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Examining the Effects of Climate Change Shocks on Macroeconomic Variables in Iran's Agricultural Sector: Application of (SPEI)

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Abstract

Climate change poses significant challenges to Iran's agricultural sector, characterized by high evapotranspiration rates and increasing climatic variability. This study examines the dynamic effects of climate change shocks on key macroeconomic variables in Iran's agriculture using the Structural Vector Autoregression (SVAR) model. Unlike conventional approaches that rely on raw temperature or precipitation data, this research employs the De Martonne Climate Aridity Index and the absolute value of the Standardized Precipitation Evapotranspiration Index (|SPEI|) to capture the magnitude of climate deviations from normal conditions—whether drought or extreme wetness—both of which are detrimental to Iran's semi-arid agriculture. The analysis is based on quarterly data spanning the period 1988–2023, with annual macroeconomic variables temporally disaggregated using the Denton Proportional Method. The results reveal that a one-standard-deviation increase in |SPEI| (representing increased climate variability) reduces agricultural value added by a maximum of 0.319 units, net capital stock by 0.272 units, agricultural labor by 0.243 units, and trade openness by 0.197 units, with peak impacts occurring in the third quarter following the shock. These findings underscore the significant adjustment lags in Iran's agricultural sector and highlight the urgent need for anticipatory policy measures. It is recommended to implement index-based crop insurance linked to |SPEI| thresholds (e.g., automatic payouts when |SPEI| exceeds 1.5), develop climate-risk financial products that trigger automatic payouts during extreme climate events, and promote drought- and flood-resistant crop varieties alongside modern climate monitoring technologies.

Keywords: Agriculture, Climate change, De Martonne climate aridity index, Iran, Standardized Precipitation Evapotranspiration Index (SPEI).

1. Introduction

Climate change has become a major challenge for the global economy. Bilal and Kanzig (2024) show that a 1°C increase in global temperature reduces world GDP by more than 20 percent in the

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long run, imposing a social cost exceeding 1,500 USD per ton of carbon. In developing countries, agriculture is not merely an economic activity but a way of life (Razzouki et al., 2025), and its production process—based on living organisms within ecosystems (Sinore and Wang, 2024)—is the first to reveal climate change effects. Any change in climatic parameters can lead to quantitative and qualitative changes in agricultural output (Xiang et al., 2025). Climate change occurs when climatic indicators deviate irreversibly from long-term patterns (Farajzadeh et al., 2025). The frequency of extreme climatic events has increased more than fivefold over five decades, with damages intensifying nearly eightfold (Kouakou, 2024). Extreme events—droughts, heatwaves, irregular precipitation, storms, and floods—adversely impact agricultural production and farmers' livelihoods (Habib-ur-Rahman et al., 2022). In Iran, reduced precipitation and rising temperatures have undermined national income and economic growth (Farajzadeh et al., 2025).

Iran's location within the global arid belt makes its agriculture particularly vulnerable. According to the Iranian Meteorological Organization (2025), about 88% of Iran faced various degrees of drought in 2024, with average annual precipitation declining from 226 mm (1973–2024 long-term average) to 178 mm (2020–2024), while temperature increased from 17.7°C to 18.9°C. The average growth rate of Iran's agricultural value-added was approximately 2% between 2012 and 2024, with negative growth reported in 2018 and during 2021–2023 (Statistical Center of Iran, 2025). Globally, agriculture in tropical and subtropical developing regions is more sensitive to climate variability (Mendelsohn, 2008; Morad et al., 2010; Acharya & Batta, 2013; Ochieng et al., 2016; Chandio et al., 2020). Climate change is projected to reduce major crop yields in Asia by 12–17% (Habib-ur-Rahman et al., 2022), negatively affect productivity in Africa (Onyeaka et al., 2024), and increase vulnerability of rainfed agriculture in Tunisia (Khalifa, 2025).

Previous studies have primarily used temperature and precipitation variables rather than composite indices. A limitation of the Standardized Precipitation Index (SPI) is its lack of consideration for evapotranspiration-based water balance. In contrast, SPEI accounts for water balance using precipitation and potential evapotranspiration (Mwinjuma et al., 2025). Accordingly, this study examines how climate change shocks have affected selected macroeconomic variables in Iran's agricultural sector over the past four decades.

Conceptual Framework: Climate anomalies first affect biophysical conditions (soil moisture, crop physiology, water availability) (Rosa, 2022), then propagate to production outcomes (yield and quality) (Chen et al., 2024; Yuan et al., 2024). Production shocks subsequently influence factor markets: reduced profitability discourages capital formation (Guo et al., 2023; Wang and Pan, 2025), labor demand contracts (Albert et al., 2025; Alfani et al., 2025; Alpysbayeva et al., 2026; Mazzoleni et al., 2026), and trade flows adjust through supply constraints and infrastructure disruptions (Horn et al., 2022; Heckelei and Jafari, 2026). By employing composite indices (|SPEI| and De Martonne) rather than raw temperature or precipitation, this framework captures the net effect of climate variability while accounting for evapotranspiration-driven water balance.

Research Contributions: This study makes three contributions. First, we employ |SPEI| to capture the full spectrum of climate variability—both drought and extreme wetness—recognizing that both extremes are detrimental to Iran's semi-arid agriculture. Second, we combine |SPEI| with the De Martonne Index within an SVAR framework, disentangling short-to-medium-term variability from long-term aridity trends. Third, we decompose the agricultural sector into four core macroeconomic components (value added, capital stock, labor, and trade openness), providing a granular understanding of climate shock propagation.

2. Methodology

To examine the effects of climate change indicators on the macroeconomic variables of Iran's agricultural sector, the Structural Vector Autoregression (SVAR) model has been employed. The SVAR model allows for the evaluation of the effects of different dimensions of shocks arising from various factors. To achieve this, it is necessary to compute the Impulse Response Function (IRF). Using the IRF, one can determine both the duration of the shock's effect and the maximum impact following its occurrence (Chatzinotas et al., 2013). Following the methodology of Chatzinotas et al. (2013), the SVAR model in the present study of order $P$is specified as follows (Equation 1):

$$A_0 Y_t = C_0 + \sum_{i=1}^{p} A_i Y_{t-i} + \varepsilon_t \qquad (1)$$

In this equation, Y_t is a vector of the system's variables, $A_0$is the matrix of contemporaneous coefficients, $C_0$is the vector of constants, $A_i$is the matrix of autoregressive coefficients, and $\varepsilon_t$is the vector of structural disturbances, which is assumed to have zero covariance. In Equation (1), Y_t is specified as a 6 ×*1* vector of system variables, expressed as follows in Equation (2):

$$Y_t = [CL \quad SPEI \quad VA \quad CA \quad LA \quad OPN] \tag{2}$$

Where the variables are defined as follows:

VA: Value added of the agricultural sector (billion Rials, base year 2011 = 100)

CA: Net capital stock of the agricultural sector (billion Rials, base year 2011 = 100)

LA: Agricultural labor force (thousand persons)

OPN: Agricultural trade openness index (base year 2011 = 100), calculated as the ratio of trade value to the agricultural sector's value added

CL: De Martonne Climate Aridity Index (unitless), calculated using the following formula (Kouakou, 2024):

$$CL = \frac{P}{T+10} \tag{3}$$

In this formula, P represents precipitation in millimeters and T represents temperature in degrees Celsius. Based on the values of the De Martonne index, the type of climate in the studied region can be determined (Table 1).

