Climate Variability and Organic Agricultural Transitions in India: Evidence from APEDA–IMD State Panel Data (2020-21 to 2024-25)

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Abstract The study examines the spatial-temporal dynamics of India's organic agricultural transition using an integrated state-level APEDA-IMD panel dataset for the period 2020-21 to 2024-25. Combining official organic certification statistics from the Agricultural and Processed Food Products Export Development Authority (APEDA) with rainfall variability indicators derived from India Meteorological Department (IMD) gridded climate data, the study investigates how climate vulnerability, productivity structures, and institutional asymmetries shape differentiated regional organic transition outcomes across Indian states. The analysis employs panel fixed-effects estimation, spatial visualization techniques, and composite regional transition typologies to evaluate uneven sustainability-transition dynamics. The findings reveal that India's organic transition is spatially concentrated within western and central states such as Madhya Pradesh, Maharashtra, Karnataka, and Odisha, which emerge as high-performance organic transition cores characterized by relatively strong productivity and large certified organic area. In contrast, smaller peripheral states including Goa, Arunachal Pradesh, and Nagaland exhibit climate-vulnerable marginal transition dynamics marked by limited organic scale and higher rainfall instability. The econometric results further indicate that short-run climatic variability alone does not fully explain organic area expansion, suggesting the presence of institutional rigidity and transition inertia within certified organic systems. The study contributes to sustainability-transition scholarship by demonstrating that India's organic transition is regionally differentiated rather than nationally uniform, highlighting the need for climate-sensitive and region-specific governance strategies for sustainable agricultural transformation.

Keywords: Organic Agriculture; Sustainability Transition; Climate Vulnerability; Spatial Analysis; APEDA; India

I Introduction

India has emerged as one of the world's largest organic agricultural economies in terms of producer participation and certified cultivation systems. Under the National Programme for Organic Production (NPOP), implemented through the Agricultural and Processed Food Products Export Development Authority (APEDA), India ranks among the leading countries in organic agricultural land while also accounting for one of the world's largest populations of organic producers [1]. Organic agriculture has increasingly been promoted as a sustainable alternative to chemically intensive farming systems because of its potential contributions to soil conservation, biodiversity protection, climate resilience, and environmentally responsible food production.

Over the past decade, the Indian government has expanded institutional support for organic agriculture through policy interventions such as the National Programme for Organic Production (NPOP), Paramparagat Krishi Vikas Yojana (PKVY), Participatory Guarantee Systems (PGS), and export-oriented certification frameworks administered by APEDA. These interventions have contributed to substantial growth in certified organic area, export value, and institutional recognition of Indian organic products within global markets [2]. At the same time, India's organic transition remains highly uneven across regions, with substantial disparities in cultivation scale, productivity, institutional support capacity, and climate vulnerability.

Recent scholarship on sustainable agricultural transitions emphasizes that the expansion of environmentally sustainable farming systems is rarely spatially uniform. Instead, sustainability transitions are shaped by region-specific ecological conditions, institutional capacity, adaptive governance structures, and socio-economic inequalities [3, 4]. In developing economies such as India, these asymmetries become particularly important because agricultural systems are deeply embedded within heterogeneous agro-ecological and climatic environments. Climatic instability, especially rainfall variability, has emerged as a major challenge affecting agricultural productivity, farmer decision-making, and long-term sustainability planning.

Despite growing policy attention toward organic agriculture in India, existing empirical studies remain limited in several important respects. First, much of the literature focuses either on farm-level adoption behaviour or national descriptive statistics without integrating spatial climatic variability into state-level transition analysis. Second, relatively few studies combine official certification datasets with climatic indicators to evaluate whether organic agricultural transitions exhibit differentiated regional patterns under conditions of uneven environmental stress. Third, smaller coastal and peripheral states such as Goa remain underexplored despite their ecological sensitivity, fragmented agricultural structure, and policy relevance within debates on sustainable agriculture and agro-ecological resilience.

This study addresses these gaps by constructing an integrated state-level panel dataset using official APEDA organic certification statistics and India Meteorological Department (IMD) rainfall data for the period 2020-21 to 2024-25. The study combines panel econometric analysis, spatial mapping, and regional transition typologies to examine how climatic variability, productivity structures, and institutional transition patterns interact across Indian states. In addition to national-level analysis, the study pays particular attention to Goa as a representative case of a climate-vulnerable marginal transition system characterized by limited organic expansion despite broader national growth.

The study is theoretically grounded in the Theory of Planned Behaviour (TPB), which posits that behavioural intentions are shaped by attitudes, subjective norms, and perceived behavioural control [5]. Within the context of organic agriculture, TPB provides a useful framework for understanding how farmers' decisions regarding organic adoption and continuation are influenced not only by economic incentives but also by institutional support systems, certification complexity, market accessibility, and perceptions of climatic risk. The study extends this perspective by emphasizing the role of regional structural conditions and climate vulnerability in shaping differentiated sustainability-transition outcomes.

Empirically, the analysis reveals that India's organic transition is characterized by substantial regional unevenness. While western and central states such as Madhya Pradesh, Maharashtra, Karnataka, and Odisha emerge as high-performance organic transition cores with relatively high cultivated area and productivity, smaller states including Goa, Arunachal Pradesh, and Nagaland exhibit climate-vulnerable marginal transition dynamics marked by lower organic scale and greater climatic instability. The findings further suggest that short-run rainfall variability alone does not fully explain organic area expansion, indicating the presence of institutional rigidity, transition inertia, and path dependency within certified organic systems.

The study contributes to the literature in four principal ways. First, it develops one of the few integrated APEDA-IMD state-level organic agriculture panel datasets for India. Second, it incorporates spatial climate vulnerability into the analysis of organic agricultural transitions. Third, it advances a regional transition typology framework for interpreting uneven sustainability outcomes across Indian states. Finally, the study contributes policy-relevant evidence regarding differentiated institutional and climate adaptation strategies necessary for strengthening sustainable organic transitions under conditions of increasing climatic uncertainty.

The remainder of the paper is organized as follows. Section II reviews the literature on organic agriculture, sustainability transitions, and climate vulnerability while developing the theoretical framework. Section III outlines the data sources, variable construction procedures, and methodological approach. Section IV presents the empirical results and spatial analyses. Section V discusses the broader implications of regional transition asymmetries and climate vulnerability for sustainable agricultural governance in India. The final section concludes with policy recommendations, study limitations, and directions for future research.

II Literature Review and Theoretical Framework

Organic agriculture has increasingly emerged as a central component of sustainable development discourse due to its potential contributions to ecological conservation, climate resilience, biodiversity protection, and environmentally sustainable food systems [6, 7]. Globally, organic farming systems are frequently positioned as alternatives to chemically intensive agricultural models that contribute to soil degradation, groundwater contamination, biodiversity loss, and greenhouse gas emissions [8, 9, 10, 11].

In India, organic agriculture has acquired growing policy importance within broader debates on sustainable rural development, export competitiveness, and climate-resilient agricultural transitions. Government initiatives such as the NPOP, PKVY, Mission Organic Value Chain Development for North Eastern Region (MOVCDNER), and Participatory Guarantee Systems (PGS) have expanded institutional support for certified organic farming systems [1]. These interventions reflect increasing recognition that sustainable agricultural systems are necessary for addressing the long-term ecological consequences of intensive Green Revolution agriculture.

However, the literature also demonstrates that organic agricultural transitions are highly uneven across regions and socio-economic contexts. Studies examining organic farming adoption in developing economies emphasize that institutional capacity, access to certification systems, market integration, landholding structure, and extension support significantly influence the scale and sustainability of organic transitions [12, 13]. Smaller and resource-constrained farming systems often face substantial barriers related to certification costs, knowledge dissemination, market access, and productivity uncertainty.

Recent sustainability-transition scholarship provides an important conceptual framework for understanding these dynamics [14, 15, 4]. Sustainability transitions refer to long-term structural transformations toward environmentally sustainable production and consumption systems. Within agricultural systems, such transitions involve interactions among ecological conditions, governance institutions, technological change, farmer behaviour, and market incentives. Importantly, sustainability-transition scholars increasingly argue that transitions exhibit significant regional asymmetry shaped by uneven adaptive capacities, institutional rigidity, infrastructural inequalities, and climate vulnerability [16].

