Exploring Climate-driven Price Variations in Carrots: A VAR Model

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Abstract

Econometric models, including Vector Autoregression (VAR), are widely used to quantify relationships among economic variables, predict outcomes, and analyze dynamic interactions over time to inform policy decisions. In this study, the objective was to understand the influence of rainfall and temperature in Nuwara Eliya on the fluctuations in prices of carrots. This study was designed to analyze the long-term impact of climatic factors on carrot price dynamics, offering insights into more informed agricultural and economic planning. Wholesale prices of carrot were collected from Hector Kobbekaduwa Agrarian Research and Training Institute (HARTI) covering twenty-three years (2000-2023). A VAR model was applied to capture the interdependencies between temperature, precipitation, and carrot prices, with an ideal lag order of 6. Granger causality tests revealed that precipitation changes significantly influenced carrot price fluctuations. VAR model coefficients further quantified the magnitude and significance of climate impacts on carrot prices.

Keywords: *Agricultural Price Volatility, Precipitation Patterns, Price Fluctuations*

JEL Classification: Q11, Q54, Q15, D40, Q12

Introduction

Vegetables are perishables that have a price variation according to supply and demand. In addition to supply and demand dynamics, several factors influenced vegetable prices, particularly in a country like Sri Lanka. Climate and weather variability are significant contributors, as they directly affect crop yield and availability (Zhang & Carter, 2018). Adverse climatic conditions such as droughts, heavy rains, or unseasonal temperature shifts led to reduced production, causing supply shortages and subsequent price increases (Tadesse *et al*., 2014; Funk & Brown, 2009). Hence vegetable prices directly impact residents' quality of life and farmers' income, which in turn influences the growth of Sri Lanka's vegetable sector and the country's overall economic balance. It is essential to forecast vegetable prices during both the harvesting season and the off-season for growers to make wise production decisions (Yoo, 2016). Forecasts of food commodity prices are essential for economic policy formulation, as agricultural price stability measures are crucial for ending the vicious cycle of poverty in developing countries (Illankoon & Kumara, 2020). Inadequate availability of agricultural commodities results in price fluctuations and places a burden on consumers, whereas excess of agricultural products leads to a decline in vegetable prices and causes financial setbacks for farming households (Xiong *et al*., 2018).

Global climate change is expected to worsen in the coming decades, leading to more frequent and severe extreme climatic events with the potential to threaten agricultural production systems (Gordeev, 2022). A study conducted by Hatfield *et al.*, (2011), explored the impacts of climate change in world food markets to find that rising temperatures can have a significant impact on crop production. The study highlighted that the yield variations due to temperature changes can vary significantly with regard to different crops in the tropics (Jat *et al*., 2016). On a certain timescale, there was a relationship between climate and agricultural futures markets. However, in extreme events, climate affects various agricultural commodities differently (Cao *et al*., 2016). However, studies of the impacts of climate change and climate variables on vegetable production, yield, and quality including preharvest and post-harvest vegetable quality have constituted the majority of research on climate factors and vegetables (Nalwanga & Belay, 2022). The effects of climate change on agriculture and crop production are complex and can vary significantly on various factors such as crop type, geographical location, and local climate conditions (Cao *et al*., 2016). Hence it is challenging for the government to create policies that adequately address the competing interests of farmers and consumers due to the imbalance in the supply and demand of agricultural products. Moreover, selecting a forecasting method to predict future prices will help policymakers and farmers make the right decisions (Sun *et al*., 2023).

It expands the understanding of climate-related factors that can impact the agricultural market and specifically focuses on vegetable prices (Schlenker & Robert, 2009). This research also offers a theoretical framework that can guide future studies on the development of early warning systems and forecasting models for vegetable prices. Furthermore, this study has practical implications for various stakeholders, including government policymakers, farmers, businesses, and consumers. Farmers can use this information to make informed decisions regarding crop planning and production. Additionally, consumers can benefit from a better understanding of climate fluctuations which influence vegetable prices, allowing them to make more informed purchasing decisions. The primary objectives of his study were to develop a VAR model based on rainfall and temperature which affects carrots and to identify the proportion of contribution of each climate factor in price fluctuations. Similarly, studying the price fluctuations influenced by climate variables in one specific crop offer insights into broader market dynamics in the vegetable sector which will be a foundation for analyzing prices concerning other crops in the future.

