

Comparative Assessment of SARIMA and SSES Models for Forecasting Cucumber Prices in Nepal

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Abstract: Cucumber, originally indigenous to Southern Asia, thrives in diverse areas of Nepal. However, despite its promising prospects, cucumber cultivation in Nepal encounters obstacles resulting in reduced profits for farmers. These challenges encompass price volatility, marketing issues, the involvement of intermediaries in pricing, susceptibility to spoilage, and the substantial importation of cucumbers from neighboring India. Moreover, the agricultural market dynamics have led to traders shifting the burden of price risks onto farmers, culminating in lower returns for their produce. In that regard, this study focuses on the forecasting of cucumber prices in Nepal using time series analysis and compare the performance of two popular forecasting models: Seasonal Autoregressive Integrated Moving Average (SARIMA) and Simple Seasonal Exponential Smoothing (SSES). The objective is to provide accurate and reliable price predictions to assist stakeholders in making informed decisions in the cucumber market. The study utilizes historical cucumber price data spanning the past decade to understand the seasonal variations and trends in cucumber prices. The SARIMA model, known for its ability to capture seasonal effects, and the SSES model, a benchmark for seasonal time-series analysis, are both employed in the comparative assessment. The results reveal that the SSES model outperforms the SARIMA model in terms of forecasting accuracy, with lower Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) values. The study's findings have significant implications for policymakers, researchers, and farmers involved in the cucumber market, offering valuable insights to optimize production and pricing strategies.

Keywords: Econometric Analysis, Time Series, Seasonality Index, Box-Jenkins, Holt-Winters

1. Introduction

Cucumber, a widely cultivated vegetable from the "Cucurbitaceae" family, is native to Southern Asia and thrives in various regions of Nepal, ranging from the Terai to high hills at different altitudes. It comes in three main forms: slicing, pickling, and burpless, with numerous cultivars available in the market [1]. Cucumber is both a subsistence and commercial crop, with potential for future processing [2]. The vegetable holds medicinal value and is commonly consumed in salads, pickles, and preserved forms [3], offering substantial income potential and contributing to food security.

Nepal's agriculture sector plays a vital role in its economy, with horticulture accounting for 21.42% of the National AGDP and vegetable production contributing 9.71% to the Agricultural Gross Domestic Product [4, 5]. Cucumber cultivation covers 9396.80 hectares, yielding 159041.80 tons with a productivity of 16.9 t/ha [6]. Despite its potential, Nepalese farmers face challenges leading to low returns, such as price fluctuations, marketing problems, middlemen intervention in pricing, perishability, and high imports from India. Agricultural marketing has witnessed traders transferring price risks to farmers, leading to lower prices [7]. Additionally, cucumber production faces hurdles from diseases, pests, high input prices, irrigation issues, and climatic uncertainties. Marketing-related constraints include

lack of information, selling price uncertainty, and insufficient marketing extension services. Value chain actors lack coordination due to a lack of market information, hindering efficient marketing systems [8].

Despite these challenges, the demand for cucumber remains high, surpassing local supply, resulting in substantial cucumber imports, particularly from India. However, there is a vast potential for cucumber production in Nepal. Unfortunately, research on the value chain of cucumber in Nepal has been limited, leaving many farmers unaware of supply chain dynamics, value chain intricacies, and marketing strategies [9]. The main aim of this research is to conduct an extensive analysis of the cucumber market's price trends, including seasonal and cyclical patterns, over the past decade. It also seeks to explore the variations in prices across different seasons and gain a comprehensive understanding of the overall market dynamics. By adopting econometric time-series analysis, the study aims to make short-term price forecasts, compare the forecasting capabilities of different forecasting techniques, providing valuable information for farmers, policymakers, researchers, and students involved in the cucumber industry. The ultimate goal is to equip stakeholders with valuable insights that will aid them in making informed decisions and implementing effective strategies to navigate the cucumber market successfully.

Accurately forecasting outcomes in intricate systems involving policymakers and consumers is challenging due to the complex interactions among influential factors. While qualitative analysis remains prominent in current methods, there is a growing demand for a quantitative forecasting approach. Among various time series models, the ARIMA model has gained popularity and relevance in forecasting [10-13]. The ARIMA model incorporates subclasses such as autoregressive (AR), moving average (MA), and autoregressive moving average (ARMA). Additionally, the seasonal ARIMA (SARIMA) model has shown significant success in forecasting seasonal time series [14, 15].

Holt-Winters' seasonal method is a type of Exponential Smoothing technique developed by Holt and Winters to incorporate seasonality into forecasting [16]. In economic data forecasting, the Holt-Winters method is considered conservative when constructing forecast intervals, and future research might explore the use of resampling methods [17]. The Double Seasonal Holt-Winters' method has shown superior performance in short-term traffic forecasting [18], while the Holt-Winters' seasonal method can be extended by incorporating Artificial Bee Colony techniques [19].

When dealing with volatile data and price predictions, models from the GARCH family, such as GARCH, APARCH, TGARCH, and EGARCH, have demonstrated greater effectiveness. These models take into account both linear and nonlinear effects, leading to improved forecasts. Hybrid models, which combine different forecasting techniques, have also shown promise in price forecasting [20, 21]. While some studies have explored the use of artificial neural networks (ANNs) and genetic algorithms in forecasting, they often neglect to consider the production

period. In recent years, there has been a modest increase in the adoption of Artificial Neural Networks (ANNs) for time series forecasting [13]. Various ANN models, such as multilayered perceptions (MLP), feedforward network (FNN), time-lagged neural network (TLNN), and seasonal artificial neural network (SANN), have been developed and applied [22, 23]. These models offer alternative approaches to forecasting and can provide valuable insights into different forecasting scenarios.

Cucumber prices in Nepal exhibit significant seasonal variations, especially during the growing season from April to November [24]. To achieve accurate forecasting, it is essential to thoroughly investigate these price fluctuations. Tailoring forecasting models to capture the unique patterns and fluctuations associated with seasonal variations can lead to more reliable predictions. The SARIMA model, designed for time series data, proves suitable for capturing the seasonal effect in cucumber price trends. Similarly, the Simple Seasonal Exponential Smoothing method serves as a well-suited benchmark for seasonal time-series analysis. In contrast, applying artificial neural networks (ANN) requires careful modifications to adapt it to time series data, originally designed for cross-sectional data. Although ANN may offer more accurate forecasts in certain cases, it is prone to overfitting with larger datasets. For this study, the comparative assessment of both SARIMA and SSES models was chosen as the preferred forecasting method for cucumber prices. The study's findings will contribute to developing a quantitative prediction tool for cucumber prices, providing valuable decision-making support to stakeholders. The analysis was conducted using IBM SPSS software, ensuring a comprehensive and robust approach to data analysis.

2. Literature Review

Numerous studies have focused on utilizing time series analysis to forecast the future production and price of agricultural commodities based on historical data. For instance, Adanacioglu and Yarcan (2012) [25] conducted an analysis of seasonal tomato price variations in Turkey and introduced a model to predict monthly tomato prices. Their study emphasized the importance of forecasting tomato prices due to their perishable nature and seasonality, with the SARIMA (1,0,0) (1,1,1)₁₂ model proving to be the most accurate. Similarly, Luo et al. (2013) [26] employed the ARIMA model with seasonal effect to develop an effective forecasting model for cucumber prices, identifying the SARIMA (1,0,1) (1,1,1)₁₂ model as the best-fit for reliable short-term predictions. Otu et al. (2014) [27] utilized the SARIMA model to forecast the monthly percentage difference in the wholesale price index value in Nigeria, providing valuable insights for economic decision-making. Souza et al. (2016) [28] focused on soybean price forecasting using the SARIMA model, aiding producers and businesses in risk reduction and economic decision-making. Moreover, Esther and Magdaline (2017) [12] used the ARIMA model to forecast pulses production in Kenya, revealing a decreasing

trend in predicted production by 2030, which could impact supply and demand dynamics. Bisht and Kumar (2019) [29] estimated price volatility in major pulses in India using the GARCH model, highlighting significant price variability due to fluctuating pulses production. Vibas and Raqueno (2019) [30] analyzed fruit and vegetable commodity movement in the Philippines, with the SARIMA model providing better forecasts for certain vegetables. Mutwiri (2019) [31] developed an analysis tool utilizing SARIMA for early warning messages regarding tomato wholesale price fluctuations in Nairobi, Kenya, benefiting stakeholders in various sectors. Divisekara et al. (2021) [32] predicted red lentil prices using SARIMA models, demonstrating exceptional accuracy with the SARIMA (2,1,2) (0,1,1)₅₂ model for weekly prices, providing valuable information for growers and end users for production planning and price risk management.

Hyndman introduced the application of ES, which was later implemented in the R software libraries [33]. Through various studies, it was demonstrated that ES performs effectively for short-term forecasts, with models evaluated based on MAPE. Interestingly, this put an end to the common hypothesis that ARIMA outperforms ES, leading to the adoption of ES for forecasting analysis [34]. While ES is widely used for time-series forecasting, there is limited literature available on its application specifically for forecasting vegetable prices, which is the focus of our study.

