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Analysis of Ragi Production, Area and Yield Trends in Odisha Using Machine Learning Techniques

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Abstract

Millets are more than simply climate-resilient crop and an ancient grain. These C4 small-seeded grasses have been grown in arid and semi-arid areas of the planet for thousands of years because they can withstand in harsh weather. Climate change is the threat for Agriculture sector and future food security. For sustainable growth of agriculture, may be effectively addressed with millet crops. Promoting millets as a means of creating a food system that is more robust and sustainable. During India's green revolution, millets were eradicated from farmers' fields and consumers' food bowls in favor of rice and wheat cereal crops. Given the rising temperatures and depleting water supplies, millets must be reintroduced as a staple grain. The rainfall requirement of millets such as Sorghum (Jowar), Pearl Millet (Bajra), Finger millet (Ragi) is less than 30% required for growing rice. It is also Found that millets have 30 to 300% more nutritional content compared with other cereals crop. This study investigates the trends in Ragi (finger millet) cultivation, production, and yield in Odisha over a 52-year period (1966-2017). By employing both statistical analysis and machine learning techniques, the research aims to provide a comprehensive understanding of historical patterns and future predictions. Key statistical analyses, including descriptive statistics, correlation analysis, histogram and density plots, moving average analysis, and decomposition, offer insights into the data's distribution, relationships, and long-term trends. The Random Forest model was utilized to predict future trends, with performance evaluated using RMSE and MAE metrics. Results indicate significant variability in Ragi agriculture, highlighting strong correlations between cultivation area and production, and emphasizing the need for improved predictive models. This study provides valuable information for policymakers and farmers to enhance Ragi production strategies, contributing to sustainable agricultural development in Odisha.

Keywords: Correlation Analysis; Decomposition; Descriptive Statistics; Machine Learning; Moving Average; Ragi and Random Forest

Introduction

In India, ragi is the colloquial name for finger millet (*Eleusine coracana L.*). It is sometimes recognized as poor man's food. Millets are minor cereal which belong Poaceae family. They are annual cereal grasses with small seeds that are characterized by their capacity to thrive in much less fertile soil and for their adaptation to withstand hot and arid environments. Cultivars include Foxtail millet (Kakum), Proso millet (Chena), Small millet (Kutki), Kodo millet (Kodon), Barnyard millet (Sanwa), and brown top millet in addition to Sorghum (Jowar). In ancient Indian Sanskrit literature, finger millet was known as "Nrttakondaka," which refers to "Dancing grain." It was also referred to "Rajika" and "Markataka" (Patil et al.,2023). Ragi, also known as finger millet, holds a significant place in the agricultural landscape of Odisha, India. This resilient crop is highly valued not only for its nutritional benefits but also for its ability to thrive in harsh climatic conditions. Despite its importance, there remains a gap in comprehensive data analysis that captures the long-term trends in Ragi cultivation, production, and yield (Ajagekar et al., 2023; Singh and Kumar, 2023; Srinivasarao and Kundu, 2023). Addressing this gap is essential for developing effective agricultural policies and practices that can enhance Ragi production and support the livelihoods of farmers in the region. Ragi is a staple food for tribal communities in Odisha, particularly in districts like Koraput, Malkangiri, and Rayagada. It's known for being a rich source of calcium, iron, and protein, making it crucial for health, especially in areas with high malnutrition rates. The Odisha Millets Mission (OMM) aims to promote ragi cultivation and consumption, including its inclusion in the Public Distribution System (PDS). Historically, Ragi has been a staple food in Odisha, providing essential nutrients such as calcium, iron, and dietary fiber. Its cultivation is predominantly rain-fed, making it a crucial crop for marginal and small farmers who rely on its robustness during periods of drought. However, fluctuations in production levels and yields over the years highlight the need for a detailed analysis of the factors influencing Ragi agriculture (Wäldchen et al., 2018; Zha, 2020; Zong et al., 2023). Understanding these trends is vital for improving crop management practices and ensuring food security.

In recent years, advancements in data analysis and machine learning have opened new avenues for agricultural research (Ferentinos, 2018; Javaid et al., 2023). These technologies enable researchers to uncover patterns and relationships within large datasets that were previously difficult to analyze (Kumar et al., 2022; Liakos et al., 2018;). By applying these methods to historical data on Ragi cultivation in Odisha, this study aims to provide a comprehensive understanding of the crop's trends and future potential (Mahto and Patil, 2023; Mishra et al., 2016; Shoaib *et al.*, 2023). This approach not only enhances our knowledge of Ragi agriculture but also supports evidence-based decision-making in agricultural planning (Singh and Yadav, 2023; Talaviya et al., 2020; Varshney et al., 2022; Virnodkar et al., 2020).

