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Forecasting of Coconut Price Using Time Series Modelling Technique

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Abstract

Coconut cultivation is widespread in India, particularly in the coastal regions, with Kerala playing a pivotal role in the country's coconut production. Accurate forecasting of coconut prices is crucial for strategic planning and decision-making among farmers, agribusinesses, and policymakers. In this study, time series forecasting is employed to predict future coconut price of Kerala by analysing historical data trends. Auto Regressive Integrated Moving Average (ARIMA) models are utilized in this research for effectively capturing discernible patterns found in historical data. The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) play a crucial role in understanding the correlation structure within the time series. They assist in identifying the order of Autoregressive (AR) and Moving Average (MA) processes incorporated into the forecasting model. Multiple combinations of AR(p) and MA (q) orders were tested, and the best model is selected based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), resulting in the ARIMA (1, 1, 0) with drift model. Forecasted prices are compared with actual prices using metrics such as Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) to evaluate the model's accuracy. This assessment process provides insights into the effectiveness of the ARIMA (1, 1, 0) with drift model in capturing and predicting fluctuations in coconut prices. The study aims to empower stakeholders in the coconut industry with valuable information, enabling them to make informed decisions amidst dynamic agricultural conditions and market dynamics.

Key words: ARIMA, coconut price, price forecasting, coconut marketing, coconut price of Kerala

JEL Classification: Q10, Q11, Q13, C22

Introduction

Coconut scientifically identified as *Cocos nucifera L.,* cultivation is widespread in India, covering a sprawling area of 21.99 lakh hectares and yielding a total production of 14301 metric tons (Ministry of Agriculture and Farmers' Welfare, 2020-21). Coconut palms are grown in several states across India, particularly in coastal regions and areas with tropical climates such as Kerala, Karnataka, Tamil Nadu, Andhra Pradesh, Odisha, West Bengal, Maharashtra, and Gujarat. Kerala is often referred to as the "Land of Coconuts" and is a major contributor to coconut production in the country. Kerala, in particular, plays a pivotal role in coconut production, boasting an area of 7.69 lakh hectares and an impressive production of 4788 metric tons (Ministry of Agriculture and Farmers' Welfare, 2020-21). Hence this study has been confined to the forecasting of coconut price for the state of Kerala.

Forecasting of price in agriculture plays a significant role in the planning and decision-making processes for farmers, agribusinesses, and policymakers. Since agriculture is inherently risky, with factors such as weather conditions, pests, and diseases affecting crop yields. Price Forecasting of price helps farmers anticipate market conditions, allowing them to make informed decisions about crop selection, production levels, and marketing strategies to manage their financial risk. Farmers need to make decisions about the types and quantities of inputs (seeds, fertilizers, pesticides) to use for their crops. Accurate price forecasts enable them to plan their input purchases more effectively, optimizing their resource allocation and improving overall farm profitability. By having insights into future price trends, farmers can time their sales to maximize profits. Understanding market dynamics allows them to choose the most opportune times to sell their produce, avoiding potential losses during periods of low prices. Accurate price forecasts assist in better supply chain management (Dellino et al., 2018). This is particularly important for coordinating the flow of agricultural products from farms to processors, distributors, and retailers. It helps all the stakeholders optimize their logistics and storage, reducing

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waste and improving overall efficiency. Governments and policymakers rely on price forecasts to formulate effective agricultural policies which includes decisions related to subsidies, import/export regulations, and other interventions to stabilize markets, extent of support-to-support farmers, and ensure food security. Price forecasting indirectly affects consumers by influencing the supply and pricing of food products. Stable and predictable prices contribute to food security and affordability, benefiting consumers and ensuring a steady food supply (IMF, 2022).

Time series forecasting is the practice of predicting future data points by analysing observed data over a specific period known as the lead time. Its primary objective is to establish a basis for effective production control, production planning, and the optimization of both industrial processes and economic planning. The ultimate goal is to achieve optimal forecasts by minimizing the mean square deviation between actual and predicted values for each lead time.

