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Agricultural Development and Inter-District Inequality in Madhya Pradesh: Evidence from a Composite Agricultural Development Index and Panel Analysis

Abstract. Madhya Pradesh has witnessed substantial agricultural expansion from 2011–12 to 2024–25, but the extent to which this progress has been shared across districts remains an important empirical issue. This study examines agricultural development and inter-district inequality in Madhya Pradesh by using a Composite Agricultural Development Index (CADI) and Principal Component Analysis. District-level agricultural capability is assessed using multiple productive indicators while changes in inter-district inequality are investigated by using Gini coefficient, Theil index and coefficient of variation. Panel regression models are used to examine the association between selected agricultural factors and district-level agricultural output while Bai–Perron structural-break analysis yields additional evidence on changes in selected agricultural indicators over time.

The results indicate overall improvements in agricultural capability, coupled with a modest reduction in inter-district inequality. Gini coefficient of CADI decreased from 0.2228 in 2011 to 0.2163 in 2024, while Theil index decreased from 0.0832 to 0.0801 and coefficient of variation dropped from 0.4066 to 0.3982. These changes indicate limited sigma-convergence rather than rapid equalisation of agricultural capability across districts. The panel estimates suggest that mechanisation has the most consistent positive association with district-level agricultural output across the estimated specifications while the relationships for irrigation, institutional credit, labour productivity and technology-related variables are less uniform across the models. Structural-break analysis detects shifts in crop yield, labour productivity, CADI and institutional credit, but these breaks are interpreted descriptively rather than as evidence of causal effects of particular policies or shocks. Overall, agricultural expansion in Madhya Pradesh has been accompanied by only gradual narrowing of inter-district disparities, underscoring the need to take district-specific approaches to productive infrastructure, irrigation, finance, technology, mechanisation and market access as well as policies aiming to increase aggregate agricultural output.

Keywords: agricultural development, inter-district inequality, Composite Agricultural Development Index, principal component analysis, agricultural output, panel analysis, Madhya Pradesh

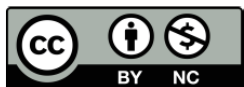
JEL Classification: O13, O18, Q15, R11, J43

Introduction

Madhya Pradesh has emerged as a significant agricultural state in India with considerable growth in food grain, irrigation and agricultural output over the last two decades. Wheat and soybeans have been a significant aspect of this growth (Government of India, 2024). However, the overall state-level performance does not provide much information about the distribution of agricultural development across districts. The districts differ in terms of irrigation, infrastructure, institutional finance, mechanisation, technology, markets and other factors that affect agricultural performance.

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The association between agricultural growth and regional inequality might not be uniform. Enhancements in infrastructure, technology and markets can enable relatively less-developed districts to increase their productive capacity, while disparities may persist if productive assets, institutional capabilities and market opportunities are unevenly distributed. Evidence from India suggests that regional differences in terms of infrastructure, public support, markets and asset distribution continue to exist despite economic growth (Vakulabharanam, 2019; Ramakumar, 2021; Himanshu, 2022; Harriss-White, 2023). Within agriculture, factors such as irrigation, formal credit, procurement, connectivity and technology also impact productivity across locations (Chand & Parappurathu, 2012; Gulati & Juneja, 2020).

Agricultural output and yield alone cannot capture differences in productive capability. The districts which have comparable output differ in terms of irrigation, mechanisation, technology, finance and labour productivity. A composite indicator can help to capture a multidimensional view of agricultural development (Nardo et al., 2008). Principal Component Analysis (PCA) provides an empirical approach for constructing such an index based on the variability between the selected indicators (Jolliffe, 2002). The study has constructed a Composite Agricultural Development Index (CADI) to examine the relative agricultural capability across districts and over time.

Madhya Pradesh has been an appropriate setting, as agricultural expansion has been considerable, while productive conditions have been heterogeneous across the districts. Previous research has focused on agricultural growth, crop production, irrigation, procurement and diversification while comparatively less attention has been paid to the evolution and distribution of multidimensional agricultural capability within the state. A district-level analysis is necessary to understand whether aggregate agricultural growth has been accompanied by a reduction of internal disparities.

A district-level analysis for 2011–12 to 2024–25 has been conducted using data from which CADI is constructed using PCA and has examined the inter-district distribution using Gini coefficient, Theil index and coefficient of variation. These indicators have been used to examine the changes in dispersion and extent of sigma-convergence. Separately, panel regression models have been examined to associate the selected agricultural factors with district-level agricultural output. Bai–Perron structural-break analysis provides supplementary evidence on the changes in selected agricultural indicators over time. The structural breaks have been interpreted descriptively and should not be considered evidence of the causal effects of specific policies or shocks.

The study has explored three questions: (i) how does agricultural capability vary across Madhya Pradesh districts, (ii) have inter-district disparities narrowed during agricultural expansion, and (iii) which selected productive and institutional factors are associated with district-level agricultural output? By combining multidimensional index construction, inequality measures and panel analysis, the study provides within-state evidence on agricultural development and the distribution of productive capability and implications for district-sensitive agricultural policy.

Objectives of the Study

This study examines agricultural development and inter-district inequality in Madhya Pradesh from 2011–12 to 2024–25. The specific objectives are:

1. To construct a Composite Agricultural Development Index (CADI) using Principal Component Analysis and assess changes in district-level agricultural capability over the study period.
2. To examine inter-district inequality in agricultural development and assess changes in dispersion using the Gini coefficient, Theil index and coefficient of variation.
3. To examine the association between selected agricultural factors and district-level agricultural output using panel regression models.
4. To identify temporal structural shifts in selected agricultural indicators using Bai–Perron structural-break analysis as supplementary evidence.

Literature and Policy Context

Agricultural Growth and Regional Inequality

Agricultural development has a strong spatial dimension: where irrigation, technology, infrastructure, market access and public investment are unevenly distributed across regions. The diffusion of modern inputs and irrigation during and after the Green Revolution, contributed to substantial differences in agricultural productivity and growth across India (Bhalla & Singh, 2010; Chand & Parappurathu, 2012). Subsequent differences in infrastructure, public support and market access have continued to shape regional agricultural outcomes.

