Geopersia 2026, 16(1): 69-88
DOI: 10.22059/geope.2025.393939.648817

RESEARCH PAPER

Evaluation and Management of Climate Change Impacts on Water Resources in Khorramabad River Basin, Iran, Using an Integrated Modeling Approach

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Received: 22 April 2025, Revised: 31 May 2025, Accepted: 28 July 2025

Abstract

Climate change is one of the most significant challenges for some arid and semi-arid regions, potentially limiting access to water resources in the future. Integrated water resource management in these areas could be a viable approach to adapt the impacts of climate change. This study examines the effects of climate change on the surface and groundwater resources of the Khorramabad River Basin using the MODFLOW and WEAP models. Initially, the current conditions of surface and groundwater resources were simulated monthly using the WEAP and MODFLOW models for the statistical period from October 2010 to September 2023. The two models were then linked, yielding values of NSE=0.87, RMSE=0.65, and R^2=0.97, indicating the acceptable performance of the WEAP-MODFLOW model in simulating surface and groundwater. Subsequently, the status of surface and groundwater resources was projected for the future (2025–2060) under SSP1-2.6, SSP2-4.5, and SSP5-8.5 scenarios. The results from these scenarios show a decline in annual average precipitation and an increase in minimum and maximum annual temperatures. According to the results of the integrated WEAP-MODFLOW model, the annual average river discharge, groundwater levels, and aquifer storage will decline under SSPs scenarios compared to the baseline period. Therefore, Climate change will hinder the availability of drinking and industrial water. Constructing the Makhmalkouh Dam could nearly fulfill the water demands for both drinking and industrial sectors across all three SSPs scenarios. This dam's construction would also mitigate groundwater level drawdown and increase aquifer storage relative to a scenario without the dam.

Keywords: Climate Change, Integrated Modeling, WEAP-MODFLOW Model, Makhmalkouh Dam, Khorramabad River Basin.

Introduction

Global population is projected to reach 9.7 billion by 2050, increasing water demand for agriculture, industry, and household uses, resulting in excessive water exploitation, quantity and quality reductions, and climate change (Singh & Panda, 2012; An-Vo et al., 2015; Sabale et al., 2022). Climate change severely affects accessible water resources, particularly in arid and semi-arid regions, leading to significant reductions in available surface water (Marchane et al., 2017; Caloiero et al., 2018; Ashofteh et al., 2024). This reduction increases groundwater use, further depleting aquifer storage (Hssaisoune et al., 2020; Hardi et al., 2022). Iran, located in an arid and semi-arid region with a growing population, expanding urban areas, and developing industrial and agricultural sectors, faces water scarcity and limited water resources (Hashemi et al., 2018; Ostad-Ali-Askari, 2022; Sheikha-BagemGhaleh et al., 2023). In such regions, surface and groundwater resources are two primary systems meeting water demands,

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and conjunctive use of these resources is a potential strategy to address declining water supplies (Schoups et al., 2006; Dehghanipour et al., 2019; Milan et al., 2023).

Today, water resource management emphasizes the conjunctive use of surface and groundwater resources, an effective tool to address water shortages in drought conditions and achieve sustainable development goals (Sabale et al., 2022). Although existing water resource management systems can handle annual variations, they face challenges in addressing long-term trends. Evaluating the long-term impacts of climate change on water resources is essential for effective future management strategies (Serrat-Capdevila et al., 2007; Zhang, 2015). Neglecting the impacts of climate change may introduce bias in management strategies for conjunctive water use under future climate conditions. Therefore, optimizing water resource management, balancing water demand and availability, and ensuring sustainable extraction and efficient water use are crucial (Ragab & Prudhomme, 2002; Bahir et al., 2021; Hadri et al., 2022). Evaluating the impacts of future conditions (climate, land use, water demand, adaptation, etc.) on water systems requires a coupling of hydrological and hydrogeological processes (Pulido-Velazquez et al., 2015). Hydrological and hydrogeological integrated modeling can provide more realistic outcomes.

Integrated water resource modeling was identified as a link between various scientific disciplines and complex environmental issues, such as climate change, in the mid-1980s (Akhtar et al., 2013; Panahi et al., 2021). Early research on coupling climate, hydrological, and hydrogeological aspects includes studies such as Allen and Scibeck (2004), Goderniaux (2011), and Droubi et al (2008 a, b). Recently, extensive research has investigated the impacts of climate change on surface and groundwater resources using integrated models for holistic water resource management. For example, Hadded et al (2018) assessed the climate change impacts on the Zeuss-Koutine aquifer in southeastern Tunisia using a decision support system (DSS) by establishing a dynamic link between WEAP (Water Evaluation and Planning) and MODFLOW software. Their predictive scenarios indicated that the Zeuss-Koutine aquifer is highly sensitive to climate change, potentially causing further groundwater level reductions compared to reference scenarios by 2030. Guevara-Ochoa et al (2020) implemented a coupled hydrological-hydrogeological model (SWAT-MODFLOW) under climate change scenarios to quantify the spatial-temporal dynamics of water balance and GW-SW interaction in the upper creek basin of Del Azul in Buenos Aires. Results showed that annual aquifer discharge to the river could increase by 5% under RCP 4.5 and 24% under RCP 8.5. River recharge to the aquifer also showed a 12% increase under RCP 4.5 and a 5% decrease under RCP 8.5. Olivos and Méllo Jr (2023) studied the conjunctive use of surface and groundwater in urban-rural watersheds of the municipality of São Carlos and assessed the impact of climate change scenarios on the system. They used a combination of the WEAP model and the RCP85 and RCP45 scenarios in their study. The simulated climate scenarios showed that the pressure on groundwater in the region could be challenging due to the gradual depletion of resources affecting the sustainability of the system, with the flow of major rivers with a 95% percentile showing a 20% decrease in some cases. The results of the study showed that this modeling approach can be used in other river basins to manage supply and demand scenarios. Sheikha-BagemGhaleh et al (2023) examined the impacts of climate change on the surface and groundwater resources in Mahabad using WEAP and MODFLOW models. Their findings revealed that, without effective changes, this region's water resources would face significant challenges due to climate change in the near future. Mundetia et al (2024) assessed groundwater sustainability under climate change scenarios using a coupling of SWAT and MODFLOW models. Their study results showed that the average recharge in RCP 4.5 would decrease from 119.4 mm in the 2011-2020 decade to 57.30 mm in the 2040-50 decade and 108 mm in RCP 8.5, which would significantly reduce groundwater resources. Rahimi Jamnani et al (2024) explored future water supply and demand impacts on surface and groundwater resources under climate change in the Qorveh-Dehgolan sub-basin using a combined WEAP-MODFLOW-ML model. Results indicated that the groundwater level in future periods is expected to decrease by approximately 1.2 meters annually compared to the baseline period. This decline would reduce reservoir inflow by about 25%, leading to a 65 million cubic meter water reduction by 2045.