Over recent decades, substantial efforts have been invested in the development and improvement of time series forecasting models. The Box-Jenkins ARIMA model has been effectively employed for making predictions. ARIMA is used as a valuable tool for price forecasting in agriculture, especially when dealing with short-term predictions and relatively stable market, is a widely used time series forecasting method, and it can be applied to price forecasting in agriculture (Jadhav et al., 2017)

The ARIMA model, a stochastic process, is characterized by three parameters: *p*, *d*, and *q*. In this context, p signifies the Auto-Regressive (AR (*p*)) process, d involves integration (essential for transforming data into a stationary stochastic process), and *q* relates to the Moving Average (MA(*q*)) process (Gupta et al., 2018). In a stationary stochastic model, data consistently exhibit the same variance and autocorrelation. However, the challenge with the ARIMA model lies in accurately estimating its parameters. To overcome this hurdle and ensure accurate forecasting, an automated model selection process becomes imperative (Siegel, 2012) to predict the future. These are based on a model (also called a mathematical model or a process

ARIMA models are particularly useful when dealing with time-dependent data, such as historical prices of agricultural commodities. Once the model is fitted and validated to the observed data, it is used to forecast future prices. The forecast will be generated based on the established patterns in the historical data. Accuracy of the ARIMA model is evaluated by comparing its forecasts to actual prices. Common metrics for evaluation include Mean Absolute Percentage Error (MAPE), and Root Mean Squared Error (RMSE). However, these models may fall short when the underlying process is nonlinear, a common characteristic of real-world systems.

Data Sources and Methodology

Data used in this study is the monthly coconut price data (per 100 Nos) spanning from January 2007 to December 2020, sourced from the Directorate of Economics and Statistics, Government of Kerala. The monthly coconut prices from January 2007 to December 2019 were used to train the model, and the data for the entire year of 2020 were reserved for model validation.

Decomposition of additive time series

To understand the underlying patterns, the acquired time series data was decomposed using the additive decomposition method. This involves breaking down the observed data into three components: trend, seasonality, and residual. The mathematical representation of the additive decomposition is given by equation (1), Y_t where is the observed value, T_t is the trend component, S_t is the seasonal component, and ε_t is the residual component.

$$Y_t = T_t + S_t + \varepsilon_t \qquad \text{...(1)}$$

where:

Y_t is the observed value at time *t*,

T_t is the trend component at time *t*,

S_t is the seasonal component at time *t*,

ε_t is the residual (error) component at time *t*.

Once the time series is decomposed into these components are can separately examine and analyse the trend, seasonality, and residuals. This decomposition aids in making more accurate predictions and understanding the underlying structure of the time series data. It is often employed in various forecasting and analytical applications, including time series modelling and forecasting.

Autocorrelation analysis

The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) were employed for understanding the correlation structure within the time series. ACF measures the correlation between a time series and its lagged values, while PACF removes intermediate lags' effects. Significant spikes in these plots aid in identifying potential processes.

AR process

An Autoregressive (AR) process (Ullrich, 2021) is a mathematical model used to describe a time series (equation 2) where the current value of the series is linearly dependent on its past values. In other words, an AR process expresses the idea that the current observation is a weighted sum of its own past observations, with an additional white noise term representing random fluctuations. The order of the AR process, denoted as *p*, indicates the number of past observations considered in the model.

$$y_t = \sigma_1 y_{t-1} + \sigma_2 y_{t-2} + ... + \sigma_p y_{t-p} + \varepsilon_t \qquad \text{...(2)}$$

where

y_t : value of time series at time t

$\sigma_1, \sigma_2, \ldots \& \sigma_p$: autoregressive coefficients

ε_t : white noise error term at time t

MA process

A Moving Average (MA) process is a mathematical model (equation 3) used to describe a time series (Ullrich, 2021) where the current value of the series is modelled as a linear combination of past white noise terms (random shocks or innovations). Unlike the Autoregressive (AR) process that depends on past values of the time series, the MA process emphasizes the influence of past random shocks on the current observation.

