

International Journal of Statistics and Applied Mathematics

ISSN: 2456-1452
NAAS Rating (2025): 4.49
Maths 2025; 10(11): 46-55
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<https://www.mathsjournal.com>
Received: 21-09-2025
Accepted: 25-10-2025

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An ARIMA model approach to forecasting and comparing black gram, green gram, and red gram production in Tamil Nadu

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DOI: <https://www.doi.org/10.22271/math.2025.v10.i11a.2199>

Abstract

The ARIMA (Autoregressive Integrated Moving Average) model is employed in this study to examine the production trends of black gram, green gram, and red gram in Tamil Nadu for the period spanning from 1991 to 2024. A comparative assessment of these three pulse crops was carried out to understand their production patterns and forecast future trends. Time series modeling was carried out using the Box-Jenkins methodology, with ACF and PACF plots applied to determine appropriate ARIMA models. To ensure the suitability for ARIMA modeling, the stationarity of the series was examined using the Augmented Dickey-Fuller test. After identifying the appropriate models, their performance was assessed and validated using the Akaike Information Criterion (AIC) and the Schwarz Bayesian Information Criterion (SBIC). The residuals from the selected models were examined using the Box-Ljung test to confirm the absence of autocorrelation. Furthermore, the Mean Absolute Percentage Error (MAPE) was calculated to evaluate the forecasting accuracy of the models.

Based on the best-fit ARIMA models, production forecasts were generated up to the year 2029. The results demonstrate that ARIMA is a reliable and effective tool for modeling agricultural time series data, providing accurate forecasts and valuable insights into the future production trends of black gram, green gram, and red gram in Tamil Nadu.

Keywords: ARIMA, MAPE, forecasting, AIC, BIC, R-language

1. Introduction

Tamil Nadu, one of the prominent agricultural states in southern India, places great emphasis on pulse cultivation as part of its farming and food systems. Pulses play a crucial role in the agricultural economy of the state as well as in the nutritional intake of its population. Among the key pulses grown in the region, blackgram (urad dal), greengram (moong dal), and redgram (pigeon pea or thuvaram paruppu) stand out for their dual benefits. These crops not only support food and nutritional security but also play a crucial role in soil enrichment and sustainable agricultural practices, thanks to their ability to fix atmospheric nitrogen and thrive with minimal inputs. In Tamil Nadu, where vegetarian diets are predominant, these pulses act as a major source of plant-based protein, fiber, and essential micronutrients. Their cultivation supports low-input agriculture and serves as a climate-resilient option for farmers operating in varied agro-climatic zones, including rainfed and drought-prone areas. Their role in biological nitrogen fixation further enhances their agricultural value by reducing the dependence on chemical fertilizers and enriching soil quality.

Blackgram, a short-duration and high-value pulse crop, holds a prominent place in the agricultural landscape of Tamil Nadu. It is extensively cultivated across several districts, including Thanjavur, Kallakurichi, Ramanathapuram, Cuddalore, Thiruvannamalai, and Thoothukudi. Due to its quick maturity, blackgram fits well into both kharif and rabi seasons, making it highly suitable for multiple cropping patterns. It is often grown as a catch crop between major crops, offering flexibility to farmers. For many small and marginal farmers, blackgram serves as a reliable source of income, thanks to its adaptability and relatively low input requirements. In recent years, blackgram has been cultivated on

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an estimated 2.5 to 4.0 lakh hectares, yielding around 1.5 to 2.5 lakh metric tonnes annually. Its increasing popularity is linked to several agronomic advantages, such as low water and nutrient requirements, faster maturity, and resistance to common diseases. Farmers in Tamil Nadu benefit from improved seed varieties like VBN 8, which offers resistance to Yellow Mosaic Virus (YMV); VBN 6, adaptable to both rainfed and irrigated conditions; CO 6, suited for short growing seasons; and ADT 5, known for its nutritional quality. These varieties contribute to stable yields and make blackgram cultivation economically attractive, especially in areas with limited resources.

Greengram, known for its nutritional value and rapid growth, is a key pulse crop widely grown across Tamil Nadu. Its high digestibility and rich protein content make it a vital part of the local diet. Greengram is especially well-suited to short-duration cropping windows, allowing farmers to cultivate it efficiently between major crops. It is extensively grown in both coastal and inland regions, particularly in districts like Cuddalore, Thiruvallur, Nagapattinam, Mayiladuthurai, Thoothukudi, and Thiruvallur. Due to its adaptability, greengram is often used in intercropping systems or sown immediately after the paddy harvest, making it an excellent choice for enhancing farm productivity and sustainability. Tamil Nadu grows greengram on approximately 1.5 to 2.0 lakh hectares, producing 0.6 to 1.5 lakh metric tonnes annually. It thrives under both irrigated and rainfed conditions, making it versatile for diverse farm settings. Popular seed varieties include VBN 3, which resists YMV and powdery mildew; VBN 4, valued for early maturity and bold grains; CO 8, suitable for intercropping; and KM 2, known for its drought tolerance and early harvest. These improved varieties have supported better adoption rates and yield stability across the state.

Redgram, or pigeon pea, is a resilient, drought-tolerant pulse that plays a crucial role in supporting dryland farming systems across Tamil Nadu. As a long-duration crop, it is well adapted to regions with limited rainfall and is primarily cultivated in Dharmapuri, Krishnagiri, Vellore, Thirupathur, and Madurai districts. The crop makes efficient use of monsoon rains and residual soil moisture, thriving in areas where water resources are scarce. Redgram is typically grown on around 0.5 to 1.0 lakh hectares, yielding an annual production of 0.3 to 0.8 lakh metric tonnes. Its deep-root system not only aids in moisture extraction but also helps in soil conservation, making it an important component of sustainable agriculture in dry zones. Its deep root system allows it to extract moisture from lower soil layers, making it suitable for soil conservation and water management in drought-prone regions. Redgram also plays an essential role in local diets, providing a rich source of protein. Improved varieties such as VBN 3 (wilt-resistant), CO(Rg), ICPL 87119 (Asha) (a drought-tolerant hybrid with bold grains), and CO 6 (a short-duration, determinate variety) are popular among farmers for their resilience and productivity.