3. Methodology

3.1. Datasets

The data utilized to forecast cucumber prices was acquired from the historical annual reports of Kalimati Fruits and Vegetable Market, Nepal's largest wholesale market. The dataset covered a 10-year period, from April 2013 (Baishakh, 2070 B. S.) to March 2023 (Chaitra, 2079 B. S.), comprising monthly wholesale prices for cucumber. For this study, the cucumber prices from 9-years (April 2013 to March 2022) were employed as training (in-sample) data, while the remaining 1-year (April 2022 to March 2023) served as test (out-sample) data.

3.2. Sarima Model

ARIMA (Auto-Regressive Integrated Moving Average) models were introduced by Box and Jenkins in 1970 and have since become widely used for time series forecasting. These models incorporate autoregressive (AR) and moving average (MA) parameters and involve differencing and logging operations to achieve stationarity, which is crucial for accurate forecasting. The ARIMA model is represented as ARIMA (p, d, q), where 'p' represents the autoregressive order, 'q' denotes the moving average order, and 'd' indicates the level of differencing. By integrating these components, ARIMA models effectively capture the underlying patterns and interdependencies present in the time series data. Equation 1 provides the formulation of the ARIMA model

[35].

$$z_t = (\mu + \phi_1 z_{t-1} + \phi_2 z_{t-2} + \dots + \phi_p z_{t-p}) + (\theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \dots + \theta_q \epsilon_{t-q} + \epsilon_t) \quad (1)$$

Where, z_t is the level of differencing, ϵ is the random shock (or error term) corresponding to time period t , ϕ is an autoregressive operator, θ is moving average operator and μ is the constant.

When dealing with time series data that exhibit seasonal variation, the appropriate model to use is Seasonal ARIMA, denoted as SARIMA. SARIMA models are represented as (p, d, q) (P, D, Q)_s, where 'P' represents the seasonal autoregressive (SAR) terms, 'D' indicates the number of seasonal differences, 'Q' represents the number of seasonal moving average (SMA) terms, and 'S' denotes the length of the seasonal period [36]. For example, in the case of quarterly data, the seasonal period 'S' would be 4, while for monthly data, the seasonal period would be 12. To establish the SARIMA model, a lag or backshift operator 'L' is used. The operator 'L_k' represents shifting the time series observation backward in time by 'k' periods, denoted as $L^k y_t = y_{t-k}$. The backshift operator enables the representation of general stationarity transformations, where a time series is considered stationary if its mean and variance remain constant over time. The general stationarity transformation is illustrated as described by [35].

$$z_t = \Delta_s^D \Delta^d y_t = (1 - L^S)^D (1 - L)^d y_t \quad (2)$$

Where 'z' is the time series differencing, 'D' is the degree of seasonal differencing and 'd' is the degree of non-seasonal differencing used. Finally, the general form of SARIMA model SARIMA (p, P, q, Q) is stated in the following manner.

$$\phi_p(L) \Phi_P(L^S) z_t = \mu + \theta_q(L) \Theta_Q(L^S) \epsilon_t \quad (3)$$

Where, the non-seasonal components are:

$$AR: \phi_p(L) = 1 - \phi_1 L - \phi_2 L^2 - \dots - \phi_p L^p \quad (4)$$

$$MA: \theta_q(L) = 1 - \theta_1 L - \theta_2 L^2 - \dots - \theta_q L^q \quad (5)$$

And the seasonal components are:

$$Seasonal AR: \Phi_P(L^S) = 1 - \Phi_1 L^S - \Phi_2 L^{2S} - \dots - \Phi_P L^{PS} \quad (6)$$

$$Seasonal MA: \Theta_Q(L^S) = 1 - \Theta_1 L^S - \Theta_2 L^{2S} - \dots - \Theta_Q L^{QS} \quad (7)$$

3.3. Box and Jenkins Procedure for Univariate Sarima Model

The widely employed Box-Jenkins (BJ) approach is popular for analyzing SARIMA models due to its ability to effectively capture trends based on historical patterns. This methodology offers several advantages, including the extraction of valuable information using minimal parameters and its capability to handle both stationary and non-stationary time series, both in seasonal and non-seasonal contexts. The Box-Jenkins technique, developed by George Box and Gwilym Jenkins, comprises simplified steps that involve identification, estimation,

diagnostic checking, and forecasting.

Step-1: Identification

- a) Test for Stationarity: In the initial phase of modeling process, it is crucial to assess the stationarity of the time series data, or in other words, to determine if the data series is 'stationary.' This step is essential as many estimation techniques are only applicable to 'stationary' series [37]. Stationarity, a fundamental concept in time series analysis, signifies the absence of systematic changes in the mean, variance, and strictly periodic variations within the data [38]. In this study, we employed a variety of methods to evaluate the 'stationer' nature of our monthly cucumber price data. These methods included the Autocorrelation Function (ACF), Augmented Dickey-Fuller test (ADF), KPSS test, as well as the Phillip-Perron (PP) test and graphical analysis. Additionally, we utilized the Seasonality Index (SI) Table, examined time plots, and assessed ACF and PACF to comprehensively evaluate the 'stationer' characteristics of our dataset.
- b) Identification of Seasonal and non-seasonal AR and MA components: In the identification phase of the SARIMA model (p, P, q, Q), a systematic approach was followed. A thorough examination of ACF and PACF plots was conducted to determine potential models for the time-series data. While these plots provided initial insights, the model selection process involved considering alternate possibilities and conducting a comparative analysis of various combinations based on stochastic methods. The final model was chosen using model selection criteria, with a focus on simplicity, guided by the principle of parsimony.

Step-2: Estimation

During the estimation stage, the parameters of the SARIMA model were determined through various model selection criteria, including the Normalized Bayesian Information Criterion (BIC), R-squared, MAE, RMSE and MAPE. These metrics assist in identifying the most appropriate model that achieves a balance between goodness of fit and model complexity. To estimate the parameters, the SARIMA model was fitted to the data, and the coefficients of the autoregressive (AR) and moving average (MA) terms were computed. The significance of these parameters was evaluated using t-test statistics and corresponding p-values. Moreover, diagnostic tests were performed in the subsequent stage to ensure the validity of the estimated model.

Step-3: Diagnostic Checking

During the diagnostic stage, the focus was on assessing the adequacy of the estimated SARIMA model and its goodness of fit. Initially, the residuals obtained from the estimated model were examined using ACF and PACF plots. These plots provided insights into whether the residuals displayed any significant autocorrelation, indicating potential inadequacies in capturing all the patterns present in the data. Additionally, the Ljung-Box Q-statistic test was employed to assess the overall autocorrelation in the residuals. The desirable conditions for a satisfactory SARIMA model

included: (1) insignificant residuals in the ACF and PACF plots, indicating that the model appropriately captured the autocorrelation structure, and (2) a non-significant Ljung-Box Q-statistic test, suggesting the absence of significant autocorrelation in the residuals. If these conditions were not met, further adjustments and iterations were undertaken until an appropriate SARIMA model was achieved.

Stage-4: Forecasting

The forecasting phase involves key steps, including data training for performance predictions. Training the data allows the SARIMA model to learn from historical observations, capturing patterns, trends, and seasonal variations [14]. By fitting the model to the data and estimating its parameters, the model becomes calibrated for accurate predictions [16]. This training phase identifies relevant patterns and relationships, enabling the model to project them into the future for reliable forecasts. For this study, cucumber prices for 9 years (Apr 2013 to Mar 2022) served as training (in-sample) data, while the following year (Apr 2022 to Mar 2023) was used as test data (out-sample).

Forecast accuracy and reliability were assessed using performance metrics such as R-squared, mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE) [39]. To prevent over-fitting, the performance metrics of in-sample and out-sample data were assessed separately and then compared.

$$R^2 = 1 - \frac{\sum_{t=1}^n (Y_t - \hat{Y}_t)^2}{\sum_{t=1}^n (Y_t - \bar{Y}_t)^2} \quad (8)$$

$$MAE = \frac{\sum_{t=1}^n |Y_t - \hat{Y}_t|}{n} \quad (9)$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^n (Y_t - \hat{Y}_t)^2}{n}} \quad (10)$$

$$MAPE = \frac{1}{n} \sum_{t=1}^n \left| \frac{Y_t - \hat{Y}_t}{Y_t} \right| * 100 \quad (11)$$

Where, Y_t is the observed price, \hat{Y}_t is the predicted (or fitted price), \bar{Y}_t is the mean observed price, and n is the total number of observations.

This study evaluated the forecasting performance using metrics for both in-sample and out-sample cases. These metrics quantified forecast errors and assessed the predictive ability of the SARIMA model. Graphical representations, including time series plots and forecasted versus actual values plots, visually assessed forecast performance, and identified patterns or deviations. The forecasting methodology aimed to offer reliable and informative predictions, enabling stakeholders to make informed decisions based on projected future values. The forecasting model was continuously updated with new data to ensure its adaptability and relevance over time [40].

3.4. Exponential Smoothing and Seasonal Exponential Smoothing

Exponential Smoothing (ES) and Simple Seasonal Exponential Smoothing (SSES) are popular methods

employed in time series forecasting. Exponential smoothing is a time series forecasting technique that assigns exponentially decreasing weights to past observations, with the most recent observations carrying the highest weight. This method is particularly useful for data with no apparent seasonal patterns. The exponential smoothing model is represented by the equation:

$$\hat{y}_{t+1} = \alpha y_t + (1 - \alpha)\hat{y}_t \quad (12)$$

where ' \hat{y}_{t+1} ' is the forecasted value for the next time period, ' y_t ' is the actual value at time t , ' \hat{y}_t ' is the forecasted value at time t , and ' α ' is the smoothing parameter ($0 \leq \alpha \leq 1$) [16].

