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Application of Multi ML-Model for Multi-Scale Meteorological Drought Monitoring under CMIP6-Climate Scenario in Data-Scarce Semi-Arid Regions

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Abstract

Meteorological drought forecasting is critically important as one of the fundamental challenges in water resources management, particularly in semi-arid regions such as the Karkheh Hydrosystem in Iran. In this study, daily precipitation data from four CMIP6 models under SSP126 and SSP585 climate scenarios for the period 2026–2039 were used to calculate the Standardized Precipitation Index (SPI) at four time-scales; 3, 6, 9, and 12 months. The climate model data were downscaled and bias-corrected using the Quantile Delta Mapping (QDM) algorithm. Subsequently, five machine learning models; including GPR, XGBoost, SVM, MLP, and Random Forest, were trained and evaluated using historical data from 1966 to 2018. The results showed that the GPR model, which achieved the highest coefficient of determination ($R^2 = 0.944$) and the lowest error values at the 6-month scale, was identified as the best-performing model, followed by XGBoost and SVM. It was also found that the 6-month scale, exhibiting the highest accuracy across all models, is the optimal time scale for drought forecasting. Analysis of SPI forecasts revealed that as the time scale increases, the percentage of drought decreases and conditions tend toward wetter periods. However, the intensity of extreme events under the pessimistic SSP585 scenario is significantly greater than under the optimistic SSP126 scenario. Overall, the optimistic SSP126 scenario, characterized by lower fluctuations and only mild drought, provides more stable conditions for water resources management. The findings of this study indicate that the GPR model is an efficient and reliable tool for forecasting and designing an early drought warning in the Karkheh Hydrosystem. Additionally, it is suggested to use 6-month timeframe for medium-term planning and a 12-month timeframe for long-term water resource management in this basin.

Keywords: Meteorological Drought, Classical Machine Learning Models, Karkheh Hydrosystem, GPR, QDM algorithm, Climate Scenarios.

Introduction

Drought, a significant natural hazard, has intensified in recent decades due to anthropogenic climate change [1]. Its multifaceted impacts are shaped by diverse societal values, leading to varying definitions and classifications [2]. Drought is broadly categorized into meteorological, hydrological, agricultural, socioeconomic, energy and governance-related types, with meteorological drought marked by reduced precipitation and atmospheric moisture serving as the precursor to other forms [3,4]. Meteorological drought, is systematically exacerbates water scarcity, that precipitates severe agricultural yield losses, and socioeconomic destabilization [5,6]. In response to escalating threats, contemporary hydroclimatic research has increasingly relied on the predictive capabilities of advanced Earth System Models to elucidate the future trajectories of extreme events. Within this context, the Coupled Model Intercomparison Project Phase 6 (CMIP6) constitutes the state-of-the-art framework for generating climate projections. Nevertheless, the operational utility of these simulations is significantly limited by inherent structural biases. for example, as outlined by Giardina et al. (2024) [7], CMIP6 outputs exhibit a pronounced systematic bias, characterized by a persistent underestimation of terrestrial water storage dynamics and an overestimation of soil moisture constraints, that these systematic errors fundamentally distort the representation of land-atmosphere feedback mechanisms and evapotranspiration partitioning, thereby introducing substantial uncertainties that can critically skew both the intensity and temporal evolution of projected drought characteristics. This inherent limitation underscores the imperative need for rigorous bias-correction frameworks such as Quantile Delta Mapping to enhance the fidelity of drought assessments, particularly in climate-sensitive semi-arid regions like the Karkheh Hydrosystem.

The Standardized Precipitation Index (SPI) has pivotal as an indispensable metric for the characterization of drought severity, owing to its multiscalar flexibility. Recommended by the World Meteorological Organization (WMO, 2016) [8], SPI's versatility enables its application across multi-SPI scales and drought types. For example, Salimi et al. (2021) [9] employed the SPI to project climate change impacts on drought, while Eini et al. (2023) [2] extended its diagnostic utility to quantify hydrological drought persistence at a 12-month accumulation period. Shayeghi et al. (2024) [10] innovatively synergized SPI with satellite-derived remote sensing proxies to enhance the detection of agricultural drought stress across heterogenous landscapes. However, the accuracy of drought projections hinges on the quality of climate model outputs, particularly as CMIP6 models exhibit regional heterogeneities. Illustratively, Zhang et al. (2023) [11] leveraged CMIP6 to analyze spatiotemporal drought patterns across China, identifying rising drought frequency and intensity under high-emission scenarios (SSP585), aligning with global trends reported by Wang et al. (2024) [12]. The intensification of hydrological extremes under anthropogenic climate change has catalyzed the use of advanced General Circulation Models (GCMs), particularly the Coupled Model Intercomparison Project Phase 6 (CMIP6) ensemble. Relative to its predecessor (CMIP5), CMIP6 features enhanced spatial resolution and refined process parametrization. Zhang et al. (2025) [13] developed 10-kilometer super-resolution climate projections based on CMIP6 for China, incorporating Potential Evapotranspiration (PET)

