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Spatio-Temporal Dynamics, Spatial Clustering and Forecasting of Selected Crop Production in Jharkhand, India

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Abstract

Agricultural production in Jharkhand exhibits substantial spatial and temporal heterogeneity, making district-level analysis important for crop planning and resource allocation. The present study examined the spatio-temporal dynamics and forecasted production of Arhar/Tur, Gram, Rapeseed & Mustard, and Wheat across 24 districts of Jharkhand using district-level Area, Production and Yield data for 2002-03 to 2022-23 obtained from the India Data Portal. The analysis integrated compound annual growth rate (CAGR), Mann-Kendall trend analysis, Sen's slope estimation, ARIMA forecasting, Global Moran's I, Local Indicators of Spatial Association (LISA), and Getis-Ord Gi* hotspot analysis. CAGR results revealed positive long-term growth in all districts for Gram, Rapeseed & Mustard, and Wheat, while Arhar/Tur recorded growth in 22 districts and decline in two districts. Rapeseed & Mustard recorded the highest mean CAGR (37.78%), whereas Wheat showed the lowest (10.14%). Mann-Kendall analysis indicated significant increasing trends in 58.3% of districts for Arhar/Tur, 87.5% for Gram, 100% for Rapeseed & Mustard, and 87.5% for Wheat. Wheat recorded the highest mean Sen's slope (616.53), followed by Rapeseed & Mustard (500.32), Gram (434.19), and Arhar/Tur (324.91). Global Moran's I indicated significant positive spatial autocorrelation only for Arhar/Tur. LISA and Gi* analysis identified crop-specific local clusters and hotspots, with the strongest spatial concentration observed for Arhar/Tur. ARIMA forecasting projected increasing production for Gram, Rapeseed & Mustard, and Wheat during 2023-24 to 2027-28, while Arhar/Tur remained approximately stable under the selected model. The findings demonstrate that temporal growth does not necessarily correspond with spatial concentration and highlight the importance of crop- and district-specific agricultural planning in Jharkhand.

Introduction

Agriculture remains a vital part of rural economy, food security and regional economic development in India. The agricultural performance is neither spatially uniform in the country nor is it a permanent feature over the years. As this performance is not the same between the districts, between the crops, and between the production systems, it differs because of the variations in the agronomic climatic circumstances, availability of irrigation, use of inputs, adoption of technology, access to the market, and other localized factors. State averages in India are concealing an important picture. Murtaza and Masood 2020 study finds out that there is persistent disparity in agricultural productivity even in the post green revolution era. Similarly, Pradeep and Rajshekhar 2024 and Govardhane and Laxman 2024 study find similar results. The spatial variation is relevant for states like Jharkhand, where agricultural production is affected strongly by dependence on rains and differences in access to agricultural resources and infrastructure facilities. As a result, an assessment that considers the crop dynamics over time, production forecast, and spatial concentration of agricultural performance is essential to understanding agricultural development. The agricultural production and productivity in India do not have the same uniform pattern of variation over a crop, place and year. The disparity in productivity of agriculture among districts is a permanent feature of the Indian agriculture. Moreover, productivity differences have shown an increase during some period instead of convergence across districts (Murtaza & Masood, 2020). Research undertaken in eastern India has suggested divergence in agricultural performance which, it is argued, arises from changes in technical and allocative efficiency. These differences are responsible for the differences between potential and realized productivity. The diversion seems to be more so post-2010 (Bhushan & Jha, 2025). What these findings show is that agricultural growth cannot be fully understood through aggregate state-level production statistics. Both climatic and non-climatic factors lead to variability in agricultural production. Climate volatility influences crop growth, water availability, sowing conditions, and yield. Similarly, distinctions in irrigation, fertilizer use, improved seed, mechanization, and access to agricultural information are likely to create differences amongst the production regions (Pramanik, 2026; Pradeep & Rajshekhar, 2024; Govardhane & Laxman, 2024). Therefore, a higher cropping intensity does not mean a uniformly higher productivity with uneven distribution of irrigation facilities, input availability and market access (Roy and Rajshekhar, 2025) Similarly, evidence from the district level indicates that assured irrigation, a better seed, mechanization and efficient usage of inputs can lead to higher productivity in agriculture (Govardhane & Laxman, 2024; Pradeep & Rajshekhar, 2024). The variations are of great importance in the Jharkhand context as the agricultural production in this state is highly dependent on climatic conditions and is highly heterogeneous among districts. Analysing historical changes in crop area, production and yield can provide a basis for assessing the direction and magnitude of agricultural change and Associate whether production increases are associated with expansion of cultivated area, changes in yield, or

both. Only through historical analysis we can know what has happened whereas agricultural planning increasingly requires information about what may happen soon. Predicting crop yield can help decide on allocation and purchase of inputs, storing inputs and managing food supply and risk in agriculture food (Pandit et al., 2023; Vs et al., 2025; Srinivas et al., 2026). Agricultural production data exhibit temporal dependence, while also containing trends, fluctuations and other systematic patterns that can be identified from historical observations which makes time-series models of relevance.

The Autoregressive Integrated Moving Average (ARIMA) is one of the time series methods that are widely used in agricultural production forecasting. ARIMA models combine three main components autoregressive, differencing and moving-average to achieve stationarity, when necessary, and to represent temporal dependence between the observations.

Due to their relatively simple structure and available statistical diagnostics, they have been useful for crop production and yield forecasting in various agricultural contexts. Earlier studies have used ARIMA and related time-series models for crop production forecasting in India, with ARIMA (0,1,1) and ARIMA (0,1,2) specifications performing reasonably well for some crop series (Karuppasamy, n.d.; Kumar et al., 2022; Vs et al., 2025; Prakash et al., 2026). However, performance in forecasting isn't the same for all crops. According to recent evidence, cereals might show better predictability than some pulses and oilseeds, suggesting a difference in production stability and temporal variability (Srinivas et al., 2026). Forecasting studies show that including relevant exogenous variables such as irrigation share adds more predictive power beyond benchmark ARIMA models (Pandit et al. 2023). In addition, as the forecasting horizon increases, the uncertainty associated with ARIMA based forecasts becomes larger, which is specifically relevant to agricultural systems exposed to the variability of rainfall along with other climatic risks (Prakash et al. 2026; Vs et al. 2025) ARIMA can be an ideal short- to medium-term forecasting framework whose limitations must, of course, be kept in mind in the interpretation of long-horizon forecasts Geographical patterns of agricultural performance cannot be mapped with temporal analysis alone. Under the same production level, the districts may have very different spatial contexts while high or low values can either occur as isolated observations of concentrated clusters geographically. Thus, ranking districts merely by crop production or yield does not determine whether neighbouring districts have similar agricultural performance levels. To identify geographical patterns, we utilize various spatial statistical techniques. The Getis-Ord Gi* statistic is especially helpful for detecting statistically significant spatial clusters of high and low values. The approach looks at the relation between an observation and its neighbours to produce a local z-score amenable to the detection of statistically significant hotspots and coldspots (Peeters et al., 2015). As a result, the Getis-Ord Gi* statistic can identify a geographically clustered group of districts with high performance as distinct from a single district that happens to have a high value but is surrounded by districts with very different performance. According to the spatial hotspot techniques, agricultural performance can be agglomerated in space significantly. According to a recent study on Indian agriculture, there is a crop-specific hotspot and coldspot pattern and productivity differs widely among spatial clusters (Pramanik, 2026). Patterns of agricultural hotspots have also been correlated with differences in irrigation, fertilizer and agricultural information access differing across space. This illustrates the potential utility of spatial statistics to identify areas needing differentiated interventions (Pramanik, 2026). In addition to the productivity of the crops, Getis-Ord Gi* has been used to identify district level risk hotspots for adaptation planning at locations (Zade et al., 2026). Consequently, spatial analysis may suggest spatial patterns that remain hidden when agricultural performance is assessed only along state average or through conventional descriptive statistics (Shynybek et al 2026). Spatial clustering is particularly pertinent to Jharkhand as agricultural conditions vary significantly across districts. Identifying statistically significant clusters of relatively high and low production or productivity will help us discern areas where the performance is geographically concentrated from individual district characteristics that appear to be driving observed values. Having this spatial perspective is important to design interventions that are sensitive to the district, not just state average. The earlier evidence indicates that agricultural performance should be studied from a time and place perspective. Analyzing area, production and yield changes through time, for forecast production future paths information may also be collected from forecasting. In contrast, spatial analysis tells where agricultural performance is concentrated and whether neighbouring districts have similar agricultural performance. Therefore, an integrated application of ARIMA and Getis-Ord Gi* provides complementary analytical perspectives. ARIMA models the temporal dimension of agriculture by applying the model to observed historical production and generating forecasts while Getis-Ord Gi* deals with the spatial dimension measuring concentrations of high and low agricultural performance. The joint use of these approaches may prove to be especially valuable for district-level agricultural planning since agricultural

interventions are seldom spatially neutral. Evidence from Indian agriculture suggests that productivity differences are related to localized combinations of irrigation, input use, technology, climate and resource-access conditions (Murtaza & Masood, 2020; Pradeep & Rajshekhar, 2024; Govardhane & Laxman, 2024).

The literature on disparities in agricultural productivity, crop forecasting and spatial clustering is extensive. However, less attention has been paid to their comparative study within the same framework at the district level for Jharkhand. It has been established by existing studies that productivity varies inter-districts in India (Murtaza & Masood, 2020); the changes in productivity and efficiency in eastern India (Bhushan & Jha, 2025); and the spatial variability in crop-specific studies in the rest of India (Govardhane & Laxman, 2024; Roy & Rajshekhar, 2025). Likewise, crop forecasting has experienced a surge of interest in the use of ARIMA and hybrid time-series approaches (Panditet et al. 2023, Kumar et al. 2022, Vs et al. 2025). Similarly, Getis-Ord Gi* has been used for detecting the agricultural and socio-climatic hotspot (Peeters et al. 2015; Pramanik 2026; Zade et al. 2026). However, these analytical dimensions are often considered in isolation. A framework at the district-level that first characterizes historical agricultural dynamics, and then forecasts production using ARIMA, and finally detects statistically significant spatial hot and cold spots, can yield a more integrated interpretation of agricultural change. This is particularly relevant for Jharkhand, where rainfall dependence, heterogeneous resource availability and district level differences may engender substantially different agricultural trajectories within the same state. By merging temporal and spatial approaches, we have a much more solid basis for understanding where agricultural change occurs, how they have developed over time and what former production indicates for future trajectories. Given this context, the current study analyzes the spatiotemporal dynamics and forecasting of crop production in Jharkhand, India. For this, district-level agricultural data for the period of 2002-03 to 2022-23 has been used. The study records crop-wise area, production and yield and develops an analytical framework that synthesizes temporal and spatial statistical methods. Examining the historic dynamics of select crops involved in the study helps understanding crop performance. After that, using temporal patterns, ARIMA models are used to forecast the production of selected major crops. Ultimately, agricultural measurements on a district level are examined through the Getis-Ord Gi* statistic for hotspot and coldspot. The study seeks to achieve the following objectives: (i) to examine the temporal behaviour (area, production and yield) of major crops during 2002-03 to 2022-23 in Jharkhand; (ii) to forecast major crops by using ARIMA model; and (iii) to identify the hotspots/coldspots of agricultural production and productivity by using Gets-Ord Gi* statistics. Through temporal forecasting and spatially clustering analysis, the study aims to generate district-sensitive evidence for agricultural change for undertaking geographic specificity in agricultural planning in Jharkhand.

