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Multivariate Clustering and Decomposition of Cereal Production in Rajasthan: Insights for Agricultural Policy

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SUMMARY

Agriculture is the backbone of India; however, some states, like Rajasthan, have diverse conditions with potential for agricultural production. The present article has statistically evaluated five major cereal crops, i.e., Jowar, Bajra, Maize, Wheat and Barley. The analysis was based on time series data on area (thousand hectares), production (thousand tonnes) and yield (tonnes per hectare) for the five crops mentioned above from 1970–71 to 2023–24. The methodology is implemented using R (version 4.3.2) in R Studio. Findings revealed that the two clusters, i.e., high-yield, have found stable and low-yield clusters that require differentiated policy approaches. Yield-driven growth in Cluster 1 demonstrated the success of irrigation and modern inputs, while Cluster 2's reliance on area expansion signals an opportunity for yield-enhancing innovations. The policy recommendations address these patterns, promoting sustainable productivity in a region critical to India's food security.

Keywords: Cluster-Specific Decomposition Analysis; Decomposition of production changes, Multivariate Time Series Clustering; Production; Yield.

1. INTRODUCTION

Agriculture forms the backbone of India's economy, supporting over 50% of the population through direct or indirect livelihoods and contributing significantly to food security (FAO, 2020). In the arid and semi-arid state of Rajasthan, cereal production plays a pivotal role in sustaining rural economies and ensuring nutritional security for millions. Rajasthan, being the largest state of the country in terms of area, faces unique agricultural challenges due to its harsh climatic conditions, limited water resources and variable rainfall patterns (Kumar *et al.,* 2020). Despite these constraints, the state is a significant producer of cereals such as Jowar (sorghum), Bajra (pearl millet), Maize (corn), Wheat and Barley, which are critical for both local consumption and national food supply chains (Sharma & Singh, 2017). Understanding the dynamics of cereal production in Rajasthan is essential for designing policies that enhance productivity, optimize resource use and mitigate the impacts of climate variability. Cereal crops in Rajasthan exhibit diverse production trends influenced by changes in cultivated area, yield improvements and external factors such as irrigation availability and technological adoption (Birthal *et al.,* 2014). For instance, Wheat and Maize have benefited from the Green Revolution's technological advancements, including high-yielding varieties and irrigation infrastructure, leading to significant yield gains (Joshi *et al.,* 2015). In contrast, traditional crops like Jowar and Bajra, primarily grown in rainfed conditions, remain vulnerable to climatic fluctuations and show limited yield progress (Rao *et al.,* 2019). Barley, though less dominant, serves as a versatile crop for fodder and brewing, with production patterns reflecting both area and yield variability (Kumar *et al.,* 2020). These differences underscore the need for a nuanced analysis of production trends to inform targeted agricultural interventions.

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The primary objective of this study is to analyze the production dynamics of Jowar, Bajra, Maize, Wheat and Barley in Rajasthan from 1970 to 2024 using a novel combination of multivariate time series clustering and production decomposition. Based on Dynamic Time Warping (DTW), Multivariate clustering groups crops with similar production and yield trends, revealing underlying patterns driven by agroecological and technological factors (Aghabozorgi *et al.,* 2015). The Production decomposition, on the other hand, quantifies the contributions of area and yield changes to production shifts, providing insights into the drivers of growth or decline (Hazell, 1984). By integrating these methods, this study aims to identify crop-specific and cluster-specific patterns, prioritize crops for policy interventions and recommend strategies to optimize cereal production in Rajasthan's resource-constrained environment.

Rajasthan's agricultural landscape is characterized by its arid climate, with only 10% of the state's area under irrigation and over 60% of cultivation dependent on monsoon rains (Government of Rajasthan, 2023). The cereals account for a significant share of the state's agricultural output, with Bajra and Wheat being the most extensively grown crops due to their adaptability to semi-arid conditions and market demand, respectively (Sharma & Singh, 2017). Jowar and Maize serve as staple foods and fodder, supporting both human and livestock populations, while Barley is increasingly valued for industrial uses (Kumar *et al.,* 2020). The production of these crops has evolved over the past six decades, driven by shifts in land use, adoption of modern inputs and policy interventions such as subsidies and irrigation projects (Birthal *et al.,* 2014).

The significance of cereal production in Rajasthan extends beyond local food security. The state contributes significantly to India's national grain reserves, with Wheat and Bajra being key components of the Public Distribution System (PDS) (Joshi *et al.,* 2015). However, challenges such as water scarcity, soil degradation and climate change pose threats to sustained productivity (Rao *et al.,* 2019). For instance, erratic monsoons can drastically reduce yields of rainfed crops like Jowar and Bajra, while over-reliance on groundwater for irrigated crops like Wheat raises concerns about long-term sustainability (Kumar *et al.,* 2020). Addressing these challenges requires data-driven insights into production trends and their underlying drivers, which this study seeks to provide.