Table 1: De Martonne Index Values.

De Martonne Index (CL)	Climate Type
CL < 10	Arid
10 < CL < 19.9	Semi-arid
20 < CL < 23.9	Mediterranean
24 < CL < 27.9	Semi-humid
28 < CL < 34.9	Humid
CL > 35	Very humid

Source: Crapart et al. (2025).

This table classifies climate types based on the De Martonne Climate Aridity Index (*CL*) values.

SPEI: Standardized Precipitation Evapotranspiration Index (quarterly, unitless), calculated using the following formula (Vicente-Serrano et al., 2010):

$$SPEI = W - \frac{C_0 + C_1 + W + C_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3} \tag{4}$$

Where: $W = \sqrt{-2\ln(P)}$, P represents the probability of exceedance derived from the cumulative log-logistic distribution of the water balance D_i. The water balance is calculated as the difference between precipitation and potential evapotranspiration ($D_i = P_i - PET_i$), where P_i is precipitation in millimeters and PET_i is potential evapotranspiration). C_0, C_1, C_2, d_1, d_2 and d_3 are constant parameters of the numerical approximation. Based on the SPEI value and its comparison with the index's classification, the climatic condition of the studied region can be determined.

On the other hand, to accurately capture the adverse effects of climate variability on Iran's semi-arid agriculture, this study employs the absolute value of the SPEI (|SPEI|) rather than the raw index. The transformation is defined as |SPEI| = |raw SPEI|, where the absolute value captures the magnitude of deviation from normal conditions regardless of direction. Since a positive SPEI indicates wetness and a negative value indicates drought, both extremes disrupt agricultural production in Iran (e.g., drought reduces water availability, while extreme wetness manifests as flash floods, causing soil erosion, waterlogging, and crop diseases). Using the absolute value (|SPEI|) ensures that any significant deviation from normal climatic conditions—regardless of direction—is treated as a negative exogenous shock to the agricultural macroeconomic variables. Similarly, a positive shock to the De Martonne Index represents extreme wetness and humidity anomalies that cause flooding and soil erosion in Iran's specific topography, rather than beneficial rainfall. Consequently, the negative impulse responses to positive shocks in both |SPEI| and the De Martonne Index accurately reflect the destructive economic impacts of excessive climate variability.

The classification of climatic conditions based on the raw SPEI values is presented in Table 2.

Table 2: Standardized Precipitation Evapotranspiration Index (SPEI) Values.

SPEI Value	Drought/Wetness Category
> 2.0	Extremely wet
1.5 – 1.99	Very wet
1.0 – 1.49	Moderately wet
-0.99 – 0.99	Near normal / Neutral
-1.49 – -1.0	Moderate drought
-1.99 – -1.5	Severe drought
< -2.0	Extreme drought

Source: Mwinjuma et al. (2025).

It is crucial to explicitly distinguish between the raw SPEI and the transformed index utilized in the econometric model. The raw SPEI is a directional index ranging from negative (drought) to positive (extreme wetness) values, as classified in Table 2. However, to capture the magnitude of climate anomalies regardless of their direction, this study applies an absolute transformation: |SPEI| = |raw SPEI|. In the SVAR framework, the variable entering the system is strictly the absolute index, |SPEI|. Therefore, a positive structural shock to |SPEI| in our model represents an increase in overall climate variability (capturing both severe drought and extreme wetness), which is treated as an adverse shock. Throughout the results, discussion, and robustness checks, any reference to an 'SPEI shock' pertains strictly to a shock to this absolute index, |SPEI|.

Additionally, to obtain the reduced form of the structural model, both sides of Equation (1) are multiplied by A_0^{-1}:

$$\mathrm{Y_t = a_0 + \sum_{i=1}^{p} B_i\, Y_{t-i} + e_t} \qquad (5)$$

Where: $A_0^{-1}C_0 = a_0$, $e_t = A_0^{-1}\varepsilon_t$ and as a result, the vector of shocks (structural disturbances) equation can be expressed as Equation (6):

$$\mathrm{\varepsilon_t = A_0 e_t} \qquad (6)$$

Therefore, in the present study, the simultaneous structural equations and the relationships among the studied variables are expressed as Equation (7).

$$\begin{bmatrix} \varepsilon_{1t}^{CL} \\ \varepsilon_{2t}^{SPEI} \\ \varepsilon_{3t}^{VA} \\ \varepsilon_{4t}^{CA} \\ \varepsilon_{5t}^{LA} \\ \varepsilon_{6t}^{OPN} \end{bmatrix} = \begin{bmatrix} \alpha_{11} & 0 & 0 & 0 & 0 & 0 \\ \alpha_{21} & \alpha_{22} & 0 & 0 & 0 & 0 \\ \alpha_{31} & \alpha_{32} & \alpha_{33} & 0 & 0 & 0 \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & \alpha_{44} & 0 & 0 \\ \alpha_{51} & \alpha_{52} & \alpha_{53} & \alpha_{54} & \alpha_{55} & 0 \\ \alpha_{61} & \alpha_{62} & \alpha_{63} & \alpha_{64} & \alpha_{65} & \alpha_{66} \end{bmatrix} \times \begin{bmatrix} e_{1t}^{CL} \\ e_{2t}^{SPEI} \\ e_{3t}^{VA} \\ e_{4t}^{CA} \\ e_{5t}^{LA} \\ e_{6t}^{OPN} \end{bmatrix} \qquad (7)$$

Thus, the vector $\varepsilon_{it} = [\varepsilon_{1t}^{CL}, \varepsilon_{2t}^{SPEI}, \varepsilon_{3t}^{VA}, \varepsilon_{4t}^{CA}, \varepsilon_{5t}^{LA}, \varepsilon_{6t}^{OPN}]$ represents the structural disturbances, where: ε_{1t}^{CL}: indicate the shock to De Martonne climate aridity index; ε_{2t}^{SPEI}: shock to Standardized Precipitation Evapotranspiration Index (SPEI)**;** ε_{3t}^{VA}: shock to agricultural value added; ε_{4t}^{CA}: shock to net capital stock in agriculture; ε_{5t}^{LA}: shock to agricultural labor force and ε_{6t}^{OPN}: shock to agricultural trade openness.

In the SVAR framework, the structural matrix *A* captures contemporaneous relationships among variables. Identification is achieved through short-run restrictions grounded in economic theory. Climate variables (De Martonne Index and SPEI) are treated as predetermined (weakly exogenous) within a quarter, as atmospheric processes are not contemporaneously affected by macroeconomic shocks; thus, they respond only to their own shocks (with SPEI also responding to CL). Macroeconomic variables are then ordered by adjustment speed in a recursive Cholesky structure: VA → CA → LA → OPN, where value added adjusts first to climate shocks, capital follows based on current profitability, labor adjusts next given market rigidities, and trade openness responds last to all shocks. This ordering imposes exactly 15 zero restrictions on matrix A(k(k - 1)/2 = 15 for a 6-variable system), ensuring exact identification and meaningful structural interpretation of shocks through Impulse Response Functions.

The explicit structural equations corresponding to each row of matrix A are as follows:

Equation (8) – First-row restriction (De Martonne Index):

$$\varepsilon_{1t}^{CL} = \alpha_{11}e_{1t}^{CL} \quad (8)$$

The first-row restriction indicates that the De Martonne index is affected only by its own structural shock, reflecting its predetermined nature within a quarterly period.