Agricultural growth does not necessarily imply a reduction in regional disparities. Convergence theory suggests that relatively less-developed regions may catch up through technology diffusion, infrastructure development and market integration (Barro & Sala-i-Martin, 1992). However, persistent differences in productive assets and institutional conditions can limit such adjustment. Evidence on regional inequality in India indicates that economic growth has coexisted with substantial spatial disparities (Bhattacharya & Sakthivel, 2004; Vakulabharanam, 2019; Ramakumar, 2021). These findings suggest that aggregate agricultural growth and spatial equalisation are analytically distinct outcomes.

The distinction is particularly important at the district level. State-level averages can hide substantial differences in irrigation, productivity, infrastructure and access to productive resources among districts. A within-state analysis can thus identify patterns that may not be evident in inter-state comparisons. Therefore, the question of whether agricultural expansion in Madhya Pradesh has been accompanied by a measurable reduction in inter-district disparities becomes a motivating force.

Measuring Multidimensional Agricultural Capability

Agricultural output and yield are important measures of performance but do not fully capture the productive conditions underlying agricultural development. Districts may achieve similar output levels while differing in irrigation, mechanisation, input use, technology

adoption, credit access and labour productivity. Composite indicators provide a way of representing several dimensions jointly and are commonly used in multidimensional regional analysis (Nardo et al., 2008).

Principal Component Analysis offers an empirical method for constructing composite measures by deriving weights from the statistical structure of the selected indicators (Jolliffe, 2002; Abdi & Williams, 2010). Its usefulness depends on the variables included, their measurement and the treatment of the resulting components. Consequently, a PCA-based index should be interpreted as a relative measure of agricultural capability rather than an absolute measure of development. In this study, CADI is used to examine differences in multidimensional agricultural capability across Madhya Pradesh districts and their evolution over time.

Productivity and the Broader Process of Structural Change

Agricultural productivity is also relevant to broader rural economic transformation. Classical development theory links agricultural productivity growth with economic transformation and the movement of labour towards higher-productivity activities (Lewis, 1954; Johnston & Mellor, 1961). Evidence from India, however, indicates that agricultural productivity growth and labour transition do not necessarily proceed at the same pace, particularly where non-farm employment opportunities and local economic diversification are limited (Bremar, 2021; Dev, 2022; Himanshu, 2022).

For the present study, this literature provides a context for considering labour productivity as one dimension of agricultural capability. It does not imply that the study directly estimates labour reallocation or structural transformation. Thus, those interpretations are treated as contextual rather than direct empirical findings.

Productive Assets, Finance and Agricultural Performance

The distribution and use of productive assets can contribute to differences in agricultural performance across locations. Irrigation can reduce dependence on rainfall and support more intensive cultivation, although its effects depend on crop choice, technology and market conditions (Chand, 2019; Gulati & Juneja, 2020). Mechanisation can improve the timeliness and efficiency of farm operations, although its relationship with output may depend on farm structure, access to finance and local production conditions (Rajkhwa & Kubik, 2021).

Institutional credit can facilitate investment in productive inputs and technology, although its availability and utilisation vary across regions (Misra et al., 2016). Procurement, extension, transportation and market access can further influence the returns to agricultural investment (Gulati & Sharma, 2021). These differences provide a basis for examining whether selected productive and institutional factors are associated with district-level agricultural output.

The literature therefore does not imply that individual inputs necessarily have uniform effects across districts. Their observed relationships may depend on differences in local conditions and whether variation occurs between districts or within districts over time. Consequently, this study treats the panel estimates as associations rather than causal effects.

Madhya Pradesh and the District-Level Evidence Gap

Madhya Pradesh has experienced substantial agricultural expansion since the mid-2000s, reflected in agricultural output, irrigation, procurement and foodgrain production (Chand, 2018; Gulati, 2020; Government of Madhya Pradesh, 2024). At the same time, official statistics and agricultural assessments indicate considerable variation across districts in irrigation, cropping intensity, productivity, finance and production conditions.

The existing literature provides important evidence on agricultural growth and regional disparities, but has given comparatively little attention to the evolution of multidimensional agricultural capability within Madhya Pradesh over an extended period. In particular, aggregate growth measures do not establish whether district-level disparities in productive capability have narrowed. This creates a specific empirical gap: examining agricultural expansion and the distribution of agricultural capability simultaneously at the district level.

Research Gap and Analytical Positioning

The literature establishes three relevant points. First, agricultural growth can coexist with persistent spatial disparities. Second, agricultural development is multidimensional and cannot be represented by output alone. Third, irrigation, mechanisation, finance, technology and productivity are important correlates of agricultural performance, with relationships varying across locations and specifications. District-level Indian evidence also shows variation in convergence across agricultural outcomes and periods: Murtaza and Masood (2020) report inter-district variation alongside absolute and conditional convergence in agricultural productivity, while Balaji and Gopinath (2023) find convergence in farm income, with slower convergence in recent periods. These findings underscore the need to examine both agricultural performance and regional disparities.

The current study examines Madhya Pradesh at the district level from 2011–12 to 2024–25. Its contribution is empirical, combining a PCA-based CADI, inter-district inequality measures and panel analysis to examine agricultural capability, its distribution and correlates of agricultural output within one state. Bai–Perron structural-break analysis provides supplementary evidence on temporal changes in selected indicators. The study thus distinguishes agricultural expansion from the pace of reduction in inter-district disparities rather than assuming that growth produces convergence.

Based on this literature and analytical positioning, the study examines the following hypotheses:

H1: Agricultural development differs across districts of Madhya Pradesh.

H2: Inter-district disparities in agricultural development show limited convergence over the study period.

H3: Selected productive and institutional factors are significantly associated with district-level agricultural output.

H4: State-level agricultural growth can coexist with persistent inter-district disparities.

Empirical mapping of hypotheses:

H1 is assessed using the district-level descriptive statistics in Table 4; H2 is assessed through the annual Gini, Theil and coefficient of variation measures in Table 7; H3 is evaluated using the pooled OLS, fixed-effects and median quantile estimates in Table 5; and H4 is assessed jointly from the evidence of agricultural expansion and persistent inter-district differences in Tables 4 and 7.