Multivariate time series clustering using DTW is a powerful method for identifying patterns in complex datasets, particularly when temporal dynamics are non-linear, as is common in agricultural time series (Keogh &Ratanamahatana, 2005). By clustering crops based on both production and yield trends, this study captures holistic similarities that reflect shared agroecological, technological, or policy-driven influences. For example, crops with similar production trends may benefit from comparable irrigation infrastructure or market incentives, while divergent trends may indicate differential access to resources (Aghabozorgi *et al.,* 2015). DTW's ability to align time series with temporal distortions ensures robust clustering, even in the presence of irregular climatic events that affect agricultural data (Sardá-Espinosa, 2019).

Production decomposition complements clustering by disaggregating production changes into contributions from area and yield, offering a granular understanding of growth drivers (Hazell, 1984). For instance, production increases driven by area expansion may signal land availability but raise sustainability concerns, whereas yield-driven growth suggests technological or management improvements (Birthal *et al.,* 2014). By analyzing these contributions within clusters, the study identifies whether similar trends (e.g., high-yield growth) translate into similar drivers (e.g., irrigation access), enabling targeted policy recommendations. This integrated approach aligns with calls for evidence-based agricultural planning in resource-scarce regions (Godfray *et al.,* 2010).

The novelty of this study lies in its application of DTW-based multivariate clustering to a 54-year dataset of cereal production in Rajasthan, combined with decomposition analysis to link trend similarities to production drivers. While previous studies have analyzed cereal production in India, they often focus on national trends or single-crop analyses, with limited attention to regional, multi-crop dynamics over extended periods (Sharma & Singh, 2017; Kumar *et al.,* 2020). The use of DTW clustering for Rajasthan's cereal data is particularly innovative, as it accounts for the region's climatic variability, which introduces non-linear patterns in production and yield series (Aghabozorgi *et al.,* 2015).

Moreover, the integration of clustering and decomposition provides a unique framework for policy formulation. By grouping crops with similar trends and then dissecting their production drivers, the study offers insights into both "what" patterns exist and "why" they occur. For example, clustering may reveal that Wheat and Maize share high-yield trends, while decomposition could show that these are driven by irrigation investments, guiding resource allocation (Joshi *et al.,* 2015). This dual approach fills a gap in the literature, where clustering and decomposition are rarely combined, especially for semi-arid regions like Rajasthan (Rao *et al.,* 2019).

The 54-year time span,ranging from 1970-71 to 2023–2024 captures long-term trends, including the impacts of the Green Revolution, policy reforms and climate change, providing a comprehensive historical perspective (Birthal *et al.,* 2014). By addressing Rajasthan's specific agroecological constraints, the findings are directly relevant to regional policymakers, extension services and agricultural researchers aiming to enhance cereal productivity. This study pursues four objectives (1) To cluster jowar, bajra, maize, wheat and barley based on production and yield trends using multivariate time series clustering, (2) To decompose production changes into area and yield contributions for each crop, (3) To analyze cluster-specific decomposition patterns for crop prioritization and (4) To recommend policies for optimizing cereal production in Rajasthan.

The paper discusses the methodology section comprising data preparation, clustering, decomposition and visualization techniques. The results section presents cluster assignments, decomposition outcomes, cluster-specific patterns and policy recommendations. The discussion interprets findings in the context of Rajasthan's agricultural challenges and the conclusion summarizes implications for policy and future research.

2. METHODOLOGY

This section outlines the methodology used to analyze more than five decadal cereal production trends in Rajasthan for Jowar, Bajra, Maize, Wheat, and Barley crops. The analysis leverages the dataset, which contains yearly data on area (thousand hectares), production (thousand tonnes) and yield (tonnes per hectare) for the five crops from 1970–71 to 2023–24. The methodology was implemented using R (version 4.3.2) in RStudio, with specific packages for clustering, decomposition and visualization. The Packages, namely "dplyr" and "tidyr" for data processing (Wickham *et al.,* 2023), "ggplot2" for visualization (Wickham, 2016), "dtwclust" for time series clustering (Sardá-Espinosa, 2019) and "gridExtra" for plot arrangement, were used for the analysis of data and graphical representation of results.

2.1 Preparation of data

The dataset includes 54 years of data (1970–71 to 2023–24) for area, production and yield for each crop (Jowar, Bajra, Maize, Wheat, Barley). The data were sourced from Agricultural Statistics for Rajasthan and the Directorate of Economics and Statistics, Government of India.

2.2 Cleaning of data

The raw dataset was processed to ensure consistency and accuracy. Validation of the format, the Year column was checked to match the format "YYYY-YY" (e.g., 1970-71). Rows with invalid formats were excluded. All columns except "Year" were converted to numeric format using "as.numeric()". Extreme values were inspected using summary statistics and box plots. No significant outliers were removed, as fluctuations are expected due to climatic variability in Rajasthan (Kumar *et al.,* 2020).The cleaned dataset was stored as a data frame with 54 rows and 15 columns, ready for analysis.