On the other hand, seasonal exponential smoothing is an extension of exponential smoothing that considers seasonal patterns in the data. It is especially suitable for time series data with recurring patterns within each seasonal period. The seasonal exponential smoothing model incorporates two smoothing parameters, α and γ , to handle both the level and seasonal component. The model is formulated as follows:

$$\hat{y}_{t+m} = (l_t + m \cdot b_t) \cdot s_{t-m+1} \quad (13)$$

where ' \hat{y}_{t+m} ' is the forecasted value for m periods ahead, ' l_t ' and ' b_t ' represent the level and trend components respectively, and ' s_{t-m+1} ' denotes the seasonal component.

To update the level component ' l_t ' and seasonal component ' s_{t-m+1} ' in each time period, SSES employs specific update equations.

For the level component:

$$l_t = \alpha y_t + (1 - \alpha)(l_{t-1} + b_{t-1}) \quad (14)$$

The smoothing parameter ' α ' controls the weight given to the most recent observation ' y_t ' in updating the level component ' l_t '. A higher value of α (closer to 1) makes the

level component more responsive to recent changes in the data.

For the seasonal component:

$$s_{t-m+1} = \delta \cdot \frac{y_t}{l_t} + (1 - \delta) \cdot s_{t-1} \quad (15)$$

The smoothing parameter ' δ ' determines the weight given to the current observed value ' y_t ' relative to the updated level component ' l_t ' in updating the seasonal component ' s_{t-m+1} '. A smaller value of δ (close to 0) indicates that the seasonal component changes slowly over time and is less influenced by recent data [16].

Both exponential smoothing and seasonal exponential smoothing techniques are widely used for forecasting in various domains, including finance, economics, and agriculture [35, 40]. They offer simple yet effective approaches to predict future values in time series data, making them valuable tools for time series forecasting.

4. Results and Discussions

4.1. Model Identification

Initially, the data was visually inspected through a time series plot of the historical data. Figure 1 showcases data points centered around a fixed mean of Rs. 56.94 per kg, though some observed variation is evident (with a standard deviation of NRs. 22.38 per kg and minimum and maximum prices of Rs. 18.11 and Rs. 125.80 per kg, respectively) in consecutive years. To validate the existence of a trend or unit roots, which might necessitate differencing or logging transformations, unit root tests like the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests were conducted.

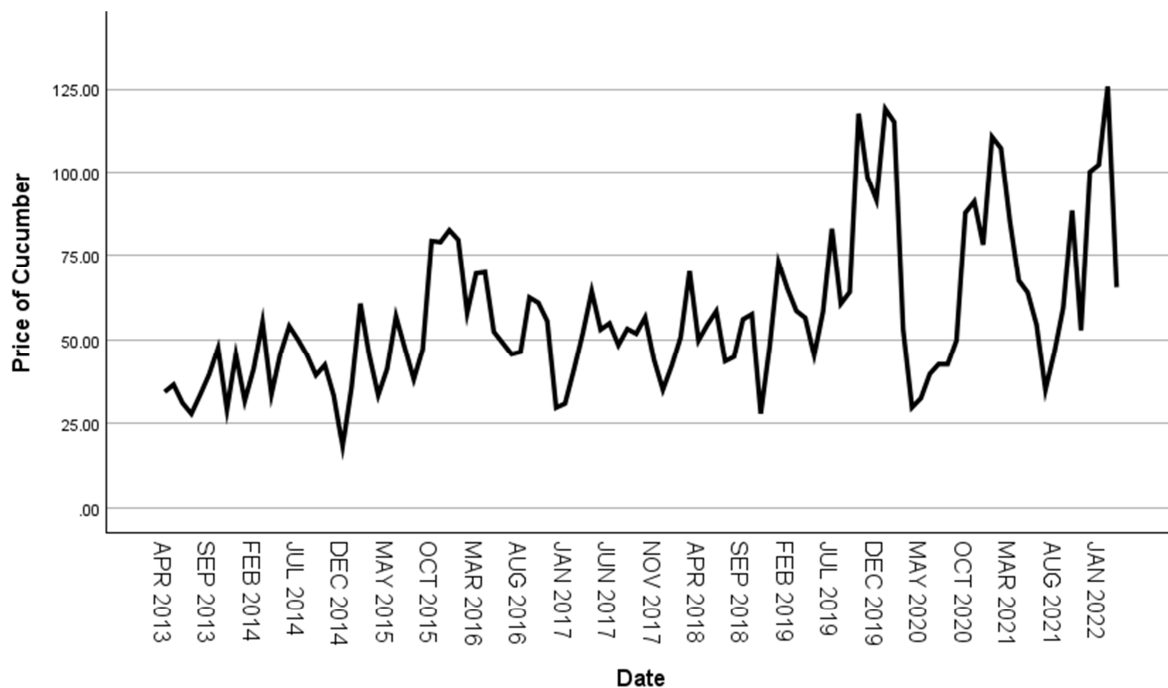


Figure 1. Time-Series Plot of Prices of Cucumber (Apr 2013 to Mar 2022).

As evident from Figure 1, the significant fluctuations in cucumber prices, particularly after September 2018, can be attributed to the government's pricing control efforts that have revealed a concerning pattern of ineffectiveness over the past decade. An analysis of cucumber prices (and almost every other fresh vegetable) shows a remarkable degree of volatility, despite government intervention and monitoring. The government's pricing control mechanisms have not been robust enough to withstand various factors, including supply chain disruptions and market dynamics [41]. This instability was further compounded by the onset of the COVID-19

pandemic, a time when consumers were already grappling with economic uncertainties [42].

4.1.1. Test of Stationarity

The outcomes presented in Table 1 reveal that the null hypothesis of the ADF, PP, and KPSS tests (H_0 : Prices of Cucumber have a unit root) has been disproved. The obtained p-values for all the tests were below 0.01, which is less than the significance level of 0.05. This rejection signifies that the series lacks a unit root, suggesting it is stationary (non-seasonal differencing 'd' = 0).

Table 1. Unit Root Test for Prices of Cucumber.

Unit Root Test	P - Value	Significance Level	Hypothesis Test Result	Stationarity
ADF Test	<0.01	0.05	Reject H_0	Series Stationary
PP Test	<0.01	0.05	Reject H_0	Series Stationary
KPSS Test	<0.01	0.05	Reject H_0	Series Stationary

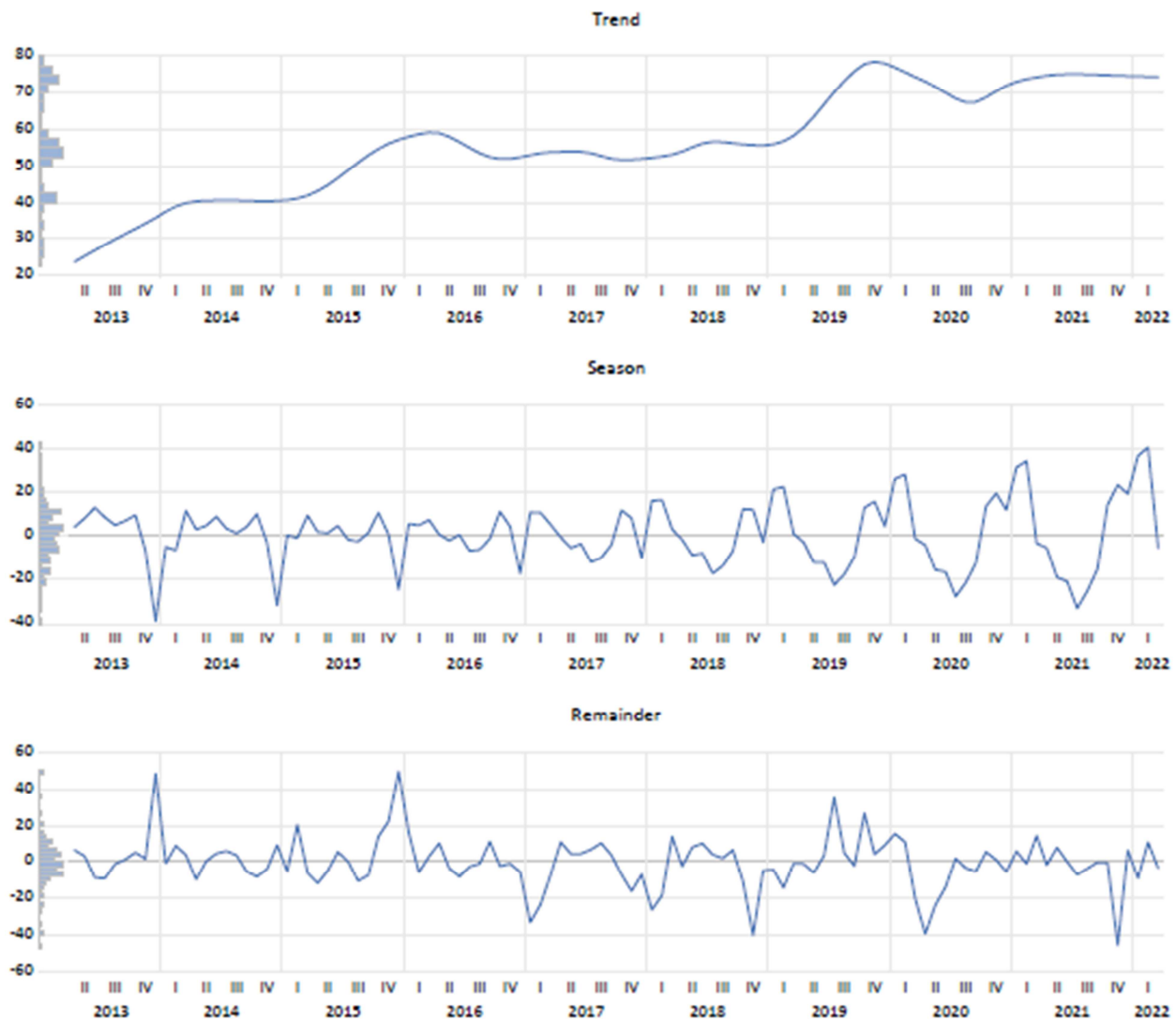


Figure 2. Seasonal and Trend Decomposition using Loess (STL) for Prices of Cucumber.

