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Future-oriented agricultural water management with scenario-based evaluation: Case study of Maize in Khuzestan

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Abstract
Amidst intensifying climatic and management pressures on water resources in Iran, this research focuses on exploring the desirable and effective future of water use in agriculture, with a case study of maize in Khuzestan Province. The LARS-WG 8 was used to project climate data up to the horizon year 2040. The biophysical crop yield was examined using AquaCrop 7.1. According to the results, the LARS-WG model generated temperature data (NRMSE≈1%) with greater accuracy than precipitation (NRMSE≤13%) at Ahvaz and Dezful stations. In addition, the AquaCrop model (R^2=0.96, RMSE<0.5 t/ha, NSE≈0.98) confirmed the high accuracy of maize yield simulation. Moreover, structural scenarios developed with the ScenarioWizard software and the MICMAC matrix included 13 significant drivers from the policy, technology, and climate domains. The findings indicate that the effect of climate change on water productivity is incremental, and shaping a desirable future is largely influenced by management. The results showed that, when moving from SSP1-2.6 to SSP5-8.5, grain maize yield and water productivity increased in both spring and summer maize. In spring, yield increased from 6.26 t/ha in SSP1-2.6 to 6.79 t/ha in SSP5-8.5, and water productivity increased from 1.13 to 1.22 kg/m^3. In summer, this trend was more pronounced, with yield rising from 8.32 to 9.15 t/ha and water productivity from 1.29 to 1.42 kg/m^3. These results indicated that under the more severe climate change scenario (SSP5-8.5), crop growth and yield were more affected, especially in summer. Furthermore, this study provides a picture of the desired future of water use in agriculture. According to the Total Impact Score in ScenarioWizard (381, 405, 408), a desirable and effective future was identified when political and technological measures were taken at a high level of intervention. According to these results, achieving a desirable future depends on the full implementation of decentralization policies, data transparency, and the use of advanced statistical systems.

Keywords: AquaCrop, Foresight, Grain Maize, LARS-WG, ScenarioWizard, SSPs

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1. Introduction

Structural foresight has emerged in recent years as an interdisciplinary science for analyzing complex structures (Manzano-Solís et al., 2019). However, it has not been used in water resources management, especially at the farm level or in relation to water productivity (George-Williams et al., 2024). Research shows that foresight complements environmental modeling and decision-making (Alexandra and Wyborn, 2023; Ednie et al., 2023). In this context, techniques like scenario analysis or uncertainty exploration are involved in foresight to enable organizations or managers to anticipate challenging future conditions (Demneh et al., 2023).

However, there are obstacles such as institutional and political constraints in applying foresight results (Sokolova, 2022; Ednie et al., 2023). "Weak governance" and "lack of institutional coordination" have been identified as the most important obstacles to improving agricultural water productivity in Iran (Dehghani et al., 2025a). These obstacles are rooted in organizational culture, which equally hinders the implementation of foresight-based strategies. As already demonstrated by Lazurko et al. (2023), resilience in social–ecological systems must be supported by institutional alignment, stakeholder engagement, and adaptive learning mechanisms.

Foresight uses Delphi, MiMac, and ScenarioWizard software. Variables with maximum influence and minimal dependence, considered drivers in the system, are extracted from the MICMAC structural analysis matrix (Yaraghi Fard and Shokouhibidhendi, 2025). The ScenarioWizard software, which is developed based on the interaction method, can generate scenarios by analyzing the relationships between drivers (Tori et al., 2023). A study undertaken in Iran by Barati et al. (2019) demonstrated that the combination of MICMAC with multicriteria decision-making techniques is highly effective for the ranking of drivers of agricultural development. A study conducted in Indonesia, applying MICMAC analysis with the help of ScenarioWizard, emphasized the role of the central government in the development of road infrastructure, along with economic growth, and also identified nine drivers (Nawir et al., 2023).

With water resources diminishing, population growth and food security threats looming, it is essential to use scenario-based approaches to map out a bright future in this area. In this regard, examining the effects of climate change on future crop yields and water productivity helps to clarify the scenarios. Climate change can potentially affect water availability. These patterns in Iran have resulted in a significant reduction in renewable water per capita and further increased pressure on agriculture (Paziresh et al., 2023). Iran is among the countries where more than 75% of agricultural production depends on irrigated lands (Farahza et al., 2019).

Several studies confirmed the accuracy of the AquaCrop model in simulating yield, biomass, and water productivity (Dehghani et al., 2025b; Jorrehnoosh et al., 2024; Zhang et al., 2025; Neysi et al., 2023). The LARS-WG model is recognized as a reliable tool for generating stochastic weather data at the station scale, capable of generating daily precipitation and temperatures under future climate conditions (Ghazizadeh et al., 2025; Maryanji et al., 2025). Marei et al. (2024) assessed the impacts of climate change on yield, water productivity, and the growth duration of sugar beet at the Feyzabad station of Qazvin using the AquaCrop model and LARS-WG software. Accordingly, the yield of sugar beet is projected to decline by more than 40%. In a different study, Hosseini et al. (2024) used the AquaCrop model to simulate the biomass and grain yield of green peas in Babol County. According to the results, the SSP5–8.5 scenario combined with full irrigation produced the highest yields in most of the study years, whereas reduced irrigation and delayed planting led to yield reductions.

Ahmadi et al. (2024) studied the future impact of climate change on wheat yield, water requirement, evapotranspiration, and water footprint using the AquaCrop model for the Qazvin Plain. The findings indicate that while water footprint and water requirement will decline, wheat yield and biomass are projected to increase in future periods. Maucieri et al. (2025) used the AquaCrop model to simulate how climate change would affect soybean yield and water demand. Results from multiple regions across Italy and Slovenia indicated that soybean yield under rainfed conditions would be negatively affected; irrigation could, however, mitigate these conditions in some areas.

In a related study, Baluch et al. (2025) demonstrated, using the AquaCrop model, that under SSP scenarios, rainfed crop yields in the Sanjiang Plain would significantly decline by the middle of the century, with maize and wheat showing declines of 42% and 12%, respectively. The work of Flores-Marquez et al. (2024) assessed the yield of ulluco (Ullucus tuberosus) under rainfed conditions in the central highlands of the Andes in Peru using the AquaCrop model. According to the findings, yield is adversely affected by rising minimum temperatures and variations in seasonal rainfall, particularly between 2050 and 2100. Li et al. (2024) investigated, using the AquaCrop model, the response of cotton yield to climate change and planting date adaptation in major cotton-producing regions of China. The findings indicated that cotton yield is projected to increase in the future, and early planting on March 31 results in better performance compared with late planting on May 10.

More than 139,000 hectares were set aside for grain maize cultivation nationwide during the 2022–2023 cropping year, producing about 962,000 tons of grain maize. At 40,095 hectares and 251,615 tons, respectively, Khuzestan led the country in both cultivated area and production volume (Agricultural Yearbook, 2024). Providing a clear picture of a desirable future in agricultural water management in strategic agricultural regions of Iran, such as Khuzestan Province, is becoming increasingly important due to the reliance on irrigated agriculture and climate change. The present study is one of the first attempts to apply structural analysis and scenario development with a focus on the agricultural water resources management system. This research reveals the effective and sustainable future of agricultural water use in the horizon of 2040 and the contribution of climate and management factors in its construction.

2. Materials and Methods

2.1. Study Area

Khuzestan Province covers an area of 64,236 square kilometers, accounting for about 4% of Iran's total land area. Geographically, it spans from 47°41′ to 50°39′ east longitude and 29°58′ to 33°04′ north latitude. Figure 1 below illustrates the geographical location of Khuzestan Province.