estimates to increase hydrological accuracy. Similarly, Zuo et al. (2023) [14] used dynamical downscaling with the Weather Research and Forecasting (WRF) model to forecast heatwaves in the Pearl River Delta, emphasizing the importance of high-resolution data for capturing local climate extremes. In addition, Marshall et al. (2025) [15] combined CMIP6 data with the Soil and Water Assessment Tool (SWAT) to assess flood risks and vegetation changes across the contiguous United States, demonstrating the benefits of integrated hydro-climate modeling frameworks. Together, these developments highlight the significant potential of CMIP6; however, raw outputs from global climate models often contain systematic biases that distort regional hydroclimatic patterns. Therefore, thorough bias correction is essential to ensure reliable impact assessments [7]. These findings emphasize the urgency of refining climate models to capture localized hydrological extremes. Collectively, these empirical insights underscore the advanced statistical downscaling, and the deployment of bias-correction algorithms to accurately resolve localized hydroclimatic extremes, particularly in topographically complex and water-stressed semi-arid basins. Drought forecasting is vital to water resources planning and management in minimizing its negative consequences.

Traditional drought forecasting methods primarily based on linear statistical relationships and lack the capacity to capture the complex, nonlinear patterns that govern drought phenomena. In recent years, machine learning models have emerged as powerful tools for forecasting climatic events, significantly improving prediction accuracy by leveraging the strengths of multiple base models. A key advantage of these models is their ability to understand complex and nonlinear interactions among climatic factors, which greatly enhances precipitation and drought forecasting. The Karkheh Hydrosystem, one of Iran's most important catchments, supplies drinking and agricultural water to millions of people and has experienced severe, consecutive droughts in recent years. However, comprehensive study has yet utilized advanced machine learning models combined with downscaled CMIP6 data to forecast drought in this basin. This study evaluates the impacts of climate change on drought in the Karkheh Hydrosystem using CMIP6 scenarios. After analyzing precipitation and estimating the Standardized Precipitation Index (SPI) at 3, 6, 9, and 12-month scales, the Quantile Delta Mapping (QDM) algorithm will be applied for downscaling and bias correction of CMIP6 data to address the bias identified by Giardina et al. (2024) [7]. The methodology is based on the high-resolution approach of Zhang et al. (2025) [13] and incorporates the emphasis on regional characteristics highlighted by Zuo et al. (2023) [14] aiming to project future drought conditions with greater accuracy. By combining the multi-scale SPI with sophisticated CMIP6 projections, this study aims to assess a region vulnerable to climate change. Accordingly, the primary objective of this research is to forecast meteorological drought in the Karkheh Hydrosystem under SSP126 and SSP585 climate scenarios using machine learning models, including Support Vector Machine (SVM), Gaussian Process Regression (GPR), Random Forest (RF), Multilayer Perceptron (MLP) and Extreme Gradient Boosting (XGBoost). The secondary objectives are to (1) evaluate and compare the performance of base and ensemble models in drought forecasting, (2) identify the best-performing model for drought forecasting in

the Karkheh Hydrosystem, and (3) analyze drought trends during the 2025–2039 period under both optimistic and pessimistic scenarios.

