

Article

Dynamic Analysis of Date Palm Producers' Price and Climate Variability: Shocks and Responses in Saudi Arabia

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Abstract

Climate change influences crop prices through its impacts on agricultural production, costs, consumer and producer behavior, and the market equilibrium. Therefore, this study aims to examine the dynamic relationship between climate variability and date palm producer prices in Saudi Arabia utilizing annual time-series data from 1991 to 2024 and applying a Vector Autoregression (VAR) method to investigate dynamic responses over shorter and longer horizons. The analysis incorporates impulse response functions (IRFs), forecast error variance decomposition (FEVD), and historical decomposition (HD). The empirical findings indicate that date palm producer prices exhibit strong persistence and are predominantly explained by their own innovations in the short run. At horizon 10, date-palm producer-price innovations account for 94.82% of the forecast-error variance, while climatic variables jointly account for approximately 5.18%. Although climate factors' shocks exert measurable short-run effects on producer prices, these responses diminish over time, indicating that the market effectively absorbs climate-related changes while maintaining persistence. However, FEVD and HD results reveal that the contribution of temperature and relative humidity to producer price fluctuations increases steadily over time, highlighting the growing importance of climate variability in shaping long-term market dynamics. The findings highlight the relevance of considering climate-smart agricultural practices, drought-tolerant date-palm varieties, and climate adaptation and risk-management strategies in the date-palm sector. While these measures were not directly evaluated in the present model, they may contribute to strengthening the sector's resilience to climatic variability, supporting price stability, and promoting sustainable agricultural development. Their specific effects on price volatility and food security, however, require further empirical investigation.

Keywords: agricultural commodity price; climate risk; future precipitation; market price shocks



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1. Introduction

Climate change has become one of the major challenges affecting agricultural production and commodity markets worldwide. It is critically affecting farming systems globally through increasing temperatures, fluctuating rainfall patterns, and more frequent extreme weather events. Accordingly, economists are increasingly manipulating weather facts and climate model outputs to evaluate the economic impacts of climate change on agricultural systems and markets [1].

Climatic conditions may affect date-palm producer prices through several interconnected channels. Changes in temperature, precipitation, and relative humidity can influence crop yields and fruit quality, alter irrigation requirements, affect production costs, and ultimately change market supply and producer prices. However, price formation is not determined by climatic conditions alone. Demand, inflation, input costs, trade, storage conditions, subsidies, and agricultural policies may also influence agricultural prices. The present study focuses specifically on the dynamic relationship between climatic variability and date-palm producer prices and does not attempt to investigate all determinants of price formation. Accordingly, the estimated relationships should be interpreted within the scope of the climatic variables included in the model.

In arid and semi-arid regions such as Saudi Arabia, agricultural production is vulnerable to harsh climatic conditions and limited water resources [2]. Agriculture plays an important role in food security and economic diversification under Saudi Vision 2030. The date-palm (*Phoenix dactylifera*) sector is particularly important due to its nutritional, cultural, and economic value. According to GASTAT [3], Saudi Arabia produced approximately 1.923 million tonnes of dates in 2024, a 1% increase from 2023, with more than 37.6 million date palms, including over 32 million productive trees. These figures highlight the substantial scale and economic importance of the date sector. Nevertheless, date production remains vulnerable to climatic variability and water constraints, with changes in temperature, precipitation, and relative humidity potentially affecting production conditions and producer prices.

Producers' prices serve as a significant indicator of agricultural market dynamics, indicating the interaction between supply and demand forces and external shocks. Understanding the relationship between climate factors and date palm producers' prices is therefore essential for designing effective agricultural policies and risk management strategies.

Despite growing evidence on climate-related agricultural impacts, empirical research on the dynamic relationship between climatic conditions and producer prices in Saudi Arabia remains limited. Previous Saudi studies have mainly examined climate effects on date-palm productivity and production, while regional and international studies have focused largely on agricultural yields, commodity markets, or other crops using different econometric approaches [4]. Limited attention has been given to how temperature, precipitation, and relative humidity shocks are transmitted to date-palm producer prices over time.

This study addresses this gap by using a VAR framework to examine the dynamic responses of date-palm producer prices to climatic shocks and the relative contribution of climatic variables to forecast-error variance. The analysis focuses on producer-price responses across forecast horizons and does not directly estimate price volatility or establish a structural long-run equilibrium. Therefore, the research hypothesized that:

H1. *Temperature variability has a significant dynamic effect on date-palm producer prices in Saudi Arabia.*

H2. *Precipitation variability has a significant dynamic effect on date-palm producer prices in Saudi Arabia.*

H3. *Relative humidity variability has a significant dynamic effect on date-palm producer prices in Saudi Arabia.*

This study offers a novel contribution by focusing on price dynamics rather than production and specifying the transmission of precipitation, temperature, and humidity shocks. It advances the literature by providing new empirical evidence on short- and long-

run adjustment mechanisms as well as climate-impacted price volatility. These findings guide decision-makers in enhancing agricultural development in arid environments and supporting the long-run sustainability of the date palm sector.

2. Literature Review

Recent climate–economy research emphasizes the importance of carefully identifying the economic effects of climatic conditions. Auffhammer et al. [1] highlight the use of historical weather data in economic analysis and stress the distinction between short-term weather variability and long-term climate variability. Dell et al. [5], further demonstrate that temperature and precipitation shocks can generate significant economic effects, including through agricultural and productivity channels, while emphasizing nonlinear responses and heterogeneous impacts. In addition, Choupi et al. [6] show that commodity-price uncertainty can generate substantial and asymmetric economic effects, highlighting the importance of accounting for price shocks and uncertainty when examining commodity-dependent markets. In the agricultural context, Emam [7] provides evidence that change in temperature and precipitation can affect date productivity in Saudi Arabia, with implications for food security. Together, these studies suggest that climatic shocks may affect agricultural markets not only through production but also through commodity-price mechanisms. However, limited attention has been given to the transmission of climatic shocks to date-palm producer prices. This study therefore contributes to the climate–economy literature by examining the dynamic responses of date-palm producer prices to temperature, precipitation, and relative humidity shocks in Saudi Arabia.

Previous studies generally show that climatic conditions can influence date-palm growth, development, and productivity, particularly through temperature and moisture conditions [7,8]. More broadly, weather and climate shocks can affect agricultural commodity prices through changes in production and market expectations, although the magnitude and timing of these effects may vary across crops, regions, and data frequencies [9,10]. Climatic conditions can influence phenology, yield, fruit quality, irrigation requirements, production costs, and market supply, thereby affecting producer prices [11–14]. However, the direction of the price response is not necessarily uniform. A reduction in supply may increase prices, whereas declines in fruit quality may reduce the prices received by producers. Moreover, irrigation, farm management, storage, and other adaptation practices may weaken or delay the effects of climatic shocks on prices. These differences highlight the need for a context-specific analysis of the Saudi date-palm market and provide a basis for examining the dynamic responses of producer prices to temperature, precipitation, and relative humidity shocks.

Several investigators indicated that climatic shocks reduce production efficiency, increase production uncertainty, and alter market supply, ultimately affecting the agricultural price mechanism [15,16].