The objectives of this study are multifaceted. Firstly, it aims to analyze the historical data on Ragi area, production, and yield using descriptive statistics to capture central tendencies and variability. Secondly, the study seeks to understand the relationships between these variables through correlation analysis. Thirdly, it employs moving average and decomposition analyses to identify long-term trends and seasonal patterns. Finally, the study leverages machine learning techniques, specifically the Random Forest model, to predict future trends and assess model performance using standard evaluation metrics. This comprehensive analysis not only provides insights into the past and present state of Ragi cultivation in Odisha but also offers predictive insights that are crucial for future planning. By combining traditional statistical methods with advanced machine learning techniques, the study bridges the gap between historical data analysis and modern predictive analytics. This holistic approach ensures a robust understanding of the factors influencing Ragi agriculture and aids in developing strategies to enhance crop production and sustainability.

This study underscores the importance of Ragi in Odisha's agricultural sector and highlights the need for detailed data analysis to support sustainable agriculture. The findings from this study are expected to inform policymakers, agricultural scientists, and farmers, enabling them to make data-driven decisions that enhance Ragi production and contribute to food security. As such, this research is a crucial step towards understanding and improving the agricultural practices surrounding this vital crop.

Materials and Methods

Data

This study employs a comprehensive methodology combining traditional statistical analysis and modern machine learning techniques to analyze and predict trends in Ragi cultivation, production, and yield in Odisha (Zhenyu, 2023). The dataset consists of annual data spanning from 1966 to 2021, including the variables Area (in thousand hectares), Production (in thousand tonnes), and Yield (in kg per hectare).

Data Collection and Preprocessing

The data was sourced from Indian Institute of Millet Research website. Initial preprocessing steps involved handling missing values and ensuring data consistency. The 'Year' variable was converted to datetime format and set as the index for time series analysis.

Statistical Analyses

Trend analysis of Ragi

It is a process of analysis time series data, which involves comparing an item over an extended period to identify board pattern in the relationship between linked components or variables and to forecast the future trajectory patterns (Kendall, 1975; Mann, 1945; Paul et al., 2022). The time series data for the period from 1971 to 2021 about area, production and productivity of ragi were collected from Indian Institute of Millet Research website. For the trend analysis Man Kendall test was used to determine the presence of the monotonic increasing and decreasing trend and the non-parametric Sen's method (Sen, 1968) for the estimating the slope of a linear trend (Tripathi et al., 2014).

A) Descriptive Statistics*:* To capture the central tendencies and variability in the data, we calculated the mean, standard deviation, minimum, maximum, and quartile values for each variable using the formulas:

$$Mean\ (\mu) = \frac{1}{N}\sum_{i=1}^{N} x_i$$

$$Standard\ Deviation\ (\sigma) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2}$$

$$Standard\ Deviation\ (\sigma^2) = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2$$

Interquartile Range (IQR) = $Q_3 - Q_1$

Where NN is the number of observations, and x_i represents each individual observation

B) Correlation Analysis*:* The correlation coefficients between Area, Production, and Yield were computed to understand the linear relationships using Pearson's correlation formula:

$$Correlation\ (r) = \frac{\sum_{i=1}^{N}(x_i - x)(y_i - y)}{\sqrt{\sum_{i=1}^{N}(x_i - x)^2 \sum_{i=1}^{N}(y_i - y)^2}}$$

C) Moving Average Analysis: To smooth out short-term fluctuations and highlight long-term trends, 5-year moving averages were calculated using the formula:

$$Moving\ Average\ (MA) = \frac{1}{k}\sum_{i=t-k+1}^{t} x_i$$

D) Decomposition Analysis: The time series data were decomposed into trend, seasonal, and residual components using the additive model:

$$y_t = T_t + S_t + R_t$$

Where y_t is the observed value, T_t is the trend component, S_t is the seasonal component, and R_t is the residual component.

E) Machine Learning Model: The Random Forest model was selected for its robustness in handling complex datasets (Boser *et al.*, 1992; Breiman, 2001). The model was trained and tested on the data, split into training and testing sets. Performance was evaluated using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), calculated as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \bar{y}_i)^2}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \bar{y}_i|^2$$

Where y_i represents the actual values and $\bar{y}_i$ represents the predicted values.

Results and Discussion

The trends of total millet showing an upward trend in area, production & yield for total millets after 2017-18. This increase reflects a renewed focus on millets as a resilient crop in Odisha. This proves, there was some trend shift in the state in millet production which can be attributed to the implementation of Odisha Millet Mission (OMM) in 2017 in the state (Mondal et al.,2023; Banerjee and Kundu, 2023; Mondal and Jena, 2023). This shift highlights the OMM's success in reversing millet decline, promoting sustainable agriculture, and potentially improving nutritional security in Odisha through ragi's revival.