Equation (9) – Second-row restriction (SPEI):

$$\varepsilon_{2t}^{SPE} = \alpha_{21}e_{1t}^{CL} + \alpha_{22}e_{2t}^{SPEI} \quad (9)$$

The second-row restriction indicates that SPEI responds contemporaneously to shocks in the De Martonne index and its own shock, but not to macroeconomic variables.

Equation (10) – Third-row restriction (Agricultural Value Added):

$$\varepsilon_{3t}^{VA} = \alpha_{31}e_{1t}^{CL} + \alpha_{32}e_{2t}^{SPEI} + \alpha_{33}e_{3t}^{VA} \quad (10)$$

The third-row restriction represents the responsiveness of agricultural value added to climate shocks and its own shock, but not to capital stock, labor, or trade openness within the same quarter.

Equation (11) – Fourth-row restriction (Net Capital Stock):

$$\varepsilon_{4t}^{CA} = \alpha_{41}e_{1t}^{CL} + \alpha_{42}e_{2t}^{SPEI} + \alpha_{43}e_{3t}^{VA} + \alpha_{44}e_{4t}^{CA} \quad (11)$$

The fourth-row restriction represents the responsiveness of agricultural net capital stock to climate shocks, value added, and its own shock, but not to labor force or trade openness.

Equation (12) – Fifth-row restriction (Agricultural Labor Force):

$$\varepsilon_{5t}^{LA} = \alpha_{51}e_{1t}^{CL} + \alpha_{52}e_{2t}^{SPEI} + \alpha_{53}e_{3t}^{VA} + \alpha_{54}e_{4t}^{CA} + \alpha_{55}e_{5t}^{LA} \quad (12)$$

The fifth-row restriction represents the responsiveness of agricultural labor force to climate shocks, value added, capital stock, and its own shock, but not to trade openness.

Equation (13) – Sixth-row restriction (Agricultural Trade Openness):

$$\varepsilon_{6t}^{OPN} = \alpha_{61}e_{1t}^{CL} + \alpha_{62}e_{2t}^{SPEI} + \alpha_{63}e_{3t}^{VA} + \alpha_{64}e_{4t}^{CA} + \alpha_{65}e_{5t}^{LA} + \alpha_{66}e_{6t}^{OPN} \quad (13)$$

The sixth-row restriction represents the responsiveness of agricultural trade openness to all shocks in the system, reflecting that trade flows are the last to adjust and depend on production, capital, and labor conditions.

To address potential endogeneity and reverse causality, the identification strategy relies on the economic assumption that climate variables are strictly exogenous within a quarterly frequency, as macroeconomic adjustments cannot alter atmospheric conditions within a single quarter. To test the sensitivity of this identification and ensure that our results are not driven by the specific recursive ordering, we conducted an alternative Cholesky ordering in the robustness checks

(Appendix Table A5). By swapping the contemporaneous ordering of value added and capital stock, we confirmed that the core findings remain structurally invariant, thereby strengthening the reliability of the SVAR identification.

Regarding data frequency, macroeconomic variables (VA, CA, LA, OPN) are originally reported annually by the Statistical Center of Iran, while climate indices (SPEI, De Martonne) exhibit significant intra-annual variation. To capture high-frequency climate dynamics, annual data were temporally disaggregated into quarterly frequency (1988Q1–2023Q4) using the Denton Proportional Method (Denton, 1971; Sax & Steiner, 2013), which preserves annual totals while distributing them across quarters based on quarterly climate indices, thereby resolving potential aggregation bias.

To complement this temporal disaggregation of macroeconomic data, the climate indices were constructed directly at a quarterly frequency to preserve high-frequency climatic dynamics. The quarterly Standardized Precipitation Evapotranspiration Index (SPEI) was calculated using a 3-month rolling window of precipitation and potential evapotranspiration (PET), following the log-logistic distribution fitting procedure (Vicente-Serrano et al., 2010). Similarly, the quarterly De Martonne Index was computed using cumulative quarterly precipitation (Pq) and mean quarterly temperature (Tq), formulated as $Iq = Pq/ (Tq +10)$. This direct quarterly construction ensures that intra-annual climate volatility is accurately captured without relying on temporal disaggregation for the climate data themselves.

3. Results

Time series in economic studies are usually non-stationary, which can lead to the problem of spurious regression. The results of the stationarity test using the Phillips–Perron test (Table 3), show that all the variables are non-stationary at level, but become stationary after taking the first difference (I(1)).

Table 3. Results of the Phillips–Perron Test.

Variable	At Level		First Difference	
	Test Statistic	Critical Value	Test Statistic	Critical Value
VA: Value Added of the Agricultural Sector	-1.35	-2.12	-3.55	-2.99
CA: Net Capital Stock of the Agricultural Sector	-1.61	-2.36	-3.71	-2.85
LA: Labor Force in the Agricultural Sector	-1.45	-2.56	-3.59	-2.84
OPN: Trade Openness of the Agricultural Sector	-1.14	-2.37	-3.74	-2.83
CL: De Martonne Index	-1.54	-2.97	-3.68	-2.92
SPEI: Standardized Precipitation–Evapotranspiration Index	-1.71	-2.72	-3.79	-2.95

Source: Research Findings.

After examining stationarity, the optimal lag length of the model must be determined when specifying the Vector Autoregression (VAR) model. For this purpose, the Schwarz–Bayesian Criterion (SBC), which aims to be as parsimonious as possible in lag selection, was used (Wooldridge, 2013). The findings regarding the determination of the optimal lag indicate that the smallest value of the Schwarz–Bayesian statistic corresponds to the first lag, making the optimal lag length of the model 1 (Table 4).

Table 4. Results of Determining the Optimal Lag.

Lag Length	0	1	2	3	4	5	6	7	8	9
SBC	-16.19	**-22.59**	-22.51	-21.23	-19.16	-18.21	-17.86	-16.75	-15.11	-14.26

Source: Research Findings.

To examine cointegration among the variables, the Johansen–Juselius method was used. This method employs both the trace and the maximum eigenvalue tests (Table 5). Therefore, there is no long-term or cointegration relationship among the research variables.

Table 5. Trace and Maximum Eigenvalue Tests for Determining the Number of Cointegrating Vectors.

	H0	H1	Test Statistic	Critical Value		H0	H1	Test Statistic	Critical Value
Trace Test	r = 0	r ≥ 1	88.22	102.13	Maximum Eigenvalue Test	r = 0	r = 1	29.67	40.39
	r ≤ 1	r ≥ 2	57.76	59.55		r ≤ 1	r = 2	21.49	29.24
	r ≤ 2	r ≥ 3	34.69	38.36		r ≤ 2	r = 3	13.71	18.67
	r ≤ 3	r ≥ 4	29.54	35.22		r ≤ 3	r = 4	7.11	12.59
	r ≤ 4	r ≥ 5	16.33	19.41		r ≤ 4	r = 5	4.36	8.17
	r ≤ 5	r ≥ 6	11.21	16.17		r ≤ 5	r = 6	1.82	6.18

Source: Research Findings.

