide food security without the need for more land, while it may shift climate vulnerabilities from precipitation to groundwater and energy infrastructures. A region that sustains two or three agricultural cycles under inadequate monsoons may seem robust in land-use metrics while experiencing aquifer strain. Consequently, intensity objectives must to be aligned with water-accounting metrics, agricultural water efficiency, energy consumption, and soil vitality assessments. Climate-conscious land policy need to incentivise crop rotations and varieties that sustain revenue while minimizing water use, rather than just maximizing the total farmed area. Connecting precipitation predictions to irrigation planning, agricultural recommendations, and land restoration may reduce urgent pumping and safeguard the productive foundation. These strategies align with the extensive adaptation research, which emphasises that technological solutions are effective only when information, financing, institutions, and equitable access are simultaneously considered (Datta *et al.,* 2022; Vij *et al.,* 2025).

Scenario analysis might subsequently evaluate whether the previous correlations endure in forthcoming hydroclimatic circumstances. District fixed effects would account for soil and institutional disparities that do not change over time, while year effects would reflect national pricing fluctuations and policy changes. Nonlinear precipitation factors and drought-duration metrics may differentiate modest shortages from critical failures. Engagements with irrigated areas would reveal how infrastructure mitigates rainfall fluctuations and where it just transfers stress to groundwater. Spatial error or Bayesian hierarchical models may more accurately depict common river basins and adjacent markets compared to centroid weights. These models need extended, meticulously coordinated datasets, however they would transform the current descriptive foundation into a more robust instrument for climate adaptation and agricultural zoning, together with clear uncertainty communication across various administrative levels.

IMPLICATIONS FOR POLICY AND PLANNING

An effective monitoring system need to integrate regional land-use documentation, seasonal satellite imagery, and precipitation predictions. Contemporary fallow irregularities might act as a preliminary signal of production risk when delineated shortly after the planting period. Priority districts need to get swift validation of seed failure, soil moisture, and potable water conditions instead of standardised assistance. Dynamic agricultural goods may facilitate this endeavour, however their categories must be aligned with official definitions and regional crop cycles (Brown *et al.,* 2022; Zhu *et al.,* 2022). Adaptation strategies must safeguard the agricultural land foundation while enhancing the sustainability of diverse cropping systems. The data substantiates the allocation of resources towards farm ponds, watershed rehabilitation, micro-irrigation, drought-resistant cultivars, soil organic matter enhancement, and groundwater management. Land repurposed for non-agricultural use must to be monitored publicly, particularly in rapidly urbanising areas. Due to the variability of state routes, objectives should focus on agroecological and water limitations instead of a standardised aim of increasing cropping intensity. Restoration approaches have to focus on consistently uncultivated or deteriorated land where ecological and economic advantages are evident.

CONSTRAINTS

Four constraints hinder interpretation. Initially, the national panel has of 10 yearly data, rendering the coefficients susceptible to fluctuations in particular years and incapable of accurately reflecting long-term climatic change. Secondly, climatic variability was primarily quantified by precipitation; corresponding state-year temperature, evapotranspiration, groundwater, and irrigation data were absent in the same verified panel. Thirdly, administrative land-use classifications may include reporting modifications and are unable to pinpoint conversions within states. Fourth, the spatial examination employs estimated centroids and endpoints instead of district polygons and a comprehensive temporal weights model. These selections make the analysis replicable but cautious. Subsequent research need to include IMD or ERA5-Land grids, regional crop calendars, SoilGrids, irrigation data, and yearly Landsat/Sentinel classifications, succeeded by fixed-effects and spatial-error models.

SUMMARY

The agricultural land framework in India underwent modifications via both reduction and intensification from 2010–11 to 2019–20. The net area cultivated and agricultural land had a notable reduction, although the overall cropped area and cropping intensity saw an increase. Inter-annual fluctuations in the monsoon were significantly linked to the present-fallow boundary: wetter anomalies corresponded with reduced current fallow and increased net sown and overall cropped area after temporal adjustment. The trajectories of the states exhibited considerable variability and failed to establish notable global geographic clusters within the 14-state sample. The null hypothesis about rainfall connection is dismissed for all four modeled outcomes, the no-trend null is dismissed for net sown area, total cropped area, cropping intensity, and agricultural land, but the spatial randomness null is upheld. The results endorse a dual approach: climate-sensitive monitoring of uncultivated and planting circumstances, with enduring conservation and sustainable enhancement of the agricultural land foundation. Due to the observational and aggregated nature of the methodology, the given coefficients indicate associations rather than causal relationships.

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