Moreover, the time series plot clearly demonstrates the presence of seasonal patterns, as the cucumber prices consistently exhibit lower values during the months of April

to September, coinciding with the harvesting season of cucumber in Nepal from April to November [24]. Conversely, prices show relatively higher values during October through

March, aligning with the festival season (October to November - Dashain and Tihar being the biggest festivals of the nation), when demand surges, and during the off-season, when local supply becomes scarce. Although the seasonality pattern is evident from the plot, it is essential to verify the presence of seasonality through seasonal decomposition (refer to Figure 2) and the seasonal index method.

The computed Seasonality Index (SI) (see Table-2) provided additional verification of the seasonal fluctuations in cucumber prices, showing values consistently below 100% from April to September and above 100% from October to March. The lowest SI was observed in August at 80.24%, while the highest was recorded in February at 129.72%, thus confirming the presence of seasonality throughout the year.

Table 2. Seasonality Index for Prices of Cucumber (Source: Kalimati Fruits & Vegetable Market, Nepal).

	Prices of Cucumber in NRs. / Kg									Month Avg	Seasonality Index (SI)
	2013/14	2014/15	2015/16	2016/17	2017/18	2018/19	2019/20	2020/21	2021/22		
Apr	34.37	33.63	33.4	69.97	64.29	49.82	56.49	29.76	67.51	48.80	85.72%
May	36.53	45.78	41.21	52.37	53.02	54.44	45.41	32.49	63.96	47.25	82.98%
Jun	31.09	54.01	56.91	49.04	54.84	58.45	58.32	39.73	54.47	50.76	89.16%
Jul	27.88	49.97	47.5	45.68	48.44	43.55	83.03	42.67	35.03	47.08	82.70%
Aug	33.59	45.43	38.12	46.4	53.19	44.89	60.65	42.62	46.26	45.68	80.24%
Sep	39.59	39.37	47.12	62.47	51.82	56.03	64.08	49.81	59.5	52.20	91.68%
Oct	47.51	42.39	79.37	60.92	56.62	57.53	117.5	87.8	88.5	70.90	124.53%
Nov	29.12	33.3	79.06	55.53	43.98	27.91	98.49	91.14	52.82	56.82	99.79%
Dec	45.56	18.11	82.6	29.7	35.02	47.97	91.67	78.28	100.16	58.79	103.25%
Jan	31.73	35.69	79.69	30.9	42.25	72.91	118.85	110.57	102.26	69.43	121.94%
Feb	41.25	60.69	57.93	41.01	50.83	65.08	114.97	107.18	125.8	73.86	129.72%
Mar	55.23	45.33	69.58	51.96	70.24	58.53	53.22	85.35	65.49	61.66	108.30%
Year Avg	37.79	41.98	59.37	49.66	52.05	53.09	80.22	66.45	71.81		
Grand Average										56.94	

According to the findings of the study, in a stationary series, all ACF and PACF values are expected to fall within the confidence limits [43]. However, in this particular series, noticeable ACF and PACF values were observed at specific lags, particularly at periodic intervals of 12 months (12, 24, 36, etc.) (Figures 3 & 4), indicating the presence of

seasonality in the data. Considering these observations, the SARIMA model should take into account the existence of seasonality in the cucumber price data. Hence, a seasonal differencing parameter ($D=1$) should be incorporated in the SARIMA model estimation to achieve stationarity and accommodate the observed seasonal patterns.