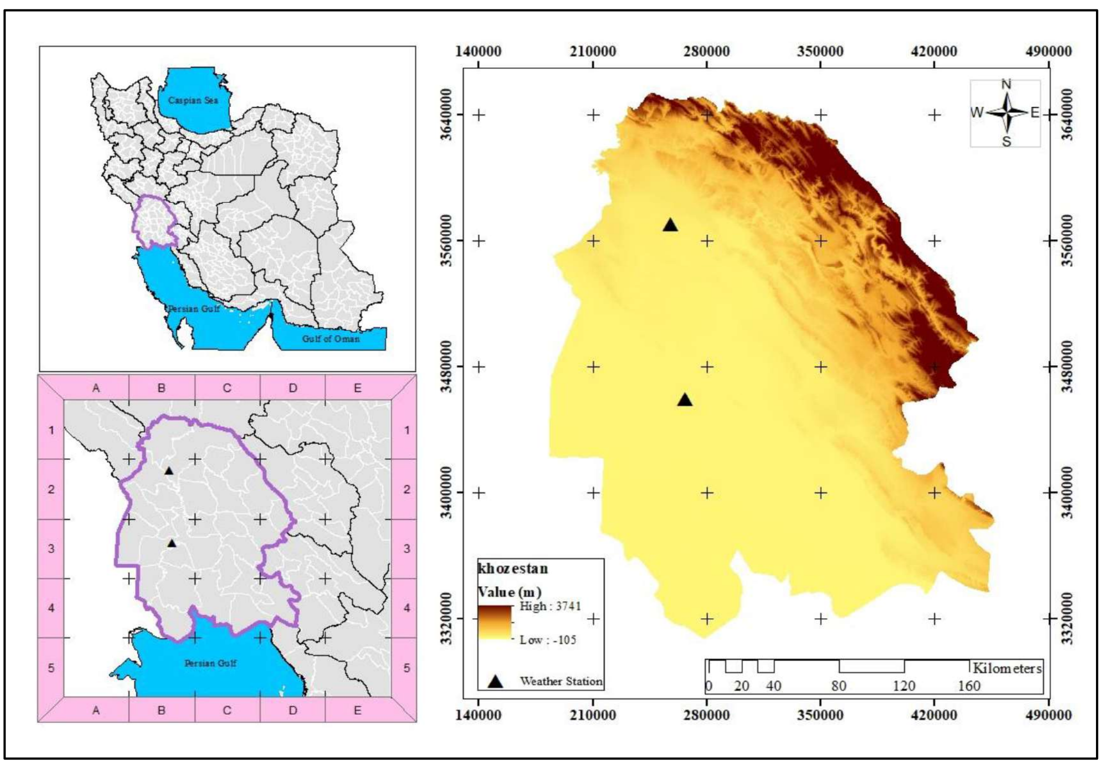

Figure 1. Geographical Location of the Study Area

2.2. Selection of Meteorological Stations

According to the methodology developed by Van Bussel et al. (2015), the first step in selecting reference stations for grain maize in Khuzestan Province starts with preparing the country's agroclimatic zoning map according to the GYGA protocol. Then, using the national distribution map of irrigated maize lands along with the spatial extent of meteorological stations, the area covered by each meteorological station is identified. Among these, only those covering more than 1% of the country's irrigated maize area are considered eligible as reference stations (Soltani et al., 2019). For maize, two stations, Ahvaz (Ahvaz City, Bavi, Dasht-e Azadegan, Hamidiyeh, Shush, Shushtar) and Dezful (Shushtar, Shush, Gotvand, Dezful, Dehloran, Dasht-e Azadegan, Andimeshk), were selected to represent Khuzestan Province. These two stations are representative of about 26.7% of the irrigated area for maize cultivation in the country.

2.3. LARS-WG Model

To generate the climate data for the year 2040, daily observational records of minimum and maximum temperatures, precipitation, and sunshine hours were obtained for two synoptic stations, Ahvaz and Dezful, from the Iran Meteorological Organization. These records were for the statistical period 1995-2024. Outputs from the HadGEM3-GC31-LL model were downscaled using LARS-WG 8 software.

Climate data is simulated by the LARS-WG model through three successive procedures: calibration, validation, and generation. Using the historical data of weather stations and the climate change scenarios, this model modifies the statistical parameters and subsequently generates daily values for minimum temperature, maximum temperature, and precipitation for any given future period (Semenov and Barrow, 1997; Abdulsahib et al., 2024). The integration of the HadGEM3-GC31-LL general circulation model within the LARS-WG 8 software is recognized as a realistic and efficient approach to downscaling climate data and analyzing climate change scenarios at both local and regional scales (Jahangir and Rouzbahani, 2024; Bagheri Khaneghahi et al., 2025).

In this study, climate prediction was performed using the HadGEM3-GC31-LL general circulation model. This model was selected based on evidence available in the scientific literature and regional assessments. Numerous studies have shown that the HadGEM family of models, especially its new versions within the CMIP6 framework, perform well in representing temperature and precipitation patterns in the arid and semi-arid regions of the Middle East, including Iran (Yazdandoost et al., 2021; Almazroui et al., 2021). The HadGEM3-GC31-LL model has been widely used to analyze climate change in Iran and has demonstrated reliable performance due to its relatively high spatial resolution, improved simulation of atmosphere-ocean physical processes, and its ability to reproduce observed climate patterns during the baseline period (Bagheri Khaneghahi et al., 2025; Lotfi et al., 2022).

2.4. AquaCrop Model

AquaCrop modeling builds on two core models: Budget and CROPWAT. It uses the equation proposed by Kassam and Doorenbos (1979) and simulates daily crop growth and yield through four sequential steps, as shown in Figure 2.

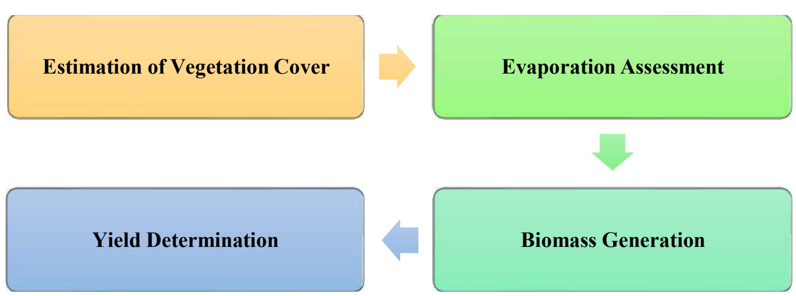

Figure 2. Simulation Steps in the AquaCrop Model

In the first step of simulating the initial stage of crop growth, canopy cover development is independent of root zone expansion. This reflects the need to account for different aspects of water stress on various plant components. Canopy cover ranges from zero to a maximum value in Equation 1. During the third stage of simulation, additional variables are considered for further development, such as parameters of canopy reduction and stress coefficient influencing canopy expansion, Ksexp. The plant transpiration simulation is shown in Equation 2 (Jorrehnoosh et al., 2024; Steduto et al., 2009).

$$CC = {}^{A_c}/_{A_t} \quad (1)$$

A_c: Area covered by the plant canopy
A_t: Total land surface area

$$T_r = Ks\, Ks_{TR}\, CC^*\, Kc_{Tr,X}\, ET_0 \quad (2)$$

T_r: Actual crop transpiration
Ks: water stress coefficient (ranging from 0 to 1)
Ks_{TR}: Temperature stress coefficient for transpiration
CC^*: Adjusted canopy cover (excluding inter-row aerodynamic effects)
$Kc_{Tr,X}$:Crop transpiration coefficient
ET_0: Reference evapotranspiration

