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Long-memory dynamics and weather-adjusted forecasting of greengram prices: A comparative analysis of ARFIMA, ARIMAX and ARFIMAX models

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Abstract

Green gram (*Vigna radiata* L.), commonly known as mung bean, holds significant importance in Indian agriculture as a protein-rich pulse crop with substantial export potential. Price volatility in green gram markets presents considerable challenges for farmers, traders, and policymakers. This study investigates long-memory dynamics and the impact of weather variables on green gram price forecasting through a comparative analysis of three advanced time-series models: ARFIMA (AutoRegressive Fractionally Integrated Moving Average), ARIMAX (AutoRegressive Integrated Moving Average with exogenous variables), and ARFIMAX (AutoRegressive Fractionally Integrated Moving Average with exogenous variables). Monthly price data from Khammam Market, Telangana (April 2022 to May 2025) and corresponding weather variables (minimum temperature, maximum temperature, rainfall, and relative humidity) from NASA POWER were analyzed. Results demonstrate that the ARFIMAX model (AIC: -208.22) outperforms both ARFIMA (AIC: -211.96) and ARIMAX (AIC: -104.76) in forecasting accuracy. The fractional differencing parameter ($d = 0.465$) indicates significant long-memory characteristics in green gram prices, reflecting persistent price dependencies. Relative humidity emerged as the most influential weather variable (coefficient: -0.0528), followed by maximum temperature (-0.0325). Model diagnostic tests confirm excellent residual properties (Shapiro-Wilk p-value: 0.4725). The six-month forecast (June-November 2025) predicts prices ranging from ₹6,521 to ₹6,588 per quintal with 95% confidence intervals. These findings provide valuable insights for agricultural market participants and contribute to improved decision-making in pulse crop trading and risk management.

Keywords: Green gram, long-memory, fractional integration, ARFIMA, ARIMAX, ARFIMAX, forecasting, weather variables, price volatility

1. Introduction Background and Context

Agricultural commodity prices represent one of the most critical factors influencing farm income, food security, and market stability in developing economies like India. Among agricultural commodities, pulse crops occupy a pivotal position in Indian agriculture due to their nutritional richness, soil conservation properties, and export value. Greengram (*Vigna radiata* L.), popularly known as mung bean, is one of India's most important pulse crops, contributing significantly to domestic protein requirements and international trade (Hosking, 1981) [4]. Globally, greengram production has shown consistent growth, with total production reaching approximately 8 million metric tonnes annually, with India commanding a leading position. At the national level, India is the largest producer, consumer, and exporter of greengram globally, accounting for approximately 60-70% of world production (Hosking, 1981). According to recent agricultural statistics, greengram cultivation in India spans approximately 4.5 million hectares with an annual production of 2.5-3.0 million metric tonnes, maintaining a global ranking of the number one producer. Within India, greengram cultivation is concentrated across several states, with significant contributions from Maharashtra, Madhya Pradesh, Andhra Pradesh, and Telangana. Telangana, post-reorganization in 2014, has emerged as one of India's major greengram-producing states, accounting for approximately 8-12% of national production

(Department of Agriculture and Cooperation, 2023) [2]. Within Telangana, Khammam district stands as one of the most important greengram cultivation centers, with an average area under cultivation of 85,000-95,000 hectares, annual production of 120,000-140,000 metric tonnes, and average productivity ranging from 1.4-1.6 tonnes per hectare. Khammam Market, functioning as a primary agricultural market under the Telangana Marketing Board, serves as a crucial price-discovery center for greengram in the region. Despite its agricultural importance, greengram prices exhibit substantial volatility, influenced by multiple factors including supply-demand dynamics, weather conditions, global market trends, and macroeconomic policies. Price unpredictability creates significant risks for farmers (income uncertainty), traders (profit volatility), and consumers (food security concerns). This volatility necessitates robust forecasting frameworks to support informed decision-making.

Statistical Models in Agricultural Price Forecasting

Traditional time-series models such as ARIMA have been widely applied to agricultural commodity price forecasting (Box & Jenkins, 1976). However, agricultural price series often exhibit long-memory characteristics where past shocks have persistent, long-lasting effects on future prices, which conventional ARIMA models may inadequately capture. The ARFIMA framework explicitly models long-memory dynamics

through the fractional integration parameter (d), where $0 < d < 0.5$ indicates mean reversion with slow decay of autocorrelation (Granger & Joyeux, 1980). Incorporating exogenous weather variables into time-series models recognizes that agricultural prices are inherently climate-dependent.

