Agriculture Association of Textile Chemical and Critical Reviews Journal (2023) 505-513

AATCC Review

09 December 2022: Received
14 April 2023: Revised
23 June 2023: Accepted
03 August 2023: Available Online

www.aatcc.peerjournals.net

Research Article

Open Access

Seasonal variations and forecasting in wholesale prices of okra in the Surat market of Gujarat, India

Ruchira Shukla *, S.Sharma,G. R..Parmar, V.S. Thorat, Surendra Kuthe and Daya Suvagiya

Centre for Research in Agricultural Marketing, ASPEE Agribusiness Management Institue, Navsari Agricultural University, Navsari, Gujarat, India

ABSTRACT

The analysis of prices and market arrivals over time is important for formulating a sound agricultural price policy. Fluctuations in market arrivals largely contribute to price instability. In order to devise the appropriate ways and means for reducing the price fluctuations of agricultural commodities, there is a need to have a thorough understanding of the price behavior over time.Forecasting the price of agricultural commodities, presents some unique challenges such as data quality issues, weather aberrations, high fluctuations, price variations across neighboring marketplaces, etc. On the demand side, the instability in the prices of agricultural commodities is influenced by a number of factors such as annual variation in production, low price elasticity of demand and seasonality of agricultural production.The study relied upon the secondary time series data on monthly market prices and arrivals of Okra collected from the Agricultural Produce Market Committee, Surat. Analysis was performed on the monthly and annual time series data on wholesale price to develop reliable forecast for 2022. Month wise Seasonal indices of Okra in the Surat market showed that the seasonal price indices were above average from November to March while below average from May to October when market arrivals are more. The seasonal pattern showed that prices declined from April to October and reached the lowest point in May and reached peak in December. Seasonal fluctuations were observed both in market arrivals as well as prices of Okra. In the present investigation, various Seasonal, Non-seasonal, and Seasonal ARIMA (Box-Jenkins) models were developed to measure the forecast accuracy. The best model was chosen on the basis of the least values of Schwarz Bayesian criteria (SBC) and Mean absolute percentage error (MAPE). After performing a series of diagnostic tests, it was observed that N-BIC (12.417) and MAPE (22.88) were the least for SARIMA (0,0,2) (0,1,1)12 model. It came out to be the most representative model for the price of Okra in the Surat market. The model can be used for reaching dependable price forecasts. The quantification of these aspects in the vegetables is an immediate need to formulate effective policies to make prices stable thereby safeguard the interest of the farmers as well as the consumer.

Keywords: *Seasonal, variations, Forecasting, Wholesale Prices, Agricultural Prices , Time series,market arrivals ,price behavior,agricultural policy*

INTRODUCTION

Okra is one of the most important vegetable crops of South Gujarat. In 2019-20 total 37041 hectares of area is under Okra cultivation with a total production of 488574 MT in South Gujarat. Surat, Tapi, Navsari and Bharuch are the major Okra growing districts of South Gujarat. The analysis of prices and market arrivals over time is important for formulating a sound agricultural price policy. Fluctuations in market arrivals largely contribute to the price instability. In order to devise the appropriate ways and means for reducing the price fluctuations of agricultural commodities, there is a need to have a through understanding of the price behavior over time. In general, a major portion of the produce reaches the market during peak season, the prices generally rule low which depress the farmer's income to a great extent. Proper planning of disposing of the produce by farmers alone can considerably increase their income without incurring much additional costs. On the demand side, the instability in the prices of agricultural commodities is influenced by a number of factors such as annual variation in production, low price elasticity of demand and seasonality of agricultural production. The quantification of these aspects in the vegetables is an immediate need to formulate effective policies to make prices stable thereby safeguard the interest of the farmers as well as the consumer. Such an analysis is also useful to the farmers in order to decide the crop planning and optimum time for disposing of the produce. Keeping in view the significance and realizing the facts above the study is carried out with the following specific objectives:

1. To estimate the trends and seasonal variations/fluctuations in the prices and arrivals of Okra in Surat market.

2. To forecast the future market prices of Okra in the Surat market.

**Corresponding Author: Ruchira Shukla*
Email Address: ruchira.shukla@nau.in

DOI: https://doi.org/10.58321/AATCCReview.2023.11.03.505

METHODOLOGY

Market

The agricultural market selected for the study is the Agricultural Produce Market Committee (APMC) , Surat market which is one of the biggest markets in Gujarat for fruits and vegetables. The selection of the market is based on the availability of required time series data consistently for a long period and the maximum quantity of average annual arrivals of Okra in this market.

Crop and time period

Okra crop was selected for the study on the basis of area, production, and importance of the vegetable crop for the region. The analysis is performed on the basis of monthly and annual time series data on wholesale price over a period of January 2004 to December 2020. The forecast was developed for 2021 and 2022 and the validity of the forecast was tested by comparing it with actual price of 2021 to develop a reliable forecast for 2022.