$$y_t = \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \ldots + \theta_q\,\varepsilon_{t-q} \quad \ldots(3)$$

where

y_t : value of time series at time t

$\theta_1, \theta_2, \ldots \& \theta_q$: moving average coefficients

ε_t : white noise error term at time t

Autoregressive integrated moving average model

The Autoregressive Integrated Moving Average (ARIMA) model is a widely used time series forecasting method (Wilson, 2016) which combines autoregression, differencing, and moving averages. ARIMA is designed to capture different patterns and trends in time series data, making it useful for predicting future values. The breakdown of the key components of the ARIMA model. The general notation for an ARIMA model is ARIMA (*p, d, q*), where '*p*', '*d*', and '*q*' are the parameters described above. The core of the ARIMA model involves the synthesis of Autoregressive (AR) and Moving Average (MA) polynomials, creating a complex polynomial representation as illustrated in equation. The ARIMA (*p, d, q*) model is then employed across all data points in the time series data

$$y_t = \mu + \sum_{i=1}^{p}(\sigma_i y_{t-1}) + \sum_{j=1}^{q}(\theta_j \varepsilon_{t-1}) + \varepsilon_t \quad \ldots(4)$$

where

μ: represents the mean value of the time series data.

p: denotes the number of autoregressive lags.

σ: signifies the autoregressive coefficients (AR).

q: stands for the number of lags in the moving average process.

θ : represents the moving average coefficients (MA).

ε: denotes the white noise in the time series data.

The parameter '*d*' indicates the number of differences needed to make the time series stationary and is given in equation (5) below:

When d=1, $\Delta y = y_t - y_{t-1}$ ...(5)

Differencing is done up to that time point when the data becomes stationary. The Augmented Dickey-Fuller (ADF) test was used to determine stationarity. The Maximum Likelihood Estimation (MLE) method is commonly used to estimate the parameters of an ARIMA model. The goal of MLE is to find the values of the model parameters that maximize the likelihood function. The likelihood function measures the probability of observing the given set of data under the assumed ARIMA model. The model selection is done using criteria such as Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) (Akaike, 1974)

Model evaluation

The predictive capabilities of the ARIMA models are assessed using the data for the year 2020 kept for validation purpose. Performance metrics such as Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) were calculated to quantify the accuracy of the model's predictions. MAPE and RMSE provide quantitative measures of how well the ARIMA model is forecasting or predicting the values compared to the observed values. Regularly evaluating the ARIMA model using MAPE and RMSE creates a feedback loop for improvement.

Results and Discussion

Time series plot

The first step in time-series analysis is to plot the data. A time series plot is a graphical representation of a series of data points in chronological order, typically with the time variable on the x-axis and the corresponding values on the y-axis. Time series plots are widely used to visualize trends, patterns, and fluctuations in time-dependent data. The time series plot of the series under consideration are given in Figure 1. A perusal of figure indicates monthly price of coconut in Kerala has increased over the years. The mean price of coconut during study was Rs.1078.2 which range between Rs.412.7 to Rs. 2103.2 as shown in Table 1.

Decomposition of additive time series

The additive decomposed plot provides a visual breakdown of distinct elements within time series data—namely, the trend, seasonality, and residuals (Figure 2). The trend component, characterized by an upward slope, signifies positive growth or a prevailing trend in the time series. On the

Table 1. Descriptive statistics of monthly coconut price of Kerala

Series	Min	Max	Mean	St. Dev.	CV (%)	Skewness	Kurtosis
Coconut Price	412.7	2103.2	1078.2	520.03	48.23	0.31	1.65