In the AquaCrop model, Water Productivity (WP) serves as a key driver of crop growth. Instead of simulating complex physiological processes, the model uses a single water productivity coefficient that is conserved under variable climatic conditions and environmental stresses (Steduto et al., 2007). In order to make this coefficient consistent over different locations and seasons, Water Productivity (WP) is normalized by atmospheric evaporative demand (ET_0) and CO_2 concentration. Normalized water productivity, WP*, as suggested by Steduto and Albrizio (2005), can be calculated using the following equation:

$$WP^* = \left[\frac{B}{\sum(\frac{Tr}{ET_0})}\right]_{[CO_2]} \quad (3)$$

Within the AquaCrop model, total biomass (B) is calculated by summing daily biomass production over the periods when accumulation occurs. The bracket notation [CO_2] outside the parentheses indicates normalization based on the annual average CO_2 concentration for that year. Using the normalized water productivity coefficient, WP*, the daily biomass production, Bi, is estimated from the daily crop transpiration, Tri, and the reference evapotranspiration for that day, $E_{0,i}$, where i denotes the day number within the growing season (Equation 4) (Steduto et al., 2009):

$$B_i = \mathrm{WP}^* \sum \frac{Tr_i}{ET_{o,i}} \quad (4)$$

The fourth step is determining yield, consistent with a biomass, and is calculated using the harvest index (HI) (Equation 5) (Dehghani et al., 2019);

$$Y = f_{HI} HI_0\, B \quad (5)$$

Y: Final crop yield (harvestable portion)
B: Total biomass
f_{HI}: Adjustment factor for stress effects on harvest index
HI_0: Reference harvest index at physiological maturity

Key inputs to the AquaCrop model include: **daily climatic data**, including maximum and minimum temperature, precipitation, and reference evapotranspiration, **soil characteristics**, including texture, water holding capacity, depth, and hydraulic conductivity, and **crop parameters**, including growth duration, leaf area index, root depth, harvest index, and management practices such as planting date, irrigation schedule, and type of irrigation (Dehghani et al., 2019). Baseline climatic data were extracted from synoptic stations in both Ahvaz and Dezful counties, while future scenarios have been generated by the LARS-WG 8 model under three Shared Socioeconomic Pathways, namely SSP1-2.6, SSP2-4.5, and SSP5-8.5. In this study, model calibration was performed using field data of the Single Cross 704 maize cultivar at Ahvaz in two cropping seasons, spring (February 17) and summer (July 19), in 2016 (Ebrahimi Pak et al., 2018).

2.5. Model evaluation

To evaluate the performance of both the LARS-WG and AquaCrop models, a set of standard statistical indicators was used, including the correlation coefficient (r), coefficient of determination (R^2), root mean square error (RMSE), normalized RMSE (NRMSE), coefficient of residual mass (CRM), and Nash–Sutcliffe efficiency (NSE). The equations applied for these indicators are presented below.

$$r = \frac{\sum_{i=1}^{n}(\mathrm{O_i} - \bar{\mathrm{O}}_i)(\mathrm{P_i} - \bar{\mathrm{P}}\mathrm{i})}{\sqrt{\sum_{i=1}^{n}(\mathrm{O_i} - \bar{\mathrm{O}}_i)^2 \sqrt{\sum_{i=1}^{n}(\mathrm{P_i} - \bar{\mathrm{P}}\mathrm{i})^2}}} \tag{6}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(\bar{\mathrm{O}}_i - \mathrm{P_i})^2}{n}} \tag{7}$$

$$\mathrm{NRMSE} = \frac{1}{\bar{\mathrm{O}}_i}\sqrt{\frac{\sum_{i=1}^{n}(\bar{\mathrm{O}}_i - \mathrm{P_i})^2}{n}} \tag{8}$$

$$R^2 = \frac{\sum_{i=1}^{n}(\mathrm{P_i} - \bar{\mathrm{O}}_i)^2}{\sum_{i=1}^{n}(\mathrm{O_i} - \bar{\mathrm{O}}_i)^2} \tag{9}$$

$$\mathrm{CRM} = \frac{\sum_{i=1}^{n}\mathrm{O_i} - \sum_{i=1}^{n}\mathrm{P_i}}{\sum_{i=1}^{n}\mathrm{O}} \tag{10}$$

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n}(O_i - \mathrm{P_i})^2}{\sum_{i=1}^{n}(O_i - \bar{\mathrm{O}}_i)^2} \tag{11}$$

In these equations, the components are defined as follows:

O_i: The observed value at time step *i*.
P_i: The model-generated (predicted) value at time step *i*.
$\bar{O}$: The mean of all observed values.
$\bar{P}$: The mean of all model-generated values.
n: The total number of observations or time steps.

Table 1 presents the statistical indices used to evaluate the performance of the LARS-WG and AquaCrop models, along with the interpretation ranges.

Table 1. Model performance evaluation indices, acceptable ranges (Dehghani et al., 2019; Jorrehnoosh et al., 2024)

Indicator	Value Range	Interpretation / Acceptable Thresholds
r (Correlation coefficient)	−1 to +1	> 0.9: Excellent 0.7–0.9: Good 0.5–0.7: Moderate < 0.5: Poor
R^2 (Coefficient of determination)	0 to 1	> 0.8: Very good 0.6–0.8: Good < 0.6: Moderate to weak
RMSE (Root Mean Square Error)	≥ 0	Lower values indicate better model performance RMSE = 0: Perfect fit
NRMSE (Normalized RMSE)	0 to 1 (or %)	< 0.1 (10%): Excellent 0.1-0.2: Good 0.2-0.3: Fair/Moderate ≥ 0.3: Poor performance
CRM (Coefficient of Residual Mass)	Negative to positive	≈ 0: Good performance > 0: Underestimation < 0: Overestimation
NSE (Nash–Sutcliffe Efficiency)	−∞ to 1	>0.9: Excellent 0.75–0.9: Good 0.5–0.75: Acceptable <0.5: Poor NSE = 1: Perfect fit

2.6. Scenario Design via Structural Analysis

Using the Delphi method, the most influential variables affecting water productivity in agriculture were collected from 18 experts. At this stage, a semi-structured questionnaire was designed and administered. The experts had between 8 and 40 years of experience in the relevant field, with expertise in water, agriculture, and environment. Given that this part of the research aimed to screen criteria, the Delphi process was conducted in a single round (Habibi et al., 2015). Consensus was reached based on the convergence of views in that round. Figure 3 presents the characteristics of the study population.

