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Research Article

Price Behaviour, Commercialization Opportunities and Forecasting Future Prices of Selected Vegetables in Sri Lanka

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Abstract

The perishable and seasonal nature of vegetables causes price fluctuations, and their volatility is particularly impactful. This study aims to analyze the price behaviour and forecast the future prices of selected vegetables. The average monthly price data from 2012 to 2022 was obtained from the Hector Kobbekaduwa Agrarian Research and Training Institute, and the Colombo Consumer Price Index served as the price deflator. The coefficient of variation was used to assess price variability, while median and frequency analyses of prices were employed to determine the span of commercialization opportunities. The time series of bean and tomato prices were predicted using Auto-Regressive Integrated Moving Average and Seasonal Auto-Regressive Integrated Moving Average models. The suggested models were validated using the Box-Jenkins methodology in R version 4.3.0. The results showed that vegetables exhibit significant price variability. The variability in wholesale prices is greater than that in the retail prices. Beans, carrots, capsicum, and bitter gourds offer excellent opportunities for commercialization. There is an increasing trend in nominal prices but not in real prices. The ARIMA (2,1,1) $_{[12]}$ model was identified as the best-fitting model for predicting wholesale prices of beans and tomatoes with accuracies of 76% and 54%, respectively. It is recommended to expand the analysis and incorporate seasonal factors into the model to enhance forecasting results.

Keywords*: ARIMA, Box-Jenkins methodology, Coefficient of Variation, Price Forecasting, Vegetable Price*

1. Introduction

Vegetable crops provide vital food constituents that meet the nutritional needs of the global population. They can be considered a low-cost and readily available healthy food for health-conscious consumer markets as well as groups that are prone to malnutrition. Vegetable prices have a direct impact on farmers' income and living conditions, which in turn influences the development of the vegetable sector and the general balance of the national economy. The fluctuation and volatility of vegetable prices have a significant impact on the lives of residents and the productivity of peasants. The price fluctuation of vegetables is higher than that of fruits, paddy, and other field crops, which means that an imbalance in supply volume and consumer needs frequently occurs for vegetables (Bambang, 2007). Furthermore, maintaining a consistent supply of vegetables through continuous production to fulfil ever-changing market demands is a massive burden for responsible regulatory agencies and market-oriented industrial sectors. Hence, an understanding of the behaviour of prices helps farmers make crop production plans and policymakers formulate long-term plans for price adjustments (Dayakar *et al*., 2003). Bridging the demand-supply gap requires revolutionary solutions that address the current limits in vegetable production, postharvest, and marketing. Hence, value-chain management demands constant technical advancements that are responsive to shifting market dynamics (Johnson, 2008). To address these issues, it is necessary to evaluate and estimate market prices for certain crops in order to aid in proper planning and decision-making. Therefore, price forecasting is a crucial step, and research on vegetable price forecasting is of great significance (Xiong *et al*., 2018).

Price forecasting is more sensitive with vegetable crops due to their nature of perishability and seasonality (Fenyves, 2008). Effective price forecasting might help vegetable farmers make rational production decisions (Zhang *et al*., 2014; Reddy, 2019) such as crop acreage and crop mix at the beginning of the production season. Furthermore, it might enable other stakeholders, such as input suppliers and policymakers, to mitigate price risk. Understanding the flow and use of market information on pricing would be beneficial in developing effective price information and dissemination techniques to assist farmers in marketing their vegetables at profitable prices and achieving positive returns. Since people are becoming increasingly concerned about ways to decrease or even avoid economic losses caused by price fluctuations, numerous academics have explored agricultural markets.

The Autoregressive Integrated Moving Average (ARIMA) model has already been used in finance and insurance, as well as social science and other sectors, with good results. ARIMA models are favoured in the literature for short-term forecasting over artificial intelligence models (Co and Boosarawongse, 2007; Zou *et al*., 2007). Exponential smoothing models are based on a description of the trend and seasonality in the data while ARIMA models aim to describe the autocorrelations in the data (Shumway, *et al.,* 2017). It helps farmers to choose the future scope of agricultural crops in the best way by using the past values and the present results. Dragan *et al.* (2015) analyzed changes and future tendencies of price parameters of tomato with descriptive statistics and found that the ARIMA was suitable for price forecasting. Boateng *et al*. (2017) formulated a model for tomato prices and found that predictability of the model increases with Seasonal Autoregressive Integrated Moving Average model (SARIMA). Ramos and Ativo (2023) applied ARIMA model for forecasting agricultural produce prices of 5 selected vegetables, livestock, and poultry in the Philippines from 2013-2022. Further, Halliyavar *et al*., (2020) used ARIMA model for analysis of the previous data of 2013-2019 to predict the values of tomato, onion and potato production in India.