Temperature is one of the most important climatic determinants of date palm growth and productivity. Date palms grow best under warm, dry conditions during flowering and fruit development [17]; however, excessive heat disrupts pollination, fruit development, and physiological processes, leading to lower yields and poorer fruit quality [18,19]. Similarly, Ahmed-Amen et al. [20] reported that warmer environments with lower humidity promote earlier fruit maturation and higher productivity. In Algeria, Faci& Benziouche [21] found that air temperature is a key determinant of date palm phenology, fruit development, and yield. Beyond biological production, several researchers applied econometric methods to examine the impact of climate variability on crop prices, for instance, Alidoost et al. [22] used a copula-based econometric approach focusing on empirical marginal probability, and the results showed that climate extremes significantly influence crop yield, production,

and prices, while, Lee [23] employed panel econometric analysis considering the simple revenue model with heterogeneity investigation, and the results conveyed that extreme weather events increase crop revenue variability despite partial price compensation for yield losses.

In addition, precipitation also plays a vital role in date palm production despite the crop's adaptation to arid environments. Excessive rainfall during flowering and fruit ripening reduces fruit quality, disrupts pollination, delays maturation, and lowers productivity [18,24]. Baaghideh et al. [25] applied the Mann–Kendall trend test together with CMIP5 climate projections and stated that future climate change will alter the climatic suitability of date palm cultivation, requiring adaptation to changing environmental conditions. Likewise, Dhaouadi et al. [26] found that poor irrigation management, inadequate water quality, and climate variability reduced palm productivity and fruit quality, threatening the long-term sustainability of production systems. In Ethiopia, Lemlem et al. [27] further showed that traditional production practices and management constraints limit date palm productivity, emphasizing the importance of improved cultivation and management strategies.

Relative humidity is an additional important climatic factor affecting date palm production and fruit quality. Low humidity favors fruit ripening, whereas excessive humidity delays maturation and increases physiological disorders and disease incidence [18,19]. Mohammed et al. [28] confirmed the importance of temperature and relative humidity in fruit development, showing that controlled environmental conditions substantially improve fruit quality and reduce postharvest losses.

Climate variability affects agricultural markets by influencing both production and producer prices. The study investigated the effects of climate change and agricultural prices on the production of crops using an econometric supply response model with country-level production, price, and climate data. The results showed climate change adversely affected agricultural production and intensified production fluctuations, contributing to increased price volatility [29].

Another study examined the impact of climate change on crop prices and price volatility in the United States using statistical crop models integrated with an economic model. The findings indicated that climate change reduced crop yields and increased yield variability. However, the effects on price volatility were relatively limited because crop storage and agricultural support policies helped stabilize markets [30].

A recent study investigated the factors influencing consumer purchasing decisions for *Khalas* dates variety in Saudi Arabia using the entropy weighting method and binary logit models. The results showed that price was among the key attributes affecting consumers' purchasing decisions, alongside size, mellowness, and color [31].

Although previous studies have extensively examined the effects of climate change on date palm growth, productivity, and fruit quality, limited attention has been given to the dynamic effects of climatic shocks on date palm producer prices, particularly in arid and semi-arid regions.

Therefore, this study addresses this gap by employing a Vector Autoregression (VAR) model to examine the dynamic effects of shocks in temperature, precipitation, and relative humidity on date palm producer prices in Saudi Arabia. The VAR framework examines dynamic interactions among producer prices and climatic variables without imposing a single dependent-independent structure. Given the small annual sample, a parsimonious lag structure was selected using information criteria. Cholesky decomposition was used to identify orthogonal shocks under a recursive ordering assumption, and alternative orderings were examined as a robustness check. Because the data are annual, the climate

variables reflect broad climatic variability rather than seasonal or short-term weather shocks.

The analysis is further supported by post-estimation analyses, including impulse-response functions (IRFs), forecast-error variance decomposition (FEVD), and historical decomposition (HD), as well as robustness tests based on alternative Cholesky orderings to assess the sensitivity of the results.

3. Materials and Methods

3.1. Data Sources

Based on data availability, this study employs annual time-series data for Saudi Arabia covering 1991–2024. Date-palm producer prices (USD/tonne) were obtained from FAOSTAT [32]. Climatic variables, including precipitation (mm), mean surface air temperature (°C), and annual average relative humidity (%), were obtained from the Global Data Lab [33]. The climate variables represent national annual averages and therefore show broad climatic variability rather than seasonal or short-term climatic conditions. Producer prices are treated as market price indicators rather than direct measures of farm income. All variables were included in the VAR framework as jointly endogenous variables.

Producer prices are interpreted as market price indicators rather than direct measures of farm income, which also depends on production quantities, input costs, subsidies, and other factors. The use of national annual climate averages provides a consistent measure of broad climatic variability across the study period; however, these averages may not fully represent conditions in major date-producing regions or during critical phenological stages. They may also conceal short-term heat extremes, rainfall timing, drought duration, and humidity conditions during flowering and ripening. This limitation should therefore be considered when interpreting the estimated climate–price relationship.

The justification for selecting the date palm producer prices is that they directly reflect farm income and economic situations of the producers, making them a suitable indicator for assessing the economic impacts of climate variability on producers. Climate variables are selected due to their direct influence on date palm water requirements and physiological development, which can ultimately affect production levels and producer prices. Also, these factors are particularly relevant in arid environments, where climate variability significantly affects agricultural supply and, consequently, producer prices and consumer behavior.

Table 1 displays statistical information and normality test results for the selected variables. The descriptive statistics indicate that while climatic variables such as temperature and humidity are relatively stable over the sample period, precipitation and date palm producer prices exhibit greater variability. Likewise, the normality test indicates that date palm producer price (DPP) and yearly average relative humidity (YARH) are normally distributed. Precipitation (PRE) and average mean surface air temperature (ASAT) deviate from normality. Therefore, all data were transformed into natural logarithms to reduce skewness and stabilize variance.

Table 1. Descriptive Analysis.

Study Variables (Units)	Abbreviation	Mean	Std. Dev.	Min	Max
Date palm producer price (USD)	DPP	3215.396	305.688	2634.70	3781.30
Precipitation (mm)	PRE	101.990	12.264	84.310	141.29
Average Mean Surface Air Temperature (°C)	ASAT	25.957	0.472	24.50	26.92

Table 1. Cont.

Study Variables (Units)	Abbreviation	Mean	Std. Dev.	Min	Max
Yearly-Average-Relative-Humidity (%)	YARH	27.218	1.008	25.470	28.98
Normality tests					
Skewness and Kurtosis normality			Jarque–Bera (JB)		
Variable	Pr (Skewness)	Pr (Kurtosis) adj	chi2(2)	χ^2	
DPP	0.0878	0.9213	3.17	2.618	
PRE	0.0064	0.0549	9.29 ***	10.35 ***	
ASAT	0.0315	0.0578	7.28 **	7.005 **	
YARH	0.8004	0.0739	3.54	1.513	

Note: *** & ** = significant at 1% and 5%, respectively. Null hypothesis (H_0): The variable is normally distributed. Alternative hypothesis (H_1): The variable is not normally distributed. Descriptive statistics are based on the original variables. The number of observations for the data is 34. Source: Authors' calculations (2026).