Methodology

The study was conducted in Jharkhand, India, using district-level agricultural data for the period 2002-03 to 2022-23. The methodology integrated temporal analysis, ARIMA-based forecasting, and spatial hotspot analysis to examine the dynamics and geographical distribution of crop production.

Data source and study period

District-level Area, Production and Yield (APY) data were obtained from the India Data Portal (IDP) under the *Crop Wise Area Production Yield (APY)* dataset, which provides crop-wise agricultural statistics from the Ministry of Agriculture & Farmers Welfare, Government of India. The dataset was accessed through the India Data Portal.

The analysis was restricted to Jharkhand and the period 2002-03 to 2022-23. The dataset included information on district, year, crop, crop type, season, area, production and yield. Records classified as “Total” and “Whole Year” were excluded to avoid duplication, and the resulting dataset was used for subsequent analysis.

Crop selection and data organization

The availability of observations for individual crops was examined across the study period. Crops with comparatively adequate temporal coverage were selected for detailed analysis and forecasting. The selected crop observations were

organized chronologically at the district-year level, with area, production and yield considered as the principal indicators of agricultural performance.

Temporal analysis

Temporal variation in crop area, production and yield was examined over the study period. Descriptive statistics and graphical analysis were used to identify changes and fluctuations in agricultural performance. The temporal analysis provided the basis for identifying suitable crop series for subsequent ARIMA forecasting.

ARIMA forecasting

The Autoregressive Integrated Moving Average (ARIMA) model was used to forecast the production of the selected crops. ARIMA models have been widely applied for agricultural production forecasting because they can capture temporal dependence, trends and fluctuations in historical agricultural series (Karuppasamy, n.d.; Kumar et al., 2022; Pandit et al., 2023; Vs et al., 2025; Srinivas et al., 2026). The production series were first examined for stationarity. Where required, differencing was applied to obtain a stationary series. Candidate ARIMA models were then estimated by considering different combinations of autoregressive (p), differencing (d), and moving-average (q) components. Model selection was based on AIC/AICc, while residual diagnostics were conducted to assess model adequacy. The Ljung-Box test was used to examine whether significant autocorrelation remained in the residuals. The selected ARIMA model was subsequently used to generate future production forecasts. The use of ARIMA for agricultural forecasting is supported by previous crop forecasting studies in India (Pandit et al., 2023; Kumar et al., 2022; Prakash et al., 2026; Vs et al., 2025).

Spatial analysis using Getis-Ord Gi*

Spatial clustering of agricultural performance was examined using the Getis-Ord Gi* statistic. The method is widely used to identify statistically significant concentrations of high and low values and has been applied in agricultural spatial analysis (Peeters et al., 2015; Pramanik, 2026). District-level values of the selected agricultural indicators were linked with the Jharkhand district boundary layer to construct the spatial dataset. The Getis-Ord Gi* statistic was then calculated using the spatial relationship among neighbouring districts. Positive and statistically significant Gi* z-scores indicated hotspots, representing clusters of relatively high values, whereas negative and statistically significant z-scores indicated coldspots, representing clusters of relatively low values (Peeters et al., 2015). The resulting spatial patterns were mapped to identify the geographical concentration of agricultural performance. Spatial hotspot analysis provides an additional dimension to conventional agricultural productivity analysis because neighbouring districts may exhibit similar agricultural conditions and performance. Previous research has demonstrated the usefulness of spatial hotspot analysis for identifying agricultural productivity clusters and geographically concentrated agricultural risks (Pramanik, 2026; Zade et al., 2026; Shynybek et al., 2026).

Integrated analytical framework

The study integrated temporal analysis, ARIMA forecasting and Getis-Ord Gi* spatial analysis. ARIMA was used to examine historical production patterns and forecast future production, while Getis-Ord Gi* was used to identify statistically significant spatial concentrations of agricultural performance. The integration of these approaches provides complementary information on the temporal trajectory and spatial distribution of crop production in Jharkhand as shown in Fig. 1.

Software and presentation of results

Data processing, statistical analysis and ARIMA modelling were performed using R/RStudio. Spatial statistical analysis and mapping were conducted using appropriate spatial-analysis packages and district boundary data. The results were presented

using descriptive tables, temporal trend graphs, ARIMA forecast plots, and Getis-Ord Gi* hotspot and coldspot maps.

Results and discussions

Temporal Coverage of Selected Crops

The temporal coverage analysis showed that Arhar/Tur, Gram, Rapeseed & Mustard, and Wheat were available continuously for the entire 21-year study period from 2002-03 to 2022-23. All four crops covered 24 districts of Jharkhand. The number of district-year observations varied among crops, ranging from 455 for Arhar/Tur to 486 for Wheat, indicating some variation in district-level data availability across years. Gram recorded 465 observations, while Rapeseed & Mustard recorded 456 observations (Table 1). Overall, the selected crops provided adequate temporal coverage for subsequent ARIMA-based forecasting and Getis-Ord Gi* spatial analysis.

Table 1
Temporal coverage of selected crops

Crop	Years available	First year	Last year	No. of districts	District-year observations*
Arhar/Tur	21	2002-03	2022-23	24	455
Gram	21	2002-03	2022-23	24	465
Rapeseed & Mustard	21	2002-03	2022-23	24	456
Wheat	21	2002-03	2022-23	24	486

District-wise Compound Annual Growth Rate (CAGR)

The district-wise CAGR analysis revealed substantial differences in the long-term growth of crop production across Jharkhand (Table 2). Arhar/Tur recorded a mean CAGR of 17.42% and a median of 15.24%, with values ranging from − 5.55% in Dumka to 63.21% in Dhanbad. Of the 24 districts, production increased in 22 districts, while two districts recorded negative CAGR. Gram showed a higher and more consistent growth pattern, with a mean CAGR of 24.21% and median CAGR of 24.22%. Its CAGR ranged from 5.54% in Pakur to 49.20% in Ramgarh, and all 24 districts recorded growth. Rapeseed & Mustard exhibited the highest average growth among the four crops. Its mean CAGR was 37.78%, while the median was 25.84%. The CAGR ranged from 14.55% in Pakur to 128.68% in Dhanbad as shown in Fig. 2. All 24 districts showed growth, although the large difference between the mean and median indicates that the exceptionally high growth recorded in some districts substantially increased the overall mean. Wheat recorded the lowest average CAGR, with a mean of 10.14% and median of 8.98%. Nevertheless, all 24 districts experienced growth, with CAGR ranging from 1.67% in Pakur to 20.47% in Saraikela Kharsawan.

Table 2
District-wise CAGR of production of selected crops in Jharkhand, 2002-03 to 2022-23

Crop	Districts	Increasing	Decreasing	Mean CAGR (%)	Median CAGR (%)	Minimum CAGR (%)	Maximum CAGR (%)	Highest CAGR district	Lowest CAGR district
Arhar/Tur	24	22	2	17.42	15.24	−5.55	63.21	Dhanbad	Dumka
Gram	24	24	0	24.21	24.22	5.54	49.20	Ramgarh	Pakur
Rapeseed & Mustard	24	24	0	37.78	25.84	14.55	128.68	Dhanbad	Pakur
Wheat	24	24	0	10.14	8.98	1.67	20.47	Saraikela Kharsawan	Pakur

ARIMA Model Identification and Fit Statistics

The ARIMA model identification results indicated that ARIMA(0,1,0) was selected for all four crops (Table 3). The estimated error variance (σ^2) ranged from 2.128×10^9 for Arhar/Tur to 8.208×10^9 for Wheat. The corresponding AIC values ranged from 488.33 to 515.33, while AICc values ranged from 488.55 to 515.55. The BIC values ranged from 489.33 to 516.32. These fitted models were subsequently subjected to residual diagnostics and out-of-sample forecasting.

Table 3
ARIMA model identification and fit statistics

Crop	Selected model	σ^2	Log likelihood	AIC	AICc	BIC
Arhar/Tur	ARIMA (0,1,0)	2.128×10^9	−243.16	488.33	488.55	489.33
Gram	ARIMA (0,1,0)	3.245×10^9	−247.38	496.76	496.99	497.76
Rapeseed & Mustard	ARIMA (0,1,0)	2.325×10^9	−244.05	490.10	490.32	491.09
Wheat	ARIMA (0,1,0)	8.208×10^9	−256.66	515.33	515.55	516.32

Ljung-Box Residual Diagnostic

The Ljung-Box test indicated that the residuals of all four fitted ARIMA models were free from statistically significant autocorrelation at the 5% significance level (Table 4). The p-values ranged from 0.305 for Arhar/Tur to 0.854 for Gram, all exceeding 0.05. The corresponding χ^2 statistics were 6.009, 1.965, 4.346, and 4.143 for Arhar/Tur, Gram, Rapeseed & Mustard, and Wheat, respectively. Thus, the residual series did not show significant remaining autocorrelation, supporting the adequacy of the fitted ARIMA models for subsequent forecasting.

Table 4
Ljung-Box residual diagnostic

Crop	Ljung-Box χ^2	df	p-value	Residual autocorrelation
Arhar/Tur	6.009	5	0.305	Not significant
Gram	1.965	5	0.854	Not significant
Rapeseed & Mustard	4.346	5	0.501	Not significant
Wheat	4.143	5	0.529	Not significant

Out-of-Sample ARIMA Forecasting Performance

The out-of-sample forecasting results showed variation in predictive performance across the four selected crops (Table 5). The RMSE ranged from 35,371.89 for Arhar/Tur to 188,745.00 for Wheat, while the MAE ranged from 31,003.50 to 182,759.25, respectively. The MAPE ranged from 11.84% for Arhar/Tur to 45.00% for Rapeseed & Mustard. The corresponding Theil's U values ranged from 0.884 for Arhar/Tur to 2.527 for Wheat. These results indicate variation in forecasting errors across the selected crops using the ARIMA(0,1,0) model.