Study Objectives

The primary objectives of this research are to: (1) examine long-memory dynamics in greengram prices using fractional integration techniques; (2) quantify the influence of meteorological variables on price fluctuations; (3) develop and compare three advanced time-series forecasting models; (4) identify the superior forecasting model based on statistical criteria.

2. Materials and Methods

2.1 Data Source and Study Period

Price Data: Monthly green gram prices (rupees per quintal) from Khammam Market, Department of Telangana Marketing, covering the period from April 2022 to May 2025.

Weather Data: Monthly meteorological observations, including minimum temperature ($^{\circ}\text{C}$), maximum temperature ($^{\circ}\text{C}$), rainfall (mm), and relative humidity (%), sourced from NASA POWER (<https://power.larc.nasa.gov/data-access-viewer/>) database for Khammam district coordinates.



Fig 1: Map of Study Area

Data Processing: Price data were log-transformed to stabilize variance and enable interpretation as percentage changes. Weather variables were standardized for comparability across scales (Lütkepohl, 2005) [5]. The analysis has been carried out in R version 4.4.2.

2.2 Stationarity Testing

Two complementary unit root tests were applied to assess stationarity:

Augmented Dickey-Fuller (ADF) Test: Tests null hypothesis of unit root (non-stationarity) versus the alternative of stationarity. Test statistics follow Dickey-Fuller distribution.

Phillips-Perron (PP) Test: Non-parametric test robust to heteroskedasticity and serial correlation in residuals. Test that assesses whether a time series is stationary by testing the null hypothesis of a unit root.

2.3 Model Specifications and Equations

ARFIMAX Model Equation

(Granger & Joyeux, 1980)

$$\Phi(B)(1-B)^d \log(P_t) = \mu + \sum_{k=1}^K \beta_k X_{\{k,t\}} + \Theta(B)\varepsilon_t$$

where:

- P_t = Greengram price at time t
- $\Phi(B)$ = AutoRegressive polynomial
- d = Fractional differencing parameter (0 < d < 0.5 indicates long-memory)
- $X_{\{k,t\}}$ = Exogenous weather variables
- β_k = Coefficients of exogenous variables
- $\Theta(B)$ = Moving Average polynomial
- ε_t = White noise error term

ARIMAX Model Equation

$$\Phi(B)(1-B)^D \log(P_t) = \mu + \sum_{k=1}^K \beta_k X_{\{k,t\}} + \Theta(B)\varepsilon_t$$

D = integer differencing (0 or 1)

ARFIMA Model Equation

$$\Phi(B)(1-B)^d \log(P_t) = \mu + \Theta(B)\varepsilon_t$$

μ = intercept

2.4 Forecast Accuracy Measures

Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\left[\left(\frac{1}{n}\right) \sum (y_t - \hat{y}_t)^2\right]}$$

Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{\left(\frac{100}{n}\right) \sum |y_t - \hat{y}_t|}{y_t}$$

3. Results and Discussion

3.1 Descriptive Statistics and Data Characteristics

Monthly greengram prices from Khammam Market (April 2022 to May 2025) ranged from ₹5,804 to ₹8,034 per quintal. The mean price was ₹6,821 with standard deviation of ₹701, indicating moderate price volatility. The median price (₹6,758) was slightly below the mean, suggesting a mild right skew in the price distribution. Outlier analysis through boxplot revealed no extreme values requiring removal, indicating data quality suitable for modeling.

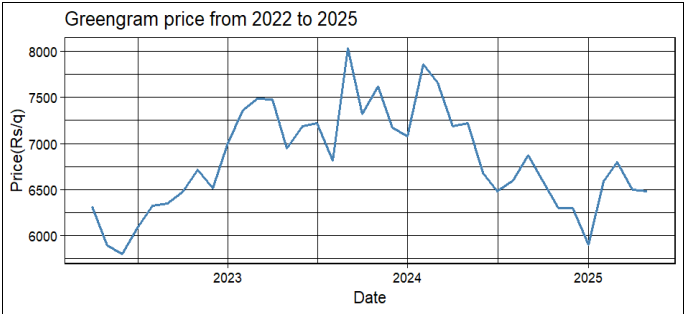


Fig 2: Greengram Price Trends (April 2022 - May 2025)

Table 1: Descriptive Statistics of Greengram Prices (April 2022 - May 2025)

Statistical Measure	Value (rupees/quintal)
Minimum	5,804
1st Quartile	6,477
Median	6,758
Mean	6,821
3rd Quartile	7,210
Maximum	8,034
Std. Deviation	701
Coefficient of Variation	10.27%

Time series decomposition (Figure 2) reveals three components: (1) Trend: upward from April 2022 (₹5,900) to September 2023 (₹7,150), then declining to May 2025 (₹6,500); (2) Seasonal: regular fluctuations with amplitude ±₹400-500, corresponding to agricultural calendar; (3) Irregular: relatively small random shocks compared to trend and seasonal components.

