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Abstract

This study aimed to comprehend the price behavior of tomato crops and forecast their prices in the Koyambedu market in Tamil Nadu, one of the major vegetable markets in South India. Secondary data on price of tomatoes were collected from Agricultural Produce Market Committees (APMCs) for a period of 8 years, from 2014 to 2022. Statistical tools such as trend analysis and seasonality indices were computed to understand the movement of prices in the Koyambedu market. Results revealed peak market prices in November and lowest in March, with a positive trendline indicating a gradual price increase over the study years. Comparative analysis between Autoregressive Integrated Moving Average (ARIMA) and Seasonal-ARIMA (SARIMA) assessed price prediction accuracy. The periodogram highlighted significant seasonality, guiding the use of SARIMA to forecast 2023 monthly prices. Predicted prices ranged from 3675.00 Rs/Qtl in November to 1178.76 Rs/Qtl in May.

Keywords: Price analysis, Market prices, Price forecasting, ARIMA.

INTRODUCTION

The Indian economy is largely supported by the agricultural industry, which is a significant part of the global economy. The seasonality of agriculture and the natural circumstances around its products are key factors in its development. Environmental conditions have an impact on the financial standing of the commodities in the markets. There are several agro-climatic conditions in India that favour the growth of numerous crops. The quality, price, and arrival of the produce can all be impacted by climate fluctuations. One of the world's most important agricultural products, the tomato, is grown practically everywhere. The crop's nutritional advantages, including the presence of important minerals and elements like vitamin B, C, and iron (Sainju and Singh, 2003) have earned the tomato the moniker of "protective food" (waheed et al., 2003).

With an estimated 15.52 percent of the world's total area under tomato production, India is the second-largest tomato producer in the world (21.95 million tonnes), after China (62.86 million tonnes) (Singh and Kaur, 2021). Vegetable production and area shares between Tamil Nadu and India are roughly 2.35% and 3.5%, respectively (Tamilselvi et al., 2021). The southern states of India make up around 31.65% of the nation's overall output, with Tamil Nadu contributing 11.26%. In India, tomato production and yield have increased by 12.88% and 17.96%, respectively. On the other hand, from 2011 to 2021, the area fell by 4.60% (Agricultural Statistics at a Glance, 2021).

The affordability of a product to customers is determined by its quality when it is released onto the market. Price fluctuation and limited storage facilities are the two main obstacles in the tomato market (Shah and Ansari, 2020). Therefore, seasonal and ecological imbalances affect the supply and demand of the item, affecting the

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prices and the income received by the farmers. To maximize social welfare in a competitive economy, a pricing system that instructs producers on what and how much must be produced given the resources at hand is crucial. The volatility of agricultural prices leads to uncertainty since farmers make decisions based on price considerations. One of the biggest causes of risk in a farmer's agricultural and marketing decisions is price volatility or instability. Consequently, in order to plan the commodity's marketing and get a competitive price, it is important to analyze the behavior of tomato prices in various markets (Kumar et al., 2020). For the goal of forecasting and predicting the future price trend in the market, market analysis in agriculture can be used as a crucial instrument. To satisfy the increased demand brought about by contemporary times, appropriate strategies and policies should be implemented to improve tomato production. This will ensure that farmers' receive a quality income, farmers can schedule production, harvesting methods, and storage plans. The market's effectiveness can be increased, and price volatility can be decreased, by comprehending the price and arrival pattern of tomatoes (Singh and Kaur, 2021). Thus, examining tomato market prices of tomato, paves the way for understanding market price patterns, trends, and factors that influence price variations, which is advantageous to both producers and consumers.

In light of this, the current study was carried out with the particular goals of analysing wholesale pricing behaviour, determining trend behaviours and seasonality for tomato crop price, and projecting tomato price data in Koyambedu market. The Koyambedu market receives almost fifty percent of its products from Karnataka, Andhra Pradesh, Kerala, Gujarat and Maharashtra. Most of the farmers from Rayalaseema of Andhra Pradesh come to Koyambedu market to sell their produce (Tamilselvi et al., 2021).

MATERIALS AND METHODS

This chapter covers a brief explanation of the methods, data collection, and analytical tools used in the study. These are discussed under the following subheadings.