3.2. Preliminary Tests

To examine the stationarity properties of the selected variables, the study employs the Phillips–Perron (PP) unit root test [34]. The PP unit-root test was conducted with a constant (intercept) and without a deterministic trend. The PP test is preferred because it suggests robust results in the presence of heteroskedasticity and serial correlation, which are common in time-series data such as climate variables and agricultural prices.

3.3. VAR Specification, Diagnostics, and Dynamic Analysis

After ensuring that the selected variables are stationary, we proceeded to estimate the VAR model. The VAR model was introduced by Sims [35] as a flexible framework for analyzing dynamic relationships among multiple time-series variables without relying on a priori theoretical constraints. The VAR methodology follows the standard framework for multivariate time-series analysis [36]. Given the relatively small annual sample, a parsimonious VAR specification with a limited lag length was employed to reduce parameterization and preserve degrees of freedom, while recognizing the potential small-sample limitations of VAR estimation [37].

In the VAR model, Y_t represents a vector of endogenous variables that includes four variables: LnDPP, LnPRE, LnASAT, and LnYARH. The VAR model can be conveyed as:

$$Y_t = \alpha + \sum_{i=1}^p \beta_i Y_{t-i} + \varepsilon_t \quad (1)$$

whereas: Y_t is a vector of endogenous variables at time, t , and Y_{t-i} signifies lagged values of all variables in the system. β_i = coefficient matrices; p = lag length & ε_t = error term.

The equation for each variable in the study can be stated as follows:

$$\text{LnDPP}_t = \alpha_1 + \sum_{i=1}^p \beta_{11,i} \text{LnDPP}_{t-i} + \sum_{i=1}^p \beta_{12,i} \text{LnPRE}_{t-i} + \sum_{i=1}^p \beta_{13,i} \text{LnASAT}_{t-i} + \sum_{i=1}^p \beta_{14,i} \text{LnYARH}_{t-i} + \varepsilon_{1t} \quad (2)$$

$$\text{LnPRE}_t = \alpha_2 + \sum_{i=1}^p \beta_{21,i} \text{LnDPP}_{t-i} + \sum_{i=1}^p \beta_{22,i} \text{LnPRE}_{t-i} + \sum_{i=1}^p \beta_{23,i} \text{LnASAT}_{t-i} + \sum_{i=1}^p \beta_{24,i} \text{LnYARH}_{t-i} + \varepsilon_{2t} \quad (3)$$

$$\text{LnASAT}_t = \alpha_3 + \sum_{i=1}^p \beta_{31,i} \text{LnDPP}_{t-i} + \sum_{i=1}^p \beta_{32,i} \text{LnPRE}_{t-i} + \sum_{i=1}^p \beta_{33,i} \text{LnASAT}_{t-i} + \sum_{i=1}^p \beta_{34,i} \text{LnYARH}_{t-i} + \varepsilon_{3t} \quad (4)$$

$$\text{LnYARH}_t = \alpha_4 + \sum_{i=1}^p \beta_{41,i} \text{LnDPP}_{t-i} + \sum_{i=1}^p \beta_{42,i} \text{LnPRE}_{t-i} + \sum_{i=1}^p \beta_{43,i} \text{LnASAT}_{t-i} + \sum_{i=1}^p \beta_{44,i} \text{LnYARH}_{t-i} + \varepsilon_{4t} \quad (5)$$

whereas: α_1 ; α_2 ; α_3 & α_4 are constant terms, $\beta_{ij,i}$ are coefficients and ε_{it} are error terms.

The optimal lag length in the VAR model (p) is clarified using universal information criteria. The lag order that minimizes these criteria is selected as the optimal specification for the model.

3.3.1. Diagnostic Validation of the VAR Model

The Autocorrelation LM diagnostic test, based on auxiliary regression, is employed to detect serial correlation in the residuals, following, Breusch [38]. After estimating a VAR, we got residuals $\hat{\varepsilon}_t$, Then the auxiliary regression takes the form:

$$\hat{\varepsilon}_t = \alpha + X_t \beta + \sum_{i=1}^p \gamma_i \hat{\varepsilon}_{t-i} + u_t \quad (6)$$

The LM test statistics are computed as:

$$LM = T \times R^2 \quad (7)$$

following a chi-square distribution.

Whereas: $\hat{\varepsilon}_t$ = residuals from the VAR model; X_t = original regressors (lagged endogenous variables); p = number of lags tested for autocorrelation; T = number of observations
 R^2 = coefficient determination from auxiliary regression; u_t = error term.

Then, to confirm the stability of the VAR results, the Eigenvalue stability condition was checked using the eigenvalues of the companion matrix. A VAR model is considered stable or stationary if all eigenvalues lie inside the unit circle. Then the VAR model is stable if it follows:

$|\lambda_i| < 1$ for all i , whereas: λ_i = eigenvalues of the companion matrix F and $|\lambda_i|$ = modulus (absolute value).

3.3.2. Post-Estimation Dynamic Analysis

Following the estimation and stability of the VAR model, post-estimation dynamic investigations are conducted using IRFs and FEVD to examine dynamic interactions amongst the selected variables. IRFs are adopted to trace the time path of the effects of structural shocks on the endogenous variables within the VAR system. The IRFs illustrate the direction (+) or (−) impact, magnitude, and persistence of shocks. Therefore, the VAR model can be expressed in its moving average (MA) form as:

$$Y_t = \sum_{i=0}^{\infty} \Phi_i \varepsilon_{t-i} \quad (8)$$

whereas: Y_t = vector of endogenous variables, Φ_i = matrices of impulse response coefficients, which measure the response of variables to shocks over time. ε_t represents the vector of innovations (shocks). IRFs are typically orthogonalized using Cholesky decomposition, which imposes an ordering of variables [35,36]. Impulse response functions (IRFs) were used to trace the dynamic responses of date-palm producer prices to shocks in the variables. IRFs show how climate shocks affect producer prices over time.

FEVD is usually used to compute the relative contribution of each structural shock to the variability of the endogenous variables over different forecast horizons (periods). The

FEVD was employed to quantify the contribution of each innovation to the forecast-error variance of producer prices [36,39]. Then the FEV for horizon h is:

$$\text{Var}(Y_{t+h} - \hat{Y}_{t+h}) = \sum_{i=0}^{h-1} \Phi_i \Sigma \Phi_i' \quad (9)$$

The contribution of shocks from variable j to variable k is:

$$\theta_{jk}(h) = \frac{\sum_{i=0}^{h-1} (e_k' \Phi_i \Sigma e_j)^2}{\sum_{i=0}^{h-1} (e_k' \Phi_i \Sigma \Phi_i' e_k)} \quad (10)$$

whereas: Σ = covariance matrix of residuals and e_j, e_k = selection vectors. In our selected variables (LnDPP, LnPRE, LnASAT, LnYARH), the FEVD reveals which variable contributes most to price variations.