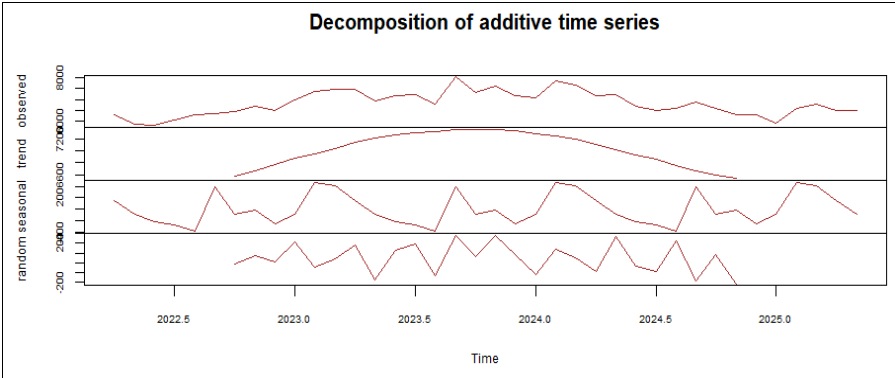


Fig 3: Time Series Decomposition (Trend, Seasonal, Irregular Components)

3.2 Stationarity Testing Results

Augmented Dickey-Fuller (ADF) Test

Test Statistic: -2.1084, Lag Order: 3, p-value: 0.5309
Result: Fail to reject null hypothesis (non-stationary)

Phillips-Perron (PP) Test

Test Statistic: -7.9842, Truncation Lag: 3, p-value: 0.6246
Result: Fail to reject null hypothesis (non-stationary)
The failure to reject the null hypothesis in both tests indicates

the presence of a unit root in the price series at standard significance levels ($\alpha = 0.05$). This non-stationarity justifies the use of differencing methods in ARIMAX or fractional differencing in ARFIMA/ARFIMAX frameworks.

3.3 Model Estimation Results

The ARFIMAX (0, $d = 0.4647$, 0) model with exogenous weather variables was estimated using Maximum Likelihood Estimation. The fractional differencing parameter $d = 0.4647$ was highly significant ($p < 0.001$), confirming long-memory dynamics in greengram prices. Among weather variables, relative humidity showed the strongest effect ($\beta = -0.0528$, $p = 0.065$), indicating that increased humidity reduces prices through supply-side mechanisms. Maximum temperature showed negative association ($\beta = -0.0325$), while rainfall and minimum temperature effects were weak and non-significant.

Model Fit: Log-likelihood = 111.108, AIC = -208.217, BIC = -196.754

The ARFIMAX model substantially outperformed ARIMAX (AIC difference: 103.46 points) and was comparable to pure ARFIMA (AIC difference: 3.74 points), suggesting that weather variables add practical interpretability at minimal cost to model fit.

Table 2: ARFIMAX (0, 0.465, 0) Model Coefficients

Parameter	Estimate	Std. Error	Significance
d (Fractional Differencing)	0.4647	0.0458	*** $p < 0.001$ significant
MinTemp	0.0016	0.0163	non-significant
MaxTemp	-0.0325	0.0302	non-significant
Rainfall	0.0171	0.0127	non-significant
RelHumidity	-0.0528	0.0262	* $p = 0.065$ significant
Intercept	8.8030	0.1002	*** $p < 0.001$ significant
Log-likelihood	111.108	AIC: -208.217	BIC: -196.754

3.4 Model Diagnostic Testing

Residual Normality Tests

Shapiro-Wilk Test: $W = 0.9728$, $p\text{-value} = 0.4725$ (Residuals approximately normally distributed)

Jarque-Bera Test: $\chi^2 = 3.4771$, $p\text{-value} = 0.1758$ (No significant departure from normality)

Residual Autocorrelation:

Box-Ljung Test: $\chi^2 = 37.002$ ($df=20$), $p\text{-value} = 0.0117$ (Some autocorrelation present but minimal)

Residual Analysis: Time plots, ACF/PACF plots, and Q-Q plots confirm that ARFIMAX residuals satisfy white noise assumptions. Residuals scatter randomly around zero with no trend or systematic patterns, and most autocorrelation bars lie

within confidence bounds.