Case studies and Data

The Karkheh River basin is located in southwestern Iran, between latitudes 30°00' and 35°00' north and longitudes 46°00' and 49°00' east, covering an area of approximately 51,000 km². As one of the primary and most productive rivers in Iran, the Karkheh River plays a crucial role in irrigating about 9% of the country's agricultural land. The basin's water is extensively utilized for agricultural irrigation, domestic water supplies, and fish farming [29]. For this study, daily precipitation data from three rain gauge stations within the basin were obtained from the Iran Water Resources Management (IWRM). The study period extends from 1966 to 2018. Figure 1(a) illustrates the Karkheh River basin along with the locations of the selected rain gauge stations. The climate of this basin is strongly influenced by its wide latitudinal range, significant altitudinal variations, and its specific position within the Zagros Mountains. Similar to the Karun basin, the Karkheh Hydrosystem has faced considerable hydrological challenges due to the development of various water resource projects [30].

Table 1. Information on stations in Karkheh Hydrosystem

n	Station name	Latitude	Longitude	Established time	Basin	Period
10	Aghajanbolaghi	34° 50'	43° 03'	1966	Karkheh	1966-2018
11	Doabmarak	34° 33'	46° 47'	1966	Karkheh	1966-2018
12	Pol Dokhtar	39° 09'	47° 46'	1966	Karkheh	1966-2018

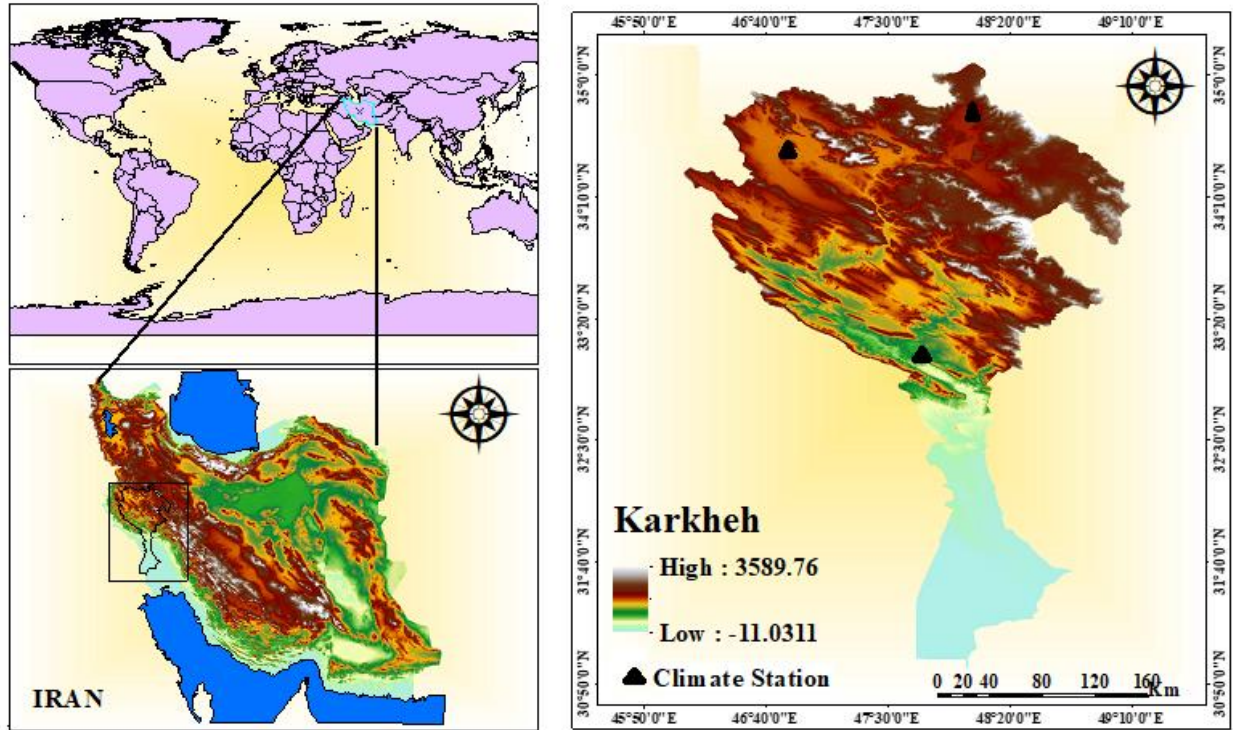


Figure 1. Location of the study site within its broader geographic context.