The effects of climate change on surface and groundwater resources of the Khorramabad basin have been studied in the research of Ashofteh et al (2024) and Moghaddam et al (2023). However, given the vagueness in their studies (according to the authors of this study), we again studied the effects of climate change on surface and groundwater resources of the central plain of Khorramabad in order to obtain more accurate results. Among the shortcomings of the aforementioned studies are the following:

In the mentioned studies, the base line period of the simulation is 1971-2000 and the forecast period is 2040-2099. There is a long-term gap (2001-2040) between these two periods. The time gap in the studies (especially for recent decades) due to the variability of time-dependent parameters in hydrological and hydrogeological processes will lead to incorrect estimation of these parameters and, as a result, undesirable effects on the results. Therefore, according to the above, we used a continuous time period (2010-2060) in all modeling stages for the base period and the future.

The modeling period for MODFLOW is 1971-2000, while according to the available data from observation wells, obtained from the Lorestan Regional Water Company, this data is available from 1995 onwards. Since the MODFLOW simulation is based on real observation data, we ran the MODFLOW model based on observational data for the time period October 2010 to September 2020. The reason for choosing this time period was the availability of complete information from 8 observation wells in this period.

In the aforementioned studies, the outputs of the WEAP model were used as inputs to the MODFLOW model. As we know, in the WEAP model, the groundwater node represents the aquifer and spatial changes in groundwater levels are not shown. In our study, we used the link between the WEAP and MODFLOW models and invoked the MODFLOW model in the WEAP software environment. This allows interactions and changes in surface and groundwater levels to be calculated on a cell-by-cell basis, providing more accurate and realistic results.

As we know, the MODFLOW model must use continuous time series to examine the effects of climate change. Because input changes in each month affect the next month. In the aforementioned studies, authors used time-slice approach for evaluating change factors while they show the results as time series.We used the transient change factor approach to generate continuous time series available in the literature.

Considering the decline in surface water resources in the Khorramabad River Basin, groundwater uses across sectors, and decreasing groundwater levels in plains due to excessive aquifer extraction, it is crucial to evaluate climate change impacts on the basin’s water resources. This study comprehensively analyzes the impacts of climate change on surface and groundwater resources of the Khorramabad Central Plain aquifer using the WEAP-MODFLOW linked model. It is also the first time that the consequences of the construction of Makhmalkouh Dam, on drinking water supply, industry, and water resources, have been assessed under climate change scenarios and shared socio-economic pathways (SSPs).

Materials and Methods

Data collection is one of the primary and essential steps in conducting any research. The required data for this study were obtained from the Lorestan Province Agricultural Jihad Organization, Lorestan Regional Water Company, Lorestan Natural Resources and basin Management Organization, Lorestan Meteorological Office, and the National Meteorological Organization of Iran.

Study Area

The study area encompasses the Khorramabad River basin, which is part of the permanent Khorramabad River basin. This basin, a sub-basin of the Karkheh River, includes a main plain (central plain) and several scattered smaller plains, such as Dehpir, Kamalvand, and Khorramabad plains. The central plain is elliptical, stretching approximately 25 kilometers in a northwest-southeast direction, with coordinates ranging from 48°21′E to 49°08′E longitude and from 33°13′N to 33°44′N latitude, located in the southern and southwestern areas of Khorramabad. The average elevation of the area is 1,903 meters, covering a basin area of 2,503 Km^2, with the central aquifer in Khorramabad plain occupying about 104 Km^2 (Fig. 1). The basin's outflow is directed into the Cham-Anjir River. The study area receives an annual average precipitation of 508 mm, with an average temperature of 17.2°C (based on 50 years of data, 1971–2020). The geological formations within the Khorramabad River basin date from the late Mesozoic to the present era and include the Telezang, Amiran, Kashkan, Asmari-Shahbazan, Gachsaran, Aghajari, Bakhtiari, and alluvial formations. The Amiran and Kashkan formations, with low permeability, are exposed in the eastern section, while the Asmari formation and the Bangestan Group cap the large Sefidkuh anticline, which has excellent permeability. Additionally, the Bakhtiari formation is exposed in the northeastern part, and the Kashkan, Gachsaran, and Asmari limestone formations are found in the southeastern area.

Groundwater Flow Modeling

In this study, groundwater flow modeling was conducted using the GMS software and MODFLOW code. MODFLOW is a 3D finite difference groundwater flow model. Groundwater flow within an aquifer is simulated in MODFLOW using a block-based finite difference approach. The partial differential equation (Equation 1) describes the groundwater flow in each network.

$$\frac{\partial}{\partial x}\left(K_{XX}\frac{\partial h}{\partial x}\right)+\frac{\partial}{\partial y}\left(K_{yy}\frac{\partial h}{\partial y}\right)+\frac{\partial}{\partial z}\left(K_{zz}\frac{\partial h}{\partial z}\right)-W=S_s\frac{\partial h}{\partial t} \tag{1}$$

In equation (1), h is the hydraulic head (m) and is an independent variable. K_{XX}, K_{yy}, and K_{zz}represent the hydraulic conductivity (m.day^{-1}) in the x, y, and z directions, respectively, S_S represents the specific storage coefficient, which is a dimensionless quantity, and the letter W represents the supply or discharge and its unit is per day (1/day).

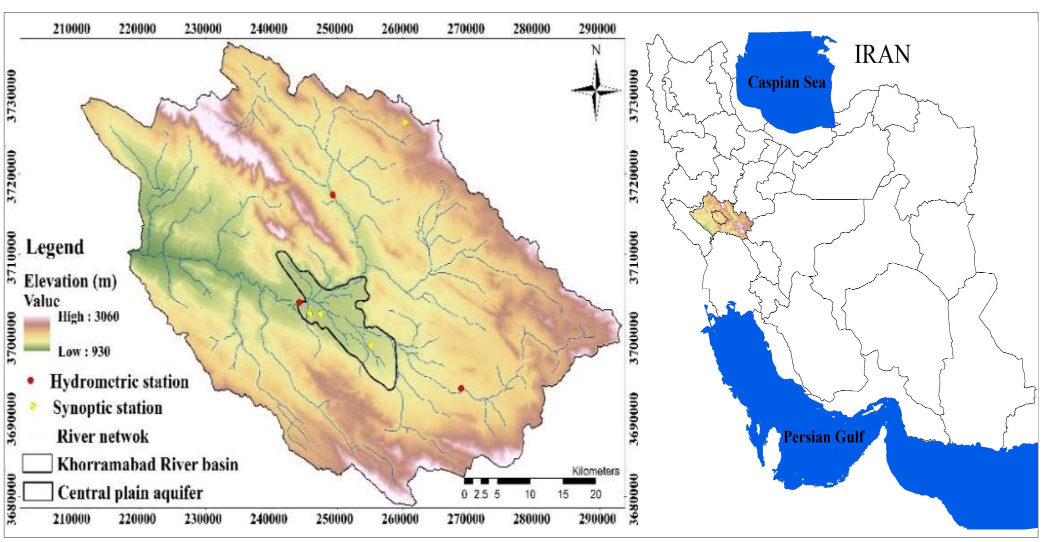


Figure 1. Geographic location of the study area

MODFLOW is used to simulate and predict groundwater conditions and groundwater-surface water interactions. The first step in groundwater modeling studies is to create a conceptual model. The conceptual model involves defining the model boundaries, hydro-stratigraphy units, flow system, and water budget preparation (Mirzaee et al., 2023; Mirzaee et al., 2022). The next step involves converting the conceptual model into a numerical model, wherein various data inputs are coded into a suitable numerical model in MODFLOW based on a grid network. After constructing the conceptual model and selecting the appropriate computer code, model construction begins. This involves spatial grid design, determining time steps, specifying boundary conditions, and assigning aquifer parameters and hydrological stresses. In most cases, model parameters need to be refined after construction and design to enhance the model's results by estimating a close relationship between observed and predicted values, a process known as calibration (Patil et al., 2020). Following calibration, model validation is required. If the validation and predictive capability are proven within acceptable independent test limits, then the model validation is considered successful. The next step involves analyzing the model's sensitivity to parameter variations. Finally, to evaluate the calibrated and validated model's accuracy, three parameters-Mean Error (ME), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE)-are used, reflecting the model's performance in estimating simulated variables compared to observed values.