Table 5
Out-of-sample ARIMA forecasting performance

Crop	Model	RMSE	MAE	MAPE (%)	Theil's U
Arhar/Tur	ARIMA (0,1,0)	35,371.89	31,003.50	11.84	0.884
Gram	ARIMA (0,1,0)	84,209.11	81,343.75	26.51	2.302
Rapeseed & Mustard	ARIMA (0,1,0)	149,097.03	142,321.75	45.00	2.108
Wheat	ARIMA (0,1,0)	188,745.00	182,759.25	37.07	2.527

Comparison of Forecasting Models

The comparison of forecasting models showed variation in predictive performance across the four selected crops (Table 6). For Arhar/Tur, the ARIMA (0,1,0), Naïve, and ETS models produced very similar forecasting errors, with RMSE values of 35,371.89, 35,371.89, and 35,370.68, respectively, while the ARIMA (0,1,0) +drift model produced an RMSE of 38,937.20. The corresponding MAPE values were approximately 11.84–12.06%, and Theil's U values ranged from 0.884 to 0.906. For Gram, the ARIMA(0,1,0)+drift model produced an RMSE of 54,153.02, MAE of 48,084.91, MAPE of 15.52%, and Theil's U of 1.495, compared with RMSE of 84,209.11, MAE of 81,343.75, MAPE of 26.51%, and Theil's U of 2.302 for the ARIMA(0,1,0) and Naïve models. The ETS model produced very similar results to the latter models. For Rapeseed & Mustard, the ARIMA (0,1,0) +drift model produced an RMSE of 123,224.38, MAE of 117,159.20, MAPE of 37.04%, and Theil's U of 1.779. The ETS model produced RMSE, MAE, MAPE, and Theil's U values of 146,358.40, 139,450.13, 44.04%, and 2.072, respectively, while the ARIMA (0,1,0) and Naïve models recorded identical values of 149,097.03, 142,321.75, 45.00%, and 2.108. For Wheat, the ARIMA (0,1,0) +drift model produced an RMSE of 156,167.38, MAE of 147,729.13, MAPE of 29.76%, and Theil's U of 2.092. The ETS model recorded corresponding values of 173,520.88, 166,990.32, 33.79%, and 2.340, whereas the ARIMA (0,1,0) and Naïve models produced 188,745.00 RMSE, 182,759.25 MAE, 37.07% MAPE, and 2.527 Theil's U. Overall, the results demonstrate that forecasting performance varied by crop and model specification, with the inclusion of drift producing different forecasting-error patterns for the four-crop series.

Table 6
Comparison of forecasting models Arhar/Tur

Model	RMSE	MAE	MAPE (%)	Theil's U
ARIMA (0,1,0)	35,371.89	31,003.50	11.84	0.884
ARIMA (0,1,0) +drift	38,937.20	27,392.00	12.06	0.906
Naïve	35,371.89	31,003.50	11.84	0.884
ETS	35,370.68	31,002.37	11.84	0.884

Gram

Model	RMSE	MAE	MAPE (%)	Theil's U
ARIMA (0,1,0)	84,209.11	81,343.75	26.51	2.302
ARIMA (0,1,0) +drift	54,153.02	48,084.91	15.52	1.495
Naïve	84,209.11	81,343.75	26.51	2.302
ETS	84,202.87	81,337.29	26.51	2.302

Rapeseed & Mustard

Model	RMSE	MAE	MAPE (%)	Theil's U
ARIMA (0,1,0)	149,097.03	142,321.75	45.00	2.108
ARIMA (0,1,0) +drift	123,224.38	117,159.20	37.04	1.779
Naïve	149,097.03	142,321.75	45.00	2.108
ETS	146,358.40	139,450.13	44.04	2.072
Wheat				

Model	RMSE	MAE	MAPE (%)	Theil's U
ARIMA (0,1,0)	188,745.00	182,759.25	37.07	2.527
ARIMA (0,1,0) +drift	156,167.38	147,729.13	29.76	2.092
Naïve	188,745.00	182,759.25	37.07	2.527
ETS	173,520.88	166,990.32	33.79	2.340

Final ARIMA Specifications Used for Forecasting

The final ARIMA specifications used for forecasting are presented in Table 7. The models were estimated using the complete 2002-03 to 2022-23 production series for each selected crop and were subsequently used to generate forecasts for a five-year horizon (2023-24 to 2027-28). For Arhar/Tur, the final specification was ARIMA (0,1,0) without drift, whereas ARIMA (0,1,0) with drift was specified for Gram, Rapeseed & Mustard, and Wheat. The inclusion of drift in these three models accounts for a systematic change in the differenced series over time, while the Arhar/Tur series was forecast using the non-drift specification.

The resulting five-year forecasts provide projected production values for the period 2023-24 to 2027-28. For Arhar/Tur, the point forecast remained constant at approximately 210,524, reflecting the ARIMA (0,1,0) specification without drift. For Gram, the forecast increased from 305,802.2 in 2023-24 to 362,466.9 in 2027-28. Similarly, the projected production of Rapeseed & Mustard increased from 335,964.8 to 399,271.8, while Wheat increased from 456,551.8 to 528,587.2 over the same forecast period. The forecast intervals also widened progressively with the forecast horizon, reflecting increasing uncertainty associated with longer-term projections. The 95% prediction intervals for Arhar/Tur, for example, expanded from 120,102.8–300,945.2 in 2023-24 to 8,336.0-412,712.0 in 2027-28. For Gram, the corresponding interval expanded from 194,857.6–416,746.7 to 114,387.3–610,546.5. Rapeseed & Mustard showed an expansion from 244,377.9–427,551.6 to 194,477.4–604,066.3, whereas Wheat showed the widest interval expansion, from 278,002.3–635,101.4 in 2023-24 to 129,338.3–927,836.1 in 2027-28. Thus, the final specifications generated both point forecasts and prediction intervals for assessing future production trajectories (Table 7).

Table 7
Final ARIMA specifications used for forecasting

Crop	Final model	Drift	Forecast horizon
Arhar/Tur	ARIMA (0,1,0)	No	5 years
Gram	ARIMA (0,1,0)	Yes	5 years
Rapeseed & Mustard	ARIMA (0,1,0)	Yes	5 years
Wheat	ARIMA (0,1,0)	Yes	5 years

Five-Year Forecast of Crop Production

The five-year ARIMA forecasts presented in Table 8 showed different projected production trajectories among the selected crops. Arhar/Tur was projected to remain constant at 210,524 throughout the forecast period from 2023-24 to 2027-28. In contrast, Gram showed a progressive increase from 305,802 in 2023-24 to 362,467 in 2027-28. Rapeseed & Mustard was projected to increase from 335,965 to 399,272, while Wheat increased from 456,552 to 528,587 during the same period. Overall, the forecast indicated an upward projected trend for Gram, Rapeseed & Mustard, and Wheat, whereas the projected production of Arhar/Tur remained unchanged over the five-year forecast horizon.

Table 8
Five-year forecast of crop production

Year	Arhar/Tur	Gram	Rapeseed & Mustard	Wheat
2023-24	210,524	305,802	335,965	456,552
2024-25	210,524	319,968	351,792	474,561
2025-26	210,524	334,135	367,618	492,570
2026-27	210,524	348,301	383,445	510,578
2027-28	210,524	362,467	399,272	528,587
95% Prediction Intervals for Forecast Production				

The 95% prediction intervals for the forecast production are presented in Table 9. The intervals generally widened as the forecast horizon increased, indicating greater uncertainty in longer-term production forecasts. For Arhar/Tur, the prediction interval widened from 120,103–300,945 in 2023-24 to 8,336–412,712 in 2027-28. For Gram, the interval increased from 194,858 – 416,747 to 114,387–610,547 over the same period. Similarly, the prediction interval for Rapeseed & Mustard widened from 244,378–427,552 in 2023-24 to 194,477–604,066 in 2027-28. Wheat showed the widest forecast range, increasing from 278,002-635,101 in 2023-24 to 129,338–927,836 in 2027-28. Overall, the widening prediction intervals indicate increasing uncertainty associated with forecasts further into the future. These values represent 95% prediction intervals for future observations and not confidence intervals for the mean forecast.

Table 9
95% prediction intervals for forecast production

Year	Arhar/Tur	Gram	Rapeseed & Mustard	Wheat
2023-24	120,103–300,945	194,858 – 416,747	244,378–427,552	278,002-635,101
2024-25	82,649 – 338,399	163,069–476,868	222,268–481,315	222,054–727,068
2025-26	53,910 – 367,138	141,973 – 526,296	208,985 – 526,251	183,313–801,826
2026-27	29,682 – 391,366	126,412–570,190	200,271–566,619	153,479–867,677
2027-28	8,336–412,712	114,387–610,547	194,477–604,066	129,338–927,836

Global Spatial Autocorrelation of Crop Production in Jharkhand

Global Moran's I was used to assess the spatial autocorrelation of production among the districts of Jharkhand during 2022-23. As presented in Table 10, Arhar/Tur showed significant positive spatial autocorrelation (Moran's I = 0.3593, Z = 3.1253, p = 0.0009), indicating a significant tendency for districts with similar levels of Arhar/Tur production to occur in spatial clusters. In contrast, Gram (Moran's I = − 0.0164, p = 0.4263), Rapeseed & Mustard (Moran's I = 0.1072, p = 0.1494), and Wheat (Moran's I = − 0.0185, p = 0.4325) showed non-significant spatial autocorrelation.

Table 10
Global Moran's I analysis of crop production in Jharkhand, 2022-23

Crop	Moran's I	Expected I	Z-value	p-value	Spatial autocorrelation
Arhar/Tur	0.3593	−0.0435	3.1253	0.0009	Significant positive
Gram	−0.0164	−0.0435	0.1859	0.4263	Not significant
Rapeseed & Mustard	0.1072	−0.0435	1.0392	0.1494	Not significant
Wheat	−0.0185	−0.0435	0.1699	0.4325	Not significant

Local Indicators of Spatial Association (LISA) Cluster Analysis

The LISA analysis identified significant local spatial associations in crop production across the 24 districts of Jharkhand during 2022-23 (Table 11). Arhar/Tur showed the highest number of significant clusters, with three High-High clusters in Garhwa, Latehar and Palamu and two Low-High clusters in Lohardaga and Chatra. Gram and Rapeseed & Mustard each recorded one High-High cluster in Hazaribagh and East Singhbhum, respectively, while Wheat recorded one Low-High cluster in Pakur. All remaining districts were non-significant.

The significant local Moran's I statistics further confirmed these spatial associations (Table 12). For Arhar/Tur, the Moran's Local I value ranged from − 0.8531 in Lohardaga to 2.4039 in Palamu, with all identified clusters statistically significant ($p < 0.01$). Hazaribagh showed a significant High-High association for Gram ($I_i = 0.7182$, $p = 0.04398$), while East Singhbhum showed a High-High association for Rapeseed & Mustard ($I_i = 0.1097$, $p = 0.04378$). Pakur exhibited a significant Low-High association for Wheat ($I_i = −1.8025$, $p = 0.03728$). The spatial distribution of these clusters is illustrated in Fig. 3, highlighting the localized concentration and spatial outlier patterns of crop production across Jharkhand.