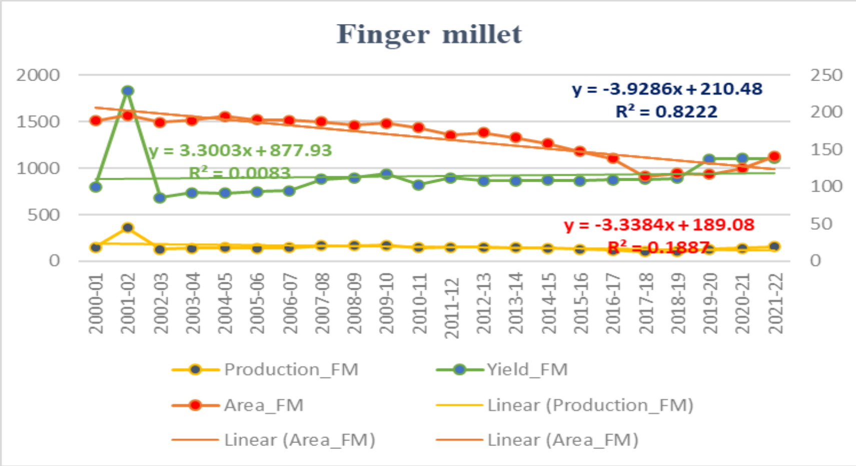

Fig. 1. Trend Analysis of Area, Production & yield of Finger millet in Odisha

Table 1. Trend Analysis of Area, Production & Yield of Finger millet in Odisha

Crops	Parameters	Time series	Test Z	Q (Rate of Change)	Significance
Finger Millet	Area	2000-2021	-5.07563	-3.56	***
	Production	2000-2021	-1.80467	-1.44538	+
	Yield	2000-2021	3.101772	11.81889	**

Where *** = 99.9% level of significance, ** = 99% of level of significance, *= 95% of level of significance, + = 90% of level of significance

Descriptive Statistics

The mean area of ragi cultivation is 148.82 thousand hectares, with a standard deviation of 92.74, indicating a considerable spread around the mean (Table 2 & Fig.2). This variability may signal challenges in maintaining consistent land allocation for ragi. The mean production is 114.59 thousand tonnes, with a standard deviation of 80.77, showing variability in production levels. Yield averages 732.03 kg per hectare, with a standard deviation of 148.52, indicating fluctuations in yield across the years. These fluctuations could be influenced by inconsistent adoption of improved farming techniques. The minimum and maximum values highlight the range of data, with Area ranging from 42.59 to 336.4 thousand hectares, Production from 28.3 to 270.9 thousand tonnes, and Yield from 460.44 to 1140.28 kg per hectare (Patra and Mahapatra, 2022). These wide ranges suggest that environmental factors, such as erratic rainfall, and policy incentives may drive the observed variability, offering opportunities for targeted interventions to stabilize ragi output.

Table 2. Descriptive statistics for Area, Production, and Yield

Parameters	Area	Production	Yield
Mean	148.8	114.6	732.0
Std	92.7	80.8	148.5
Min	42.6	28.3	460.4
25%	69.8	44.5	618.3
50%	104.7	77.6	718.3
75%	248.6	190.1	815.9
Max	336.4	270.9	1140.3

Correlation Analysis

There is a very strong positive correlation (0.958) between Area and Production, indicating that increases in the area of ragi cultivation are associated with increases in production. This near-perfect correlation emphasizes area as a primary driver of production gains. The correlation between Area and Yield is moderate (0.418), suggesting a moderate relationship between the extent of cultivation and the yield per hectare (Fig. 3). The correlation between Production and Yield is strong (0.636), indicating that higher production levels are associated with higher yields per hectare. This linkage highlights yield's pivotal role in amplifying output beyond mere area expansion. The correlation analysis shows a very strong positive relationship between Area and Production, highlighting that expanding the cultivation area significantly impacts production. The moderate correlation between Area and Yield suggests that factors other than the cultivation area, such as soil fertility and farming practices, might influence yield. The strong correlation between Production and Yield underscores the importance of improving yield to boost overall production. These insights are crucial for devising strategies to enhance ragi production in Odisha. By focusing on increasing the cultivation area and improving yield, policymakers and farmers can potentially achieve higher production levels. This dual approach could optimize resource use and address food security challenges in rain-fed regions like Odisha.