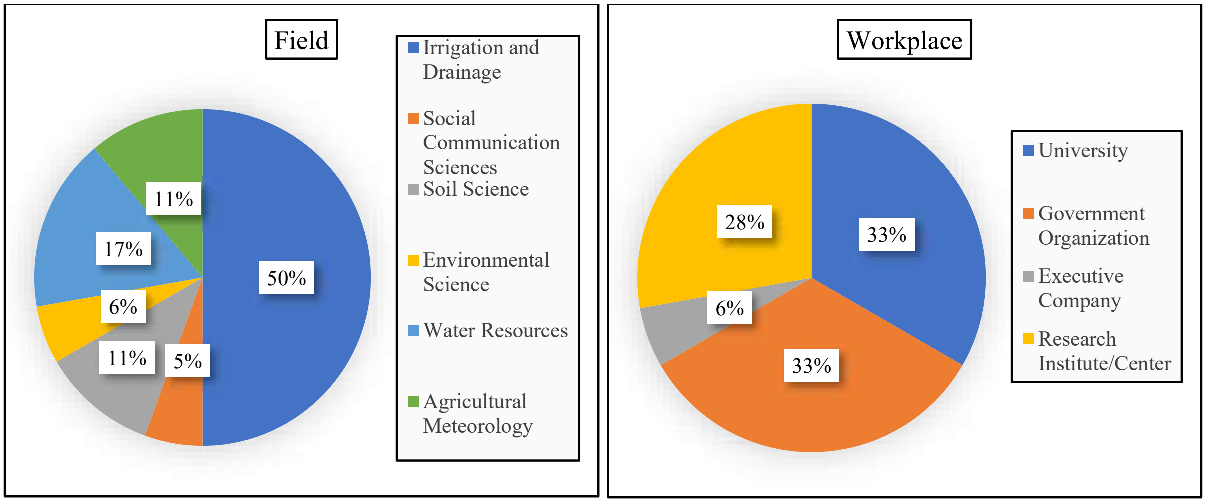

Figure 3. Characteristics of the Statistical Population of the Study

In the next step, a structural analysis matrix was constructed based on the MICMAC technique to analyze influence-dependence relationships among the variables and identify the drivers within the system (Barati et al., 2019). Table 2 displays the structural analysis matrix used to identify drivers via the MICMAC approach. The values of the structural analysis matrix represent the intensity of influence exerted by a row element on a column element. The values 0 and 3 indicate no influence and strong influence, respectively. The symbol "P" is used to represent potential for future influence (Godet, 2007).

Table 2. Partial View of the Structural Analysis Matrix

	CL-2-02	CL-2-04	CL-2-05	CL-3-04	PO-1-03	PO-1-10	PO-1-11	PO-1-12	PO-2-08	PO-2-09	PO-2-10	PO-2-13	PO-2-17	PO-2-18	PO-2-19	PO-2-23	PO-3-02	PO-3-03	PO-5-02	PO-5-03	PO-5-04	PO-6-05
CL-2-02	0	2	3	1	1	1	1	P	P	P	P	2	1	1	P	P	P	P	1	1	2	0
CL-2-04	1	0	3	1	1	1	1	P	P	P	P	2	1	1	P	P	P	P	1	1	2	0
CL-2-05	2	2	0	0	1	1	1	P	P	P	P	1	1	1	P	P	P	P	1	1	2	0
CL-3-04	2	2	1	0	1	1	0	P	P	P	P	0	1	1	P	P	P	P	2	0	1	0
PO-1-03	2	3	2	0	0	P	P	P	P	2	2	2	2	1	P	1	1	P	0	2	1	P
PO-1-10	2	1	1	1	1	0	2	P	2	2	1	1	2	1	P	P	1	1	1	0	1	P
PO-1-11	2	1	1	1	1	1	0	P	P	P	P	0	1	P	P	P	1	1	2	0	1	P
PO-1-12	3	1	1	2	1	1	1	0	2	1	1	2	2	2	1	1	2	2	2	2	2	1
PO-2-08	2	1	1	1	1	1	0	1	0	2	2	1	1	1	1	1	1	2	1	1	1	1
PO-2-09	2	2	2	1	2	2	1	1	2	0	3	3	3	2	1	P	2	3	1	2	2	2
PO-2-10	2	2	2	2	2	1	2	2	1	2	0	2	2	1	1	1	P	1	1	1	1	1

After designing the Structural Analysis Matrix, 13 out of the 32 identified influencing factors were identified as drivers of the agricultural water productivity system. These drivers were further used in the Cross-Impact Matrix, which formed the basis for scenario development (Kosow et al., 2024). Three possible states of each of the 13 drivers were defined as shown in Table 3 below.

Table 3. Defined States for Driving Variables

Driver	Code	State	Operational Definition
Occurrence of extreme heat waves	A1	Severe increase	SSP5–8.5: Represents an extreme scenario, with high emissions and a sharp increase in heat waves
	A2	Moderate increase	SSP2–4.5: Represents a middle scenario, with moderate emission trends and a moderate increase in heat waves
	A3	Mild increase	SSP1–2.6: Represents a sustainable scenario, with reduced emissions and a mild increase in heat waves
Government support for the modernization of traditional equipment	B1	Limited coverage	Subsidies will be provided to less than 30% of agricultural lands by 2040
	B2	Moderate support	Subsidies will be provided to 30–60% of agricultural lands by 2040
	B3	Extensive support + technical services	Subsidies provided to more than 60% of agricultural lands + technical services to at least 50% of farmers by 2040
Empowerment of local communities in water management	C1	Minimal government action	Establishment of fewer than 10 local water management institutions by 2040
	C2	Limited government action	Establishment of 10–20 local water management institutions by 2040
	C3	Effective government action	Establishment of more than 20 local institutions with budget and legal authority by 2040
Training and equipping cooperatives for sustainable irrigation	D1	Minimal coverage	Training will be provided to less than 20% of agricultural cooperatives by 2040
	D2	Limited coverage	Training provided to 20–50% of agricultural cooperatives by 2040
	D3	Extensive coverage	Training provided to 50–80% of agricultural cooperatives by 2040
Tax incentives for water-saving agricultural methods	E1	No or limited action	Tax reduction applied to less than 10% of farmers by 2040
	E2	Moderate action	Tax reduction applied to 15–25% of farmers by 2040
	E3	Extensive action	Tax reduction applied to more than 25% of farmers by 2040
Water quota allocation based on climate	F1	No quota	No water quota applied in any region by 2040
	F2	Uncontrolled quota	Quotas applied without monitoring in more than 30% of regions by 2040
	F3	Mandatory quota with monitoring	Quotas applied in 80% of agricultural regions + seasonal monitoring by 2040
Installation of smart water meters in wells	G1	Low coverage	Smart meters will be installed in less than 20% of wells by 2040
	G2	Medium coverage	Smart meters installed in 20–60% of wells by 2040
	G3	High coverage	Smart meters installed in 60–90% of wells by 2040
Establishment of the national agricultural water productivity database	H1	No database	No national database will be established by 2040
	H2	Initial version	Initial database with limited access established by 2040
	H3	Researcher access	National database with online access and up-to-date data available by 2040
Provision of national and regional water productivity indicators	I1	No reporting	No water productivity reports will be published by 2040
	I2	Annual national reporting	Annual national water productivity reports will be published by 2040
	I3	Online dashboard	Online dashboard with crop- and region-based indicators established by 2040
Deployment of online water monitoring systems	J1	Limited monitoring	Sample-based monitoring in less than 20% of water resources by 2040
	J2	Regional smart system	Coverage of 30–60% of water resources with smart systems by 2040

Driver	Code	State	Operational Definition
	J3	National integrated system	Coverage of 60-90% of water resources with a national integrated system + remote sensing by 2040
Public release of water resource data	K1	Limited access	Data remain non-public or restricted by 2040
	K2	Public access without raw data	Public access to aggregated data without raw datasets by 2040
	K3	Full access	Full release of water resource data and documentation with open access by 2040
Delegation of water resource management to local institutions	L1	Centralized management	Full management by the central government by 2040
	L2	Pilot delegation	Delegation of management to local institutions in less than 30% of regions by 2040
	L3	Local management	Delegation of management to local institutions in more than 70% of regions by 2040
Farmer participation in irrigation monitoring	M1	No participation	No farmer participation in irrigation monitoring by 2040
	M2	Limited participation	Voluntary participation in less than 30% of sample farms by 2040
	M3	Extensive co-monitoring	Participation of more than 60% of farmers with field tools and incentives by 2040

Then, the cross-impact supermatrix was filled in by a panel of experts, as illustrated in Figure 4. In the Cross-Impact Matrix, values ranging from −3 to +3 represent the intensity and direction of influence exerted by a row element on a column element; with −3 indicating a strongly diminishing effect and +3 indicating a strongly enhancing effect (Nawir et al., 2023).