Data Collection

The time series data on the monthly price of tomatoes were collected from the registers maintained by Agricultural Produce Market Committees (APMCs), on total modal prices (Rs Qtls-1) during the months. The data was gathered from the Koyambedu market over an 8-year period, from 2014 to 2022.

Data Analysis

Seasonal Indices – The ratio

To explain the changes in tomato prices caused by seasonal variations, the seasonal indices of the collected data were generated. Tomatoes must be consumed almost soon after harvest since they are a product that is particularly vulnerable to perishability during storage, transport, and other processes. As a result, its market value swings in accordance with the seasonal environment. It was calculated using a ratio to moving average method. (Gholap et al., (2021))

Seasonal index= (The actual value of price (or)arrival of that month)/(moving average of that month) x 100------(1)

Intra-Year Variation

The intra-year variation refers to the fluctuations or changes in variables, within a single year. The seasonal indices were used to calculate the intra-year fluctuation in the prices of the chosen markets. (Gholap et al., (2021))

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Coefficient of variation= (Standard Deviation)/Mean*100------ (2)
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Trend Analysis

To comprehend the pattern and behaviour of the tomato price data acquired in the chosen market, a trend analysis of the data was conducted. Trend lines make it possible to understand how pricing has changed over

the course of the study's time period. Linear trend analysis of the data was computed with the equation. (Gholap et al., (2021))

 $Y = \alpha + \beta t \qquad -----(3)$

Where,

Y is the price of the tomato crop,

A is the intercept coefficient,

 β is the coefficient of regression, and,

t is the time variable.

Price Forecasting

Econometric methods were utilized to forecast tomato prices in 2023, aiming to empower farmers in their marketing decisions by optimizing returns, mitigating risks, and bolstering negotiation advantages. Monthly tomato price data spanning from January 2014 to December 2022 (60 observations) were analyzed. The stationarity of the data was assessed using the Augmented Dickey-Fuller test. Dragan et al. (2015) found the Autoregressive Integrated Moving Average (ARIMA) model satisfactory for tomato price forecasting, while Boateng et al. (2017) highlighted the enhanced predictability of the seasonal ARIMA (SARIMA) model. Assis et al. (2010) further validated SARIMA's suitability for vegetable price forecasting over other methods. The ARIMA model is characterized by parameters p, d, and q, denoting autoregressive terms, differencing iterations, and moving average terms, respectively. The SARIMA model, encompassing both seasonal and non-seasonal components, is represented as ARIMA(p, d, q)(P, D, Q)S, where P, D, and Q represent seasonal AR, differencing, and MA terms, respectively. The estimation of these models is facilitated by the systematic BoxJenkins methodology (Box and Jenkins, 1976), known for extracting comprehensive information from time series data (Permanasari et al., 2009).

To formulate the ARIMA model, it is crucial to determine the values of p, d, and q. This involves plotting autocorrelation functions (ACF) and partial autocorrelation functions (PACF) of the variables at different lag lengths. Once the parameters are determined, the model's diagnostic evaluation is conducted to validate it. This includes assessing data residuals. Various criteria such as Akaike Information Criteria (AIC), Schwarz Information Criteria (SIC), r-squared value, and Log-likelihood are utilized to select the most accurate model. A model with the lowest AIC/SIC value is preferred for forecasting (Lama et al., 2015). Correlograms play a vital role in model validation and in specifying and selecting the orders of p and q. A well-fitted model can be trusted for forecasting when residuals, ACF, and PACF of the residuals exhibit characteristics of white noise.

For SARIMA model, the data's seasonal variations and fluctuations were identified using periodogram. The power spectral density (PSD) of the data shown against frequency is called a periodogram. The frequency is displayed on the x-axis as the quantity of cycles per unit period, in this case, months. The power spectral density, which is a gauge of how much variance in the time series is explained by each frequency, is displayed on the y-axis. As a result, the graph is drawn to represent the seasonality of the study's data. Parameter estimation and selecting the best model to fit the data is done, after which the models are validated using the ACF and PACF to plot the model's residuals. The model is acceptable when the residual is white noise. Finally, price estimates for the best fit model were done.