The combined agronomic and economic importance of blackgram, greengram, and redgram cannot be overstated. From an agronomic perspective, these crops are highly beneficial to the farming ecosystem. Their nitrogen-fixing capabilities reduce fertilizer use and enhance soil fertility, supporting long-term sustainability. They also require fewer resources, such as water and fertilizers, making them suitable for regions affected by climate variability. From an economic standpoint, pulses are a profitable crop choice for smallholder and marginal farmers. They generate consistent income due to

their steady market demand, both in domestic consumption and trade. Additionally, the availability of high-yielding, disease-resistant seed varieties has improved productivity and made pulse cultivation a viable income source, especially in rural and economically weaker areas. Furthermore, the inclusion of these pulses in crop rotation and intercropping systems helps improve land use efficiency and reduce pest and disease build-up, thus reducing reliance on chemical inputs. This holistic role in nutrition, income generation, soil health, and climate resilience underlines the centrality of pulses in Tamil Nadu's agricultural development strategy.

2. Review of Literature

Widely recognized for its capabilities in statistical computing, R programming has become a preferred platform for time series forecasting. Its adaptability and extensive library support enable effective implementation of models such as ARIMA (Auto Regressive Integrated Moving Average). The ARIMA modeling framework was originally developed by Box and Jenkins (1970) ^[4] in their pioneering publication *Time Series Analysis: Forecasting and Control*, which introduced a comprehensive procedure for selecting, estimating, and validating time series models. This work remains the gold standard for time series forecasting. Complementing this, Gupta and Kapoor (2001) ^[7] provided a broader statistical perspective in their book *Fundamentals of Applied Statistics*, offering essential knowledge that has supported the application of ARIMA and related models in various practical domains. The ARIMA model has been particularly effective in agricultural forecasting. Mandal (2005) ^[8] demonstrated the utility of ARIMA in forecasting sugarcane production in India, which highlighted the model's role in facilitating better agricultural decision-making and policy planning. Likewise, Ramakrishna and Vijayakumari (2017) ^[9] used the ARIMA model to forecast rice production trends in India. Their study underscored the model's capacity to handle seasonality and variability in agricultural data. Ramesh Reddy *et al.* (2017) ^[10] applied ARIMA to analyze monthly rainfall patterns in the Rayalaseema region. Their work showed the model's ability to manage climatic time series data, which is essential for water-dependent crop planning. Further agricultural applications of ARIMA include the study by Sakuntala Deka *et al.* (2022) ^[6], who used it to forecast tea production in India. Their findings supported the model's robustness and long-term forecasting reliability in agricultural sectors. Although Bhattacharyya *et al.* (2021) ^[3] employed linear regression instead of ARIMA, their study on the influence of weather variables on crop yields in Manipur complements time series analysis by highlighting the interdependencies between climate and crop production, which ARIMA can also model effectively.

In the domain of economic and financial forecasting, ARIMA has been widely applied. Ayık and Erkal (2021) ^[2] used ARIMA to predict unemployment and economic growth in Turkey, demonstrating its effectiveness in modeling economic indicators. Al-Qazzaz and Yousif (2022) ^[1] adopted the Auto ARIMA variant for forecasting Brent crude oil prices. Their results showed that ARIMA models can manage high-variance financial datasets with reasonable accuracy. Hybrid models have also emerged to enhance forecasting performance. Camara *et al.* (2016) ^[5] combined seasonal ARIMA with artificial neural networks to forecast energy consumption, and the hybrid model outperformed standalone ARIMA in terms of accuracy. This reflects the growing trend of integrating classical statistical models with machine

learning to capture both linear and nonlinear patterns. Finally, Tharwat and Hassanien (2023) ^[11] provided a comprehensive review comparing ARIMA with machine learning approaches. Their study concluded that while machine learning models may outperform ARIMA in complex, nonlinear data settings, ARIMA remains valuable due to its interpretability, transparency, and strong performance with structured, linear, or seasonal datasets particularly when data availability is limited.

3. Overview of the Dataset

This study makes use of data obtained from the Department of Economics and Statistics, Government of Tamil Nadu, specifically extracted from the 'Season and Crop Report'. This comprehensive 59 years dataset spans the period from 1966 to 2024 and offers detailed insights into the cultivation and production of three major pulse crops in Tamil Nadu: black gram, green gram, and red gram. Over nearly six decades, Tamil Nadu's agricultural scenario has experienced considerable shifts, shaped by climatic factors, agronomic innovations, and changing land-use patterns. Among these pulses, black gram emerges as the most prominently cultivated crop, both in terms of area and total output. On average, black gram covers approximately 232,873 hectares, with an average annual production of 114,607 tonnes, making it a staple component of the state's pulse cultivation. Green gram ranks second, with an average area of about 117,624 hectares and an average annual production of 48,706 tonnes. Although red gram occupies the least area approximately 66,350 hectares it contributes significantly to overall pulse output, with an average production of 44,255 tonnes per year. Despite its smaller scale of cultivation, red gram demonstrates the highest productivity among the three crops, indicating better yield efficiency. This productivity is estimated at about 0.67 tonnes per hectare, compared to 0.49 tonnes for black gram and 0.41 tonnes for green gram.

From the 1960s to the mid-2010s, a general upward trend is observed in both the area under cultivation and total output across all three crops. The period between 2014 and 2017 was particularly notable, marking peak production and cultivation levels. For example, black gram reached its historical high in 2015 with a production volume of 358,895 tonnes. During the same year, green gram and red gram also attained their highest outputs, at 180,726 tonnes and 90,950 tonnes

respectively. These record-breaking figures could be attributed to a combination of favorable climatic conditions, the adoption of high-yielding seed varieties, improved irrigation practices, and the implementation of supportive agricultural policies. However, this positive trend has not been consistent. Post-2017, there has been a noticeable decline in both cultivated area and production levels, especially in red gram. A sharp drop in red gram production was recorded in 2009, falling to just 16,703 tonnes, underscoring the crop's vulnerability to adverse weather and agronomic instability. In more recent years, particularly by 2024, all three pulses recorded significant reductions in both area and yield. Black gram production decreased to 179,261 tonnes from its 2020 high of over 317,000 tonnes. Green gram and red gram also followed this downward trend. The findings underscore the central role of black gram in Tamil Nadu's pulse economy while drawing attention to the need for stabilizing and enhancing the output of green and red gram. Focused interventions, such as introducing climate-resilient varieties, promoting efficient water management practices, and ensuring timely policy support, are vital for sustaining pulse production. Long-term strategies must emphasize increasing productivity, minimizing yield variability, and fostering sustainable agricultural practices to strengthen food security and rural livelihoods in Tamil Nadu.