$$ME = \frac{\sum_{i=1}^{n}(h_0 - h_s)_i}{n} \tag{2}$$

$$MAE = \frac{\sum_{i=1}^{n}|(h_0 - h_s)_i|}{n} \tag{3}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}((h_0 - h_s)_i)^2}{n}} \tag{4}$$

In the above equations: h_s represents the hydraulic head simulated by the software, h_0 is the hydraulic head of the observation wells in the plain, and n denotes the number of piezometers (Mirzaee et al., 2023).

Linking WEAP and MODFLOW Models

WEAP is a computer modeling tool for integrated water resource planning, developed by the Stockholm Environment Institute (Tellus Institute) in the United States. WEAP functions as an integrated decision support system (DSS) designed to assist water planning by balancing water resources across multiple users (SEI, 2019).

The general approach to developing a WEAP model involves several stages. Initially, the spatial boundaries of the study area and the temporal scale of the system modeling process must be defined. Boundaries are typically delineated by basin areas, such as rivers or springs. Based on this definition, the elements of the system (e.g., supply and demand sites, reservoirs) are identified and linked via transfer or diversion pathways. Data are assigned to flow paths, transfer links, and supply-demand sites. After data entry, flow quantification and model calibration are performed. Following calibration, the model requires validation. To evaluate the accuracy of the developed model, metrics such as the Nash-Sutcliffe Efficiency (NSE), RMSE, and coefficient of determination (R^2) can be used. Finally, by defining various scenarios, a comprehensive analysis of water-related issues can be conducted. These scenarios can address climate variability, basin conditions, projected demands, ecosystem needs, regulatory environments, operational goals, and existing infrastructure (Yates et al., 2005; Rajendran et al., 2020).

$$R^2 = \left[\frac{\sum_{i=1}^{n}(O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{1}^{n}(O_i - \bar{O})^2}\sqrt{(M_i - \bar{M})^2}}\right]^2 \tag{5}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}} \tag{6}$$

$$NSE = 1 - \sqrt{\frac{\sum_{i=1}^{n}(O_i - P_i)^2}{n}} \quad (7)$$

In these equations, O_i, P_i, $\bar{O}$, $\bar{P}$, and n represent observed data, predicted data, the mean of observed data, the mean of predicted data, and the number of data points, respectively (Nassery et al., 2021).

To link the MODFLOW model to WEAP, the MODFLOW model must first be prepared and calibrated externally. The connection between WEAP nodes and MODFLOW cells is established through a shapefile linking MODFLOW cells to basin areas, groundwater nodes, and demand sites supplied by wells. This shapefile provides a physical link between wells and the supplied demand sites (Hadded et al., 2013).

Climate Change Simulation

To simulate climate change, historical data from fifteen Global Climate Models (GCMs) based on the IPCC Sixth Assessment Report (CMIP6) were downloaded and compared with observation data. In the initial step, climate variables (temperature and precipitation) were extracted for each of the six selected GCM models from the ESGF site for the historical period. These data were then compared with observational data, using R^2, RMSE, and NSE criteria for model selection (Equations 5, 6, and 7).

Following the comparison and selection of the optimal GCM, three SSPs scenarios: SSP1-2.6, SSP2-4.5, and SSP5-8.5 were used to generate future temperature and precipitation data (2025-2060). Meteorological data from the Khorramabad synoptic station (chosen for its suitable time series) were used for climate change analysis. Finally, using the LARS-WG model, future climate variable projections were simulated.

Downscaling

In this study, the Long Ashton Research Station Weather Generator (LARS-WG) (Semenov & Barrow, 2002) was used to downscale the precipitation and temperature data produced by MRI-ESM2 model. LARS-WG has demonstrated good performance in reproducing various climate statistics, including extreme weather events, under different climatic conditions (Semenov & Stratonovitch, 2010). LARS-WG uses a serial approach to determine wet and dry days throughout a calendar year (Semenov & Barrow, 2002). This model uses fitting of monthly semi-empirical distributions on the lengths of the wet and dry days and daily precipitation amounts to simulate daily precipitation. In the first stage, the minimum and maximum daily temperatures are conditioned on wet and dry days. Then semi-empirical distribution functions are fitted to the residual temperatures. The residual temperatures (R) for each month and series are given by:

$$RX_i = \left(X_i - \bar{X}_j\right)/SD_i \quad (8)$$

where X, $\bar{X}$, SD and i are the observed, mean, standard deviations of the temperature data, and the day respectively.

Minimum and maximum temperatures are generated using the normalization method (Racsko et al., 1991). In the first stage, temperatures are classified into two series of wet and dry days. The mean and standard deviation of each specific month are calculated for each series. The finite Fourier series of order 3 is fitted to the mean and standard deviation of each series. Then the observed residual series RX_i is constructed using Equation 1 (Richardson 1981). The time autocorrelation coefficient of wet and dry conditions is calculated using the corresponding residuals (Semenov & Stratonovitch, 2010). The Synthesized residuals are generated using the fit semiempirical function, time autocorrelation, and cross-correlation coefficients (Naderi & Raeisi, 2020). Daily data are calculated using Equation 8 with the mean and standard deviation of the synthesized residuals

(Richardson, 1981; Semenov & Stratonovich, 2010, Naderi & Raeisi, 2020).

The observed daily precipitation, minimum and maximum temperature data (1971–2016 period) at the Khorramabad synoptic station are input into the weather generator to develop the monthly statistical distribution functions. The LARS-WG is separately verified at each station using the 36-year generated daily precipitation, minimum and maximum temperature data. The monthly statistical distributions and monthly mean values of generated precipitation, minimum and maximum temperature are compared with observed ones using the Kolmogorov-Smirnov test and Student's t test, respectively, at the significance level of 0.01 (Naderi & Raeisi, 2016, Semenov & Barrow, 2002). All tests are accepted in the Khorramabad synoptic stations at this significance level.

The WG uses a perturbation method to downscale GCM outputs for each station, in which precipitation data, minimum and maximum temperatures predicted for the future are calculated using a combination of observed distribution functions and parameters known as change factors (Semenov & Barrow, 2002). The change factors (CF) for precipitation depth, mean wet spell length, mean dry spell length, and mean standard deviation temperature for each calendar month (i) are calculated with the following equation (Semenov & Barrow, 2002; Roosmalen et al., 2009):

$$CF_i = \frac{\left(\sum_{j=1}^{m} x_{i,j}\right)/m}{\left(\sum_{j=1}^{n} x_{i,j}\right)/n} \quad i = 1,2,\ldots,12 \tag{9}$$

in which $X_{i,j}$ denotes the corresponding variable for calendar month i and year j for the future and base line periods of m and n years, respectively.

