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**Dr. Soumya VS**
Asst. Professor, Department of Economics, TM Jacob Memorial Govt. College, Manimalakkunnu, Ernakulam, Kerala, India

**Dr. Joben K Antony**
Associate Professor, Department of Economics, St Thomas college, Pala, Kottayam, Kerala, India

**Dr. Deepa K Thomas**
Assistant Professor, Department of Economics, BK college for women, Amalagiri, Kottayam, Kerala, India

**Lidiya George**
Assistant Professor, Department of Economics, St. George's College Aruvithura, Kottayam, Kerala, India

**Corresponding Author:**
**Dr. Soumya VS**
Asst. Professor, Department of Economics, TM Jacob Memorial Govt. College, Manimalakkunnu, Ernakulam, Kerala, India

# Forecasting India's Agricultural Production Using ARIMA Models: Trends, Challenges, and Policy Implications

**Soumya VS, Joben K Antony, Deepa K Thomas and Lidiya George**

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**Abstract**
Accurate forecasting of agricultural production is critical for food security, policy planning, and economic stability in India. This study employs the Auto-Regressive Integrated Moving Average (ARIMA) model to forecast food grain production using annual time series data from 1950 to 2024, sourced from the Reserve Bank of India (RBI). Following the Box-Jenkins methodology, the Augmented Dickey-Fuller (ADF) test confirmed stationarity ($p < 0.05$). Among competing models, ARIMA (0,1,1) was selected as optimal due to its lowest Akaike Information Criterion (AIC = 12.254) and statistically significant coefficients ($p < 0.0001$). Diagnostic checks, including the Ljung-Box Q test ($p > 0.05$) and Jarque-Bera test (p= 0.284), confirmed residual white noise and normality. The model forecasts a continued decline in food grain production, projecting values of 489.46, 451.64, and 413.81 (units) for 2025-2027, respectively. While the ARIMA model effectively captures short-term temporal patterns, its linear assumptions and exclusion of exogenous variables (e.g., climate, policy) limit long-term accuracy. This study underscores the utility of ARIMA as a policy tool for short-term planning while advocating for future integration of multivariate or machine learning models to enhance predictive robustness.

**Keywords:** ARIMA, agricultural forecasting, food grain production, time series, India, Box-Jenkins, policy planning

## Introduction

Agriculture remains the backbone of India's economy. According to the Economic Survey, the Indian agriculture sector provides livelihood support to about 42.3% of the population and contributes 18.2% to the country's GDP at current prices. The sector has shown resilience, registering an average annual growth rate of 4.18% at constant prices over the last five years. However, provisional estimates for 2023-24 indicate a slowdown to 1.4%, highlighting the sector's vulnerability to climatic variability, policy shifts, and market fluctuations. Accurate forecasting of agricultural output is therefore essential for ensuring food security, guiding policy formulation, and enabling economic stability.

Historically, the Green Revolution of the 1960s marked a transformative phase in Indian agriculture, significantly boosting food grain production—particularly in states like Punjab and Haryana—through the adoption of high-yielding variety (HYV) seeds, chemical fertilizers, and expanded irrigation. This era established India as self-sufficient in staple crops like wheat and rice. Scholars such as Singh (2018) and Chand (2019) [11, 3] emphasize the success of this period in addressing food shortages and enhancing productivity. However, long-term studies by Birthal *et al*. (2015) and Kaur and Singh (2020) [2, 7] reveal adverse environmental consequences, including soil degradation, groundwater depletion, and biodiversity loss, especially in intensively farmed regions.

Over time, India has witnessed a shift in cropping patterns, with a growing diversification from food grains to high-value commercial crops such as cotton, oilseeds, fruits, and vegetables—particularly in states like Maharashtra, Gujarat, and Andhra Pradesh. While food grains remain dominant, this diversification reflects changing consumer preferences, market liberalization, and government policies promoting horticulture and allied sectors (Birthal *et al*., 2017, 2020) [10].

Despite progress, regional disparities persist. Eastern and northeastern states continue to lag due to inadequate infrastructure, fragmented landholdings, and limited access to credit and technology (Jha, 2011; Mohanty, 2013) [6, 8].

In recent years, India has emerged as one of the world's top agricultural producers. For 2023-24, total food grain production was estimated at 3288.52 Lakh Metric Tons (LMT), with projections for 2025 reaching around 332 million metric tons. Uttar Pradesh, Punjab, Madhya Pradesh, and West Bengal are among the leading agricultural states, each specializing in key crops—wheat in Punjab and Uttar Pradesh, rice in West Bengal, and oilseeds in Madhya Pradesh. Technological advancements, including satellite-based monitoring, drones, artificial intelligence, and the Internet of Things, are driving a paradigm shift toward smarter, data-driven farming (Reddy *et al*., 2021) [10].

Despite these developments, agricultural forecasting remains a challenge. Traditional methods often fail to capture the complex temporal dependencies and autocorrelation inherent in agricultural time series data. In contrast, time series models such as ARIMA, grounded in the methodology, have demonstrated robustness in modeling and forecasting economic and agricultural trends. ARIMA models are particularly suited for data exhibiting trends, seasonality, and serial correlation—common features in agricultural production series.

This study addresses the critical need for reliable, data-driven forecasting of India's food grain production by employing the ARIMA model. The primary research problem lies in the sector's sensitivity to exogenous shocks—climate change, policy changes, and market dynamics—which traditional models often overlook. By analyzing annual time series data from 1950 to 2024 sourced from the Reserve Bank of India (RBI), this study aims to: (1) examine historical trends in food grain production, (2) develop an optimal ARIMA model for forecasting, and (3) provide evidence-based insights for policymakers. The findings contribute to the growing literature on agricultural forecasting in developing economies and offer a replicable framework for regional and crop-specific analyses.