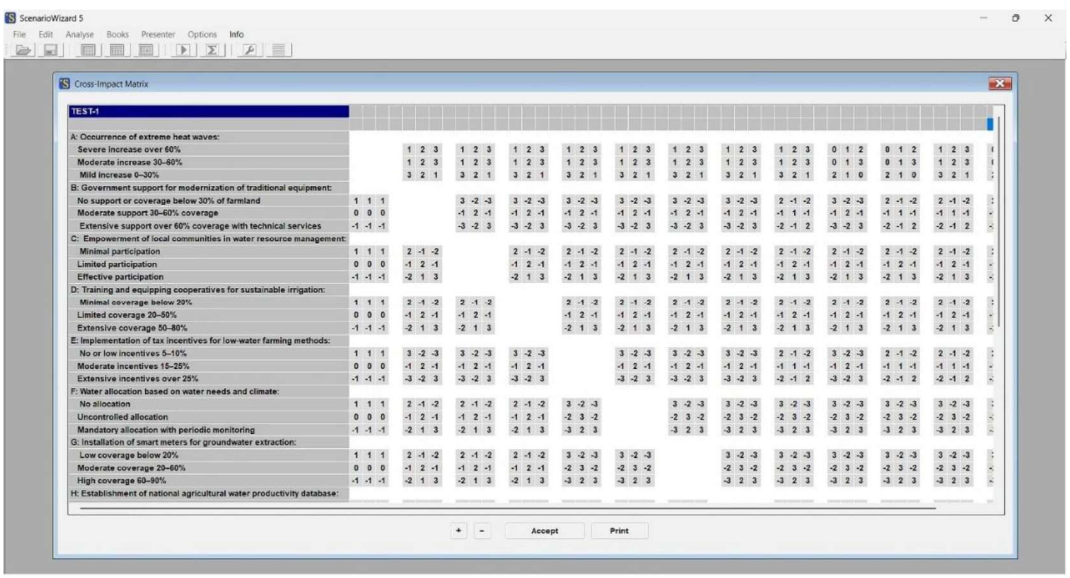

Figure 4.| Cross-Impact Matrix in Scenario Wizard Software

2.7. Total Impact Score

In ScenarioWizard, the Total Impact Score (TIS) is a quantitative measure used to assess the impact of each scenario on the system, based on the relationships between variables and the intensity of their interactions. Scenarios with higher total impact scores have greater impact on the system and are prioritized in policy, goal-setting, and decision-making analyses (Weimer-Jehle, 2023). The Total Impact Score in the Cross-Impact Analysis framework and ScenarioWizard is an indicator for measuring the structural importance of each scenario in the system. This indicator shows the extent to which a scenario is involved in the causal network of the system and the degree to which it simultaneously affects and is affected by other variables. The TIS calculation is based on the sum of the active effects of each variable. The active effect is equal to the sum of the row values of the variable in the interaction matrix (representing the extent to which it influences other variables), and the passive effect is equal to the sum of the column values of the same variable (representing the extent to which it is influenced by other variables) (Weimer-Jehle, 2009).

3. Results and Discussion

3.1. Analysis of Future Climate Pathways (SSPs) Toward 2040

To generate future climate scenarios, the performance of the LARS-WG 8 model was evaluated according to Table 4. The results showed that the model exhibited a very good fit at both Ahvaz and Dezful stations. However, its accuracy in generating temperature (Tmin and Tmax) was higher than its accuracy in generating precipitation (Jahangir and Rouzbahani, 2024; Bagheri Khaneghahi et al., 2025).

Table 4. Performance evaluation of the LARS-WG model for Ahvaz and Dezful stations

Station	Ahvaz			Dezful		
Parameter	P	Tmin	Tmax	P	Tmin	Tmax
r	0.96	1	1	0.97	1	1
R^2	0.93	1	1	0.94	1	1
RMSE (mm/ °C)	6.43	0.21	0.25	6.14	0.23	0.26
NRMSE	13	1	1	9	1	1

Figure 5 illustrates temperature trends at Dezful and Ahvaz stations. At both stations, the maximum and minimum temperatures are projected to increase by 0.8 and 1.3°C, respectively, in the worst-case scenario. The results of Dehaghi et al. (2022) also showed that the air temperature will increase by about 5°C by 2070 at the Dezful and Ahvaz stations.

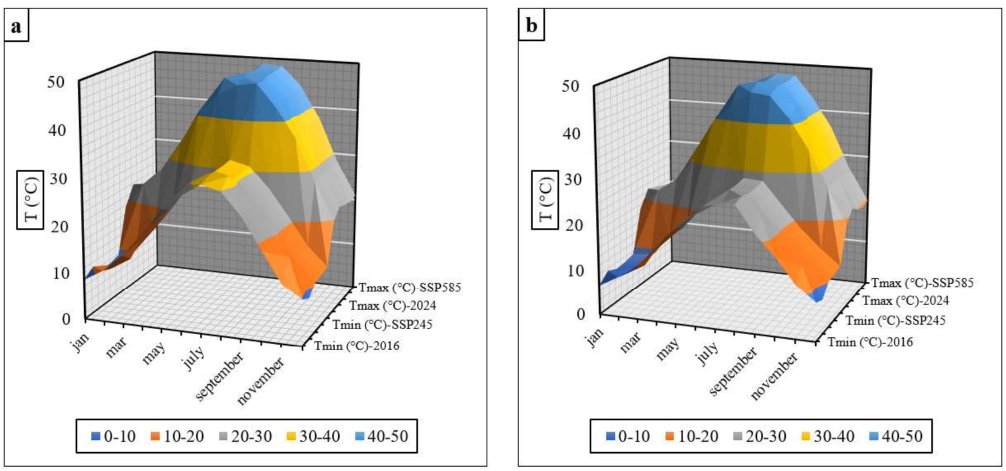

Figure 5. Temperature Variations at the Ahvaz (a) and Dezful (b) Stations

Climate scenarios for 2040 suggest changes in reference evapotranspiration (ET_0) and precipitation at both Ahvaz and Dezful stations, especially during the warm months of the year (Figure 6). For example, in scenario SSP5-8.5, ET_0 values during the summer months in Dezful are projected to increase from an average of 233 mm to more than 280 mm, while in Ahvaz they are projected to decrease from 269 mm to 265 mm. Overall, total precipitation in future scenarios is projected to increase by 30 to 50% at the Dezful station and by 60 to 100% at the Ahvaz station. Reference evapotranspiration changes are also projected to range from 0 to -20% at the Ahvaz station and from +10 to +20% at the Dezful station. According to the findings of Adib et al. (2023), rising temperatures at Dezful station led to a marked increase in ET_0, especially during the hot months, while temperature remains a primary driver of ET_0 growth in this area. Southern stations in Khuzestan Province, including Ahvaz, appear more vulnerable to drought and reduced rainfall during warm and autumn months, with the notable increase in precipitation occurring during winter (Nejadrekabi et al., 2022).