The change factor for minimum and maximum temperatures is the absolute difference between the monthly averages of the future and base periods.

$$CF_i = \left(\sum_{j=1}^{m} X_{i,j}/m\right) - \left(\sum_{j=1}^{n} X_{i,j}/n\right) \quad i = 1,2,\ldots,12 \tag{10}$$

The change factors for each year are calculated using the method proposed by Iizumi et al (2012). In their study, 20-year time windows are chosen to calculate change factors, with each time window being shifted forward one year. Choosing a 20-year time window (long time) to calculate change factors may result in smooth trends, which are likely not to reflect precipitation trends at small scales (Iizumi et al., 2012). Furthermore, selection along the time window may exclude wet or dry periods of short duration, while they are very important in hydrogeological studies. Therefore, Naderi and Raisi (2016) used the 1-year forward shift method to calculate the change factors in a transient manner, in which future time windows were selected as 5-year periods. They showed that when the impact of climate change on water resources needs to be assessed, a 5-year time window is appropriate for studying climate change (Naderi & Saatsaz, 2020). Therefore, in this study, we used a 5-year time window to calculate change factors for each year between 2025 and 2060.

Discussion and Results

Groundwater Flow Modeling

To assess the impacts of climate change on groundwater resources in the central Khorramabad plain aquifer, the MODFLOW code within GMS software was utilized. Initially, a conceptual model of the central Khorramabad plain aquifer was spatially and temporally gridded. Spatially, a three-dimensional grid was created with 122 rows (x-dimension) and 114 columns (y-dimension), with each cell measuring 150 × 150 meters. Temporally, the conceptual model was divided into 120 monthly time steps. Subsequently, the model was populated with data for three parameters: topography, bedrock, and initial hydraulic head. Additional parameters were applied to the conceptual model through appropriate packages.

The central Khorramabad plain aquifer model was calibrated under both steady-state and transient conditions. For the steady-state condition, October 2011 was selected as the reference month. For transient modeling, groundwater flow was simulated over a 120-month period (10 years), from October 2010 to September 2020. After calibrating the model under steady-state conditions, it was then executed under transient conditions. In the transient state, all time-dependent inputs, including water table levels, observation wells, recharge rates, extraction from operational wells, boundary water levels in the General Head Boundary (GHB) package, and river conductance over 120 months, were prepared and incorporated into the transient model.

Model calibration was performed both manually and automatically (PEST). In both methods, adjustments were made to hydraulic conductivity, specific yield (Fig. 2), and inflows and outflows. Calibration errors under steady-state and transient conditions are provided in Table 1. Following calibration, the model's accuracy for predictive purposes was verified by validating it over a 36-month period from October 2020 to September 2023. The results of the model validation confirm the accuracy of the developed central Khorramabad plain aquifer model (Table 1).

Surface-Groundwater Simulation

To conduct surface and groundwater simulations in the WEAP software environment, sources, demands, and other influencing factors were first assessed and then introduced into the model. Within the study area, water demands were categorized into domestic, agricultural, and industrial uses. Water supply sources included rivers and groundwater. After examining water demand centers and supply sources in the study area, the hydraulic relationships among them were established.

Table 1. Model Performance Metrics Used in the Research for MODFLOW and WEAP-MODFLOW Models

Model	Modeling Steps	Model Performance Metrics				
		NSE	R^2	RMSE	MAE	ME
MODFLOW	Calibration of steady state			0.53	0.47	0.015
	Calibration of transient state			0.57	0.48	-0.04
	Verification			0.96	0.81	-0.03
WEAP-MODFLOW	Calibration	0.87	0.97	0.65		
	Verification	0.69	0.96	1.49		

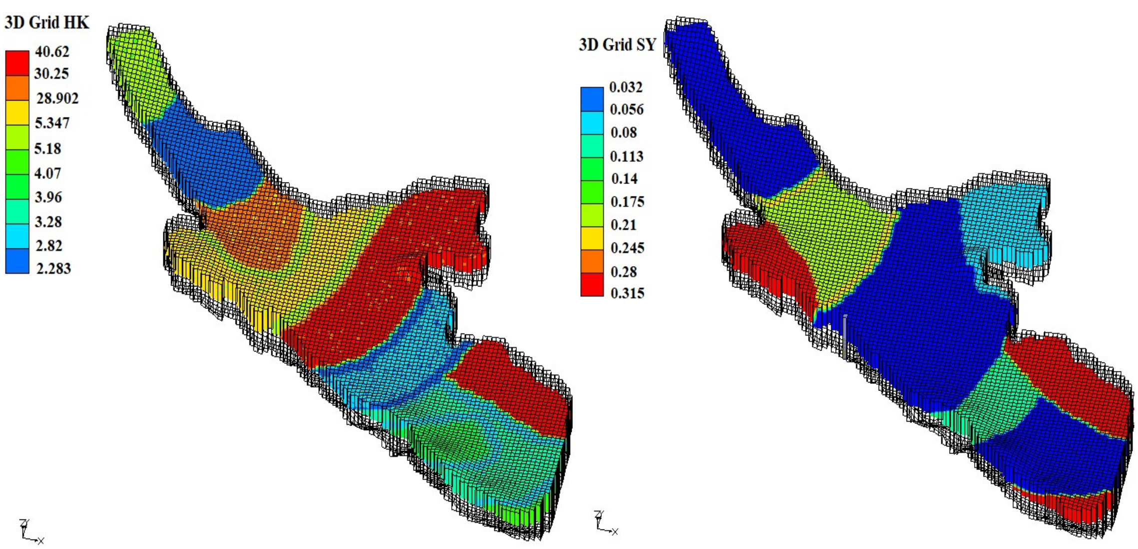


Figure 2. Final Values of Hydraulic Conductivity (HK) and Specific Yield (SY)

For rainfall-runoff simulation, the soil moisture method available in the WEAP model was employed, chosen based on available data for the basin under study. Once data were inputted for each component, the WEAP model was run, followed by calibration and validation. WEAP modeling was conducted on a monthly scale over a 13-year period, with 10 years (October 2010 to September 2020) allocated for calibration and 3 years (October 2020 to September 2023) for validation. Calibration was performed using both manual and automatic (PEST) methods.