In addition, historical decomposition (HD) was employed to attribute observed fluctuations in the variables to current and past shocks. Based on the moving average of the VAR model, HD expresses each variable as the cumulative effect of current and past structural shocks. HD is obtained via Cholesky decomposition and follows the form:

$$y_t = \mu + \sum_{j=1}^n \sum_{i=0}^t \Psi_i^j \varepsilon_{j,t-i} \quad (11)$$

In this expression, y_t represents a vector of endogenous variables at time t ; μ represents a deterministic component (constant or trend); Ψ_i^j stands for impulse response coefficients examining the effect of a shock j at lag i ; $\varepsilon_{j,t-i}$ is the structural shock j at time $t - i$ and n is the number of variables (shocks).

IRFs, FEVD, and HD were derived from the estimated VAR system using consistent notation and matrix definitions.

4. Results

4.1. Unit Root Results

As shown in Table 2, the Phillips–Perron unit root results indicate that all selected variables are stationary at levels. Specifically, LnPRE and LnYARH are stationary at the 1% significance level, suggesting strong verification against the presence of a unit root. In contrast, LnDPP and LnASAT reject the unit-root null at the 10% significance level based on the $Z(t)$ statistic, indicating acceptable evidence of stationarity. Therefore, the findings confirm that the variables are integrated of order zero, $I(0)$, supporting their suitability for estimation within a VAR framework. Furthermore, the Phillips–Perron results indicate that all variables are stationary in first differences $I(1)$, at the 1% significance level. The test statistics are significantly more negative than the corresponding critical values, and the MacKinnon p -values are effectively zero.

Table 2. Phillips–Perron Unit Root Results.

Phillips–Perron Unit Root Test at Level			
Variable	$Z(\rho)$ Statistic $Z(\rho)$	$Z(t)$ Statistic	MacKinnon p -Value for $Z(t)$
LnDPP	−12.509 *	−2.681 *	0.07
LnPRE	−18.256 **	−3.329 **	0.01
LnASAT	−10.118	−2.686 *	0.07

Table 2. Cont.

Phillips–Perron Unit Root Test at Level			
LnYARH	−20.886 ***	−3.926 ***	0.00
Phillips–Perron Unit Root Test at First Difference			
ΔLnDPP	−30.966 ***	−6.114 ***	0.00
ΔLnPRE	−41.330 ***	−10.292 ***	0.00
ΔLnASAT	−44.415 ***	−12.452 ***	0.00
ΔLnYARH	−35.007 ***	−7.963 ***	0.00

Note: H_0 : The variable has a unit root; H_1 : The variable is stationary. ***, ** & * = significant at 1%, 5% and 10%, respectively. For $Z(\rho)$, the Interpolated Dickey–Fuller critical values at 1%, 5%, and 10% significance levels are −17.744, −12.756, and −10.360, respectively. For $Z(t)$, the corresponding critical values at 1%, 5%, and 10% levels are −3.696, −2.978, and −2.620, respectively. Source: Authors' calculations (2026).

4.2. VAR Results

The VAR results indicate strong persistence in producer prices of date palms, as the LnDPP(−1) has a positive and statistically significant coefficient, suggesting that past producer prices exert a strong influence on current price levels (coefficient = 0.7651, $t = 3.6929$). In contrast, none of the lagged climatic variables are statistically significant in the LnDPP equation, indicating limited direct statistical effects of climatic variables on producer prices. The coefficient of LnASAT(−2) is positive and marginally significant at the 10% level (0.3375; $t = 1.8030$) in the LnASAT equation, indicating persistence in temperature rather than an effect of temperature on date-palm producer prices (Table 3).

Table 3. VAR Estimates for the Date Palm Price–Climate Nexus.

Model	LnDPP	LnPRE	LnASAT	LnYARH
LnDPP(−1)	0.765093 [3.69289] ***	−0.207118 [−0.85718]	−0.029547 [−1.00049]	0.030103 [0.31556]
LnDPP(−2)	−0.174523 [−0.78513]	−0.325309 [−1.25483]	0.031124 [0.98228]	−0.137285 [−1.34130]
LnPRE(−1)	0.006150 [0.03181]	0.078254 [0.34707]	−0.005097 [−0.18497]	−0.021597 [−0.24261]
LnPRE(−2)	−0.051143 [−0.29283]	0.323536 [1.58840]	−0.014438 [−0.57995]	−0.043970 [−0.54677]
LnASAT(−1)	0.915721 [0.75946]	−1.581260 [−1.12447]	0.217636 [1.26625]	0.049722 [0.08956]
LnASAT(−2)	−1.676230 [−1.27651]	−0.472065 [−0.30824]	0.337484 [1.80297] *	−0.559700 [−0.92568]
LnYARH(−1)	0.347094 [0.70977]	0.207421 [0.36368]	0.009675 [0.13880]	0.332520 [1.47675]
LnYARH(−2)	−0.558556 [−1.14718]	−0.880611 [−1.55077]	0.042370 [0.61047]	−0.148997 [−0.66460]
C	6.685990 [1.10007]	15.96977 [2.25296]	1.357135 [1.56647]	5.524118 [1.97394] **

Table 3. *Cont.*

Model	LnDPP	LnPRE	LnASAT	LnYARH
General results indicators				
Determinant of the residual covariance matrix (adjusted)			1.01×10^{-11}	
Determinant resid covariance			2.68×10^{-12}	
Log likelihood			244.6859	
Akaike information criterion			−13.04287	
Schwarz criterion			−11.39392	

Note: t-statistics in []. ***, ** & * = significant at 1%, 5% & 10%. Source: Authors' calculations (2026).

The general system results indicate strong model performance. The determinant of the residual covariance matrix is very small (1.01×10^{-11} , adjusted; 2.68×10^{-12} , unadjusted), suggesting low residual interdependence across equations. The results also show a high log-likelihood value (244.686), implying a good fit. In addition, the information criteria are negative (AIC = −13.043 and SC = −11.394), validating the suitability of the VAR conditions and supporting the reliability of the estimates.

4.3. VAR Diagnosis Results

4.3.1. VAR Lag Order Selection Analysis

To determine the appropriate lag length for the VAR system and adequately evaluate the dynamic relationships among the variables, five standard lag-selection criteria were considered: the Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan–Quinn Criterion (HQ). As shown in Table 4, the LR, FPE, AIC, and HQ criteria select one lag as the preferred specification, whereas the SC criterion selects zero lags.

Table 4. Lag Length Results at 5% Level.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	213.0944	NA	2.48×10^{-11}	−13.06840	−12.88518 *	−13.00767
1	235.4384	37.70562 *	1.69×10^{-11} *	−13.46490 *	−12.54882	−13.16125 *
2	244.6859	13.29330	2.71×10^{-11}	−13.04287	−11.39392	−12.49629

Note: * Signifies lag order selected by the criterion; LR: sequential modified LR test statistics, at the 5% level of significance. Source: Authors' calculations (2026).

Although alternative lag lengths were evaluated, lag 1 was selected based on the information criteria and deliberately adopted as the preferred specification. Accordingly, all subsequent analyses, including diagnostic tests, IRFs, FEVD, historical decomposition, and sensitivity analysis, were conducted using the VAR (1) specification.