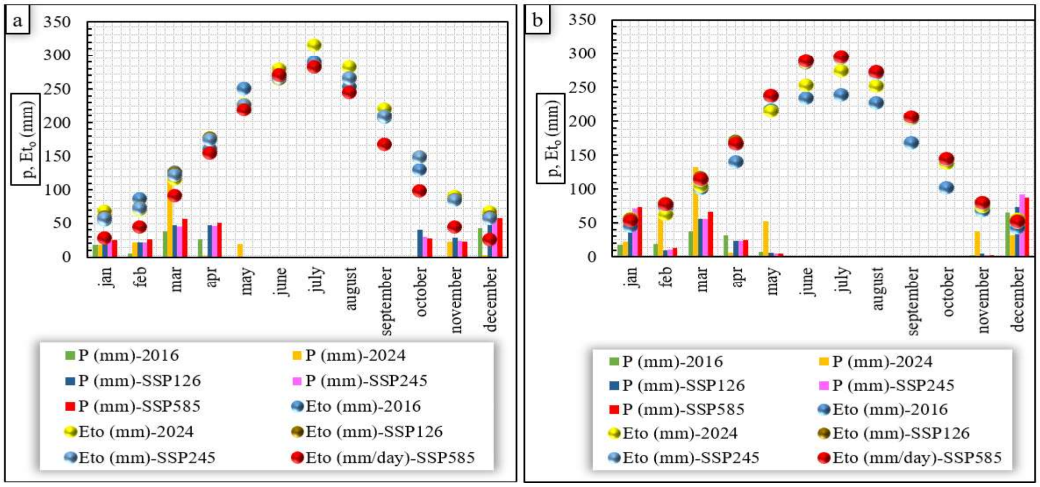

Figure 6. Precipitation and Evapotranspiration Variations at Ahvaz (a) and Dezful (b) Stations

3.2. Grain Maize Water Productivity under SSP Scenarios (2040)

The table below presents the performance of the AquaCrop model in the calibration and validation stages. The results indicate that the model has a very high accuracy and goodness of fit, with an R^2 value of 0.96 and high NSE values (0.99 and 0.98). In addition, the low RMSE and NRMSE values reflect low prediction error of the model. The CRM index also shows that the model exhibits very slight underestimation or overestimation. Evaluation and validation of the AquaCrop model under full irrigation conditions have shown that the model performs with high accuracy in simulating crop yield and growth parameters (Dehghani et al., 2025b). In canola cultivation under full irrigation in Tabriz, the model achieved an R^2 of up to 0.93 and an NRMSE of about 5.9% (Khorsand et al., 2024). Similarly, a study on wheat and barley in the Dehloran plain reported R^2 values of up to 0.97 for grain yield, with NRMSE values below 5% (Khoshsirat et al., 2022).

Table 5. Performance evaluation of the AquaCrop model

Stage	calibration	validation
R^2	0.96	0.96
RMSE (ton/ha)	0.35	0.45
NRMSE (%)	7	8
CRM	0.04	-0.05
NSE	0.99	0.98

At the Ahvaz station, summer and spring maize yields under SSP5-8.5 show the highest increase, with an increase of 18.2% and 23.9%, respectively, compared to 2024 (Figure 7). These results align with previous studies by Hajivand Paydar et al. (2023), who examined the impacts of future climate variations on grain maize yields in Khuzestan Province under two CMIP3 emission scenarios (A2 and B1), assuming unchanged planting dates and full irrigation. Ahmadi et al. (2024) conducted a wheat yield study in the Qazvin Plain and found that wheat yield is projected to increase under future climate conditions.

While the estimate by Moradi et al. (2013) showed that climate change in Mashhad could reduce maize yield by 11-38% compared to current conditions, these contrasting yield responses between Khuzestan and Mashhad can be ascribed to baseline climate differences. According to Rezaei and Lashkari (2019), across Mashhad and other cooler regions, rising temperatures will shorten the growing season and increase the risk of heat stress during sensitive stages of growth, leading to yield reductions in the range of 8-18%. Khordadi et al. (2019) found similar results. Kipkulei et al. (2025) concluded in their study that the impact of climate change across eastern Africa is spatially heterogeneous. In semi-arid areas, a temperature rise of up to 3°C combined with a reduction in rainfall of up to 30% can result in yield losses of up to 30%. However, where increased rainfall may offset the damage caused by increased heat, yield gains of up to 18% are possible.

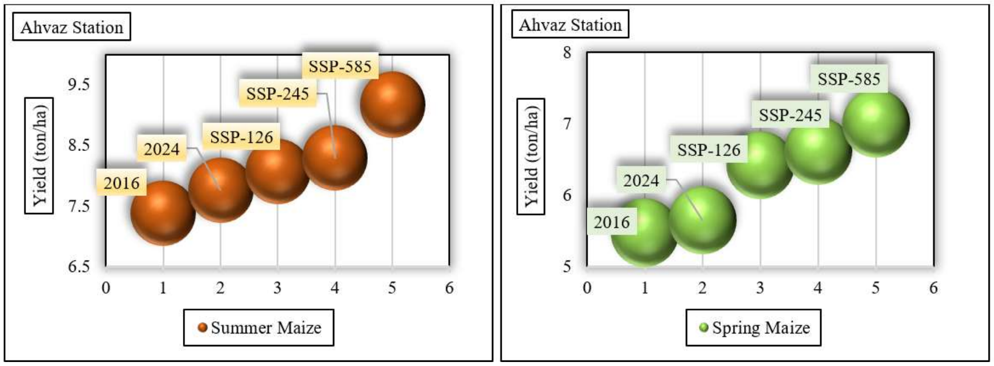

Figure 7. Grain Maize Yields under SSP Climate Scenarios by 2040 at Ahvaz Station

At the Dezful station, summer and spring maize yields increased by 17.5% and 12.1%, respectively, under SSP5-8.5 (Figure 8). The results of Qin et al. (2023) showed that with a 1°C increase in maximum temperature, the crop yield decreases by 4.21%, while with a 1% increase in precipitation, the yield increases by 0.43%. In addition, effective management strategies and elevated CO_2 would significantly offset the negative effects of warming. Zhang et al. (2021) projected maize, rice, and wheat yields in China to remain stable or slightly increase during the 2030s and 2050s. Regarding the impacts of climate change, Nazari et al. (2021) investigated rainfed wheat yield under various climate scenarios and revealed a decline in Khuzestan (between −7.3% to −54.4%) and an increase of up to 16.7% in East Azerbaijan.

Similarly, the research conducted by Moazazi et al. (2021) on the Hamedan Plain showed that due to climate change, the regions experienced increased temperatures, reduced rainfall, and declining water availability. In general, these conditions have resulted in reduced yields of strategic crops. However, some vegetables and horticultural crops have shown improved productivity across all climate scenarios.