Pradeep and Wickramasinghe (2015) found uncontrollable price fluctuations of vegetables in Sri Lanka due to a high number of middlemen, seasonality, increasing population, highly perishable nature, consumer preference, and a low level of farmers' knowledge about price behaviour. According to Rathnayake *et al*., (2016), vegetable prices are greatly influenced by the season, and the authors recommended that the SARIMA models be better for univariate time-series modeling when the series shows a seasonal pattern. In addition, Wickramarathne and Chandrasekara (2021) and Perera *et al*., (2019) implied that the SARIMA model provides more accurate predictions in the price forecasting of onion and potato production in Sri Lanka. Champika and Mugera (2023) investigated the price behaviour of selected fresh vegetables using time-series techniques. They emphasized that the lack of price analysis and forecasting has made it difficult to establish an effective early warning system for the vegetable farming sector in Sri Lanka and recommended further research on the prediction of fresh vegetable prices by applying different forecasting models. Studies on an array of commercialization opportunities and price variations are scarce in the recent past. Moreover, the lack of use of SARIMA and ARIMA models on vegetable price forecasting is a necessity for the vegetable sector's expansion.

Research questions developed;

- What is the price variability between wholesale and retail prices?
- How does the price of vegetables behave?
- Which crops are more likely to be commercialized
- What are the best-fit models for predicting vegetable prices?
- Hence, the main objective of this study was to;

Analyze price variability and behaviour to determine the span of commercialization and forecast future prices of selected vegetables using time series techniques.

2. Materials and Methods

2.1. Data Collection

The monthly average wholesale and retail price data was collected from Hector Kobbekaduwa Agrarian Research and Training Institute (HARTI) over a period of 2012-2022 for selected vegetables.

2.2. Price Variation

Coefficient of Variation of Price: Variability of vegetable prices was examined using coefficient of variation (CV). Prices at both wholesale and retail levels in 2018-2022 were used.

$$Coefficient\ of\ Variation\ = \frac{Standard\ Deviation\ of\ Prices}{Mean\ of\ Prices} \times 100$$

Span of Commercialization Opportunities: All the items (18) which included in the vegetable group by HARTI was considered for the price analysis. Monthly average wholesale prices from 2012-2022 were used. Frequency analysis of the prices of each vegetable was performed to determine the months within a year with the highest prices. These months represent the best chances for farmers to sell their products to increase their profit. Thus, the monthly prices within a year were sorted from the smallest to the largest. Then monthly prices were classified into two categories: good and high. A monthly price was considered "good" when the price is higher than the median of the monthly prices and was considered "high" when the price is higher than Q3. According to previous consideration, a month was classified as "a month with a great commercialization opportunity" for a product when its price during that month was "high" for at least seven years, and "a month with a good commercialization opportunity" when its price during that month was "good" for at least nine years. Commercialization opportunities appeared as isolated months or as a sequence of several months and methodology was adopted from (Garcia *et al.*, 2019). The adopted methodology is referenced in Figure 1.

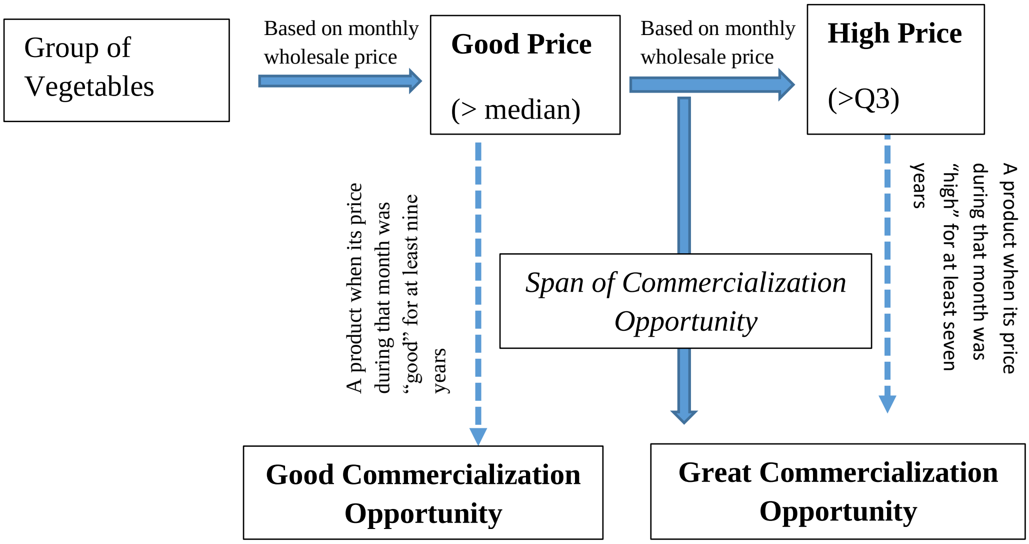


Figure 1: Methodology Workflow for Span of Commercialization Opportunities of Vegetables

Model and Forecast Future Prices for the Vegetables Selected: The nominal prices of vegetables were converted into real prices using the Colombo Consumer Price Index (CCPI) to avoid the impact of inflation in the analysis. For this analysis, only CCPI of 2006/07, 2013 and 2021 were considered. The CCPI of 2006/07 and 2013 base years were converted into 2021 base year using a conversion factor employing both base years (Perera *et al.*,2016). There were four missing values and 132 observations for each vegetable in the time series data sets for beans and tomatoes. Linear interpolation technique was used to impute the missing values.