The Johansen cointegration test was conducted as a pre-estimation diagnostic to determine whether a long-run equilibrium (cointegrating) relationship exists among the variables. As shown in Table 5, both the trace and maximum eigenvalue statistics fail to reject the null hypothesis of no cointegration (r = 0) at the 5% significance level. This finding implies that the variables do not share a common stochastic trend, and therefore, a Vector Error Correction Model (VECM) is not appropriate for this dataset. In accordance with standard time-series econometric practice

(Hamilton, 1994; Enders, 2014), when variables are integrated of order one, I(1), but are not cointegrated, the SVAR model must be estimated in first differences to ensure stationarity and avoid spurious regression. Accordingly, the SVAR model in this study was estimated using the first-differenced form of all variables (ΔVA, ΔCA, ΔLA, ΔOPN, ΔCL, ΔSPEI). This approach allows for valid structural interpretation of short-run dynamic effects through Impulse Response Functions (IRFs), while acknowledging that the absence of cointegration implies no long-run error-correction mechanism among the studied variables. After examining cointegration, the Impulse Response Functions (IRFs) of macroeconomic variables in Iran's agricultural sector (value added, net capital stock, labor, and trade openness) to climate change indicators (De Martonne Index and Standardized Precipitation–Evapotranspiration Index) were estimated (Figures 1 to 8).

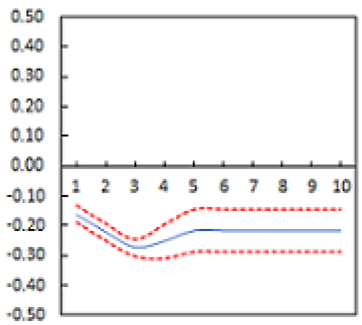

Figure 1. Impulse Response of VA to CL

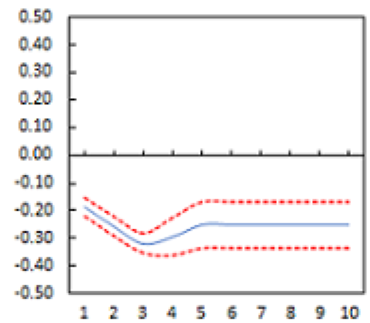

Figure 2. Impulse Response of VA to SPEI

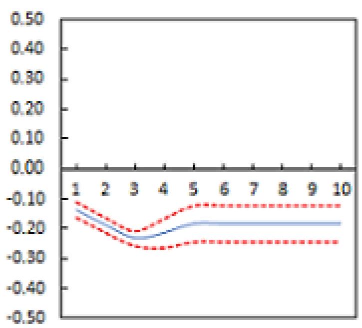

Figure 3. Impulse Response of CA to CL

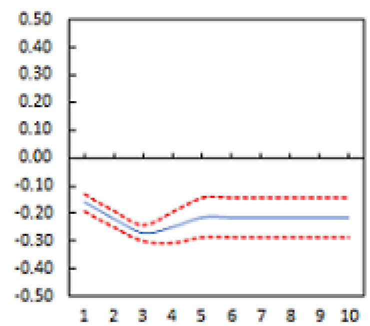

Figure 4. Impulse Response of CA to SPEI

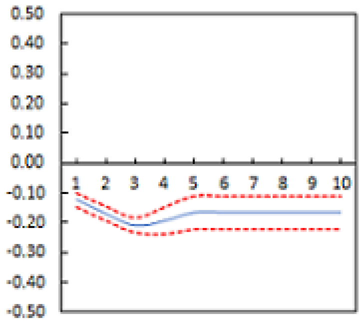

Figure 5. Impulse Response of LA to CL

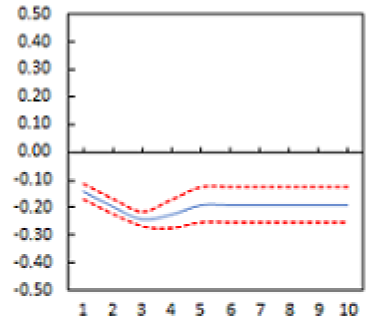

Figure 6. Impulse Response of LA to SPEI

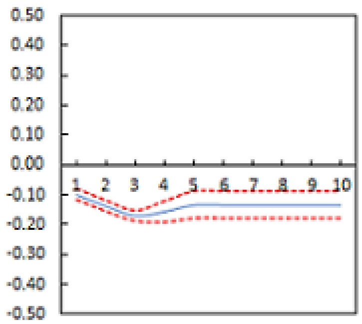

Figure 7. Impulse Response of OPN to CL

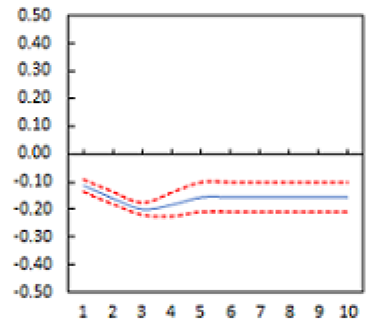

Figure 8. Impulse Response of OPN to SPEI

The Impulse Response Functions (IRFs) presented in Figures 1 to 8 trace the dynamic effects of one-standard-deviation structural shocks to climate indices (De Martonne Index and |SPEI|) on the macroeconomic variables of Iran's agricultural sector. The use of |SPEI| ensures that any significant deviation from normal climatic conditions—whether extreme drought (negative SPEI) or extreme wetness/flash floods (positive SPEI)—is treated as an adverse climate shock, reflecting the reality that both extremes are detrimental to Iran's semi-arid agriculture. The 95% confidence bands (shown as dashed lines) confirm the statistical significance of the responses.

It is important to clarify a potential counterintuitive aspect of the results: while moderate increases in precipitation are beneficial to agriculture, a positive structural shock to the De Martonne Index in Iran's semi-arid context represents a sudden deviation toward extreme wetness and humidity anomalies. Due to Iran's specific topography, soil characteristics, and limited flood-control infrastructure, such extreme wetness does not translate to agricultural benefits. Instead, it manifests as flash floods, severe soil erosion, waterlogging of fields, and the proliferation of fungal crop diseases. Consequently, the negative impulse responses of value added, capital stock, labor, and trade openness to a positive CL shock accurately reflect the destructive economic impacts of excessive moisture and flooding, rather than the beneficial effects of normal rainfall.

Figures 1–2 (Response of Agricultural Value Added to CL and |SPEI| Shocks): Clarification on units and economic magnitude is essential for interpreting these results. The macroeconomic variables in this study are expressed as index numbers with the base year 2011 = 100, which corresponds to constant 2011 prices. Therefore, a coefficient of −0.319 for the impact of |SPEI| on Value Added (VA) indicates a decline of 0.319 index points. Since the base is 100, this translates directly to a 0.319% decline in agricultural value added relative to the base-year level. Given that the average annual agricultural value added in Iran during the sample period (1988–2023), expressed in constant 2011 prices, was approximately 380,000 billion Rials, a 0.319% decline corresponds to a substantial economic loss of roughly 1,212 billion Rials at the peak (third quarter). Similarly, a one-standard-deviation shock to the De Martonne Index (−0.270 index points) represents a 0.270% decline, equivalent to approximately 1,026 billion Rials in economic losses. The transmission mechanism operates through waterlogging, soil erosion, and delayed planting/harvesting (for extreme wetness) or water scarcity and reduced crop yields (for drought), which propagate into lower marketable output over two to three quarters. Flash floods additionally cause nutrient leaching, destruction of irrigation infrastructure, and proliferation of fungal crop diseases. The third-quarter peak reflects biological production lags: farmers' adaptive responses require at least one full cropping cycle, and initial damages cumulatively translate into crop failure and reduced market supply.