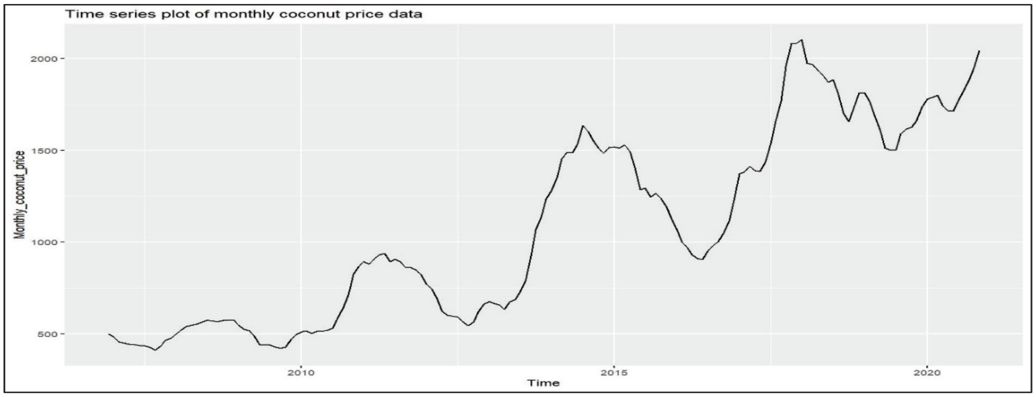

Figure 1: Time series plot of monthly coconut price of Kerala

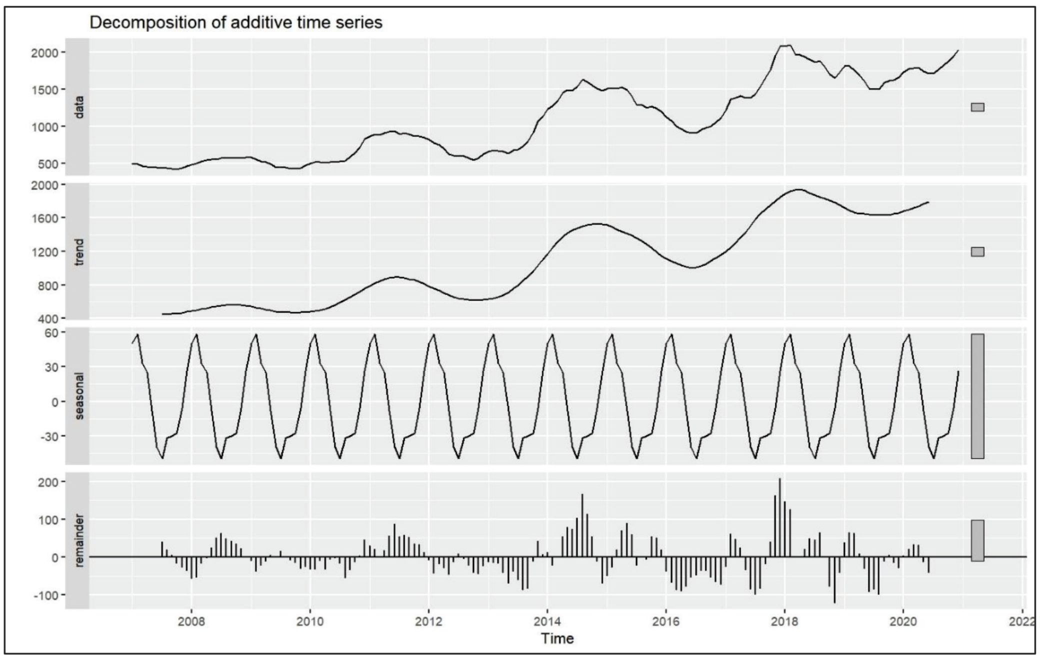

Figure 2: Decomposition of coconut price time series into additive components

other hand, the seasonal component showed some patterns or cycles, as evidenced by regular peaks and troughs, which may indicate a seasonal nature of the time series data. The residual (error) component exhibits random fluctuations without any apparent pattern. Notably, the residuals maintain a mean value close to zero, suggesting an unbiased representation of the observed data. In essence, interpreting an additive decomposed plot entails scrutinizing each component to glean insights into trends, seasonality, and residuals. This holistic approach enhances our comprehension of the inherent patterns within the time series data.