Figure 1 illustrates the expansion and contraction trends in the cultivation area of three major pulse crops in Tamil Nadu. The area under black gram cultivation rose significantly from 44,000 hectares in 1966 to a peak of 429,784 hectares in 2017, before declining to 354,917 hectares by 2024. Green gram area expanded from 42,779 hectares to a maximum of 238,842 hectares in 2016, although it exhibited considerable fluctuations, particularly after the year 2000. Red gram, which peaked at 125,028 hectares in 1990, has since stabilized within a narrower range of 40,000 to 60,000 hectares. All three crops reached their highest cultivation areas during the mid-2010s. Figure 2 presents corresponding production trends: black gram production climbed from 14,100 tonnes in 1966 to a high of 358,895 tonnes in 2015, before falling to 179,261 tonnes by 2024. Similarly, green gram and red gram peaked in 2015, then declined sharply. These trends reflect the sensitivity of pulse production to environmental and policy changes.

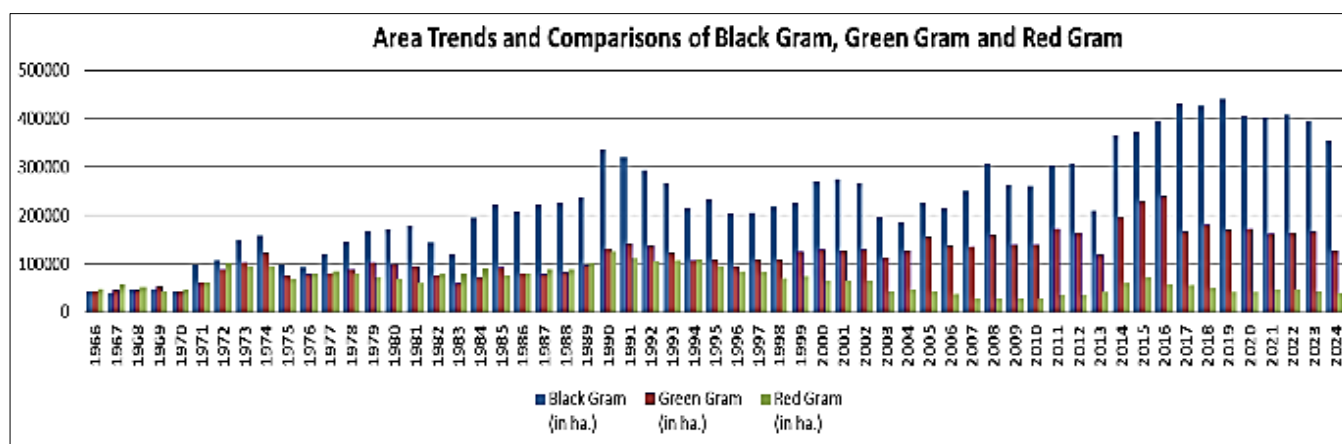


Fig 1: Trends in Cultivated Area for Major Pulse Crops in Tamil Nadu: 1966-2024.

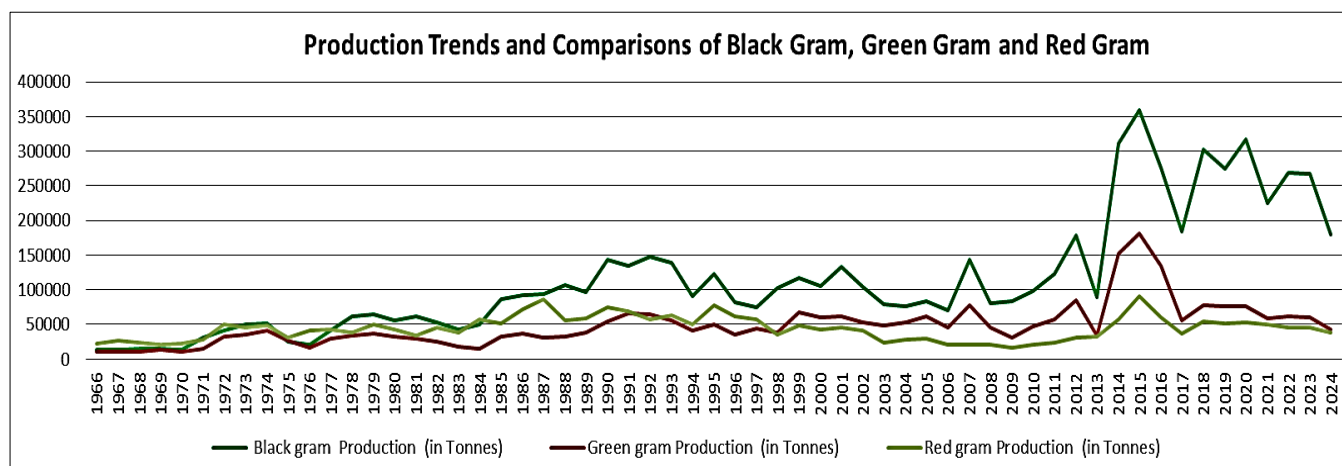


Fig 2: Changes in Pulse Crop Production in Tamil Nadu from 1966 to 2024.