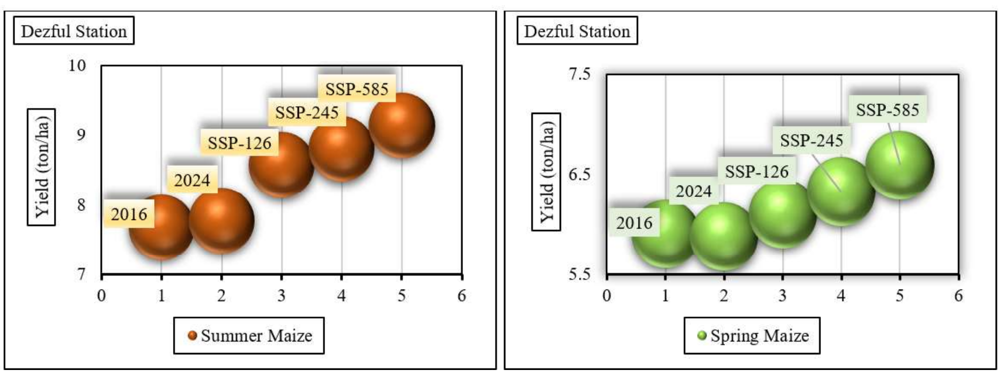

Figure 8. Grain Maize Yield under SSP Climate Scenarios by 2040 at Dezful Station

At the Ahvaz station, water productivity in summer and spring maize increased in all three scenarios. It increased from 1.20 kg/m^3 and 1.02 kg/m^3 to 1.42 kg/m^3 and 1.26 kg/m^3 in the warmest scenario, respectively. At the Dezful station, summer and spring maize water productivity increased from 1.21 kg/m^3 and 1.06 kg/m^3 in the base year to 1.42 kg/m^3 and 1.19 kg/m^3 in the SSP5-8.5 scenario, respectively (Figure 9). These findings suggest that elevated CO_2 concentrations, together with warming, can enhance yield per unit of water used due to positive effects on photosynthesis. Provided that warming remains within tolerance thresholds, full irrigation accelerates plant growth and shortens the growth cycle (Mirgol et al., 2020).

Despite the pessimistic nature of the SSP5-8.5 scenario, yield increases could result from a combination of the "carbon dioxide fertilizer" effect and the warm, relatively suitable baseline climatic conditions for growth in Khuzestan. At higher temperatures, increased CO_2

concentrations improve water use efficiency by reducing stomatal conductance and evapotranspiration (Wang et al., 2024). Although corn is a C4 plant and its direct photosynthetic sensitivity to CO_2 is lower than that of C3 plants, reducing water loss and maintaining leaf water status under high CO_2, especially in combination with appropriate irrigation, can make photosynthesis more sustainable and increase biomass formation (Kimball, 2016).

In the hot climate of Khuzestan, if crop growth coincides with temperatures close to the optimal range for corn during the early season, increased heat can accelerate the accumulation of heat units and enhance vegetative growth. When adequate irrigation and nutrient management are provided, the negative effects of heat are moderated, ultimately benefiting yield (Correia et al., 2021). Also, heat can be compensated for by changes in other climatic variables, such as increasing effective precipitation or reducing vapor pressure deficit in some months, which alleviate water stress and enhance grain filling.

In addition, management and phenological adaptation (selecting planting dates that avoid heat peaks during sensitive stages such as pollination and using heat-tolerant hybrids) can also enhance yield increases (Wang et al., 2023). In a way that maintains the effective grain filling period and prevents yield loss. In such a context, heat does not necessarily mean deterioration; When elevated CO_2 increases water-use efficiency, water and nutrient management is properly implemented, and phenology is aligned with favorable temperature windows, the combined effect of these factors can—even under a warmer scenario—lead to increased yield.

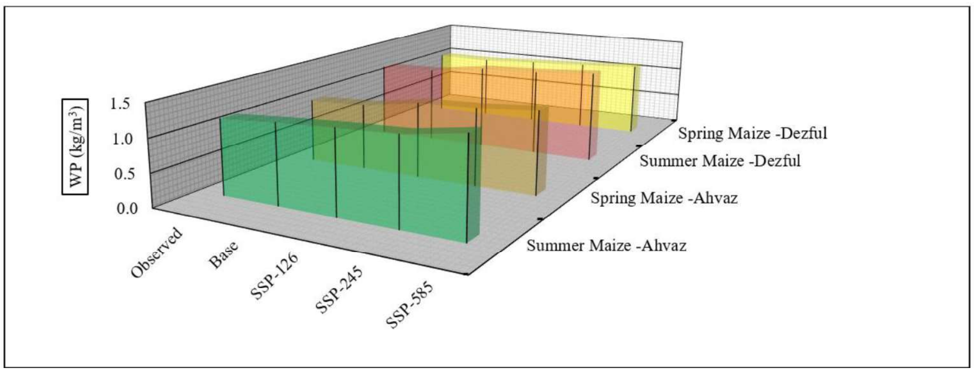

Figure 9. Water Productivity of Grain Maize under SSP Climate Scenarios by 2040

3.3. Scenario Design via Structural Analysis

Figure 10 presents nine internally consistent scenarios generated via ScenarioWizard. The high compatibility among scenario components ensures the absence of internal contradictions. The horizontal axis shows the driving forces (drivers), and the vertical axis shows the three discrete states assigned to each variable in the scenario framework.

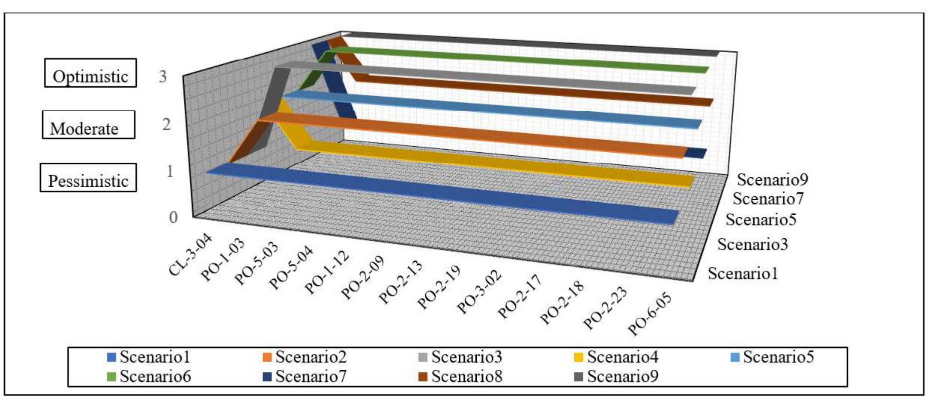

Figure 10. Generated Consistent Scenarios

Figure 11 illustrates that scenario 3, 6, and 9 have a relatively higher total impact score than the other scenarios. This means that they represent the most impactful possible futures for the water productivity system. Therefore, these scenarios have high importance in strategic foresight research.

The higher Total Impact Score (TIS) for Scenario 6 is due to the greater influence and effectiveness of its components within the causal network of the system. In other words, the variables and states selected in this scenario exhibit the highest intensity of mutual interactions with other variables. This means that Scenario 6 has the greatest structural weight in the model and plays a more central role in shaping the system's dynamics. Therefore, a higher TIS reflects that the variable states occupy a more central position in the system, giving them greater priority in policy and decision-making analyses.

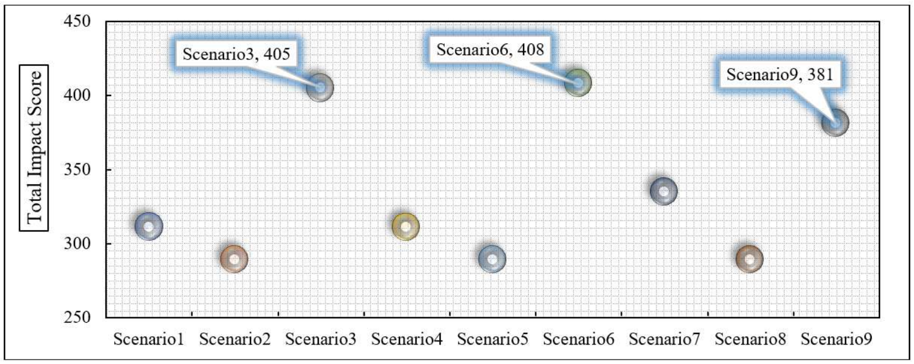

Figure 11. Comparison of Total Impact Scores Across Consistent Scenarios

3.4. Integration of Modeling Results and Scenario Frameworks

Three structural scenarios (3, 6, and 9) with the highest total impact scores were identified for the 2040 horizon. The climate change elements considered in these scenarios include SSP1-2.6, SSP2-4.5, and SSP5-8.5, and the biophysical response of maize yield under each of them was estimated with the AquaCrop model (Table 6).