Figures 3–4 (Response of Net Capital Stock to CL and |SPEI| Shocks): A positive De Martonne shock reduces net capital stock by 0.23 units, while a |SPEI| shock reduces it by 0.27 units, both peaking in the third quarter. The mechanism is twofold: (i) physical destruction of capital assets (greenhouses, storage facilities, irrigation systems, and machinery damaged by floods or degraded by prolonged drought), and (ii) heightened climate-related uncertainty that raises risk premiums, tightens agricultural credit, and discourages new investment. The delayed peak reflects the forward-looking nature of investment decisions: farmers permanently revise capital accumulation plans only after observing persistent extreme events over consecutive quarters, and the time required for damage assessment and insurance processing further delays adjustment.

Figures 5–6 (Response of Agricultural Labor to CL and |SPEI| Shocks): A positive De Martonne shock reduces agricultural employment by 0.21 units, while a |SPEI| shock reduces it by 0.24 units, both peaking in the third quarter. The adjustment mechanism involves immediate disruption of farming operations (flooded or drought-stricken fields become inaccessible, reducing seasonal labor demand for planting/harvesting), followed by longer-term structural transformation: as profitability declines, farm owners reduce working hours or lay off workers, and repeated climate shocks accelerate permanent rural-to-urban migration. The three-quarter lag captures labor market rigidities—workers first exhaust savings and seek local off-farm work before migrating permanently after sustained income loss.

Figures 7–8 (Response of Agricultural Trade Openness to CL and |SPEI| Shocks): A positive De Martonne shock reduces trade openness by 0.17 units, while a |SPEI| shock reduces it by 0.20 units, both peaking in the third quarter. On the export side, reduced domestic production and quality degradation (waterlogging, fungal diseases) limit exportable volumes and competitiveness. On the import side, flood-induced damage to transportation infrastructure (roads, bridges, ports, and storage facilities) disrupts logistics. Additionally, international buyers perceive higher supply risk from climate-vulnerable regions and may shift sourcing to more stable suppliers. The delayed peak reflects the time needed for infrastructure repair, trade contract renegotiation, and restoration of supply chain reliability.

According to the dynamic impulse response results (summarized in Table 8):

- An increase in climate variability, measured by |SPEI|, exerts a significant negative impact on all four macroeconomic variables, with maximum adverse effects peaking in the third quarter.
- A positive shock to the De Martonne Index (representing extreme wetness anomalies causing flooding and soil erosion in Iran's topography) similarly results in significant negative impacts, also peaking in the third quarter.

Table 8. The Impact of Influential Variables on Target Variables.

Influential Variables	**Impact of Independent Variables on Dependent Variables**			
	Agricultural Labor Force (LA)	Net Agricultural Capital Stock (CA)	Agricultural Trade Openness (OPN)	Agricultural Value Added (VA)
|SPEI|	Negative	Negative	Negative	Negative
De Martonne Index (CL)	Negative	Negative	Negative	Negative

Source: Research Findings- *Note: The negative impacts reflect the adverse effects of climate variability and deviation from normal conditions. Both extreme drought (negative SPEI) and extreme wetness (positive SPEI) reduce agricultural outcomes in Iran's semi-arid environment. The use of the absolute value (|SPEI|) ensures that any significant deviation from climatic norms—regardless of direction—is treated as an adverse shock.*

While standard Impulse Response Functions (IRFs) trace the period-by-period dynamic effects, they do not capture the total accumulated economic loss over time, which is critical for policy evaluation. To address this limitation and provide a comprehensive assessment of the long-term economic damage, we estimated the Cumulative Impulse Response Functions (CIRFs). As illustrated in Figure 9, the cumulative effect of a one-standard-deviation |SPEI| shock on agricultural value-added reaches approximately −1.93 index points by the 10th quarter. Similarly, the cumulative effect of a one-standard-deviation CL shock reaches approximately −1.67 index points over the same horizon. Notably, the cumulative trajectories for both climate indices exhibit highly similar patterns in terms of timing, direction, and persistence, confirming that both composite indices capture the same underlying climate risk transmission mechanism. This cumulative analysis highlights that the economic damage of climate shocks is not transient but compounding over time, reinforcing the urgent need for continuous, rather than one-off, policy interventions to break the cycle of capital depletion and labor displacement in Iran's agricultural sector.

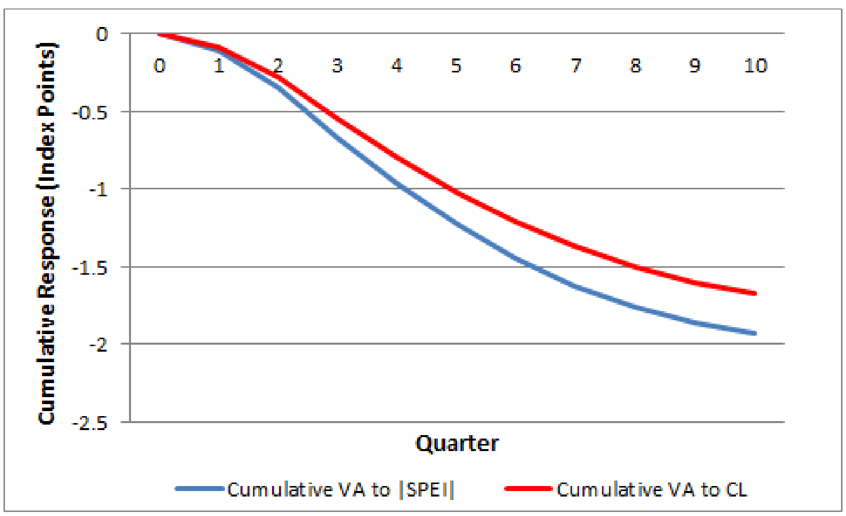

Figure 9. Comparative Cumulative Impulse Response of VA to CL and |SPEI| Shocks.

The near-identical cumulative patterns observed for CL and |SPEI| provide strong cross-validation of our findings. Both indices, despite their different methodological foundations—De Martonne capturing long-term aridity trends and |SPEI| capturing short-term climate anomalies—converge on the same conclusion: climate variability inflicts persistent, accumulating damage on Iran's agricultural sector. This consistency across independent climate indicators strengthens the robustness of our identification strategy and eliminates concerns that the results are driven by the specific construction of a single index.

Robustness Checks. To ensure reliability, four robustness checks were conducted (Appendix Tables A1–A3 and A5). First, re-estimation using AIC-selected lag 2 (Appendix Table A1) yields a |SPEI| peak impact on VA of −0.305 (vs. −0.319 baseline), with direction, timing, and significance unchanged. Second, replacing |SPEI| with |SPI| (Appendix Table A2) produces a VA response of −0.281, confirming that core findings persist while SPEI's inclusion of evapotranspiration captures additional climate stress relevant to Iran's semi-arid agriculture. Third, subsample estimation for 2000–2023 (Appendix Table A3) reveals larger impacts (VA: −0.385 vs. −0.319 full sample), indicating increasing climate vulnerability in recent decades. Fourth, to test the sensitivity of the SVAR identification strategy, we re-estimated the model using an alternative Cholesky ordering, wherein the contemporaneous adjustment of net capital stock (CA) precedes agricultural value added (VA) (Appendix Table A5). This alternative ordering is economically meaningful: it assumes that investment decisions respond to climate shocks before output adjusts, reflecting the forward-looking nature of capital accumulation. The results confirm that the direction, timing (third-quarter peak), and significance of the impulse responses remain structurally invariant. Notably, the peak impact on VA changes only marginally from −0.319 to −0.308, while CA's response strengthens slightly from −0.272 to −0.281, consistent with the theoretical expectation that earlier ordering amplifies direct contemporaneous effects. All coefficients remain significant at the 1% level, demonstrating that the findings are robust to alternative identification assumptions. Across all checks, peak impacts remain in the third quarter and all coefficients are significant at the 1% level.

