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A nonlinear time series framework for forecasting weekly tomato prices in Chikkaballapura Market, Karnataka

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Abstract

Frequent price fluctuations in perishable agricultural commodities complicate decision-making for farmers, traders, and policymakers. This study develops and compares linear and nonlinear time series models for predicting weekly tomato prices in the Chikkaballapura market of Karnataka. Weekly data covering January 2010 to November 2018 were analysed. Stationarity was evaluated using the Augmented Dickey–Fuller procedure. Since the original series exhibited non-Stationarity, first-order differencing was applied. A linear ARIMA structure was estimated to model the conditional mean, while conditional variance dynamics were captured through a GARCH specification. Residual diagnostics from the ARIMA model revealed significant volatility clustering, justifying nonlinear modelling. Comparative forecast evaluation based on RMSE, MAE, and MAPE demonstrated that the GARCH (1, 1) formulation produced more accurate short-term predictions than the ARIMA (2, 1, 1) model. The results underline the importance of accounting for time-varying volatility when forecasting highly unstable agricultural prices.

Keywords: Tomato price forecasting, time series analysis, Conditional variance, ARIMA, GARCH, volatility modelling

1. Introduction

Price instability is a defining feature of vegetable markets in India. Tomato, due to its perishability and high market turnover, frequently experiences sharp price swings within short intervals. Supply disruptions arising from seasonal effects, weather variability, pest outbreaks, and transportation bottlenecks amplify uncertainty in wholesale markets. These rapid changes in price levels influence farm income, consumer welfare, and policy planning.

Forecasting price movements provides a mechanism for mitigating risk and improving production and marketing strategies. In situations where structural economic variables are either unavailable or lagged, Univariate time series techniques offer a practical alternative. Traditional linear models such as ARIMA effectively describe the evolution of the mean process but assume constant variance over time. However, agricultural price series often demonstrate Heteroscedastic behaviour characterized by clusters of high and low variability.

To address this limitation, volatility-based models are employed. The ARCH framework introduced by Robert F. Engle (1982) ^[3] and its extension, the GARCH formulation proposed by Tim Bollerslev (1986) ^[1], all

ow conditional variance to evolve as a function of past shocks and previous variances. These models are particularly useful when the magnitude of fluctuations changes over time.

The present study aims to (i) model the mean and variance behaviour of weekly tomato prices in Chikkaballapura market, (ii) test for volatility clustering, and (iii) compare the predictive performance of ARIMA and GARCH models.

2. Data Description

Weekly wholesale prices of tomato from Chikkaballapura market were obtained from the AGMARKNET database maintained by the Government of India. The sample spans January 2010 through November 2018. Observations from the final five weeks were withheld for validation of out-of-sample forecasts. All computations were performed using R statistical software (version 4.2.1).

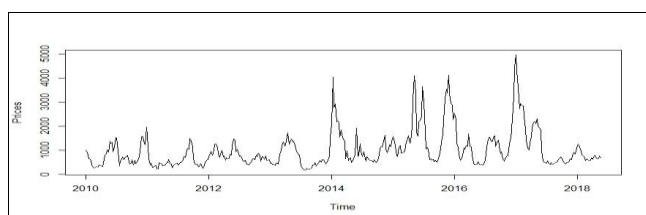


Fig 1: weekly Price series of Tomato in Chikkaballapura market

3. Methodology

3.1 Testing for Stationarity

Let P_t denote the observed weekly price at time 't' to examine whether the series is stationary, the Augmented Dickey-Fuller (ADF) regression was estimated.

$$\Delta P_t = \gamma P_{t-1} + \sum_{i=1}^k \delta_i \Delta P_{t-i} + u_t$$

Where $\Delta P_t = P_t - P_{t-1}$

γ measures persistence,

u_t is a white-noise disturbance

The null hypothesis $H_0: \gamma=0$ implies the presence of a unit root.

If non-Stationarity was detected, first differencing was applied until Stationarity was achieved.

3.2 ARIMA Model for Conditional Mean

After differencing, the transformed series Y_t was modelled using an ARIMA structure given by Box and Jenkins (1970) [2]. The general ARIMA (p,d,q) representation may be expressed using the lag operator L as:

$$\Phi(L)(1-L)^d P_t = \theta(L)\epsilon_t$$

$$\Phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \dots - \phi_p L^p$$

$$\theta(L) = 1 + \theta_1 L - \theta_2 L^2 - \dots - \theta_q L^q$$

And $\epsilon_t \sim N(0, \sigma^2)$, d denotes the order of differencing

Model identification relied on ACF and PACF behaviour. Parameter estimation was carried out via maximum likelihood. Model adequacy was assessed using residual diagnostics and information criteria:

$$AIC = -2 \ln(\hat{L}) + 2k$$

$$BIC = -2 \ln(\hat{L}) + k \ln(T)$$

Where

$\hat{L}$ is the maximized likelihood, K is number of parameters, T is sample size

3.3 Testing for Conditional Heteroscedasticity

To verify whether variance remained constant, squared residuals from the ARIMA model were examined. The ARCH-LM test was implemented using the auxiliary regression (Straumann, 2005) [8].

$$\hat{\epsilon}_t^2 = \alpha_0 + \sum_{i=1}^m \alpha_i \hat{\epsilon}_{t-i}^2 + v_t$$

The hypothesis $H_0: \alpha_1 = \alpha_2 = \dots \alpha_m = 0$ implies homoscedasticity.