2.3. Stationarity of the Time Series

Preliminary investigation of the time series data was carried out using the summary statistics, time series plots, Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). Stationarity of respective time series were checked using Augmented Dickey Fuller (ADF) test, Kwiatkowski Phillips Schmidt Shin (KPSS) test and Phillips–Perron (PP) test.

2.4. Model Specifications

Box and Jenkins (1970) introduced ARIMA models. The main application of this methodology is in the area of short term forecasting and it requires at least 50 data points to carry out an analysis using Univariate Box Jenkins (UBJ) approach. ARIMA model is a generalization of an Auto-Regressive Moving Average (ARMA) model. The ARMA models can be used for stationary time series data. If the series is non-stationary, it can be stationary using by differencing and hence the term "integrated" can be used. Seasonal Auto-Regressive Integrated Moving Average is an extension of ARIMA that explicitly supports univariate time series data with a seasonal component. The SARIMA model incorporates non-seasonal and seasonal factors in a multiplicative model. A 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.

Box and Jenkins was base the model selection on four stages i.e. identification, estimation, diagnostic checking and forecasting. Identification of the model was concerned with deciding the appropriate values of (p, d, q) (P, D, Q). It was done by observing ACF and PACF values up to 24 lags. To avoid fitting an over parameterized model, the Akaike Information Criterion (AIC) was employed in selecting the best model. The model with the minimum values of AIC was considered as the best.

The model was validated for accuracy by examining the residuals of the model by using ACF and PACF. If model shows random residuals, it indicates that the identified model is adequate and accurately predicts future prices and vice versa. The ACF and PACF residuals are considered random when all their ACFs were within the limits. Normality test and the heteroscedasticity test were draw in order to check whether the model is adequate. The Ljung and Box test was carried out to determine whether the residual terms are uncorrelated. If the model chosen is a good fit, then the estimates of the error terms are expected to be uncorrelated random variables with zero mean. After satisfying the adequacy of the fitted model, it can be used for forecasting future prices, which was done with R software (version 4.3.0) and after checking the validity of the model, forecasting the future prices was done.

It is essential to minimize the difference between actual and the forecasted values because the model performance relies on that. That is the smaller the difference, the better the model is. In this study Mean Absolute Percentage Error (MAPE) has been used to assure the forecasting accuracy. Data from January 2012 to December 2021 was regarded as the training data set while data from January- December 2022 were used as the validation data set.

3. Results and Discussion

Variability of Prices in Vegetables: Variability of vegetable prices over last five years (2018-2022) was examined by computing the coefficient of variation of prices. Table 1 and Table 2 shows the variation of wholesale and retail prices.

Table 1: Coefficient of Variation of Wholesale Prices from 2018-2022

Vegetable Type	**2018**	**2019**	**2020**	**2021**	**2022**
Green Beans	37.61	40.96	33.40	37.06	29.89
Carrot	46.77	50.99	65.27	48.01	25.62
Leeks	43.68	*90.33**	*68.51**	50.61	40.51
Beetroot	49.94	47.95	49.83	59.10	33.25
Knol-Khol	47.11	42.03	41.16	41.43	28.31
Raddish	51.25	44.19	25.81	47.95	36.09
Cabbage	51.56	61.69	30.19	51.84	45.29
Tomatoes	*75.59**	41.03	67.67	*64.97**	*48.23**
Ladies Fingers	34.27	41.46	65.30	33.96	39.88
Brinjals	27.23	46.21	31.77	33.80	26.27
Capsicum	51.22	35.77	37.09	43.27	30.42
Pumpkin	36.12	57.69	52.67	47.06	34.78
Cucumber	32.64	38.21	34.92	49.67	31.81
Bitter Gourd	37.72	31.73	25.19	42.26	25.02
Snake Gourd	28.23	33.77	23.98	36.73	23.11
Luffa	31.93	31.07	30.18	37.79	18.16
Long Beans	44.07	39.80	35.99	45.86	24.81
Ash Plantains	15.19	16.75	22.48	24.34	46.86

Source: Authors Calculation based HARTI Price Data (2018-2022)
*Note: * Highest CV value in the respective year*

Table 2: Coefficient of Variation of Retail Prices from 2018-2022

Vegetable	2018	2019	2020	2021	2022
Green Beans	26.30	30.50	28.21	28.80	25.95
Carrot	31.06	32.25	46.31	32.97	17.80
Leeks	26.91	*48.81**	*52.33**	32.92	26.19
Beetroot	28.98	30.98	34.42	43.45	27.05
Knol-Khol	24.00	19.59	27.55	26.80	21.43
Raddish	23.81	17.66	14.48	27.27	22.48
Cabbage	27.08	26.85	15.55	36.14	31.36
Tomatoes	*55.19**	25.93	46.24	*49.17**	*41.58**
Ladies Fingers	17.65	19.49	37.62	25.79	23.77
Brinjals	16.72	28.51	25.42	26.46	21.24
Capsicum	35.32	25.44	22.75	38.84	24.21
Pumpkin	12.51	26.31	31.68	32.51	21.20
Cucumber	13.31	15.21	17.17	21.36	17.52
Bitter Gourd	24.23	22.72	16.99	31.11	20.54
Snake Gourd	15.87	18.30	17.76	25.50	17.54
Luffa	17.14	14.42	26.25	22.04	11.34
Long Beans	21.10	19.88	24.32	31.47	20.43
Ash Plantains	6.12	8.14	8.20	17.85	29.26