Table 11
LISA cluster classification of selected crops in Jharkhand, 2022-23
Significant LISA districts

Crop	District	Production	LISA cluster	p-value
Arhar/Tur	Garhwa	16,710	High-High	0.00013
Arhar/Tur	Latehar	39,058	High-High	0.00485
Arhar/Tur	Palamu	24,700	High-High	0.00674
Arhar/Tur	Lohardaga	4,253	Low-High	0.00325
Arhar/Tur	Chatra	5,887	Low-High	0.00810
Gram	Hazaribagh	18,756	High-High	0.04398
Rapeseed & Mustard	East Singhbum	13,662	High-High	0.04378
Wheat	Pakur	3,539	Low-High	0.03728

Table 12
Significant local spatial association identified by LISA

Crop	District	Moran's Local I (Ii)	Z-value	p-value	Cluster
Arhar/Tur	Garhwa	2.3500	3.8293	0.00013	High-High
Arhar/Tur	Latehar	1.9647	2.8170	0.00485	High-High
Arhar/Tur	Palamu	2.4039	2.7093	0.00674	High-High
Arhar/Tur	Lohardaga	−0.8531	−2.9432	0.00325	Low-High
Arhar/Tur	Chatra	−0.4141	−2.6478	0.00810	Low-High
Gram	Hazaribagh	0.7182	2.0143	0.04398	High-High
Rapeseed & Mustard	East Singhbum	0.1097	2.0162	0.04378	High-High
Wheat	Pakur	−1.8025	−2.0827	0.03728	Low-High

Getis-Ord Gi* Hotspot and Coldspot classification

The Getis-Ord Gi* statistic was used to identify statistically significant spatial concentrations of high and low crop production across the districts of Jharkhand during 2022-23. As presented in Table 13, Arhar/Tur showed the strongest concentration of high-production clusters, with five districts classified as Hotspots at the 99% significance level, while the remaining 19 districts were non-significant. No 95% or 90% hotspots or coldspots were identified for Arhar/Tur. For Gram, one district each was classified as a 95% hotspot and a 90% hotspot, while 22 districts were non-significant. Rapeseed & Mustard showed one 95% hotspot, one 90% hotspot, and one 90% coldspot, with the remaining 21 districts being non-significant. Wheat showed one 95% hotspot, while the other 23 districts were non-significant.

Table 13
Getis-Ord Gi* hotspot and coldspot classification

Crop	Hotspot 99%	Hotspot 95%	Hotspot 90%	Coldspot 99%	Coldspot 95%	Coldspot 90%	Not significant
Arhar/Tur	5	0	0	0	0	0	19
Gram	0	1	1	0	0	0	22
Rapeseed & Mustard	0	1	1	0	0	1	21
Wheat	0	1	0	0	0	0	23

Getis-Ord Gi* Hotspot and Coldspot Analysis

The significant Getis-Ord Gi* clusters identified across the selected crops are presented in Table 14. Arhar/Tur exhibited the largest concentration of statistically significant hotspots, with five districts classified as Hotspots at the 99% significance level. These included Garhwa (Gi* Z = 3.8293), Lohardaga (2.9432), Latehar (2.8170), Palamu (2.7093), and Chatra (2.6478). This indicates a strong spatial concentration of relatively high Arhar/Tur production across these districts. For Gram, Hazaribagh was identified as a 95% hotspot (Gi* Z = 2.0143), while Ramgarh was classified as a 90% hotspot (Gi* Z = 1.8022). For Rapeseed & Mustard, East Singhbum emerged as a 95% hotspot (Gi* Z = 2.0162), whereas Chatra was identified as a 90% hotspot (Gi* Z = 1.6850). In contrast, Bokaro was identified as a 90% coldspot for Rapeseed & Mustard (Gi* Z = − 1.7557), indicating a significant concentration of relatively low production values. For Wheat, Pakur was identified as a 95% hotspot, with a Gi* Z-score of 2.0827 as shown in Fig. 4.

Table 14
Significant Getis-Ord Gi* hotspots and coldspots

Crop	District	Production	Gi* Z-score	Classification
Arhar/Tur	Garhwa	16,710	3.8293	Hotspot 99%
Arhar/Tur	Lohardaga	4,253	2.9432	Hotspot 99%
Arhar/Tur	Latehar	39,058	2.8170	Hotspot 99%
Arhar/Tur	Palamu	24,700	2.7093	Hotspot 99%
Arhar/Tur	Chatra	5,887	2.6478	Hotspot 99%
Gram	Hazaribagh	18,756	2.0143	Hotspot 95%
Gram	Ramgarh	14,090	1.8022	Hotspot 90%
Rapeseed & Mustard	East Singhbum	13,662	2.0162	Hotspot 95%
Rapeseed & Mustard	Chatra	9,455	1.6850	Hotspot 90%
Rapeseed & Mustard	Bokaro	6,603	−1.7557	Coldspot 90%
Wheat	Pakur	3,539	2.0827	Hotspot 95%

Mann-Kendall Trend and Sen’s Slope Analysis of Selected Crops in Jharkhand

The Mann-Kendall trend analysis revealed that crop production showed predominantly increasing trends across the districts of Jharkhand. Arhar/Tur exhibited a significant increasing trend in 14 out of 24 districts, while 10 districts showed non-significant increasing trends. The mean and median Sen’s slopes were 324.91 and 179.12, respectively. Gram showed a significant increasing trend in 21 districts and a non-significant increasing trend in 3 districts, with mean and median Sen’s slopes of 434.19 and 348.67, respectively. Rapeseed & Mustard recorded a significant increasing trend across all 24 districts, with mean and median Sen’s slopes of 500.32 and 438.37. Similarly, Wheat showed significant increasing trends in 21 districts and non-significant increasing trends in 3 districts, with mean and median Sen’s slopes of 616.53 and 532.60, respectively. No significant or non-significant decreasing trends were observed for any of the four crops. These results indicate a consistent long-term increase in crop production across the study districts, although the magnitude of change varied among crops as shown in Table 14 and Fig. 5.

Table 14
Mann-Kendall trend and Sen's slope analysis

Crop	Districts	Significant Increasing	Non-significant Increasing	Significant Decreasing	Non-significant Decreasing	Mean Sen's Slope	Median Sen's Slope
Arhar/Tur	24	14	10	0	0	324.91	179.12
Gram	24	21	3	0	0	434.19	348.67
Rapeseed & Mustard	24	24	0	0	0	500.32	438.37
Wheat	24	21	3	0	0	616.53	532.60

Spatial-Temporal Analysis of Selected Crops in Jharkhand

The spatial-temporal analysis integrated Mann-Kendall trend results, Sen’s slope estimates, Getis-Ord Gi* hotspot analysis, and Local Indicators of Spatial Association (LISA) to examine both temporal trends and spatial clustering of crop production

across the 24 districts of Jharkhand. Table 15 presents the Getis-Ord Gi* spatial clustering results. Arhar/Tur recorded five significant 99% hotspots, while Gram showed one 95% and one 90% hotspot. Rapeseed & Mustard exhibited one 95% hotspot, one 90% hotspot, and one 90% coldspot. Wheat showed one 95% hotspot. The remaining districts were not statistically significant. Table 17 presents the LISA cluster analysis. Arhar/Tur had three High-High and two Low-High clusters, whereas Gram and Rapeseed & Mustard each had one High-High cluster. Wheat recorded one Low-High cluster. All remaining districts were classified as non-significant. The integrated spatial-temporal results in Table 17 show that Rapeseed & Mustard had a significant increasing trend in all 24 districts (100%), followed by Gram and Wheat (87.5% each) and Arhar/Tur (58.3%). The mean and median Sen's slopes were highest for Wheat (616.53 and 532.60), followed by Rapeseed & Mustard (500.32 and 438.37), Gram (434.19 and 348.67), and Arhar/Tur (324.91 and 179.12). Significant Gi* clusters accounted for 20.8% of Arhar/Tur districts, 12.5% of Rapeseed & Mustard districts, 8.3% of Gram districts, and 4.2% of Wheat districts. Significant LISA clusters were identified in 20.8% of Arhar/Tur districts and 4.2% of the districts for each of the other three crops. The district-level Gi* results in Table 18 identify the specific significant hotspots and coldspots. Arhar/Tur hotspots were concentrated in Chatra, Garhwa, Latehar, Lohardaga, and Palamu, all at the 99% significance level. Gram hotspots occurred in Ramgarh and Hazaribagh, while Rapeseed & Mustard showed hotspots in Chatra and East Singhbhum and a coldspot in Bokaro. Pakur was identified as a significant Wheat hotspot. The LISA results in Table 19 further identify the local spatial associations. Garhwa, Latehar, and Palamu formed High-High clusters for Arhar/Tur, while Chatra and Lohardaga showed Low-High associations. Hazaribagh represented a High-High cluster for Gram, East Singhbhum a High-High cluster for Rapeseed & Mustard, and Pakur a Low-High cluster for Wheat. Together, Tables 15–19 demonstrate the spatial concentration and local clustering patterns of crop production alongside their temporal trends across Jharkhand.

Table 15
Getis-Ord Gi* spatial clustering

Crop	Hotspot 99%	Hotspot 95%	Hotspot 90%	Coldspot 90%	Not significant
Arhar/Tur	5	0	0	0	19
Gram	0	1	1	0	22
Rapeseed & Mustard	0	1	1	1	21
Wheat	0	1	0	0	23

Table 16
LISA cluster analysis

Crop	High-High	Low-High	Not significant
Arhar/Tur	3	2	19
Gram	1	0	23
Rapeseed & Mustard	1	0	23
Wheat	0	1	23

Table 17
Integrated spatial-temporal results

Crop	Significant increasing (%)	Mean Sen's slope	Median Sen's slope	Significant Gi* (%)	Significant LISA (%)
Arhar/Tur	58.3	324.91	179.12	20.8	20.8
Gram	87.5	434.19	348.67	8.3	4.2
Rapeseed & Mustard	100.0	500.32	438.37	12.5	4.2
Wheat	87.5	616.53	532.60	4.2	4.2

Table 18
Districts showing significant Gi* clusters

Crop	Gi* class	District
Arhar/Tur	Hotspot 99%	Chatra
Arhar/Tur	Hotspot 99%	Garhwa
Arhar/Tur	Hotspot 99%	Latehar
Arhar/Tur	Hotspot 99%	Lohardaga
Arhar/Tur	Hotspot 99%	Palamu
Gram	Hotspot 90%	Ramgarh
Gram	Hotspot 95%	Hazaribagh
Rapeseed & Mustard	Coldspot 90%	Bokaro
Rapeseed & Mustard	Hotspot 90%	Chatra
Rapeseed & Mustard	Hotspot 95%	East Singhbhum
Wheat	Hotspot 95%	Pakur

Table 19
Significant LISA clusters

Crop	LISA cluster	District
Arhar/Tur	High-High	Garhwa
Arhar/Tur	High-High	Latehar
Arhar/Tur	High-High	Palamu
Arhar/Tur	Low-High	Chatra
Arhar/Tur	Low-High	Lohardaga
Gram	High-High	Hazaribagh
Rapeseed & Mustard	High-High	East Singhbum
Wheat	Low-High	Pakur

Discussion

The spatio-temporal dynamics of selected crops in Jharkhand

The spatio-temporal dynamics of Arhar/Tur, Gram, Rapeseed & Mustard, and Wheat in Jharkhand reveal considerable **inter-district heterogeneity in crop production, long-term growth, and spatial distribution**. The district-wise CAGR results further strengthen this observation by showing that the magnitude and direction of production growth varied considerably among districts and across crops (Table 2). Although all four crops were available across 24 districts during the study period, their long-term production growth was not spatially uniform. The pattern observed in the present study is in conformity with the conventional understanding that agricultural development in India is spatially differentiated. Furthermore, spatial differences in agricultural development are conditioned by variations in rainfall, cropping systems, land-use conditions, irrigation and agricultural inputs. In their district-level study of Indian agriculture, Kurosaki and Wada (2015) showed that long-term agricultural transformation has distinct spatial patterns because rainfall, initial cropping and land-use conditions, and irrigation

development differ across regions. Raina and Sharma (2021) also highlighted substantial inter-district variation in agricultural production and productivity and emphasized the need for district-specific agricultural development strategies.