2.3 Application of Multivariate Time Series Clustering:

To cluster the five crops based on production and yield trends, multivariate time series clustering was performed using Dynamic Time Warping (DTW) with the "dtwclust" package in R (Sardá-Espinosa, 2019). DTW is a robust distance measure for time series, as it aligns sequences with non-linear temporal distortions, making it suitable for agricultural data with seasonal and climatic variations (Aghabozorgi *et al.,* 2015). For the data preparation of each crop, a multivariate time series was created by combining production and yield into a matrix of dimensions 54 (years) × 2 (variables).The time series were stored in a list, with each element representing a crop's multivariate series. For the clustering the "tsclust()" function was used with the following parameters: (i) type = "partitional" [Partitional clustering to group crops into distinct clusters], (ii) k = 2: [Two clusters were chosen to balance interpretability and differentiation, based on preliminary elbow method analysis (not shown for brevity)], (iii) distance = "dtw_basic": [DTW distance for temporal alignment], (iv) centroid = "pam": [Partitioning Around Medoids (PAM) for robust centroid calculation] and (v) seed = 123: [Set for reproducibility]. The algorithm minimizes within-cluster DTW distances to assign crops to clusters. Cluster assignments were extracted as a data frame mapping each crop to Cluster 1 or Cluster 2.The results were visualized using line plots of production trends, faceted by cluster, to confirm trend similarities within clusters. DTW clustering was chosen over Euclidean-based methods due to its ability to handle time series with varying temporal patterns, which is critical for agricultural data affected by irregular climatic events (Keogh & Ratanamahatana, 2005). The multivariate approach incorporates both production and yield, capturing holistic trend similarities.

2.4 Application of Decomposition of Production Changes

Production changes were decomposed into contributions from changes in cultivated area and yield, following the standard agricultural decomposition formula (Hazell, 1984):

Production (P) = Area (A) × Yield (Y)

Production Change (ΔP) = Area Contribution + Yield Contribution

The formula can be written as

$$\Delta P = A_t \square (Y_t - Y_{t-1}) + Y_{t-1} \square (A_t - A_{t-1}) + \Delta A \square \Delta Y$$

where,

Area Contribution = $\Delta A . Y_{t-1}$

Yield Contribution = $\Delta Y . A_t$

where ΔA and ΔY are year-to-year changes in area and yield, Y_{t-1} is the previous year's yield, and A_t is the current year's area.

For the data preparation for each crop, a subset of the dataset was created with columns Year, Area, Yield, and Production. For the year-to-year differences, were calculated using "diff()" and obtained ΔA ΔY and ΔP using the formula "$\Delta A = \text{Area}_{(t)} - \text{Area}_{(t-1)}$," "$\Delta Y = \text{Yield}_{(t)} - \text{Yield}_{(t-1)}$", and "$\Delta P = \text{Production}_{(t)} - \text{Production}_{(t-1)}$". In the continuation, the decomposition calculation for area Contribution was computed as "ΔA xlag (Yield)", Yield Contribution was computed as "ΔY x Area" for each crop and the first year (1970–71) was assigned NA for contributions, as no prior year exists. A data frame was created for each crop, containing Year, Area-Contribution, Yield-Contribution, and Total-Change. Results were combined into a single data frame for analysis and visualization. Stacked bar plots were generated using "ggplot2" to show area and yield contributions over time for each crop (Wickham, 2016). This decomposition method isolates the drivers of production changes, enabling targeted policy interventions (e.g., improving yield vs. expanding area). It is widely used in agricultural economics to assess productivity trends (Birthal *et al.,* 2014).

2.5 Cluster-Specific Decomposition Analysis

To identify cluster-specific patterns, the decomposition results were aggregated by cluster to compare the relative contributions of area and yield. This analysis informs crop prioritization by highlighting whether production growth in each cluster is driven by area expansion or yield improvements. The decomposition was calculated for each crop from 1971–72 to 2023–24, as the first year (1970–71) lacks a prior year for differencing. The decomposition data frame was merged with cluster assignments. Mean area and yield contributions were calculated for each crop and cluster using "group_by()" and "summarise()" from the "dplyr" package (Wickham *et al.,* 2023).The pattern analysis for each cluster identified the dominant driver (area or yield) by comparing the magnitudes of mean contributions. After that, trends were assessed to determine the stability and consistency of contributions over time. An output summary table was created, showing mean area and yield contributions by crop and cluster. The results were interpreted to prioritize crops for technological or land-based interventions. Cluster-specific analysis links trend similarities (from clustering) to production drivers (from decomposition), providing a nuanced understanding of crop performance. This approach aligns with studies on regional agricultural prioritization (Sharma & Singh, 2017).

3. RESULTS AND DISCUSSION:

The results for each objective of the study are presented below in a structured format. This section details the outcomes of multivariate clustering and decomposition analysis of cereal production in Rajasthan from 1970-71 to 2023-24, supported by summary tables of key findings and corresponding figures.