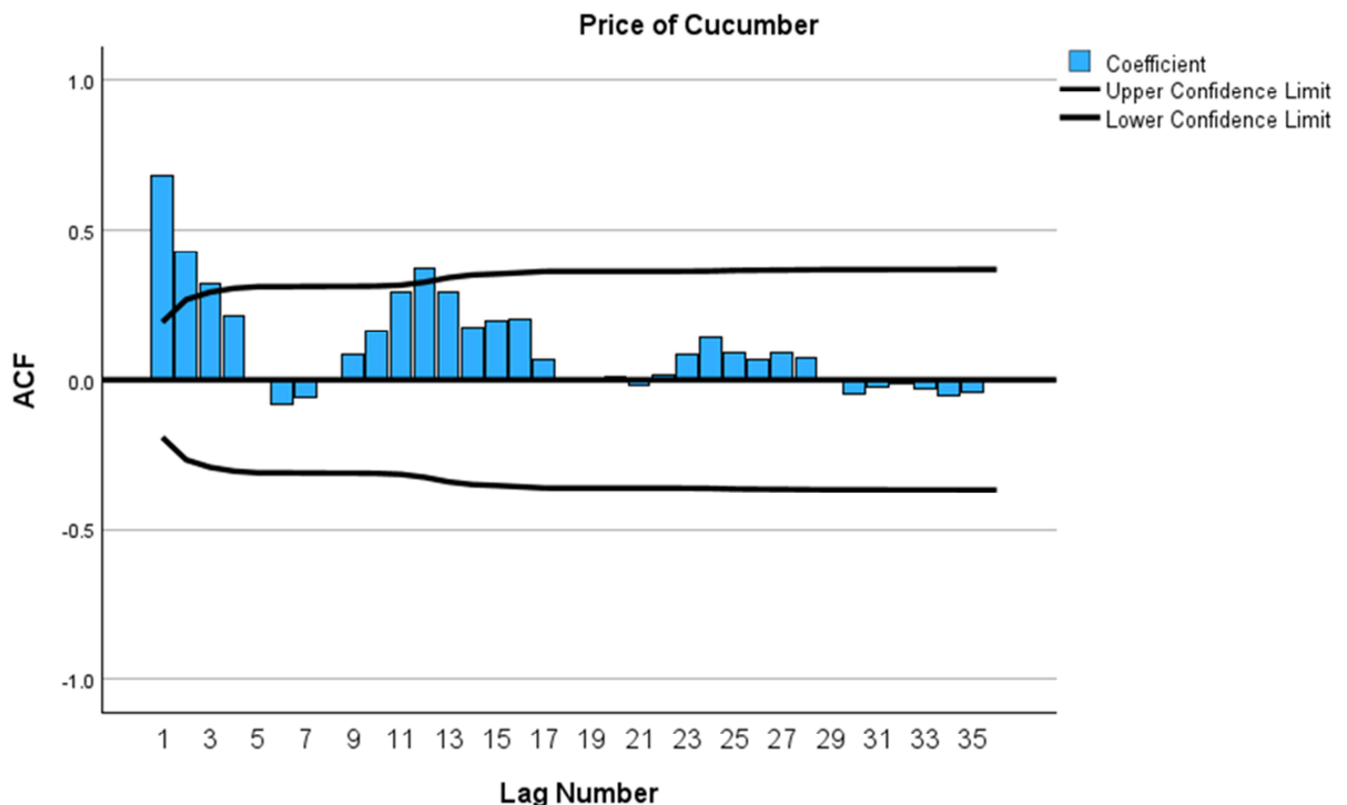
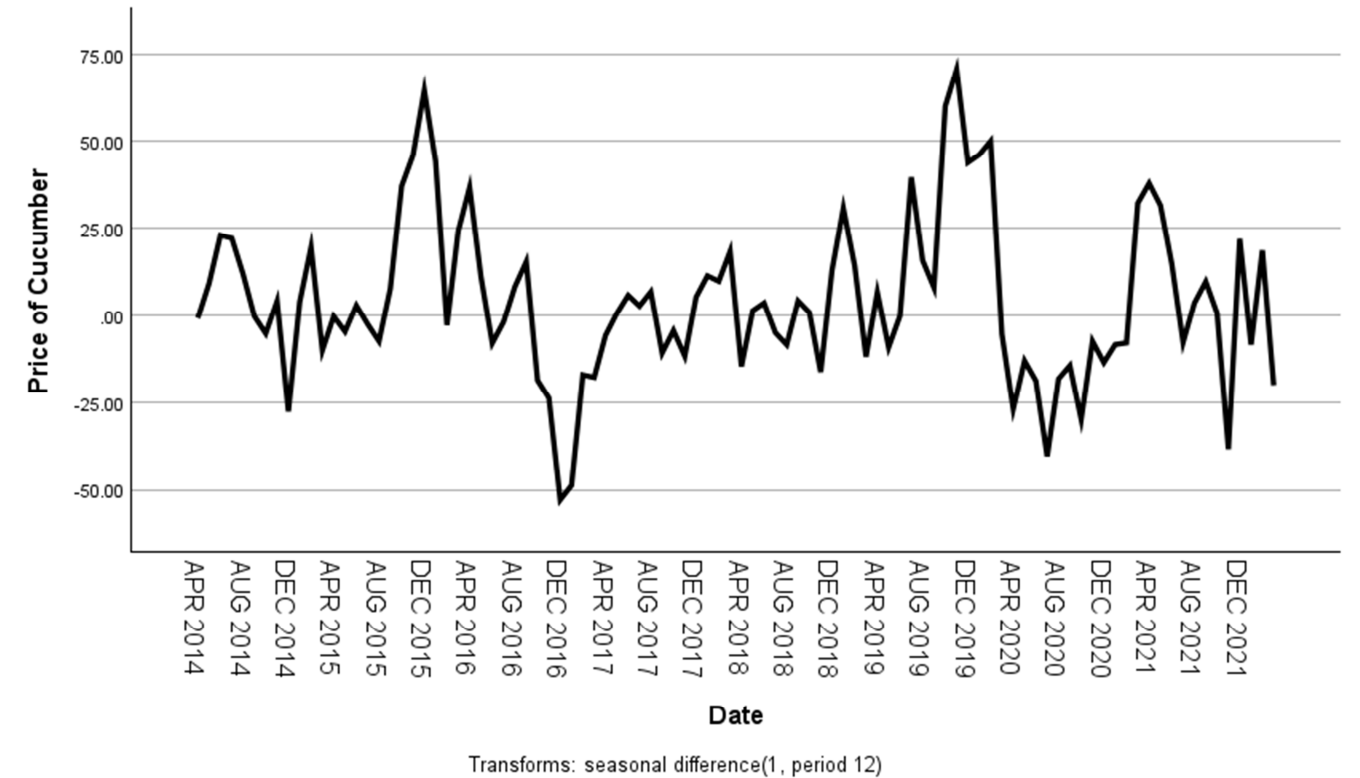
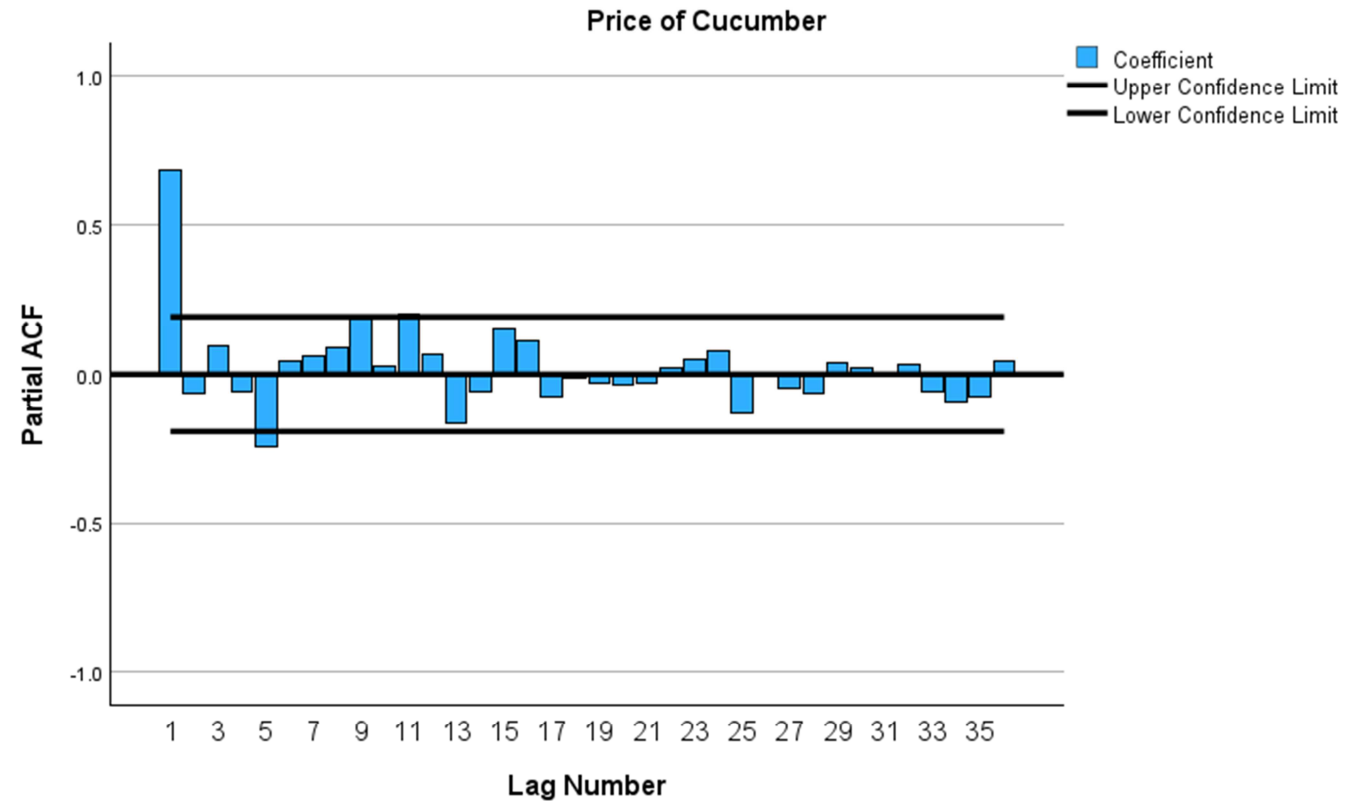


Figure 3. ACF Plot for Non-Differenced Prices of Cucumber.

Figure 5 displays the time series plot after applying seasonal differencing ('D' = 1) to the prices of cucumber, while Figures 6 & 7 exhibit the ACF and PACF plots following the seasonal differencing.



4.1.2. Identification of Seasonal and Non-Seasonal AR and MA Components

Following the application of seasonal differencing, the seasonal spikes in ACF and PACF at 1 lag (12, 24, 36, etc.) were removed, suggesting a potential seasonal model with SAR (1) and SMA (1). For the (P, D, Q) part of the model, the most suitable choice appeared to be (1, 1, 1). Regarding the non-

seasonal part of the model (p, d, q), the discontinuation of ACF after 2 lags and PACF value after 1 lag indicates that adding the AR (1) and MA (1 or 2) term might be appropriate (refer to Figures 6 & 7). However, the behavior of the PACF plot is less conclusive, showing an increase after a certain lag. As a result, five alternative possibilities were considered to identify the most optimal configuration for the SARIMA model.

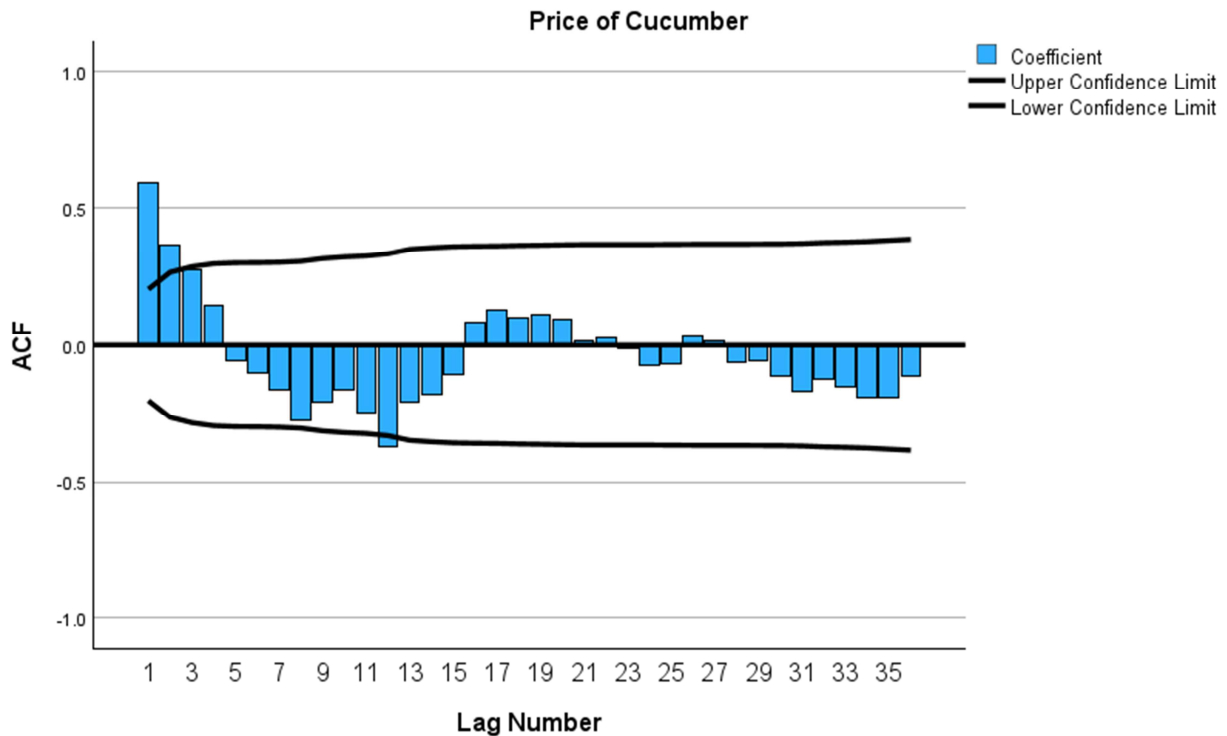


Figure 6. ACF Plot for Seasonally Differenced Prices of Cucumber.