The **CAGR analysis provides additional evidence of this spatial differentiation**. Arhar/Tur recorded a mean CAGR of **17.42%** and a median CAGR of **15.24%**, with substantial variation between districts, ranging from **– 5.55% in Dumka to 63.21% in Dhanbad**. Production increased in 22 of the 24 districts, whereas two districts experienced declining production. In comparison, Gram recorded a higher mean CAGR of **24.21%**, with all 24 districts showing positive growth. Its CAGR varied from **5.54% in Pakur to 49.20% in Ramgarh**. Rapeseed & Mustard exhibited the highest mean CAGR (**37.78%**) among the four crops, with values ranging from **14.55% in Pakur to 128.68% in Dhanbad**, and all 24 districts recording positive growth. Wheat showed the lowest average growth, with a mean CAGR of **10.14%**, ranging from **1.67% in Pakur to 20.47% in Saraikela Kharsawan**. Thus, the CAGR results indicate that long-term production growth has been particularly pronounced for Rapeseed & Mustard and Gram, while Wheat experienced comparatively moderate growth. The large difference between the mean and median CAGR for Rapeseed & Mustard also suggests that exceptionally high growth in some districts, particularly Dhanbad, contributed substantially to the overall average.

As per the findings of the study, different spatial perspectives of production of selected crops are observed in Jharkhand. The differences between initial and final production values, together with the inter-district differences in CAGR, indicate that crop development has not followed a uniform trajectory across the state. This type of variation can be expected in a region where agricultural conditions differ considerably between districts. Raina and Sharma (2021) reported considerable differences in crop production and productivity between districts due to variations in agro-climatic conditions. The present CAGR results similarly demonstrate that neighbouring or geographically separated districts can experience substantially different rates of production growth.

District-wise differences in the production of **Arhar/Tur** are particularly heterogeneous. The crop recorded positive growth in 22 districts, but negative growth in two districts, with the highest CAGR in Dhanbad and the lowest in Dumka. Pigeon pea is sensitive to rainfall, soil conditions and crop management; hence, differences in local growing environments can contribute to substantial variation between districts. Thus, the present findings indicate that Arhar/Tur production and its long-term growth vary according to the agricultural environment of individual districts rather than being governed by a common production environment across the entire state. This interpretation is in line with broader evidence that crop patterns at the district level in India are associated with differences in rainfall, land use and irrigation conditions (Kurosaki & Wada, 2015).

The **Gram** distribution across districts also shows considerable variation. The crop recorded positive CAGR in all 24 districts, but the magnitude of growth differed substantially, from 5.54% in Pakur to 49.20% in Ramgarh. Gram, being a rabi crop, is influenced by winter moisture, soil conditions and irrigation availability. In view of differences in these production conditions, the district-level differences observed in the present study can be interpreted as reflecting variations in local production environments. Research on Indian agriculture shows that climatic variables can have strong crop-specific effects, although the magnitude and direction of these effects vary by crop and production environment. For example, Bhardwaj et al. (2022) found statistically significant relationships between climatic variables and both wheat and rice production in India, indicating the importance of climate-sensitive crop analysis at the district level.

Rapeseed & Mustard displayed the highest long-term production growth among the selected crops. The crop recorded a mean CAGR of 37.78%, with all 24 districts showing positive growth. However, the range between the minimum and maximum CAGR was very wide, particularly because Dhanbad recorded an exceptionally high CAGR of 128.68%, whereas Pakur recorded 14.55%. Such variation indicates that although the overall direction of growth was positive throughout the state, the rate of expansion differed considerably among districts. Production of this important rabi oilseed is related to winter-season conditions, soil characteristics, moisture availability and crop management. The differences observed across districts therefore suggest that suitable production environments and crop-management conditions are not uniformly distributed across Jharkhand. These patterns can be interpreted in the context of the spatially differentiated nature of Indian agriculture described by Kurosaki and Wada (2015).

In **Wheat**, the spatial pattern was comparatively different. Wheat recorded positive CAGR in all 24 districts, but the mean CAGR was only 10.14%, which was the lowest among the four crops. The highest growth was observed in Saraikela Kharsawan (20.47%), whereas Pakur recorded the lowest growth (1.67%). Wheat production is sensitive to temperature, rainfall and water availability at different stages of crop growth. Bhardwaj et al. (2022) reported that climatic variables, including minimum temperature, maximum temperature and rainfall, influence wheat production. Therefore, the district-level differences observed for wheat in Jharkhand may reflect the interaction between local climatic conditions and available agricultural resources. Nevertheless, because the present study is primarily descriptive and spatial in nature, these variations should not be interpreted as the direct effect of any single climatic or management factor.

The **CAGR patterns also provide an important basis for interpreting the subsequent spatial analysis**. The presence of substantial differences in growth rates among districts raises the question of whether districts with similar production growth are geographically concentrated. For example, the high CAGR observed in selected districts for Arhar/Tur, Gram and Rapeseed & Mustard may potentially correspond with geographically connected areas, whereas relatively low-growth districts may form separate spatial patterns. However, CAGR alone cannot establish whether such geographical concentration is statistically significant. This requires formal spatial statistical analysis.

The finding that a district with comparatively high production or production growth of one crop does not necessarily exhibit similarly high production or growth for another crop is particularly important. This indicates the presence of **crop-specific production environments in Jharkhand**. The crop-wise differences in mean CAGR further support this interpretation: Rapeseed & Mustard showed the highest average growth, followed by Gram, Arhar/Tur and Wheat, while the geographical locations of the highest and lowest growth districts also differed among crops. Similar spatial differentiation has been identified in Indian agricultural studies, where crop shares, land-use intensity, irrigation conditions and production characteristics vary considerably across districts (Kurosaki & Wada, 2015).

The spatial statistical analysis undertaken in the later stages of the study therefore rests substantially on the spatial heterogeneity observed in production and CAGR. Descriptive differences between districts alone are not sufficient to determine whether high or low production values are geographically clustered. **Global Moran's I** can be used to assess whether neighbouring districts exhibit similar production levels, while **Local Moran's I/LISA** can identify specific local clusters and spatial outliers. Similarly, the **Getis-Ord Gi*** statistic can identify statistically significant concentrations of high or low production values. Xie et al. (2024), for example, successfully applied Local Moran's I and Getis-Ord Gi* to identify spatial patterns and statistically significant clusters in an agricultural context.

Accordingly, the combined temporal and spatial findings demonstrate that crop production in Jharkhand is **neither spatially uniform nor temporally homogeneous**. The CAGR results show that all districts experienced positive long-term growth for Gram, Rapeseed & Mustard and Wheat, while Arhar/Tur experienced growth in most districts but decline in two districts. At the same time, the magnitude of growth differed considerably between districts, with particularly high CAGR values for Rapeseed & Mustard and substantial inter-district variation for Arhar/Tur. These findings indicate that the four crops have distinct production trajectories and spatially differentiated agricultural environments.

The observed variations provide a strong empirical basis for the subsequent application of **Moran's I, LISA and Getis-Ord Gi*** to determine whether the spatial differences identified through production and CAGR are statistically concentrated. Thus, the district-oriented temporal and spatial approach adopted in this study provides a more detailed understanding of crop dynamics than state-level aggregate indicators alone. This approach is consistent with previous Indian agricultural research emphasizing the importance of analysing spatial variation at the district level (Kurosaki & Wada, 2015; Raina & Sharma, 2021).

Spatial autocorrelation and temporal trends of selected crops in Jharkhand

The spatial autocorrelation, local clustering and temporal trend analysis of Arhar/Tur, Gram, Rapeseed & Mustard, and Wheat showed that these commodities displayed distinct spatial and temporal patterns across the 24 districts of Jharkhand. The findings show the four crops have different degree of spatial dependency, local clustering and the rate of temporal growth

(Table 10–14). By employing Global Moran's I, LISA, Getis-Ord Gi*, Mann-Kendall-Sen's slope analysis a comprehensive assessment of the spatial concentration and temporal changes in the production of agriculture can be carried out. The results of Global Moran's I in Table 10 show significant positive spatial autocorrelation of Arhar/Tur. The value of Moran's I is 0.3593, Z-value is 3.1253 and p-value is 0.0009 show that similar districts of Arhar/Tur production tend to occur closer than what is prescribed by random location. Global Moran's I is utilized by many researchers to determine whether observations are clustered, random or dispersed (A et al., 2020; B et al., 2026). The observed large positive autocorrelation for Arhar/Tur indicates a specific statewide spatial structure for this crop. On the other hand, the Moran's I values of Gram, Rapeseed & Mustard and Wheat were − 0.0164 (p value 0.4263) non-significant, 0.1072 (p value 0.1494) non-significant and − 0.0185 (p value 0.4325) non-significant, respectively. Consequently, these crops did not have any statistically significant evidence of global spatial autocorrelation. Crop-specific variations in production have been observed in the past. These variations can be attributed to differences in agro-ecological conditions, differences in input use, differences in irrigation, and differences in the production environment (Kurosaki & Wada, 2015; Pradeep & Rajshekhar, 2024). The results therefore suggest that spatial dependence in Jharkhand agriculture is not uniform. Table 11 presents the results of the linear spatial autocorrelation (LISA), which discloses further information. The LISA disintegrates international spatial dependence into location-specific clusters and spatial outliers allowing to detect areas of local association (Amelin, 2010; Xie et al., 2024) Arhar/Tur was recorded to have 3 high-high and 2 low-high districts while 19 districts were non-significant. Gram and Rapeseed & Mustard recorded one High-High cluster each with 23 districts being non-significant. Wheat generated one low-high cluster, 23 districts non-significant. For the four crops, there were no High-Low or Low-Low clusters. Table 12 presents the district level LISA Results of the study that Garhwa, Latehar and Palamu formed High-High clusters of Arhar/Tur. Lohardaga and Chatra were classified as Low-High cluster. For Gram, High-High Cluster formed Hazaribagh and for Rapeseed & Mustard it was East Singhbhum. Wheat Pakur is identified as Low-High cluster. Local spatial association was concentrated in certain areas in Jharkhand as indicated by the few significant clusters and large number of non-significant districts. According to local spatial statistics' similar applications it is shown that local clustering reveals spatial patterns that are not clearly observable according to global statistics (Amelin, 2010; B et al. 2026; Atwal et al. 2026). The outcomes of the Getis-Ord Gi* as represented in Table 13 further identify the hot and cool spot values. The Getis-Ord Gi* statistic is effective for identifying statistically significant hotspots and coldspots in spatial distributions (Xie et al., 2024; Peeters et al., 2015). Five districts of Arhar/Tur recorded Hotspot 99% and 19 districts were non-significant. Gram exhibited the presence of one Hotspot 95% and one Hotspot 90%. Similarly, the analyst noted that Rapeseed & Mustard recorded one Hotspot 95%, one Hotspot 90% and one Coldspot 90%. Wheat had one hotspot 95% with 23 districts non-significant. Given the findings, crop production that was statistically significant was relatively localised. The identification of the specific districts through Gi* analysis has been presented in Table 14. For Arhar/Tur, Garhwa, Lohardaga, Latehar, Palamu and Chatra were Hotspot 99% districts. According to Gram, Hazaribagh recorded a hotspot likelihood of 95% and Ramgarh of 90%. The East Singhbhum hotspot for rapeseed & mustard was identified at 95% high. Chatra was also identified as a hotspot at 90% high. Bokaro was identified as a Coldspot at 90% high. Pakur was identified as a Hotspot 95% for Wheat. The presence of intense hotspots in a few districts suggests that high production areas are not uniformly distributed in the state. Hotspot analysis through spatial clustering studies can help identify the production zones that are geographically concentrated but are masked from averages that are computed at the state-level (Peeters et al., 2015; Xie et al., 2024). According to the temporal trend analysis presented in Table 14, all four crops have recorded increasing production trends. The Mann-Kendall test used for detecting monotonic trends in agricultural and environmental times series while Sen's slope provides an estimate of magnitude of temporal change (Bhalerao et al. 2026; Banerjee et al. 2026). Of four tehsils in district Bhopal, some portion reported as significant trend, as given below. The mean slope of Sen was found to be 324.91 with the median of 179.12. This suggests an overall positive temporal trend, but the increase at levels was statistically significant only in some districts. The Gram exhibited an increasing trend in a larger number of districts with 21 districts having significant and three districts non-significant. The average Sen's slope was 434.19 while the median was 348.67 Wheat also witnessed a significant increase in 21 out of the 24 districts with the remaining three districts showing a non-significant increase The Sen's slopes of the data set have mean and median value of 616.53 and 532.60, respectively. More recently, similar studies at the district level have also pointed towards significant spatial variations in trends of crop production along with its magnitude (Bhalerao et al, 2026; Sharma et al, 2022; Oganja et al, 2024). The agricultural outputs of rapeseed and mustard showed the most widespread statistically significant increase over the years. All 24 districts exhibited significant