Literature Review

Fluctuation of vegetable prices plays a crucial role in shaping the economy and influencing consumers' everyday lives. This has led to a growing interest in conducting comprehensive and large-scale studies on vegetable pricing, as highlighted in various medical and societal research (Miller et al., 2016). These studies revealed that vegetable consumption remained low globally, especially in low-income regions, and emphasized the need for policies to improve the accessibility and affordability of these products (Li et al., 2021). Similarly, research have examined how pricing impacts food choices while exploring whether cost serves as a barrier to fruit and vegetable consumption among low-income families by analyzing the average expense of a fruit and vegetable market basket (French, 2003). Researchers have studied vegetable prices by examining various influencing factors, with a focus on specific regions and varieties of vegetables. Numerous studies investigated the impact of petroleum prices on vegetable costs, along with the influence of petroleum prices (Du et al., 2022). These energy sources are critical for powering agricultural machinery, maintaining optimal growth conditions, especially in greenhouses, and transporting produce to markets and among other stakeholders.

Time-series analysis was a common approach in many studies, offering critical insights into the dynamics of a system and enabling predictions of its behavior (Sun et al., 2023). These methods have been effectively applied across various fields, including physical, economic, and biological systems (Sun et al., 2023). Most traditional methodologies assume linear system behavior with stochastic noise, often overlooking nonlinear dynamic effects. The time series analysis method mainly included autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA), seasonal autoregressive integrated moving average (SARIMA), autoregressive conditional heteroskedasticity (ARCH), generalized autoregressive conditional heteroskedasticity (GARCH) (Sun et al., 2023).

Clustering techniques, including hierarchical clustering, are also valuable for grouping items based on shared characteristics without predefined categories (Wang et al., 2021).

Combining clustering with other analytical methods resulted in a more comprehensive categorization that accounts for various dynamic aspects of the system. Notably, these methodologies did not require the time series to be stationary, which was a prerequisite for traditional techniques like autocorrelation analysis (Wang et al., 2021). The integration of clustering with other analytical methods frequently resulted in more comprehensive categorizations that capture various dynamic aspects of the system (Wang et al., 2021). Importantly, these methodologies offered the advantage of not necessitating stationarity in the time series data, a key requirement for conventional approaches like autocorrelation analysis (Brown et al., 2017).

Temperature and rainfall were identified as the primary climatic factors significantly influencing food production in Sri Lanka. Historical climate data revealed a consistent trend of both extreme and systematic warming over time (Ahmed & Suphachalasai, 2014). Analysis of rainfall data spanning the past century revealed a decreasing trend in up-country regions situated at an elevation of 900 meters above sea level, while distinct patterns in dry zone rainfall were absent. Notably, comparable warming patterns were observed in the seasonal average temperatures during the crucial agricultural phases of the Yala season (April to September) and Maha season (October to March). Moreover, rainfall variability plays a critical role in crop production, as the timing of cropping seasons heavily depends on rainfall patterns (Zubair *et al*., 2015). Interestingly, there has been a recent increase in the inter-decadal variability of rainfall, contrasting with trends observed in earlier decades. According to regional climate model predictions, the temperature was projected to increase by 2°C to 3°C by the end of the twenty-first century and another projection, utilizing the General Circulation Model (GCM), suggests an expected temperature increase of 2.84°C by the conclusion of the twenty-first century (Zubair *et al*., 2015). In line with the Special Report on Emissions Scenarios, downscaled scenarios indicate that by the year 2080, temperatures are expected to rise by approximately 2.5°C to 4.5°C under the A2 scenario and approximately 2.5°C – 3.25°C under the B2 scenario. Additionally, a temperature increase of 1.1°C to 2.4°C and 1.5°C to 2.8°C for the two major crop seasons is projected to occur in 2025 (Jayawardhana & Warnakulasooriya, 2020).

According to regional climate model predictions, temperatures in Sri Lanka are projected to rise by 2.9°C to 3.5°C compared to the baseline of 1986 to 2005 by the 2090s (Jayawardhana & Warnakulasooriya, 2020). However, under the least emission scenario, a warming of 0.8°C to 1.2°C is predicted for the same period. It is anticipated that minimum temperatures will increase more rapidly than average temperatures. The increase in extreme heat poses a significant threat to Sri Lanka, with a significant rise in the number of days experiencing temperatures of at least 35°C projected under different emission pathways. It is important to note that the projected increase in average temperatures in Sri Lanka is expected to be relatively lower than the global temperature rise. According to the CCKP model, the average temperature in Sri Lanka is estimated to increase by approximately 3.2°C by the 2090s (Jayasankar, *et al*., 2015).