Rejection of H_0 indicates ARCH effects.

3.4 GARCH Model for Conditional Variance

When volatility clustering was confirmed, a GARCH model was estimated.

The GARCH (1, 1) formulation can be written as:

Mean equation

$$P_t = \mu + \epsilon_t$$

Variance equation

$$h_t = \omega + \alpha \epsilon_{t-1}^2 + \beta h_{t-1}$$

Where $h_t = \text{Var}(\epsilon_t | \mathcal{F}_{t-1}, \omega > 0, \alpha \geq 0, \beta \geq 0$

For covariance Stationarity: $\alpha + \beta < 1$

Parameters were estimated through maximum likelihood assuming conditional normality.

3.5 Forecast Evaluation

Forecast accuracy was evaluated using given by Fan and Yao (2003) [4]:

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (P_t - \hat{P}_t)^2}$$

$$MAE = \frac{1}{n} \sum_{t=1}^n |P_t - \hat{P}_t|$$

$$MAPE = \frac{100}{n} \left| \frac{P_t - \hat{P}_t}{P_t} \right|$$

Lower values of these statistics indicate superior predictive performance.

4. Results and Discussion

4.1 Stationarity Findings

The ADF test indicated that the level price series contained a unit root. After applying first-order differencing, the test statistic became significant, confirming Stationarity of the transformed series.

Table 1: Augmented Dickey-Fuller Stationarity Test for Tomato prices of Chikkaballapura Market

Level data		
	t-Statistic	Prob*
ADF Test value	-5.652	0.000
1% Level	-3.44	
5% Level	-2.867	
10% Level	-2.570	

4.2 ARIMA Estimation

Among several candidate specifications, ARIMA (2, 1, 1) provided statistically significant coefficients and relatively lower AIC and BIC values. Residual autocorrelation was minimal, suggesting adequacy of the mean specification. However, inspection of squared residuals revealed clusters of large and small fluctuations, indicating time-varying

Table 3: AR-GARCH Model selection for the tomato Price for Chikkaballapura Market Using AIC and SBC

	Coefficient	Std. Error	Z-Statistics	Prob.
Mean Equation				
θ_0	709.77	33.792	21.00	0.000
θ_1	0.736	0.012	56.80	0.000*
Variance Equation				
α_0	78697.97	5844.18	10.868	0.000*
α_1	1.136	0.104	0.8909	0.000
α_2	1.066	0.082	12.874	0.000
β_1	-0.928	0.045	-20.266	0.000
R ²	0.727			
Akaike info criterion	14.410			
Schwartz criterion	14.464			
Durbin-Watson stat	1.466			

$$\sigma_t^2 = 3.40 + 0.304\epsilon_{t-1}^2 + 0.666\epsilon_{t-2}^2 + 0.651\sigma_{t-1}^2$$

4.4 Forecast Comparison

Out-of-sample predictions for five weeks demonstrated that:

- RMSE was lower under GARCH
- MAE was substantially reduced
- MAPE showed improved percentage accuracy

The nonlinear specification generated forecasts closer to observed market prices, especially during weeks exhibiting sharp price swings.

Table 4: Forecast Accuracy of tomato Prices and using ARIMA and GARCH

Month/week	Chikkaballapura		
	Actual	ARIMA	GARCH
47 th week	667.00	698.24	646.97
48 th week	654.14	749.27	635.45
49 th week	655.14	799.47	626.84
50 th week	764.50	843.81	619.66
51 st week	670.25	881.88	613.55
Accuracy statistics	RMSE	309.80	73.48
	MAPE	20.34	7.83
	MAE	194.63	53.71

5. Discussion

variance.

Table 2: ARIMA Model parameters for Tomato prices of Chikkaballapura Market

	Estimate	SE	Test stat.	Sig.
Difference	1			
AR Lag 1	1.100	0.023	46.83	0.000
AR Lag2	-0.214	0.026	-8.34	0.000
MA Lag1	-0.99	0.009	-105.04	0.000

4.3 Volatility Modelling

The ARCH-LM statistic rejected the null hypothesis of constant variance. Consequently, a GARCH (1,1) model was fitted (Bollerslev, 1986) [1]. Estimated parameters satisfied positivity and Stationarity conditions. The persistence parameter ($\alpha + \beta$) was less than unity, indicating mean-reverting volatility.

The empirical evidence suggests that modelling conditional variance enhances forecasting reliability in volatile agricultural markets. While ARIMA effectively captures serial dependence in the mean process, it fails to account for Heteroscedastic behaviour. The GARCH framework accommodates changing variance and therefore performs better when volatility clustering exists; such behaviour is common in perishable commodity markets where supply shocks produce irregular price spikes.

6. Conclusion

This study compared linear ARIMA and nonlinear GARCH models for forecasting weekly tomato prices in Chikkaballapura market. Although ARIMA (2,1,1) adequately represented mean dynamics, it did not capture volatility patterns. The GARCH (1,1) model demonstrated superior predictive accuracy across multiple error measures (Hanumanthaiah and Abhishek Singh, 2019) [6]. These findings highlight the importance of incorporating conditional variance modelling in agricultural price forecasting when price instability is pronounced. Future research may incorporate exogenous drivers such as arrivals, rainfall, and policy interventions to further improve forecasting performance.

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