increasing trends in the agriculture output of rapeseed and mustard. The mean Sen's slope was 500.32 and the median was 438.37. The positive Sen's slopes suggest an increasing temporal trend, and the district level significance results indicate that this was significant in the entire study area. Applications of Mann-Kendall and Sen's slope methods have been used to identify significant temporal changes of crop-specific agricultural production (Gelata & Han, 2023; Oganja et al., 2024). No significant decreasing trends were noted for any of the four crops in Table 14. Thus, the temporal analysis was dominated by an increasing trend, although the extent and magnitude of the increases differed. The temporal increases were spatially structuring specific to crops, as spatial analysis shows. This combination of temporal change and spatial heterogeneity is consistent with previous district-level agricultural research indicating that crop production trajectories can differ considerably across locations and between crops (Kurosaki & Wada, 2015; Pradeep & Rajshekhar, 2024). The results as shown in Tables 10 to 14, the selected crops showed distinct space and time parameters in Jharkhand. Arhar/Tur peculiarity had highly significant positive global spatial autocorrelation and the maximum number of significant local clusters and Gi* hotspots. Global Moran's I calues, Gram, Rapeseed & Mustard and Wheat were not significant, but their LISA and Gi* analysis identified specific localised clusters and hotspots. All four crops, at the temporal level, have shown increasing production trends. The proportion of districts with significant increase in production shows a range of 58.3% for Arhar/Tur to 100% for Rapeseed & Mustard. These findings highlight that to understand the agricultural production dynamics at the district level in Jharkhand, it is important to analyses global and local spatial statistics with temporal trends.

Spatial-Temporal Analysis of Selected Crops in Jharkhand

The spatial-temporal analysis integrated the Mann-Kendall trend findings, Sen's slope estimates as well as Getis-Ord Gi* hotspot analysis and Local Indicators of Spatial Association (LISA) to examine the temporal trends and spatial clustering of crop production in all the 24 districts of Jharkhand. The information presented in Tables 15–19 shows that crop production in the state exhibits high spatial variability, aggregated clustering, and crop-specific temporal trends. The complementary use of spatial statistics is particularly useful because global as well as local measures capture different dimensions of spatial dependence. Getis-Ord Gi* identifies concentrations of a characteristic with significant values, while the Local Moran's I identify other local spatial associations and outliers. Likewise, the Mann-Kendall test assesses the direction and significance of a temporal change, and Sen's slope determines the magnitude of that change (Amelin, 2010; Xie et al., 2024). According to Table 15, five districts of Arhar/Tur are categorized as 99% significant hotspots. The remaining 20 districts marked as non-significant. Thus, there are maximum number of statistically significant hotspots in it. Gram had one hotspot at 95% and another at 90% with 22 districts non-significant. Hotspot at 95% level, hotspot at 90% level and coldspot at 90% level for Rapeseed & Mustard were found. The wheat crop had one hotspot at 95% level and the other 23 districts show no Gi* clustering. The results show that spatial concentration was not uniform across the crops. On the contrary, sizeable clusters were concentrated in specific districts, indicating that crops are influenced by local agriculture. According to studies (Kurosaki & Wada, 2015; Pradeep & Rajshekhar, 2024; Atwal et al., 2026) at the district-level, there is considerable spatial variation in agricultural production as well as productivity according to agro-ecological conditions, availability of resources, use of inputs, and regional character.

The strong Gi* clustering for Arhar/Tur indicates the geographic concentration of production of this crop group in a specific set of neighbouring districts. Grouping together could be due to similarities in agricultural settings, crops and soil conditions or any other site-specific reasons. Spatial analysis identifies concentration patterns, but individual factors' causal contribution is not implicated by the analysis itself. The weaker and localized Gi* patterns for Gram, Rapeseed & Mustard and Wheat indicate that their high-production zones are spatially more dispersed or restricted to isolated pockets. The identification of a hotspot and coldspot for Rapeseed & Mustard is particularly significant because it shows that production systems which are either neighbouring or geographically connected may have contrasting levels of crop production. The Getis-Ord Gi* method is effective in detecting concentrations of high or low values that are not obvious from overall spatial averages (Peeters et al. 2015; Xie et al. 2024).

The LISA results in Table 16 give more information on local spatial association. There were three High-High and two Low-High cluster registered for Arhar/Tur. For Gram and Rapeseed & Mustard one High-High cluster each was registered. Wheat has

documented one Low-High cluster. Each crop's remaining districts were deemed as non-significant. The local spatial dependence, as evidenced by these findings, was highly concentrated in only a few districts. High-High clusters for Arhar/Tur indicate that districts with relatively high production were spatially associated with neighbouring districts that also exhibited relatively high production. In contrast, the Low-High classification identifies regions with a relatively low production surrounded by regions with a relatively high production. LISA is especially relevant to distinguishing such local patterns since a statistically significant global spatial association does not necessarily take place uniformly across the region under study. The application of Gi* and LISA is innovative and revolutionary which can be seen in Tables 15 and 17. The Gi* Analysis pinpoints hotspot and coldspot concentrations, while LISA determines the type of local spatial association. Hence, the two approaches supply complementary information but not replicate results. Recent applications of these methods have likewise exploited local spatial statistics to identify sets of spatial concentrations, local clusters, and spatial outliers that can easily remain undetected by global statistics alone (Peeters et al., 2015; Xie et al., 2024). University of Nebraska Omaha would consider creating more opportunities for service-learning in other classrooms and developing faculty training materials for emulated and placement service-learning.

The combined results in Table 17 reveal an important temporal dimension to the spatial patterns. Rapeseed & Mustard exhibited a significant increasing trend in all 24 districts (100%) while Gram and Wheat experienced significant increasing trends in 87.5% of districts each. Arhar/Tur has a significant increasing trend in 58.3% of districts. Accordingly, all four crops exhibited temporal increases, though the magnitudes of statistical increases differed greatly among crops. Mann-Kendall test is a statistical test used to identify the presence of a monotonic trend in time series data. Analysis of the times series data collected from the agricultural and environmental samples using Mann-Kendall test has been on the rise in recent years. Also, the application of Sen’s slope to estimate the magnitude of the trend has gained popularity (Gelata and Han, 2023, Bhalerao et al., 2026, Banerjee et al., 2026). The results from Sen’s slope in Table 17 further show differences over time between specific crops. The mean and median Sen’s slope followed the order wheat > Rapeseed & Mustard > Barley > Maize > Minor Cereals > Pulses > Oilseeds. Wheat registered the highest mean and median Sen’s slope of 616.53 and 532.60, respectively. Rapeseed & Mustard showed the second highest mean and median slope of 500.32 and 438.37, respectively. Gram observed the highest average and median slopes at 434.19 and 348.67, respectively, with Arhar/Tur showing the lowest average and median values at 324.91 and 179.12, respectively. Sen’s slope estimates the magnitude of change over a certain period. Thus, Wheat experienced the maximum estimated increase in production per temporal unit among the crops studied. On the contrary, the estimated slope of Arhar/Tur was found to be the lowest. Prior research on crop trends similarly indicates that production trends can vary quite differently in terms of their magnitude and significance across districts (Bhalerao et al., 2026; Oganja et al., 2024).

It is particularly instructive to compare significant trends of time to significant clusters of space. Arhar/Tur exhibited a 20.8% significant Gi* clustering along with a 20.8% significant LISA clustering, despite only 58.3% of its districts having significant increasing trends. All districts showed a significant increasing trend for Rapeseed & Mustard but only 12.5% showed significant Gi* clustering and 4.2% significant LISA clustering. Similarly, the Gram was characterized by 87.5% significant increasing trends and 8.3% significant Gi* and 4.2% significant LISA clustering. On the other hand, the Wheat experienced 87.5% significant increasing trends and 4.2% significant Gi* and 4.2% significant LISA clustering. Temporal growth does not mean spatial clustering in this comparison. A crop may not manifest in most or all districts, but its production does not remain spatially concentrated in significant clusters. The distinction is important in understanding agricultural development; temporal improvement and spatial concentration reflect different dimensions of agricultural change (Kurosaki & Wada, 2015; Pradeep & Rajshekhar, 2024).

The Gi* results for individual districts in Table 18 show how the significant spatial concentrations are distributed across space. The hotspots for arhar/tur were Chatra, Garhwa, Latehar, Lohardaga, and Palamu at 99% significance. There is a marked concentration of Arhar/Tur production in these districts, with five extremely important hot spots. The 90% level gram hotspots occurred in Ramgarh and Hazaribagh at 95%, indicating a localized concentration in these districts. East Singhbhum was assigned a 95% hotspot for Rapeseed & Mustard followed by Chatra (90%). For this crop, Bokaro is a coldspot at 90%. The hotspot of wheat has been a 95% in pakur.

The observation of a coldspot of Rapeseed & Mustard in Bokaro, combined with hot spots of the crop in Chatra and East Singhbhum, indicates the spatial heterogeneity. The Gi* analysis demonstrates that high or low production values are not generally distributed across the state but rather are spatially concentrated in specific areas. Hotspot analysis, which is similar of Getis-Ord statistics has been proved useful in delineating concentrated high- and low-value areas within agricultural landscapes (Peeters et al. 2015; Xie et al. 2024). Nonetheless, the statistical classification should be taken as evidence of spatial concentration and should not, on its own, be interpreted as proof of the underlying causes of socioeconomy, climate, or agronomy.