Source: Authors Calculation based HARTI Price Data (2018-2022)
*Note: * Highest CV value in the respective year*

Tomatoes and leeks show high price variations over a five-year' period. The lowest variability of price was recorded from ash plantain. This indicates the variability of vegetable price changes over the time creating a price risk. The variability of wholesale and retail prices in vegetables is influenced by several factors, including seasonal changes, geographic differences, supply-demand dynamics, and specific market conditions. In addition, lack of bargaining power of farmers, peak market arrival of vegetables, highly perishable nature of vegetables are possible causes to increase price variation of vegetables. For most of the vegetables, the wholesale level variation in prices is higher than the retail level variation. Thus, the retailers support to reduce the variation in prices by adjusting their margins. This indicate that the retail market is more stable than the wholesale market. This result is in accordance with the findings of Rupasena *et al*., (1999) and Vidanapathirana, (2008).

3.1. Commercialization Opportunities of Vegetables

Though the majority of vegetables have reasonable prices, capsicum, bean, bitter gourd, and carrot lead the high-priced vegetable group. Beetroot has a good commercialization opportunity in the January, June, and July months. Brinjal prices are really good in August and September. August gives cabbage a good commercialization opportunity. Tomatoes have good prices in the April, May, and July months. In addition, lufa prices are good in May and the first three months of the year. Similarly, long beans have good prices in the March, June, October, and November months. Knolkol, radish, okra, pumpkin, and cucumber, on the other hand, do not have good prices in any month of the year with comparison to other vegetables.

Only four of the 18 vegetables chosen for the study; capsicum, beans, bitter gourd, and carrot show the greatest commercialization potential. Capsicum has the highest potential, which shows great commercialization opportunity over the year. Furthermore, except for the month of November, beans have excellent commercialization potential throughout the year. Considering the carrots, it has great commercialization opportunities in the months of April, June, July, and November. The months of February, March, June, July, October, and November are great commercialization months for bitter gourds.

3.2. Price Behaviour of Key Vegetables Selected

The vegetables which showed great commercialization was used to analyze the price behaviour. Table 3 presents the descriptive statistics of the real prices of selected vegetable. Lowest prices were observed in 2012- 2013 and the highest prices occurring in 2020, 2021 and 2022. The reason for the highest prices in 2021 and 2022 could be the country's economic crisis. Kurtosis, which denotes the degree of peak in a distribution, was less than three in real prices studied. It can be interpreted as flatter price distributions than the standard normal distribution, indicating a wider spread of real prices around its average price.

Table 3: Descriptive Statistics of the Real Prices of Selected Vegetables

Type of Vegetable	Mean	Minimum	Maximum	Standard Deviation	Skew	Kurtosis
Bean	114.68	46.82 (Apr, 2013)	245.59 (May, 2022)	42.43	0.77	0.38
Carrot	100.42	35.39 (Apr, 2012)	271.54 (Jan, 2020)	47.51	1.14	1.11
Tomato	76.33	16.84 (Sep, 2017)	238.01 (May. 2022)	45.97	1.03	1.01
Capsicum	151.69	38.57 (Sep, 2013)	402.39 (Dec, 2021)	68.23	0.96	0.91

Bitter Gourd	102.86	32.14 (Aug, 2013)	207.96 (Nov, 2021)	38.82	0.43	-0.19

Source: Authors Calculation based HARTI Price Data (2012-2022)

Note: Values within parenthesis are year and month of the minimum and maximum prices were seen.