4.3.2. Autocorrelation LM Test

As shown in Table 5, the VAR residual serial-correlation test based on LM statistics does not detect statistically significant residual autocorrelation. At lags 1, 2, and 3, the corresponding *p*-values are 0.2751, 0.8424, and 0.4399, respectively, all exceeding the 5% significance level. Similarly, the joint tests for lags 1–3 are statistically insignificant (*p*-values = 0.2751, 0.2544, and 0.0975), indicating that the null hypothesis of no residual serial correlation cannot be rejected. These results suggest that no statistically significant

residual autocorrelation is detected at the tested lags, supporting the adequacy of the VAR specification.

Table 5. VAR Residual Serial Correlation LM Tests.

H_0: No Serial Correlation at Lag h						
Lag	LRE * stat	df	p-value	Rao F-stat	df	p-value
1	18.87598	16	0.2751	1.227172	(16, 49.5)	0.2819
2	10.44446	16	0.8424	0.628187	(16, 49.5)	0.8455
3	16.18853	16	0.4399	1.026467	(16, 49.5)	0.4469
H_0: No serial correlation at lags 1 to h						
Lag	LRE * stat	df	p-value	Rao F-stat	df	p-value
1	18.87598	16	0.2751	1.227172	(16, 49.5)	0.2819
2	36.85066	32	0.2544	1.192599	(32, 45.8)	0.2881
3	61.07490	48	0.0975	1.358395	(48, 32.9)	0.1788

Note: * Edgeworth expansion corrected likelihood ratio statistic. p -value > 0.05 = no autocorrelation. The Authors' calculations (2026).

4.3.3. Eigenvalue Stability Results

To assess the stability of the estimated VAR system, the roots of the characteristic polynomial were examined. As reported in Table 6, all estimated roots lie inside the unit circle, ranging from 0.223 to 0.774, indicating that the VAR system satisfies stability condition. This result indicates that the dynamic system is stable and that the effects of shocks gradually dissipate over time. However, VAR stability does not imply cointegration or a long-run equilibrium relationship among date-palm producer prices (DPP), precipitation (PRE), mean surface air temperature (ASAT), and relative humidity (YARH). The stability condition supports the use of impulse-response functions (IRFs) and forecast-error variance decomposition (FEVD) to examine the dynamic responses and shock contributions over the forecast horizon.

Table 6. Roots of Characteristic Polynomial.

Eigenvalue (Root)	Modulus
0.769178 – 0.094252i	0.774931
0.769178 + 0.094252i	0.774931
0.236943 – 0.583818i	0.630068
0.236943 + 0.583818i	0.630068
0.554331	0.554331
–0.475030 – 0.061789i	0.479032
–0.475030 + 0.061789i	0.479032
–0.223009	0.223009

Note: No root lies outside the unit circle. The VAR satisfies the stability condition. The letter i stands for the imaginary unit. Endogenous variables: LnDPP; LnPRE; LnASAT and LnYARH. Source: Authors' calculations (2026).

4.4. Dynamic Analysis: Innovations, Shocks, and Forecasting

To further explore the dynamic interactions between the variables, IRF, FEVD, and HD methods were employed.

4.4.1. Impulse Response Functions Results

The IRF results are interpreted together with their confidence bands. Responses that fall within the confidence bands around zero are not considered statistically dis-

tinguishable from zero. Accordingly, the IRFs provide evidence of the direction and persistence of responses, while their statistical significance and economic magnitude are considered separately.

Based on the results depicted in Figure 1, the IRF traces the dynamic transmission of climatic shocks to date palm producer prices throughout a 10-year forecast horizon. A one-standard-deviation shock to LnDPP generated an immediate and substantial own response of approximately 0.08 units, which declined gradually but remained positive throughout the forecast horizon. This persistent response indicates a high degree of price persistence, suggesting that adjustments to producer price shocks occur gradually over time. Regarding the climate–price nexus, a shock to LnASAT caused a reasonable increase in producer prices, peaking in the second period before gradually converging to equilibrium. In contrast, LnPRE shocks caused a negligible positive response, indicating a limited short-run influence on producer prices. Cross-variable responses remained small throughout the forecast horizon, and all impulse response functions converged to zero by the end of the analysis period, confirming the stability of the estimated VAR system.

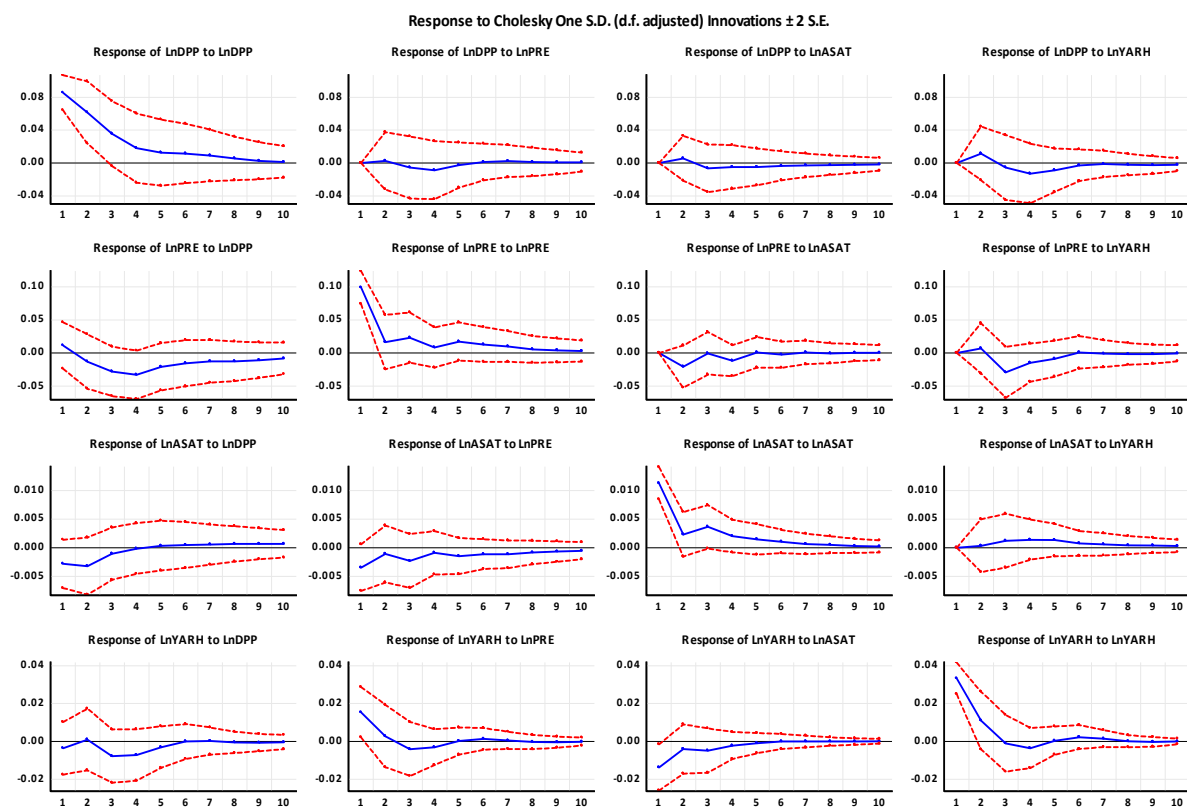


Figure 1. Impulse Response Functions of the VAR Approach. Note: The solid blue lines represent the estimated impulse responses to one-standard-deviation Cholesky shocks, while the dashed red lines indicate the ± 2 standard error confidence bands. The horizontal axis shows the forecast horizon (1–10 years), and the vertical axis represents the magnitude of the impulse response. Original Cholesky ordering: LnDPP LnPRE LnASAT LnYARH.