4. Methods and Forecasting Models

3.1 Box-Jenkins methodology - Time Series

The Autoregressive Integrated Moving Average (ARIMA) model is a widely recognized technique for time series forecasting particularly suited for analyzing and predicting the behavior of a single variable over time. Often referred to as the Box-Jenkins model after its originators Box and Jenkins (1970) [4] ARIMA effectively captures the underlying structures in temporal data. In the present study, the Box-Jenkins methodology was utilized to apply the ARIMA model in assessing the production trends of black gram, green gram, and red gram. The ARIMA model is expressed as ARIMA (p, d, q), where p denotes the number of autoregressive terms, d signifies the order of differencing required to achieve stationarity, and q represents the number of moving average terms. The modeling process involves a structured sequence of steps to identify, estimate, and validate the most suitable model

Step 1: Time Series Identification

- **Visual Inspection:** Plot the time series data to observe overall trends, seasonality, and fluctuations in mean and variance over time.
- **Check for Stationarity:** Assess whether the series has a constant mean and variance using visual cues and statistical methods.
- **Statistical Tests:** Conduct unit root tests, including the Augmented Dickey-Fuller (ADF) test, to rigorously assess the stationarity of the series
- **ACF and PACF Analysis:** Evaluate the patterns in the ACF and PACF plots to select appropriate autoregressive and moving average orders for the model

Step 2: Differencing (Making the Series Stationary)

- When non-stationarity is detected, differencing is employed to transform the series by removing trends and ensuring a constant mean.
- Determine the appropriate number of differences (d), usually starting with first-order differencing. Repeat differencing if needed, until stationarity is achieved.

Step 3: Model Selection and Parameter Estimation

- Use the ACF and PACF plots to tentatively select values for:
- P indicates the AR order and q indicates the MA order in the ARIMA model.

- Optimize model parameters by minimizing AIC and BIC values.

Step 4: Model Diagnostics and Validation

- Assess the model residuals to ensure they approximate white noise, with no autocorrelation and a mean close to zero.
- Use tools like the Ljung-Box test for checking autocorrelation, and assess residual normality through ACF/PACF plots, histograms, and Q-Q plots.

Step 5: Forecasting and Model Evaluation

- Generate future values using the finalized ARIMA model and Evaluate forecast accuracy with performance metrics such as: RMSE, MAE and MAPE

The ARIMA model can be expressed in its general form as follows: " $\phi(B)(1-B)^d Y_t = \theta(B) \varepsilon_t$ (Box & Jenkins -1970)" (1)

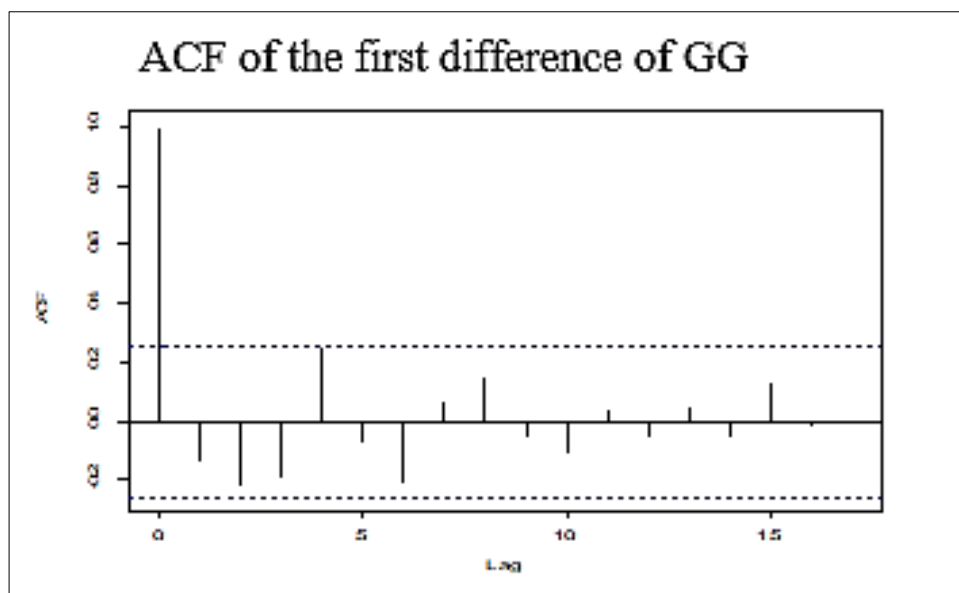
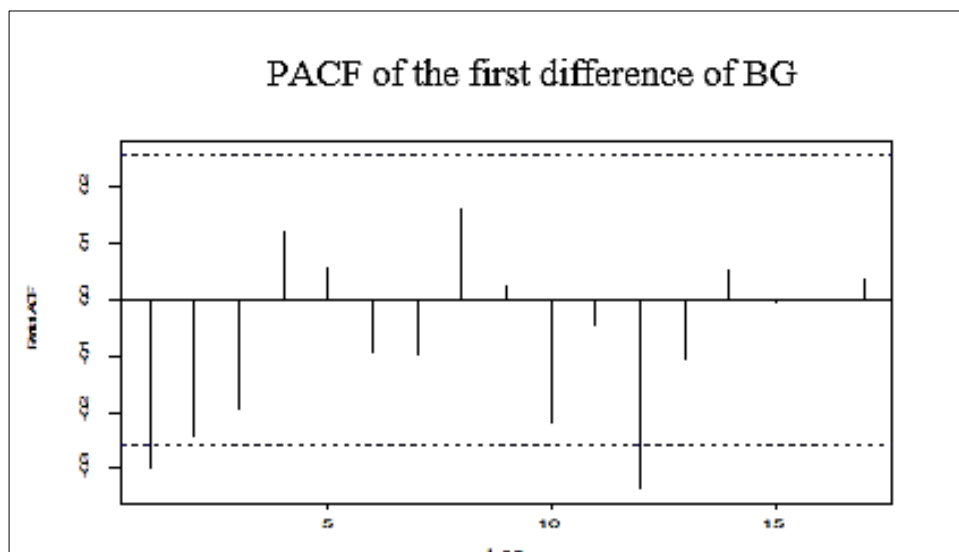
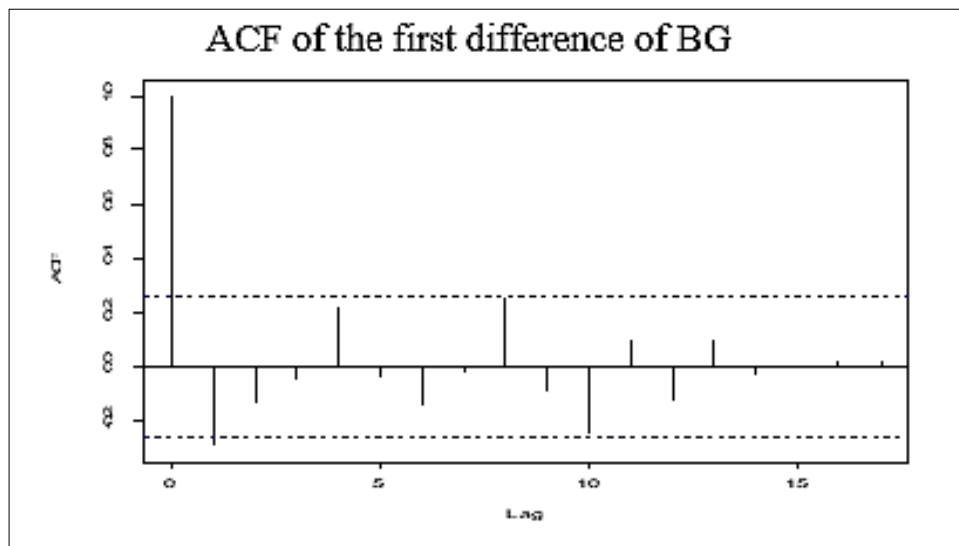
Where, Y_t : is the observed value at time t , B : backward shift operator, so $BY_t = Y_{t-1}$