3.3. Monthly Wholesale Price Behaviour of Selected Vegetables

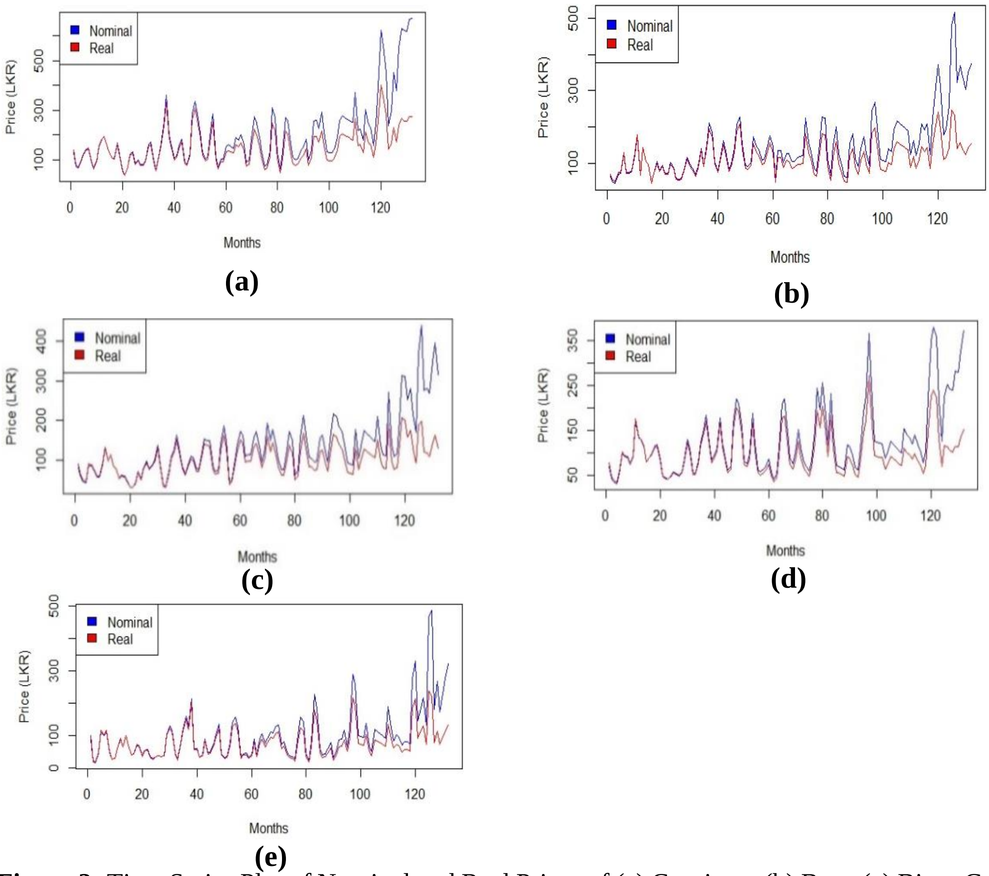


Figure 2: Time Series Plot of Nominal and Real Prices of (a) Capsicum (b) Bean (c) Bitter Gourd (d) Carrot and (e) Tomato

Time series plots of nominal and real prices for the selected vegetables are shown in Figure 2. Although nominal prices showed a clear upward trend, there is no such upward trend in real prices. This signifies the fact that real vegetable prices have been fairly steady over time. Consequently, the trend perceived in nominal vegetable prices can be recognized as a consequence of rising inflation. The nominal prices rise sharply after 2021, as all vegetables amply illustrate. The prices of the vegetables under examination exhibit seasonality. It gives a clear picture of how some vegetable crop prices have changed over the course of the year. Selected vegetables have high prices normally in middle months of the year and Figure 3, shows the monthly distribution of wholesale prices of selected vegetables.