Data: The study relied upon the secondary time series data on monthly market prices and arrivals of Okra collected from the Agricultural Produce Market Committee, Surat.

Analytical Framework

With a view to examine the various objectives stated above the following statistics tools were used. To analyze the trend and seasonal variations in market prices, a multiplicative model of the following form was used. $Y = T \times C \times S \times I$

Trends in Market Prices

To ascertain the general direction of movement of prices, the method of least square trend line was fitted for selected markets.

The following equation was used =a+bt

Where,

Y=Trend values for annual average price in rupees per quintal

a = intercept;

b=Regression coefficient.

t=time period

Seasonal Variations

To analyze the seasonality in prices, the moving average method was utilized to assess seasonal variations. The relative seasonal fluctuations were calculated after eliminating the trends, cycle and irregular fluctuations with the help of following equation.

$$Y = \frac{T \times C \times S \times I}{T \times C \times I}$$

Where,

Y = original data on monthly market prices

T = trend component

S = Seasonal variations

C = Cyclical component

I = Irregular variations

In this method firstly the effect of trend and cyclical variations (T×C) is removed from time series to get adjusted specific seasonal indices.

Thus,

$$\frac{T \times C \times S \times I}{T \times C} \times 100 = \text{Adjusted specific seasonal index}$$

Then the monthly averages of these adjusted specific indices were worked out to remove the irregular fluctuations and show general pattern of seasonal variations alone. The monthly averages of all these months are divided by average of monthly averages to estimate the seasonal indices.

$$\text{Seasonal indices} = \frac{\text{Monthly average each month}}{\text{Average of monthly averages}} \times 100$$

Price Forecasting Model

Various time series-based forecasting methods including seasonal (Simple Non-Seasonal, Holts Linear Trend, Brown's Linear Trend and Damped Trend) and non seasonal (Simple Seasonal, Winter Additive and Winter Multiplicative) models were used to forecast two year ahead of the monthly Okra price series.

Price Forecasting Model (ARIMA)

In this study, SARIMA (seasonal ARIMA or seasonal autoregressive integrated moving average) model was used to forecast two year ahead of the monthly Okra price series by applying Box-Jenkins approach[1]. The SARIMA model is useful in situations when the time series data exhibit seasonality-periodic fluctuations that recur with about the same intensity each year.Because of popularity, the ARIMA model has been used as a benchmark to evaluate some new modeling approaches.

The seasonal ARIMA model incorporates both non-seasonal and seasonal factors in a multiplicative model. One shorthand notation for the model is :

ARIMA (p, d, q) × (P, D, Q)S,

with p = non-seasonal AR order, d = non-seasonal differencing, q = non-seasonal MA order, P = seasonal AR order, D = seasonal differencing, Q = seasonal MA order, and S = time span of repeating seasonal pattern (in a monthly data s = 12).

Without differencing operations, the model could be written more formally as

$(\Phi(B^S)\varphi(B)(x_t - \mu) = \Theta(B^S)\theta(B)w_t$

The non-seasonal components are:

AR: $\varphi(B) = 1 - \varphi_1 B - \dots - \varphi_p B^p$

MA: $\theta(B) = 1 + \theta_1 B + \dots + \theta q B^q$

The seasonal components are:

Seasonal AR: $\Phi(B^S) = 1 - \Phi_1 B^S - \dots - \Phi_P B^{PS}$

Seasonal MA: $\Theta(B^S) = 1 + \Theta_1 B^S + \dots + \Theta_Q B^{QS}$

The Box-Jenkins approach is widely used to examine the SARIMA model because of it's capability to capture the appropriate trend by examining historical patterns. Box-Jenkins' methodology refers to set of procedures, namely identification, estimation, testing and application of SARIMA models with time series data. The SARIMA model is used to produce forecasts based on autocorrelation patterns. The pattern of sample autocorrelation calculated from the time series is matched with the known autocorrelation pattern associated with the particular ARIMA model. The process of formulating of the fitted model is repeated until a stationary model is found.

ARCH Model

The autoregressive conditional heteroscedastic (ARCH) model, was introduced by Engle in 1982. This model allows the conditional variance to change over time as a function of squared past errors leaving the unconditional variance constant. The presence of ARCH-type effects in financial and macro-economic time series is well established fact. The combination of ARCH specification for conditional variance and the Autoregressive (AR) specification for conditional mean has many appealing features, including a better specification of the forecast error variance.