d : is the differencing order for stationarity, ε_t : represents the random error or white noise

$\phi(B)$ and $\theta(B)$ are the AR and MA operators of orders p and q , respectively. Therefore, the AR Part is $\phi(B) = 1 - \phi_1 B - \dots - \phi_p B^p$ and the Moving Average part: $\theta(B) = 1 + \theta_1 B + \dots + \theta_q B^q$

3.2. ARIMA model development Box & Jenkins (1970) [4]

The initial step in ARIMA model development involves assessing whether the time series is stationary. A stationary series exhibits a constant mean and variance over time, along with consistent, predictable patterns of fluctuation. To assess this, the Augmented Dickey-Fuller (ADF) test was applied to the production data for black gram, green gram, and red gram. Results indicated non-stationarity in all three series. Since the data includes zero values, a logarithmic transformation was not feasible. Therefore, to induce stationarity, first differencing ($d=1$) were performed. Following differencing, the series were further examined using the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots to confirm stationarity. Figure 3 (correlograms) presents the ACF and PACF plots of the differenced series, providing insights into selecting appropriate ARIMA parameters for each crop.



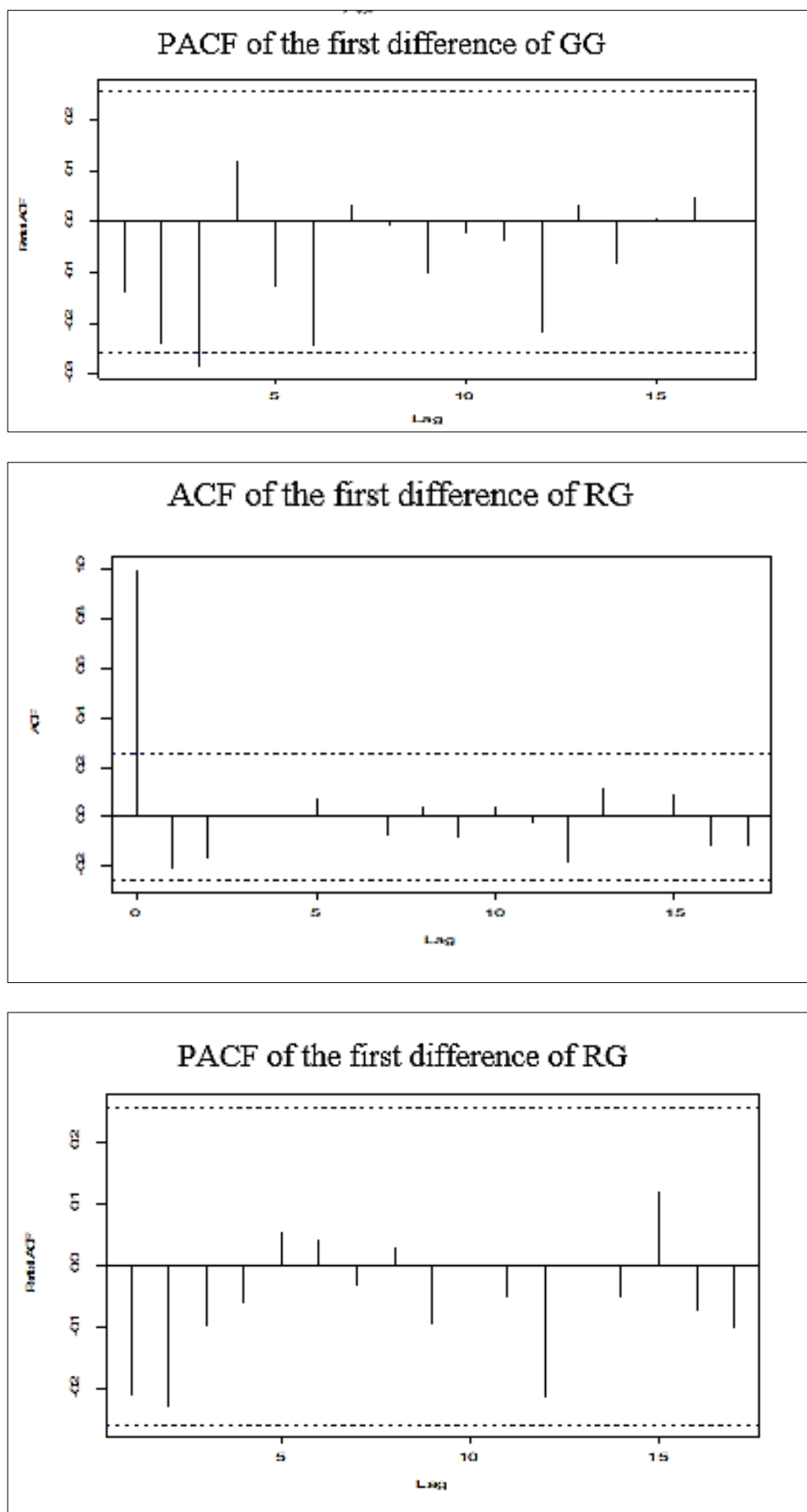


Fig 3: ACF and PACF Plots of First-Differenced Production Series for BG, GG, and RG.