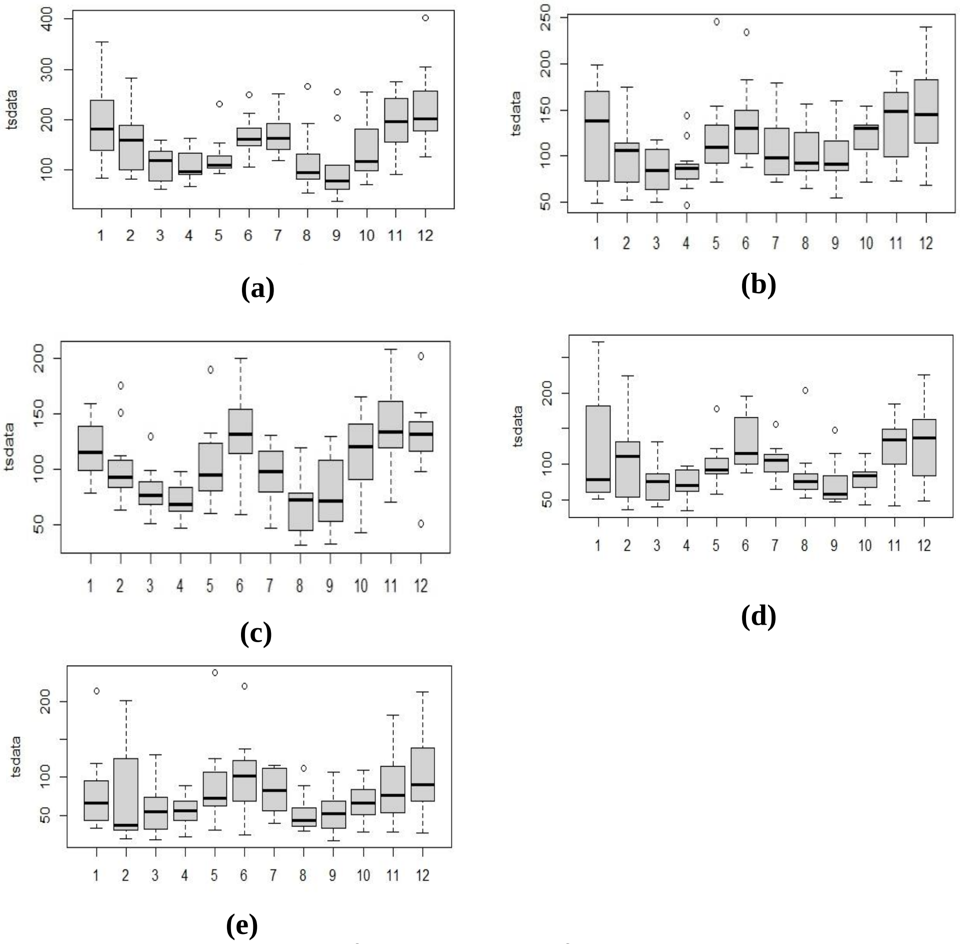


Figure 3: Monthly distribution of wholesale prices of (a) Capsicum (b) Bean and (c) Bitter Gourd (d) Carrot and (e) Tomato in Sri Lanka

Tomatoes have high variability in prices, and beans are the most consumed vegetable (321.91 g/person/month) in Sri Lanka (HIES, 2019). Hence, the SARIMA and ARIMA models are used to forecast future bean and tomato prices. Real prices were used to avoid the effects of inflation.

Stationarity Test on the Time Series Data:

According to the results of ADF and PP tests all original real price time series were 'stationary'. The outcome of KPSS test, however, indicated that they were 'non-stationary' (Table 4). By matching these results with respect to ACFs and PACFs

(Annex 01), it was found that both real price series were 'non-stationary'. Hence first difference was taken and results of the stationarity was presented in the Table 5.

Table 4: Test Results of Stationary Test

Type of Vegetable	ADF Test	PP Test	KPSS Test
Bean	-6.9474***	-57.86***	0.01
Tomato	-6.3742***	-64.575***	0.01

Source: Authors Calculation based HARTI Price Data (2012-2022)
*Note: * p-value ≤0.1, ** p-value ≤0.05, *** p-value ≤0.01, For ADF test; H0: The data is non-stationary and p-value >0.05, ** for KPSS test; H0: Trend/Level is stationary.*

Table 5: Estimates of ADF, PP and KPSS Tests for 1st Order Differenced Data

Type of Vegetable	ADF Test	PP Test	KPSS Test
Bean	-12.295***	-86.752***	0.1**
Tomato	-9.6006***	-102.88***	0.1**

Source: Authors Calculation based HARTI Price Data (2012-2022)
*Note: * p-value ≤0.1, ** p-value ≤0.05, *** p-value ≤0.01, For ADF test; H0: The data is non-stationary and p-value >0.05, ** for KPSS test; H0: Trend/Level is stationary.*

Model Identification and Estimation:

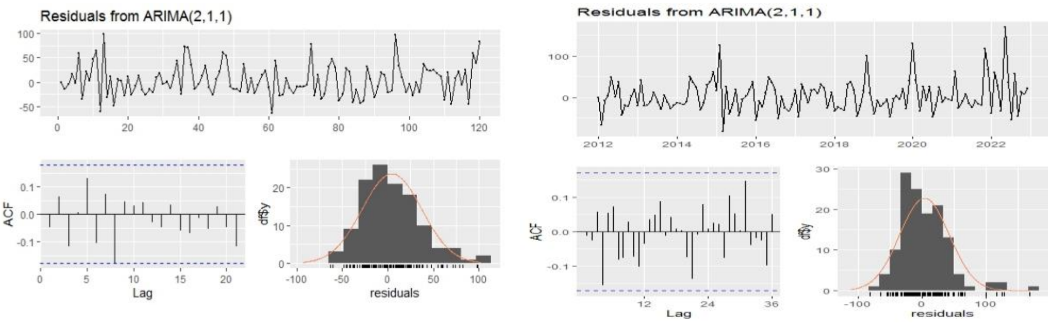
The minimum AIC values were used to identify possible SARIMA and ARIMA models

Table 6: AIC Values with Ljung-Box and Engel's ARCH test results of Selected Models

Model	AIC	Ljung-Box Test* (Auto Correlation)	Engel's ARCH Test** (Heteroscedasticity)
Tomato			
ARIMA $(1,1,2)_{12}$	1341.88	Yes (0.0031)	No (0.4103)
ARIMA $(2,1,1)_{12}$	1341.80	No (0.7486)	No (0.6289)
SARIMA (2,1,1) $(1,0,0)_{12}$	1343.87	Yes (0.0004)	Yes (0.0039)
SARIMA (2,1,1) $(0,0,1)_{12}$	1343.87	Yes (2.285e-05)	Yes (0.0047)
Bean			
ARIMA $(3,1,1)_{12}$	1298.671	No (0.1291)	No (0.6000)
ARIMA $(2,1,1)_{12}$	1297.679	No (0.4200)	No (0.7724)
SARIMA (2,1,1) $(1,0,0)_{12}$	1299.872	Yes (0.0004)	No (0.1375)
SARIMA(2,1,1) $(0,0,1)_{12}$	1299.873	Yes (0.0003)	No (0.1291)