Table 6. Integrated Results of ScenarioWizard and AquaCrop under SSPs for Spring and Summer Maize (Two-station average)

Scenario	Corresponding SSP	Spring Yield (t/ha)	Spring WP (kg/m³)	Summer Yield (t/ha)	Summer WP (kg/m³)
Scenario 3	SSP1 – 2.6	6.26	1.13	8.32	1.29
Scenario 6	SSP2 – 4.5	6.47	1.16	8.54	1.32
Scenario 9	SSP5 – 8.5	6.79	1.22	9.15	1.42

As shown in Table 7, the desired future is one with decentralized and participatory governance of water resources, in which the role of government shifts from direct management to setting smart regulations, creating monitoring infrastructure, and facilitating access to data and technology. In this future, the government plays only a facilitating role in providing new technologies and in data collection and dissemination. Only under such conditions can water consumption in the agricultural sector be sustained in the long term. In each of these scenarios, it is assumed that policy and technological indicators, including smart monitoring systems, access to public data, and decentralized water management, are at their optimal level. Therefore, changes in maize biophysical performance across the scenarios are attributed to the severity of climate change. Scenario 9 (SSP5-8.5), which represents the warmest climate, has the highest average water productivity (WP= 1.32 kg/m³), while Scenario 6 (SSP2-4.5), with a water productivity of 1.24 kg/m³, records the highest total impact score (TIS= 408). This contrast highlights the different impacts of climate change. Examining the three scenarios with high total impact indicates that under climate change, water productivity has increased in all three scenarios. Therefore, shaping a desirable future is achievable by applying technologies at the highest level and delegating water resource management to local communities.

Although the warmer scenario (SSP5–8.5) shows better results in terms of biophysical performance and water productivity under favorable management conditions, the choice of the favorable future path based on scenario 6 (SSP2–4.5) was made due to the higher score of the "Total Impact Factor" (TIS). This indicates that the future suitability depends not only on biophysical performance, but also on the degree of institutional flexibility, structural coherence, and policy enforceability. Under very harsh and stressful climatic conditions (SSP5–8.5), the full realization of decentralized and participatory management is less likely, and more ecological and social pressures arise. In contrast, scenario 6, despite its moderate productivity, provides a more balanced combination of bioefficiency, institutional sustainability, and enforceability and is therefore selected as the favorable future path. This result shows that shaping a desirable future depends more than anything on the quality of management and governance, and not simply on the severity of climate change.

Table 7. Combined ScenarioWizard–AquaCrop Results across SSPs

Drivers	Indicator	Scenario3	Scenario6	Scenario9
CL-3-04	Climate Change	SSP1 – 2.6	SSP2 – 4.5	SSP5 – 8.5
Average spring–summer productivity	WP (kg/m^3)	1.21	1.24	1.32
PO-1-03	Policy support		Extensive (>60%) + technical	
PO-5-03	Stakeholder participation		Effective	
PO-5-04	Local irrigation support (%)		50–80%	
PO-1-12	Incentives		High (>25%)	
PO-2-09	Allocation		Mandatory + monitoring	
PO-2-13	Smart well metering (%)		60–90%	
PO-2-19	Database		Open and updated	
PO-3-02	Reporting		Online dashboard	
PO-2-17	Monitoring system		National remote-sensing	
PO-2-18	Data access		Open API + docs	
PO-2-23	Governance		Decentralized	
PO-6-05	Co-monitoring		Widespread + incentives	

4. Conclusion

According to the results, the three proposed desirable futures jointly emphasize the use of technologies and the implementation of participatory management policies at high levels, which differ according to the probability of occurrence of each climate scenario. In cases where political and technological indicators are defined at high levels in all scenarios, the driver of outcomes is climate change. Moreover, the targeting of documents with a long-term horizon should not rely solely on the WP indicator, because, as shown, Scenario 6 with the intermediate WP value recorded the highest Total Impact Factor. In this context, Scenario 6 emerges as a desirable future path for agricultural water policy, as it combines good biophysical performance with strong structural cohesion and institutional capacity. This scenario provides a strategic basis for the development of a policy roadmap, with a special emphasis on the development of technological infrastructure and the establishment of targeted monitoring systems at the local and participatory water governance levels. Under Scenario 6 in 2040, Khuzestan province faces a warmer climate, but water resources management is fully decentralized. Farmers, through local unions, guide water allocation using smart systems and real-time data, and open access to satellite and ground data through online dashboards maximizes agricultural productivity.

The findings of this study can serve as a foundation for designing policies and implementation plans in agricultural water management. The results indicate that strengthening technological infrastructure, developing smart monitoring systems, and promoting participatory management mechanisms at the local level are among the key measures that can enhance the resilience of the agricultural sector to climate uncertainties. Accordingly, policymakers can enable improvements in water productivity and reduce climate-related risks by prioritizing investments in modern irrigation technologies, remote sensing tools, and early warning systems. Moreover, strengthening local institutions and ensuring the active participation of water users in decision-making play a critical role in the long-term sustainability of water policies.

This study has several limitations that should be considered when interpreting the results. First, the future climate scenarios were generated based on a single general circulation model (GCM). Relying on one does not capture the full range of intermodel uncertainties typically associated with climate projections and may therefore overlook part of the actual variability of future climate conditions. Furthermore, the AquaCrop simulations were conducted under optimal management and irrigation assumptions. Although these assumptions allow for the examination of crop biophysical responses to climate change, they do not necessarily reflect real-world conditions in the field. The foresight part of this study also focused primarily on climate, technology, and domestic policy factors. While water resource management in agriculture is influenced by a broader set of factors, including economic conditions, institutional capacity, operator behavior, market dynamics, international trade, and even unpredictable political and environmental shocks.

Several key directions for future research can be suggested: using an ensemble of general circulation models (GCM Ensemble) to better cover uncertainties, comparing and evaluating statistical and dynamical downscaling methods at regional scales, and combining climate scenarios with socio-economic dimensions to make analyses more realistic. Also, simulating real-world farm conditions (water scarcity, nutrient fluctuations, suboptimal management) and examining the role of local institutions and farmer participation in water resource monitoring and management can help improve the accuracy and efficiency of future policies.

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In the preparation of this manuscript, artificial intelligence tools (Copilot) were used solely for language refinement and translation improvement. The intellectual content, analysis, and interpretation remain entirely the responsibility of the authors.

Author Contributions

Tahmine Dehghani: Data Collection, Data Analysis, Investigation, Methodology, Resources, Software, Writing – original draft, Writing – review and editing.

Bijan Nazari: Conceptualization, Validation, Supervision, Writing – review and editing

Abdolmajid Liaghat: Investigation, Methodology, Writing – original draft, Writing – review and editing.

Conflicts of interest

The authors of this article declared no conflict of interest regarding the authorship or publication of this article.

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Data are available from the corresponding author upon reasonable request.

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