The findings suggest that although date palm producer prices respond to short-term climatic shocks, these effects are temporary and do not compromise the long-run stability of the date market.

4.4.2. Empirical Results of FEVD

As reported in Table 7, the FEVD results are interpreted over the short-run (periods 1–4) and long-run (periods 5–10) horizons. In the short run, the FEVD of LnDPP is

overwhelmingly explained by its own innovations (approximately 96–100%), whereas the contributions of LnPRE, LnASAT, and LnYARH remain negligible. These findings indicate strong price persistence and suggest that climatic factors exert only limited short-run influence on producer price dynamics. LnPRE is also largely driven by its own innovations (around 73–99%), although the influence of LnDPP starts to emerge by periods 3–4. For LnASAT, own shocks dominate (about 78–86%), with limited effects from LnDPP and LnPRE, while LnYARH is mainly influenced by LnASAT (around 66–72%) rather than its own shocks. In the long run (periods 5–10), the importance of own shocks declines slightly across all variables, and cross-variable effects become more evident: LnDPP remains predominantly self-driven (around 95%) but shows increasing contributions from LnYARH and LnASAT; LnPRE is increasingly influenced by LnDPP (about 17–20%); LnASAT reflects stronger contributions from LnPRE and LnDPP (above 20%); and LnYARH continues to be largely explained by LnASAT (around 66%).

Table 7. Forecast Error Variance Decompositions results.

FEVD of LnDPP:					FEVD of LnPRE:			
Period	LnDPP	LnPRE	LnASAT	LnYARH	LnDPP	LnPRE	LnASAT	LnYARH
1	100.000	0.000	0.000	0.000	1.280	98.720	0.000	0.000
2	98.472	0.067	0.276	1.185	2.745	92.847	3.968	0.439
3	97.818	0.312	0.569	1.301	8.318	81.393	3.304	6.985
4	95.925	0.876	0.719	2.479	14.984	73.392	3.881	7.743
5	95.208	0.907	0.883	3.002	17.040	71.446	3.681	7.833
6	95.104	0.907	0.962	3.027	18.142	70.601	3.626	7.631
7	95.031	0.940	1.013	3.015	18.850	70.064	3.572	7.513
8	94.958	0.950	1.060	3.032	19.612	69.417	3.532	7.440
9	94.878	0.954	1.092	3.076	20.151	68.944	3.505	7.401
10	94.821	0.961	1.112	3.106	20.475	68.669	3.490	7.366
FEVD of LnASAT:					FEVD of LnYARH:			
Period	LnDPP	LnPRE	LnASAT	LnYARH	LnDPP	LnPRE	LnASAT	LnYARH
1	5.468	8.228	86.304	0.000	0.858	15.297	12.270	71.576
2	11.227	8.123	80.588	0.063	0.839	14.430	12.155	72.575
3	10.554	10.118	78.488	0.840	4.167	14.537	12.790	68.506
4	10.190	10.183	77.798	1.828	6.737	14.425	12.512	66.325
5	9.934	10.967	76.432	2.667	7.191	14.348	12.490	65.971
6	9.886	11.458	75.764	2.892	7.165	14.390	12.445	66.001
7	9.905	11.985	75.087	3.023	7.157	14.386	12.429	66.029
8	10.034	12.244	74.636	3.086	7.169	14.388	12.427	66.016
9	10.204	12.405	74.248	3.143	7.193	14.391	12.422	65.994
10	10.377	12.492	73.964	3.167	7.200	14.390	12.421	65.989

Note: original Cholesky ordering: LnDPP LnPRE LnASAT LnYARH. Source: Authors' calculations.

At horizon 10, own innovations account for approximately 94.82% of the forecast-error variance of date-palm producer prices, while precipitation, temperature, and relative humidity account for approximately 0.96%, 1.11%, and 3.11%, respectively. Thus, climatic variables jointly explain about 5.2% of price forecast variance at the ten-year horizon.

Although their contribution increases relative to the short-run horizon, it remains quantitatively modest compared with the dominant role of own-price innovations. Therefore, the results suggest that climatic factors contribute to date-palm price dynamics but should not be interpreted as the primary drivers of price variability.

Table 7 highlights that while own shocks dominate in the short run, climate variables, particularly temperature, play a more significant role in explaining variations in the long run (periods 5–10).

The FEVD results can be explained by the persistence of producer prices and the gradual transmission of climatic effects. In the short run, the dominance of own innovations, particularly for date palm producer prices and precipitation, indicates that market adjustments occur gradually and that immediate climatic influences on producer prices are limited. Across the long run, the increasing contribution of cross-variable innovations suggests that climatic conditions progressively influence producer price dynamics through their cumulative effects on agricultural production. These findings indicate that short-run dynamics are primarily driven by internal market persistence, whereas long-run variations increasingly reflect climate–price interactions.

We conclude that.

4.4.3. Historical Decomposition Results

As shown in Figure 2, the historical decomposition illustrates the relative value contributions of own and climatic shocks to date palm producer price (DPP) fluctuations from 1994 to 2024. Fluctuations in log date palm producer prices (LnDPP) are almost entirely self-driven, peaking at positive value contributions of +0.18 log units (an approximate +18% deviation in USD) during 2008–2013 and experiencing their most pronounced negative contributions of −0.18 log units between 2014 and 2018, with negligible contributions (near 0.00 log units) from climatic shocks. For the remaining log-transformed variables, own innovations similarly dominate short-run dynamics, though cross-variable contributions emerge: precipitation (LnPRE) experiences major negative contributions down to −0.17 log units from its own shocks while receiving up to +0.11 log units from LnDPP in 2019–2020; average mean surface air temperature (LnASAT) self-contributes peaks of +0.03 log units (2010) with a minor +0.01 log unit input from LnDPP; and yearly average relative humidity (LnYARH) records negative contributions reaching −0.08 log units (2017) alongside positive inputs up to +0.05 log units. The results indicate that own innovations dictate short-term price volatility, whereas climatic factors, particularly temperature and relative humidity, provide gradual, cumulative value contributions to long-term producer price variability.