The temperature rises patterns exhibited by the model ensemble show distinct seasonality, with temperatures expected to rise more rapidly between March and July compared to the period from August to February (Naumann *et al*., 2018). The long-term consequences of climate change have significant implications, particularly for agriculture and food security (Naumann *et al*., 2018). These implications were further compounded by two interrelated factors: population growth and shifting dietary preferences. It is projected that these factors will lead to a 60% surge in global food consumption by 2050 compared to the levels in 2006 (Naumann *et al*., 2018). The persistent impact of climate change on global food systems continued to be a pressing concern, as highlighted by the FAO in 2006.

In the context of Sri Lanka, the country is particularly vulnerable to the effects of climate change. Sri Lanka faces heightened exposure to climate change, increased sensitivity to its effects, and limited adaptability. The country exhibits an immense sensitivity to multiple aspects of climate change, including increasing temperatures, alterations in rainfall patterns, sea-level elevation, and intensification of severe extreme weather events. The primary investigation into the direct impact of weather on agricultural prices has been conducted through two main methods. The initial method involved employing time series methodologies on combined data sets of prices and weather metrics while the other method utilizes weather and price information through a panel approach (Dell *et al*., 2014). When compared with time series methodologies; a panel approach utilizes weather and price information that is disaggregated temporally and spatially while taking into account localized weather anomalies that can impact local prices (Dell *et al*., 2014). This provides a more realistic representation of the causal effect that weather has on price formation, which could be obscured when using aggregated data (Blanc & Schlenker, 2017). The panel approach was the ability to control for unobserved factors that correlate with weather using fixed effects. This helped reduce the threat of omitted variable bias (Blanc & Schlenker, 2017). However, time series methodologies were utilized for future price projections.

Time series forecasting methods typically operate under the assumption that future patterns of change will mirror historical trends. However, in practical applications, external factors frequently disrupt these patterns, resulting in biased and inaccurate forecasts (Sun et al., 2023). Variables such as climate change, policy shifts, and unexpected events introduced structural changes to the time series, thereby diminishing the reliability of historical data as a predictor of future behavior (Sun et al., 2023). This highlighted the need for adaptive forecasting techniques capable of accounting for such dynamic influences. However, from a broader perspective, such studies focused on understanding price dynamics and making predictions played a pivotal role in managing central markets and formulating policies related to vegetable prices and consumption. Recognizing shared dynamic behaviors among commonly consumed vegetables was essential for identifying product groupings and understanding how external factors, such as greenhouse usage, influence price fluctuations (Wang et al., 2021). This information helped in market decisions, price correlation studies, and classifications based on cultivation methods and product usage patterns. However, there was a research gap in the grouping of vegetables based on their dynamic price behavior or exploring the relationship between these dynamics and factors such as cultivation methods such as field-grown, greenhouse, or combined (Karakasidou et al., 2024).

Research on price dynamics and forecasting plays a pivotal role in central market management and the development of governmental or private policies regarding vegetable prices and consumption (Du et al., 2022). Identifying common patterns in the dynamic behavior of frequently consumed vegetables was particularly important. This helped classify products for better market decisions, pricing strategies, or planning based on factors like cultivation methods, such as greenhouse and open-air farming (Du et al., 2022). These approaches provided a framework for studying individual product price dynamics and their interrelations. Traditional methods for agricultural price forecasting, including regression analysis, time series models, and gray forecasting techniques, are generally effective when variables are independent, data follow a normal distribution, and the relationships are linear or mildly nonlinear (Karakasidou et al., 2024). However, in practical scenarios, agricultural price forecasting frequently deviates from these ideal conditions, posing challenges such as high dimensionality, limited sample sizes, and pronounced nonlinearity.