In this study, daily precipitation data from three rain gauge stations in the Karkheh Hydrosystem, obtained from Iran's Water Resources Management Organization for the period 1966 to 2018, were collected. Additionally, precipitation data from four CMIP6 models under the SSP126 and SSP585 scenarios for 2026 to 2039 were acquired. The climate model data were first downscaled and bias-corrected using the Quantile Delta Mapping (QDM) method. Next, the Standardized Precipitation Index (SPI) was calculated based on the Gamma distribution for four time-scales: 3, 6, 9 and 12 months. Then, five machine learning models including Support Vector Machine (SVM), Gaussian Process Regression (GPR), Random Forest (RF), Multilayer Perceptron (MLP) and Extreme Gradient Boosting (XGBoost) were trained on historical data. Their performance was assessed using RMSE, MAE, and R^2 metrics. The trained models were subsequently used to predict the SPI for 2026 to 2039 under the SSP126 and SSP585 climate scenarios. Finally, the models' performance and drought forecasting results were presented through tables, comparative charts, and ranking maps. Figure 2 illustrates the steps of the research methodology.

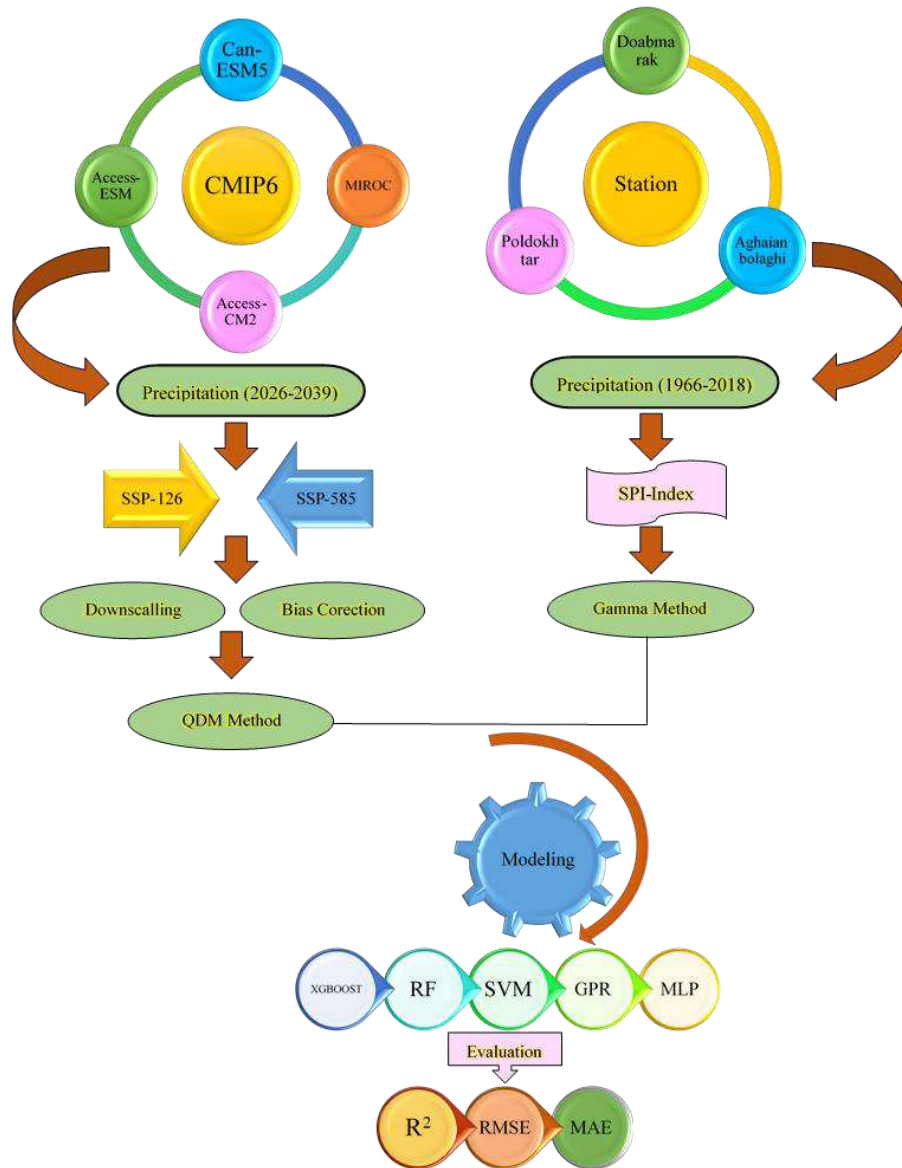


Figure 2. Flowchart of the research methodology

GCM Data

This study uses Shared Socio-Economic Pathways (SSPs) to simulate precipitation in the Karkheh Hydrosystem. General Circulation Models (GCMs) play a crucial role in forecasting future climate conditions under various emission scenarios [17]. SSPs provide detailed projections of future population trends, including economic growth, technological progress, lifestyles, policies, and other social factors, outlining five distinct potential climate futures [18]. These five pathways SSP1, SSP2, SSP3, SSP4, and SSP5 are part of the CMIP6 framework. Since datasets originate from multiple reports, this research utilizes data from the Sixth Assessment Report (CMIP6). Daily precipitation data from four models under two scenarios, SSP1-2.6 and SSP5-8.5, representing

sustainable development and fossil fuel-driven growth, respectively, are used. Details about the models are presented in Table 2.

SSP1: Sustainable Pathway

This scenario envisions a global shift toward sustainability characterized by balanced and inclusive development. The shared use of international resources fosters increased investments in education and healthcare, which in turn influence population dynamics and economic growth, ultimately enhancing human well-being [19].

SSP5: Fossil Fuel–Driven Development