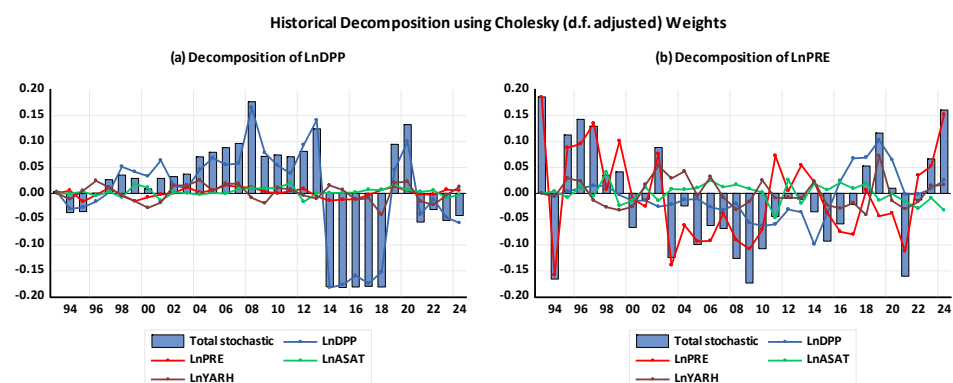


Figure 2. Cont.

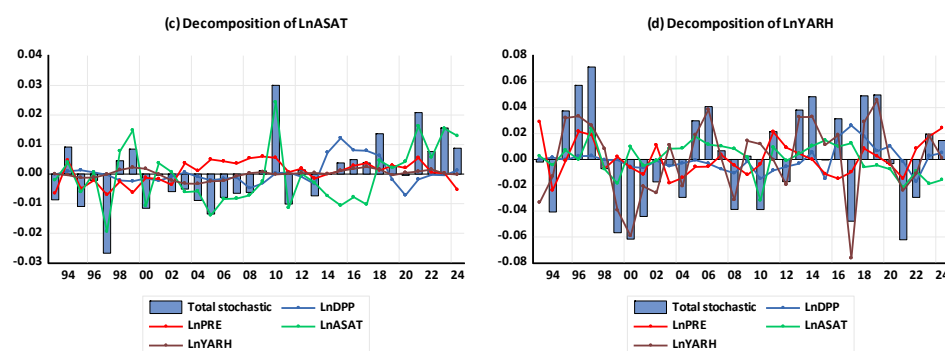


Figure 2. Historical Decomposition of Date Palm Producer Prices and Climatic Factors. Note: The blue bars represent the total historical innovations (actual deviations from the baseline) for each variable. The colored lines indicate the contributions of Cholesky-identified innovations from each endogenous variable to these fluctuations.

4.5. Sensitivity Analysis: Alternative Cholesky Ordering and Structural Stability

To verify the sensitivity of the IRFs to the specific causal assumptions of the model, a robustness check was conducted by altering the Cholesky ordering, placing date palm producer prices after the climatic factors. As shown in Figure 3, the impulse response functions maintain consistent directional signs, comparable magnitudes, and stable confidence intervals across ordering sequences. In particular, the strong persistence of date palm producer prices and their delayed responses to temperature and relative humidity shocks were consistently observed across specifications. These findings demonstrate that the estimated impulse responses and their statistical significance are robust to alternative variable orderings, confirming the empirical stability of the dynamic relationship between producer prices and climatic factors.

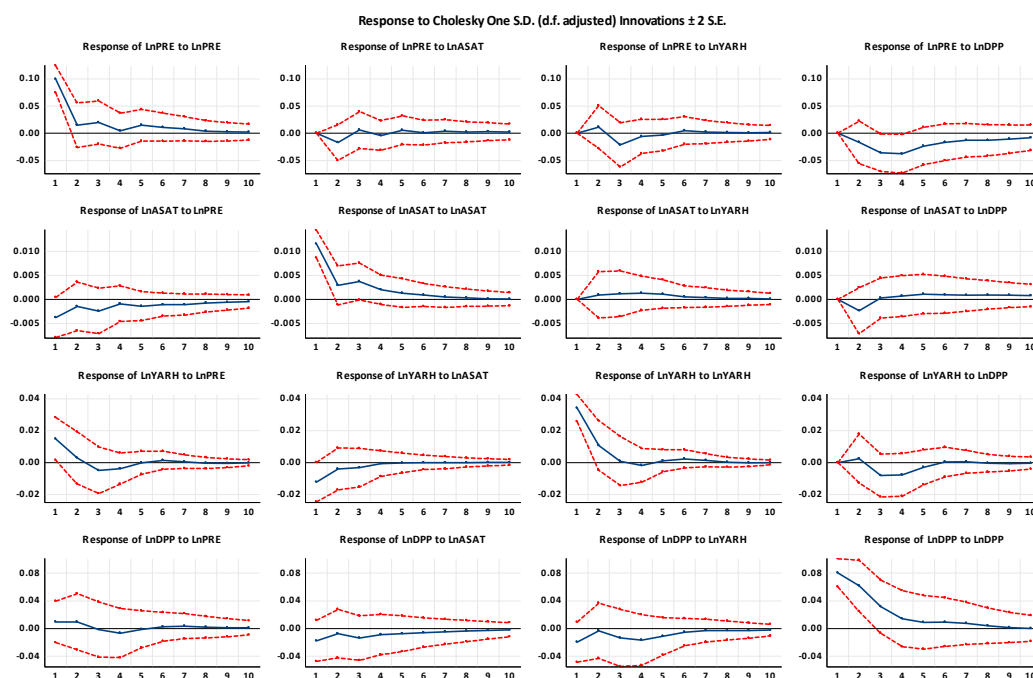


Figure 3. Alternative Ordering IRFs for Model Validation. Note: The solid blue lines represent the estimated impulse responses to one-standard-deviation Cholesky shocks, while the dashed red lines indicate the ± 2 standard error confidence bands. The horizontal axis shows the forecast horizon (1–10 years), and the vertical axis represents the magnitude of the impulse response. This figure presents the IRF results using a changed Cholesky ordering to test model sensitivity. Cholesky Ordering: LnPRE LnASAT LnYARH LnDPP.

5. Discussion

The findings indicate that date palm producer prices exhibit a high degree of persistence, with current prices being largely explained by their own past innovations. This pattern indicates substantial price persistence; however, own innovations should not be interpreted as evidence that internal market mechanisms alone determine producer-price dynamics. Within the VAR framework, own innovations represent the component of producer-price variation not explained by the other variables included in the model and may include inflation, exchange-rate movements, production changes, input costs, government support, trade conditions, or structural changes. Since these factors were not explicitly included in the model, the precise sources of price persistence cannot be identified. The strong persistence observed is consistent with previous studies on Saudi Arabian agricultural markets, which report that producer prices are largely influenced by domestic market conditions, production structures, and institutional characteristics, thereby limiting the immediate transmission of external shocks [40].

In contrast, climatic variables, including precipitation, temperature, and relative humidity, exhibit limited short-run effects on date palm producer prices and other endogenous variables, indicating that climatic shocks are not immediately transmitted into price fluctuations. The findings provide limited evidence for the roles of temperature and relative humidity at longer horizons, although their contributions remain relatively small. In contrast, the hypothesis for precipitation variability (H2) is not supported, showing a negligible impact on producer prices across all horizons. Therefore, the evidence for the hypotheses H1 and H3 should be interpreted cautiously as limited or partial support rather than as evidence of strong climate effects.