The ARCH (q) model for series ($\mathcal{E}_t$)is defined by specifying the conditional distribution of $\mathcal{E}_t$ given information available up to time t-1. Let ψ_{t-1}denote this information. It consists of the knowledge of all available values of the series and anything which can be computed from these values. In principle, it may include knowledge of the values of other related time series, and anything else which might be useful for forecasting and is available by time t-1.

The process $\mathcal{E}_t$in ARCH (q), if the conditional distribution of $\mathcal{E}_t$for given available information $\psi_{t-1}$is

$$(\varepsilon_t)\,\psi_{t-1} \sim N(O, h_t) \text{ and } h_t = a_0 + \sum_{i=0}^{q} a\, \varepsilon_{2_{i-1}}$$

$$\text{Where, } a_o > 0,\ a_i > 0 \text{ for all I and } \sum_{i=0}^{q} a < 1$$

Where ($\mathcal{E}_t$) is the stochastic error condition on the realized values of the set of variables ψ_{t-1} = (y_{t-1}, x_{t-1}, y_{t-2}, x_{t-2},+.......), h_t is conditional variance and N is number of variables.

GARCH Model

The ARCH(q) model for the series {ε_t} is defined by specifying the conditional distribution of ε_t given the information available up to time t-1. Let ψ_{t-1} denote this information. ARCH (q) model for the series {ε_t} is given by $\varepsilon_t/\psi_{t-1} \sim N(0,h_t)$ ....(2)

$$h_t = a_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 \quad \text{....(3)}$$

where, a_0>, a_i≥ 0, for all i and< 1 are required to be satisfied to ensure non-negative and finite unconditional variance of stationary {ε_t} series.

However, ARCH model has some drawbacks. Firstly, when the order of ARCH model is very large, estimation of a large number of parameters is required. Secondly, the conditional variance of ARCH(q) model has the property that the unconditional autocorrelation function (ACF) of squared residuals; if it exists, decays very rapidly compared to what is typically observed, unless maximum lag q is large. To overcome the weaknesses of ARCH model, Bollerslev (1986) proposed the Generalized ARCH (GARCH) model in which conditional variance is also a linear function of its own lags and has the following form :

$$\varepsilon_t = \xi_t h_t^{1/2}$$
$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i\, \varepsilon_{t-1}^2 + \sum_{j=1}^{p} b_j h_{t-j} \quad \text{....(4)}$$

which shows that the denominator of the prior fraction is positive.

EGARCH Model

The EGARCH model will be developed to allow for asymmetric effects between positive and negative shocks on the conditional variance of future observations. Another advantageis that there are no restrictions on the parameters. In the EGARCH model, the conditional variance, h_t, is an asymmetric function of lagged disturbances. The model is given by

$$\varepsilon_t = \xi_t h_t^{1/2}$$

where, ξ_t ~ IID($0,1$). A sufficient condition for the conditional variance to be positive is:a_0> 0, a_i≥0,i= 1,2,...,q. b_j≥0, j = 1,2,..., p

The GARCH (p, q) process is weakly stationary if and only if

$$\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} b_j < 1$$

The conditional variance defined by Equation (4) has the property that the unconditional autocorrelation function of ε_t^2; if it exists, can decay slowly. For the ARCH family, the decay rate is too rapid compared to what is typically observed in financial time series, unless the maximum lag q is long. As Equation (4) is a more parsimonious model of the conditional variance than a high-order ARCH model, most users prefer it to the simpler ARCH alternative.

The most popular GARCH model in applications is the GARCH (1,1) model. To express GARCH model in terms of ARMA model, we denote $\eta_t = \varepsilon_t^2 - h_t$. Then from Equation (4), we get,

$$\varepsilon_t^2 = \alpha_0 + \sum_{i=1}^{Max(p,q)} (\alpha_i + b_i)\varepsilon_{t-i}^2 + \eta_t + \sum_{j=1}^{p} b_j \eta_{t-j} \quad \text{....(5)}$$

Thus, a GARCH model can be regarded as an extension of the ARMA approach to squared series {ε_t^2}. Using the unconditional mean of an ARMA model, we have

$$E(\varepsilon_t^2) = \frac{\alpha_0}{1-\sum_{i=1}^{Max(p,q)}(\alpha_i + b_i)} \quad \text{....(6)}$$

$$\ln(h_t) = \alpha_0 + \frac{1 + b_i B + \cdots + b_{q-1} B^{q-1}}{1 - \alpha_i B + \cdots + \alpha_p B^p} g(\varepsilon_{t-1}) \quad \text{....(7)}$$

where,

$$g(\varepsilon_t) = \begin{cases} (\theta + \gamma)\varepsilon_t - \gamma E(|\varepsilon_t|), & if\, \varepsilon_t \geq 0, \\ (\theta + \gamma)\varepsilon_t - \gamma E(|\varepsilon_t|), & if\, \varepsilon_t < 0, \end{cases}$$

B is the backshift (or lag) operator such that

$Bg(\varepsilon_t) = g(\varepsilon_{t-1})$

The EGARCH model can also be represented in another way by specifying the logarithm of conditional variance as

$$\ln(h_t) = \alpha_0 + \beta \ln(h_{t-1}) + \alpha \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \quad \text{....(8)}$$

This implies that the leverage effect is exponential, rather than quadratic, and the forecasts of the conditional variance are guaranteed to be non-negative.