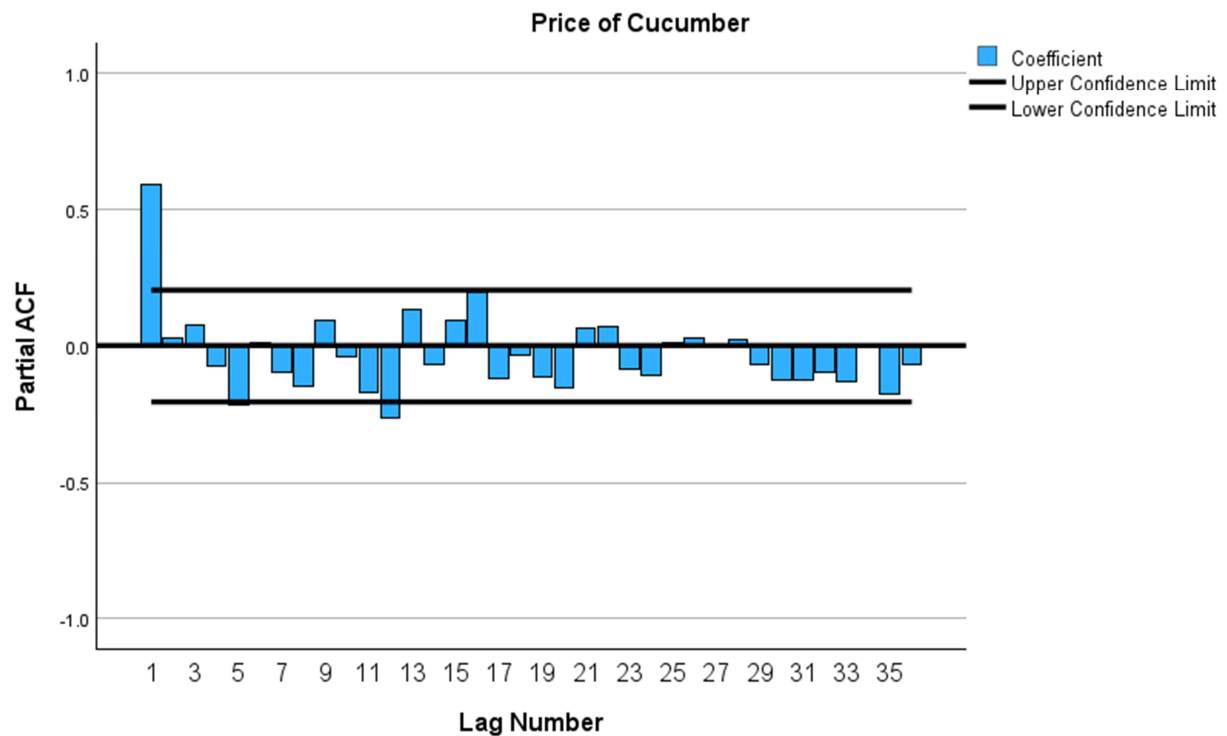


Figure 7. PACF Plot for Seasonally Differenced Prices of Cucumber.

Meanwhile, although the Simple Seasonal Exponential Smoothing (SSES) model appears to be the most suitable Exponential Smoothing (ES) model for this study, a comparative evaluation of Non-Seasonal ES, Winters' Additive ES, and Winters' Multiplicative ES was also conducted to identify the most optimal ES model.

4.2. Model Estimation and Selection

After a rigorous identification process, SARIMA (1,0,2) (1,1,1)₁₂ and Simple Seasonal Exponential Smoothing (SSES) were determined to be the most appropriate models for the study. The initial assumption of a simple seasonal model for ES was validated, with alpha (level) found to be highly significant at less than 0.01 p-value, and delta (seasonal

damping) set to the common assumption of 1.00.

However, for SARIMA model, it was observed that the coefficients MA (2), MA (1), and SAR (12) were statistically insignificant (refer to Table 3). As a result, various alternative models, including SARIMA (1,0,1) (1,1,1)₁₂, SARIMA (1,0,0) (1,1,1)₁₂, SARIMA (1,0,0) (0,1,1)₁₂, and SARIMA (1,0,1) (0,1,0)₁₂, were carefully assessed. Among these options, SARIMA (1,0,0) (0,1,1)₁₂ showed statistical significance for all regressor coefficients and exhibited the lowest values of BIC, MAE, and MAPE.

Detailed results of the model estimations can be found in Table 3, while Table 4 and Table 5 summarize the parameter estimation results specifically for SARIMA (1,0,0) (0,1,1)₁₂ and SSES respectively.

Table 3. Model Estimation with BIC, RMSE, MAE and MAPE criterion for SARIMA (p, 0, q) (P, 1, Q)₁₂ and ES.

Time Series Model	R-Squared	RMSE	MAPE	MAE	Normalized BIC	Remarks
SARIMA (1,0,2) (1,1,1) ₁₂	0.492	16.522	22.854	12.210	5.895	MA (1): 0.841; MA (2): 0.949; SAR (12): 0.975
SARIMA (1,0,1) (1,1,1) ₁₂	0.492	16.435	22.855	12.216	5.837	MA (1): 0.693; SAR (12): 0.981
SARIMA (1,0,0) (1,1,1) ₁₂	0.491	16.362	22.802	12.163	5.780	SAR (12): 0.929
SARIMA (1,0,0) (0,1,1) ₁₂	0.491	16.276	22.819	12.175	5.722	All Regressors Significant
SARIMA (1,0,1) (0,1,0) ₁₂	0.319	18.821	26.811	14.352	6.013	MA (1): 0.854
Simple Non-Seasonal ES	0.392	17.527	24.173	12.744	5.771	$\alpha < 0.01$
Simple Seasonal ES	0.550	15.149	21.147	11.238	5.523	$\alpha < 0.01$; $\delta = 1.00^*$
Winters' Additive SES	0.552	15.194	21.421	11.306	5.572	$\alpha < 0.001$; $\gamma = 1.00$; $\delta = 0.99$
Winters' Multiplicative SES	0.344	18.381	25.343	13.556	5.953	$\alpha = 0.969$; $\gamma = 0.971$; $\delta = 0.025$

Table 4. Parameter estimators of SARIMA (1, 0, 0) (0, 1, 1)₁₂.

Variable	Coefficient	Std. Error	t-statistic	Probability
C	4.119	1.805	2.283	0.025
AR (1)	0.591	0.084	7.064	<0.01
SMA (12)	0.651	0.120	5.400	<0.01

Based on the results of parameter estimators, the equation for the SARIMA (1,0,0) (0,1,1)₁₂ with its corresponding coefficients is as follows:

$$y_t = 4.119 + 0.591y_{t-1} + 0.651\varepsilon_{t-12} + \varepsilon_t \quad (16)$$

Where, ' ε_t ' term represents the error term in the model.

Table 5. Parameter estimators of SSES.

Variable	Estimate	Std. Error	t-statistic	Probability
Level (α)	0.800	0.101	7.906	<0.01
Seasonality (δ)	8.781E-5	0.284	0.000	1.00

The findings of the study reveal that the Simple Seasonal Exponential Smoothing (SSES) model outperforms the SARIMA (1,0,0) (0,1,1)₁₂ model in several key forecasting metrics. The SSES model exhibited a higher R-squared value of 0.550, indicating a better fit to the data compared to the SARIMA model's R-squared of 0.491. Additionally, the SSES model demonstrated better performance in terms of in-sample Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Squared Error (RMSE) with values of 11.238, 21.147, and 15.149, respectively. These metrics indicate that the SSES model's predictions were more accurate and precise, with smaller errors and better overall fit to the observed data. The

statistically significant values of alpha (0.8) and delta (1.00) further validate the suitability of the SSES model for capturing seasonal patterns in the cucumber price data. However, the superiority of the model can only be validated after assessing diagnostic check and out-sample forecasting performance metrics.

4.3. Diagnostic Checking

Following the parameter estimation of the SARIMA (1, 0, 0) (0, 1, 1)₁₂ and SSES models, a thorough examination was conducted to assess the independence of the model's residuals. Autocorrelation and partial autocorrelation were

computed up to 24 lags, and their significance was evaluated using the Ljung-Box test. Figure 8 shows that the residuals of the SARIMA (1, 0, 0) (0, 1, 1)₁₂ model fall within the upper and lower confidence limits, indicating a good fit. However, for the SESS model, the residual ACF and PACF plots (Figure 9) reveal slight crossings of the confidence limits at

the 5th and 8th lags. Nonetheless, the Ljung-Box test results (Table 6) show that the p-values of the test statistics are greater than 0.05 for both models, indicating that the residuals are white noise and independent. While there are nominal crossings in the SESS residuals, they have been disregarded for the purpose of this study.

Table 6. Ljung-Box Test for SARIMA (1,0,0) (0,1,1)₁₂ and SSES Model.