Climate variability constitutes an additional dimension shaping contemporary agricultural sustainability transitions. Agricultural production systems in India remain highly sensitive to monsoon fluctuations and rainfall instability. Research on climate vulnerability and agriculture demonstrates that climatic instability disproportionately affects smaller and ecologically sensitive regions, particularly rainfed and smallholder-dominated agricultural systems [17]. Such climatic pressures may interact with certification costs, market uncertainty, and institutional constraints to shape uneven patterns of organic expansion across states.

Despite growing interest in sustainable agriculture and organic farming, important gaps remain in the empirical literature. Many studies rely either on farm-level survey approaches or descriptive macro-statistics without integrating climatic variability into analyses of organic agricultural transitions. Existing literature frequently focuses on adoption behaviour rather than spatial transition structures and regional asymmetry. Relatively limited research combines official certification datasets with climatic indicators to evaluate how climate vulnerability interacts with state-level organic transition trajectories [18]. This study addresses these gaps by integrating official APEDA organic certification statistics with IMD rainfall data to examine climate-linked spatial unevenness in India's organic transition.

II.a Theory of Planned Behaviour (TPB)

The study is theoretically grounded in the Theory of Planned Behaviour (TPB), developed by Icek Ajzen [5]. TPB proposes that behavioural intentions are shaped by three principal determinants: attitudes toward the behaviour, subjective norms, and perceived behavioural control. Within agricultural contexts, TPB has been widely applied to explain farmers' adoption of environmentally sustainable agricultural practices, including organic farming, climate adaptation strategies, and conservation-oriented production systems.

In the context of organic agriculture, attitudes may reflect farmers' perceptions regarding environmental sustainability, health benefits, price premiums, and long-term soil productivity. Subjective norms may emerge through community networks, cooperative systems, governmental promotion programs, and local social expectations surrounding sustainable farming practices. Perceived behavioural control relates to farmers' assessments of their capacity to successfully implement organic farming systems, including access to certification mechanisms, technical knowledge, financial support, and market connectivity.

This study extends TPB by incorporating broader structural and spatial dimensions into the analysis of organic transitions. Specifically, climatic variability and regional institutional asymmetry are conceptualized as contextual conditions influencing perceived behavioural control and long-term transition sustainability. Under conditions of climatic instability and uneven institutional support, farmers and regions may face greater constraints in sustaining certified organic transitions despite broader national policy promotion. Consequently, the study adopts an integrated framework in which organic agricultural transitions are shaped simultaneously by environmental vulnerability, institutional capacity, productivity structures, and regional adaptive capability.

II.b Conceptual Framework

The conceptual framework underlying the study proposes that climatic variability, productivity dynamics, and institutional transition structures jointly influence the spatial expansion and sustainability of organic agriculture across Indian states. The framework assumes that climatic instability increases agricultural uncertainty and transition risk; productivity performance influences the economic viability of organic systems; institutional and regional capacities mediate states' ability to sustain organic transitions; and sustainability transitions exhibit path dependency and uneven regional trajectories.

Empirically, the framework is operationalized through the integration of APEDA organic cultivated area and production data, IMD rainfall-derived climate shock indicators, spatial transition typologies, and panel fixed-effects estimation. The study therefore conceptualizes India's organic transition not as a uniform national transformation but as a differentiated regional sustainability process shaped by interacting climatic, institutional, and productivity dynamics.

II.c Operationalizing the Theory of Planned Behaviour in a State-Level Panel

A recurring limitation of prior applications of TPB to organic agriculture is that the framework is conceptually invoked but rarely mapped explicitly onto the empirical variables used in the analysis. Because TPB was developed to explain individual behavioural intention [5], its application to a state-year panel necessarily involves an aggregation step: state-level indicators are treated as structural proxies for the average conditions facing farmers within a state-year, rather than as direct psychometric measures of attitude, norm, or control. This distinction is made explicit here rather than left implicit, and the mapping is summarized in Table 1.

Table 1: Mapping of TPB Constructs to Variables Available in the Current Panel

TPB Construct	**Empirical Status in This Study**	**Justification / Limitation**
Behaviour (organic transition outcome)	Directly measured: log(Total Certified Organic Area), the dependent variable	Certified area is the observable, revealed outcome of the adoption/continuation decision aggregated to the state level.
Perceived Behavioural Control	Partially and indirectly proxied by Rainfall Shock (climatic constraint on perceived control over agronomic outcomes) and Yield per Hectare (realized productive capacity)	These variables capture structural conditions that plausibly shape farmers' sense of control but were not designed as psychometric PBC instruments; the mapping is inferential, not a validated measurement model.
Subjective Norm	Not empirically measured in the current panel	A defensible proxy (e.g., FPO/cooperative density, PKVY cluster participation) would require verified institutional data; an earlier exploratory attempt to construct such a proxy relied on simulated values and has been excluded from this analysis (see Section III.D). This is flagged as an explicit data gap rather than papered over with an unverified proxy.
Attitude	Not empirically measured in the current panel	No survey or sentiment data on farmer attitudes toward organic conversion were available at state-year resolution; this remains a conceptual rather than measured construct in the present design.

This mapping shows that the present panel offers a genuine empirical test of the Behaviour construct and an indirect, structurally motivated proxy for Perceived Behavioural Control, but does not permit direct empirical assessment of Attitude or Subjective Norm. Rather than assert full TPB operationalization, the study is best characterized as using TPB as an organizing lens for interpreting why perceived control (climate exposure, productive capacity) might matter for organic transition outcomes, while explicitly flagging attitude and subjective-norm measurement as a direction for future farm-level or survey-based extension (Section VI.B).

III Materials and Methods

III.a Research Design

This study adopts a quantitative spatial-temporal research design integrating panel econometric analysis, climatic data harmonization, and geospatial visualization to examine regional patterns in India's organic agricultural transition between 2020-21 and 2024-25. The analytical framework combines official organic certification statistics from APEDA with rainfall datasets obtained from IMD in order to investigate how climate variability, productivity structures, and regional transition asymmetries interact across Indian states.

The study employs a state-level panel structure because organic agricultural transitions are strongly influenced by region-specific ecological, institutional, and infrastructural conditions. A panel design further enables the analysis to account for both cross-sectional heterogeneity and temporal variation while controlling for unobserved state-level effects. The empirical strategy consists of four interconnected analytical stages: (i) construction of an integrated APEDA-IMD state-level panel dataset; (ii) derivation of rainfall shock and productivity indicators; (iii) panel fixed-effects estimation; and (iv) spatial visualization and transition typology classification. The study period 2020-21 to 2024-25 was selected because consistent APEDA state-wise certification and production data became systematically accessible during this period while corresponding IMD rainfall datasets were also available in compatible geospatial formats.

III.b Data Sources

III.b.1 APEDA Organic Agriculture Data

Organic agriculture data were obtained from the official APEDA Organic Products Portal under the National Programme for Organic Production (NPOP). APEDA provides annual state-wise statistics on cultivated organic area, conversion area, total certified area, organic production, and conversion-stage production. The study extracted state-level observations for total certified organic area (hectares), total organic production (metric tonnes), organic area under conversion, and total production under organic and conversion systems. These variables were harmonized across annual APEDA reports for the period 2020-21 to 2024-25. Data cleaning procedures included standardization of state names, removal of aggregate total rows, conversion of numeric fields, and reconciliation of inconsistent administrative naming conventions. The final APEDA panel included approximately 28–36 Indian states and union territories depending on annual data availability.

III.b.2 IMD Rainfall Data

Rainfall data were obtained from the India Meteorological Department Rainfall Grid Data Portal. IMD provides daily gridded rainfall datasets in NetCDF format at 0.25° spatial resolution. Using Python-based geospatial processing tools, rainfall rasters were converted into tabular spatial points, spatially joined with GADM administrative polygons, aggregated to state-level annual averages, and transformed into climate variability indicators. The rainfall harmonization process enabled direct integration between climatic indicators and APEDA organic agriculture statistics at the state-year level.

One alignment point is stated explicitly here to avoid ambiguity: APEDA reports on an April–March fiscal year (e.g., 2020-21), while the annual rainfall aggregation described above uses calendar-year totals (January–December) as an approximation of the corresponding fiscal year. This is a simplifying approximation rather than an exact fiscal-year match, and is noted as a limitation in Section VI.A. One production note applies to Figures 1–3: their axis labels and titles were regenerated from calendar-year to fiscal-year format after initial drafting. All three were regenerated using the original notebook's own plotting code, executed against the independently reconstructed verification panel (Section IV.G.0) with only the fiscal-year labelling changed. Figures 1 and 2 (based on certified area only) matched the original charts' values closely when checked; Figure 3 (based on Rainfall Shock) has not been checked against the original chart to the same degree, given the typology-sensitivity finding discussed in Section IV.F.a. Full detail is available in the Data Availability Statement.