Theoretical Framework

This study followed an experimental procedure outlined in Figure 1, which consisted of data processing, construction of a VAR model, variance decomposition analyses, and impulse response analyses. The first step involved subjecting the time series data of carrot price and climate factors to first-order differencing to capture the volatility of the variables. The data were then tested for unit root to ensure the stationarity of the time series. Once the stationarity was confirmed, a VAR model was constructed using the carrot price and climate factors. The optimal lag order for the model was determined based on the Akaike information criterion (AIC) and the final prediction error (FPE) criterion. The lag structure that generated the minimum AIC or SIC was selected as the optimal lag structure. The AIC was a measure that balances the model's predictive performance with the number of parameters it required. The FPE assessed the quality of the model by considering the prediction error and the number of samples.

By selecting the lag order that minimized these criteria, the VAR model was constructed and used for further analysis. The Granger causality test of the carrot price and climate factors was conducted using the optimal lag order. The VAR model was then reconstructed using selected climate variables and prices, repeating this process until a stable lag order was achieved.

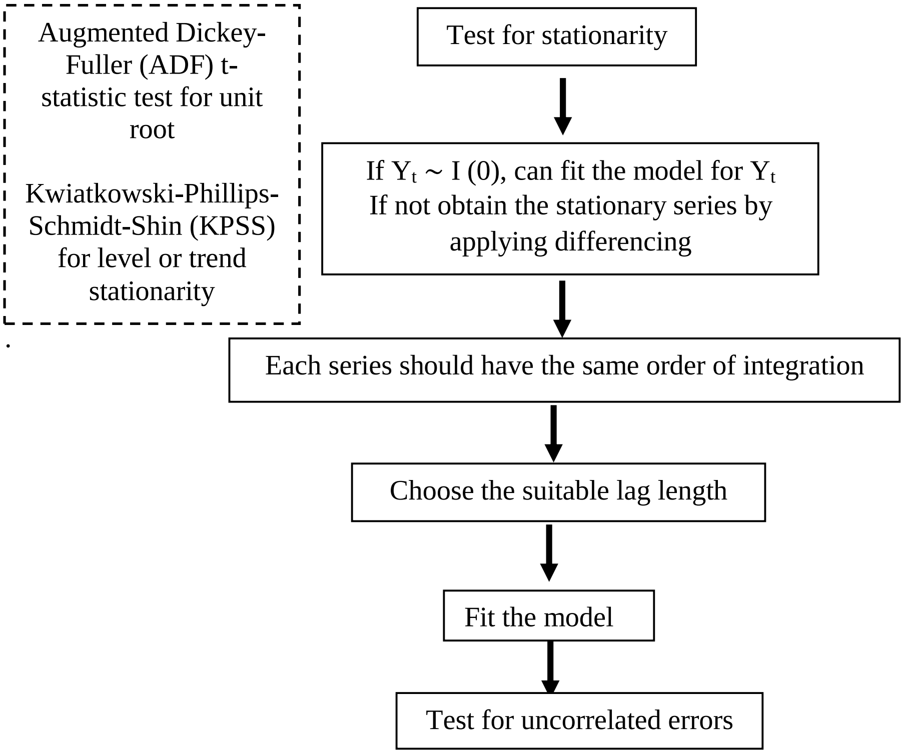


Figure 1: Framework to estimate a VAR model

Source: Authors

In the Sri Lankan scenario: some recent studies have demonstrated the effectiveness of VAR models in understanding the dynamic interactions among economic variables in Sri Lanka, providing valuable insights for policymakers and researchers. Kaluarachchi & Jayathilaka (2024), applied a VAR model to examine how GDP per capita income, unemployment, higher education, and economic growth influence migration in Sri Lanka. Some studies explored the impact of fuel costs on the prices of food items, including Samba rice and coconut, in Sri Lanka. While using Granger causality and cointegration tests, the research found that changes in petroleum prices significantly affect food prices, highlighting the interconnection between energy costs and agricultural commodity prices (Samarasinghe et al., 2024). Perera & Jayawickrama (2023), empirically investigated the effects of monetary policy shocks on the Sri Lankan economy, focusing on the strength of credit and exchange rate channels and it employed a VAR model. Another recent research examined the impact of government expenditure and tax revenue shocks on real GDP, inflation, and real interest rates in Sri Lanka. That study applied a VAR methodology and found that fiscal shocks have a moderate impact on macroeconomic variables, with fiscal multipliers being moderate in size (Rajakaruna , 2022).