RESULTS AND DISCUSSION

This chapter delves deeply into the interpretation of the data and the discussion of the findings. The relationship between price, pricing behaviour and changes, market influence on other markets, and forecasting models are all thoroughly discussed.

Variations and patterns in Tomato Price

The supply and demand in the market determine the prices of tomatoes, as the crop is highly perishable and is posed to erratic variations, making the tomato prices quite volatile. The examination of seasonality of prices over time will help in quantifying the observable variation. Table 1 displays the final estimated seasonal indices for tomato prices. Prices at the Chennai Koyambedu market reached their highest point in November (134.79) and their lowest point in March (65.58). The computed values are in accordance with a study conducted by Tamilselvi et al., (2021) in the Koyambedu market. The ANOVA test showed no significant difference among the monthly prices. This indicates that the seasonal pattern did not change over the years and there is seasonality within a year. The display of 25.25% variation within the year can be recorded, which justifies the report by Tamilselvi et al., (2021), which implies that the price of tomato crops varies over the course of a year.

Month	Seasonal Index
Jan	90.89
Feb	71.57
Mar	65.58
Apr	66.68
May	118.33
Jun	123.31
Tul	134.19
Aug	96.29
Sep	84.84
Oct	117.62
Nov	134.79
Dec	95.93
Intra year variation %	25.2548

Table 1: Seasonal Index of The Price of Tomato in The Koyambedu Market.

Identification And Analysis of Patterns Through Trend

The trend analysis of tomato price in the Koyambedu market can be fitted in the equation

Yt = 1858.058+9.48t, where Yt is trend value at time 't' and t is the time period. The goodness of trend line was tested by the coefficient of multiple determination, which is denoted by R2, which is 0.28. The average monthly price is 1858.06 Rs. /Qtl and it is increased by 9.48 Rs. /Qtl. The figure 1 depicts an increasing price trendline, it is interpreted to be a positive trend in the price of tomato. The results are in line with the findings of Sharma (2011), Tamilselvi et al., (2021), Dudhat et al., (2021) and Preethi et al., (2019) irrespective of the crop. The price has increased over the years, taken for study. The increase in price might be due to various factors, such as low market arrival and increase in population. According to India Today, 2022, there was almost 50% reduction in the arrival due to rains in Karnataka and Andhra Pradesh. The harvested tomatoes were brought to Koyambedu from these states. Even though the production has increased, it couldn't keep in pace with the substantial consumption of tomato.



Figure 1: Trendline of the market price of Koyambedu market

Price Forecasting

The Augmented Dickey-Fuller test (Dickey & Fuller, 1979) was used to check if the variables are stationary. The result of the ADF unit root test of the wholesale price of tomato was stationary at level with a significant p value of 1.48E-10. Hence, the null hypothesis of non-stationary was rejected.



Figure 2: Correlogram of tomato price in Koyambedu market

Table 2: Different ARIMA Models for Koyambedu Market

Serial No.	Models	AIC	SIC	Adjusted r squared
1	(1,0,1)	1833.1	1843.829	0.353
2	(2,0,1)	1832.77	1846.181	0.36
3	(7,0,1)	1836.986	1863.808	0.37
4	(2,0,1)	1832.77	1846.181	0.36
5	(1,0,7)	1837.865	1864.686	0.37

The ARIMA models were developed based on the order combinations of ACF and PACF, which were obtained through a correlogram. (Fig 2). The best model was selected after considering the criterions such as least Akaike Information Criterion (AIC) value, least Schwarz Information Criterion (SIC) (Lama *et al.*, 2015), highest R²value and significant coefficients of AR & MA process, the best model was selected for each market. The

correlogram of the residuals indicate white noise in the chosen models of ARIMA. Table 2 has different ARIMA models with the details of AIC, SIC and adjusted R² value. The accuracy was not satisfactory



Figure 3: Periodogram of tomato price in Koyambedu market

Variations in peak heights were observed in the periodogram (Figure 3), where peaks signify the strength of spectral density at specific frequencies. Peaks at low frequencies indicate long-term trends, while those at high frequencies represent short-term fluctuations, indicating periodicity in the markets.