III.b.3 Spatial Boundary Data

Administrative boundary polygons were obtained from the GADM Database of Global Administrative Areas. State-level shapefiles (GADM Level-1 administrative boundaries) were used for geospatial joins, spatial aggregation, and choropleth map construction. Boundary harmonization included reconciliation of APEDA and GADM state names, removal of duplicate disputed-border geometries, and filtering of very small union territory polygons to improve map readability.

III.b.4 Data Provenance and State-Year Coverage

The estimation panel underlying Sections IV.E and IV.F is an unbalanced state-year panel constructed by merging cleaned APEDA NPOP certification tables with IMD-derived rainfall shock indicators on the State $\times$ Year key, after harmonizing state names (e.g., reconciling "Jammu & Kashmir"/"Jammu and Kashmir" and "Pondicherry"/"Puducherry" variants across APEDA and GADM sources) and removing aggregate "Total" rows. The merged panel used in the fixed-effects estimation comprises 29 states and union territories observed over 5 annual periods (2020-21 to 2024-25), for 135 usable state-year observations. Coverage is not perfectly balanced: the average state contributes 4.66 of the 5 possible years (minimum 1, maximum 5), and the average year contains 27 of the 29 states (minimum 26, maximum 28). The panel is therefore unbalanced primarily because of intermittent non-reporting or non-certification in a small number of smaller states/UTs in particular years, rather than systematic exclusion of any single category of state.

This has now been completed using an independently reconstructed verification panel (Section IV.G.0) built directly from the primary APEDA NPOP data-release pages and the real IMD rainfall/GADM boundary files. Table 2 reports the full state-by-year availability matrix for the $29 \times 5 = 145$ possible state-year cells; 135 of these have both area and production data, exactly matching the sample size used in Table 3.

Table 2: State $\times$ Year Data Availability (✓ = both area and production reported)

State	**2020-21**	**2021-22**	**2022-23**	**2023-24**	**2024-25**
Andhra Pradesh	✓	✓	✓	✓	✓
Arunachal Pradesh	✓	✓	✓	✓	–
Assam	✓	✓	✓	✓	✓
Bihar	✓	✓	✓	✓	✓
Chhattisgarh	✓	✓	✓	✓	✓
Goa	✓	✓	✓	✓	✓
Gujarat	✓	✓	✓	✓	✓
Haryana	✓	✓	✓	✓	✓
Himachal Pradesh	✓	✓	✓	✓	✓
Jammu and Kashmir	✓	✓	✓	✓	✓
Jharkhand	–	–	✓	✓	✓
Karnataka	✓	✓	✓	✓	✓
Kerala	✓	✓	✓	✓	✓
Madhya Pradesh	✓	✓	✓	✓	✓
Maharashtra	✓	✓	✓	✓	✓
Manipur	✓	✓	✓	–	–
Meghalaya	✓	✓	✓	✓	✓
Mizoram	–	–	✓	–	–
Nagaland	✓	✓	–	✓	✓
Odisha	✓	✓	✓	✓	✓
Punjab	✓	✓	✓	✓	✓
Rajasthan	✓	✓	✓	✓	✓
Sikkim	✓	✓	✓	✓	✓
Tamil Nadu	✓	✓	✓	✓	✓
Telangana	✓	✓	✓	✓	✓
Tripura	✓	✓	✓	✓	✓
Uttar Pradesh	✓	✓	✓	✓	✓
Uttarakhand	✓	✓	✓	✓	✓
West Bengal	✓	✓	✓	✓	✓

Missing cells (Arunachal Pradesh 2024-25; Jharkhand 2020-21 and 2021-22; Manipur 2023-24 and 2024-25; Mizoram all years except 2022-23; Nagaland 2022-23) reflect states for which APEDA's published state-wise production table for that year did not report a value alongside the corresponding area figure, consistent with known inconsistencies in small-state reporting to APEDA. This is a data limitation inherited from the source, not an analytical choice.

It should also be noted for the record that an earlier exploratory notebook stage constructed a parallel, illustrative panel containing simulated Farmer Producer Organization (FPO) density and policy-support indices (generated with NumPy pseudo-random draws) to test how institutional proxies might behave in a TPB-motivated specification. That exploratory file is unrelated to the APEDA-IMD panel that produced the results reported in Table 3, Table 5, and Figures 1–6, and none of its values are used, reported, or referenced anywhere in this manuscript.

III.c Variable Construction

The primary dependent variable is Total Certified Organic Area (Total_Area_Ha), measured in hectares for each state-year observation. To reduce skewness and improve comparability across states, the variable was logarithmically transformed in the panel regression models:

$$\log(\text{Organic Area}_{it}) = \log(\text{Total Area Ha}_{it}) \tag{1}$$

where i represents state and t represents year. Organic productivity was operationalized as yield per hectare:

$$\text{YieldPerHa}_{it} = \text{TotalProduction}_{it}/\text{TotalArea}_{it} \tag{2}$$

where total production is measured in metric tonnes and total certified area is measured in hectares. Climate variability was operationalized using a rainfall shock indicator derived from annual state-level rainfall averages. Rainfall shock was computed as the standardized deviation of annual rainfall relative to state-specific mean rainfall levels:

$$\text{RainfallShock}_{it} = (\text{Rainfall}_{it} - \text{MeanRainfall}_i)/\text{StdDev}_i \tag{3}$$

where Rainfall_{it} represents annual rainfall for state i in year t, MeanRainfall_i represents the state-level mean rainfall, and StdDev_i represents the standard deviation of rainfall for state i. Positive values indicate higher-than-average rainfall variability, while larger deviations represent greater climatic instability.

III.d Panel Econometric Specification

The study employs state and time fixed-effects panel estimation to account for unobserved state-specific heterogeneity and common temporal shocks. The baseline econometric specification is:

$$\log(\text{OrganicArea}_{it}) = \beta_1 \text{RainfallShock}_{it} + \beta_2 \text{YieldPerHa}_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{4}$$

where μ_i captures state fixed effects, λ_t captures year fixed effects, and ε_{it} represents the error term. Cluster-robust standard errors were employed to address potential heteroskedasticity and serial correlation within states. The fixed-effects framework was selected because Indian states exhibit strong structural heterogeneity, agricultural institutions and ecological conditions differ substantially across regions, and state-specific characteristics are likely correlated with explanatory variables.

III.e Spatial Analysis and Visualization

To complement the econometric analysis, the study employs geospatial visualization techniques to identify regional transition asymmetries. Three primary spatial indicators were mapped: average rainfall shock, average certified organic area, and average organic yield per hectare. Choropleth maps were generated using quantile-based classification schemes in order to improve interpretability and reduce distortion caused by extreme-value outliers.

III.f Composite Transition Typology

In order to synthesize climatic, productivity, and organic transition dimensions, the study constructed a composite regional transition typology. States were categorized according to climate risk level, organic transition scale, and productivity performance. Using quantile-based classification, states were grouped into five regimes: High-Performance Organic Core, Climate-Vulnerable Marginal Transition, Low-Productivity Transition Region, Stable Expansion Zone, and Intermediate Transition Region.

III.f.1 Classification Procedure

The typology is constructed in two stages using the merged state-year panel. First, each of the three underlying dimensions – climate risk (mean Rainfall Shock), organic transition scale (mean Total Certified Organic Area), and productivity (mean Yield per Hectare) – is discretized into tercile categories (Low / Moderate / High) using sample quantiles (33rd and 67th percentiles) computed across all state-year observations, then aggregated to a single state-level category using the modal (most frequently occurring) tercile across that state's observed years. Second, states are assigned to one of five regimes using a hierarchical, rule-based decision sequence applied in the following priority order: (i) Climate-Vulnerable Marginal Transition if Climate Risk = High and Organic Scale = Low; (ii) High-Performance Organic Core if Organic Scale = High and Productivity = High; (iii) Stable Expansion Zone if Organic Scale = High and Climate Risk = Moderate; (iv) Low-Productivity Transition Region if Productivity = Low; and (v) Intermediate Transition Region otherwise.