Data and Analytical Framework

Data Sources and Variables

The study uses district-level data for Madhya Pradesh for 2011–12 to 2024–25. Data were compiled from official state and central sources: the Directorate of Economics and Statistics, Agricultural Census and land-use statistics, the Soil and Land Use Board, Madhya Pradesh Economic Surveys, IMD and CGWB. The dataset covers agricultural output and productivity, irrigation, cropping intensity, mechanisation, fertiliser use, HYV adoption, institutional credit, labour productivity, landholding size and rainfall.

Agricultural productivity is measured as crop production relative to cropped area; irrigation as the percentage of net sown area irrigated; cropping intensity as gross cropped area relative to net sown area; mechanisation using tractors per 1,000 hectares; credit as institutional agricultural credit relative to cultivated area; and labour productivity using agricultural output relative to agricultural labour. Agricultural GVA at constant prices is used to construct the dependent variable, expressed in logarithmic form as LogAgGSDP.

Data Consistency

The final analytical panel comprises 15 districts observed over 14 annual periods from 2011–12 to 2024–25, yielding 210 district-year observations. The panel is balanced for the variables included in the reported specifications, with no missing observations in the final estimation sample and no observations interpolated. Accordingly, the pooled OLS, district fixed-effects and median quantile specifications reported in Table 5 each use the same 210 district-year observations.

Analytical Framework

The empirical analysis combines four components. First, a Composite Agricultural Development Index (CADI) is constructed using Principal Component Analysis (PCA) from standardised agricultural development indicators. KMO and Bartlett's tests are used to assess PCA suitability. The reported eigenvalues and component loadings are used to determine the final index specification.

Second, inter-district inequality is examined using the Gini coefficient, Theil index and coefficient of variation (CV). Declining dispersion is interpreted as sigma-convergence; however, beta-convergence cannot be inferred from these measures alone.

Third, panel models examine associations between LogAgGSDP and selected agricultural factors using pooled OLS, district fixed effects and median quantile estimation. The analysis is interpreted as associative rather than causal because reverse causality and omitted time-varying factors cannot be ruled out.

Lastly, Bai–Perron structural-break analysis is used as a supplementary assessment of changes in selected aggregate agricultural indicators. Breaks are interpreted descriptively rather than as evidence of causal effects.

PCA Results and Methodological Measures

Table 1 reports the results of PCA suitability tests. The KMO value of 0.8484 indicates good sampling adequacy. Bartlett's test is significant ($\chi^2 = 3,780.45$, $df = 21$, $p < 0.001$), rejecting the null hypothesis that the correlation matrix is an identity matrix and indicating sufficient correlation among the variables for PCA. Cronbach's alpha (0.4254) is reported descriptively; it is not used as a criterion for PCA suitability.

Table 1. Reliability and Sampling Adequacy Tests

Test	Value
Cronbach Alpha	0.4254
KMO Measure	0.8484
Bartlett Chi-square	3780.45
Bartlett df	21
Bartlett p-value	0.0000

Source: Authors' calculations based on the compiled dataset.

Table 2 shows that PC1 explains 83.21% of total variance and PC2 explains 14.92%, with the two components jointly explaining 98.13%. PC1 has substantial loadings on crop yield, irrigation, fertiliser use, mechanisation, HYV adoption and labour productivity, while institutional credit loads strongly on PC2.

Table 2. PCA Eigenvalues and Explained Variance

Component	Eigenvalue	Variance (%)	Cumulative (%)
PC1	5.852	83.21	83.21
PC2	1.050	14.92	98.13
PC3	0.049	0.69	98.83
PC4	0.034	0.48	99.31
PC5	0.027	0.39	99.70
PC6	0.019	0.27	99.97
PC7	0.002	0.03	100.00

Source: Authors' calculations based on PCA results.

Table 3 shows that PCA results indicate a common dimension associated with agricultural productive capacity, while institutional credit forms a distinct second component. Since both PC1 and PC2 have eigenvalues above one, the manuscript should state explicitly which component or combination of components was used to construct CADI and apply that procedure consistently throughout the analysis

Table 3. PCA Component Loadings

Variable	PC1	PC2	PC3
Crop_Yield	-0.408	0.046	-0.415
Irrigation_Coverage	-0.392	-0.261	-0.692
Fertiliser_Use	-0.408	-0.152	0.241
Tractors_Per_1000Ha	-0.407	-0.137	0.350
Credit_Per_Ha	-0.134	0.923	-0.125
HYV_Adoption	-0.409	0.005	0.338
Labour_Productivity	-0.402	0.187	0.196

Source: Authors' calculations based on PCA results.

Inter-district dispersion is assessed using the Gini coefficient, Theil index and coefficient of variation (CV). Falling dispersion values are interpreted as sigma-convergence. This set of indicators does not allow us to confirm beta-convergence. To do this, one would have to perform a separate regression testing the hypothesis that initially lower performers grew faster.

The panel estimates explore the associations between LogAgGSDP and the explanatory variables reported in the regression results using pooled OLS, district fixed effects and median quantile estimation. Since the relationships found are not necessarily causal, we use the wording associations rather than effects due to reverse causality or the omission of time-varying confounders.

Bai–Perron tests were used to detect structural changes in selected agricultural indicators. As structural breaks are not causal variables, the breaks detected in this way are interpreted purely descriptively. Spatial claims based on Moran's I or LISA are excluded from the empirical interpretation unless the corresponding results are reported.