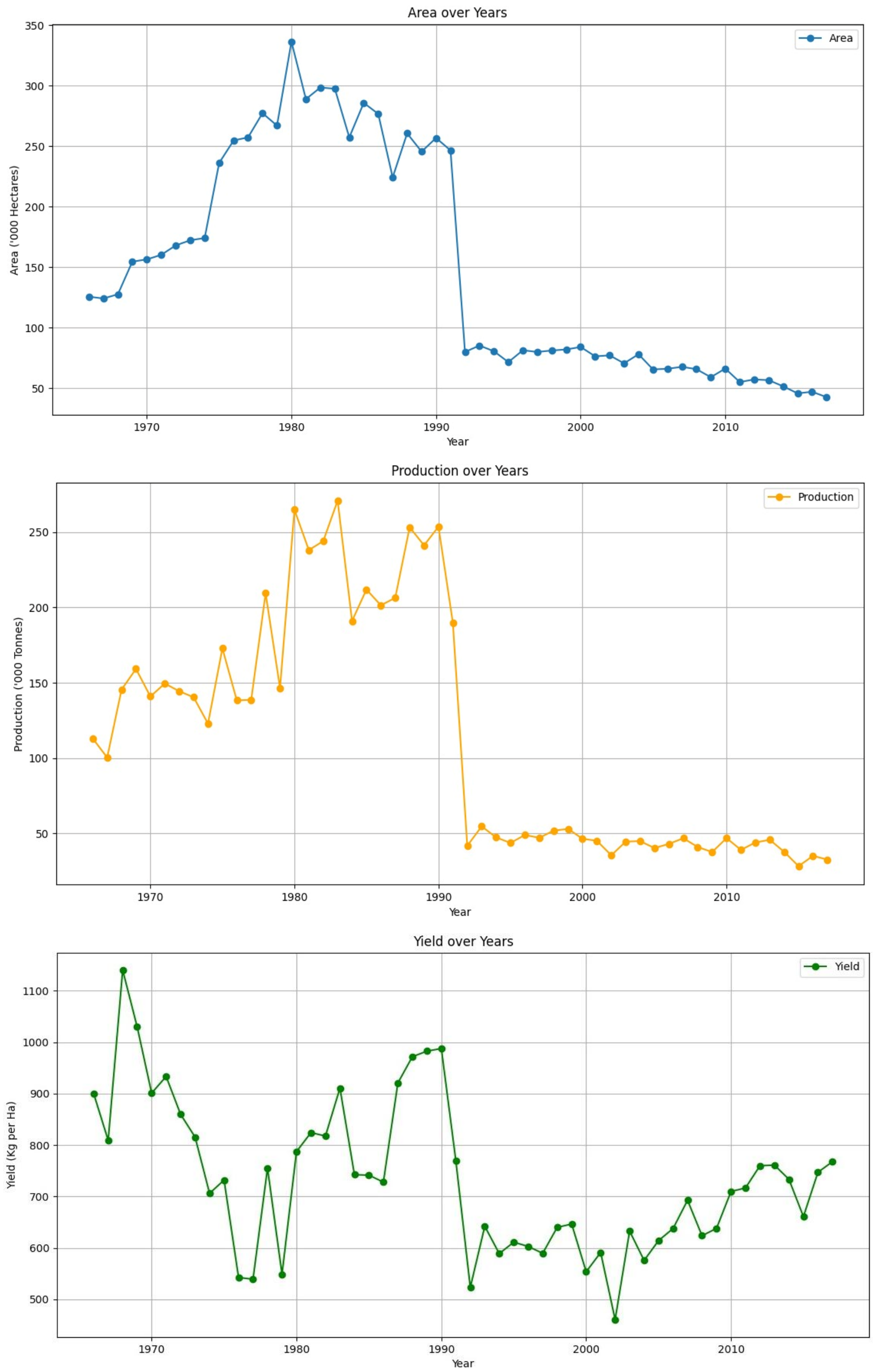

Fig. 2. Descriptive statistics for Area, Production, and Yield

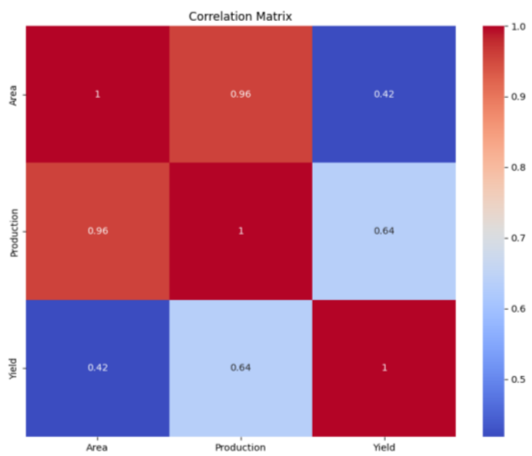

Fig. 3. Correlation analysis of Area, Production & Yield

Moving Average Metrics

The 5 years moving average for the area under ragi cultivation is approximately 153.98 thousand hectares (Fig. 4). These average smooth out yearly variations and provides a clearer picture of long-term trends in the cultivation area. This smoothing reveals a steady baseline despite short-term disruptions. The 5-year moving average for ragi production is approximately 117.78 thousand tones. This highlights the overall production trend, minimizing the impact of annual production fluctuations. The 5-year moving average for ragi yield is approximately 724.31 kg per hectare. This indicates the general trend in yield, smoothing out yearly variations and providing a more stable estimate of productivity. These smoothed trends suggest a gradual stabilization in ragi agriculture, potentially reflecting the OMM's long-term impact on farming consistency.