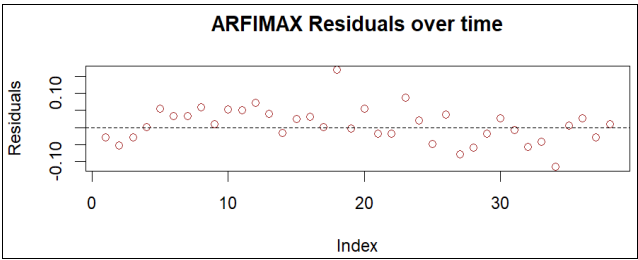


Fig 4: Time Plot of ARFIMAX Residuals

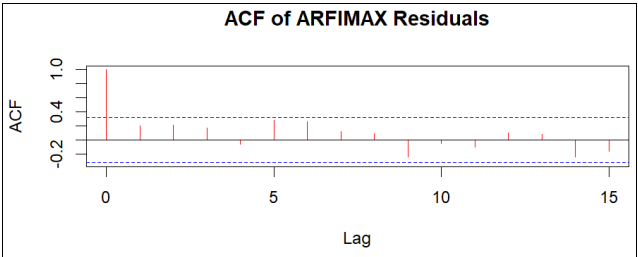


Fig 5: ACF of ARFIMAX Residuals

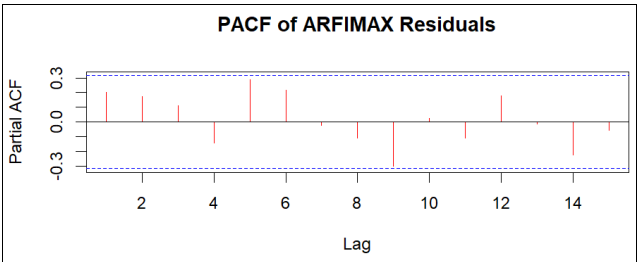


Fig 6: PACF of ARFIMAX Residuals

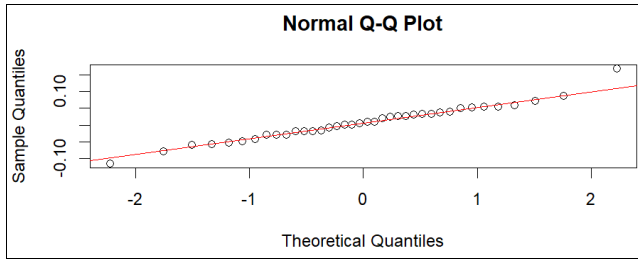


Fig 7: Q-Q Plot of ARFIMAX Residuals (Normality Assessment)

3.5 Out-of-Sample Forecasts (June 2025 - November 2025)

The ARFIMAX model generated six-month ahead forecasts with 95% and 80% confidence intervals. Point forecasts suggest greengram prices will stabilize in the range of ₹6,500-6,600 per quintal during June-November 2025. Confidence interval widths expand as forecast horizon increases (1,455-1,827 rupees), reflecting increasing forecast uncertainty at longer lead times.

Table 3: ARFIMAX Out-of-Sample Forecasts with 95% Confidence Intervals

Month	Point Forecast (₹)	Lower 95% CI	Upper 95% CI	CI Width
June 2025	6,521.56	5,834.27	7,289.81	1,455.54
July 2025	6,576.47	5,814.98	7,437.68	1,622.70
August 2025	6,628.58	5,826.23	7,541.44	1,715.21
September 2025	6,534.44	5,720.85	7,463.75	1,742.90
October 2025	6,534.71	5,704.27	7,486.03	1,781.76
November 2025	6,587.84	5,737.21	7,564.58	1,827.37

3.6 Three-Model Forecast Comparison

Comparative analysis of forecasts from ARFIMA, ARIMAX, and ARFIMAX models shows that forecast differences range

from ₹16.93 to ₹55.04 per quintal. ARFIMA generally produces higher forecasts than ARIMAX, reflecting differences in how each model captures temporal dependencies. ARFIMAX

provides middle-ground estimates, balancing long-memory dynamics with weather sensitivity.