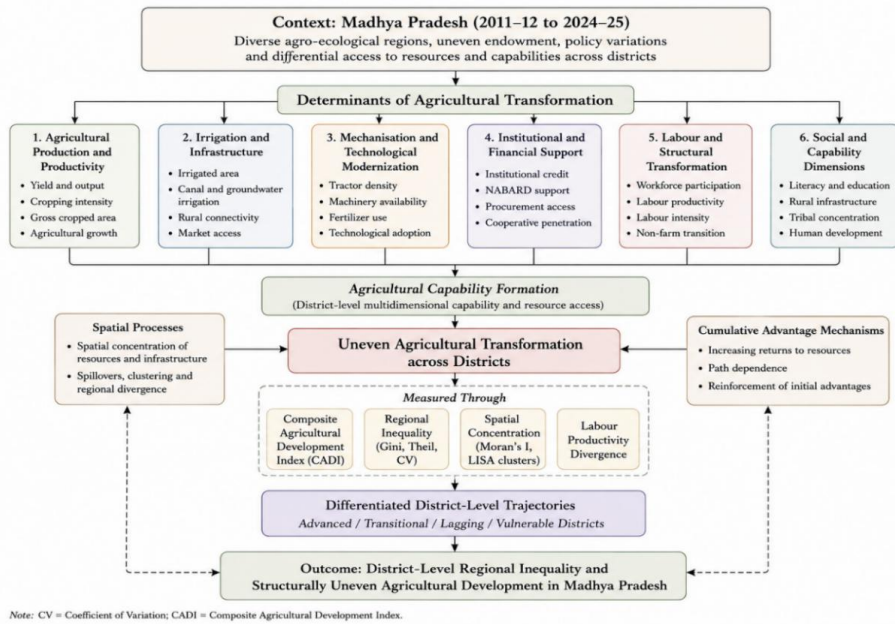


Fig. 1. Conceptual Framework of Inter-District Differences in Agricultural Development in Madhya Pradesh

Source: Authors' elaboration.

The framework links agricultural productivity and productive capacity with differences in irrigation, mechanisation, technology adoption, institutional support and labour productivity across districts. These dimensions underpin the CADI and the assessment of inter-district inequality and agricultural performance.

Methodology

Research Design

The study explores inter-district differences in agricultural development in Madhya Pradesh from 2011–12 to 2024–25. Particular attention is paid to three issues: the patterns of heterogeneity in agricultural development across districts, changes in dispersion of these indicators among districts over time, and associations of agricultural performance with selected productive factors. A descriptive analysis, construction of the Composite

Agricultural Development Index (CADI), inequality measures, panel estimation and structural-break analysis are used.

Variable Selection and Economic Rationale

The analysis includes agricultural productivity, irrigation, mechanisation, institutional credit, HYV adoption, fertiliser use, labour productivity, rainfall and average landholding. Agricultural performance is captured by logarithm of district agricultural GVA (LogAgGSDP). These variables embody productive conditions that are potentially different across districts and are related to agricultural performance. Infrastructure and diversification are treated as contextual dimensions of agricultural development and are not estimated as covariates in the reported panel models.

Variable Relationship and Regional Disparity Specification

The analysis studies evolutionary paths of productive capacities of agricultural performance and potential heterogeneity of relations between them across districts. Irrigation, mechanisation, institutional credit, HYV adoption, fertiliser use and labour productivity are identified as major productive and institutional factors. Agricultural performance is captured by logarithm of district agricultural GVA (LogAgGSDP). The Composite Agricultural Development Index (CADI) is used as measure of district ranking and inequality and convergence analysis, thus avoiding specification in which it is explained by the variables to which it is also a regressor.

The baseline model is specified as:

$$\ln(\text{AgGSDP}_{it}) = \alpha + \beta_1 \text{Irrigation}_{it} + \beta_2 \text{Mechanisation}_{it} + \beta_3 \text{Credit}_{it} + \beta_4 \text{HYV}_{it} + \beta_5 \text{Fertilizer}_{it} + \beta_6 \text{LabourProductivity}_{it} + \beta_7 \text{Rainfall}_{it} + \beta_8 \text{Landholding}_{it} + \mu_i + \tau_t + \varepsilon_{it}$$

where i denotes district and t denotes year. The terms μ_i and τ_t represent district and year fixed effects, respectively. District effects absorb differences in geographical, agro-climatic, infrastructural, and institutional location-specific attributes, while year effects account for contemporaneous shocks that may simultaneously affect all districts.

The estimates are interpreted as conditional associations rather than causal effects, given potential reverse causality, omitted time-varying factors and measurement issues. Differences between pooled and fixed-effects estimates are therefore interpreted cautiously as reflecting different sources of variation across specifications. The analysis focuses on inter-district differences using descriptive statistics, inequality measures, CADI and panel estimation. No spatial econometric analysis is undertaken.

Inequality and Convergence

Inter-district inequality is measured using the Gini coefficient, Theil index and coefficient of variation (CV) for CADI. A reduction in these coefficients demonstrates a lower dispersion and suggests sigma-convergence. The study does not infer beta-convergence from a lower Gini, Theil or CV coefficient. A beta-convergence test requires a growth-regression analysis of absolute or relative convergence of initially lower vs higher districts.

Descriptive statistics report the mean, standard deviation and range for the main variables. In addition, the districts are compared across their initial positions for the main indicators to identify any differences between the higher and lower CADI districts.

The Gini, Theil index and the coefficient of variation (CV) measure inter-district inequality in agricultural development using the following indicators. A reduction in these coefficients demonstrates a lower dispersion and suggests sigma-convergence, but not beta-convergence (Shorrocks, 1980).

Construction of the Composite Agricultural Development Index (CADI)

The Composite Agricultural Development Index (CADI) was constructed using seven indicators representing agricultural productive capacity: crop yield, irrigation coverage, fertiliser use, tractor density, institutional credit per hectare, HYV adoption and labour productivity. Each indicator was standardised using the z-score transformation:

$$Z_{kit} = (X_{kit} - \bar{X}_k) / s_k \dots\dots\dots(1)$$

where X_{kit} denotes the value of indicator k for district i in year t , $\bar{X}_k$ denotes its sample mean, and s_k denotes its standard deviation. PCA was then applied to the correlation matrix of the seven standardised indicators. The Kaiser–Meyer–Olkin (KMO) measure was 0.8484, while Bartlett's test of sphericity was significant ($\chi^2 = 3780.45$, $df = 21$, $p < 0.001$) confirming the suitability of the data for PCA. Cronbach's alpha was 0.4254 and is reported descriptively; it was not used as a criterion for retaining or rejecting the PCA.