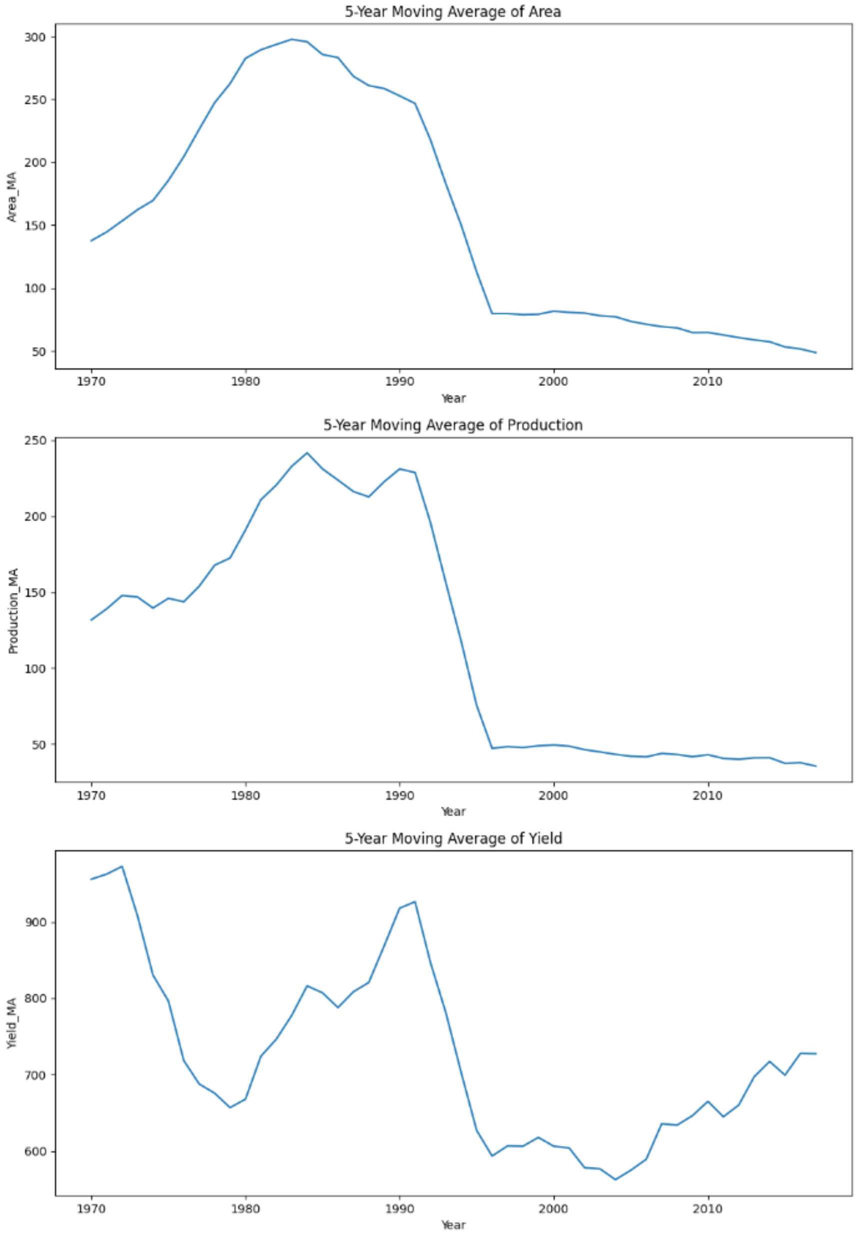

Fig. 4. Moving Average Metrics of Area, Production & Yield

Histogram Analysis

The histograms for Area, Production, and Yield display the frequency distribution of these variables across the years (Fig. 5). The Area histogram reveals a mean value of 148.82 thousand hectares with a standard deviation of 92.74, indicating considerable variability in cultivation area. This spread suggests periodic peaks possibly linked to favourable conditions or incentives. The minimum and maximum values range from 42.59 to 336.4 thousand hectares. The Production histogram shows a mean of 114.59 thousand tones and a standard deviation of 80.77, with production values spanning from 28.3 to 270.9 thousand tones. For Yield, the histogram depicts a mean of 732.03 kg per hectare and a standard deviation of 148.52, indicating yields ranging from 460.44 to 1140.28 kg per hectare. These histograms provide a clear visualization of the data's spread and central tendencies, highlighting significant year-to-year fluctuations in Ragi cultivation and production.