RESULTS AND DISCUSSION

Trends and seasonal Fluctuations in Price and Arrivals of Okra

Okra is one of the most important vegetable crops of South Gujarat. In 2020-21 total 34689 hectares of area is under Okra cultivation with a total production of 4.5 lakh MT in South Gujarat. Surat, Tapi, Navsari and Bharuch are the major Okra growing districts of South Gujarat. The analysis of prices and market arrivals over time is important for formulating a sound agricultural price policy. Fluctuations in market arrivals largely contribute to price instability. In order to device the appropriate ways and means for reducing the price fluctuations of agricultural commodities, there is a need to have a through understanding of the price behavior over time.

Long term trend in the wholesale prices and arrivals of Okra

The analysis of trend components in the monthly average wholesale price series of Okra was carried out by ascertaining the direction of movement of prices over a period in the Surat market. The results revealed that a monthly increase in wholesale prices of Okra in the Surat market was Rs. 5.05 per quintal. The value of R^2 for the Surat market was 0.30 indicating that the contribution of time to change in prices was to the extent of 30% (Table 1). The results also revealed that, a monthly increase in arrivals of Okra in the Surat market was 7.74 quintal. The value of R^2 for Surat market was 0.56 indicating that the contribution of time to change in arrivals was to the extent of 56% [2](Table 1).

Table 1: Linear trend equation of Monthly Wholesale price and arrivals of Okra in Surat Market (January - 2004 to December - 2021)

Market	Trend for	Intercept (a)	Slope of coefficient (b)	R^2
Surat	Arrivals	55.7	7.74***	0.56
		(13.21)	(16.76)	
	Prices	23.96	5.05***	0.30
		(2.58)	(9.87)	

Values in parenthesis are t-values. ****Significant at 1% level*

The market arrivals and price behavior of Okra from 2004 to 2021 was examined using descriptive statistics like mean and coefficients of variation (Table 2). The mean prices of Okra varied between Rs. 1171.21 per quintal in May to Rs. 2174.90 per quintal in March in Surat market. The coefficient of variation of prices ranges between 0.26 to 0.44 indicating low variation in prices during various months. The mean arrivals of Okra varied between 582.94 quintals in March to 820.16 quintals in July in the Surat market. The coefficient of variation of arrivals ranges between 0.72 to 1.10 indicating high variation in arrivals during various months because of seasonal production of okra in a year.

Table2: Variability in the market arrivals and prices of Okra in the Surat market (January-2004 to December-2021)

Surat Market				
Months	**Arrivals (quintals)**		**Price (Rs per quintal)**	
	Mean	**CV**	**Mean**	**CV**
Jan	589.29	**1.10**	1815.98	0.42
Feb	699.77	1.06	1846.70	0.42
Mar	**582.94**	1.08	**2174.90**	**0.44**
Apr	586.01	0.98	1643.52	0.34
May	687.91	0.83	**1171.21**	**0.26**
Jun	675.01	0.81	1561.95	0.31
Jul	**820.16**	0.74	1409.74	0.40
Aug	727.75	0.76	1469.76	0.38
Sep	800.46	**0.72**	1274.44	0.40
Oct	714.56	0.91	1624.78	0.38
Nov	638.07	0.98	1940.59	0.28
Dec	661.46	1.04	2124.37	0.36

Seasonal variations in wholesale market Price of Okra

The pattern of variation in price within a year was studied by seasonal indices computed for each month from 2004 to 2021.[3] In order to identify the long-run seasonal variations relating to monthly price and arrivals of Okra were subjected to a percentage centered 12 months moving average method.

The seasonal indices of arrival and prices are presented in Table 3 and in Fig.1.The highest seasonal index for arrivals was observed in September followed by July and August as the indices stood at 131.53, 130.10 and 115.31 respectively in every year. The lowest seasonal index for arrivals was observed in March (73.60) followed by April (81.38). The seasonal arrival indices were more than 100 from May to October while for the rest of the months less than 100 indicating lower arrivals.

The highest seasonal index for Prices was observed in December followed by March and November as the indices stood at 127.32, 125.72, and 117.83 respectively. The lowest seasonal index for prices was observed in May (72.97) followed by September (76.85) and July (85.61). The seasonal price indices were above average from November to March while below average from April to October. The seasonal pattern showed that the price declined from April to October and was lowest in May. Seasonal fluctuations were observed both in market arrivals as well as prices of Okra.[4 and 5] It can further be observed that variations in market arrivals and prices of Okra are in general inversely related.