The first principal component (PC1) had an eigenvalue of 5.852 and explained 83.21% of total variance. Although PC2 had an eigenvalue of 1.050, PC1 was retained because it captures the dominant common variation across the seven indicators and provides a single composite measure of overall agricultural development. The PC1 loadings were -0.408 for crop yield, -0.392 for irrigation, -0.408 for fertiliser use, -0.407 for tractors, -0.134 for institutional credit, -0.409 for HYV adoption, and -0.402 for labour productivity. Accordingly, the oriented CADI score is represented as:

$$CADI_{it} = -\sum_{k=1}^7 w_k Z_{kit} \dots\dots\dots(2)$$

where w_k denotes the PC1 loading for indicator k . The negative sign reverses the component orientation so that higher CADI values indicate higher agricultural development. The resulting index was used to rank districts and assess inter-district inequality and convergence. CADI was not included as a regressor alongside its constituent indicators to avoid mechanical collinearity.

Convergence Analysis

Convergence is evaluated with respect to inter-district differences in agricultural development during the study period. A sigma-convergence is determined based on changes in Gini coefficient, Theil index and coefficient of variation (CV) – a decrease of which imply that there is a smaller spread between the districts in terms of levels of agricultural development. These convergence indicators reflect changes in distribution and hence can be used to infer sigma-convergence (Shorrocks, 1980).

Beta-convergence describes a situation where initially poorer districts tend to grow faster compared to initially richer ones thus reducing the initial gaps. It should be noted that no beta-convergence regression is presented in this study. Hence, based on the absence of increase in Gini, Theil or CV measures, beta-convergence cannot be inferred.

Panel Econometric Analysis

The panel analysis investigates the relationship between district-level agricultural performance, as indicated by LogAgGSDP, and a range of productive and institutional factors including irrigation, mechanisation, institutional credit, HYV adoption, fertiliser use, labour productivity, rainfall and average landholding. CADI is excluded in such regressions as it is a composite measure constructed from agricultural development indicators and including it along with its components would mechanically create overlaps.

The empirical specification is estimated through pooled OLS, district fixed effects and year effects. While district fixed effects account for unobserved heterogeneity that may be constant across the districts over time such as agro-climatic conditions, soil characteristics and institutional or investment differences, the year effects account for common shocks (Wooldridge, 2020; Baltagi, 2021). The models therefore offer complementary insights based on pooled and district level variations.

A median quantile specification is also estimated to assess if the relations hold across the conditional distribution of agricultural performance. For all specifications, interpretation of the coefficients is in the form of conditional associations and not causal effects, as reverse causality and time-varying factors could influence agricultural performance as well as variables such as irrigation, credit, mechanisation or technology adoption.

Quantile Regression Analysis

The pooled models' average effects may mask heterogeneity across districts with differing levels of agricultural performance. Irrigation, mechanisation, institutional credit and labour productivity may therefore exhibit differing associations across the agricultural performance distribution. To investigate this heterogeneity, median quantile regression is estimated with LogAgGSDP as the dependent variable (Koenker & Bassett, 1978; Koenker, 2005). The quantile specification complements the pooled and fixed-effects models by investigating conditional associations at the median of the agricultural performance distribution. For Madhya Pradesh, this approach is particularly suitable in light of differing resource endowments, irrigation and market access across districts. The estimates are interpreted as conditional associations rather than causal effects due to potential reverse causality and other unaccounted factors affecting the observed associations.

Bai–Perron Structural Break Analysis

The Bai–Perron multiple structural-break methodology is used to examine potential changes in the trajectories of selected agricultural indicators over time (Bai & Perron, 1998, 2003). The analysis considers LogAgGSDP, crop yield, the Composite Agricultural Development Index (CADI), labour productivity, irrigation coverage, institutional credit, mechanisation, fertiliser use and high-yielding variety (HYV) adoption.

The structural-break analysis is supplementary to the principal analyses of inter-district inequality and panel relationships. Given the short annual time series, any identified break dates are interpreted cautiously. They indicate potential changes in the temporal patterns of the selected indicators and do not, by themselves, establish causal effects of specific policies, climatic events or the COVID-19 pandemic. Statistical significance and the preferred number and location of breakpoints should be established from the corresponding test output before the results are interpreted as confirmed structural changes.

Empirical Scope, Robustness and Interpretation

The empirical strategy examines conditional associations and regional heterogeneity rather than causal relationships. Robustness is assessed by comparing pooled OLS, district fixed-effects and median quantile specifications. CADI is excluded from regressions containing its constituent indicators to avoid mechanical overlap.

Variations in coefficient magnitude and sign across specifications may reflect differences between cross-district and within-district variation, omitted time-varying factors, measurement issues, multicollinearity, reverse causality or specification differences. Diagnostic tests indicate heteroskedasticity, serial correlation, cross-sectional dependence and substantial multicollinearity among several explanatory variables. OLS estimates therefore use HC3 robust standard errors to address heteroskedasticity; however, HC3 does not address serial correlation or cross-sectional dependence. These diagnostics highlight important sources of uncertainty and require cautious interpretation of individual coefficients. The fixed-effects estimates should therefore not be interpreted as causal effects. The consistently positive association of mechanisation across specifications indicates a robust statistical association, but does not establish mechanisation as a causal driver, determinant or complement of agricultural development.

Reverse causality remains a limitation, as higher agricultural performance may be associated with greater access to credit, irrigation and mechanisation. Other limitations include the sensitivity of CADI to indicator selection and PCA specification, the short annual series used for structural-break analysis, and district-boundary harmonisation and missing-observation constraints. The findings should therefore be interpreted as conditional associations rather than causal effects.

Data Transparency and Replicability

The study uses official and publicly available district-level data from 2011–12 to 2024–25. Original observations are retained, and missing values are not interpolated. District boundaries were harmonised to maintain consistency across the study period by aligning observations with the corresponding district units in the official district-level records. Variable definitions, measurement units and data-processing procedures are recorded. The construction of CADI and the computations reported in Tables 5 and 6 and Figures 2 and 3 follow the stated procedures. The number of observations used in each specification is reported with the corresponding results. Replication remains subject to the availability and redistribution conditions of the original data sources.