LISA results in Table 19 give a finer description of the local spatial association. Garhwa, Latehar and Palamu have formed High-High clusters for Arhar/Tur which indicates these districts and their neighbours have comparatively high production. Chatra and Lohardaga were engaged in Low-High associations, indicating low production values with high production neighbours. According to Gram, Hazaribagh was a High-High cluster whereas East Singhbhum was a High-High cluster for Rapeseed & Mustard. Pakur showed a Low-High association for Wheat. The patterns indicate that spatial relationships vary between crops and districts, and that the level of production in a district should be viewed in relation to its geographical neighbours rather than in isolation. The High-High configuration for Arhar/Tur in Garhwa, Latehar and Palamu is consistent with the broad concentration detected by the Gi* assessment in Table 18. The Low-High associations in Chatra and Lohardaga are informative because these districts are not just low production districts but instead spatially associated with producing districts having higher values. Likewise, the High-High classification of Gram for Hazaribagh and Rapeseed & Mustard for East Singhbhum show concentrations of production that are localized and not widespread enough at the state level to generate strong clustering. LISA is thus useful to identify these specific spatial relationships and complement the hotspot results (Amelin, 2010; Xie et al., 2024).

The evidence suggests there is no single common pattern in the spatial and temporal dimensions of crop production in Jharkhand. The highest concentration of significantly spatial clusters was noticed in arhar/tur while rapeseed & mustard showed a consistent increase temporally across districts. Wheat, among the four crops under study, was found to have the highest mean and median Sen's slope value. High - High associations of Gram and Rapeseed & Mustard were localized whereas the Wheat displayed a localized Low - High association. These differences suggest that not assuming a common geographical structure to produce crops and spatially planning the crop may be more informative.

The results are also consistent with more general evidence about agricultural production changes through time and across district inhomogeneity. A series of district-level analyses in India has shown that agricultural performance differences could persist because production environments, resource availabilities, technology participations, climate conditions, and agricultural practices are not uniform across space (Kurosaki & Wada, 2015; Pradeep & Rajshekhar, 2024). Spatial clustering studies show that Moran's I, LISA, and Getis-Ord statistics can help establish local agricultural patterns. As a result, significant areas in spatial terms can be isolated from non-significant areas (Amelin, 2010; Peeters et al., 2015; Xie et al., 2024). Looking at Tables 16–20, it can be said that there were positive temporal changes in the production of four selected crops in Jharkhand. However, there were crop-specific spatial expressions. The findings highlight the significance of linking trend analysis with spatial statistics: while applied Mann-Kendall and Sen's slope yield information on the direction and magnitude of temporal change, Gi* and LISA reveal where production is concentrated spatially and how neighbouring districts are associated. This framework provides an integrated view of agricultural dynamics which is more comprehensive than a temporal or spatial Consequently, the findings may assist in interpreting crop production patterns at the district level without presuming that increasing levels of production suggests uniform spatial development in Jharkhand.

Conclusion

The analysis utilized temporal trend analysis combined with spatial statistical techniques to analyze spatial and temporal dynamics of Arhar/Tur, Gram, Rapeseed & Mustard and Wheat production in 24 districts of Jharkhand. Combining Mann-Kendall trend analysis, Sen's slope estimation, Global Moran's I, LISA and Getis-Ord Gi* provided information on the change in crop production and their depopulation patterns. The temporal examination indicated a rising trend in production of all the selected four crops. However, the magnitude of increase and significance of increase differed in various crops and districts.

The most temporally consistent crop - Rapeseed & Mustard - had a significant increasing trend in all 24 districts (100%). Gram and Wheat registered significant increases in 87.5% of districts, while that of Arhar/Tur was substantial in 58.3% of the districts. The metrics related to the Sen's slope estimates pointed towards Wheat having the highest mean and median slope value of 616.53 and 532.60 respectively, followed by Rapeseed & Mustard at 500.32 and 438.37. Further down the line were Gram at 434.19 and 348.67 and Arhar/Tur at 324.91 and 179.12. Spatial analysis revealed that production was not uniformly distributed in the entire Jharkhand. Arhar/Tur was the most spatially concentrated crop with positive global spatial autocorrelation and several significant local clusters. The analysis of Getis-Ord Gi* detected five hotspots for Arhar/Tur at 99% level in Chatra, Garhwa, Latehar, Lohardaga and Palamu. Gram experienced intense hotspot activities in Ramgarh and Hazaribagh while Rapeseed & Mustard has shown hotspot activities in Chatra and East Singhbhum and coldspot in Bokaro. The Pakur region displayed a significant hotspot for wheat. LISA analysis also demonstrated that local spatial relationships were species specific. In Chatra and Lohardaga, arhar/tur formed high- low associations and in Garhwa, Latehar, Palamu high-high associations. A High-High cluster of Gram was discovered in Hazaribagh, while East Singhbhum had a High-High cluster of Rapeseed & Mustard. Furthermore, Pakur had a Low-High association of Wheat. The spatial analysis shows that the concentration of production takes place in particular districts and not all over the state. Another valuable distinction which the study highlights are that between temporal growth and spatial concentration. A significant increasing trend was observed for Rapeseed & Mustard in all districts, but a limited number of districts formed significant Gi* and LISA clusters. On the contrary, Arhar/Tur showing relatively strong spatial clustering despite the lesser proportion of districts showing significant increasing trends. This shows that the time-growing production does not necessarily equal greater space concentration. According to the research results, the agricultural production in Jharkhand recorded a positive temporal change and exhibited substantial crop-specific spatial variability. According to the findings, it is crucial to look at agricultural planning at the district level. Doing so helps avoid your overlook of important factors. Also, figures at the state level average can mask essential production trends and spatial concentration. Recognizing important areas of concern and integration can form a spatial basis for prioritizing crop-specific interventions and devising resource allocation strategies. This study utilizes a spatial-temporal framework which provides an effective analytical tool for understanding the evolving agricultural production landscape of Jharkhand.

Implications / Policy Implications

The findings have several implications for crop planning and agricultural development in Jharkhand:

- Crop-specific planning: The strong spatial concentration observed for Arhar/Tur and localized clusters in other crops indicate that interventions should be tailored to individual crop-district combinations rather than applying uniform state-level strategies.
- Targeted hotspot development: Districts identified as significant hotspots, particularly for Arhar/Tur, Gram, Rapeseed & Mustard, and Wheat, can be prioritized for improved seed supply, extension services, irrigation, storage, and market infrastructure.
- Support for low-performing areas: Coldspot and Low-High districts require location-specific interventions focusing on productivity improvement, resource access, and appropriate crop management.
- Strengthening climate-resilient agriculture: The increasing production trends should be supported through drought-tolerant varieties, efficient water management, and climate-smart farming practices, particularly in predominantly rainfed areas.
- Spatially informed agricultural planning: Integration of Mann-Kendall, Sen’s slope, Moran’s I, LISA, and Getis-Ord Gi* can provide a scientific basis for district-level prioritization, monitoring, and resource allocation.
- Future planning: Agricultural policies should combine temporal trends with spatial clustering information to identify emerging production zones and address persistent spatial disparities.

Limitations of the Study

- The study is based on district-level secondary data, which may mask variation within individual districts.

- The analysis primarily considers crop production, while factors such as rainfall, irrigation, soil quality, input use, and market access were not incorporated directly.
- Spatial results depend on the neighbourhood/weight matrix used for spatial analysis.
- Mann-Kendall and Sen's slope identify temporal trends but do not establish causal relationships.
- The analysis covers selected crops-Arhar/Tur, Gram, Rapeseed & Mustard, and Wheat-and therefore may not represent all crops grown in Jharkhand.
- The study period and available secondary data may limit the interpretation of recent changes in agricultural production.

Recommendations / Suggestions

- Arhar/Tur: Strengthen production support in the identified hotspot districts-Chatra, Garhwa, Latehar, Lohardaga, and Palamu-through improved seed, moisture conservation, and location-specific extension services.
- Gram: Focus interventions in Hazaribagh and Ramgarh, particularly on improved varieties, irrigation and improved crop management.
- Rapeseed & Mustard: Consolidate production gains in East Singhbhum and Chatra, while examining the production constraints associated with the Bokaro coldspot.
- Wheat: Give targeted support to Pakur, particularly through irrigation, timely sowing, and improved varieties.
- District-specific agricultural planning should be preferred over a uniform state-level strategy, considering the crop-specific spatial patterns.
- Hotspot districts can be developed as production and technology dissemination zones, while low-performing areas should receive targeted resource and infrastructure support.

Future Research Directions

- Integrate rainfall, temperature, irrigation, soil, fertilizer use, and market-access data with crop production.
- Apply spatial panel-data models to identify factors influencing district-level production.
- Examine the effects of climate variability and climate change on crop-specific trends.
- Extend the analysis to all major crops and finer spatial units, such as blocks.
- Use spatial machine-learning and predictive models to identify future production hotspots and potential risk zones.
- Conduct field-level studies to validate the spatial patterns identified through Moran's I, LISA, and Getis-Ord Gi*.

Declarations

Competing Interests

The authors declare that they have no competing interests that are directly or indirectly related to this work.

Author Contributions

Vikash Kumar: Conceptualization, methodology, data analysis, visualization, and manuscript preparation.

Paritosh Kumar, Supriti Chatterjee, Rakesh Choudhary, and Swati Singh: Data analysis, interpretation, and manuscript review.Mohsin Hussain: Supervision, critical revision, and final approval of the manuscript.

All authors read and approved the final manuscript.

Ethics Approval

Not applicable. This study used secondary publicly available agricultural datasets and did not involve human participants or animal experiments.

Consent to Participate

Not applicable.

Consent for Publication

Not applicable.

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Data Availability

Data Availability: The datasets analysed during the current study were obtained from the India Data Portal (IDP) under the Crop Wise Area Production Yield (APY) dataset provided by the Ministry of Agriculture & Farmers Welfare, Government of India. The processed datasets and analytical outputs generated during the study are available from the corresponding author upon reasonable request.