Model	Ljung-Box Statistics	Degrees of Freedom	Significance (p-Value)
SARIMA (1, 0, 0) (1, 1, 1) ₁₂	15.622	16	0.480
Simple Seasonal ES	24.511	16	0.079

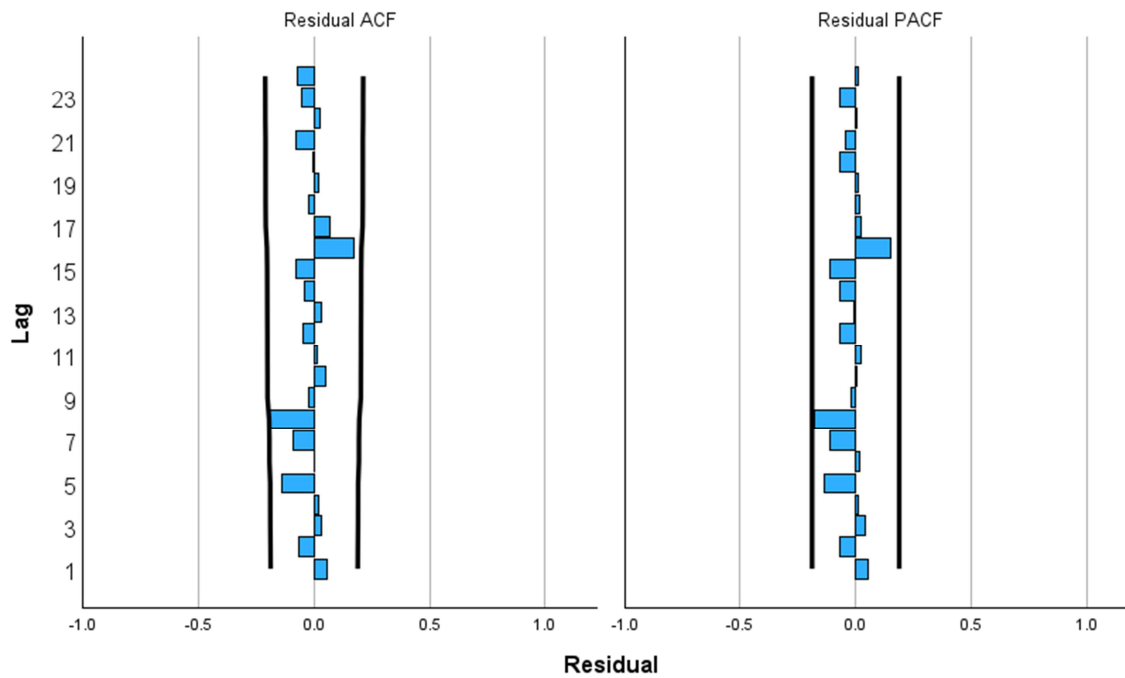


Figure 8. Residual ACF and PACF Plots for SARIMA (1,0,0) (0,1,1)₁₂.

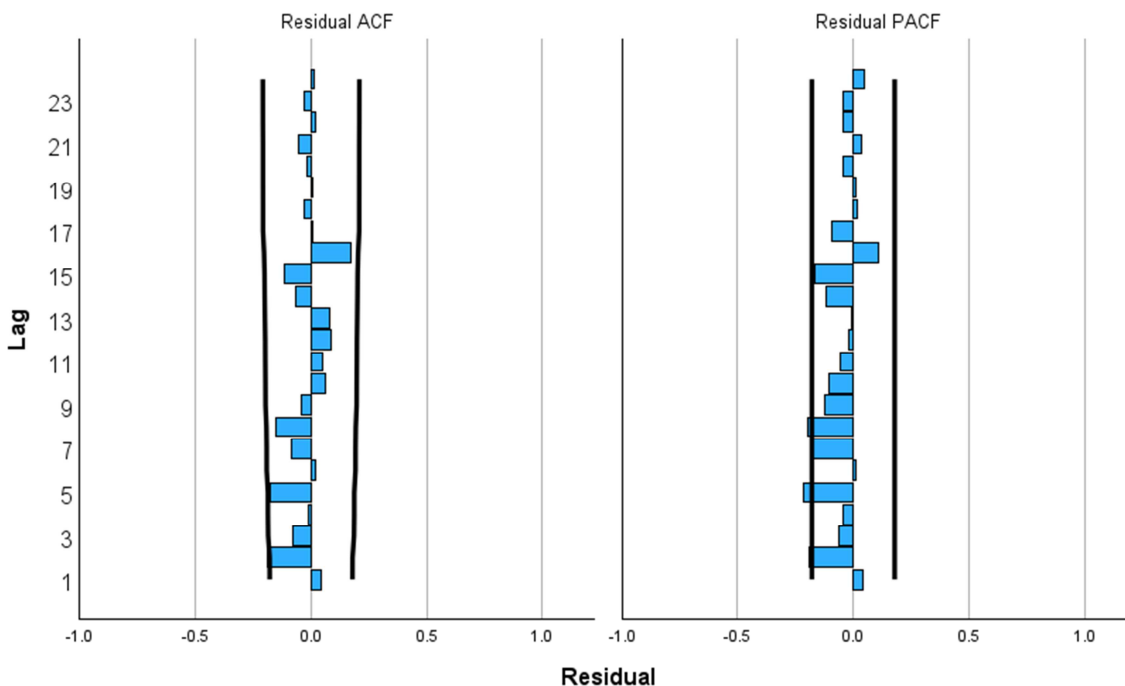


Figure 9. Residual ACF and PACF Plots for SSES.

4.4. Forecasting Performance & Forecasting

The SARIMA (1,0,0) (0,1,1)₁₂ and SSES models were employed to forecast the average monthly real cucumber prices from April 2022 to March 2023. The forecasting was based on observed data spanning from April 2013 to March 2022. A comprehensive comparison of performance metrics for both in-sample and out-sample fits for both models is presented in Table 7. The forecasted real cucumber prices exhibit a close alignment with the observed prices, indicating a satisfactory fit for the models. Notably, the SSES model performs significantly better than SARIMA in both cases.

On the contrary, there were slight discrepancies between

the predicted and actual prices for both models during the months of October and November. These variations can be attributed to the presence of major festivals in Nepal, such as Dashain and Tihar, which lead to unpredictable and inflated prices. During these festivities, there is an increased demand and limited supply of cucumbers despite being the harvesting season, and the country relies on imports in addition to local produce, contributing to the heightened unpredictability and variability during this period. It is widely recognized that these months experience the highest level of unpredictability and volatility throughout the year [44].

Table 7. Forecasting Metrics Calculation for SARIMA (1,0,0) (0,1,1)₁₂ and SSES.

Model	Sample Type	R-Squared	RMSE	MAPE	MAE	BIC
SARIMA (1, 0, 0) (1, 1, 1) ₁₂	In-Sample	0.491	16.276	22.819	12.175	5.722
Simple Seasonal ES	In-Sample	0.550	15.149	21.147	11.238	5.523
SARIMA (1, 0, 0) (1, 1, 1) ₁₂	Out-Sample	0.487	16.165	22.367	12.218	5.696
Simple Seasonal ES	Out-Sample	0.530	15.438	21.630	11.704	5.553

After achieving satisfactory forecasting results over a short period, the selected SARIMA (1,0,0) (0,1,1)₁₂ and SSES models were utilized to forecast the monthly average cucumber prices in Nepal from April 2023 to March 2025.

Table 8 displays the forecasted prices using both models, and Figure 10 and Figure 11 compare these predictions with the observed prices for SARIMA and SSES models respectively.

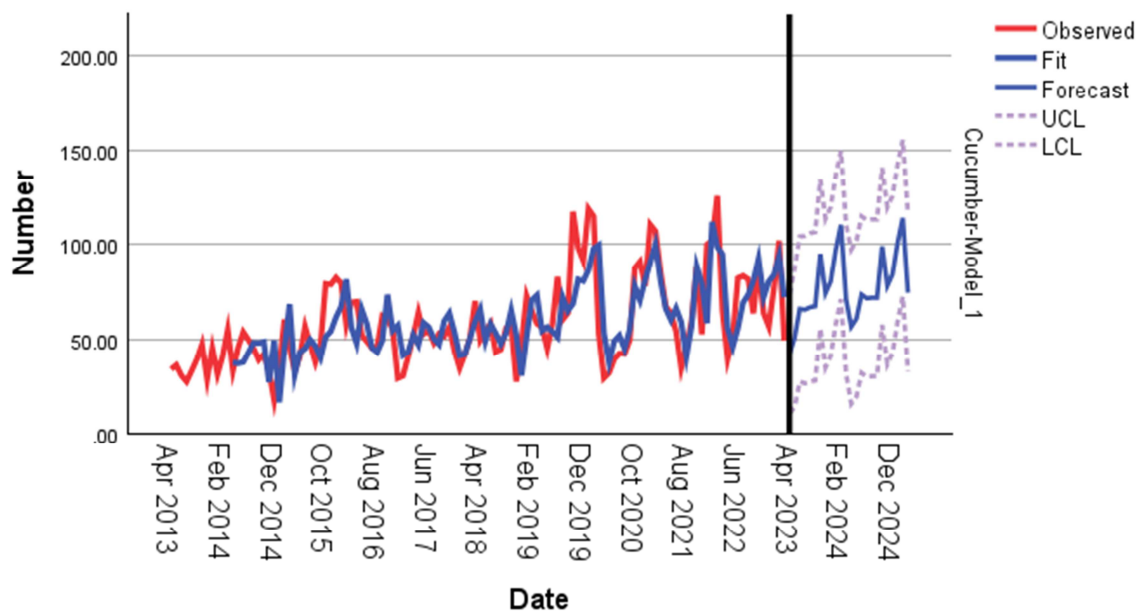


Figure 10. Comparison of Forecasted versus Observed Prices for Cucumber using SARIMA (1,0,0) (0,1,1)₁₂.