Methodology

The VAR model combines multiple factors into a cohesive framework and allows for the visualization of the impact of these factors through variance decomposition. By utilizing the variance decomposition function of the VAR model, the contribution ratio of each climate element's variation to the fluctuations in carrot price can be derived. The VAR model assumed that the calculated coefficients and the variance of the disturbance factors remain constant over time. When the associated time series were not cointegrated, VAR models can be used to forecast a stationary time series based on both its historical realizations and the realizations of other stationary series. However, over time, various external factors, such as economic crises, laws and regulations, and technological advancements, can lead to significant changes and sudden shocks. In such cases, the conventional VAR model becomes inadequate for capturing shifting model parameters. Hence to address this issue, the time-varying parameter vector autoregressive (TVP-VAR) model was a useful approach (Primiceri, 2005). Figure 2 shows the experimental design of the current study (Affoh *et al.*, 2022).

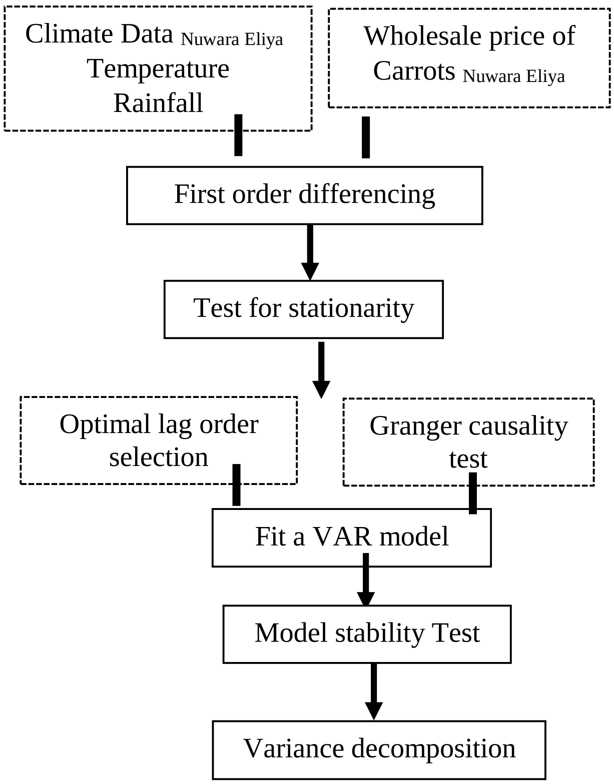


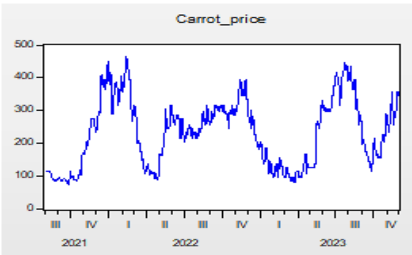
Figure 2: Experimental flowchart

Source: Authors

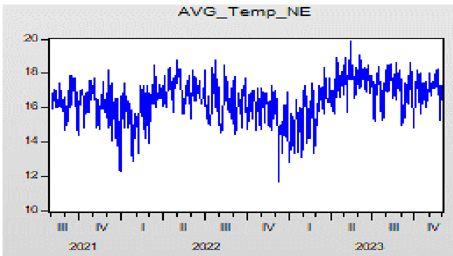
In this study carrot wholesale price data were collected from Hector Kobbekaduwa Agrarian Research and Training Institute (HARTI) based across 23 years (2000-2023). The climate data for maximum temperature (degrees Celsius), minimum temperature (degrees Celsius), and rainfall (mm) of Nuwara Eliya was collected from the Meteorology Department from 2000 to 2023. Data volatility of the monthly data was first-order differenced. This allowed all the time series to pass the unit root test and satisfy the ensuing modeling requirements. Each time series has 852 values following the first-order difference processing. Data were analyzed using statistical software EViews (Version 13) and R-studio (Version 3).

Results and Discussion

Handling missing data and seasonal tests was a prominent aspect of time series analysis. Due to issues of data collection errors, holidays, or operational challenges, certain days may not have been recorded. Therefore, interpolation methods were used to estimate these missing values by filling in the gaps, ensuring that the time series remains continuous, and creating a more uniform dataset for analysis. When handling Outliers, some data points might have been excluded as being identified as extreme outlier values. Interpolation ensured a continuous series by estimating reasonable values for these removed points, thus maintaining data integrity.