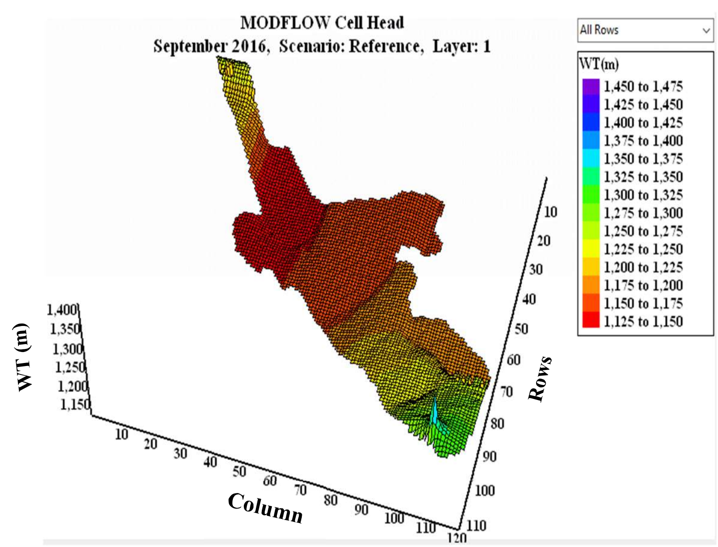
In the WEAP model, groundwater is represented as a reservoir, without incorporating detailed groundwater features such as water table levels in each part of the aquifer. Thus, WEAP alone cannot model aquifer details without integrating a groundwater model. One of WEAP’s advantages is its compatibility with the MODFLOW groundwater model. Linking these models allows for detailed aquifer modeling within WEAP’s surface water framework. The purpose of linking these models is to observe the effects of surface and groundwater allocations on their interactions. A Shapefile acts as the linkage between the two models. This Shapefile, created in GIS, overlays the groundwater model grid onto the study area and connects each defined layer in WEAP to the corresponding cell that represents that layer. The Shapefile defines cells for land use, wells, existing demand points, aquifer zones, river cells, and more.

Once WEAP and MODFLOW were linked, the combined model (Fig. 3) was calibrated for the study area. Calibration of the linked model is crucial for accurately simulating runoff, aquifer-river interactions, return flows, losses, and infiltration. To evaluate the calibration results and match them with observational data, the error coefficients NSE, RMSE, and R^2 were used (Table 1).

Climate Change Simulation

To simulate climate change, historical data for precipitation and temperature from fifteen GCMs (based on CMIP6) were downloaded from the ESGF website. These data, in NC file format, were subsequently extracted using GIS software. The monthly long-term averages of climate variables from the GCM models were then compared with observational data. Performance metrics, including NSE, RMSE, and R^2, were used for comparison (Table 2).

Based on this comparison, the MRI-ESM2 model was selected as the best-performing GCM. Given the large spatial scale of this model’s computational cells, downscaling was necessary for finer spatial detail. LARS-WG7 was used for downscaling and generating future climate data.



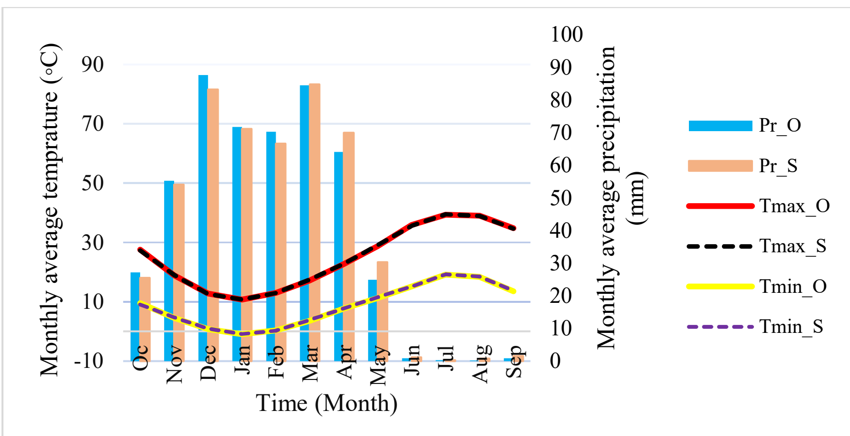
Figur 3. WEAP-MODFLOW Linked Model

For LARS-WG calibration, 45 years of observational data from the Khorramabad synoptic station (1971-2016) served as the baseline period. The performance metrics from comparing simulated climate variables with observations demonstrated LARS-WG's satisfactory accuracy in simulating climate variables (Table 2). Figure 4 illustrates the monthly averages of observed and simulated precipitation (Pr), minimum temperature (Tmin), and maximum temperature (Tmax) during the baseline period.

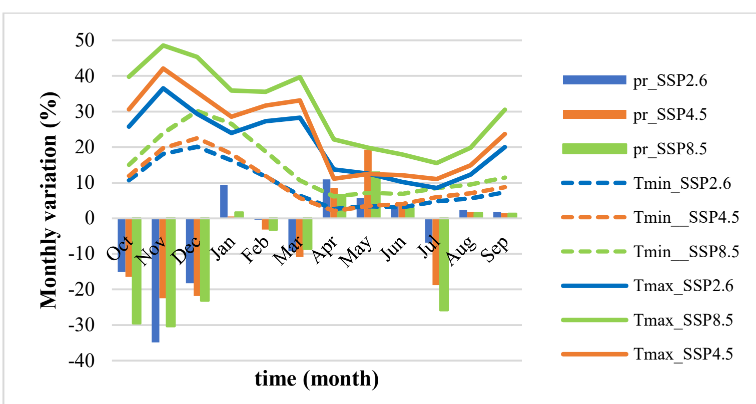
After validating LARS-WG's efficacy, climate variables were projected for a 36-year period (2025-2060) under three SSPs scenarios: SSP1-2.6, SSP2-4.5, and SSP5-8.5. Figure 5 shows the percentage changes in monthly average precipitation, minimum temperature, and maximum temperature in the future period compared to the baseline period. As illustrated, all three scenarios indicate decreased precipitation in autumn and in February and March, with increases in spring.

Table 2. Model Performance Metrics for Climate Parameters

Climate Parameters	NSE	RMSE	R^2
Monthly precipitation average	0.983	1.13	0.986
Monthly minimum temperature average	0.99	0.064	0.99
Monthly maximum temperature average	0.99	0.070	0.99
Monthly radiation average	0.99	0.089	0.98



Figur 4. Monthly Average Observed and Simulated Pr, Tmin, and Tmax, Observation data (O), Simulated data (S)



Figur 5. Percentage Changes in Monthly Average Pr, Tmin, and Tmax in SSP scenarios Compared to the Baseline

Overall, the average annual precipitation is projected to decrease under all scenarios in the future compared to the baseline (508.8 mm). Average annual precipitation for the future period was estimated at 466.2, 451.1, and 446.9 mm under SSP1-2.6, SSP2-4.5, and SSP5-8.5, respectively. The average minimum and maximum monthly and annual temperatures are also projected to rise under the three scenarios. Minimum temperature increases are projected to be 1.9°C, 2°C, and 2.4°C, respectively. Likewise, maximum annual temperature increases are estimated at 1.8°C, 1.9°C, and 2.3°C, respectively, for the scenarios mentioned. According to the results, in general, the temperature is increasing and precipitation is decreasing in the studied area. These results are consistent with the results of other studies (Iranshahi et al., 2022; Moghaddam et al., 2023; Ashofteh et al., 2024).