Test for stationarity

PP test (Phillips and Perron, 1988) and Augmented Dickey Fuller (ADF) test (Dickey & Fuller, 1979) test are employed to see the presence of unit root in the data set. The results of the test are reported in Table 2. It is clear from the results of both test that the null hypothesis of unit root test is not rejected at 5% level of significance indicating non stationarity of the series. Table 2 also shows that the time series become stationary after first order differencing.

Table 2: Tests for stationarity

Test for stationarity on raw data			
ADF test		**PP test**	
d	**p-value**	***Z***	**p-value**
-3.38	0.06	-12.1	0.42
Test for stationarity on differenced data			
ADF test		**PP test**	
d	**p-value**	***Z***	**p-value**
-3.79	0.02	-57.63	<0.01

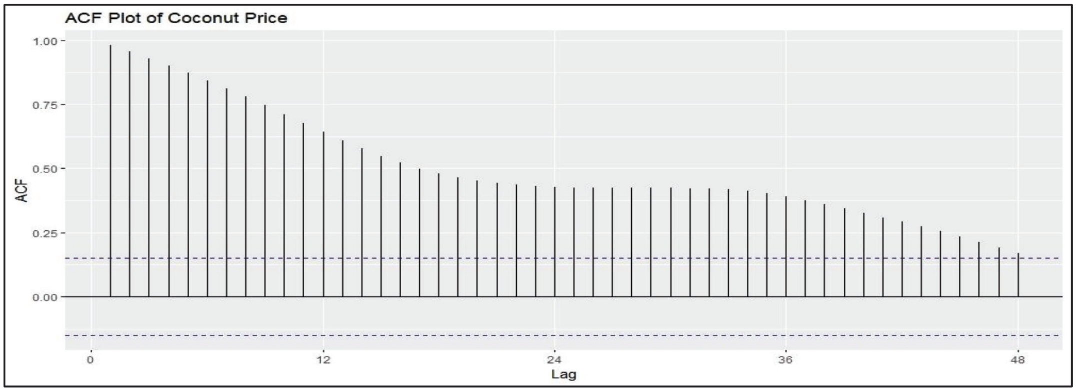

Figure 3: ACF plot of monthly coconut price (raw data)

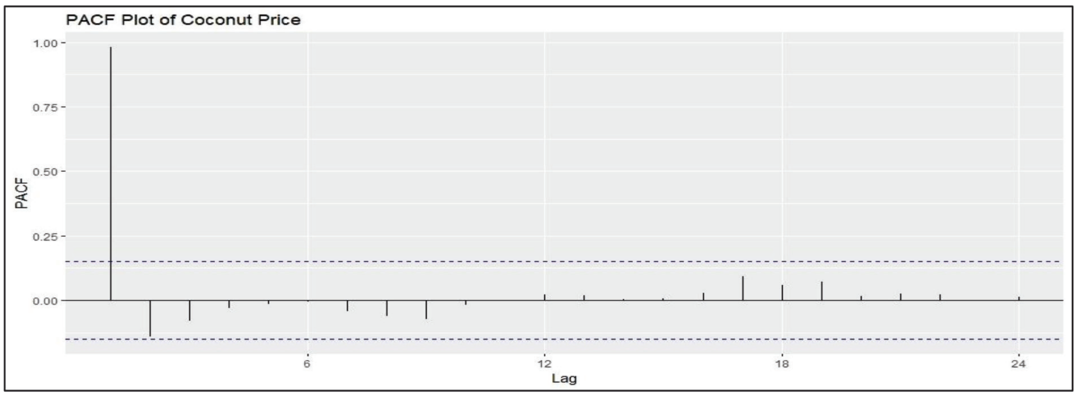

Figure 4: PACF plot of monthly coconut price (raw data)