(A)



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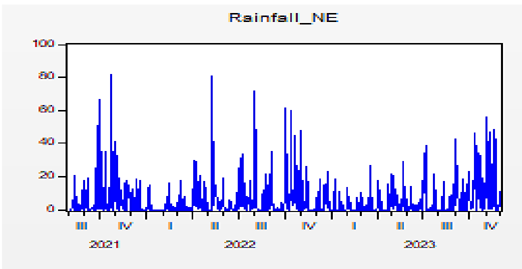

(C)

Figure 3 (A) Time series plot of monthly carrot wholesale price in Nuwara Eliya from 2020 to 2023; (B) Time series plot of monthly average temperature from 2020 to 2023; (C) Time series plot of monthly rainfall in Nuwara Eliya from 2020 to 2023
Source: Authors

According to Figure 3, it was evident that carrot price data, average temperature data, and rainfall data were not stationary. Hence first difference was taken in every variable and made those variables stationary. However, to address this issue and ensure the validity of subsequent analyses, the first difference of each variable was calculated. By applying this transformation, the non-stationary variables were converted into stationary series, allowing for more accurate modeling and forecasting. This step was essential to eliminate potential biases and to facilitate the application of time series techniques that assume stationarity in the data.

Table 1: Descriptive statistics of the carrot prices

Description	Carrot Prices
Mean	232.30
Median	245
Maximum	465
Minimum	72.50
Standard Deviation (Std. Dev.)	102.71
Coefficient of variation (CV)	1.51
Observations	852

Source: HARTI, Data Bank

Table 2: Descriptive statistics of the climate factors

Description	Average Temperature (^{0}C)	Precipitation (mm)
Mean	16.4	5.4
Median	16.6	10.6
Maximum	19.9	81.3
Minimum	11.65	22.5
Standard Deviation (Std. Dev.)	1.2	10.5
Coefficient of variation (CV)	1.34	10.3
Observations	852	852

Source: Department of Meteorology

Granger Causality Analysis

The stationarity of the climate factors and carrot price data was tested using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests; the test results are shown in Table 3. The presence of unit roots was ruled out as the null hypothesis, and all data cleared the 1% significance level. This indicated that all of the data were non-stationary, and the first differenced data could be utilized to build VAR models and perform further Granger causality tests. This transformation ensured that the variables met the prerequisites for VAR modeling and Granger causality analysis, allowing for a strong examination of interrelationships. This transformation was essential to satisfy the stationarity assumptions required for VAR modeling and Granger causality analysis, enabling a robust investigation of the dynamic interrelationships among the variables.

Table 3: Stationary test

Secondary Variables	ADF			PP			
	Intercept	Trend and Intercept	None	Intercept	Trend and Intercept	None	Conclusion
Carrot	0.1167	0.3169	0.4721	0.1572	0.3915	0.5073	Non-Stationary
AT	0.0000	0.0000	0.5698	0.0000	0.0000	0.5774	Non-Stationary
PR	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	Non-Stationary

**** indicate the statistical significance at the 1% levels, respectively*

** Average temperature (AT) and precipitation (PR)*

The lag selection criteria were the Akaike information criterion (AIC), Schwarz Criterion (SIC), and Sequential modified LR test (LR) whereas the AIC and SIC criterion used to select the lag order. Accordingly, for this symmetric lag model, the AIC-based criteria picked the correct lag more frequently than the other criteria. According to the different error criteria, different VARs were fitted. According to AIC and SIC, a sixth lag can be selected. Table 4 displays the findings of Granger causality tests conducted between the variables in each unit of analysis and the related optimum lag ordering. The climate factor variables that passed the unidirectional Granger causality test were average temperature (AT) and precipitation (PR). The ideal lag order of the carrot analysis was 6.

Table 4: Granger causality test

Analysis Units	The Null Hypothesis	Lag	*P-V*alue	Conclusion
Carrot	AVG_TEM does not Granger Cause carrot price	Lag 6	0.0570	Accepted
	PR does not Granger Cause carrot	Lag 6	0.0447**	Reject

**** indicate the statistical significance at the 1% and 5% levels, respectively*

Granger causality test, results concluded that the carrot price fluctuations were affected by precipitation changes and also average temperature did not significantly predict carrot prices (p-value = 0.0570), hence accepting the null hypothesis. This suggested that temperature changes have limited predictive value for carrot prices in this model. However, precipitation significantly predicted carrot prices (p-value = 0.0447), hence rejecting the null hypothesis in this case. Therefore, precipitation appeared to have a meaningful effect on carrot prices, unlike temperature.