Source: Authors Calculation based HARTI Price Data (2012-2022)
Note: H0: The residuals are independently distributed*
*Note**: H0: no ARCH effects*

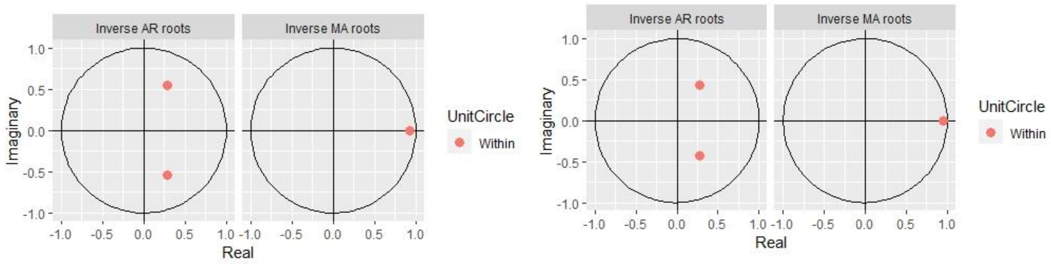
Diagnostic Checking and Model Validation: The model fitness was checked using ACF and PACF plots and distribution of residuals by Ljung–Box test results (Table 6) which is a statistical test that assesses whether any of a group of autocorrelations of a time series are different from zero and which will influence accuracy of the model. Residual plots (Figure 4) evaluate autocorrelations of the selected model. Only the ARIMA (2, 1, 1)$_{12}$ model of bean and tomato showed the most spikes fallen within significance limits which indicates that the model residuals are not auto-correlated and the fitted model is valid and could be used for making forecast and the residuals are normally and independently distributed. The Arch test results of bean and tomato fail to reject the null hypothesis of no Arch effect at 0.05 significant level (Table 6). Considering the results of diagnostic tests, models of ARIMA (2,1,1)$_{12}$ for beans and tomatoes do not show lack of fit due to residuals are white noise, random and normally distributed. Hence, best fitted models of ARIMA (2,1,1)$_{12}$ for beans and tomatoes were used for the forecasting.



(a) (b)

Figure 4: Residual Plots for the ARIMA (2, 1, 1) model of (a) Bean and (b) Tomato

Stability of the Models: Employing inverse characteristic roots for the fitted models it can be seen whether the model is close to invertibility or stationarity by a plot of the roots in relation to the complex unit circle, as they should all lie within the unit circle. According to Figure 5, they are all inside the unit circle, as we would expect because R ensures the fitted model is both stationary and invertible.



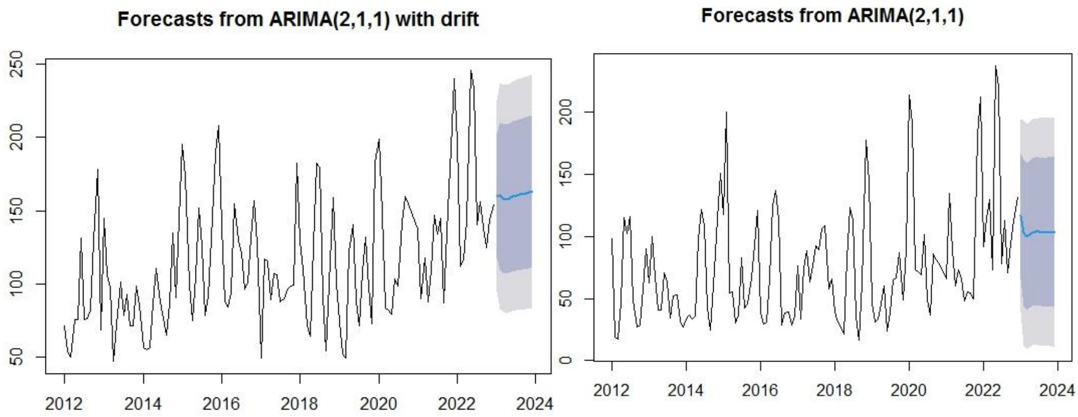
(a) **(b)**

Figure 5: Inverse characteristic roots for the fitted models of (a) Bean and (b) Tomato

Low values are apparent for the ordinary AR and MA components of the models given in Table 6, suggesting that the current month's real prices are significantly serially dependent on the real prices that prevailed in the previous one or two months.

Accuracy of the Models: MAPE has the advantage of being scale-independent and is the frequently used measure to find forecast performance (Yecan and Adanacioglu, 2012; Champika, 2016; Reddy, 2018). Therefore, MAPE has selected as the main decisive criteria to measure forecasting performance in the behaviour of wholesale prices of tomato and bean. Forecasting errors of the models are reported around 24% and 46% in bean and tomato respectively which is a good indicator that these models would produce accurate forecasts. The error at the estimation is at an acceptable level considering the extraordinary factors like, perishable nature and seasonality. These MAPE results are in accordance with the previous studies conducted using vegetable prices. Tomato prices- 24.35%- 47.00% (Yecan and Adanacioglu, 2012; Reddy, 2018), cucumber price- 25% (Luo *et al*., 2013) cabbage prices- 24.18 (Mao *et al*., 2022), onion prices 21% (Areef *et al*., 2020).