Results and Discussion

Agricultural Growth and District Differences

The averages in Table 4 reveal a certain heterogeneity across districts. AgGSDP ranges from 280.0 to 5,241.4 and crop yield from 1,680 to 5,307, while CADI is between 0.220 and 0.980. Similar differences exist for irrigation, mechanisation, credit, fertiliser use and labour productivity. These variations suggest that districts entered the process of agricultural development with rather different productive resources.

Table 4. Descriptive Statistics of Core Agricultural Variables

Variable	Mean	Std. Dev.	Min	Max
AgGSDP	1 664.52	1 132.75	280.00	5 241.40
LogAgGSDP	7.165	0.741	5.635	8.564
CropYield	3 378.48	929.79	1 680.00	5 307.00
CADI	0.639	0.252	0.220	0.980
LabourProductivity	15,382.65	4 970.53	6 200.00	26,974.00
IrrigationCoverage	49.955	17.786	18.200	75.700
FertiliserUse	54.297	19.439	16.400	85.700
TractorsPer1000Ha	28.819	11.118	8.200	49.200
CreditPerHa	2 373.36	1 033.71	938.00	4 279.00
HYVAdoption	67.725	11.444	42.400	84.400
AvgLandholding	1.908	0.305	1.420	2.480
AnnualRainfall	1 072.79	91.896	892.00	1 245.00
WPIAgriculture	129.750	18.745	100.00	164.20

Source: Authors' calculations based on Directorate of Economics and Statistics, Government of Madhya Pradesh, Agricultural Census, NABARD, and related secondary datasets.

Regional differences seem to exist as well. Malwa, Nimar and Chambal generally possess better access to irrigation, procurement and market facilities, whereas Bundelkhand, Baghelkhand and the tribal belt face more limitations in water and infrastructure. The former allows the latter to cope better with rainfall uncertainty and adopt a more intensive cropping pattern, although such benefits are not systematically observed (Chand, 2019; Gulati & Juneja, 2020). Agricultural development has therefore been heterogeneous across districts.

Persistence of District-Level Disparities

The disparities observed in Table 4 are not restricted to agricultural output but also encompass production assets and market institutions. Reliable irrigation can reduce production risk and increase the potential returns to improved seeds, fertilizer, mechanisation and multiple cropping (Ranade, 2005). Differences in irrigation can also be linked to variation in market participation and access across districts. Transportation infrastructure may shape procurement opportunities and the organisation of agricultural marketing, including storage and processing. Likewise, investments in roads, irrigation and extension can enhance access to capital, technology and human capital, thus generating enduring advantages for better-equipped districts. The subregional clustering of such resources is apparent in Madhya Pradesh and is related to differences in agricultural performance (Diwakar, 2014; Vakulabharanam, 2019; Ramakumar, 2021).

What the Regression Results Reveal

Table 5 presents further evidence of the relationships between agricultural performance and the selected explanatory variables. Mechanisation is the only variable with a consistently positive and statistically significant association with LogAgGSDP across all three

specifications. Irrigation, institutional credit and labour productivity are positive in the pooled and median specifications but negative in the fixed-effects model, while HYV adoption changes from negative or insignificant in the pooled and median specifications to positive in the fixed-effects model.

The different signs may reflect the different sources of variation captured by the models. The pooled estimates capture cross-district variation, while the fixed-effects estimates capture within-district variation after controlling for time-invariant district characteristics and common year effects. The diagnostic results also indicate substantial multicollinearity among several explanatory variables, alongside heteroskedasticity, serial correlation and cross-sectional dependence. These factors, together with omitted time-varying factors, measurement issues, reverse causality and specification differences, warrant cautious interpretation of individual coefficients. The consistent positive association of mechanisation is hence an important empirical finding, but does not establish mechanisation as a causal driver, determinant or complement of agricultural development. Overall, the results indicate that the associations between agricultural inputs and performance are varying across specifications and should be interpreted as conditional rather than causal relationships.

Table 5. Determinants of Agricultural Development: Integrated Regression Results

Variables	OLS-HC3	Fixed Effects	Quantile Regression (Q50)
Labour Productivity	2.18e-05***	-1.05e-08*	2.64e-05***
Irrigation Coverage	0.0092***	-0.0059***	0.0084***
Tractors / Mechanisation	0.0436***	0.0239***	0.0445***
Institutional Credit per Hectare	8.64e-05***	-0.0007***	8.12e-05***
HYV Adoption	-0.0029*	0.0067***	-0.0044
Rainfall	0.0001*	0.0013***	0.0001
Fertiliser Use	—	0.0253***	—
Average Landholding	—	0.0534***	—
Agricultural WPI	—	0.0382***	—
Constant	4.9651***	—	5.0499***
Observations	210	210	210
R ² / Within R ²	0.9888	0.91	0.87
Variables	OLS-HC3	Fixed Effects	Quantile Regression

Notes: Dependent variable: LogAgGSDP. OLS estimates use HC3 robust standard errors. Fixed-effects estimates include district and year effects. Quantile regression is estimated at the median (Q50). All specifications use the same balanced panel of 15 districts over 14 annual periods (210 district-year observations). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Source: Authors' calculations based on district-level panel data.

Table 5 cont.

Diagnostic	Statistic	p-value	Interpretation
Variance Inflation Factor (VIF) – Labour Productivity	28.25	—	High multicollinearity
VIF – Irrigation Coverage	16.36	—	High multicollinearity
VIF – Tractors/Mechanisation	33.64	—	High multicollinearity
VIF – Institutional Credit	4.41	—	Moderate
VIF – HYV Adoption	26.31	—	High multicollinearity
VIF – Rainfall	1.06	—	Low
Breusch–Pagan test	81.91	<0.001	Heteroskedasticity detected
White test	170.19	<0.001	Heteroskedasticity detected
Breusch–Godfrey LM test	172.08	<0.001	Serial correlation detected
Pesaran CD test†	–2.60	0.009	Cross-sectional dependence detected

Note: VIF diagnostics are based on the pooled OLS explanatory variables. Breusch–Pagan, White and Breusch–Godfrey tests are based on the pooled OLS specification. The Pesaran CD test is based on the two-way fixed-effects residuals. OLS estimates therefore use HC3 robust standard errors as reported in Table 5.