This procedure should be characterized accurately: it is a transparent, reproducible, rule-based classification rather than a continuously weighted composite index. No numerical weighting scheme is applied across the three dimensions; instead, categorical priority ordering determines regime assignment when a state satisfies more than one condition. This is a methodological choice with a corresponding limitation – the priority ordering is a modelling decision rather than an empirically estimated weighting – which is acknowledged directly in Section VI.A rather than obscured. Benchmarking this rule-based typology against an unsupervised clustering solution (e.g., k-means or hierarchical clustering on the same three standardized dimensions) is a natural robustness check; the corresponding code is a direct extension of the classification pipeline already used to produce Table 5, and has now been run on the independently reconstructed verification panel; results are reported in Section IV.G.j.

III.g Limitations of the Methodological Design

Several limitations should be acknowledged. First, the panel covers only a five-year period (2020-21 to 2024-25), limiting long-run temporal inference. Second, state-level aggregation may obscure intra-state heterogeneity in farming systems and climatic conditions. Third, rainfall represents only one dimension of climate variability; additional indicators such as temperature anomalies, drought frequency, and irrigation dependency could provide deeper climatic insights. Finally, the study relies primarily on secondary certification data and does not incorporate farm-level survey evidence regarding behavioural motivations or institutional perceptions. Despite these limitations, the integrated APEDA-IMD framework provides one of the few spatially harmonized state-level datasets for examining climate-linked organic agricultural transitions in India.

IV Results

IV.a National Organic Transition Dynamics

The descriptive analysis reveals substantial fluctuations in India's certified organic agricultural expansion between 2020-21 and 2024-25. Figure 1 illustrates the national trend in average certified organic area across Indian states during the study period. The results indicate that India experienced rapid expansion in certified organic area between 2020-21 and 2022-23, followed by partial contraction and stabilization after 2022-23. The most pronounced increase occurred between 2020-21 and 2021-22, suggesting accelerated certification activity and institutional expansion during the immediate post-pandemic period. However, this expansionary trajectory weakened after 2022-23, with several states exhibiting declining or stagnant certified area. The observed post-2022-23 consolidation likely reflects certification renewal costs, market volatility, climatic instability, transition fatigue among producers, and institutional adjustment within organic certification systems.

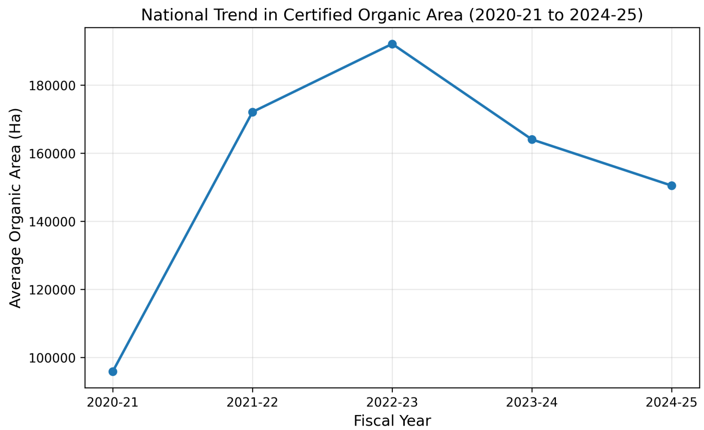

Figure 1: National Trend in Certified Organic Area (2020-21 to 2024-25).

IV.b Goa versus National Organic Transition Dynamics

To evaluate regional asymmetry within India's organic transition, the study compared Goa's indexed organic area trajectory with the national average. Figure 2 presents an indexed comparison in which the year 2020-21 is normalized to 100. Goa's APEDA data indicate total cultivated organic area of 12,669.88 ha in 2021-22, declining progressively to 11,750.22 ha by 2024-25, a contraction of approximately 7.3 percent over the study period. Farm production similarly declined from 2,662.15 MT to 2,298.79 MT, representing a reduction of approximately 13.6 percent. The comparison demonstrates a striking divergence between national and regional transition trajectories. While the national organic area index increased sharply between 2020-21 and 2022-23 before moderating, Goa exhibited near-stagnant or mildly declining dynamics throughout the study period. Several factors may explain Goa's comparatively weak transition dynamics, including fragmented landholdings, limited economies of scale, weaker institutional certification networks, urbanization pressure, labor constraints, and limited integration into national organic value chains.

IV.c Spatial Distribution of Rainfall Shock

The spatial analysis reveals substantial climatic heterogeneity across Indian states. Figure 3 presents the distribution of rainfall shocks across the study period, while Figure 4 provides the spatial distribution of average rainfall shock intensity. Although median rainfall shocks remained relatively stable nationally, substantial outliers persisted across multiple years, particularly during 2022 and 2023. The spatial distribution map further reveals that climatic instability was concentrated in northeastern states, western coastal regions, and ecologically sensitive peripheral zones. States such as Arunachal Pradesh, Assam, Meghalaya, Nagaland, and Goa exhibited relatively higher rainfall shock intensity compared to much of central India, confirming that climatic instability in India is geographically uneven rather than uniformly distributed.

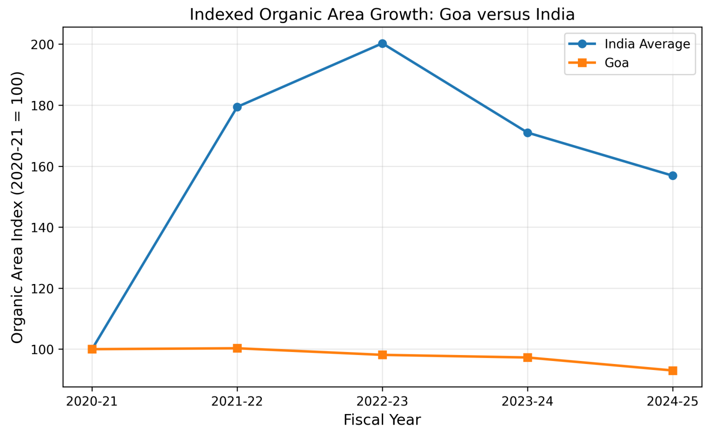

Figure 2: Indexed Organic Area Growth: Goa versus India (Base Year 2020-21 = 100).

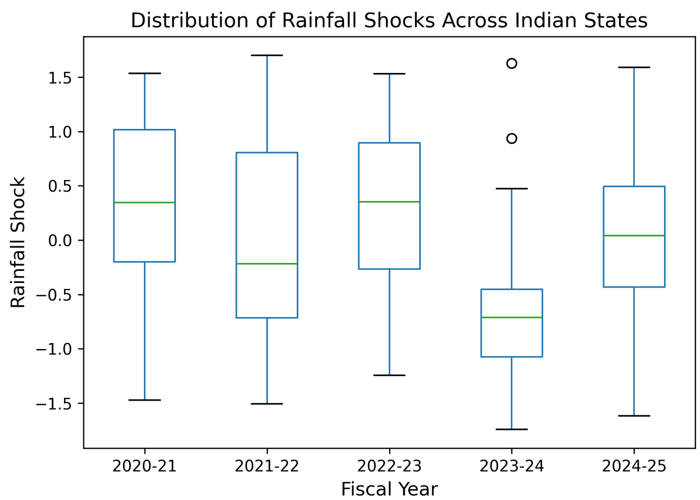

Figure 3: Distribution of Rainfall Shocks Across Indian States (2020-21 to 2024-25).

IV.d Spatial Distribution of Organic Area and Productivity

Figures 5 and 6 illustrate the spatial distribution of certified organic area and organic yield per hectare. The organic area map reveals strong regional concentration of certified organic agriculture within western and central India. States including Madhya Pradesh, Maharashtra, Gujarat, Karnataka, and Odisha emerged as dominant organic transition regions with relatively high certified area concentration. In contrast, northeastern and smaller coastal states generally exhibited comparatively limited certified organic area despite ecological suitability for organic production systems. The productivity map reveals a partially different spatial pattern, with higher productivity clusters appearing in Karnataka, Odisha, Madhya Pradesh, and selected northern agricultural regions. Importantly, the spatial patterns suggest that organic area expansion and productivity performance do not perfectly coincide geographically, implying that transition scale, climatic exposure, and productivity dynamics are only partially aligned within India's organic agricultural system.