Price Forecasting: All the actual prices were included in the 95% confidence interval of the price forecasts, which provides further evidence to prove that the selected models would produce acceptable real price forecasts. Figure 6, shows the forecasts of the wholesale prices of bean and tomato.



(a) **(b)**

Figure 6: Forecasts of the Wholesale Prices of (a) Bean and (b) Tomato Using the ARIMA (2, 1, 1) Model
Note: 95% prediction intervals are shown

The price trend for tomato which is having decreasing trend, then producers need to consider market information and plan the cultivation accordingly. However, bean prices have increasing trend and the extent of any increase in production needs to be managed so that the supply of vegetables does not outstrip demand and lead to a back-log of stocks.

Table 7: Forecast Values of Bean Prices with Comparing Actual Prices

Vegetable Type	Point Forecast	Confidence Interval (95%)		Actual Price
		Low	High	
January	177.59	112.22	242.97	196.36
February	125.87	47.85	203.88	111.80
March	120.02	41.73	198.32	115.97
April	135.36	56.91	213.81	143.45
May	145.88	67.41	224.34	245.59
June	146.15	67.13	225.17	233.99
July	142.52	62.71	222.34	140.37
August	140.44	60.06	220.82	156.40
September	140.59	59.83	221.36	138.33
October	141.43	60.31	222.55	124.44
November	141.83	60.31	223.35	143.96

December	141.75	59.80	223.70	153.78

Source: Authors Calculation based HARTI Price Data (2012-2022)

Table 8: Forecast Values of Tomato Prices with Comparing Actual Prices

Month	Point Forecast	Confidence Interval (95%)		Actual Price
		Low	High	
January	177.59	112.22	242.97	91.94
February	125.87	47.84	203.88	114.77
March	120.02	41.74	198.32	129.65
April	135.36	56.92	213.81	72.83
May	145.88	67.41	224.34	238.01
June	146.15	67.13	225.17	220.25
July	142.52	62.71	222.34	78.33
August	140.44	60.06	220.82	112.63
September	141.43	59.83	221.36	70.49
October	141.43	60.31	222.55	93.92
November	141.83	60.31	223.35	113.29
December	141.75	59.80	223.70	131.86

Source: Authors Calculation based HARTI Price Data (2012-2022)

It can be inferred that selected vegetable prices tends to be high during the middle few months of the year. Especially in May and June. The actual observed prices were more or less high than the forecasted prices from both the ARIMA models (Table 7 and Table 8). According to the literature, Mbugua (2021) and Mao *et al.*, (2022) revealed that the actual observed prices were more or less high than the anticipated prices from both ARIMA models, which may be attributed to the COVID-19 global pandemic and economic crisis, in addition to seasonal influences. Furthermore, the abrupt and unanticipated closure of markets, fuel shortage, fertilizer and agro chemical banning were reduce the market supply of fresh vegetables. Therefore, the decreased supply of vegetables in the market means that buyers had less bargaining power and hence would have to offer more than the normal price.

4. Conclusion

Vegetable prices follow a seasonal pattern, with most prices peaking in the middle of the year. According to the coefficients of variation, vegetable prices fluctuates throughout the years and the wholesale level variation in prices is higher than the variation at the retail level. Seasonality, oversupply and highly perishable nature of vegetables lead to the seasonal variation and variability of vegetable prices. Therefore, knowledge of price fluctuations and price behaviour can lead to economic success for especially small-scale farmers. When planning the cropping calendar, small scale farmers can prioritize months and crops with high commercialization potential. The results showed that nominal prices are increasing but not real prices. As a result, the apparent rising trend in nominal vegetable prices may be governed largely by the country's rising inflation rather than the issues inherent in the vegetable industry. Hence, policymakers should consider this issue when developing sectoral policies, particularly when it comes to pricing and regulation.

Residuals of all the SARIMA models show lack of fit for the forecasting. Hence, ARIMA is best compared to SARIMA when considering bean and tomato wholesale price forecasting. The ARIMA $(2, 1, 1)_{12}$ was identified as the 'best-fitted model' for the forecasting real prices of beans and tomatoes based on the least AIC. However, despite the strengths of ARIMA models, several challenges remain, including sensitivity to parameter estimation, assumptions of linearity, and the need to incorporate external factors into the forecasting process. Based on the models found, it can be concluded that the price information available in the past one or two months would diffuse into the month ahead, thus determining the vegetable prices of the month. The capacity to forecast vegetable price trends has a direct impact on the sector's future growth as well as the welfare of farmers and consumers. To plan and make efficient decisions, analysis should extend to other vegetables and further investigation is required to determine the reasons for this seasonality and the price behavior explained by the models.

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