Source: Authors' calculations based on district-level panel data.

Labour Productivity and Structural Transformation

Labour productivity differs substantially across districts ranging from 6,200 to 26,974 (Table 4). Higher levels of agricultural productivity may allow scope for reallocation of labour to agriculture-compatible non-agricultural activities especially in districts with better urban connectivity and non-farm opportunities. Better infrastructure and capitalisation can help diversification into different occupations. At the same time, the lack of employment opportunities constrains such a transformation. Since districts differ substantially in their agricultural productivity, and since they exhibit substantial differences in other characteristics, these variations may well be associated with differences in transformation capacity. However, as the study does not directly measure transformation or employment in non-agricultural activities, the conclusion reflects differences in labour productivity associated with transformations.

Change Over Time

Table 6 presents the results of testing various agricultural development indicators for different structural breaks over time. It can be seen that while LogAgGSDP did not exhibit statistically significant preferred break, crop yield and labour productivity showed breaks in 2016 and 2021, respectively. CADI and institutional credit showed breaks in 2015 and 2020, while those for 2016 and 2020 for their respective means were higher after the breaks. The results further indicate that there were no breaks for irrigation, mechanisation, fertiliser use or HYV adoption implying that the trends were more or less consistent over time. Taken together, the results suggest that agricultural development exhibited uneven growth patterns as indicated by the various indicators.

Table 6. Structural Breaks in Selected Agricultural Development Indicators in Madhya Pradesh

Variable	Break Year(s)	No. of Breaks	Mean Values Across Structural Phases	Interpretation
LogAgGSDP	No statistically preferred break	0	Overall Mean: 7.165	No statistically preferred change point identified.
CropYield	2016, 2021	2	Phase I: 3010.05; Phase II: 3405.65; Phase III: 3805.03	Indicates distinct phases in crop-yield performance.
CADI	2015, 2020	2	Phase I: 0.602; Phase II: 0.635; Phase III: 0.671	Indicates changes in the trajectory of agricultural development capability.
LabourProductivity	2016, 2021	2	Phase I: 12753.65; Phase II: 15516.79; Phase III: 18501.23	Indicates distinct phases in labour-productivity performance.
IrrigationCoverage	No statistically preferred break	0	Overall Mean: 49.955	No statistically preferred change point identified.
CreditPerHa	2016, 2020	2	Phase I: 1280.80; Phase II: 2285.75; Phase III: 3536.00	Indicates changes in the trajectory of institutional credit.
TractorsPer1000Ha	No statistically preferred break	0	Overall Mean: 28.819	No statistically preferred change point identified.
FertiliserUse	No statistically preferred break	0	Overall Mean: 54.297	No statistically preferred change point identified.
HYVAdoption	No statistically preferred break	0	Overall Mean: 67.725	No statistically preferred change point identified.

Source: Authors' calculations based on district-level panel data.

Several break dates fall in 2020–2021, which coincides with the COVID-19 period. However, the short annual series does not permit the pandemic to be identified as the cause of these breaks. The structural-break results are therefore interpreted as statistical change points rather than evidence of specific shocks or causal turning points.

How Much Convergence Occurred?

Table 7 shows a modest decline in inter-district agricultural development inequality. The Gini coefficient declined from 0.2228 to 0.2163, the Theil index from 0.0832 to 0.0801, and the coefficient of variation from 0.4066 to 0.3982 between 2011 and 2024, with most of the decline occurring after 2020. Overall, the findings indicate limited sigma-convergence. However, these measures do not establish beta-convergence, which would require evidence that initially lower-performing districts grew faster than higher-performing districts.

Did Agricultural Growth Reduce District Disparities?

Agricultural growth was accompanied by a modest reduction in inter-district inequality. All three CADI-based measures declined over the study period, with most of the reduction occurring after 2020. However, the magnitude of change remained limited, indicating gradual rather than strong convergence. These results suggest that agricultural expansion has not automatically translated into substantial equalisation of productive capacity across districts.

Table 7. Annual CADI-Based Inter-District Inequality Measures in Agricultural Development Across Madhya Pradesh

Year	Gini CADI	Theil CADI	Coefficient of Variation
2011	0.2228	0.0832	0.4066
2012	0.2229	0.0833	0.4068
2013	0.2228	0.0832	0.4066
2014	0.2227	0.0832	0.4065
2015	0.2228	0.0832	0.4066
2016	0.2226	0.0831	0.4063
2017	0.2227	0.0832	0.4065
2018	0.2228	0.0832	0.4067
2019	0.2228	0.0832	0.4066
2020	0.2227	0.0831	0.4064
2021	0.2213	0.0825	0.4047
2022	0.2198	0.0818	0.4026
2023	0.2182	0.0810	0.4006
2024	0.2163	0.0801	0.3982

Source: Authors' calculations using PCA-based agricultural capability indicators.

The results indicate that Madhya Pradesh experienced agricultural expansion alongside only gradual convergence in productive capability. The evidence therefore points to limited, rather than strong, reduction in inter-district disparities. This distinction is important for interpreting agricultural development, as improvements in aggregate output may not automatically produce balanced productive capacity across districts.

Contribution to Literature and Policy Debates

The Madhya Pradesh (MP) experience provides insight into the assessment of agricultural development and regional convergence. While agricultural output and productive capacity generally increased over the period under review, their distribution across districts

remained uneven and the reduction in inter-district disparities was modest. This provides a within-state, district-level perspective to a literature that has more commonly examined regional convergence from a cross-state or cross-regional perspective. The districts vary in production endowments, institutional capacity and market linkages, contributing to heterogeneous agricultural outcomes. This finding is consistent with the regional and district-level disparities highlighted by Diwakar (2014), Vakulabharanam (2019), and Ramakumar (2021).