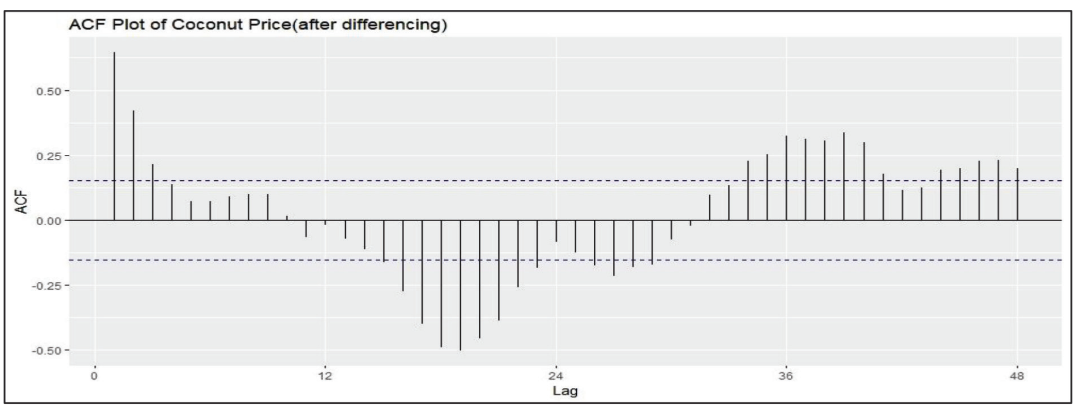

Figure 5: ACF plot of monthly coconut price (after differencing)

ACF and PACF plots

Figure 5 and 6 indicated the presence of significant spikes or peaks in the ACF and PACF plots of differenced series at certain lags indicate strong autocorrelation at those lags. We will not consider higher order of p and q because those model selections may violate law of parsimony. Hence looking at these ACF and PACF plots of differenced series, we select up to two orders of p and q on a trial-and-error method.

Fitting ARIMA model

In this section, on the basis of value and AIC value and BIC value, best fitted ARIMA model is selected for the series. The best fitted model is ARIMA(1, 1, 0) with drift since it has the lowest AIC value (1579.864) and second lowest BIC value (1596.47) as shown in Table 3. ARIMA (1, 1, 0) without drift model has lowest BIC value (1592.14) because BIC added penalty for adding one additional drift parameter in the model.

Parameter estimates of selected ARIMA (1,1,0) with drift along with corresponding p-values are presented in the Table 4. The p-values suggest that the parameters are

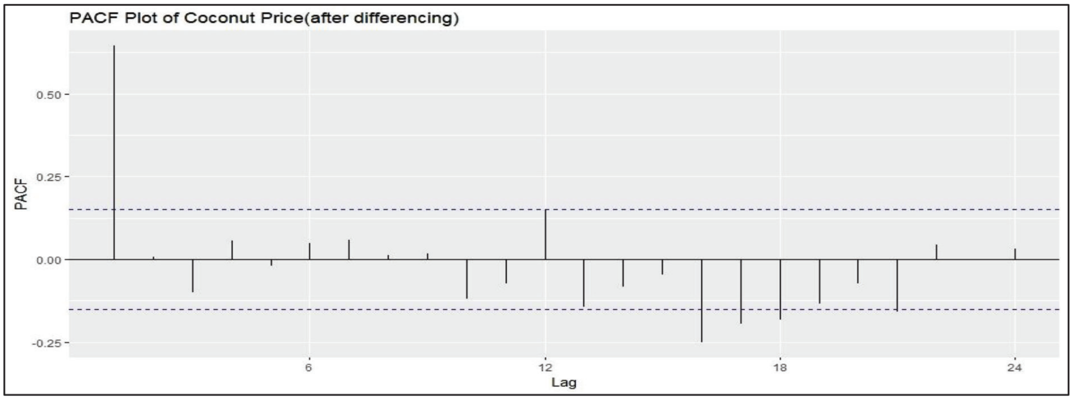

Figure-6: PACF plot of monthly coconut price (after differencing)