In this scenario, the global economy grows rapidly, powered by fossil fuels. Despite fluctuations in population size, environmental issues such as air pollution are effectively managed (19).

Table 2. Information on models chosen for this study under the two scenarios, SSP1-2.6 and SSP5-8-5

Model	Institution	Resolution	SSP126	SSP585	Historical
Access-ESM	Australian Community Climate and Earth System Simulator	$1.8^0 \times 1.25^0$	2014-2100	2015-2100	1850-2014
Can-ESM5	Canadian Center for Climate Modeling and Analysis	$2.8^0 \times 2.8^0$	2014-2100	2015-2100	1850-2014
MIROC	Atmosphere and Ocean Research Institute; Center for Climate system Research-National Institute for Environment Studies	$1.4^0 \times 1.4^0$	2014-2100	2015-2100	1850-2014
Access-CM2	Australian Community Climate and Earth System Simulator	$1.87^0 \times 1.25^0$	2014-2100	2015-2100	1850-2014

Methodology

Downscaling and Bias Correction

A key challenge when using output from Atmosphere-Ocean General Circulation Models (AOGCMs) is that their data are at a much coarser scale compared to specific case studies. Therefore, it is crucial to apply techniques that downscale and bias-correct AOGCM outputs to the regional level [20]. Several approaches are available to adapt AOGCM data for regional applications [21]. Currently, machine learning techniques are employed for downscaling and bias correction, including quantile delta mapping (QDM) [22] and multivariate bias correction (MBC) [23]. The QDM algorithm has been applied for downscaling and bias correction in the karkheh river basins.

Quantile Delta Mapping (QDM)

QDM is an algorithm designed to preserve changes in quantiles and operates similarly to quantile mapping (QM). Initially, quantiles are adjusted based on model projections, and then QM corrects the bias in simulated values using a transfer function derived during the calibration period. Finally, the bias-corrected model incorporates projected absolute changes for temperature or relative changes for precipitation in the quantiles. To accurately capture the climate variable x at time t , the non-exceedance probability associated with the observed values is first estimated [22]:

$$\tau_{m,p}(t) = F_{m,p}^t[x_{m,p}(t)], \quad \tau_{m,p}(t) \in \{0,1\} \quad (1)$$

Where $\tau_{m,p}$ is non-exceedance probability that evaluated with time; $x_{m,p}$ indicates the modeled value in the projection period (p). And then relative change for precipitation in quantile between historical data and time (t) estimated by:

$$\Delta_m(t) = \frac{F_{m,p}^{(t)-1}[\tau_{m,p}(t)]}{F_{m,c}^{-1}[\tau_{m,p}(t)]} = \frac{x_{m,p}(t)}{F_{m,h}^{-1}[\tau_{m,p}(t)]} \quad (2)$$