The correlogram and the values of the ACF and PACF (Figure 3) indicate that a first-order seasonal differencing is adequate to achieve stationarity. Thus, a single differencing ($d = 1$) is sufficient for the given time series. Prior to model development, confirming the stationarity of the differenced

series is crucial. This is achieved by conducting the Augmented Dickey-Fuller (ADF) test, which assesses the presence of a unit root. Confirming stationarity at this stage ensures that the series is suitable for ARIMA modeling.

3.3. ADF Test for Stationarity of Pulses Production Series

In order to test whether the time series data for black gram, green gram, and red gram production were stationary, the hypotheses outlined below were proposed:

- **H₀**: The production time series of all three crops are non-stationary.
- **H₁**: The production time series of all three crops are stationary.

Using the Augmented Dickey-Fuller (ADF) test on the first-differenced data ($d = 1$), the hypothesis was assessed. The test statistics are summarized as follows:

Sample Crops	DF values	Lag order	p-value
Black Gram	-3.8721	3	0.021
Green Gram	-4.2175	3	0.01
Red Gram	-4.5952	3	0.01

Since the p-values are all below the 0.05 significance threshold, the null hypothesis is rejected for each crop, indicating that the first-differenced series ($d = 1$) is stationary

in both mean and variance. With stationarity confirmed at this level of differencing, no further differencing is required. The subsequent stage in ARIMA model development is to determine the appropriate non-seasonal orders: p (autoregressive order) and q (moving average order). This is achieved by examining the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots of the stationary series. Accordingly, the preliminary model for all three crops is specified as ARIMA ($p, 1, q$).

3.4 Selecting the Appropriate Model for Forecasting:

Preliminary ARIMA models were developed for each pulse crop by examining the ACF and PACF plots of the differenced production data. Seven candidate models were initially selected, as shown in Table 1. To determine the best model, each candidate was evaluated using the Akaike Information Criterion (AIC) and Schwarz Bayesian Information Criterion (SBIC). The model with the lowest AIC and SBIC values was chosen as the optimal fit. The provisional models along with their final best-fitting ARIMA versions are summarized in Tables 1 and 2, respectively.

Table 1: Initial Fitted ARIMA Model for Sample Pulses Yields

Sample ARIMA Model	Black Gram Model Fit		Green Gram Model Fit		Red Gram Model Fit	
	AIC	BIC	AIC	BIC	AIC	SBIC
(1,1,1)	1414.05	1422.29	1330.1	1338.34	1266.38	1274.62
(1,1,0)	1416.8	1422.98	1340.23	1346.41	1267.42	1273.6
(0,1,1)	1412.51	1418.69	1338.76	1344.94	1265.54	1271.72
(2,1,1)	1415.47	1425.77	1330.9	1341.2	1267.78	1278.09
(2,1,2)	1417.1	1429.47	1332.89	1345.26	1269.43	1281.79
(1,2,2)	1415.87	1426.17	1331.14	1341.44	1267.88	1278.18
(2,1,0)	1414.84	1423.09	1338.81	1347.05	1266.4	1274.64

Table 2: Final Selected Model for Pulses Production Forecasting

Final Selected ARIMA Model	Coefficients				Model Fit	
	AR1	MA1	Drift	MAPE	AIC	SBIC
Black Gram (0,1,1)	-	-0.5018	3716.89	27.26473	1412.51	1418.69
Green Gram (1,1,1)	0.5035	-1.000	1149.114	25.16957	1330.1	1338.34
Red Gram (0,1,1)	-	-0.3474	318.7939	19.76147	1265.54	1271.72

The final ARIMA models chosen to forecast production of black gram, green gram, and red gram were based on minimizing the Akaike Information Criterion (AIC) and Schwarz Bayesian Information Criterion (SBIC), ensuring optimal model performance. For black gram, the selected model was ARIMA (0,1,1), with an MA(1) coefficient of -0.5018 and a drift term of 3716.89. This model produced a Mean Absolute Percentage Error (MAPE) of 27.26, indicating satisfactory accuracy, with AIC and SBIC values of 1412.51 and 1418.69, respectively. Green gram's production was best represented by an ARIMA (1,1,1) model, having AR(1) and MA(1) coefficients of 0.5035 and -1.000, and a drift value of 1149.11. This model showed improved accuracy with a MAPE of 25.17 and AIC and SBIC values of 1330.10 and 1338.34. The red gram production followed the ARIMA (0,1,1) structure as well, with an MA (1) coefficient of -0.3474 and drift of 318.79, yielding the highest accuracy among the three with a MAPE of 19.76 and AIC and SBIC values of 1265.54 and 1271.72. Specifically, the ARIMA (0,1,1) model for black gram describes a moving average

process on the first differenced series. The model is represented by the following equation:

$$X_t = X_{t-1} + \epsilon_t - \theta_1 \epsilon_{t-1} \quad (2)$$

The Green gram ARIMA (1,1,1) model includes one autoregressive and one moving average term:

$$X_t = \phi_1 (X_{t-1} - X_{t-2}) + X_{t-1} + \epsilon_t - \theta_1 \epsilon_{t-1} \quad (3)$$

Similar to black gram, Red gram follows the ARIMA (0, 1, 1) model:

$$X_t = X_{t-1} + \epsilon_t - \theta_1 \epsilon_{t-1} \quad (4)$$

These results confirm that the selected ARIMA models are suitable for capturing production trends and can support future forecasting efforts for pulse crops in Tamil Nadu. Furthermore, to assess the presence of autocorrelation among

successive forecast errors, the fit of the ARIMA models was evaluated using the Box-Ljung test. This diagnostic test checks whether the residuals from the fitted models resemble white noise. The outcomes of these tests for each model are summarized below.

3.5. Test for Autocorrelation in Model Residuals

The presence of autocorrelation in the residuals was examined using the Box-Ljung test on the lag values of the ACF and PACF. The test results are presented below.

Autocorrelation test for residuals				
Selected Crop	Test	X ²	df	Sig-Value
Black Gram	Box-Ljung	16.329	14	0.2937
Green Gram	Box-Ljung	15.968	14	0.3153
Red Gram	Box-Ljung	6.9704	14	0.9358

The residuals of the fitted ARIMA models for black gram, green gram, and red gram were examined for autocorrelation using the Box-Ljung test. The results revealed no significant

autocorrelation, as all p-values exceeded the 0.05 threshold. Specifically, the black gram model recorded a test statistic of 16.329 (df = 14, p = 0.2937), while green gram showed 15.968 (df = 14, p = 0.3153). The red gram model had the lowest test statistic at 6.9704 (df = 14, p = 0.9358). These results imply that the ARIMA models adequately represent the intrinsic structures within the time series data, thereby confirming their suitability and reliability for forecasting applications.