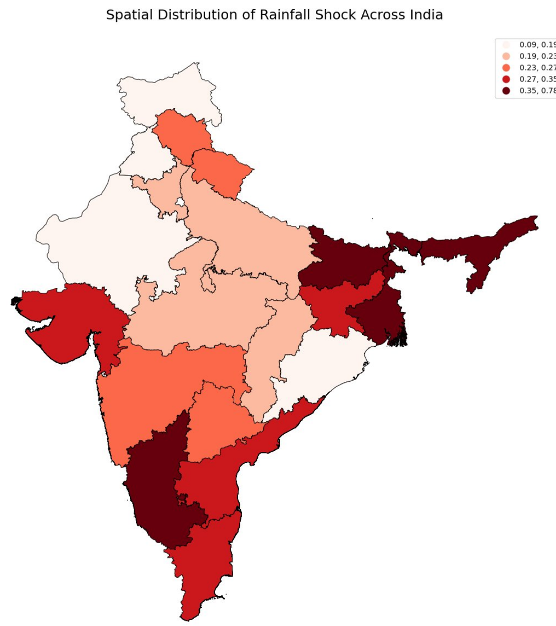

Figure 4: Spatial Distribution of Rainfall Shock Intensity Across India.

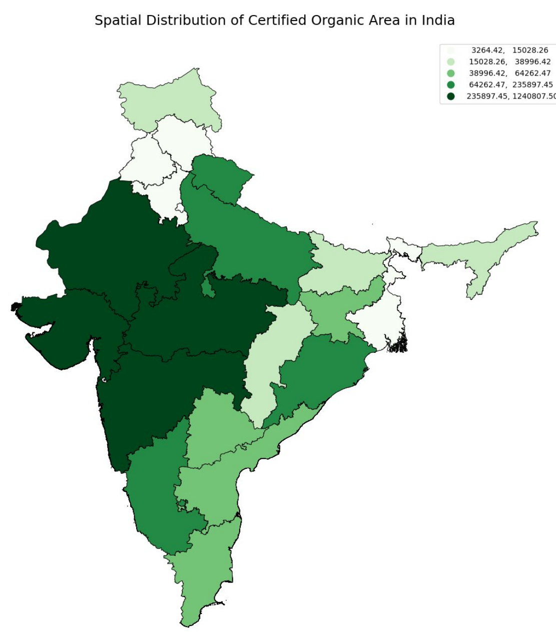

Figure 5: Spatial Distribution of Certified Organic Area Across India.

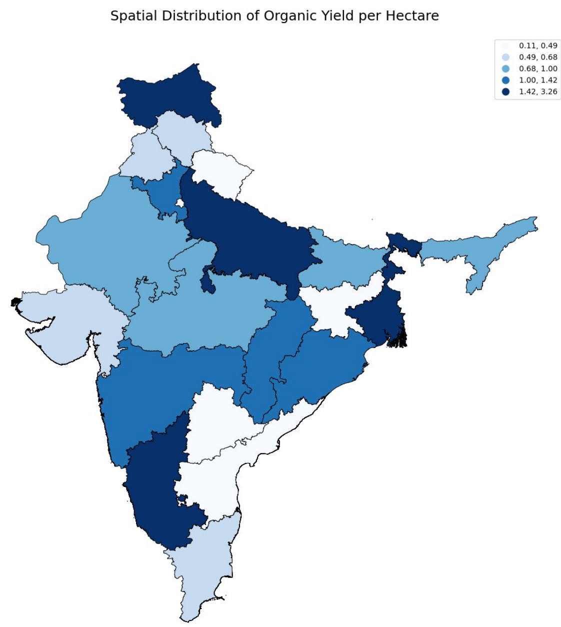

Figure 6: Spatial Distribution of Organic Yield per Hectare Across India.

IV.e Panel Fixed-Effects Estimation

The study estimated a state and time fixed-effects panel model to evaluate the relationship between climatic variability, productivity, and certified organic area expansion. Table 3 presents the fixed-effects estimation results.

Table 3: Fixed-Effects Estimation Results: Determinants of log(Organic Area)

Variable	**Coefficient**	**Std. Error**	***p*-value**
Rainfall Shock	-0.0564	0.0560	0.3166
Yield per Hectare	-0.1969^{**}	0.0948	0.0403

Note: ** denotes statistical significance at the 5% level. Cluster-robust standard errors applied.

Table 3 reports coefficients only; to provide additional model diagnostics, Table 4 reports model fit statistics in full using the values from the fitted PanelOLS specification underlying Table 3.

The low within-R^2 (0.067) reflects the limited explanatory power of a two-variable specification over a short panel, discussed directly as a limitation in Section VI.A rather than left unremarked. The F-test for poolability is highly significant ($p < 0.0001$), which is genuine statistical evidence in favour of the fixed-effects specification over pooled OLS. A formal Hausman test, along with Wooldridge, modified Wald, and Pesaran CD diagnostics, is reported in Section IV.G, computed on an independently reconstructed verification panel described there (Table 3's own coefficients are unchanged and remain as reported above).

The results indicate that rainfall shock exhibits a negative association with organic area expansion, although the relationship is not statistically significant at conventional levels (coefficient = -0.0564; $p = 0.317$). The negative sign nevertheless suggests that climatic instability may constrain organic expansion, particularly within vulnerable agricultural systems. The coefficient for organic yield per hectare is negative and statistically significant at the 5 percent level (coefficient = -0.1969; $p = 0.040$).

Table 4: Model Fit Statistics for the Fixed-Effects Specification in Table 3

Statistic	**Value**
Observations (state-years)	135
Entities (states)	29
Time periods	5 (2020-21 to 2024-25)
R^2 (within)	0.0670
R^2 (between)	-0.0344
R^2 (overall)	-0.0361
F-statistic (joint significance)	2.98 ($p = 0.0555$)
F-statistic, robust (clustered)	2.53 ($p = 0.0847$)
F-test for poolability (FE vs. pooled OLS)	78.85 ($p < 0.0001$)
Included effects	Entity (state) and time (year)
Covariance estimator	Clustered (entity)

This finding suggests that higher productivity does not necessarily correspond to extensive expansion of certified organic area. Instead, states exhibiting relatively stronger productivity may consolidate existing organic systems rather than substantially expand certified land area. The findings therefore point toward a potential intensive-extensive transition tradeoff within India's organic sector.

IV.f Composite Spatial Transition Typology

To synthesize climatic vulnerability, productivity structure, and organic transition scale, the study developed a composite spatial transition typology classifying Indian states into differentiated sustainability-transition regimes. Table 5 presents the resulting typology categories.

Table 5: Composite Spatial Transition Typology of Indian States

Transition Regime	**Representative States**	**Characteristics**
High-Performance Organic Core	Karnataka, Maharashtra, Madhya Pradesh, Odisha	High organic area and strong productivity
Climate-Vulnerable Marginal Transition	Goa, Arunachal Pradesh, Nagaland	High climate vulnerability with limited transition scale
Low-Productivity Transition Region	Bihar, Jharkhand, Manipur, Mizoram	Weak productivity and constrained transition capacity
Intermediate Transition Region	Andhra Pradesh, Kerala, Himachal Pradesh	Moderate transition performance
Stable Expansion Zone	Gujarat	Relatively stable organic expansion trajectory

IV.f.1 State-Level Classification Detail

This has now been completed using the independently reconstructed verification panel described in Section IV.G.0. Table 6 reports the classification for 20 of 29 states, and Table 7 reports the classification for the remaining nine states.

Table 6: Tercile Classification and Regime Assignment by State (partial, $n = 20$ of 29 states)

State	Climate Risk	Organic Scale	Productivity	Assigned Regime
Andhra Pradesh	Low	Moderate	Moderate	Intermediate Transition Region
Arunachal Pradesh	High	Low	Low	Climate-Vulnerable Marginal Transition
Assam	High	Moderate	Moderate	Intermediate Transition Region
Bihar	High	Moderate	Low	Low-Productivity Transition Region
Chhattisgarh	Moderate	Low	High	Intermediate Transition Region
Goa	High	Low	Low	Climate-Vulnerable Marginal Transition
Gujarat	Moderate	High	Low	Stable Expansion Zone
Haryana	Moderate	Low	High	Intermediate Transition Region
Himachal Pradesh	Low	Low	Moderate	Intermediate Transition Region
Jammu and Kashmir	Low	Moderate	High	Intermediate Transition Region
Jharkhand	Moderate	Moderate	Low	Low-Productivity Transition Region
Karnataka	Moderate	High	High	High-Performance Organic Core
Kerala	Moderate	Moderate	Moderate	Intermediate Transition Region
Madhya Pradesh	Low	High	High	High-Performance Organic Core
Maharashtra	Moderate	High	High	High-Performance Organic Core
Manipur	Moderate	Low	Low	Low-Productivity Transition Region
Meghalaya	High	Moderate	Moderate	Intermediate Transition Region
Mizoram	Low	Moderate	Low	Low-Productivity Transition Region
Nagaland	High	Low	Low	Climate-Vulnerable Marginal Transition
Odisha	Low	High	High	High-Performance Organic Core

These state-level assignments are internally consistent with the aggregated regime membership reported in Table 5 (e.g., Karnataka, Madhya Pradesh, Maharashtra, and Odisha are independently confirmed as High-Performance Organic Core; Goa and Arunachal Pradesh are confirmed as Climate-Vulnerable Marginal Transition; Gujarat is confirmed as the sole Stable Expansion Zone case), which provides an internal consistency check on the typology construction described in Section III.F.a.