Where $F_{m,c}^{-1}$ is inverse CDF for simulation in calibration period. Moreover, $\tau_{m,p}$ quantile in projection period (p) in calibration period corrected using observation value which estimated:

$$\hat{x}(t) = F_{o,c}^{-1}[\tau(t)] \quad (3)$$

Where $F_{o,c}^{-1}$ is inverse CDF is estimated from observed values of x_o, c in the calibration period. As result, bias correction in the projection period equals to bias correction of $\hat{x}(t)$ multiple relative change in the precipitation:

$$x_{bc}(t) = \hat{x}(t) \times \Delta(t) \quad (4)$$

MBC package in R (<https://cran.r-project.org/web/packages/MBC/index.html>) is used to downscale and bias-correct AOGCM data for the Karkheh Hydrosystem. The calibration period was chosen from 1966 to 1998, and the validation period was selected from 1999 to 2014 for the Karkheh station. Following the approaches of Cannon et al. (2020) [23], Firoozi et al. (2024) [24], all scenarios are bias-corrected using historical data from each model alongside observational data to carry out downscaling and bias correction, ensuring that changes are preserved.

Performance of QDM algorithm

The mean absolute error (MAE) is used as an evaluation metric to assess the performance of the quantile delta mapping (QDM) method compared to reference data during the calibration period for Karkheh (1966–1998) and the validation period for Karkheh (1999–2014). This metric has also been utilized by other researchers [24,25]. The MAE is calculated as follows:

$$MAE = \frac{1}{N} \sum_i^N |X_{obs,i} - X_{sim,i}| \quad (5)$$

Where $X_{obs,i}$ observed value; $X_{sim,i}$ is simulated value. If the MAE value was lower, it considers lower bias. MAE for references data and simulated data is calculated.

Standard Precipitation drought index (SPI)

The Standardized Precipitation Index (SPI) was introduced by McKee et al. (1993) [26] to evaluate drought conditions using precipitation data. Its simplicity of calculation and applicability over various time scales are two key reasons for its widespread use. Consequently, this index is used to investigate meteorological drought [24], hydrological drought (2), and agricultural drought [27]. The (SPI) for different time scales was calculated by fitting the best probability distribution to precipitation data, specifically the Gamma distribution (26). Drought classification is based on Table 3. A drought event begins when SPI values fall below -1, while SPI values between -1 and 1 indicate normal conditions [28]. This study calculates SPI for 3, 6, 9, and 12 month scales for the Karkheh Hydrosystem using mean monthly precipitation. The SPI is calculated by:

$$SPI = s \frac{t - (c_2 t + c_1)t + c_0}{((d_3 t + d_2) + d_1) + 1} \quad t = \sqrt{\ln \frac{1}{H(X)^2}} \quad (6)$$

$$G(x) = \frac{1}{\beta \gamma \Gamma(\gamma)} \int_0^x X^{\gamma-1} e^{-\frac{x}{\beta}} dx \quad X > 0(\gamma) = \int_0^\infty X^{\gamma-1} e^{-x} dx \quad (7)$$

Where X is precipitation value; β and γ are scale and shape parameters of Γ function; s is positive and negative coefficients; c_0, c_1, c_2 and d_1, d_2, d_3 are calculated parameters. Their value by: $c_0 = 2.515517, c_1 = 0.802853, c_2 = 0.010328, d_1 = 1.432788, d_2 = 0.189269$ and $d_3 = 0.001308$.

$G(x)$ denotes the probability distribution of precipitation. When $G(x) > 0.5$, then $H(x) = 1 - G(x)$ and $S = 1$; otherwise, $H(x) = G(x)$ and $S = -1$.

Table 3. classification SPI in this research

SPI value	Classification
SPI > 1	Wetness
-1 < SPI < 1	Normal
SPI < -1	Drought
SPI < -2	Severe
Drought	

Machine Learning Models

In this study, the five machine learning models were evaluated and compared for forecasting the Standardized Precipitation Index (SPI) drought index across four time-scales: 3, 6, 9, and 12 months. The objective was to identify the best-performing model and assess the strengths and weaknesses of each in predicting drought conditions in the Karkheh Hydrosystem under the impact of climate change. The results of this study can serve as a foundation for selecting an appropriate model for water resource management and drought Resilience. The following sections provide a brief introduction to each model.

Extreme Gradient Boosting (XGBoost)

The XGBoost model is an ensemble learning algorithm that belongs to the boosting category. It uses decision trees as its base learners and employs a gradient-boosting technique to minimize loss

when adding new models. XGBoost aims to enhance both the training speed and predictive performance of gradient-boosted decision trees. Foundational knowledge about the mechanism and implementation of XGBoost can be found in the paper by Chen and Guestrin (2016) [31] and further discussed by Li et al. (2025) [32].