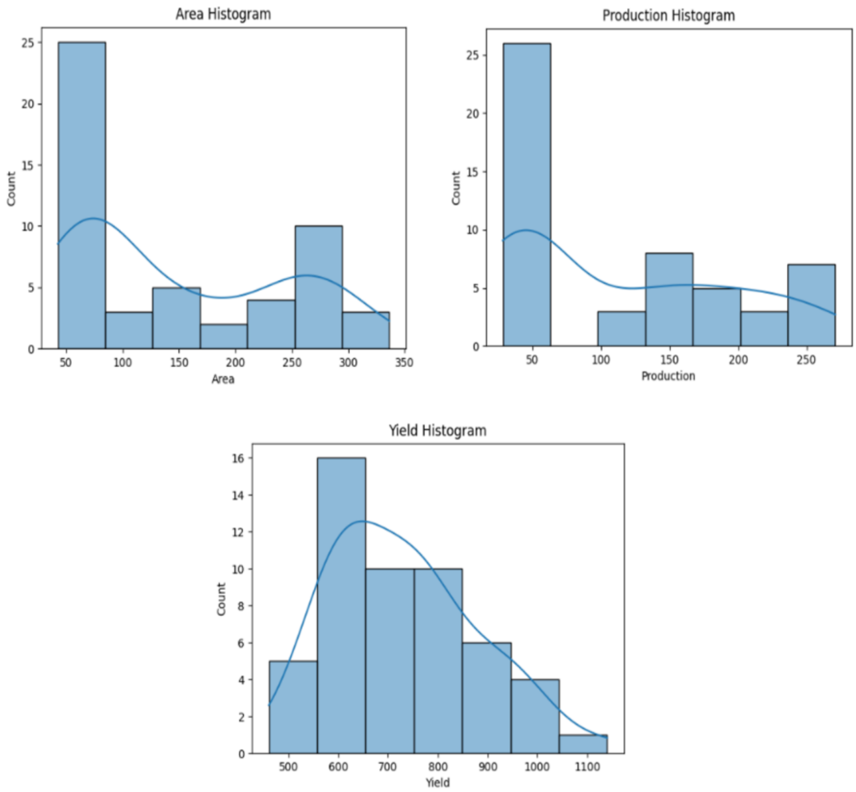

Fig. 5. Histogram Analysis of Area, Production & Yield

Density Plot Analysis

The density plots for Area, Production, and Yield offer a smooth distribution curve, illustrating the probability density of these variables (Fig 6). The Area density plot highlights the concentration of data points around the mean of 148.82 thousand hectares, with a noticeable peak indicating the most common cultivation areas. This peak underscore a typical cultivation scale despite overall variability. The Production density plot similarly shows a peak around the mean of 114.59 thousand tonnes, reflecting the typical production levels observed over the years. The Yield density plot indicates the highest density around the mean value of 732.03 kg per hectare, demonstrating common yield levels. These density plots provide a more detailed understanding of the data distribution, smoothing out the variability to present a clearer picture of the most likely values.

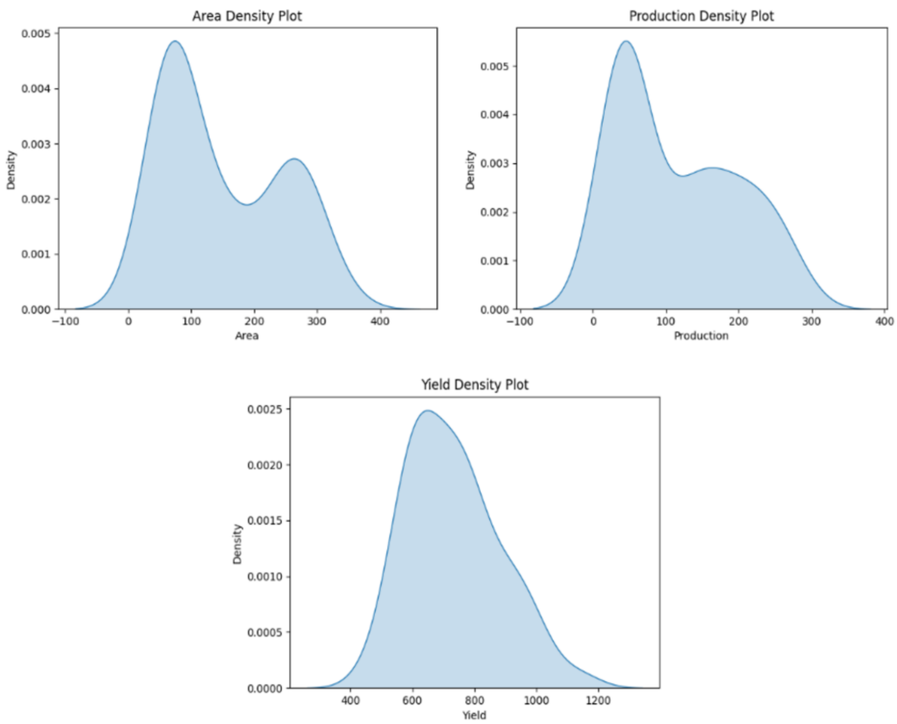

Fig. 6. Density Plot Analysis of Area, Production & Yield

Seasonal Trend Analysis - Decomposition

The trend component for Area, Production, and Yield indicates the long-term direction of the data (Fig. 5). The values are 148.82 for Area, 114.59 for Production, and 732.03 for Yield, aligning with the average values. This alignment confirms the reliability of the trend as a long-term indicator. The seasonal component is consistent across all metrics, indicating a stable seasonal pattern with a value of 1. e residual component is also consistent across all metrics, with a value of 1, suggesting minimal variation after accounting for trend and seasonal effects (Roy et al., 2023). This consistency reflects ragi's dependence on monsoon-driven cultivation cycles. This stability likely stems from ragi's reliance on monsoon cycles, limiting seasonal variability and reinforcing its suitability for Odisha's climate.