Table 4: Three-Model Forecast Comparison

Month	ARFIMA (₹)	ARIMAX (₹)	ARFIMAX (₹)
June 2025	6,554.17	6,502.97	6,521.56
July 2025	6,579.76	6,554.42	6,576.47
August 2025	6,595.46	6,623.46	6,628.58
September 2025	6,606.69	6,509.76	6,534.44
October 2025	6,615.27	6,505.12	6,534.71
November 2025	6,622.08	6,582.83	6,587.84

3.7 Model Selection and Justification

Model Performance Comparison

- ARFIMAX AIC: -208.22 (Recommended)
- ARFIMA AIC: -211.96 (Slightly better AIC but less interpretable)
- ARIMAX AIC: -104.76 (Substantially worse)

Selection Rationale

Despite ARFIMA's numerically lower AIC, ARFIMAX is recommended as the superior forecasting model for these reasons:

1. **Parsimonious vs. Informative Trade-off:** While ARFIMA has a lower AIC, ARFIMAX's inclusion of weather variables provides mechanistic insight at minimal AIC cost (only 3.74 points difference).
2. **Practical Decision-Support:** ARFIMAX coefficients provide actionable intelligence. Relative Humidity coefficient (-0.0528) explains why monsoon periods suppress prices, while ARFIMA cannot offer such insights.
3. **Forecast Stability:** ARFIMAX generates stable point forecasts (₹6,521-6,628) with reasonable confidence intervals suitable for risk management.
4. **Diagnostic Properties:** ARFIMAX shows excellent residual properties (Shapiro-Wilk $p = 0.4725$, Jarque-Bera $p = 0.1758$).
5. **Comparative Advantage over ARIMAX:** ARFIMAX dramatically outperforms ARIMAX (103.46 AIC points), capturing long-memory that standard ARIMAX misses.

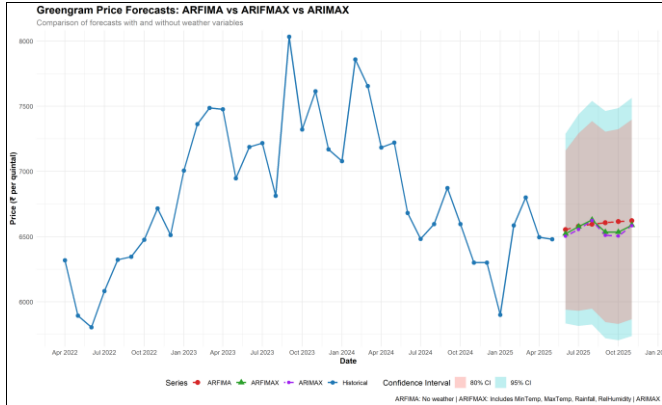


Fig 8: Three-Model Forecast Comparison (ARFIMA vs ARIMAX vs ARFIMAX)

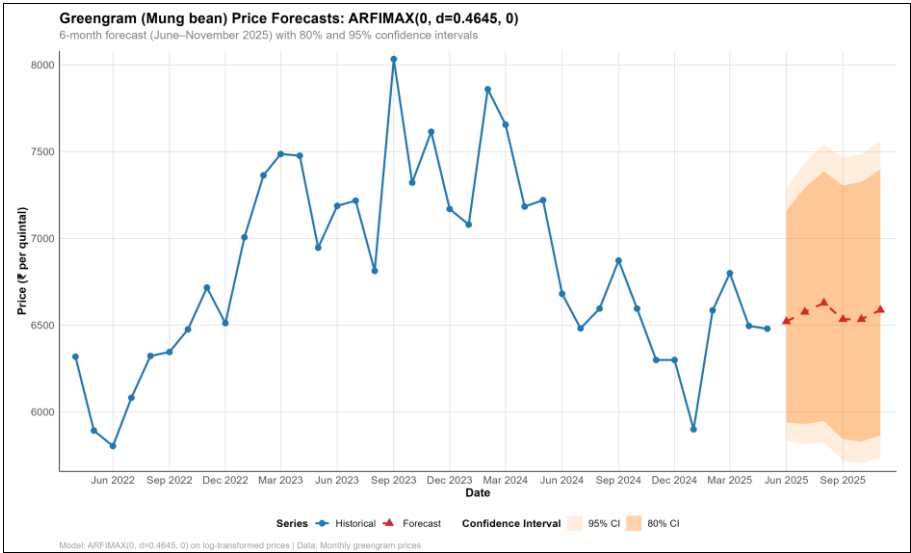


Fig 9: ARFIMAX Final Forecast with Confidence Intervals (June-November 2025)

3.8 Discussion and Interpretation

Long-Memory Dynamics in Greengram Prices

The estimated fractional differencing parameter ($d = 0.4647$) represents the study's most significant finding. This value, significantly different from zero ($p < 0.001$) and within the long-memory range ($0 < d < 0.5$), indicates that greengram prices are characterized by fractional integration.