The overall seasonality has been estimated for the market arrivals as well as prices taking into the lowest and highest monthly index value. It was found that the price seasonality of Okra was 74 percent, whereas, in case of market arrivals seasonality was 79 percent. This shows that seasonality in arrivals was higher as compared to market price.

Table 3: Seasonality in arrivals and wholesale price of Okra in Surat markets of Gujarat (2004 to 2021)

Surat Market		
Months	**Seasonal Index**	
	Arrivals	**Prices**
Jan	81.70	105.18
Feb	105.04	106.66
Mar	**73.60**	125.72
Apr	81.38	99.83
May	104.17	**72.97**
Jun	101.98	95.71
Jul	130.10	85.61
Aug	115.31	89.68
Sep	**131.53**	76.85
Oct	102.31	96.62
Nov	86.76	117.83
Dec	86.11	**127.32**
Seasonality %	**79.00**	**74.00**

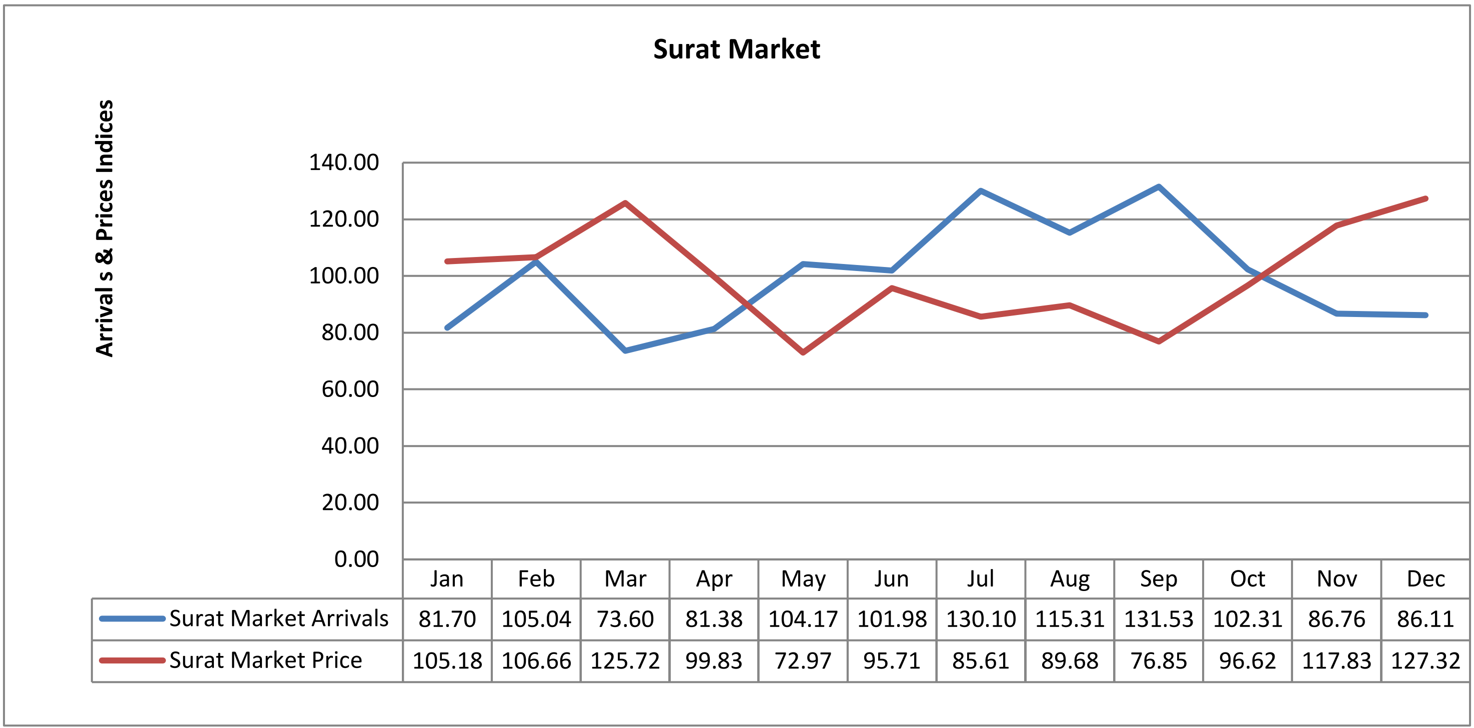

Figure.1: Month wise seasonal indices in arrivals and wholesale prices of Okra in Surat (2004 to 2021)

Forecasting of monthly wholesale prices of Okra

In order to ascertain the best model for forecasting, we compare various seasonal and non-seasonal models accompanying with seasonal ARIMA. Results are present in Table 4. Further, the best models have been selected based on different selection criteria like R^2, MAPE & SBC Values.[6]

On the basis of monthly price data, prices have been forecasted with the help of the SARIMA model. The first step in developing a SARIMA model is to determine if the monthly Okra price series are stationary. As observed from Figure 2, Okra prices do not indicate a significant trend. This indicates that the series is in a stationary structure.