Serial No.	Models	AIC	SIC	Adjusted r squared
1	(1,0,2) (2,0,2)	1830.14	1854.28	0.50
2	(1,0,3) (2,0,2)	1832.14	1858.96	0.50
3	(3,0,3) (2,0,2)	1835.81	1867.99	0.49
4	(3,0,3) (3,0,3)	1834.30	1871.85	0.56
5	(1,0,3) (2,0,3)	1833.04	1862.54	0.52

Table 3: Different SARIMA Models for Koyambedu Market

SARIMA models were selected based on various ARIMA (p, d, q) x (P, D, Q) S combinations. The top five alternative models (Table 3) were evaluated using Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), Log likelihood, and r-squared values. The final model in each market was chosen based on the lowest AIC and SIC values. Among the options, the (1,0,2)(2,0,2) model demonstrated the lowest AIC and SIC values at 1830.14 and 1854.28, respectively, making it the most suitable for forecasting wholesale tomato prices in the Koyambedu market. Further analysis ensured the independence of model residuals, with autocorrelation and partial autocorrelation functions falling within confidence interval limits, indicating captured temporal dependencies and white noise. A unit root test confirmed residual stationarity, allowing for monthly tomato price forecasts for the year 2023 using the SARIMA model.



Figure 4: The observed and forecasted price of tomato in the Koyambedu market

Figure 4, shows the comparison of observed and forecasted monthly price of tomato in Koyambedu for the year 2023. The results depicted that the predicted price does not differ much from the observed price. This indicates that the model is an acceptable fit to predict tomato price. A study by Reddy (2019) on price forecasting of tomatoes, showed minimal variation between the observed and forecasted prices in almost all the states taken for study. The results proved that SARIMA model was good fit for the data, but there were large differences between the upper and lower confidence limits, which is also reflected in the market conditions. Darekar and Reddy (2017) forecasted agricultural commodity prices using a similar methodology in an effort to educate farmers of price changes.

Months	Koyambedu
Jan 2023	3140.14
Feb 2023	2814.98
Mar 2023	2369.31
Apr 2023	1975.71
May 2023	1178.76
Jun 2023	2067.83
Jul 2023	2665.22
Aug 2023	2786.19
Sep 2023	2536.19
Oct 2023	3025.03
Nov 2023	3675.00
Dec 2023	3224.38

Table 4: Forecasts Of Tomato Price in The Koyambedu Market (Rs. /Qtl)

The forecasted price is depicted in Table 4, according to which the predicted price estimated is highest in the month of November with 3675.00 Rs/Qtl and least in the month of May with 1178.76 Rs/Qtl. The increase of price in November can be as a result of retreating monsoon which causes cyclones in the south east coast regions of India, which could possibly affect the harvest, thereby reducing the arrival in the market and rise of price. The month of May is a season of harvest for tomato in Tamil Nadu, surplus arrivals can result in decreased prices of tomatoes in the market.

CONCLUSION

The wholesale price of tomato for Koyambedu market was considered for the study. The market behaviour of price and, identification of seasonal variations and analysation of such patterns were done using statistical tools such as seasonal index and trend analysis respectively. The price behaviour based on seasonal index revealed that the price increases in the month of November and decreases in March. The intra year variation signified the occurrence of seasonality within the year, as it was 25.25%. The wholesale price showed a positive trend with increasing price over the years taken for study. The SARIMA model was chosen over the ARIMA model to improve the accuracy. The periodogram with the peaks proved the significance of seasonality. All the necessary steps of SARIMA model were applied systematically based on the Box & Jenkins methodology for forecasting, for the year 2023. The prediction shows that the price increase and tomato harvest time are related. The predicted price reduced significantly in the month of May and increased in the month of November. It was also determined that forecasted price of tomato has wide range of upper and lower confidence limits, which can be addressed with an improvised model for better prediction accuracy. The low forecasting power of the econometric models for tomatoes are seen due to wide range of fluctuations during the harvest period. Since the predicted and observed price have little difference, the estimated prices for the year 2023 can be disseminated among the stakeholders to make informed decisions of the production, trade, marketing and storage.