3.6. Production Forecasts Based on Optimal ARIMA Models for Sample Crops

Using the final selected ARIMA models, five-year production forecasts have been made for black gram, green gram, and red gram in Tamil Nadu. The forecasted values are presented in tabular format along with their corresponding confidence intervals, indicating the expected range of future outcomes. Graphical representations comparing actual and predicted values for each crop are shown in Figures 4, 5, and 6.

Table 3: Crop wise Yield production Forecast values

Crop	Year	Yield Production Forecast Value (in tonnes)	95% Confidence Limits	
			Lower	Upper
Black Gram	2024-25	230237.1	141437	319037.2
	2025-26	233954	134743.7	333164.2
	2026-27	237670.9	129043.6	346298.1
	2027-28	241387.7	124097.1	358678.4
	2028-29	245104.6	119748	370461.3
Green Gram	2024-25	62726.17	20102.8	105349.5
	2025-26	73659.74	25631.03	121688.5
	2026-27	79735.03	30279.87	129190.2
	2027-28	83364.32	33479.08	133249.6
	2028-29	85762.13	35730.83	135793.4
Red Gram	2024-25	41671.67	16623.843	66719.49
	2025-26	41990.46	12080.082	71900.84
	2026-27	42309.26	8223.068	76395.44
	2027-28	42628.05	4824.538	80431.56
	2028-29	42946.84	1760.161	84133.53

Table 3 presents forecasted yield production for Black Gram, Green Gram, and Red Gram from 2024-25 to 2028-29, showing steady growth across all crops. Black Gram is expected to increase from about 230,237 to 245,105 tonnes, with wide confidence intervals indicating some uncertainty.

Green Gram's yield is projected to rise notably from 62,726 to 85,762 tonnes, with expanding confidence ranges. Red Gram shows modest growth from 41,672 to 42,947 tonnes, with more stable confidence limits. Overall, the outlook is positive for pulse yields.

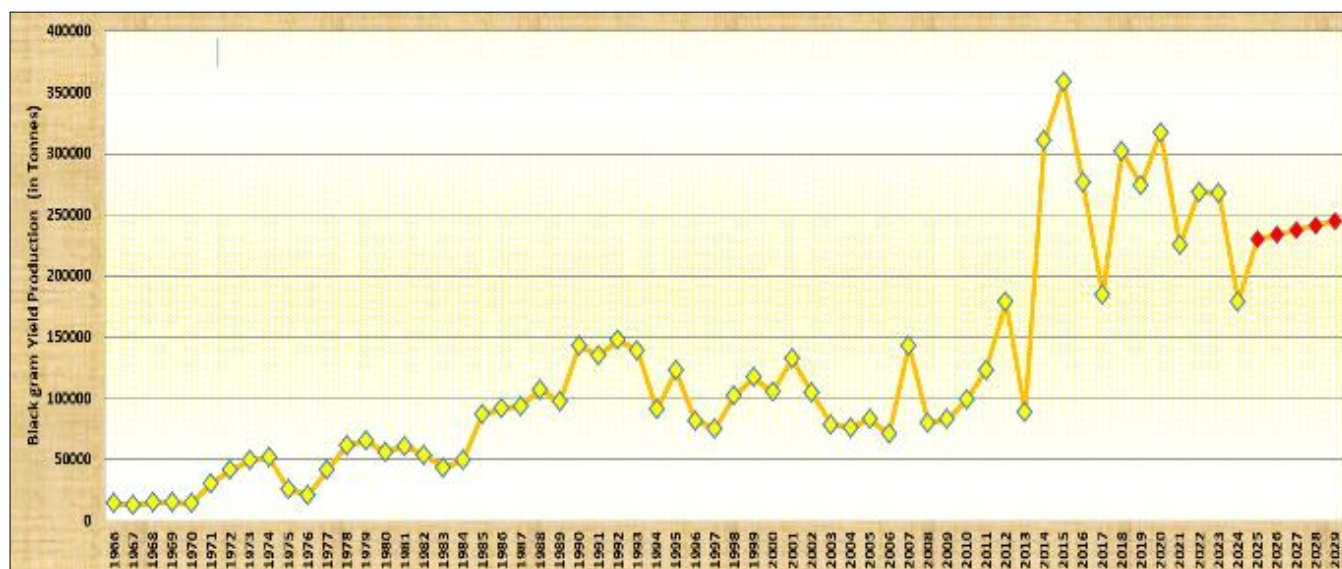


Fig 4: Observed and forecasted values of Black gram yield production in Tamil Nadu

Figure 4 illustrates the historical yield of Black Gram from 1966 to 2024, marked by fluctuations and overall growth, especially from the 1980s and a peak in 2015. Despite recent declines, forecasts for 2025 to 2029 indicate a steady increase

from around 230,237 to 245,105 tonnes, suggesting a period of stabilization and cautious optimism for improved yields ahead.