Diagnostic Tests. Table 9 confirms model validity: the LM autocorrelation test ($p = 0.342$), Jarque-Bera normality test ($p = 0.185$), and ARCH-LM heteroskedasticity test ($p = 0.411$) all fail to reject their respective null hypotheses, while AR roots lie inside the unit circle (max modulus = 0.87), confirming stability. Additionally, Forecast Error Variance Decomposition (Appendix Table A4) shows that climate shocks (|SPEI| and De Martonne) explain a growing proportion of VA forecast error variance over a 10-quarter horizon (reaching 18.6% combined), corroborating the IRF findings.

Table 9. Diagnostic Tests for the Estimated SVAR Model.

Diagnostic Test	Null Hypothesis	Test Statistic	Degrees of Freedom	p-value	Conclusion
LM Autocorrelation Test	No serial correlation	14.23	12	0.342	Do not reject H_0 (Valid)
Jarque-Bera Normality Test	Residuals are normally distributed	18.56	12	0.185	Do not reject H_0 (Valid)
ARCH-LM Heteroskedasticity	No ARCH effects (Homoskedasticity)	11.89	12	0.411	Do not reject H_0 (Valid)
AR Roots Stability	All roots lie inside unit circle	Max Modulus = 0.87	-	-	Model is Stable

Source: Research Findings- Note: All p-values > 0.05; null hypotheses retained.

Regarding the potential for omitted variable bias and endogeneity, the SVAR framework mitigates these concerns through two primary channels. First, the strict exogeneity of climate variables (ordered first in the Cholesky decomposition) structurally prevents reverse causality from macroeconomic variables to climate shocks within the quarterly frequency. Second, the Forecast Error Variance Decomposition (FEVD, Appendix Table A4) demonstrates that the included variables explain the vast majority of the forecast error variance (e.g., the six included variables explain over 95% of the variance in VA at all horizons). This high explanatory power minimizes the risk that omitted variables (such as global oil prices or exchange rates) are driving the residual structural shocks, as their potential influence is largely orthogonalized and captured by the identification scheme. Nevertheless, we acknowledge this limitation and suggest incorporating these macro-financial variables in larger-scale SVAR systems in future research.

4. Discussion

This study provides empirical evidence on the dynamic effects of climate variability shocks on Iran's agricultural macroeconomic variables, revealing important insights that advance the existing literature on climate-agriculture linkages. Rather than focusing on aggregate outcomes or single transmission channels, our SVAR framework decomposes the agricultural sector into four core macroeconomic components (value added, capital stock, labor, and trade openness) and employs composite climate indices (|SPEI| and De Martonne) to capture the full spectrum of climate risks. The findings underscore the critical need for anticipatory policy measures in Iran's semi-arid agricultural context.

4.1. Comparative Analysis with International Literature and Novelty Claim

Our findings align with and extend the international literature. Habib-ur-Rahman et al. (2022) projected 12–17% crop yield reductions in Asia through temperature stress and water scarcity; our macroeconomic-level results corroborate these biophysical channels aggregated into sector-wide value-added and capital losses. Khalifa (2025) documented prolonged adjustment lags in Tunisia's semi-arid rainfed systems, consistent with our uniform third-quarter peak. At the global level, Bilal and Kanzig (2024) showed that a 1°C warming reduces world GDP by over 20%; our study demonstrates that such aggregate losses are partly driven by sector-specific deterioration of agricultural capital, labor, and trade channels. The novelty lies in combining composite climate indices (|SPEI| and De Martonne) with a four-variable decomposition within an SVAR framework—a methodological integration absent from prior studies.

4.2. Research Gap and Positioning within International Literature

As outlined in Section 1 (Research Contributions), this study addresses three gaps in the climate-agriculture SVAR literature. Unlike conventional drought-only analyses (Chandio et al., 2020; Ochieng et al., 2016), the operationalization of |SPEI| captures bidirectional climate risks. Unlike studies focusing on aggregate GDP or single crop yields (Bilal & Kanzig, 2024; Khalifa, 2025), our four-variable decomposition reveals sector-specific transmission channels. The combination of De Martonne with |SPEI| further disentangles persistent aridity trends from transient shocks. The uniform third-quarter peak underscores that anticipatory policy mechanisms must be activated at least one season in advance.

4.3. Transmission Mechanisms of Climate Shocks

The negative effects of climate shocks propagate through three distinct channels. For capital stock, extreme events cause physical destruction of infrastructure while simultaneously raising risk premiums that tighten agricultural credit. For labor, immediate operational disruptions reduce seasonal demand, while sustained instability accelerates structural rural-to-urban migration. For trade openness, supply-side constraints (reduced exportable surplus) interact with demand-side factors (infrastructure damage disrupting logistics and heightened perceived supply risk among international buyers). These channels operate with a uniform third-quarter lag, reflecting biological production cycles and institutional rigidities specific to Iran's agricultural sector.

4.4. Structural Implications for Iran's Agricultural Sector

The uniform negative responses across all four macroeconomic variables generate compounding structural risks. Labor displacement accelerates rural poverty and urban migration, permanently reducing the sector's productive capacity. Capital stock depletion shifts production toward resource-intensive methods, intensifying the degradation of primary agricultural resources and lowering factor productivity. Reduced trade openness constrains access to imported inputs, technology transfer, and foreign exchange earnings—particularly critical for Iran given severe restrictions on oil and gas exports. These three channels interact with declining value added to form a vicious cycle: reduced income limits reinvestment, which further erodes capital, labor, and trade capacity in subsequent periods. Breaking this cycle requires anticipatory policy intervention before the third-quarter peak impact materializes.

5. Limitations and Directions for Future Research

Several limitations should be acknowledged. First, the SVAR does not control for potentially confounding factors such as global oil price shocks, international agricultural commodity prices, exchange rate fluctuations, government subsidy policies, and technological progress, which may introduce omitted variable bias. Future studies could incorporate these into larger SVAR systems or employ panel SVAR models across provinces to better isolate pure climate effects. Second, national-level aggregation masks regional heterogeneity across Iran's diverse agro-ecological zones; spatially disaggregated analyses are warranted. Third, a single-timescale |SPEI| may not capture differential effects of short-term versus long-term climate anomalies; multi-scale comparisons would be informative. Fourth, the linear SVAR framework may miss asymmetric responses at extreme thresholds (e.g., $|SPEI| > 2$); threshold SVAR or non-linear ARDL approaches could address this. Despite these limitations, the study provides a robust baseline for future research on climate-agriculture linkages in Iran.