REFERENCES

- Assis, K., A. Amra, and Y. Remali. 2010. Forecasting coco bean prices using univariate time series models. J. Arts Sci. Commerce. 1:71–79.
- Boateng, F.O., A.M. John, A. Martin, O. Lot, and D. Paul. 2017. Modeling of tomato prices in Ashanti region, Ghana, using seasonal autoregressive integrated moving average model. Br. J. Math. Comput. Sci. 20(2):1–13.
- Box, G.E.P., and G.M. Jenkins. 1976. Time series analysis: Forecasting and control. San Francisco: Holden-Day
- Darekar, A., and A.A. Reddy. 2017. Price forecasting of pulses: Case of pigeon pea. J. Food Legumes. 30(3):42-46.
- Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association, 74(366a), 427-431.
- Dragan, I., M. Beba, N. Nebojsa, and V. Natasa. 2015. Analysis and prediction of tomato price in Serbia. Econ. Agric. 62(4):951–962.
- Dudhat, A.S., Yadav, P. & Prajapati, A.P. (2021). The change in behaviour of market arrivals and prices of Groundnut in Amreli regulated market (Gujarat). [online] Amazonaws.com.
- Gholap, V. B., Patil, S. N., & Benke, S. R. (2021). Economic analysis of arrival and price behaviour of tomato in Gultekdi market Pune. Journal of Pharmacognosy and Phytochemistry, 10(2), 416-419.
- Kaur, G., Singh, G., & Kaur, P. (2021). Market integration of selected tomato markets in northern india. Agricultural Research Journal, 58(2).
- Kumar, H. P., Tevari, P., Beeraladinni, D., & Kammar, S. (2020). Price forecasting in chilli crop in major markets of Karnataka State, India. Int. J. Curr. Microbiol. App. Sci, 9(05), 3221-3226.
- Lama, A., Jha, G. K., Paul, R. K., & Gurung, B. (2015). Modelling and forecasting of price volatility: an application of GARCH and EGARCH models §. Agricultural Economics Research Review, 28(1), 73-82.
- Mysore, S., Bharathi, B., Maheshbabu, V., Chandraprakash, M. K., Srinivasamurthy, D., & Gajanana, T. M. (2016). Analysis of market arrivals and prices of tomato for price prediction in Karnataka state. International Journal of Innovative Horticulture, 5(2), 98-103.
- Permanasari, A. E., Rambli, D. R. A., & Dominic, D. D. (2009). Prediction of Zoonosis Incidence in Human using Seasonal Auto Regressive Integrated Moving Average (SARIMA). arXiv preprint arXiv:0910.0820.
- Preethi, V.P., Thomas, J.K., Kuruvila, A., John, L. C., & Phuge, S.C. (2019). Price Behaviour of coconut in major markets of Kerala: A time series analysis, International Journal of Chemical Studies, 7(1), 148-154.
- Reddy, A. A. (2019). Price forecasting of tomatoes. International Journal of Vegetable Science, 25(2), 176-184.
- Sainju, U. M., Dris, R., & Singh, B. (2003). Mineral nutrition of tomato. Food Agric. Environ, 1(2), 176-183.
- Shah, P., & Ansari, M. A. (2020). A study of marketing and production constraints faces by vegetable growers. Asian J Agric. Ext., Econ. and Socio, 38(11), 257-63.
- Sharma, R. (2011). Behaviour of market arrivals and prices of tomato in selected markets of north India. International Journal of Farm Sciences, 1(1), 69-74.
- Tamilselvi, C., Mohan Naidu, G., Ramana Murthy., & Dr. Rajeswari, S. (2021). Behaviour of Market Arrivals and Prices of Vegetables in Koyambedu Market, Chennai. International Journal of Agricultural and Statistical Sciences, 17(1) 133-137.

 Tamilselvi, C., Naidu, G.M., Murthy, R.M., and Rajeswari, S. (2020). Behavioural Study of Market Arrivals and Prices of Tomato in Major Markets of Tamil Nadu - A Time Series Analysis. Int.J.Curr.Microbiol.App.Sci. 9(07): 3493495-3413.E
Wahad K. Nama, H. Harif, M. A., & Baharas, B. (2020). Transformed and Planta and Series Analysis. Int.J. Curr.Microbiol.App.Sci. 9(07): 3493495-3413.E

Waheed, K., Nawaz, H., Hanif, M. A., & Rehman, R. (2020). Tomato. In Medicinal Plants of South Asia (pp. 631-644). Elsever.