The observed pattern may be consistent with gradual adjustment through agricultural production, market supply, and price formation; however, the present analysis does not directly identify such transmission mechanisms. These findings are consistent with [41] who demonstrated that crop prices are shaped by the combined effects of climate-related factors, technological developments, and broader economic conditions, with the magnitude and direction of impacts varying across production systems and contexts. Biological cycles, adaptation practices, irrigation, and gradual market adjustment provide plausible explanations for why climate effects may not appear immediately in producer prices, but these mechanisms were not directly measured in this study. Thus, the results are consistent with the possibility of gradual climate–price interactions, but they do not establish a specific delayed transmission mechanism.

The integrated evidence from impulse response functions (IRFs), historical decomposition (HD), and forecast error variance decomposition (FEVD) suggests that price persistence is the dominant feature of date-palm producer-price dynamics, while the direct contribution of climate variables is comparatively limited. The IRF results show strong price persistence, with producer prices responding primarily to their own innovations, while climatic shocks generate relatively gradual and limited effects. This pattern may be consistent with gradual changes in production conditions and market supply, although these channels were not directly measured in the present study.

Similarly, Dehghanisanij et al. [40] demonstrated that climatic conditions influence date palm productivity through cumulative effects on crop growth and water-use efficiency across successive growing seasons. Al-Wabel et al. [42] further highlighted that water scarcity and climate-related environmental stresses can affect date palm performance and fruit quality, emphasizing the importance of long-term adaptation strategies. Collectively, these studies support the present findings by suggesting that climatic shocks may potentially influence date palm markets indirectly through gradual changes in biological

productivity, although this mechanism cannot be directly established from the present VAR results.

The FEVD results further show that producer prices are predominantly explained by their own innovations in the short run, indicating strong market persistence and limited immediate transmission of climatic shocks. At horizon 10, the three climate innovations jointly explain approximately 5.18% of producer-price variation, compared with 94.82% explained by own-price innovations. Although the contribution of relative humidity is larger than that of temperature at this horizon, the contribution of climate variables remains modest. The relatively small contribution of precipitation may partly reflect the use of national annual averages, which can conceal important regional and seasonal variation. In addition, irrigation may reduce the direct dependence of date-palm production on rainfall. The larger contribution of relative humidity than temperature may also indicate that humidity could be more closely related to fruit quality or other production conditions than to production volume. These explanations are plausible rather than directly tested in the present study and should therefore be interpreted cautiously.

The HD results provide additional evidence that own-price innovations accounted for a substantial share of historical price movements, while climate innovations contributed to fluctuations during some periods. However, these own-price contributions may also reflect economic, production, institutional, and structural factors that were not included in the VAR. These findings are consistent with Wheeler et al. [43], who highlighted the growing importance of climate-related supply shocks in shaping agricultural price dynamics. We confirmed that the findings suggest that date-palm producer prices are characterized primarily by strong price persistence, while climate variability has a comparatively modest direct contribution within the estimated VAR. Therefore, the climate–price relationship should be interpreted cautiously, particularly because important economic and production determinants were not explicitly modeled.

6. Conclusions and Policy Implications

This study examined the dynamic relationship between climate variability and date palm producer prices in Saudi Arabia using annual time-series data from 1991 to 2024. A Vector Autoregression (VAR) framework was employed to analyze the interactions among producer prices, precipitation, mean surface air temperature, and relative humidity. The analysis incorporated impulse response functions (IRFs), forecast error variance decomposition (FEVD), and historical decomposition (HD), while an alternative Cholesky ordering was examined as a limited robustness assessment of the identification assumptions.

The empirical findings indicate that date palm producer prices exhibit strong persistence and are primarily explained by their own innovations in the short run. Climatic shocks generate relatively limited immediate responses, suggesting that climate effects are transmitted gradually through agricultural production and market adjustment processes. However, the FEVD and HD results show that the contribution of temperature and relative humidity to producer price fluctuations becomes more evident over longer horizons, highlighting the increasing relevance of climatic conditions in explaining long-term price dynamics. The robustness analysis further confirms that these results are not sensitive to the ordering of variables within the VAR framework.

The findings demonstrate that while the Saudi date palm market remains resilient to short-term climatic disturbances, long-term price stability increasingly depends on the sector's capacity to adapt to changing climatic conditions. The empirical findings indicate that date-palm producer prices are driven predominantly by their own price dynamics, while climatic variables, particularly temperature and relative humidity, have relatively limited but observable effects over longer horizons. Accordingly, policy attention

should primarily consider market-based factors underlying price persistence while also recognizing the relevance of climatic risks in longer-term agricultural planning. Although the VAR model does not directly evaluate specific adaptation measures, the findings are consistent with the importance of considering climate adaptation and risk management in the date-palm sector. However, the effectiveness of specific interventions, such as irrigation investment, climate-smart technologies, or other adaptation measures, requires further empirical evaluation.

7. Limitations and Future Research

Moreover, important transmission variables, including production, yield, fruit quality, irrigation and input costs, storage, demand, subsidies, and other policy interventions, were not included in the model. Consequently, the precise mechanisms through which climate variability may affect producer prices cannot be identified, and the results should be interpreted as model-dependent dynamic associations rather than causal effects. Also, the use of annual and national-level data may limit the ability to examine regional and seasonal variations in climatic conditions and market responses. National annual climate averages may also mask conditions in the principal date-producing regions, critical phenological periods, and extreme climatic events such as droughts and heatwaves. Furthermore, aggregated producer prices may conceal differences across date varieties, quality grades, production systems, and regional markets. The relatively small sample size of only 34 annual observations relative to the number of parameters estimated in the four-variable VAR may also limit statistical power and create potential overparameterisation concerns and may contribute to instability in the estimated impulse responses. The marginal stationarity evidence at the 10% significance level and the possibility of structural breaks over the study period should also be acknowledged. In addition, the use of nominal producer prices means that some persistence may reflect inflation and exchange-rate movements. Finally, the results may be sensitive to the Cholesky identification ordering, although an alternative ordering was examined as a robustness check and therefore provides only a limited sensitivity assessment rather than definitive evidence of identification robustness.

Furthermore, although the VAR treats all variables as jointly endogenous, this does not imply that producer prices physically determine climate conditions. Temperature and precipitation are treated as exogenous environmental processes, while their inclusion in the VAR investigates joint temporal dynamics and statistical relationships. Accordingly, the impulse-response analysis focuses on the economically plausible effects of climatic shocks on date producer prices, without interpreting reverse responses as physical causality.

Thus, the estimated IRFs, FEVD, and historical decomposition should not be interpreted as establishing causal effects or as directly measuring market resilience or farmers' adaptive capacity.

Future studies could use regional and higher-frequency data, real producer prices, and indicators of climatic extremes, while incorporating additional production, economic, and institutional variables. Alternative approaches, such as VARX, structural VAR, distributed-lag, nonlinear, and structural-break models, could further examine climate–price transmission mechanisms. Comparative studies across major date palm-producing countries could also provide broader insights into climate-related risks, price dynamics, and adaptation capacity.

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Conflicts of Interest: The authors declare no conflicts of interest.

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