limitations, uncertainty and parameter sensitivity in climate projections

GCM models are complex tools used to simulate and predict the state of the atmosphere and climate. Due to the complexities of the Earth system, these models have limitations such as: heavy and time-consuming computations, low spatial resolution, insufficient data for training, etc. Also, the use of GCM models is always accompanied by uncertainties. Although several factors cause uncertainty in predicting future climate parameters, the uncertainty of GCM models is known to be the main factor causing errors in meteorological forecasts (Hawkins & Sutton, 2009). Therefore, using a single GCM model usually does not provide a very good estimate of meteorological parameters. In such situations, it is necessary to reduce the uncertainty of these models by combining different GCM models (Gohari et al., 2013). There are two general methods for combining different GCM models. In the first method, the probability of prediction accuracy of each GCM model is considered to be the same (Tao & Zhang, 2010), but in the second method, GCM models are weighted based on their ability to predict meteorological parameters, which increases the accuracy of meteorological parameter estimates compared to the first method (Connolley and Bracegirdle 2007; Elmahdi et al., 2008). In this study, the MRI-ESM2 model outputs were used, considering that it showed the best performance compared to other GCM models based on NSE, RMSE, and R^2 criteria. This model showed the minimum error for all climate parameters in SSP1-2.6, SSP2-4.5, and SSP5-8.5 scenarios.

In addition to the uncertainty that GCM models have in predicting meteorological parameters, another factor that reduces the usability of GCM models is the large-scale nature of GCM model output. In other words, GCM models predict meteorological data on a large-scale grid at high altitudes in the atmosphere (IPCC 2007). The most common way to address this problem is to use downscaling methods. These methods convert the output of GCM models to a local scale using data from weather stations (Strauss et al., 2013). In this study, the LARS-WG model was used for downscaling.

In general, it can be said that understanding the limitations, uncertainties, and sensitivity of parameters in GCM models leads to better predictions of climate change and its impacts on Earth. Sensitivity analysis is used to find sensitive parameters. In sensitivity analysis, small changes in input parameters (precipitation, temperature, solar radiation, greenhouse gases, etc.) have a significant impact on model outputs. In this study, precipitation was identified as the most sensitive input parameter.

The Impact of Climate Change on Surface and Groundwater Resources

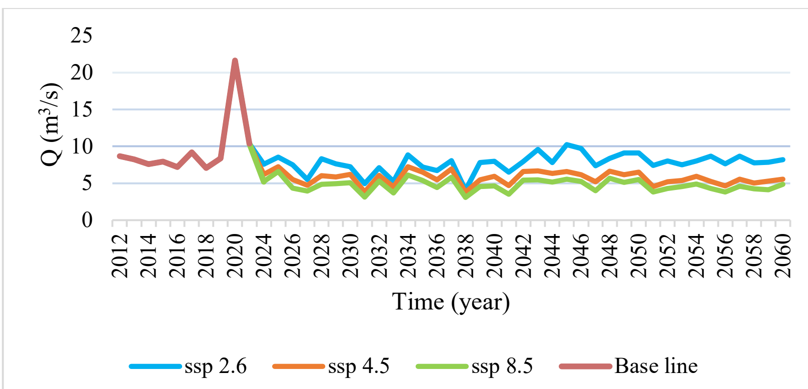
Based on climate change simulations, alterations in surface runoff, groundwater level and aquifer storage under three SSPs scenarios (SSP1-2.6, SSP2-4.5, and SSP5-8.5) were evaluated. For this purpose, the results from each climate scenario were independently applied to the

WEAP-MODFLOW model. The findings from the WEAP-MODFLOW model indicate that, due to increased temperatures, decreased precipitation, population growth, and consequently higher water demand across domestic, industrial, and agricultural sectors, both surface and groundwater resources will decline in all three climate scenarios in the future period (2025–2060) compared to the baseline period (2011–2020).

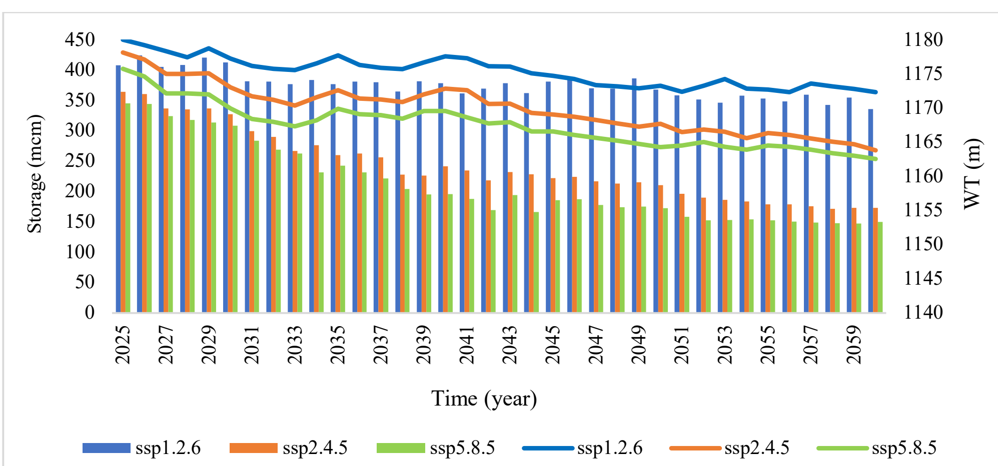
Figure 6 illustrates the average annual flow rate of the river under scenarios SSP1-2.6, SSP2-4.5, and SSP5-8.5. The results show that the river's average annual flow rate will be 7.74, 5.73, and 4.75 cubic meters per second (m^3/s) in scenarios SSP1-2.6, SSP2-4.5, and SSP5-8.5, respectively. This signifies a reduction of 1.89, 3.9, and 4.88 m^3/s from the baseline period's average (9.63 m^3/s). The most significant changes in monthly average flow rate between the future and baseline periods, across all three climate scenarios, occur during the autumn season and the months of January and June.

In previous studies by Moghaddam et al. (2023) and Ashofteh et al. (2024) the runoff rate in the optimistic scenario shows a slight increase (0.02 cubic m^3/s) compared to the base period. While in this study, in the optimistic scenario (SSP1-2.6), the runoff rate shows a decrease compared to the base period (1.89 m^3/s). In the pessimistic scenario (SSP5-8.5), according to previous studies, the runoff rate decreases compared to the base period (4.88 m^3/s) and its value in this study is almost equal to the other studies mentioned.

Examining the aquifer status of the central plain in Khorramabad under climate change effects indicates that groundwater levels will decrease under all three scenarios (SSP1-2.6, SSP2-4.5, and SSP5-8.5) compared to the baseline model period (Fig. 7).



Figur 6. Average annual river flow in the future period in SSPs scenarios



Figur 7. Average annual groundwater level and aquifer storage in SSP scenarios

The average water level will decline by 13.65, 25.54, and 28.24 meters in scenarios SSP1-2.6, SSP2-4.5, and SSP5-8.5, respectively, compared to the baseline average (1187 m). The most significant drop in groundwater levels is expected in September and October, largely due to increased water demand, especially for irrigating autumn wheat crops. Although these results show a decrease in water table, similar to the studies of Moghaddam et al. (2023) and Ashofteh et al. (2024) they show a significant difference in the decrease in water table. In previous studies, the water table has decreased by an average of 5.4 meters in the optimistic scenario and 7.6 meters in the pessimistic scenario. In this study, the water table has decreased by an average of 13.65 and 28.24 meters in the optimistic and pessimistic scenarios, respectively.