It is indicated that all ACF and PACF values should extend within the confidence limits in stationary series. ACF and PACF values were found to be high at specific lags for this series. These values were determined as making sudden peaks and not disappearing especially at periodic lags of 12 months (12, 24, 36, etc) (Figure 2). This demonstrates that the series has a seasonal structure. To

provide the stationary at average, seasonal differences should be taken. It was corrected through appropriate differencing of the data.
The best model was chosen from the following SARIMA models viz., SARIMA (0,0,2) (0,1,1)12, SARIMA (1,0,0) (1,1,1)12, SARIMA (1,0,2) (1,1,1)12, SARIMA (2,0,1) (1,1,1)12 on the basis of the least Schwarz Bayesian Criteria (SBC). The SARIMA model (0,0,2) (0,1,1)12 observed the least N-BIC (SBC) values. The MAPE for SARIMA (0,0,2) (0,1,1)12 was (22.88). Thus, SARIMA model (0,0,2) (0,1,1)12 was the most representative model for the price forecast of Okra in Surat market.
Diagnostic checking of residuals was carried out to check the adequacy of the models. The residuals of ACF and PACF were obtained from the model which is identified as best fit.[7] The adequacy of the model was judged based on the value of SBC. The comparative performances of different seasonal ARIMA models are presented in Table 4. The model (0,0,2) (0,1,1)12 was found to be the best model for prices in the Surat market.It can be seen in the table that though the value of SBC/NBIC of this model is the least.[8]
The autocorrelation and partial autocorrelation of various orders of the residuals of Seasonal ARIMA (0,0,2) (0,1,1)12 upto 24 lags were computed and shown in Figure 2. The figures depicted the absence of autocorrelation as the autocorrelation and partial autocorrelation functions at various lags fall within the 95 percent confidence interval. This proved that the selected seasonal ARIMA model (0,0,2) (0,1,1)12 was most appropriate for forecasting the price of Okra during the period under study.
After estimating the parameters of this model, further analysis was done with the selected SARIMA (0,0,2) (0,1,1)12 model to check whether the residuals of the model are independent. The autocorrelation and partial autocorrelation up to 24 lags were computed and their significance was tested using Box-Ljung test.[9] Given the high p-value associated with the statistics, we cannot reject the null hypothesis of independence in this residual series. The results indicate that none of these correlations are significantly different from zero at a 95 percent confidence level. This shows that the selected SARIMA (0,0,2) (0,1,1)12 model is the appropriate model for the monthly Okra price forecasting.
The actual prices of Okra in Surat market and the statistically predicted price values for these months through seasonal ARIMA models are presented in Table 7. In order to check the validity of these statistically forecasted price values, they were compared with the actual values of price of Okra during the period from January-2021 to December-2021. Price Forecasts from a seasonal ARIMA model that passes the required checks for 2022 are shown in Figure 3**.** The forecasts follow the recent trend in the data.

Table 4: Residual analysis of monthly prices of Okra in Surat Market

Market	Model		MAPE	N-BIC (SBC)
Surat Market	Non-Seasonal	Simple Non-Seasonal	27.94	12.71
		Holts Linear Trend	27.96	12.73
		Brown's Linear Trend	30.05	12.77
		Damped Trend	27.89	12.76
	Seasonal	Simple Seasonal	24.40	12.41
		Winter Additive	24.44	12.43
		Winter Multiplicative	24.22	12.48
	SARIMA	**(0,0,2) (0,1,1)12**	**22.88**	**12.41**
		(1,0,0) (1,1,1)12	23.04	12.42
		(1,0,2) (1,1,1)12	22.81	12.47
		(2,0,1) (1,1,1)12	22.63	12.48

Testing of ARCH Effect
The basic assumption of the Box-Jenkins approach is that the residuals remain constant over time. Thus, the ARCH – Lagrange multiplier (LM) test of Engle, 1982 was carried out on the square of the residuals obtained after fitting the ARIMA model on the wholesale price series of Okra to test whether residuals do in fact remain constant. The results of the test revealed that there is no presence of ARCH effect. Because the LM test shows a p-value of 0.2338, which is well above 0.05, we cannot reject the null hypothesis of no ARCH (1) effects. The results of the test are given in Table 5.