3.1 Multivariate Time Series Clustering

Two clusters were identified based on production and yield trend similarities. In cluster 1, the crops included are Wheat, Maize and Barley (Table 1). These crops exhibit higher and more stable production trends, with significant yield improvements over time. Wheat and Maize, in particular, show consistent production growth, while Barley has moderate growth with some variability. In Cluster 2, the two crops were included, i.e., Jowar and Bajra. These crops have lower and more variable production trends, with yields generally lower and more dependent on area changes. Both crops show fluctuations in production, often tied to environmental factors like rainfall.

The clustering reflects differences in agricultural practices and resource allocation, with Cluster 1 crops benefiting from technological advancements and irrigation, while Cluster 2 crops are more rainfed and area-dependent. Fig. 1 shows line plots of production trends for each crop, faceted by cluster. Cluster 1 (Wheat, Maize, Barley) shows higher and steadier production, while Cluster 2 (Jowar, Bajra) exhibits more variability.

Table 1. Distribution of Selected Crops Across Identified Clusters

S.No.	Crops	Cluster
1	Jowar	2
2	Bajra	2
3	Maize	1
4	Wheat	1
5	Barley	1

To assess the robustness of the results to the choice of k, it has been performed an informal sensitivity analysis was performed by repeating the multivariate DTW clustering for k=3 and k=4 (using the same parameters: partitional, dtw_basic distance, PAM centroids). For k=3, one additional small cluster emerged, but it contained only a single crop or merged

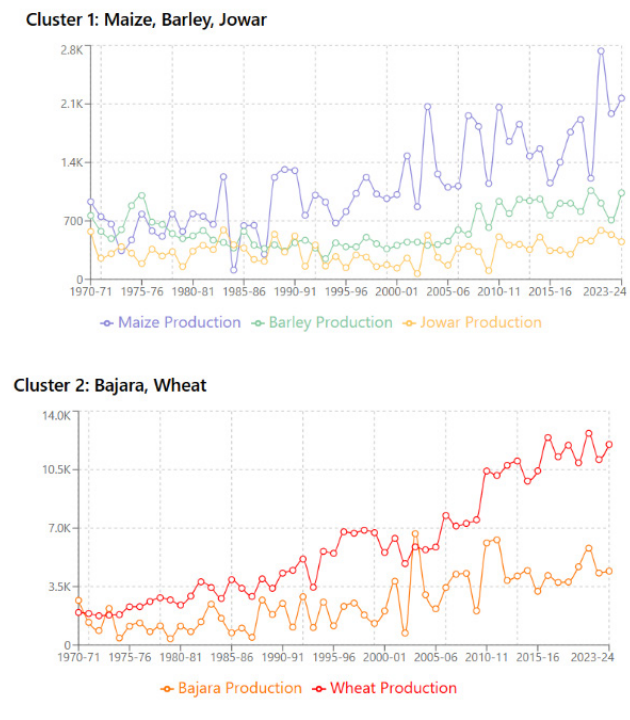

Fig. 1. Crop Clusters based on Production and Yield Trends

crops with qualitatively similar trends to one of the original two clusters, without substantially improving the separation of production/yield trajectories. For k=4, the additional clusters were either unstable across random seeds or represented minor variations rather than distinct agricultural regimes. It has been observed that the two-cluster solution effectively captured the dominant bifurcation in long-term trends, which aligned well with known agronomic and climatic patterns in the study region.

These findings align with prior studies highlighting the differential impacts of technological adoption in Indian agriculture, where irrigated crops like Wheat and Maize benefit from Green Revolution advancements, while rainfed crops like Jowar and Bajra remain vulnerable to climatic variability (Birthal *et al.,* 2014; Kumar *et al.,* 2020).

3.2 Decompose Production Changes into Area and Yield Contributions for Each Crop

The Jowar production changes are primarily driven by area changes, with yield contributions being smaller and more variable (Table 2). Negative area contributions in some years (e.g., 1975–76, 1991–92) reflect reduced cultivation, impacting production declines. In the case of Bajra area, contributions dominate production changes, especially in years with significant production spikes (e.g., 2003–04, 2010–11). Yield contributions are positive but smaller, indicating limited yield improvements. While Maize crop Yield contributions are significant, particularly in recent decades (e.g., 2020–21), reflecting improved farming practices. Area contributions are smaller and more stable, as the Maize cultivation area has not fluctuated greatly.

The Wheat cropyield contributions are the primary driver of production increases, with consistent positive contributions reflecting technological advancements (e.g., high-yielding varieties). Area contributions are smaller and sometimes negative due to land reallocation. However, Barley production changes show a mix of area and yield contributions, with yield improvements playing a larger role in recent years (e.g., 2018–19). Area changes are less consistent, reflecting Barley's smaller cultivation base.