Furthermore, a contribution concerns the relationship between agricultural inputs and performance. The results do not indicate a uniform association between irrigation, institutional credit, technology adoption, mechanisation and agricultural output across specifications. Mechanisation is the only variable that shows a consistently positive and statistically significant association with LogAgGSDP across the reported models, whereas irrigation, institutional credit, labour productivity and HYV adoption display differences in sign or statistical significance across pooled, fixed-effects and median specifications. These differences highlight the importance of distinguishing between cross-district and within-district variation when interpreting agricultural input-performance relationships. The findings therefore support a differentiated interpretation of agricultural development rather than an assumption that individual inputs have uniform associations with agricultural performance across districts.

The findings also contribute to the discussion of structural transformation while remaining within the empirical scope of the study. The substantial variation in labour productivity across districts highlights differences in agricultural productive conditions that are relevant to the broader process of labour reallocation and economic diversification. However, the present study does not directly measure changes in employment shares, labour movement from agriculture, or non-farm employment transitions. Accordingly, the findings should not be interpreted as direct evidence of the pace or extent of structural transformation. Rather, they identify differences in labour productivity and agricultural conditions that are relevant to the broader structural-transformation debate, consistent with the concerns raised by Breman (2021) and Himanshu (2022).

The study also contributes to agricultural policy debates by demonstrating that aggregate agricultural growth and the distribution of productive capacity represent related but distinct dimensions of development. The observed differences across districts suggest that the potential effectiveness of investments in irrigation, finance, technology, mechanisation and market infrastructure may depend on the productive conditions already prevailing in a district. For example, irrigation expansion may have limited effectiveness where complementary market, financial or infrastructure constraints remain binding. Similarly, improved access to credit or technology may be associated with different agricultural outcomes across districts depending on the availability of other productive resources. These findings support a more context-specific approach to agricultural investment, particularly in districts with persistently lower levels of productive capacity.

Overall, the study's principal contribution is empirical rather than methodological. Its originality lies in combining a multidimensional CADI with district-level inequality measures and panel analysis to examine agricultural development within Madhya Pradesh. The evidence shows that aggregate agricultural expansion can coexist with persistent differences in district-level productive capacity and only limited sigma-convergence. The study therefore adds a within-state dimension to the literature on agricultural

development and regional disparities, and highlights the importance of considering the distribution of productive capacity alongside aggregate agricultural performance.

Policy Implications

Targeting Productive Constraints across Districts

The large variation across districts in irrigation, mechanisation, finance, infrastructure, procurement and market access suggests that agricultural investment may have varying relevance depending on the local conditions. Policy therefore has to be more district-targeted. Rain-fed areas may require a greater emphasis on irrigation, whereas others may require greater support of the market, financial, storage, technological or transport sectors. Districts with multiple constraints may require a coordinated intervention rather than focussing on a single input.

Convergence as a Separate Policy Objective

Agricultural growth and spatial convergence should be treated as related but distinct policy objectives. Despite the observed reduction in inter-district disparities, substantial differences in productive capacity remain. Districts with persistently lower productive capacity may therefore require greater attention to irrigation, finance, infrastructure, procurement, extension and market development. Because initial constraints differ across districts, convergence-oriented policies should be based on district-specific assessments rather than uniform resource allocation.

Agricultural Productivity and Labour Transition

The variation in labour productivity indicates differences in agricultural productive conditions, but the study does not directly measure labour transition from agriculture or non-farm employment. As such, structural transformation must be considered as a broader policy consideration rather than a directly established empirical outcome. In districts with limited non-farm opportunities, agricultural policy should be complemented by agro-processing, services and rural enterprises that can expand the opportunities for alternative employment. It is aligned with the broader structural transformation concerns discussed by Breman (2021) and Himanshu (2022).

Water Security and the Durability of Agricultural Gains

The variation in irrigation coverage highlights the importance of water availability for agricultural development. However, the change in irrigation coefficient across the econometric specifications does not establish a causal effect. Policy should therefore focus on the sustainability and efficiency of existing water resources which include groundwater management, irrigation efficiency and appropriate crop selection. Rain-fed areas may require complementary measures to improve their resilience to rainfall variability.

Conclusion

This study examined agricultural development and inter-district inequality in Madhya Pradesh from 2011–12 to 2024–25, using the Composite Agricultural Development Index (CADI), inter-district inequality measures and panel econometric analysis. The results indicate that while agricultural development has improved over the study period, large differences in productive capacity remain across districts. As such, the study shows that aggregated agricultural growth has not been accompanied by a proportional reduction in inter-district disparities.

The CADI-based measures show a modest reduction in dispersion. The Gini coefficient declined from 0.2228 in 2011 to 0.2163 in 2024, the Theil index from 0.0832 to 0.0801, and the coefficient of variation from 0.4066 to 0.3982. These results indicate limited sigma-convergence rather than strong equalisation, while beta-convergence cannot be established because the analysis does not test whether initially lower-performing districts grew faster than higher-performing districts.

The panel results also indicate that mechanisation is the only variable that consistently has a positive and statistically significant association with LogAgGSDP across the reported specifications. Irrigation, institutional credit, labour productivity and HYV adoption have differences in sign or significance between pooled, fixed effects and median specifications that suggest that the relationships between agricultural inputs and performance depend on the type of variation that the model captures. As such, the estimates should be interpreted as conditional associations rather than causal effects, given the possibility of reverse causality and omitted time-varying factors.

The study's contribution is mostly empirical rather than methodological. Its application of the CADI, inequality measures and panel analysis at the district level demonstrates that agricultural expansion can take place alongside the persistence of differences in productive capacity in a single state. The study's findings also suggest that improving aggregate agricultural performance alone might not be sufficient to achieve balanced agricultural development across districts.

The findings should still be interpreted in the context of the study's limitations. The study does not establish causality; CADI might be sensitive to indicator selection and PCA specification; and structural break analysis is based on a short annual series from which it detects statistically detectable changes rather than causal turning points. Moreover, the study does not directly measure labour reallocation and non-farm employment, and therefore provides no direct evidence on the pace of structural transformation.

Overall, the evidence indicates that Madhya Pradesh has experienced agricultural development alongside only limited sigma-convergence in productive capacity at the district level. The persistence of inter-district differences points towards the necessity of targeted rather than uniform policy interventions, especially for infrastructure, institutions, finance and market access, which depend on the specific constraints faced by individual districts.

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