The annual average aquifer storage also declines across all climate scenarios (Fig. 7), with reductions of 82.88, 143.11, and 171.58 million cubic meters (mcm) in SSP1-2.6, SSP2-4.5, and SSP5-8.5, respectively, compared to the baseline storage average of 480 mcm.

Optimal Water Resource Management in the Future Period under Climate Change

Considering the significant impacts of climate change, rising temperatures, and declining rainfall on water resources in the Khorramabad basin, steps must be taken to ensure a long-term and sustainable drinking water supply for Khorramabad city. Currently, Khorramabad, the largest city and capital of Lorestan Province, relies on groundwater sources (springs and wells) for its drinking water supply, which is not a reliable or sustainable solution and could be impacted by short-term droughts. Sustainable water production could involve advanced treatment systems, renewable water resources, and dam construction. To secure water for both domestic and industrial uses, the construction of the Makhmalkouh Dam has been prioritized, with an annual supply goal of 55 mcm for urban drinking water and five million cubic meters for industrial use.

This section assesses the impact of the absence and presence of the Makhmalkouh Dam on groundwater resources and the capacity to meet drinking and industrial water needs under emission scenarios SSP1-2.6, SSP2-4.5, and SSP5-8.5.

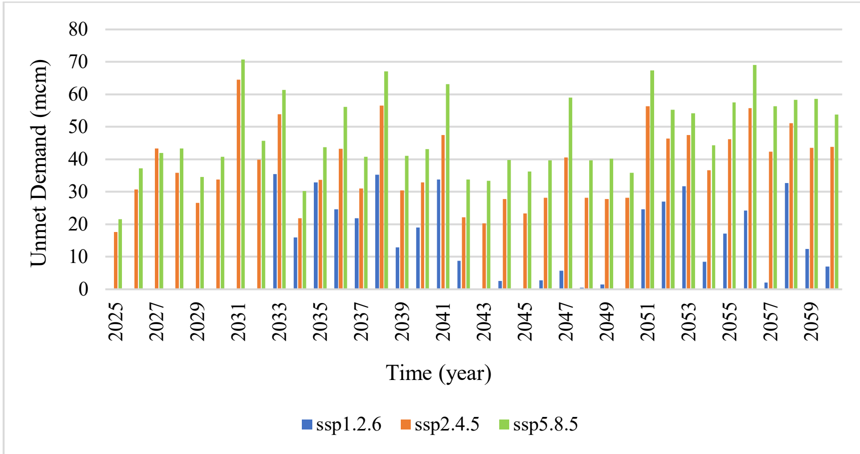
Absence of the Makhmalkouh Dam

In the baseline period, Khorramabad's drinking and industrial water demands were fully met. However, under climate change, drinking and industrial water supplies will face challenges in scenarios SSP1-2.6, SSP2-4.5, and SSP5-8.5. Figures 8 and 9 show unmet water demand for various scenarios.

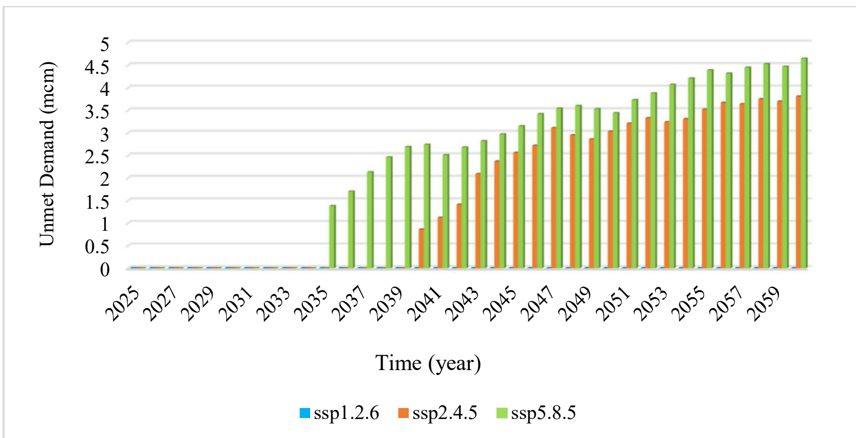
In the drinking water sector, scenario SSP1-2.6 meets demand from 2025 to 2033, but an average of 15.75 million cubic meters remains unmet annually from 2034 to 2060. In scenarios SSP2-4.5 and SSP5-8.5, drinking water demand is not fully met throughout the future period (2025–2060), with unmet demand averaging 37.7 and 47.65 mcm annually, respectively. According to the results, most unmet demand occurs during warmer months due to increased seasonal demand, with average monthly fluctuations of unmet demand reaching 0.74, 2.29, and 2.79 mcm in scenarios SSP1-2.6, SSP2-4.5, and SSP5-8.5, respectively.

In the industrial sector, in the SSP1-2.6 scenario, the required water is fully met. In scenarios SSP2-4.5 and SSP5-8.5, industrial water demand is not fully met throughout the future period (2040–2060) and (2035-2060), with unmet demand averaging 1.67 and 2.43 mcm annually, respectively.

The effects of climate change on groundwater resources without the Makhmalkouh Dam were analyzed in the previous section on the impact of climate change on surface and groundwater resources.



Figur 8. Unmet drinking water demand in SSP scenarios



Figur 9. Unmet industrial water demand in SSP scenarios

Construction of the Makhmalkouh Dam

The findings indicate that the construction of the Makhmalkouh Dam in the coming period, under the SSPs scenarios 1-2.6, 2-4.5, and 5-8.5, would substantially meet water demands for both drinking and industrial purposes. According to Figure 10, the drinking water demand under the SSP1-2.6 scenario is fully met from 2025 to 2050. However, between 2051 and 2060, there is an average annual unmet demand of approximately 2.77 mcm. In the SSP2-4.5 and SSP5-8.5 scenarios, drinking water demand is fully met from 2025 to 2039, while the average annual unmet drinking water demand from 2040 to 2060 is 7.16 and 12.3 mcm, respectively. In the industrial sector, water demands are fully met in all three scenarios (SSP1-2.6, SSP2-4.5, and SSP5-8.5). Since both drinking and industrial water needs are nearly fully met under SSP1-2.6, the average monthly fluctuation in unmet demand is zero. In the SSP2-4.5 and SSP5-8.5 scenarios, the average monthly fluctuation in unmet demand is 0.6 and 0.92 mcm, respectively.

After the construction of the Makhmalkouh Dam, Khorramabad's drinking and industrial water supply will come from both groundwater and the dam. The combined use of groundwater and dam water for meeting water demands reduces pressure on the groundwater source. According to the results, the average groundwater level declines by 11.32, 21.9, and 25.1 meters below the baseline average level in the SSP1-2.6, SSP2-4.5, and SSP5-8.5 scenarios, respectively. Moreover, the average annual groundwater level rises by 2.32, 3.64, and 3.61 meters, respectively, in the SSP1-2.6, SSP2-4.5, and SSP5-8.5 scenarios, compared to the scenario where the dam is not built (Fig. 11).