## Materials and Methods.

The study utilized annual time series data on total food grain production in India from 1950 to 2024, obtained from the Reserve Bank of India's (RBI) official database on the Index of Agricultural Production (https://www.rbi.org.in/). The variable "Total Foodgrains" served as the proxy for agricultural output.

Data analysis was conducted using R software (version 4.3.1), employing packages such as `forecast` and `tseries`, for time series modeling and diagnostic testing. The Box-Jenkins (1976) ARIMA modeling framework was adopted, which involves three main stages: identification, estimation, and diagnostic checking.

The Augmented Dickey-Fuller (ADF) test was applied to assess the stationarity of the time series. In cases of non-stationarity, differencing is performed to achieve stationarity. Based on the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots, various ARIMA (p, d, q) models were estimated. Model selection was based on information criteria, including the Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (BIC), and Hannan-Quinn Criterion (HQC), with preference given to models with lower values and fewer parameters.

The best-fitting model was subjected to residual diagnostic checks using the Ljung-Box Q statistic to test for autocorrelation in residuals and the Jarque-Bera test to assess normality. Additionally, the ARMA roots plot was used to verify stationarity and invertibility. Forecasting was performed for the years 2025-2027, with accuracy evaluated using metrics such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Theil's Inequality Coefficient. No field experiments or physical instruments were used, as the study is entirely based on secondary time series data analysis.

## Results

Descriptive statistics revealed that the mean food grain production from 1950 to 2024 was 1626.26 units, with a standard deviation of 771.97, indicating high variability. The time series plot showed a consistent downward trend, particularly after 2000, suggesting structural or environmental challenges affecting production.

The Augmented Dickey-Fuller (ADF) test yielded a test statistic of 14.44642 with a p-value of 0.0001, which is significantly lower than the 1%, 5%, and 10% critical values, confirming that the series is stationary without requiring additional differencing.

Among the models—ARIMA (0,1,1), ARIMA (1,1,0), and ARIMA (1,1,1)—the ARIMA(0,1,1) model was selected as optimal due to its lowest AIC (12.254), BIC (12.348), and HQC (12.292), despite a marginally lower R-squared compared to ARIMA(1,1,1).

The estimated coefficients for ARIMA (0,1,1) were statistically significant: the MA (1) coefficient was -0.544 ($p < 0.0001$), and the constant term was -37.825 ($p < 0.0001$), indicating a negative drift in the differenced series.

Residual diagnostics confirmed the adequacy of the model. The Ljung-Box Q test showed p-values greater than 0.05 across all lags (ranging from 0.590 to 0.966), indicating no significant autocorrelation in residuals. The Jarque-Bera test resulted in a p-value of 0.284, confirming the normality of residuals.

Forecasting results projected a continued decline in food grain production: 489.46 units in 2025, 451.64 units in 2026, and 413.81 units in 2027. The model's forecasting accuracy was supported by a low Theil's Inequality Coefficient (0.0857) and a MAPE of 19.80%, although the bias proportion of 0.761 indicated a systematic deviation in predictions.

## Discussion and Conclusion

The findings of this study reveal a concerning long-term decline in India's food grain production, as captured by the ARIMA (0,1,1) model. The forecasted drop from 489.46 units in 2025 to 413.81 units in 2027 contradicts some official projections, such as the anticipated 332 million metric tons for 2024 (Government of India, 2024), suggesting a possible discrepancy in data units or definitions—likely due to the use of an index value rather than absolute production figures. This highlights the importance of contextual interpretation when applying statistical models to policy planning.

The selection of ARIMA (0,1,1) as the optimal model aligns with prior studies, such as Padhan (2012) [9], which also found MA components effective in capturing shock adjustments in agricultural output. The significant negative MA (1) coefficient indicates that unanticipated negative shocks—such as droughts or pest outbreaks—have a persistent dampening effect on production, consistent with the sector's vulnerability to climatic risks (Aggarwal, 2009) [1]. While the model demonstrated strong statistical performance—confirmed by white noise residuals and normal error distribution—its limitations are notable. The ARIMA model is purely univariate and does not account for exogenous variables such as rainfall, temperature, fertilizer use, or policy interventions like MSP hikes or subsidies. This restricts its long-term reliability, as agricultural output is inherently influenced by multidimensional factors.

Moreover, the high residual standard deviation (106.86) and wide error range (-278.97 to 267.07) suggest unexplained volatility, possibly due to omitted variables or structural breaks. The high bias proportion (76.1%) further indicates that the model may systematically underestimate or overestimate actual values, potentially due to the linear assumptions of ARIMA in a non-linear real-world context.

Nonetheless, the study reaffirms the utility of ARIMA models in short-term forecasting and trend identification, particularly in data-scarce or rapidly changing environments. For policymakers, these forecasts serve as an early warning signal, urging immediate interventions such as investment in climate-resilient crops, expansion of irrigation infrastructure, and strengthening of market linkages.

Future research should explore multivariate models like VAR or machine learning approaches (e.g., LSTM, Random Forest) that can incorporate climate, economic, and policy variables to improve predictive accuracy. Additionally, state-level or crop-specific ARIMA models could provide more targeted insights.

In conclusion, this study successfully applied the ARIMA (0,1,1) model to forecast India's food grain production, revealing a statistically significant downward trend. While the model is robust for short-term planning, its limitations underscore the need for integrated, data-rich forecasting frameworks to ensure long-term food security in India's evolving agrarian landscape.

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