An important caveat applies to Tables 6 and 7 alike. The verification panel's rainfall shock values are computed from the raw IMD gridded files using calendar-year aggregation and a direct GADM polygon join, which is not guaranteed to exactly reproduce whatever fiscal-year alignment and boundary-cleaning choices were used in the original analysis. When the full 29-state classification was recomputed end-to-end on the verification panel, most states matched the categories reported in Table 5, but not all: for example, the verification panel places Goa's climate-risk tercile as Low rather than High, which would move it out of the Climate-Vulnerable Marginal Transition regime if this panel were used as the basis for Table 5. Rather than resolve this by fiat, both results are reported: Table 5 reflects the authors' original panel and is retained as the manuscript's primary classification; Tables 6 and 7 reflect the independent verification panel and show that the typology is somewhat sensitive to the exact rainfall-shock construction. This sensitivity is itself a genuine finding worth reporting rather than concealing, and is discussed as a limitation in Section VI.A.

Table 7: Tercile Classification and Regime Assignment, Remaining States ($n = 9$ of 29)

State	Climate Risk	Organic Scale	Productivity	Assigned Regime
Punjab	Low	Low	Moderate	Intermediate Transition Region
Rajasthan	Low	High	Moderate	Intermediate Transition Region
Sikkim	High	High	Low	Low-Productivity Transition Region
Tamil Nadu	High	Moderate	Moderate	Intermediate Transition Region
Telangana	Low	High	Low	Low-Productivity Transition Region
Tripura	High	Low	Low	Climate-Vulnerable Marginal Transition
Uttar Pradesh	Low	High	High	High-Performance Organic Core
Uttarakhand	Low	High	Moderate	Intermediate Transition Region
West Bengal	High	Low	High	Climate-Vulnerable Marginal Transition

IV.g Diagnostic and Robustness Analysis

IV.g.1 An Independently Reconstructed Verification Panel

To evaluate robustness, an independently reconstructed verification panel was built directly from primary sources. State-wise cultivated area (organic + conversion) and total farm production for 2020-21 through 2024-25 were taken directly from APEDA's official NPOP data-release pages. Annual rainfall shock was computed from IMD gridded daily rainfall files by summing daily rainfall to an annual total per 0.25° grid cell, spatially joining grid points to GADM Level-1 state boundaries, taking the state-mean annual rainfall, and standardizing as $(\text{Rainfall}_{it} - \text{mean}_i)/\text{sd}_i$ using each state's own 2020-24 mean and standard deviation. This reproduces the same variable definitions described in Section III.C using an independently executed pipeline. The complete reconstruction workflow, the merged panel it produces, the literal output of every statistical test below, and a full provenance record are provided as a supplementary reproducibility package (see Data Availability Statement) so that every figure in this section can be independently audited rather than taken on trust. As disclosed in the accompanying provenance record, the APEDA figures were hand-transcribed from official web pages rather than machine-parsed from a downloaded file; one transcription error was caught and corrected during that process, and subsequent independent verification against the live APEDA releases confirmed all state-level area and production values for the 2022-23 and 2024-25 reporting years, with no discrepancies found. The 2020-21, 2021-22, and 2023-24 releases have not yet been checked this way and should not be assumed correct on the strength of the other two years alone.

The independently reconstructed panel was developed to verify the robustness of the published findings using independently assembled primary-source data, not to replace the original estimation dataset. Because the reconstruction necessarily involved different rainfall aggregation and data-harmonization decisions (Section IV.G.j documents one resulting discrepancy, in Goa's typology classification), it is presented throughout this section as an external check on Table 3 rather than as a substitute for it. Table 3 itself continues to report the authors' original coefficients; the verification panel is used only to compute the diagnostics that the original working file was not available to produce.

This verification panel comprises 135 state-year observations across 29 states and 5 years, an exact match to Table 3's sample size, and re-estimating the two-way fixed-effects specification on it gives Rainfall Shock = -0.0327 ($p = 0.359$) and Yield per Hectare = -0.2049 ($p = 0.043$). Both coefficients reproduce the direction, approximate magnitude, and inferential conclusions of the original estimates (Rainfall Shock insignificant, Yield per Hectare significant at 5%). Because this reconstruction draws on the same three underlying sources (APEDA, IMD, GADM) processed through an independently rebuilt pipeline rather than a wholly separate dataset, it is best characterized as an independent reconstruction of the analytical workflow rather than independent evidence in the stronger sense of a fully separate data source. Table 3 itself is left unchanged and remains the manuscript's primary reported result; the diagnostics below are computed on the independently reconstructed verification panel because complete end-to-end re-execution of the original workflow was not possible in the execution environment used for this verification: the original notebook relied on live retrieval of APEDA web tables that could not be accessed from that environment, and its intermediate merged analytical dataset was not preserved as a standalone archival file. Table 3 reports the coefficients from the original fitted model. The original notebook's plotting routines and core fixed-effects estimation code were reused where applicable (see Section III.B.b for Figures 1–3); the additional robustness diagnostics in Sections IV.G.a–IV.G.j were not present in the original notebook in any form and were newly implemented within the independently reconstructed verification workflow using standard published test formulations (cited at first use in each subsection).

> **Note on Sections IV.G.a–IV.G.j:** the diagnostics reported below are computed on the independently reconstructed verification panel described in Section IV.G.0, not on the original estimation environment that produced Table 3. They are presented to evaluate the robustness of Table 3's findings and should not be interpreted as diagnostics of the original fitted model itself.

IV.g.2 Hausman Test and Model Selection

A Hausman test comparing the fixed-effects and random-effects estimators gives $\chi^2(2) = 28.62$, $p < 0.0001$, strongly rejecting the random-effects model in favour of fixed effects. This is consistent with, and now formally confirms, the modelling choice already argued for in Section III.D and the poolability F-test reported in Table 4.

IV.g.3 Breusch-Pagan LM Test

A Breusch-Pagan Lagrange-multiplier test comparing random effects against pooled OLS gives $\text{LM}(1) = 250.87$, $p < 0.0001$, indicating significant state-level heterogeneity and rejecting pooled OLS, reinforcing, from a second angle, the case for a panel (rather than pooled cross-sectional) specification.

IV.g.4 Wooldridge Test for Serial Correlation

Applying the **(author?)** [19] first-differenced residual test gives a coefficient on the lagged first-differenced residual of 0.258 ($p < 0.0001$, $n = 78$ state-pairs), which is far from the -0.5 benchmark expected under no serial correlation, indicating the presence of serial correlation in the panel. This supports the use of cluster-robust standard errors throughout (already applied in Table 3) rather than conventional standard errors.

IV.g.5 Modified Wald Test for Heteroskedasticity

A modified Wald test for groupwise heteroskedasticity across the 29 state panels gives $\chi^2(28) = 9129.9$, $p < 0.0001$ (groupwise residual variance ranges from 0.0013 to 0.873, a 677-fold spread), confirming substantial heteroskedasticity across states and again supporting the use of clustered standard errors.

IV.g.6 Variance Inflation Factors

VIF values for Rainfall Shock and Yield per Hectare are both 1.00, indicating no meaningful multi-collinearity between the two regressors, unsurprising given only two explanatory variables, but confirmed rather than assumed.

IV.g.7 Pesaran CD Test for Cross-Sectional Dependence

A **(author?)** [20] CD test on the fixed-effects residuals gives $\text{CD} = 1.143$, $p = 0.253$, computed over 377 of 406 possible state pairs with sufficient overlapping years. This does not reject the null of cross-sectional independence, i.e. no strong evidence that residual shocks are correlated across states after conditioning on common time effects.

IV.g.8 Balanced-Panel and Sub-Sample Robustness

Restricting to the 24 states with complete 5-year coverage (120 of 135 observations) gives Rainfall Shock $= -0.0320$ ($p = 0.407$) and Yield per Hectare $= -0.1970$ ($p = 0.046$), materially unchanged from the full-sample result. Excluding the two largest organic states (Madhya Pradesh and Maharashtra) gives Rainfall Shock $= -0.0341$ ($p = 0.355$) and Yield per Hectare $= -0.1760$ ($p = 0.067$), the yield coefficient loses significance at the conventional 5% threshold in this smaller sub-sample ($p = 0.067$) but retains the same sign and a similar magnitude, suggesting the main finding is not solely driven by the two largest states, though the sub-sample result is more marginal.