Impulse Response Analysis

After conducting model estimation and parameter testing, two types of impulse response analysis were used to examine the dynamic effects of climate changes on vegetable price fluctuations. The first type, equal-interval impulse response analysis, aimed to investigate the response trend of the dependent variable to a one-unit standard deviation positive change in the independent variable at fixed time intervals throughout the time series horizon. The second type, time point impulse response analysis, focused on exploring the short-term, mid-term, and long-term response changes of the dependent variable to the independent variable by selecting three intervals of different lengths.

In the equal-interval impulse response analysis, the response of vegetable prices to a one-unit standard deviation increase in climate factors of temperature and precipitation was examined at fixed time intervals. This analysis showed a clear response trend where prices initially reacted negatively to changes in the climate variable diminishing over time. In the equal-interval impulse response analysis, a one-unit standard deviation increases in precipitation resulted in an immediate increase of 2.8% in carrot prices. This positive impact peaked at 1.2% in the third time interval, then gradually declined, stabilizing around 0.6% after eight intervals. This indicated that the initial effect of precipitation on prices was strong but diminished over time as the market adjusted.

In the time point impulse response analysis, vegetable prices demonstrated distinct reactions in the short-term, mid-term, and long-term. Short-term responses were more immediate but tended to stabilize, while mid-term and long-term responses revealed prolonged adjustments, suggesting that climate fluctuations can have lasting effects on market prices. In the short term (within the first two intervals), a one-unit increase in temperature caused a 0.7% drop in carrot prices, indicating a negative immediate response. By the mid-term (intervals three to six), the effect became neutral, with prices returning close to the baseline. In the long term (beyond six intervals), the response reversed slightly, showing a gradual increase of 0.4%, suggesting that market forces eventually accommodate initial climate impacts.

VAR stability condition and residual diagnosis

The stability condition of a VAR model refers to the requirement that the model's dynamics remain well-behaved over time. Residual diagnosis was an essential step in VAR modeling to assess the quality of the model's fit and the presence of any remaining patterns or issues in the residuals. Various diagnostic tests were performed to evaluate the residuals, from the assessment of residual autocorrelation (Figure 4). According to Figure 4, most of the autocorrelations were within two standard error bounds.