Table 5: LM test for autoregressive conditional heteroskedasticity (ARCH)

Lags (p)	Chi^2	df	Prob > Chi^2
1	1.417	1	0.2338
2	1.791	2	0.4083
3	1.993	3	0.5738
4	2.072	4	0.7225
5	2.668	5	0.7510
6	2.890	6	0.8226

Ho: No ARCH effect vs. H1: ARCH (p)

Table 6: Test to find ARCH effect

DependantVariable : RESID^2 (Residual Square)				
Variable	**Coefficient**	**Std. Error**	**t-Statistics**	**Prob.**
C	256516.3	43195.17	5.938542	0.0000
Lagged Residual Squared	0.118739	0.084676	1.402275	0.1623
R-square	0.009190			
Adjusted R-squared	0.004516			
Log likelihood	-3127.158			
F-statistics	1.966376			
Prob (F-statistic)	0.162296			
Mean dependant var	288030.6			
Akaike info criterion	29.24446			
Schwarz criterion	29.27592			
Heteroskedasticity Test: ARCH				
F-statistic	1.966376			
Prob. F(1,212)	0.1623			
Prob. Chi-Square(1)	0.1608			

The Heteroscedasticity test was also carried out on the wholesale price series of Okra. Results show that the test is non-significant with a p-value of 0.1608 in Table 6.

Table 7: Forecasted price and their validation in Okra for Surat Market ARIMA {(0,0,2) (0,1,1)12}

Month	Actual prices	Forecasted prices	APE Value	Lower Value	Upper Value
Jan-21	2606.55	2311.06	-0.11336	1397.39	3224.74
Feb-21	3093.51	2647.56	-0.14416	1733.9	3561.23
Mar-21	3497.68	3244.36	-0.07243	2330.7	4158.03
Apr-21	946.81	2560.22	1.704048	1646.56	3473.89
May-21	2025.63	867.97	-0.57151	-45.69	1781.64
Jun-21	1940.44	2215.8	0.141906	1302.14	3129.47
Jul-21	1750.00	2000.08	0.142903	1086.42	2913.74
Aug-21	1138.88	1905.75	0.673355	992.09	2819.41
Sep-21	1573.75	1517.13	-0.03598	603.47	2430.8
Oct-21	2505.68	2173.61	-0.13253	1259.94	3087.27
Nov-21	2618.61	2618.91	0.000115	1705.24	3532.57
Dec-21	4523.00	2608.12	-0.42337	1694.46	3521.78
Jan-22		3577.72		2664.09	4491.35
Feb-22		3179.11		2169.57	4188.65
Mar-22		3147.06		2117.64	4176.48
Apr-22		2153.6		1124.18	3183.02
May-22		1734.15		704.73	2763.57

Jun-22		2087.41		1057.99	3116.83
Jul-22		1927.52		898.1	2956.94
Aug-22		1980.67		951.25	3010.09
Sep-22		1941.14		911.72	2970.56
Oct-22		2428.94		1399.52	3458.36
Nov-22		2559.19		1529.77	3588.61
Dec-22		2990.74		1961.33	4020.16

The predicted Okra prices were found close to the observed prices, except for the months of April and May 2021. These results indicate that the model provides an acceptable fit to predict the Okra price. Higher and lower price estimates for April and May respectively compared to the observed values may be because of seasonal effects and cob-web price behavior due to fluctuating demand.

After obtaining satisfactory forecasting results over a short period, the selected ARIMA (0,0,2) (0,1,1) 12 model was employed to forecast prices for twelve months in 2022. It can be said that there was not any evidence found of high price fluctuations in the short term. Future prices may remain at their peak in the month of January - March 2022 and its low in the month of July - September 2022.