Table 2. Relative Contribution of Area and Yield to Mean Changes in Crop Production

S.No.	Crops	Mean Area Contribution	Mean Yield Contribution	Mean Total Production Change
1	Jowar	2.33	5.30	7.63
2	Bajra	31.46	43.54	75.00
3	Maize	2.60	21.99	24.59
4	Wheat	-10.94	208.30	197.36
5	Barley	-0.29	9.64	9.35

Note: Values are in the same units as production (thousand tonnes). Negative values indicate reductions in production due to decreased area or yield.

The decomposition of production changes into area and yield contributions further elucidates these dynamics. For Cluster 1 crops, yield improvements are the dominant driver of production growth, with Wheat showing a remarkable 193% yield increase from 1970–71 to 2023–24, reflecting investments in irrigation, high-yielding varieties, and fertilizers (Joshi *et al.,* 2015). Maize and Barley also exhibit significant yield-driven growth, though Barley's smaller cultivation base introduces variability. In contrast, Cluster 2 crops rely heavily on area expansion, with Jowar and Bajra showing limited yield progress (mean yields of 8.86 and 10.33 tonnes/ha in 2023–24, respectively). This dependence on area is unsustainable given Rajasthan's land and water constraints, underscoring the need for yield-enhancing interventions (Rao *et al.,* 2019).

3.3 Analyze Cluster-Specific Decomposition Patterns for Crop Prioritization

This objective analyzed the decomposition results within each cluster to identify patterns that inform crop prioritization. By aggregating the mean area and yield contributions for crops within each cluster, we assessed whether production changes are driven by area expansion or yield improvements, guiding resource allocation strategies.

In Cluster 1 (Wheat, Maize, Barley), the pattern shows that the production growth is predominantly driven by yield improvements (Table 3). Wheat and Maize show large positive yield contributions, reflecting investments in irrigation, fertilizers, and high-yielding varieties. Barley also benefits from yield gains, though its smaller production base makes contributions less pronounced. These crops should be prioritized for continued technological investments (e.g., precision agriculture, quality seeds) to sustain yield-driven growth. Wheat, with the highest yield growth (193% from 1970–71 to 2023–24), is a key candidate for further optimization.

The Cluster 2 (Jowar, Bajra) shows the pattern of Production changes are heavily influenced by area changes, with yield contributions being smaller and less consistent. This reflects the rainfed nature of these crops and limited technological adoption. Jowar and Bajra require interventions to boost yields, such as drought-resistant varieties and improved irrigation. Area expansion is less sustainable due to land constraints, making yield enhancement critical. Fig. 2 presents stacked bar plots for each crop, showing the area and yield contributions to production changes over time. Each facet represents a crop, with bars indicating the magnitude and direction of contributions.

Table 3. Cluster-Specific Summary of Mean Area and Yield Contributions to Production Change

S.No.	Cluster	Crops	Mean Area Contribution	Mean Yield Contribution	Dominant Driver
1	1	Wheat, Maize, Barley	-2.88	79.98	Yield
2	2	Jowar, Bajra	16.90	24.42	Area

Note: Mean contributions are averaged across crops within each cluster. Negative area contributions in Cluster 1 reflect reductions in cultivated area for Wheat and Barley in some years.

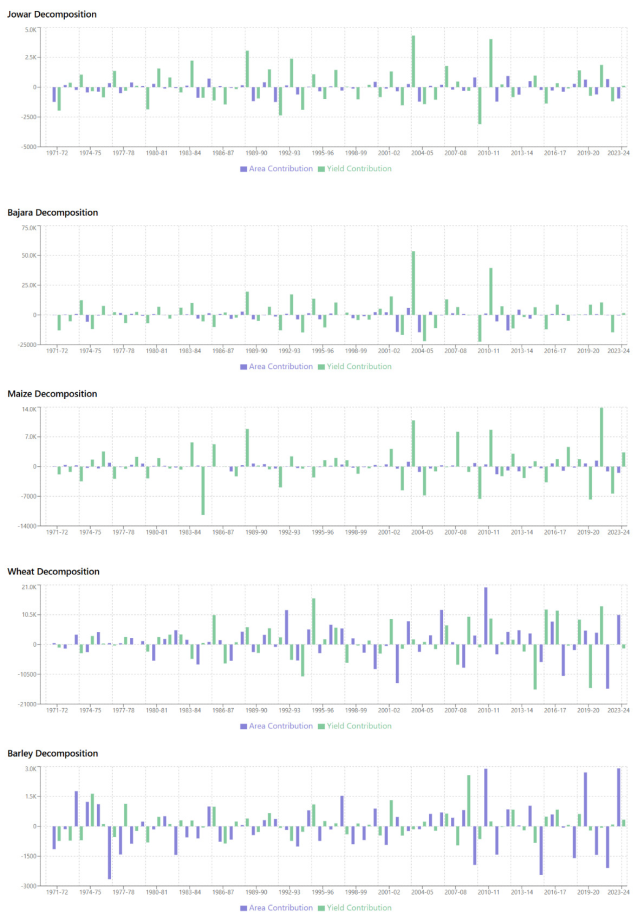

Fig. 2. Comparative Analysis of Area and Yield Effects on Production Changes Across Crops