Table 3. AIC and BIC values of ARIMA models

Sl. No	Model	AIC	BIC
1	ARIMA (2, 1, 2) with drift	1591.44	1609.7
2	**ARIMA (1, 1, 0) with drift**	**1579.864**	**1596.47**
3	ARIMA (0, 1, 1) with drift	1615.73	1624.86
4	ARIMA (2, 1, 0) with drift	1589.27	1601.44
5	ARIMA (1, 1, 1) with drift	1589.29	1601.46
6	ARIMA (2, 1, 1) with drift	1589.02	1604.24
7	ARIMA (1, 1, 0) without drift	1586.05	1592.14
8	ARIMA (2, 1, 0) without drift	1587.95	1597.08
9	ARIMA (1, 1, 1) without drift	1587.97	1597.1
10	ARIMA (0, 1, 1) without drift	1615.82	1621.91
11	ARIMA (2, 1, 1) without drift	1587.7	1599.88

significant at 1% level of significance. After that, residuals of best fitted models are investigated. Residuals didn't show any significant pattern, which indicates that it is a white noise process.

Table 4: Parameter estimates of ARIMA (1, 1, 0)

Parameter	Estimate	p-value
AR (1)	0.64	<0.01
Drift	7.53	<0.01

Residual diagnostics

After fitting an ARIMA (1, 1, 0) model with drift to the coconut time series, we conducted the Box test to assess the presence of autocorrelation in the residuals. The null hypothesis of this test posits that there is no autocorrelation in the residuals. Examining the results presented in Table 6, we observe that the p-value exceeds the chosen significance level. Consequently, we do not reject the null hypothesis. This implies that there is no significant evidence of autocorrelation in the residuals.

The findings suggest that our ARIMA (1, 1, 0) model with drift effectively captures the underlying patterns in the coconut time series, leaving no discernible autocorrelation in the residuals. Therefore, we can assert that our model provides a comprehensive fit to the data, and no additional information is left unexplained in the residuals. In essence, the coconut time series is well-represented by our model, and it appears to be a suitable and complete description of the observed data.

Model validation

A comparative performance of the results of ARIMA model has been carried out in terms of Mean absolute percentage error (MAPE) and Root mean square error (RMSE) and is reported in Table 5. Model selection is typically carried out using AIC and BIC values. Based on these criteria, we initially chose an ARIMA (1, 1, 0) model with drift. However, during model validation, we compared several models using MAPE and RMSE values to ensure the chosen model's superiority.

Table 5: Validation of ARIMA (1, 1, 0) with drift model

Sl. No	Model	Training data		Testing data	
		RMSE	MAPE	RMSE	MAPE
1	ARIMA (2, 1, 2) with drift	39.28	2.84	96.57	3.87
2	**ARIMA (1, 1, 0) with drift**	**39.53**	**2.82**	**99.5**	**4.01**
3	ARIMA (0, 1, 1) with drift	43.36	3.1	122.23	5.03
4	ARIMA (2, 1, 0) with drift	39.52	2.82	98.85	3.99
5	ARIMA (1, 1, 1) with drift	39.53	2.82	98.96	3.99
6	ARIMA (2, 1, 1) with drift	39.21	2.82	103.54	4.22
7	ARIMA (1, 1, 0) without drift	39.62	2.79	134.39	5.29
8	ARIMA (2, 1, 0) without drift	39.61	2.79	132.73	5.23
9	ARIMA (1, 1, 1) without drift	39.61	2.79	133.02	5.24
10	ARIMA (0, 1, 1) without drift	43.65	3.05	169.44	7.47
11	ARIMA (2, 1, 1) without drift	39.29	2.79	137.17	5.42

Table 6: Ljung-Box test on residuals from ARIMA (1, 1, 0) with drift model

Q	df	p-value
5.78	9	0.76

The ARIMA (2, 1, 2) model with drift exhibited only a marginal improvement over our selected ARIMA (1, 1, 0) model with drift. Considering the principle of parsimony (Epstein, 1984), we prioritize simpler models with fewer parameters. Though additional parameters can add more information into the model, they are not preferred unless they significantly reduce errors during fitting on another dataset for the same commodity.