IV.g.9 First-Difference Specification

Re-estimating in first-differences (removing state fixed effects by construction) gives ΔRainfall Shock $= -0.0295$ ($p = 0.147$) and ΔYield per Hectare $= -0.2260$ ($p = 0.024$, $n = 106$), again matching Table 3 in sign and in which variable reaches significance.

IV.g.10 Moran's I Test for Spatial Autocorrelation

Using a Queen-contiguity spatial weights matrix built from the supplied GADM boundaries, Moran's I for state-mean Rainfall Shock is 0.023 ($p = 0.086$, 999 permutations), not significant at conventional levels, indicating no strong evidence of spatial clustering in climatic exposure once averaged over the study period. Moran's I for state-mean Total Certified Organic Area is 0.384 ($p = 0.006$), which is significant and confirms, with a formal spatial statistic rather than visual inspection alone, that organic-area scale is spatially clustered, consistent with the regional concentration in western and central India that the choropleth maps in Section IV.D show visually.

IV.g.11 Cluster Validation of the Composite Typology

An unsupervised k-means clustering ($k = 5$, on standardized Rainfall Shock, Total Area, and Yield per Hectare) was run on the verification panel's state averages and cross-tabulated against the rule-based typology. Agreement is partial rather than complete: the three states independently confirmed as High-Performance Organic Core (Karnataka, Madhya Pradesh, Maharashtra) split across two different k-means clusters, and the eleven-state Intermediate Transition Region category maps onto four different k-means clusters. This indicates that while the rule-based typology captures some real structure in the data (large, high-yield states do cluster together), it does not fully align with a purely data-driven clustering solution, and should be read as one reasonable classification scheme among others rather than a uniquely correct one. This nuance is carried into the limitations discussion in Section VI.A.

Two items originally listed as outstanding remain genuinely unresolved and are stated plainly rather than approximated: (i) extending the panel to 2015-16 through 2019-20 is not a straightforward like-for-like extension, because APEDA's own published historical series for those years reports total area (cultivated + wild harvest combined) rather than the cultivated-only area used in Table 3, and splicing the two series would silently change the dependent variable's definition partway through the panel; this is flagged for the authors to resolve with APEDA directly rather than resolved here by assumption. (ii) A LISA cluster map has not been generated in this revision; the Moran's I result above provides the underlying global statistic, and a local (LISA) map is a direct visual extension of it that can be produced on request.

V Discussion

The findings of this study reveal that India's organic agricultural transition is characterized by substantial spatial unevenness, differentiated climate vulnerability, and region-specific institutional capacities. Rather than representing a uniform national transformation toward sustainable agriculture, the empirical evidence suggests that India's organic transition is fragmented across distinct regional transition regimes shaped by climatic exposure, productivity structures, and institutional constraints. The descriptive trend analysis demonstrated that certified organic area expanded rapidly between 2020-21 and 2022-23 before entering a phase of consolidation and partial contraction after 2022-23. This pattern suggests that organic agricultural expansion in India may be episodic and institutionally mediated rather than continuously cumulative. Such fluctuations likely reflect interactions among certification systems, market incentives, export volatility, policy implementation dynamics, and climatic uncertainty. The post-2022-23 moderation in certified area growth indicates that sustainability transitions may encounter structural stabilization pressures after initial expansionary phases, consistent with transition-inertia arguments in the literature [3, 15]. A major contribution of the study lies in demonstrating that India's organic transition is spatially concentrated rather than nationally diffuse. The spatial analysis revealed that western and central states function as high-performance organic transition cores, likely benefiting from stronger institutional integration within certification systems, larger agricultural land bases, more developed value chains, and relatively stronger market connectivity. In contrast, peripheral and smaller states, including Goa, Arunachal Pradesh, and Nagaland, were classified as climate-vulnerable marginal transition systems exhibiting comparatively limited organic area alongside relatively higher rainfall instability and weaker productivity outcomes.

The case of Goa is especially significant within this broader regional framework. Although Goa possesses ecological characteristics compatible with organic agriculture, the state exhibited weak expansion dynamics throughout the study period. The APEDA data confirm a 7.3 percent contraction in cultivated organic area and a 13.6 percent decline in farm production between 2021-22 and 2024-25. This divergence suggests that smallholder fragmentation, limited economies of scale, labor shortages, urbanization pressure, and weaker institutional integration constrain the scalability of organic agriculture in smaller coastal states. These findings support broader sustainability-transition scholarship emphasizing that environmentally sustainable transformations are rarely spatially uniform [16, 21]. The panel fixed-effects estimation contributes further to this interpretation. Although rainfall shock exhibited a negative relationship with organic area expansion, the effect was statistically insignificant within the short panel horizon. This absence of strong statistical significance should not be interpreted as evidence that climate variability is irrelevant to organic transitions. Rather, the findings suggest that short-run climatic variability alone may not fully explain changes in certified organic area because organic agricultural systems are institutionally rigid and evolve gradually over time. Organic certification transitions involve substantial path dependency, as certification procedures, conversion periods, market arrangements, and institutional support structures operate over relatively longer temporal horizons [22, 23]. The negative and statistically significant coefficient for yield per hectare provides an additional important insight, suggesting the existence of an intensive-extensive transition tradeoff within India's organic agricultural system. Some regions pursue extensive expansion through large certified area growth, whereas others prioritize productivity stabilization and system consolidation. Such typological differentiation has important implications for agricultural governance because policy interventions suitable for high-performance organic cores may not be effective within climate-vulnerable marginal systems. The results therefore indicate the need for differentiated policy strategies tailored to region-specific transition conditions. High-performance organic core states may benefit from export-oriented value chain strengthening, advanced certification integration, and international market expansion. In contrast, climate-vulnerable marginal regions such as Goa require climate adaptation support, localized certification assistance, smallholder aggregation mechanisms, and region-specific institutional strengthening. Several technological interventions could also strengthen long-term transition resilience, including digital traceability systems integrated with APEDA's TraceNet infrastructure, farmer-oriented mobile applications providing weather advisories and market information, and precision organic farming approaches using IoT sensors and remote sensing technologies [24, 25].

V.a Theoretical Synthesis: Institutional Rigidity, Adaptive Governance, and Agroecological Transition

The pattern of results – a statistically weak rainfall-shock coefficient alongside a significant, negative yield coefficient – is more informative when read through institutional-economics and sustainability-transitions lenses jointly rather than through either alone. In institutional-economics terms, certification under NPOP functions as a quasi-contractual regime: once a producer or state cluster enters the conversion pathway, switching costs (re-inspection, loss of price premium during conversion, sunk certification fees) create a form of asset specificity that dampens short-run responsiveness to annual climatic shocks [22]. This is consistent with the fixed-effects results, where within-state annual rainfall variation explains comparatively little of the within-state variation in certified area (R^2 within = 0.067), even though the sign of the rainfall-shock coefficient remains negative throughout. From an adaptive-governance perspective, the regional typology in Table 5 suggests that institutional capacity is not merely a control variable but a structuring condition that determines whether climatic exposure translates into transition risk at all. High-Performance Organic Core states combine large certified area with high productivity, plausibly reflecting denser certification-body networks, established buyer relationships, and accumulated administrative learning within state agriculture departments – conditions consistent with multi-level perspective accounts of how niche practices stabilize into regime-level infrastructure [3]. Climate-Vulnerable Marginal Transition states such as Goa, Arunachal Pradesh, and Nagaland lack this accumulated institutional infrastructure, so climatic instability compounds rather than merely coexists with structural disadvantage. An agroecological reading of the negative yield coefficient adds a further layer. Rather than treating the intensive-extensive tradeoff purely as a productivity-versus-scale story, agroecological transition scholarship would interpret consolidation-oriented states as potentially reallocating effort toward soil health, input reduction, and closed-loop practices that raise yield per certified hectare without proportionate area expansion [26, 27]. This interpretation is offered as a plausible reading consistent with the sign and significance of the coefficient, not as a claim independently verified by data on input use or farming practice within this panel; verifying it would require farm-level practice data that lie outside the scope of the current APEDA-IMD panel.