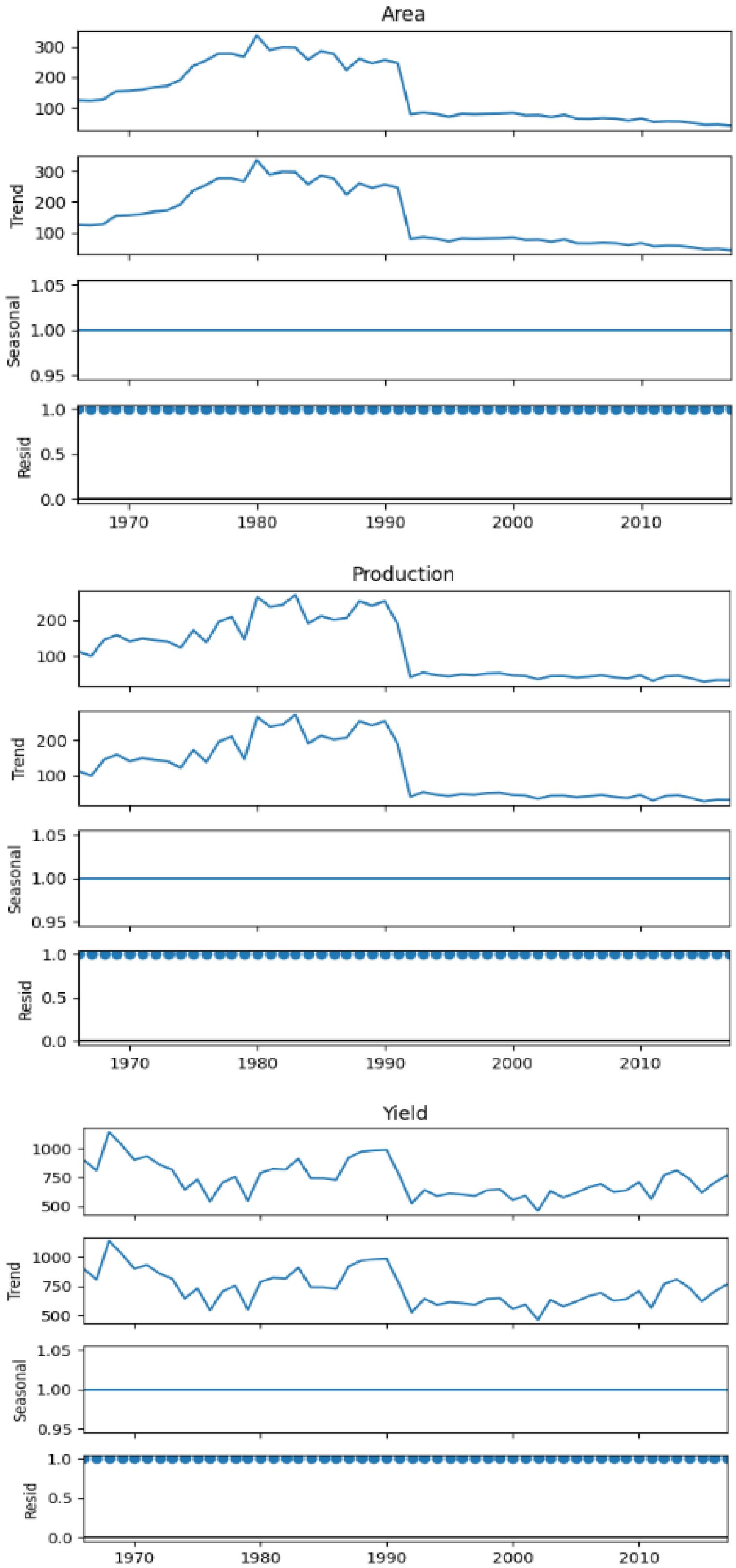

Fig. 5. Seasonal Trend Analysis of Area, Production & Yield

Machine Learning Model Performance

The Random Forest model demonstrated a Train RMSE of 10.68 and a Test RMSE of 41.20, with Train MAE of 5.95 and Test MAE of 20.09 (Table 3). This indicates a reasonable fit on the training data but a higher error on the test data, suggesting some room for improvement. This discrepancy may indicate limitations in generalizing to new data sets. The model showed a Train RMSE of 12.31 and a Test RMSE of 39.29, with Train MAE of 7.55 and Test MAE of 20.78. Similar to Area, the model performs reasonably on training data but shows higher error on test data. The model exhibited a Train RMSE of 36.20 and a Test RMSE of 130.79, with Train MAE of 29.54 and Test MAE of 100.40. This metric shows a significant difference between training and testing errors, indicating potential overfitting. The larger error gaps, especially for yield, may reflect unmodeled factors like weather anomalies or soil variations affecting prediction accuracy.

Table 3. Machine Learning Model Performance

Metric	Train RMSE	Test RMSE	Train MAE	Test MAE
Area	10.6828	41.20297	5.946239	20.09445
Production	12.30591	39.2859	7.554098	20.77936
Yield	36.19815	130.794	29.54454	100.4025

Model Predications Vs Actual

The model predictions for Area are relatively close to the actual values, although some years show significant deviations (e.g., 1992 and 1968) (Fig.6). These deviations could indicate periods of unpredicted disruption in cultivation patterns. Similarly, the model predictions for Production align well with the actual values, but there are notable discrepancies in certain years (e.g., 1992 and 1968). The Yield predictions also show a good fit with the actual values, but with some larger deviations (e.g., 1992 and 1970). The comparison of actual and predicted values highlights the model's ability to capture the general trends in Area, Production, and Yield. However, the deviations in certain years suggest areas for model improvement, such as incorporating additional features or refining the model parameters (Saha and Sharma, 2023; Ullah et al., 2023). These outliers likely correspond to extreme climatic events or unaccounted agricultural shifts, emphasizing the need for broader data inputs.