Here our ARIMA (1, 1, 0) with drift model has performed much reasonably with a smaller number of parameters as compared with ARIMA (2, 1, 2) with drift model. It reaffirms our selection of ARIMA (1, 1, 0) with drift model as the best suited forecasting model for the time series under consideration with relatively lower RMSE and MAPE value for both testing and training data set.

Graphical representation of actual and fitted values of monthly coconut price of Kerala is represented below in Figure-4. Blue line represents actual data series and red line represents fitted value series. It is clear from the Figure 4 that two lines are nearly overlapping to each other, which shows that our fitted model is capture almost all the variations in the actual time series data and is a best fit.

Conclusion and Policy Implications

In this study, our primary objective was to develop a robust forecasting model for coconut prices in Kerala using monthly price data. Initial assessments through Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests revealed that the raw data was non-stationary. To address this, we applied differencing to the data, rendering it stationary. Subsequently, by analysing the Autocorrelation Function and Partial Autocorrelation Function plots of the differenced time series data, we systematically experimented with various combinations of ARIMA parameters (*p, d, q*).

The selection process involved evaluating the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values for each candidate model. Our final choice was an ARIMA (1, 1, 0) model with a drift component. To validate the model's performance, we conducted thorough assessments on both training and testing datasets, employing metrics such as RMSE and MAPE.

Although certain models with a greater number of parameters exhibited marginal improvements in accuracy compared to our chosen ARIMA (1, 1, 0) with drift model, these advantages were deemed negligible. This decision aligns with the principle of parsimony (Epstein, 1984), reinforcing our confidence in the selected model's ability to effectively forecast coconut prices in Kerala.

The development of a robust forecasting model for coconut prices in Kerala, employing an ARIMA (1, 1, 0) model with a drift component, carries significant financial implications for stakeholders in the coconut industry. The accurate prediction of future coconut prices, facilitated by rigorous statistical analyses and model selection based on AIC and BIC values, enhances decision-making across the supply chain. Growers, traders, and businesses can optimize resource allocation, mitigate risks, and streamline operations, leading to cost efficiencies and improved profit margins. Investors benefit from informed decision-making, aligning their strategies with anticipated market trends, while the government can utilize the insights to formulate effective policies supporting agricultural stability. Overall, the adoption of this forecasting model not only strengthens financial

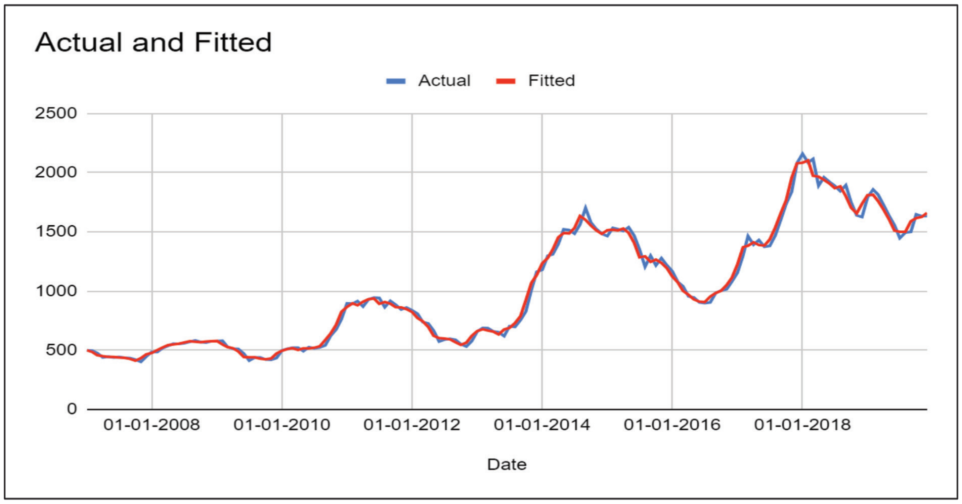

Figure 7: Actual vs Fitted values of monthly coconut price of Kerala

performance at various levels of the coconut industry but also fosters a more resilient and competitive market environment in Kerala.

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