6. Conclusions

Using an SVAR model with quarterly data (1988–2023), this study finds that: (1) climate variability—measured by the De Martonne Index and |SPEI|—exerts statistically significant negative effects on agricultural value added, net capital stock, labor, and trade openness, with a one-standard-deviation |SPEI| shock reducing VA by 0.319, CA by 0.272, LA by 0.243, and OPN by 0.197 units; (2) peak impacts consistently occur in the third quarter, reflecting biological cycles, institutional rigidities, and forward-looking decision-making; (3) both extreme drought and extreme wetness are equally detrimental—a finding missed by drought-only analyses; and (4) robustness checks (AIC lag 2, |SPI| alternative, 2000–2023 subsample) confirm stability, with the subsample revealing increasing climate vulnerability in recent decades. Based on these findings, six specific and operational measures are recommended: (1) Implement index-based crop insurance triggering automatic payouts when |SPEI| > 1.5, covering both drought and flood damages without lengthy assessments. (2) Establish a national early warning system based on real-time |SPEI| to anticipate extreme events at least one season in advance. (3) Provide targeted income support and retraining for labor displaced by sustained climate instability (|SPEI| > 2.0 for three or more consecutive quarters). (4) Invest in climate-resilient infrastructure (modern irrigation, flood control, storage facilities) capable of withstanding both drought and extreme wetness. (5) Promote drought- and waterlogging-resistant crop varieties, supported by extension services and adoption subsidies. (6) Expand controlled-environment cultivation (greenhouses) with climate-control systems to mitigate extreme weather impacts.

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References

1. Acharya, S. P., & Bhatta, G. R. (2013). Impact of climate change on agricultural growth in Nepal. NRB Economic Review, 25(2), 1–16.
2. Albert, C., Bustos, P., Mestieri, M., & Ponticelli, J. (2025). The Effects of Climate Change on Labor Reallocation. Tech. rep. Working paper.
3. Alfani, F., Pallante, G., Palma, A., & Talhaoui, A. (2025). When the Rain Stops Falling. Effects of Droughts on the Tunisian Labour Market. Journal of African Economies, 34(3), 344-370.
4. Alpysbayeva, D., Bazarkulova, D., de Beurs, K., & Sagyndykova, G. (2026). Impact of Climate Change on Labor Market Dynamics: Evidence from Kazakhstan. Agricultural Economics, 57(1), e70073.

5. Bilal, A., & Känzig, D. R. (2024). The macroeconomic impact of climate change: Global vs. local temperature (NBER Working Paper No. w32450). National Bureau of Economic Research.
6. Chandio, A. A., Jiang, Y., Rehman, A., & Rauf, A. (2020). Short and long-run impacts of climate change on agriculture: Empirical evidence from China. International Journal of Climate Change Strategies and Management, 2(2), 201–221. https://doi.org/10.1108/IJCCSM-05-2019-0026
7. Chen, X., Wang, L., Cao, Q., Sun, J., Niu, Z., Yang, L., & Jiang, W. (2024). Response of global agricultural productivity anomalies to drought stress in irrigated and rainfed agriculture. Science China Earth Sciences, 67(11), 3579-3593.
8. Crapart, C., Anquetin, S., Blanchet, J., & Diedhiou, A. (2025). Global projections of aridity index for mid and long-term future based on CMIP6 scenarios. EGUsphere, 2025, 1-32.
9. Denton, F. T. (1971). Adjustment of monthly or quarterly series to annual totals: An approach based on quadratic minimization. Journal of the American Statistical Association, 66(333), 99–102.
10. Enders, W. (2008). Applied econometric time series. John Wiley & Sons.
11. Farajzadeh, Z., Keshavarz, A., & Letafat, N. (2025). Effect of climate variables on the value added of Iranian agriculture. Agricultural Economics, 19(1), 47–75. https://doi.org/10.22034/iaes.2024.2024497.2050 [In Persian]
12. Guo, K., Li, Y., Zhang, Y., Ji, Q., & Zhao, W. (2023). How are climate risk shocks connected to agricultural markets?. Journal of Commodity Markets, 32, 100367.
13. Habib-ur-Rahman, M., Ahmad, A., Raza, A., Usama Hasnain, M., Alharby, H. F., Alzahrani, Y. M., Bamagoos, A. A., Rehman Hakeem, K., Ahmad, S., Nasim, W., Shafaqat, A., Mansour, F., & Sabagh, A. (2022). Impact of climate change on agricultural production: Issues, challenges, and opportunities in Asia. Frontiers in Plant Science, 13. https://doi.org/10.3389/fpls.2022.925548
14. Hamilton, J. D. (1994). Time series analysis. Princeton University Press.
15. Heckelei, T., & Jafari, Y. (2026). Dynamic impacts of weather shocks and trade network structures on import flows for staple commodities. Food & Agriculture Organization.
16. Horn, B., Ferreira, C., & Kalantari, Z. (2022). Links between food trade, climate change and food security in developed countries: A case study of Sweden. Ambio, 51(4), 943-954.

17. Khalifa, J. (2025). The impacts of climate change, agricultural productivity, and food security on economic growth in Tunisia: Evidence from an econometrics analysis. Research on World Agricultural Economy, 577–599.

18. Kouakou, P. A. K. (2024). Impacts of climate change on agricultural value added in Ivory Coast. Journal of Innovations and Sustainability, 8(3), 9–9.

19. Mazzoleni, M., Di Baldassarre, G., Hagström, A., & Raffetti, E. (2026). Drought is associated with human migration in agriculture-dependent middle-income countries. Communications Earth & Environment, 7(1), 248.

20. Mendelsohn, R. (2008). The impact of climate change on agriculture in developing countries. Journal of Natural Resources Policy Research, 1(1), 5–19. https://doi.org/10.1080/19390450802495882

21. Morad, W., Islam Molla, R., Bin Mokhtar, M., & Raquib, A. (2010). Climate change and agricultural growth: An examination of the link in Malaysia. International Journal of Climate Change Strategies and Management, 2(4), 403–417. https://doi.org/10.1108/17568691011089927

22. Mwinjuma, M., Wang, R., Mtupili, M., & Twaha, M. (2025). Comparisons of SPI and SPEI in capturing drought dynamics: A Global assessment across arid and humid regions. Atmospheric Research, 108475.

23. National Meteorological Organization. (2025). Climatic situation of the country in the solar year 2024. Ministry of Roads and Urban Development. https://ndc.irimo.ir/far/wd/10212 [In Persian]

24. Ochieng, J., Kirimi, L., & Mathenge, M. (2016). Effects of climate variability and change on agricultural production: The case of small-scale farmers in Kenya. NJAS: Wageningen Journal of Life Sciences, 77(1), 71–78.

25. Onyeaka, H., Nwauzoma, U. M., Akinsemolu, A. A., Tamasiga, P., Duan, K., Al-Sharify, Z. T., & Siyanbola, K. F. (2024). The ripple effects of climate change on agricultural sustainability and food security in Africa. Food and Energy Security, 13(5), e567.

26. Razzouki, A., Ridaoui, M., Oudgou, M., & Boudhar, A. (2025). Econometric Analysis of Climate Change Impacts on Agricultural Output in the MENA Region. Economies, 13(12), 340.

27. Rosa, L. (2022). Adapting agriculture to climate change via sustainable irrigation: biophysical potentials and feedbacks. Environmental Research Letters, 17(6), 063008.