Cluster-specific decomposition patterns highlight the importance of tailored policy approaches. Cluster 1's yield-driven growth suggests that sustaining investments in precision agriculture, quality seeds, and irrigation expansion is critical to maintaining productivity (Godfray *et al.,* 2010). However, the negative area contributions for Wheat in some years indicate land reallocation pressures, possibly due to urbanization or competing crops, which warrant careful land-use planning (Sharma & Singh, 2017). For Cluster 2, the reliance on area changes reflects the rainfed nature of Jowar and Bajra, which are grown in marginal lands with limited access to irrigation (Kumar *et al.,* 2020). Policies promoting drought-resistant varieties and micro-irrigation could shift these crops toward yield-driven growth, aligning with sustainable agriculture goals (FAO, 2020).

4. DISCUSSION

The multivariate DTW clustering and decomposition analyses reveal a clear bifurcation in Rajasthan's cereal crops: Cluster 1 (Wheat, Maize, Barley) exhibits stable, yield-dominated production growth, while Cluster 2 (Jowar, Bajra) shows greater variability and reliance on area changes. These patterns strongly align with prior regional studies on differential agricultural performance in Rajasthan and northwest India. Irrigated rabi crops like wheat and maize have benefited substantially from Green Revolution technologies, including high-yielding varieties, expanded irrigation (e.g., canal and tube-well systems), and fertilizer use, leading to consistent yield improvements and production stability (Birthal *et al.,* 2014; Joshi *et al.,* 2015). In contrast, rainfed kharif coarse cereals such as jowar and bajra remain vulnerable to climatic fluctuations, with limited technological adoption and yields heavily influenced by monsoon variability and area expansion (Kumar *et al.,* 2020; Rao *et al.,* 2019). Rajasthan-specific analyses confirm that wheat and maize dominate irrigated production, often showing positive productivity growth, while bajra and jowar exhibit stagnation or decline in yields despite their dominance in marginal, arid lands.

These cluster-specific dynamics are further amplified by recent climate trends in Rajasthan (approximately 2010–2025), which exacerbate differential crop vulnerabilities. While long-term data indicate rising mean temperatures (with increases of ~0.6–1.2°C in recent decades) and more frequent extreme events, precipitation patterns have become increasingly erratic and intense. Western Rajasthan (including Thar desert districts) has experienced higher annual rainfall in some recent years (e.g., 2023–2024 departures from normal of up to 145% in districts like Jaisalmer), driven by intensified monsoon events and occasional floods, yet prolonged dry spells and drought frequency persist, particularly in semi-arid zones. Studies highlight increased drought severity in districts like Ganganagar and Churu, with more moderate-to-severe events post-1970s, alongside projections of declining annual rainfall under higher-emission scenarios in basins like Banas. These trends favor drought-tolerant, low-input crops like bajra and jowar in marginal rainfed areas (Cluster 2), where production fluctuates with rainfall and area, but challenge water-sensitive irrigated systems supporting wheat, maize, and barley (Cluster 1), where yield gains depend on stable water access amid groundwater depletion and heat stress.

The decomposition results reinforce this climate-agriculture linkage: Cluster 1's strong yield contributions (e.g., wheat's remarkable 193% increase) reflect sustained irrigation and input investments that buffer some climatic variability, whereas Cluster 2's area dominance underscores the unsustainability of expansion in water-scarce Rajasthan. These findings echo calls for tailored interventions—continued support for precision agriculture and irrigation in Cluster 1 to sustain yield-driven growth, and promotion of drought-resistant varieties, micro-irrigation, and millet-focused strategies in Cluster 2 to enhance resilience amid shifting rainfall and aridity (FAO, 2020; Godfray *et al.,* 2010). Overall, the results highlight opportunities for crop prioritization and diversification to align with Rajasthan's evolving agro-climatic realities, ensuring food security and sustainable land-water use.

4.1 Recommend Policies for Optimizing Cereal Production

Based on the clustering and decomposition results, this objective developed policy recommendations to optimize cereal production in Rajasthan. The recommendations focus on addressing cluster-specific patterns, prioritizing crops, and aligning with the region's resource constraints (Table 4).

(i) Enhance Yield for Cluster 2 Crops (Jowar, Bajra): Cluster 2 crops rely heavily on area changes, which is unsustainable due to land and water limitations. Their lower yields (e.g., Jowar: 8.86 in 2023–24; Bajra: 10.33) indicate untapped potential. It can be overcome through investing in drought-resistant varieties, micro-irrigation systems, and soil health programs to boost yields. Promote farmer training on modern agronomic practices.

(ii) Sustain Cluster 1 Productivity (Wheat, Maize): Cluster 1 crops, especially Wheat and Maize, show strong yield-driven growth (e.g., Wheat yield: 38.69 in 2023–24; Maize: 24.64). Maintaining this requires continued support. It should support precision farming, access to high-quality seeds, and subsidized fertilizers. Expand irrigation infrastructure to stabilize Maize production.