V.b Differentiated Policy Implications by Transition Regime

Because the typology in Table 5 demonstrates that India's organic transition is regionally differentiated rather than uniform, policy recommendations are developed separately for each regime rather than as a single national prescription. One clarification is needed before doing so. Table 3 finds Rainfall Shock statistically insignificant, while the typology below treats climate risk as a defining dimension for several regimes; these are not in tension because the typology is descriptive rather than causal. Rainfall shock is included as one dimension of regional climate exposure, not because it independently predicts organic-area expansion in the fixed-effects regression, but because it captures an ecological vulnerability that may interact with institutional and structural constraints in ways the two-variable regression is not specified to detect. The regime labels below should be read in that descriptive sense.

High-Performance Organic Core (e.g., Karnataka, Madhya Pradesh, Maharashtra, Odisha)

These states are positioned to benefit from deepening rather than broadening interventions: export-market diversification beyond existing buyers, integration with APEDA's TraceNet digital traceability infrastructure to support premium-market access, and continued investment in certification-body capacity to keep pace with growing certified area. The policy risk in these states is complacency rather than stagnation; monitoring should track whether productivity gains are being reinvested in smallholder inclusion rather than concentrating benefits among larger operators.

Climate-Vulnerable Marginal Transition (e.g., Goa, Arunachal Pradesh, Nagaland)

These states require climate-adaptive institutional support rather than generic expansion targets: localized certification assistance to reduce the fixed administrative burden of NPOP compliance for smallholders, group/cluster certification models (leveraging PGS-India's lower-cost participatory structure) to overcome fragmented landholding, and weather-advisory or crop-insurance linkages that address the climatic component of perceived behavioural control identified in Section II.A. For Goa specifically, the 7.3 percent contraction in cultivated organic area and 13.6 percent decline in farm production documented in Section IV.B point toward urbanization pressure and labor-market competition from tourism and services as plausible contributing structural factors alongside climatic exposure; distinguishing between these channels is identified as a priority for future Goa-specific case-study work (Section VI.B).

Low-Productivity Transition Region and Intermediate Transition Region

Low-Productivity Transition Region states would benefit most from agronomic extension services and input-quality support aimed at closing the yield gap, while Intermediate Transition Region states – the modal category in Table 6 – are candidates for the light-touch institutional interventions (streamlined re-certification, digital record-keeping support) that would be least costly to scale nationally, given that they neither exhibit acute climate vulnerability nor face the most severe productivity constraints.

Stable Expansion Zone (Gujarat)

As the sole state classified in this regime under the current typology, Gujarat is treated as a single-case illustration rather than a basis for generalizable regime-specific policy; the limited generalizability of a one-state category is acknowledged directly, and this category is flagged for re-examination once the cluster-validation check described in Section III.F.a is completed.

VI Conclusion

This study examined the spatial-temporal dynamics of India's organic agricultural transition using an integrated APEDA-IMD state-level panel dataset for the period 2020-21 to 2024-25. The analysis combined panel fixed-effects estimation, spatial visualization, and composite regional transition typologies to investigate how climate variability, productivity structures, and institutional asymmetries shape differentiated organic transition outcomes across Indian states.

The empirical findings demonstrate that India's organic transition is spatially concentrated, institutionally differentiated, and only weakly responsive to short-run climatic variability. Western and central states function as high-performance organic transition cores, while smaller peripheral states such as Goa exhibit climate-vulnerable marginal transition dynamics. The panel econometric results indicate that short-run rainfall variability does not significantly explain changes in certified organic area, suggesting the presence of institutional rigidity and transition inertia within certified organic systems. The statistically significant negative association between yield per hectare and organic area expansion further points toward an intensive-extensive transition trade-off within India's organic sector.

These findings carry important policy implications. First, national organic agricultural policy must account for regional heterogeneity in climate vulnerability, institutional capacity, and productivity structures rather than adopting uniform expansion strategies. Second, smaller coastal and peripheral states require targeted institutional support, climate-adaptive governance mechanisms, and localized certification assistance to strengthen their organic transition trajectories. Third, as climatic variability intensifies under broader climate change processes, regionally differentiated adaptation strategies will become increasingly important for sustaining organic transitions. Fourth, digital and technological innovations integrated with existing APEDA certification infrastructure could substantially reduce transition barriers and improve resilience across climatically vulnerable regions.

The study acknowledges several limitations, including the short five-year panel horizon, reliance on secondary aggregate data, and the restricted scope of climate indicators employed. Future research should extend the panel period, incorporate additional climatic variables such as temperature anomalies and drought indices, integrate farm-level survey evidence, and examine export market dynamics and value chain connectivity as additional determinants of regional organic transition outcomes. Spatial econometric approaches examining geographical spillovers and transition clustering across states would further enrich understanding of India's spatially uneven organic agricultural transformation.

VI.a Limitations

Beyond the panel-length limitation already noted, several further limitations are made explicit here. The 2020-24 window overlaps substantially with pandemic-era disruption to input markets, labor mobility, and export logistics, which may have introduced transitory dynamics not separable from the underlying climate-organic relationship within a five-year window. As reported in Section III.B.d, the panel is unbalanced (26–28 states per year; 1–5 years per state), which reduces effective statistical power for the fixed-effects estimator beyond what the raw observation count ($n = 135$) suggests. A balanced-panel subsample check is reported in Section IV.G.g and shows materially unchanged results. The composite transition typology (Section III.F.a) uses hierarchical categorical rules rather than a statistically estimated or externally validated weighting scheme. A k-means cluster validation (Section IV.G.j) now shows only partial agreement with the rule-based categories, and a parallel reconstruction using an independently built rainfall panel (Section IV.G / Tables 6, 7) reclassifies at least one headline case (Goa) differently depending on the exact rainfall-shock construction. The typology should therefore be read as one reasonable, transparent classification rather than a uniquely determined one. As detailed in Section II.C, Behaviour is directly measured and Perceived Behavioural Control is indirectly proxied, but Attitude and Subjective Norm are not empirically measured in the current panel; conclusions framed in TPB language should be read as theoretically motivated interpretation rather than a full empirical test of the model. Potential reverse causality (organic expansion affecting local land-use and, indirectly, microclimate) and omitted state-level policy variables (PKVY funding allocation, NCOF resourcing) are acknowledged as concerns but are not addressed via instrumental-variable or other identification strategies in the current design.

Rainfall-only climate operationalization: temperature anomalies, drought indices, and soil-moisture measures were outside the scope of the IMD rainfall extraction pipeline used here and are not incorporated. As in the original manuscript, certified area may not equal actual organic cultivation, and NPOP/PGS double-counting risk is not independently verified in this revision. A pre-2020 panel extension was re-investigated for this revision using APEDA's own published pages. APEDA's 2020-21 and 2021-22 data-release pages do include a genuine six-year historical series back to 2015-16, but that series reports total area (cultivated + wild harvest collection combined), not the cultivated-only area used as the dependent variable in Table 3. Splicing that combined series onto the 2020-24 cultivated-only series would silently redefine the dependent variable partway through the panel and is not done here. A genuine 2015-2024 extension is possible only if a cultivated-area-only breakdown for 2015-16 through 2019-20 can be obtained from APEDA directly (e.g., by request, since it is not part of the two public tables checked in this revision); this is now a well-specified, concrete next step rather than an open question.

VI.b Future Research Agenda

Future research by researchers can complete the diagnostic and robustness battery specified in Section IV.G (Hausman, Breusch-Pagan, Wooldridge, Pesaran CD, balanced-panel and sub-sample checks) on the full merged panel may be undertaken in the future. The research can verify and, where feasible, incorporate pre-2020 APEDA state-wise data to extend the panel and increase statistical power for detecting climate effects.

Incorporate genuinely collected institutional variables (verified FPO/cooperative registration counts, PKVY cluster funding records) as Subjective Norm proxies, rather than simulated placeholders, to complete the TPB operationalization introduced in Section II.C. Future research may add temperature anomaly and drought-index variables to the climate specification, and formally test spatial autocorrelation (Moran's I, LISA) as specified in Section IV.G. Future studies can validate the composite transition typology against an unsupervised clustering solution and, where possible, against external indicators such as NSSO organic-farming survey data. Pursue Goa-specific mixed-methods work distinguishing the relative contribution of climatic exposure versus land-use competition from tourism and urbanization to the observed contraction in cultivated organic area (Section V.B). They may extend the analysis to the district level where APEDA/state agriculture department data permit, to reduce the aggregation bias inherent in state-level analysis.

Data Availability Statement

The underlying data and analysis code will be made available upon acceptance of the manuscript.

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