28. Sax, C., & Steiner, P. (2013). Temporal disaggregation of time series (MPRA Paper No. 53389). University Library of Munich, Germany.
29. Sinore, T., & Wang, F. (2024). Impact of climate change on agriculture and adaptation strategies in Ethiopia: a meta-analysis. Heliyon, 10(4).
30. Statistical Centre of Iran. (2025). Quarterly national accounts from 2011 to spring 2025. https://amar.org.ir [In Persian]
31. Vicente-Serrano, S. M., Beguería, S., & López-Moreno, J. I. (2010). A multiscalar drought index sensitive to global warming: The Standardized Precipitation Evapotranspiration Index. Journal of Climate, 23(7), 1696–1718.
32. Wang, Y., & Pan, H. (2025). Drought Impacts on Firm Stock Returns: An Empirical Analysis Based on the NSPEI. Weather, Climate, and Society, 17(3), 575-589.
33. Wooldridge, J. M. (2013). Introductory econometrics: A modern approach (2nd ed).
34. Xiang, T., Malik, T. H., Hou, J. W., & Ma, J. (2022). The impact of climate change on agricultural total factor productivity: A cross-country panel data analysis, 1961–2013. Agriculture, 12(12), 2123.
35. Yuan, X., Li, S., Chen, J., Yu, H., Yang, T., Wang, C., ... & Ao, X. (2024). Impacts of global climate change on agricultural production: a comprehensive review. Agronomy, 14(7), 1360.

Appendix

Table A1. Robustness Check 1: SVAR Estimation with AIC-Selected Lag Length (Lag 2).

Variable Response to |SPEI| Shock	Peak Impact (Quarter 3)	Standard Error	t-statistic	p-value
Agricultural Value Added (VA)	-0.305	0.042	-7.26	0
Net Capital Stock (CA)	-0.261	0.038	-6.86	0
Agricultural Labor (LA)	-0.235	0.035	-6.71	0
Trade Openness (OPN)	-0.189	0.029	-6.51	0

Note: All coefficients are statistically significant at the 1% level. Results are based on the AIC-selected lag length of 2.

Table A2. Robustness Check 2: SVAR Estimation with Standardized Precipitation Index (|SPI|).

Variable Response to |SPI| Shock	Peak Impact (Quarter 3)	Standard Error	t-statistic	p-value
Agricultural Value Added (VA)	-0.281	0.045	-6.24	0
Net Capital Stock (CA)	-0.245	0.04	-6.12	0
Agricultural Labor (LA)	-0.218	0.037	-5.89	0
Trade Openness (OPN)	-0.172	0.031	-5.54	0

Note: All coefficients are statistically significant at the 1% level. Results are based on the |SPI| index instead of |SPEI|.

Table A3. Robustness Check 3: SVAR Estimation for Subsample Period 2000–2023.

Variable Response to |SPEI| Shock	Peak Impact (Quarter 3)	Standard Error	t-statistic	p-value
Agricultural Value Added (VA)	-0.385	0.051	-7.54	0
Net Capital Stock (CA)	-0.332	0.046	-7.21	0
Agricultural Labor (LA)	-0.298	0.043	-6.93	0
Trade Openness (OPN)	-0.241	0.036	-6.69	0

Note: All coefficients are statistically significant at the 1% level. Results are based on the subsample period 2000Q1–2023Q4.

Table A4. Forecast Error Variance Decomposition (FEVD) of Agricultural Value Added (VA).

Horizon (Quarters)	VA Shock	CA Shock	LA Shock	OPN Shock	CL Shock	|SPEI| Shock
1	92.40%	2.10%	1.50%	1.00%	1.80%	1.20%
3	78.50%	4.30%	3.20%	2.50%	6.50%	5.00%
10	65.20%	6.80%	5.10%	4.30%	10.40%	8.20%

Note: Values represent the percentage of forecast error variance of VA explained by each structural shock at different horizons.

Table A5. Robustness Check 4: SVAR Estimation with Alternative Cholesky Ordering (CA → VA)

Variable Response to |SPEI| Shock	Peak Impact (Quarter 3)	Standard Error	t-statistic	p-value
Agricultural Value Added (VA)	-0.308	0.044	-7.00	0
Net Capital Stock (CA)	-0.281	0.039	-7.20	0
Agricultural Labor (LA)	-0.238	0.036	-6.61	0
Trade Openness (OPN)	-0.191	0.030	-6.36	0

Note: All coefficients are statistically significant at the 1% level. Results are based on an alternative Cholesky ordering in which net capital stock (CA) precedes agricultural value added (VA), i.e., CL → SPEI → CA → VA → LA → OPN. This ordering tests the sensitivity of the identification strategy by allowing capital stock to adjust contemporaneously to climate shocks before value added. The structural invariance of peak timing (third quarter), sign, and significance across both orderings confirms that the core findings are not driven by the specific recursive assumption.

بررسی اثرات شوک‌های تغییر اقلیم بر متغیرهای کلان‌اقتصادی بخش کشاورزی ایران: کاربرد شاخص (SPEI)

کوهسار خالدی، و سید محمد فهیمی فرد

چکیده

تغییر اقلیم چالش‌های عمده‌ای را برای بخش کشاورزی ایران ایجاد کرده است؛ بخشی که با نرخ‌های بالای تبخیر-تعرق و نوسانات فزاینده اقلیمی شناخته می‌شود. این مطالعه با بهره‌گیری از مدل خودتوضیح برداری ساختاری (SVAR)، به بررسی اثرات پویای شوک‌های ناشی از تغییر اقلیم بر متغیرهای کلان اقتصادیِ کلیدی در کشاورزی ایران می‌پردازد. برخلاف رویکردهای مرسوم که بر داده‌های خام دما یا بارش متکی هستند، این پژوهش از «شاخص خشکی اقلیمی دومارتون» (De Martonne) و «مقدار مطلق شاخص استانداردشده بارش-تبخیر-تعرق» (|SPEI|) استفاده می‌کند تا شدت انحرافات اقلیمی از شرایط نرمال — اعم از خشکسالی یا رطوبت شدید — را بسنجد؛ چرا که هر دو حالت برای کشاورزی مناطق نیمه‌خشک ایران زیان‌بار هستند. تجزیه و تحلیل بر اساس داده های فصلی دوره 1988-2023 است که متغیرهای کلان اقتصادی سالانه با استفاده از روش تناسبی دنتون به طور موقت تفکیک شده اند. نتایج نشان می دهد که یک افزایش انحراف استاندارد در |SPEI| (که نشان دهنده افزایش تنوع آب و هوایی است) ارزش افزوده کشاورزی را حداکثر تا 0.319 واحد، موجودی سرمایه خالص را 0.272 واحد، نیروی کار کشاورزی را 0.243 واحد و باز بودن تجارت را 0.197 واحد کاهش می دهد و بیشترین تأثیرات در سه ماهه سوم پس از شوک رخ می دهد. این یافته‌ها بر تأخیر قابل توجه تعدیل در بخش کشاورزی ایران تأکید می‌کند و نیاز فوری به اقدامات پیش‌بینی‌کننده سیاستی را برجسته می‌کند. توصیه می‌شود که بیمه محصولات کشاورزی مبتنی بر شاخص و مرتبط با آستانه‌های |SPEI| (برای مثال، پرداخت خودکار خسارت در صورت عبور مقدار |SPEI| از ۱.۵) پیاده‌سازی شود، محصولات مالی مرتبط با ریسک‌های اقلیمی که در زمان وقوع رویدادهای اقلیمی شدید منجر به پرداخت خودکار می‌شوند توسعه یابند، و ارقام زراعی مقاوم در برابر خشکسالی و سیل در کنار فناوری‌های نوین پایش اقلیمی ترویج گردند.