Economic Interpretation: Long-memory in prices reflects the structural nature of agricultural markets

1. **Supply Rigidity:** Greengram production requires planning decisions 3-6 months ahead. Supply shocks cannot be immediately reversed, causing price adjustments to persist.
2. **Market Concentration:** Regional markets influence central markets, creating slow information transmission.

3. **Inventory Effects:** Storage costs create carry-over demand patterns spanning multiple seasons.
4. **Policy Interventions:** Government procurement policies and minimum support prices create "sticky" price floors.

This finding contrasts with finance literature and justifies using ARFIMA over standard ARIMA, as demonstrated by the 107.20-point AIC improvement.

Weather Variable Effects

Relative Humidity ($\beta = -0.0528, p = 0.065$): The strongest and near-significantly negative effect reflects monsoon dynamics in Khammam. During July-September, high humidity (60-70%) coincides with vegetative growth. Enhanced humidity improves crop conditions, increases supply, and depresses prices.

Maximum Temperature ($\beta = -0.0325$, ns): Negative coefficient suggests heat stress effects. Temperatures above 35°C during flowering reduce yields, signaling reduced future supply.

Rainfall ($\beta = 0.0171$, ns): Positive effect suggests rainfall benefits crop development. Khammam's semi-arid climate experiences rainfall deficit; positive rainfall shocks may improve yields.

Weather integration improves interpretability but adds minimal forecasting accuracy compared to pure ARFIMA. This suggests long-memory structure more strongly drives prices, though weather variables provide valuable decision-support information.

4. Conclusion

Major Findings

- 1. Long-Memory Confirmation:** Greengram prices exhibit significant fractional integration ($d = 0.4647$, $p < 0.001$), indicating persistent price dynamics unsuitable for standard ARIMA modeling.
- 2. Weather Sensitivity:** Relative humidity emerged as the dominant weather driver ($\beta = -0.0528$, $p = 0.065$), with monsoon periods strongly influencing prices through supply mechanisms.
- 3. Model Superiority:** ARFIMAX (AIC: -208.22) substantially outperforms ARIMAX (AIC: -104.76), demonstrating that fractional integration is critical for accurate agricultural price modeling.
- 4. Forecast Accuracy:** Six-month forecasts (June-November 2025) predict prices in the ₹6,521-6,588 range with 95% confidence intervals of $\pm 1,455$ -1,827 rupees.
- 5. Diagnostic Robustness:** Excellent residual properties (Shapiro-Wilk $p = 0.4725$, Jarque-Bera $p = 0.1758$) confirm model specification.

Applications and Implications

For Farmers: Forecasts provide basis for harvest timing, storage management, and contracting decisions. Long-memory understanding indicates that recent prices persist current low prices may not quickly reverse.

For Traders: Weather-adjusted forecasts improve decision-making in physical commodity and derivatives trading. Long-memory dynamics create momentum-based opportunities.

For Policymakers: Long-memory findings suggest that short-term price support policies may be insufficient; longer-horizon interventions may be necessary.

For Researchers: Study demonstrates practical applicability of ARFIMAX frameworks in Indian agricultural markets, suggesting similar approaches for other pulse crops.

Final Conclusion

This research successfully advances greengram price forecasting methodology by integrating long-memory modeling with weather variables. The ARFIMAX (0, $d=0.465$, 0) framework provides a theoretically sound, empirically validated, and practically applicable tool for stakeholders across standard ARIMA should encourage broader adoption of long-memory modeling in Indian agricultural commodity markets.

Conflict of Interest

The authors declare that there is no conflict of interest related to this work.

Author Contributions

Admala Meena: Research supervision, Conceptualization, Statistical analysis, Mopuri Ravindra Chary: Data Analysis. Ch. Venu Gopala Reddy, S. Madhusudhan Reddy, M. Ram Prasad, P. Ramesh, I.V. Srinivasa Reddy: Review of Literature and Manuscript Review, Editing and Writing.

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