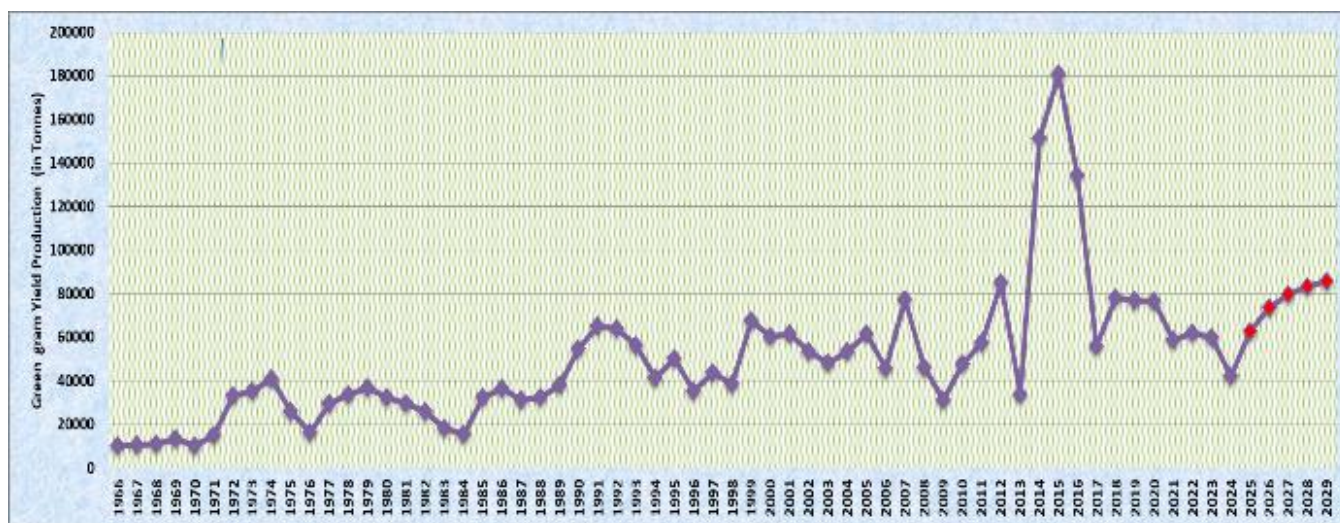


Fig 5: Observed and forecasted values of Green gram yield production in Tamil Nadu

Figure 5 shows Green Gram yields fluctuated from 1966 to 2024, with moderate early production and significant growth from the 1990s, peaking at 180,726 tonnes in 2015. After recent declines, forecasts for 2025-2029 predict a steady

increase from 62,726 to 85,762 tonnes, indicating a gradual recovery and optimism for improved yield stability in the coming years.

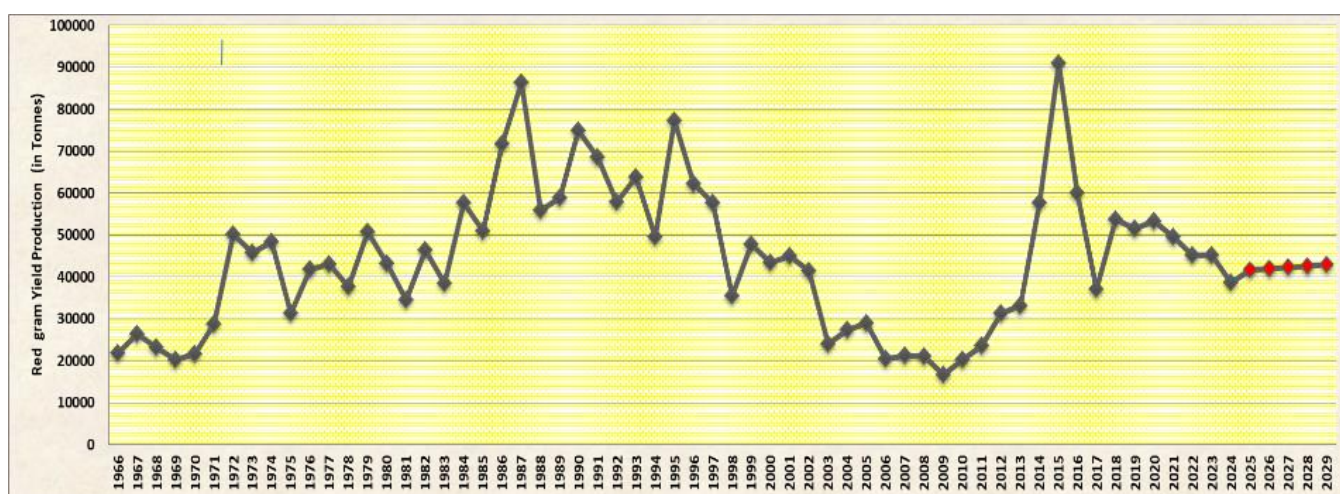


Fig 6: Observed and forecasted values of Red gram yield production in Tamil Nadu

Figure 6 highlights Red Gram's yield fluctuations from 1966 to 2024, with peaks in the late 1980s and mid-2010s exceeding 86,000 and 90,000 tonnes. Despite variability and recent declines, forecasts for 2025-2029 predict a gradual increase from 41,672 to 42,947 tonnes, indicating slow but steady growth and cautious optimism for yield stability and recovery.

Findings and Conclusions

This extensive study utilizes a detailed dataset covering 59 years (1965-1966 to 2023-2024), sourced from the Department of Economics and Statistics, Government of Tamil Nadu. Employing ARIMA modeling techniques, the research analyzed historical production trends and generated forecasts for three principal pulse crops black gram, green gram, and red gram in Tamil Nadu, with projections extending through 2029. The results reveal distinct production patterns across the crops. Black Gram has demonstrated a

consistent upward trend, particularly with notable surges during the 2010s. Although recent years have seen some fluctuation, forecasts from 2025 to 2029 suggest a steady and moderate increase in production. Green Gram has shown considerable variability historically but indicates a promising recovery, with yields expected to grow steadily in the coming years. In contrast, Red Gram has experienced the most subdued growth, with forecasted values suggesting only modest improvements and relatively stable but lower production levels.

Based on these insights, several key strategies are recommended. First, targeted research should be intensified to develop improved seed varieties with enhanced pest and drought resistance, particularly for Red Gram, which shows limited growth potential. Promoting sustainable farming practices and the adoption of climate-resilient technologies, including efficient irrigation methods, is essential to mitigate the impact of environmental fluctuations. Furthermore,

strengthening agricultural extension services will ensure that farmers are better equipped with updated knowledge on cultivation techniques, weather patterns, and market trends. Investing in storage and processing infrastructure can help reduce post-harvest losses and stabilize market prices. Encouraging crop diversification through intercropping pulses with cereals can also enhance soil health and farmer income. Lastly, ensuring accessible minimum support prices and updating forecasting models using advanced statistical tools will support better planning, policy-making, and resilience in pulse production across the state.

Acknowledgement

I sincerely thank the Department of Economics and Statistics, Government of Tamil Nadu, for providing the vital datasets essential to this research. I am especially grateful to the Principal Secretary/Commissioner for their support and encouragement throughout the study. I also extend heartfelt thanks to my family and friends for their unwavering support and motivation during the preparation and completion of this paper.

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