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Figures

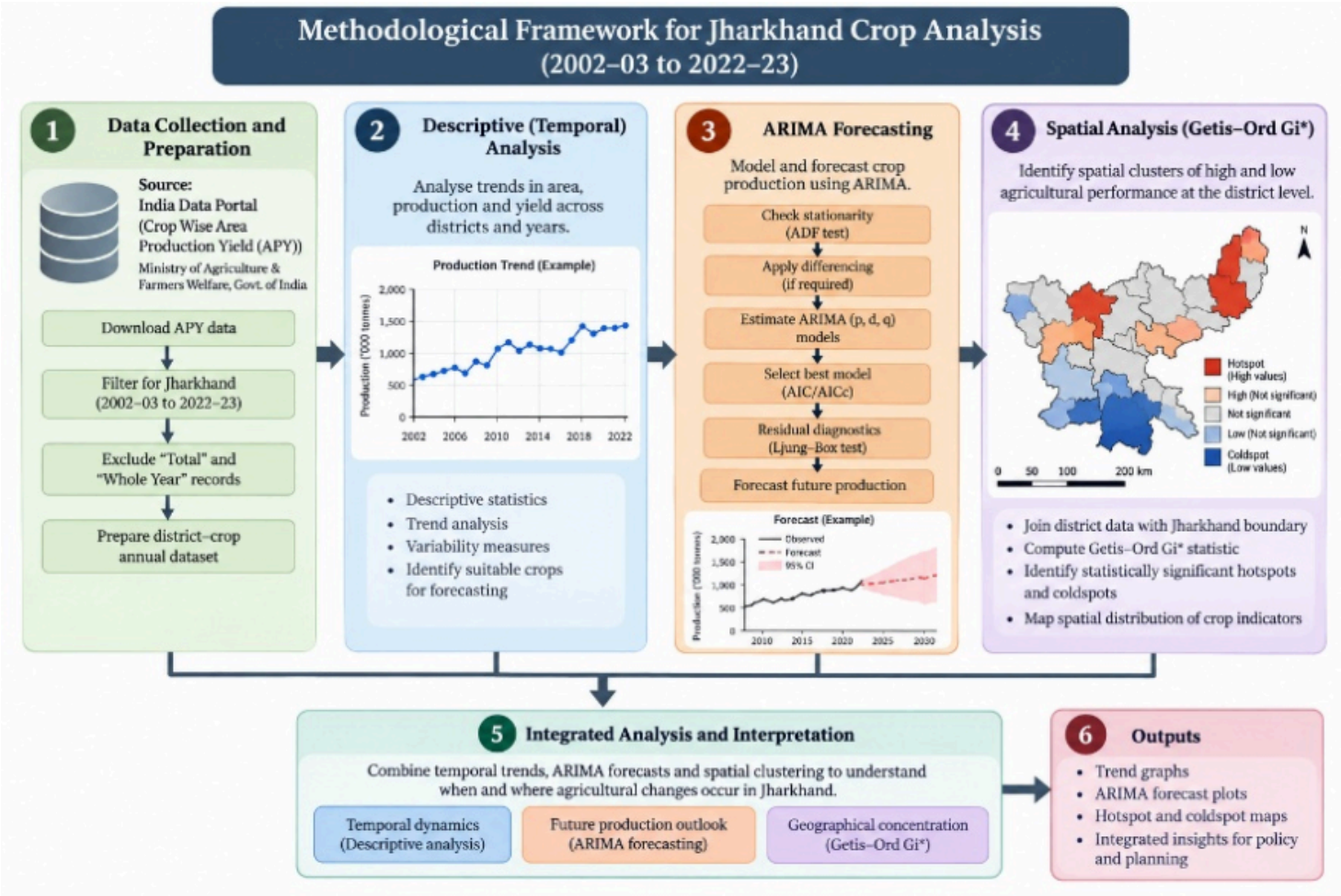


Figure 1

Integrated methodological framework for temporal, ARIMA forecasting, and spatial analysis of crop production in Jharkhand (2002-03 to 2022-23).

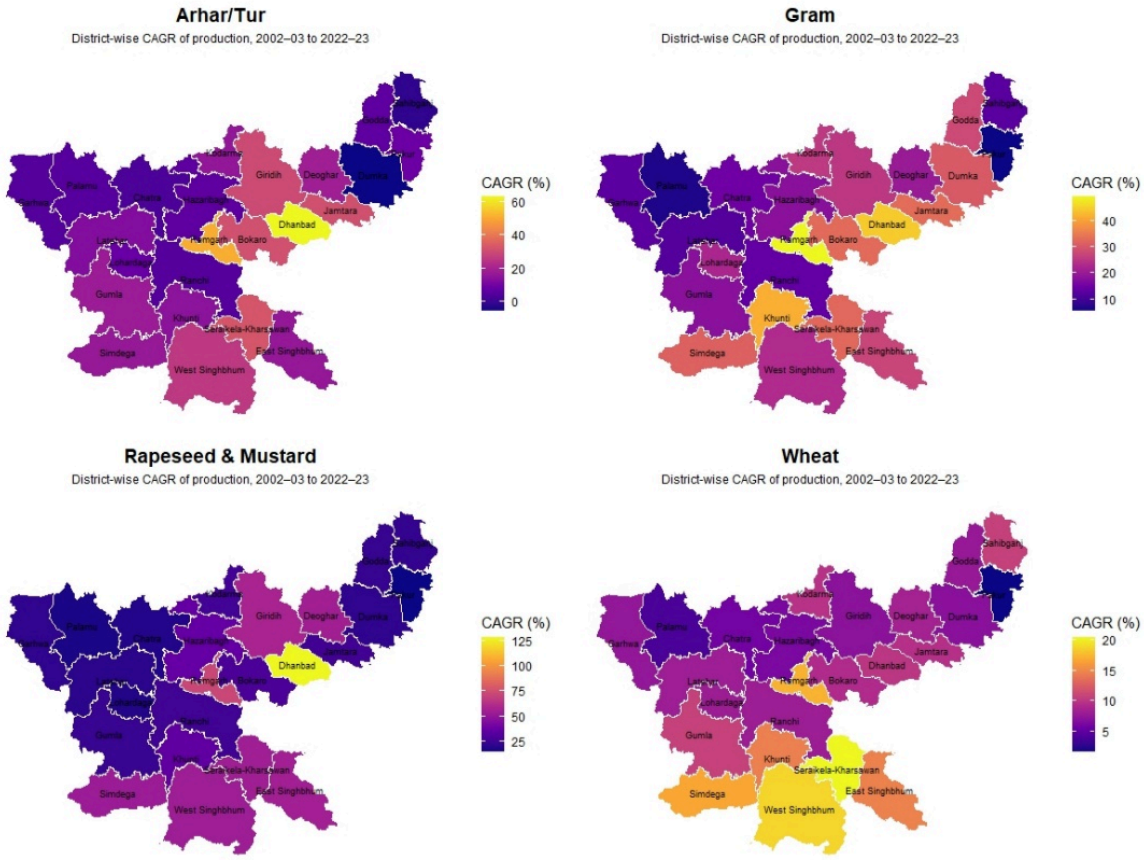


Figure 2

District-wise spatial distribution of CAGR (%) in crop production for Arhar/Tur, Gram, Rapeseed & Mustard, and Wheat in Jharkhand, 2002-03 to 2022-23.

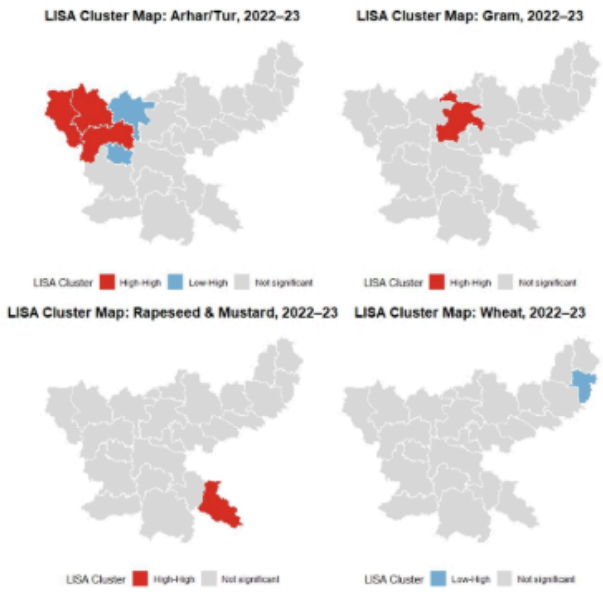


Figure 3

District-wise LISA cluster classification of Arhar/Tur, Gram, Rapeseed & Mustard, and Wheat production in Jharkhand, 2022-23.

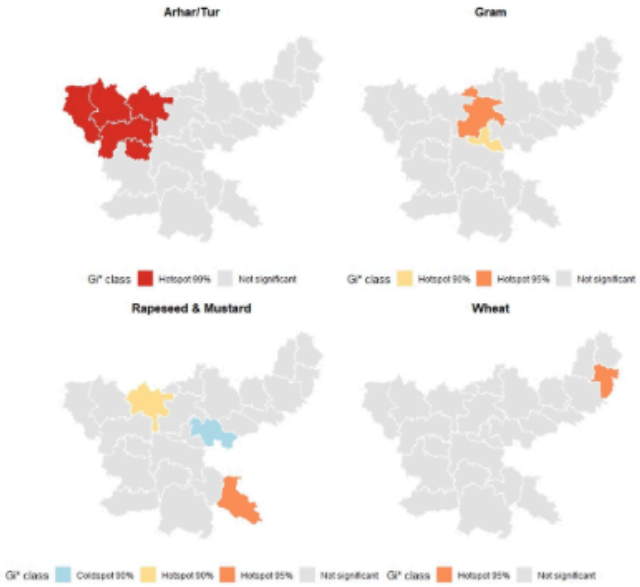


Figure 4

District-wise spatial distribution of Getis-Ord Gi hotspots and coldspots for Arhar/Tur, Gram, Rapeseed & Mustard, and Wheat production in Jharkhand, 2022-23.*

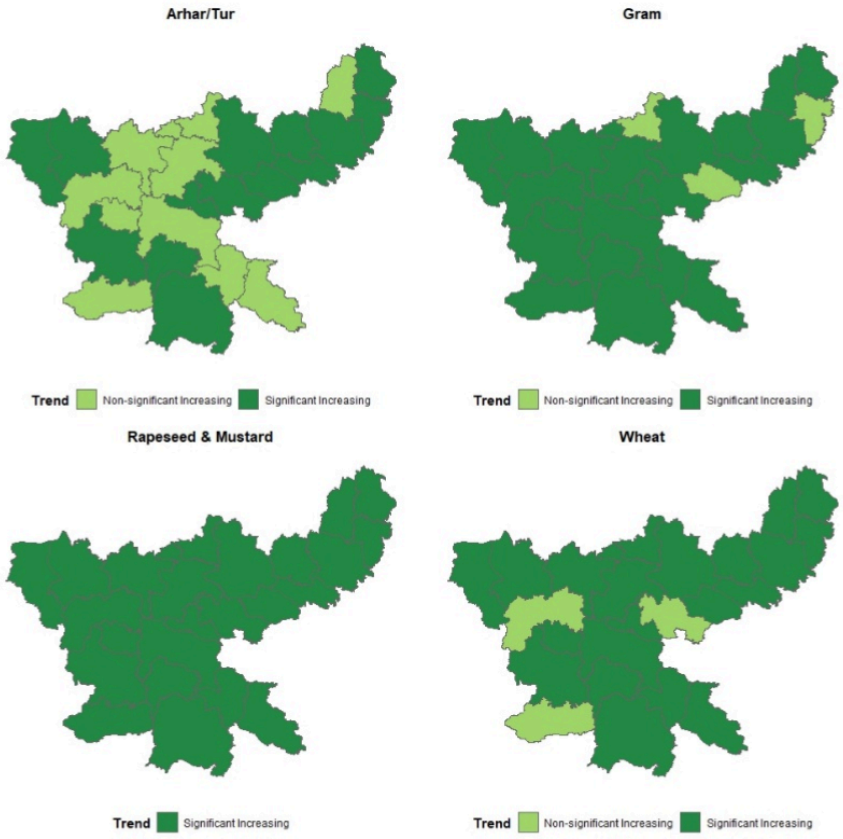


Figure 5

District-wise spatial distribution of Mann-Kendall trend classifications for selected crop production in Jharkhand, 2002-03 to 2022-23