(iii) Resource Allocation by Cluster: Cluster 1 crops are high-performing and benefit from technology, while Cluster 2 crops need basic infrastructure improvements. From a policy point of view,allocate advanced technologies (e.g., drones, IoT) to Cluster 1, and direct land and water management programs (e.g., watershed development) to Cluster 2.

(iv) Monitor Barley Trends: Barley shows moderate yield growth but variable production, possibly due to its smaller cultivation area and competition with other crops.From the policy point of view, it should conduct studies to understand Barley's production constraints and promote its cultivation in marginal lands with tailored support.

Table 4. Recommended Policy Actions for Enhancing Crop Productivity Across Clusters

Recommendation	Target Crops	Key Actions
Enhance Yield for Cluster 2	Jowar, Bajra	Drought-resistant varieties, micro-irrigation, and soil health programs
Sustain Cluster 1 Productivity	Wheat, Maize	Precision farming, quality seeds, subsidized fertilizers, and irrigation
Resource Allocation by Cluster	All	Technology for Cluster 1; land/water management for Cluster 2
Monitor Barley Trends	Barley	Research constraints, promote cultivation in marginal lands

The policy recommendations enhancing yields for Jowar and Bajra, sustaining Wheat and Maize productivity, optimizing resource allocation by cluster, and monitoring Barley trends are grounded in these findings. For instance, the emphasis on drought-resistant varieties for Cluster 2 addresses Rajasthan's water scarcity, a critical constraint in semi-arid regions (Rao *et al.,* 2019). Similarly, prioritizing technology for Cluster 1 leverages existing infrastructure, such as canal irrigation systems, to maximize returns (Joshi *et al.,* 2015). Barley's variable production suggests a need for further research into its market and agronomic potential, particularly as a climate-resilient crop for marginal lands (Kumar *et al.,* 2020).

The study's findings have broader implications for semi-arid regions globally, where balancing productivity and sustainability is a pressing challenge (FAO, 2020). The integrated clustering-decomposition framework offers a replicable approach for other regions, such as parts of Sub-Saharan Africa, where similar agroecological constraints prevail (Godfray *et al.,* 2010). By linking trend similarities to production drivers, the study provides a model for evidence-based agricultural planning, contributing to global food security discussions.

5. SUMMARY AND CONCLUSION

This study reveals a persistent structural divide in Rajasthan's cereal production: irrigated, technology-intensive crops (Wheat, Maize, Barley) have achieved sustained yield-led growth, while rainfed coarse cereals (Jowar, Bajra) remain constrained by area dependence and climatic vulnerability in the state's semi-arid environment. This bifurcation—evident over five decades—reflects the uneven penetration of Green Revolution benefits, where access to irrigation, high-yielding varieties, and inputs has disproportionately favored rabi crops, leaving kharif millets reliant on unpredictable monsoons and marginal lands.

The findings carry significant implications for agricultural resilience and food security in arid regions. Yield-driven success in Cluster 1 demonstrates that targeted investments in water management and modern inputs can deliver substantial productivity gains, even under resource constraints. Conversely, Cluster 2's patterns highlight the limits of area expansion in water-scarce Rajasthan, underscoring the urgency of shifting toward yield enhancement for Jowar and Bajra through drought-tolerant varieties, micro-irrigation, and improved agronomic practices.

These insights align with national priorities, including the promotion of millets as climate-resilient "nutri-cereals" under initiatives like the National Food Security Mission–Nutri Cereals and Rajasthan's Millet Promotion Mission. Prioritizing yield-focused interventions for Cluster 2 crops could enhance nutritional security, reduce environmental pressure on groundwater, and support diversification amid climate change pressures such as erratic rainfall and rising temperatures. For Cluster 1, sustaining gains will require careful land-use planning to counter negative area trends and groundwater depletion.

Ultimately, the differentiated trajectories call for tailored, evidence-based policies: continued technological support for irrigated systems alongside accelerated innovation and incentives for rainfed millets. By addressing these cluster-specific needs, Rajasthan can build more equitable, sustainable cereal production systems, contributing to national food security and climate adaptation goals in semi-arid agro-ecosystems.

6. LIMITATIONS

This study has several limitations. The decomposition assumes production equals area × yield, which may overlook minor data discrepancies in official statistics, such as reporting errors, measurement inconsistencies, or unaccounted post-harvest losses.

The analysis excludes external variables such as rainfall, temperature, irrigation availability, fertilizer use, or policy interventions. This focus on internal production and yield trends enables clear descriptive clustering but restricts causal inference. For example, it cannot directly link observed cluster differences (yield-driven vs. area-dependent growth) to specific climatic or technological drivers.

The choice of exactly two clusters (k=2) in DTW clustering, although justified by preliminary elbow analysis and interpretability for only five crops, remains a methodological assumption. Sensitivity checks for k=3 and k=4 revealed that additional clusters were often small, unstable, or redundant, offering limited improvement in separating production/yield trajectories. Different k values or alternative clustering algorithms might produce varying groupings.