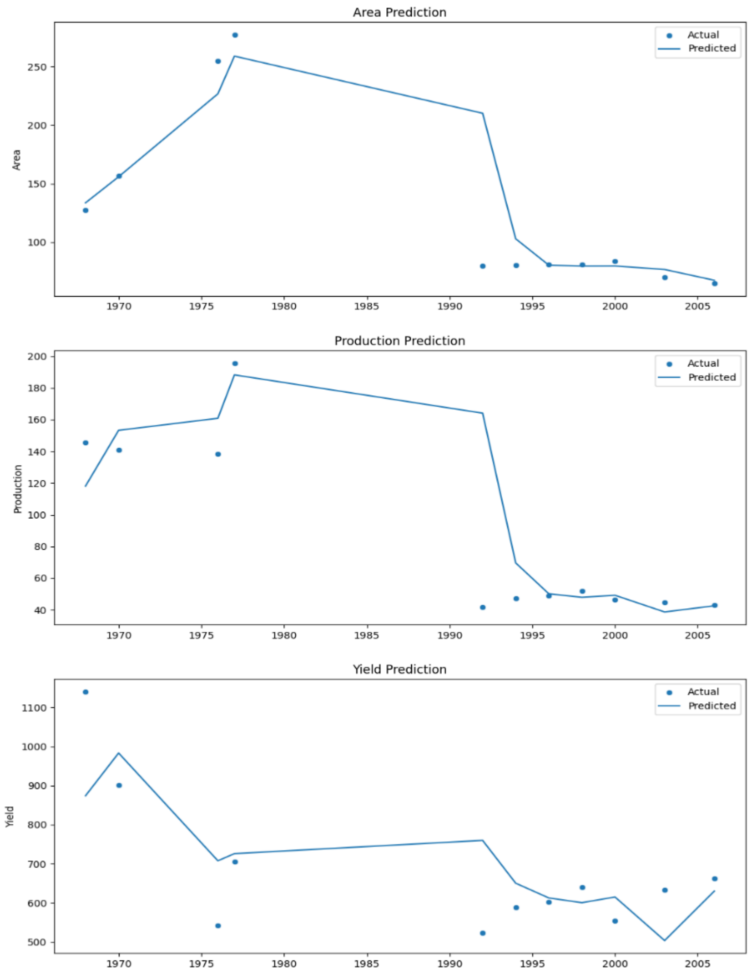

Fig. 6. Model Predications Vs Actual of Area, Production & Yield

Conclusion

This study offers a detailed assessment of ragi cultivation dynamics in Odisha across a 52-year period (1966–2017), employing a combination of statistical tools and machine learning methodologies to analyze historical trends and predict future patterns. The results demonstrate considerable variability in area, production, and yield, with area ranging from 42.59 to 336.4 thousand hectares, production from 28.3 to 270.9 thousand tonnes, and yield from 460.44 to 1140.28 kg ha^{-1}. This variability reflects the interplay of environmental factors, such as monsoon reliability, and human influences, including shifts in agricultural policy. A significant upward trend post-2017-18, coinciding with the Odisha Millet Mission (OMM), underscores the initiative's role in revitalizing millet cultivation. Correlation analyses reveal a near-linear relationship between area and production ($r = 0.958$) and a robust linkage between production and yield ($r = 0.636$), indicating that both expanded cultivation and enhanced productivity are pivotal for increasing ragi output. These relationships suggest that strategic interventions targeting both land use and agronomic practices could substantially elevate production, reinforcing ragi's potential as a climate-resilient staple. The Random Forest model effectively delineates general trends but exhibits predictive limitations, as evidenced by elevated testing RMSE values (41.20 for area, 39.29 for production, and 130.79 for yield) compared to training RMSE (10.68, 12.31, and 36.20, respectively). This disparity, particularly pronounced for yield, points to overfitting and the omission of critical variables such as precipitation anomalies or soil nutrient profiles, which likely influence annual fluctuations. Notable prediction deviations in years like 1992 and 1968 further highlight these gaps. Such discrepancies emphasize the need for a more comprehensive dataset to capture extreme events and improve model robustness. These findings provide essential guidance for policymakers, researchers, and farmers aiming to refine ragi production strategies in Odisha. By addressing variability and leveraging the OMM's momentum, stakeholders can enhance ragi's contribution to sustainable agriculture and nutritional security, aligning with broader climate adaptation goals. Future investigations should prioritize integrating additional explanatory factors such as rainfall variability, soil fertility, and farmer training levels to refine predictive accuracy. Incorporating 2021 data and real-time monitoring could also align models with current agricultural conditions, enhancing their relevance. Strengthening the Random Forest model through feature expansion or alternative algorithms could mitigate overfitting, offering more reliable forecasts. These advancements would not only bolster ragi production but also position Odisha as a model for millet-based resilience in rain-fed agroecosystems. This study thus lays a foundation for data-driven agricultural planning, supporting Odisha's efforts to sustain ragi as a vital crop for food security and environmental sustainability.

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