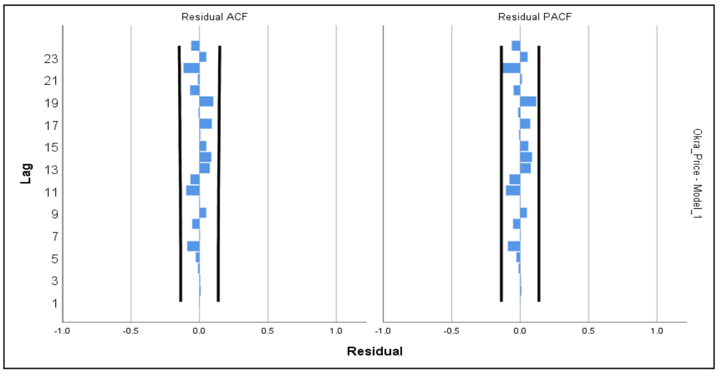

Figure.2 :ACF and PACF of residual from SARIMA (0,0,2) (0,1,1)12

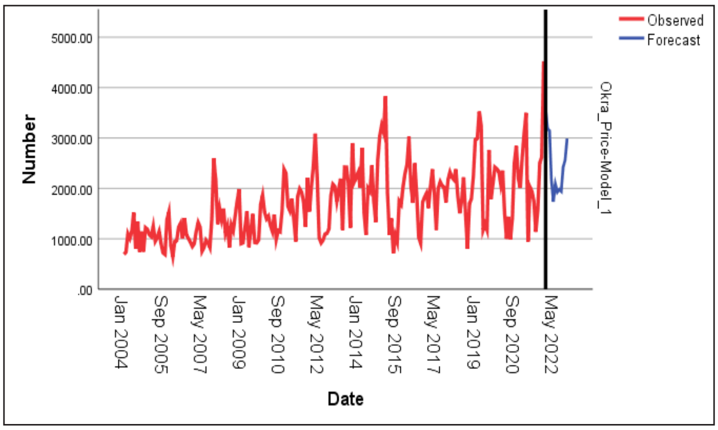

Figure.3: Price Forecast from SARIMA (1,0,0) (0,1,1)12

CONCLUSION

The study conducted over a period of 2004 to 2021 revealed that there is a monthly increase in the price of Rs. 5.05 per quintal in the Surat market. Month wise Seasonal indices of Okra in Surat market showed that the seasonal price indices were above average from November to March while below average from May to October when market arrivals are more. The seasonal pattern showed that prices declined from April to October and reached the lowest point in May and reached a peak in December. Seasonal fluctuations were observed both in market arrivals as well as prices of Okra. In the present investigation, various Seasonal, Non-seasonal and Seasonal ARIMA (Box-Jenkins) models were developed to measure the forecast accuracy. The best model was chosen on the basis of least values of Schwarz Bayesian criteria (BIC) and Mean absolute percentage error (MAPE). After performing series of diagnostic test, it was observed that N-BIC (12.417) and MAPE (22.88) were least for SARIMA (0,0,2) (0,1,1)12model. It came out to be the most representative model for the price of Okra in the Surat market. The model can be used for reaching dependable price forecasts. Seasonal ARIMA model to develop dependable monthly wholesale price forecasts for Okra in Surat market was found to be more effective as compared to various non-seasonal models (viz. Simple non-seasonal, Holts linear trend, Brown's linear trend, Damped trend) as well as various seasonal models (viz. Simple seasonal, Winter additive, Winter multiplicative) on the basis of different model selection criteria like minimum Mean Absolute Percentage Error (MAPE) and minimum Bayesian information criteria (BIC).

Future Scope of study: Future work may include constructing forecasting mechanisms with rapid learning and preciseness by combining different types of forecasting methods for various agricultural commodities.

ACKNOWLEDGEMENT

Researchers are thankful to the Directorate of Research and Dean PG Studies, Navsari Agricultural University, Navsari,Gujarat for providing the facilities and all the required support during the research work.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

REFERENCES

1. Box, G.E.P. and Jenkin, G.M. 1976. Time Series of Analysis, Forecasting and Control, Sam Franscico, HoldenDay, California. USA.

2. Govardhana Rao, G., Solmonraju Paul, K., Vishnu Sankarrao, D. and Dayakar, G .2014.Seasonal Variations And Forecasting In Wholesale Prices Of Rice (Paddy) In guntur District Of Andhra Pradesh International Journal of Development Research Vol. 4, Issue, 11, pp. 2418-2422.

3. Sujoy H, Sutradhar T, Nagpure SC 2019. Effect of Seasonal and Cyclical Variation in Prices of Natural Rubber in India. Int J Hort Agric 4(1): 1-4

4. Bogahawatte, C 1988. Seasonal variations in Retail and Wholesale prices of Rice in Colombo Markets, Sri Lanka. Indian Journal of Agricultural Economics. 43 (2): 139- 147.

5. Salam, S., Alam, S and Moniruzzaman, Md. 2012. Price behaviour of major cereal crops in Bangladesh. FoodScience and Quality Management.3: 23-34.

6. Verma, V., Kumar, P., Singh, S. and Singh, H. 2016. Use of ARIMA modeling in forecasting coriander prices for Rajasthan. International Journal of Seeds and Spices, 6 (2):40-45.

7. Darekar, A. and Reddy, A. A. 2018. Forecasting wheat prices in India.Wheat and Barley Research.10 (1): 54-60.

8. Burark, S. S., Pant, D. C., Sharma, H and Bheel, S. 2011. Price forecasting of Coriander-a case study of Kota market of Rajasthan. Indian Journal of Agricultural Marketing. 25(3): 72-81.

9. Jadhav, V., Reddy, C. and Gaddi, G M. 2017. Application of ARIMA model for forecasting agricultural prices. Journal of Agri. Science & Technology.19: 981-992