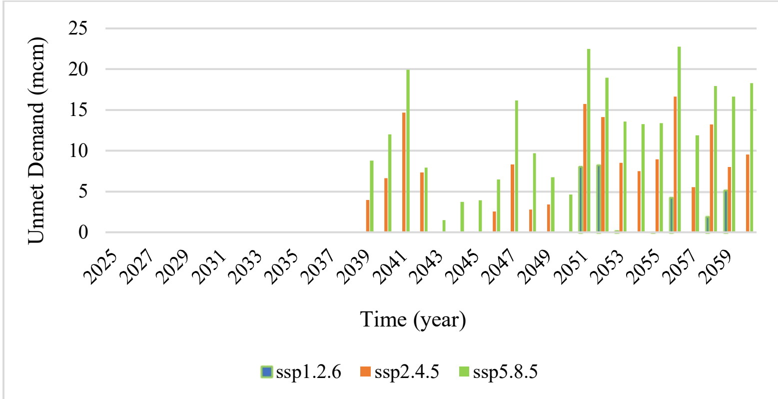


Figure 10. Unmet Drinking water demand in SSP scenarios

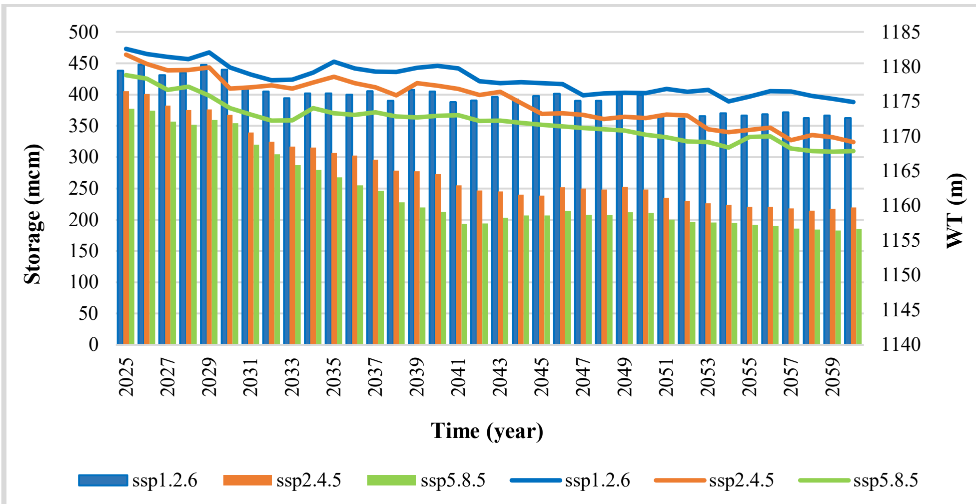


Figure 11. Annual average groundwater level and aquifer storage in SSP scenarios

According to Figure 11, the average annual aquifer storage volume decreases by 55.67, 90.84, and 123.53 mcm, respectively, compared to the baseline period. However, compared to the scenario without the dam, the annual average aquifer storage volume increases by 27.2, 52.27, and 48.05 mcm in the three scenarios.

Conclusion

In general, the results suggest that future climate change will significantly impact the surface and groundwater resources of the Khorramabad River basin. Climate variable projections under SSP1-2.6, SSP2-4.5, and SSP5-8.5 indicate reduced precipitation and increased minimum and maximum temperatures over the next 36 years compared to the baseline period. Based on the projected percentage changes in climate variables for the coming period relative to the baseline, a decrease in autumn and winter precipitation and an increase in spring precipitation are anticipated. The percentage changes in minimum and maximum temperatures indicate a rise across all seasons.

The results of integrating emission scenarios with the WEAP-MODFLOW model reveal a decrease in the average annual flow rate in the future relative to the reference scenario. The average river flow rate is projected to decline by 1.89, 3.9, and 4.88 m^3/s under the SSP1-2.6, SSP2-4.5, and SSP5-8.5 scenarios, respectively, compared to the reference scenario. Reduced surface water availability and increased water demand in various sectors in the future period will likely lead to increased groundwater withdrawals. Therefore, according to the results of this study, groundwater level and aquifer storage will decline in the future under SSP1-2.6, SSP2-4.5, and SSP5-8.5 scenarios. In the entire future period, the average groundwater level in SSP1-2.6, SSP2-4.5, and SSP5-8.5 decreases by 13.65, 25.54, and 28.24 meters, respectively, while the average aquifer storage in the three scenarios declines by 82.88, 143.11, and 171.58 mcm, respectively.

Given the results, under climate change conditions in the SSP1-2.6, SSP2-4.5, and SSP5-8.5 scenarios, drinking and industrial water supplies will face challenges, with average annual unmet demand of 15.57, 37.7, and 47.65 mcm, respectively, in the SSP1-2.6 (2034-2060), SSP2-4.5, and SSP5-8.5 scenarios.

The construction of the Makhmalkouh Dam would nearly meet all water demands for drinking and industry in SSP1-2.6, SSP2-4.5, and SSP5-8.5 scenarios. Additionally, building this dam is expected to reduce the decline in groundwater level and increase aquifer storage compared to a scenario without the dam. Although the dam would fully meet drinking and industrial water demands under different scenarios, groundwater level and aquifer storage in SSP1-2.6, SSP2-4.5, and SSP5-8.5 still show significant decreases relative to the baseline period. This is due to the extensive groundwater use in agriculture. Therefore, it is recommended to adopt multiple and appropriate management approaches and strategies to optimize water resource management and reduce the pressure on surface and groundwater resources in this basin. Recommended water resource management strategies include monitoring permitted wells, preventing unauthorized well drilling, selecting appropriate crop patterns, using modern irrigation methods, and prioritizing water allocation to different sectors in the study area.

Climate change is causing changes in precipitation patterns, especially in arid and semi-arid regions, which is leading to water scarcity in many parts of the world. In arid and semi-arid regions, in addition to changes in precipitation patterns, socio-economic factors, including urbanization and population growth, are putting pressure on water resources, resulting in increased demand for water. The simultaneous operation of these factors will have a significant impact on the future availability of water resources in the Khorramabad watershed. The results of this study clearly demonstrate how socio-economic variables and climate change affect water resources in the Khorramabad catchment and provide guidance for regional resource planning and management. This study highlights the critical role of integrated modeling in developing and implementing effective IWRM plans, contributing to sustainable water resources management in the Khorramabad catchment and other similar areas.

Acknowledgemen

The authors thank Shahid Chamran University of Ahvaz and Regional Water Company of Lorestan for providing various research facilities.

Conflicts of interest or competing interests

The authors have no relevant financial or non-financial interests to disclose.
Ethics approval and consent to participate: Not applicable
Consent for publication: Not applicable

Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Funding: The work was financially supported by a grant (SCU.EG1402.77) of Shahid Chamran University of Ahvaz, Iran.

Declaration of Generative AI and AI-assisted technologies in the writing process

The authors declare that no generative AI or AI-assisted technologies were used in the writing process.

Authors' contributions

All authors (Roghayeh Amiri, Seyed Yahya mirzaee, Manuchehr Chitsazan) have an equal share in writing all parts of the article.

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