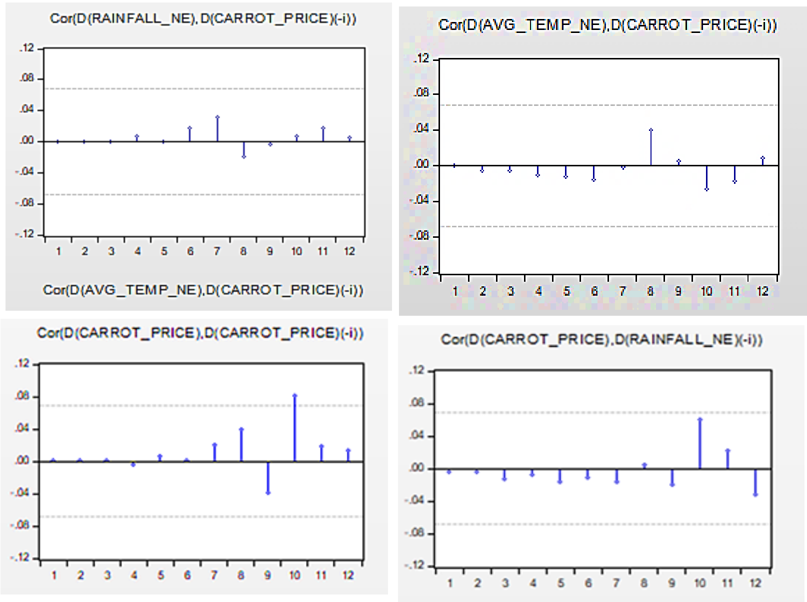

Figure 4: Autocorrelations with Approximate 2 Std. Err. Bounds

The VAR model's stability condition test confirmed that all characteristic roots lie within the unit circle, with the largest root at 0.92, indicating model stability and suitability for long-term analysis. This stability meant that any shocks in the variables gradually scatter rather than cause persistent fluctuations. For residual diagnostics, the autocorrelation test showed p-values above 0.10 for all lags, confirming that there is no significant autocorrelation, suggesting that the model captured the temporal dependencies effectively. The heteroscedasticity test resulted in a p-value of 0.15, indicating homoscedasticity, or constant variance, across residuals. These findings validated the model's reliability, showing it was well-specified and appropriate for analyzing dynamic relationships over time. Considering System Residual Portmanteau Tests for carrots, at Lag 6, the p-value was 0.9749, indicating that there was no significant autocorrelation. Hence, it concluded that there were no autocorrelations in the residuals of the returns. As autocorrelation was not detected, it suggested that the model adequately captured the temporal dependencies present in the data. Then the following models were derived.

$$\text{Equation}_{\text{General}}: \; Y_t^{(1)} = \alpha_{10} + \alpha_{11} Y_{t-1}^{(1)} + \alpha_{12} Y_{t-1}^{(2)} + \alpha_{13} Y_{t-1}^{(3)} + \beta_{11} Y_{t-2}^{(1)} + \beta_{12} Y_{t-2}^{(2)} + \beta_{13} Y_{t-2}^{(3)} + \epsilon_{1t}$$

Where Yt (1) – VAR1 Equation, Yt−1 – variables and α / β – Constants

Specific Model for Carrot Price Dynamics:

$$D\,(\text{Carrot Price}) = C(1).\, D\,(\text{Carrot Price}_{t-1}) + C(2).\text{Temperature}_{t-1} + C(3).\text{Rainfall}_{t-1} + C(4)$$

Specific coefficient values were: C(1)= 0.141777; C(2)= 0.000060 ; C(3)= -16.09719; C(4)= 0.214183;

The weights of each factor in the differenced carrot price equation were determined by the respective coefficients: the weight of the lagged differenced carrot price (D (Carrot Price $_{t-1}$)) was given by the coefficient C(1), which is 0. 141777. The weight of the lagged fuel price (Temperature $_{t-1}$) was given by the coefficient C(2), which is 0.000060. The weight of the lagged rainfall (Rainfall $_{t-1}$) was given by the coefficient C (3), which is -16.09719. The constant term C(4) represented an additional weight in the equation, which is 0.214183. These weights determined the impact of each lagged variable and the constant term on the current differenced carrot price in the VAR model. The interpretation of the VAR model involved understanding the lag structure and the effects of lagged variables on the differenced carrot price. The coefficients provided information about the magnitude and direction of the relationships between the variables, and the weights indicated the relative impact of each factor on the current differenced carrot price.

In the equation for the differenced carrot price, the lagged differenced carrot price showed a positive effect with a coefficient of 0.141777, indicating that past changes in carrot prices positively influence current changes. The lagged temperature showed a negligible impact (0.000060), while the lagged rainfall had a significant negative effect (-16.09719), suggesting that increased rainfall substantially lowers current carrot prices.

Conclusion

The VAR model revealed important insights into the factors influencing carrot price fluctuations. The stability and residual diagnostic tests confirmed that the model was well-specified, stable, and free from significant autocorrelation, indicating its reliability for analyzing the impact of climate variables on carrot prices. The Granger causality tests showed that precipitation significantly predicts carrot price changes, while temperature did not, highlighting rainfall as a key driver of price variability. The impulse response analysis further supported this, as a positive rainfall shock led to an initial increase in carrot prices, which gradually stabilized over time, whereas temperature had minimal impact in the short term but slightly influenced prices in the long term. The VAR model coefficients indicated that past changes in carrot prices have a positive effect on current prices, while rainfall had a substantial negative effect on price changes, suggesting that increased rainfall can significantly lower current carrot prices. These results revealed the critical impact of precipitation in influencing carrot prices and suggested that strategies for agricultural planning and market prediction should focus on rainfall patterns.

Based on the aforementioned analysis, it is important to restate that the findings of this study are applicable within specific spatial and temporal contexts. Generalizing the conclusions drawn from this study requires further verification and examination across different vegetable varieties, conditions, and settings.

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