Future studies could incorporate climate and irrigation data, explore dynamic or variable-cluster methods, or apply ensemble approaches to improve explanatory power and robustness (Aghabozorgi *et al.,* 2015; Sardá-Espinosa, 2019).

Despite these constraints, the study provides meaningful insights into long-term cereal crop patterns in Rajasthan and supports targeted policy recommendations.

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REFERENCES

Aghabozorgi, S., Shirkhorshidi, A.S., and Wah, T.Y. (2015). Time-series clustering – A decade review. *Information Systems*, **53**, 16-38. https://doi.org/10.1016/j.is.2015.04.007

Birthal, P.S., Khan, M.T., Negi, D.S., and Agarwal, S. (2014). Impact of climate change on yields of major food crops in India: Implications for food security. *Agricultural Economics Research Review*, **27**(2), 145-155.

FAO. (2020). *The State of Food and Agriculture 2020: Overcoming water challenges in agriculture*. Food and Agriculture Organization of the United Nations. https://www.fao.org/documents/card/en/c/cb1447en

Godfray, H.C.J., Beddington, J.R., Crute, I.R., Haddad, L., Lawrence, D., Muir, J.F., and Toulmin, C. (2010). Food security: The challenge of feeding 9 billion people. *Science*, **327**(5967), 812-818. https://doi.org/10.1126/science.1185383

Government of Rajasthan. (2023). *Rajasthan Agricultural Statistics at a Glance* 2022-23. Directorate of Economics and Statistics, Government of Rajasthan.

Gupta, R., Kalia, A., and Chauhan, S.S. (2017). Handling missing data in agricultural statistics: Methods and applications. *Journal of the Indian Society of Agricultural Statistics*, **71**(3), 215-224.

Hazell, P.B.R. (1984). Sources of increased food production in developing countries. *American Journal of Agricultural Economics*, **66**(5), 685-691.

Joshi, P.K., Kishore, A., and Roy, D. (2015). Making pulses affordable again: Policy options from the farm to the kitchen. *Economic and Political Weekly*, **50**(52), 37-44.

Keogh, E., and Ratanamahatana, C.A. (2005). Exact indexing of dynamic time warping. *Knowledge and Information Systems*, **7**(3), 358-386. https://doi.org/10.1007/s10115-004-0154-9

Kumar, S., Raizada, A., Biswas, H., and Mondal, B. (2020). Climate-resilient crop production systems in semi-arid regions of India. *Current Science*, **118**(6), 867-874.

Rao, C.S., Gopinath, K.A., Prasad, J.V.N.S., and Singh, A.K. (2019). Climate resilient agriculture in India: Opportunities and challenges. *Journal of Agrometeorology*, **21**(3), 255-265.

Sardá-Espinosa, A. (2019). dtwclust: Time series clustering along with optimizations for DTW in R. *Journal of Statistical Software*, **88**(3), 1-24. https://doi.org/10.18637/jss.v088.i03

Sharma, P., and Singh, I.P. (2017). Prioritization of crops for agricultural development in Rajasthan. *Indian Journal of Agricultural Economics*, **72**(4), 512-523.

Wickham, H. (2016). *ggplot2: Elegant graphics for data analysis*. Springer. https://doi.org/10.1007/978-3-319-24277-4

Wickham, H., François, R., Henry, L., Müller, K., and Vaughan, D. (2023). *dplyr: A grammar of data manipulation*. R package version 1.1.4. https://CRAN.R-project.org/package=dplyr.

Yadav, S., Kumari, B., Al Khatib, A.M.G., Raghav, Y.S., Sharma, D., Alshaib, B.M., Nayak, H., Ray, S., Biswas, T., Mishra, N., and Mishra, P. (2025). Fish production modeling and forecasting in India using the XGBoost algorithm. *Journal of Animal & Plant Sciences,* **35**(2), 522-530.

Ado Osi, A.H., Raghav, Y.S., Sabo, S.A., and Musa, I.Z. (2025). The new transformed Sine G family of distribution with inference and application. *Brazilian Journal of Biometrics,* **43**, 1-15.

Raghav, Y.S., Rather, K.U.I., Abd Elwahab, M.E., Sharma, V.K., Mishra, R., Ray, S., and Mishra, P. (2025). Advanced statistical modeling of agricultural potato data using a novel compound distribution. *Potato Research,* **68**, 3319-3338.

Bhat, A.A., Mir, A.A., Ahmad, S.P., Alnssyan, B.S., Alsubie, A., and Raghav, Y.S. (2025). A novel alpha-power X family: A flexible framework for distribution generation with focus on the half-logistic model. *Entropy,* **27**(6), 632. https://doi.org/10.3390/e27060632

Bhatt, R.J., Saini, M., Kumar, A., and Raghav, Y.S. (2025). Optimization of resource allocation using integer programming of improved ratio estimator under stratified random sampling. *Reliability: Theory & Applications,* **20**(1[82]), 227-241.