Table 8. Forecasted Prices for Cucumber using SARIMA (1,0,0) (0,1,1)₁₂ and SSES at 95% Confidence Interval.

Date	SARIMA Prediction (95% CI)	SSES Prediction (95% CI)	Date	SARIMA Prediction (95% CI)	SSES Prediction (95% CI)
Apr 2023	42.49 (74-11)	43.53 (74-13)	Apr 2024	56.89 (98-16)	43.53 (134-(-47))
May 2023	50.94 (87-14)	43.26 (82-4)	May 2024	61.05 (102-20)	43.26 (137-(-50))
Jun 2023	66.17 (104-28)	49.54 (96-3)	Jun 2024	73.69 (115-32)	49.54 (146-(-47))
Jul 2023	65.79 (105-27)	46.35 (99-(-6))	Jul 2024	71.74 (113-30)	46.35 (146-(-53))
Aug 2023	67.03 (106-28)	44.91 (103-(-13))	Aug 2024	72.03 (113-31)	44.91 (147-(-58))
Sep 2023	67.59 (107-28)	48.98 (112-(-14))	Sep 2024	72.02 (113-31)	48.98 (154-(-56))
Oct 2023	95.17 (134-56)	68.36 (136-1)	Oct 2024	99.25 (141-58)	68.36 (177-(-40))
Nov 2023	74.52 (114-35)	53.14 (125-(-18))	Nov 2024	78.39 (120-37)	53.14 (164-(-58))

Date	SARIMA Prediction (95% CI)	SSES Prediction (95% CI)	Date	SARIMA Prediction (95% CI)	SSES Prediction (95% CI)
Dec 2023	80.58 (120-41)	54.23 (130-(-21))	Dec 2024	84.32 (126-43)	54.23 (168-(-59))
Jan 2024	97.47 (137-58)	65.83 (145-(-14))	Jan 2025	101.13 (143-60)	65.83 (182-(-50))
Feb 2024	110.50 (150-71)	72.31 (155-(-11))	Feb 2025	114.12 (156-73)	72.31 (191-(-46))
Mar 2024	71.09 (110-32)	56.07 (143-(-31))	Mar 2025	74.69 (116-33)	56.07 (177-(-65))

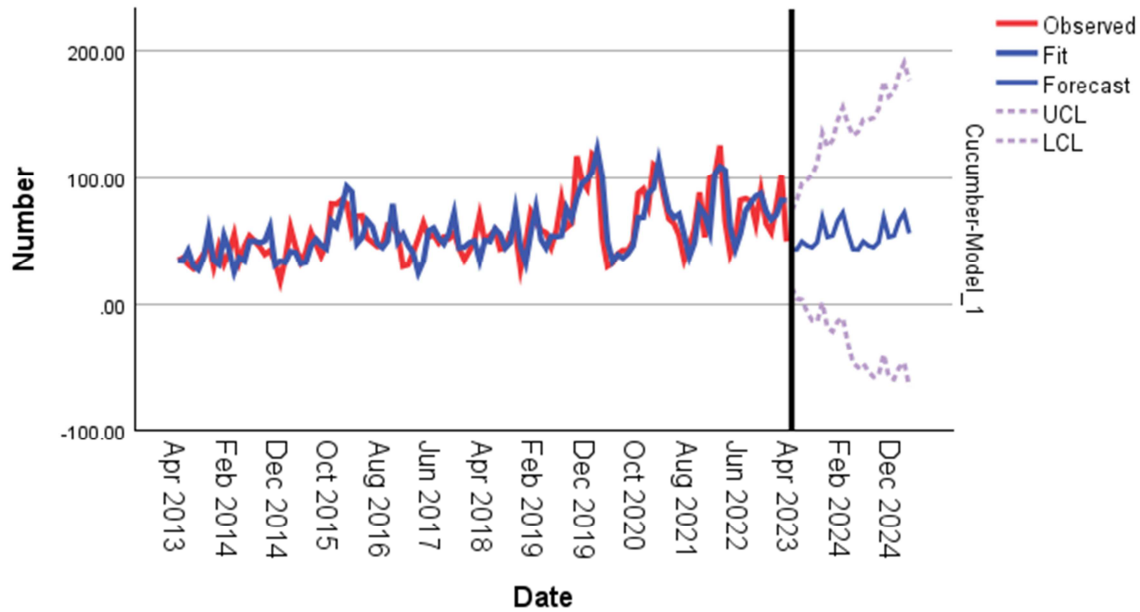


Figure 11. Comparison of Forecasted versus Observed Prices for Cucumber using SSES.

Both the SARIMA model and SSES model have demonstrated their effectiveness in capturing the underlying trend in cucumber price data, as evidenced by the close alignment of the forecasted series with the actual series over the specified period. The accuracy of the models was evaluated using the Mean Absolute Percentage Error (MAPE), yielding values of approximately 22.367% and 21.630%, respectively. This suggests that the forecasts deviate by around 22% on average for both models, with SSES having a slight advantage. Considering the potential influence of external factors on cucumber prices, such as climate conditions, pest infestations, the impact of recent pandemics like COVID-19, and reliance on imports during festival seasons (September to November), these forecast accuracies are considered acceptable. Additionally, market dynamics, trade policies, and export conditions can also contribute to unpredictable price fluctuations. The forecasted prices exhibit a stationary structure, implying that significant price changes are not anticipated under normal conditions until the first quarter of 2025. The results of these forecasts, presented with graphical representations and numerical tables, are valuable for policymakers, educators, farmers, traders, and other stakeholders in the cucumber market, providing them with valuable insights to make informed decisions and plan accordingly.

5. Conclusion and Recommendations

Using IBM SPSS for time series data, the SARIMA and ES models were employed to analyze cucumber prices with a

95% confidence interval. Quantitatively, the results indicate that the cucumber price data exhibits seasonality and level components, but no trend, which was effectively captured by the Simple Seasonal ES (SSES) model. The model's goodness of fit was assessed using residual ACF and PACF plots and the Ljung Box statistic, all within the 95% confidence interval, affirming the suitability of the selected model. Comparing the two models, the SSES model outperformed SARIMA based on various metrics, including the lowest values of MAE, RMSE, MAPE, and BIC, along with a higher R-squared fit of 53% compared to SARIMA's 48.7%. Consequently, the ES model demonstrated superior forecasting capabilities for cucumber prices.

The study's findings reveal that cucumber prices in Nepal follow a stationary structure with seasonality, but no significant upward or downward trends. The ES model forecasts minimal price changes in cucumber until the first quarter of 2025. However, this stable price structure could pose challenges to the sustainability of cucumber production, particularly concerning potential increases in input costs, leading to reduced income for growers. To tackle this, farmers can adopt alternative strategies, such as leveraging the knowledge of high price fluctuations during festival seasons, specifically from September to November. By recognizing these fluctuations, farmers can focus on off-season and periods of high demand for cucumber cultivation to reduce reliance on imports, securing significant profit margins and fostering more sustainable agricultural practices in the long run.

In summary, the article sheds light on the recurring

challenges posed by price fluctuations in vegetable markets, particularly during festive seasons and crises like the COVID-19 pandemic. These fluctuations reveal the critical need for accurate forecasting models, such as SSES and SARIMA, to anticipate and effectively manage price variations in the face of often ineffective government pricing

controls. By harnessing the power of these models, we can not only stabilize cucumber prices but also ensure a consistent supply, addressing issues related to food security and affordability in Nepal during both normal and challenging times.

List of Abbreviations

ADF	Augmented Dickey-Fuller Test
ANN	Artificial Neural Network
APARCH	Asymmetric Power ARCH
AR	Auto Regressive
ARIMA	Auto Regressive Integrated Moving Average
ARIMAX	Auto Regressive Integrated Moving Average with Exogenous Variables
ARCH	Auto Regressive Conditional Heteroskedasticity
BIC	Bayesian Information Criteria
BJ	Box-Jenkins
EGARCH	Exponential Generalized Auto Regressive Conditional Heteroskedasticity
ES	Exponential Smoothing
FNN	Feedforward Neural Network
GARCH	Generalized Auto Regressive Conditional Heteroskedasticity
IBM	International Business Machines Corporation
KPSS	Kwiatkowski-Phillips-Schmidt-Shin
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MA	Moving Average
MLP	Multi-Layer Perceptron
p-value	Probability Value
PACF	Partial Auto Correlation Function
PP	Phillips-Perron Test
RMSE	Root Mean Square Error
SANN	Seasonal Artificial Neural Network
SARIMA	Seasonal Auto Regressive Integrated Moving Average
SI	Seasonal Index
SPSS	Statistical Package for the Social Sciences
SSES	Simple Seasonal Exponential Smoothing
TGARCH	Threshold GARCH
t/ha	Tons per hectare
TLNN	Time-Lagged Neural Network

Competing Interests

The authors declare that they have no competing interests.

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Availability of Data and Materials

All datasets for this study have been included as supplementary files. The original datasets in uncompiled form can be downloaded from: <https://kalimatimarket.gov.np/notices/publication>.

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