Random Forest (RF)

Random Forest (RF) is a supervised machine learning algorithm that reduces uncertainty and overfitting by averaging the results of multiple decision trees [33,34]. Moreover, Random Forest effectively handles large datasets, is more interpretable, and can incorporate multiple features [34]. The Random Forest method can rank the relative importance of each predictor variable based on the expected structure of the tree arrangement, all of which are evaluated using the same distribution. The model begins by constructing a forest of decision trees using the bootstrap approach, in which each tree is built separately using a random subset of predictor data. Without pruning, the trees grow to their maximum size, and the average of the outputs from all the multiple decision trees is the final result [34,35], delivering effective regression performance and selecting the best answer by voting [34,36].

Gaussian Process Regression (GPR)

Gaussian processes (GPs) offer a powerful and flexible approach to regression and classification problems, moving beyond the limitations of simple parametric forms. Their strength lies in their non-parametric nature, allowing them to model complex relationships within data by defining a distribution over functions rather than just parameters [37,38]. A key feature of GPs is the wide array of covariance functions available. These functions determine the degrees and characteristics of the modeled functions, enabling researchers to tailor the GP to the specific structure of their data [39]. This flexibility makes GPs particularly well-suited for addressing diverse engineering and modeling challenges [40].

Gaussian process regression (GPR) leverages this concept by assuming that past observations contain valuable information about future ones and, unlike the Gaussian distribution, the Gaussian process is over functions [41]. This data-driven, non-parametric approach allows GPR to model complex relationships without the need for explicit model validation to generalize them [42]. Several advantages make GPR appealing for various applications, including easy implementation, adaptable hyperparameter tuning, and the ability to provide probabilistic predictions, quantifying uncertainty in a statistically sound manner. This led to a surge in interest in GPR from both industry and academia. Notably, specialized kernels such as the PUK kernel, designed for large datasets, further expanded the applicability of GPR in fields such as hydrology and climate research [43].

Multilayer Perceptron (MLP)

The MLP network is one of the most important architectures in artificial neural networks. These networks consist of layers of sensory units (neurons), including an input layer, one or more hidden layers, and an output layer. The input signal is transmitted forward through the network, from the input layer to the hidden layers and then to the output layer [44,45]. The output of each neuron is multiplied by weight coefficients and given as input to a nonlinear excitation function. During the training phase, the training data is fed into the perceptron, and network weights are adjusted to

minimize the error between the target and the model output or until the number of training times to the default value. Subsequently, as in all modeling processes, different inputs (not present in the training phase) are used for model validation. Training neural networks is generally very complex and can be considered an optimization problem involving a large number of variables [46].

Support Vector Machine (SVM)

SVM determines the decision boundary, or the optimal hyperplane, that divides an n-dimensional space. The algorithm selects key points called support vectors, which are essential for forming this hyperplane [47,48,49]. It is a widely used supervised machine learning technique applicable to both classification and regression [50]. The linear SVM can be represented by Equation (8) as follows:

$$x_1, y_1 \dots \dots x_n, y_n$$

where y_1 is either 1 or -1, depending on the linkage between the class and point x_1 . The hyperplane divides the set of points, x_1 , when $y_1=1$ and $y_1=-1$. This hyperplane is determined by optimizing the distance between itself and the nearest point x_1 from either group. The hyperplane that satisfies Equation (9) for a given set of points can be expressed as below:

$$wTx-b=0$$

where w is the hyperplane's normal vector. The parameter, $b/\|w\|$ indicates how far away from the origin the hyperplane is from the normal vector. The linear regression model is a fundamental tool used to predict the dependent variable, Y , based on the independent variable, X . It is a statistical and machine learning algorithm that maps numeric inputs to numeric outputs by fitting a best-fit straight line to the dataset. The model's accuracy is evaluated using the least squares estimation method. Equation (10) for linear regression is expressed as follows:

$$Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_n + \epsilon$$

where X_i and Y_i are the independent and dependent variables, respectively; β_0 is constant; β_n is the slope coefficient of each X_i ; and ϵ is the model error term or residual [48].

Result and Discussion

Downscaling and Bias Correcting

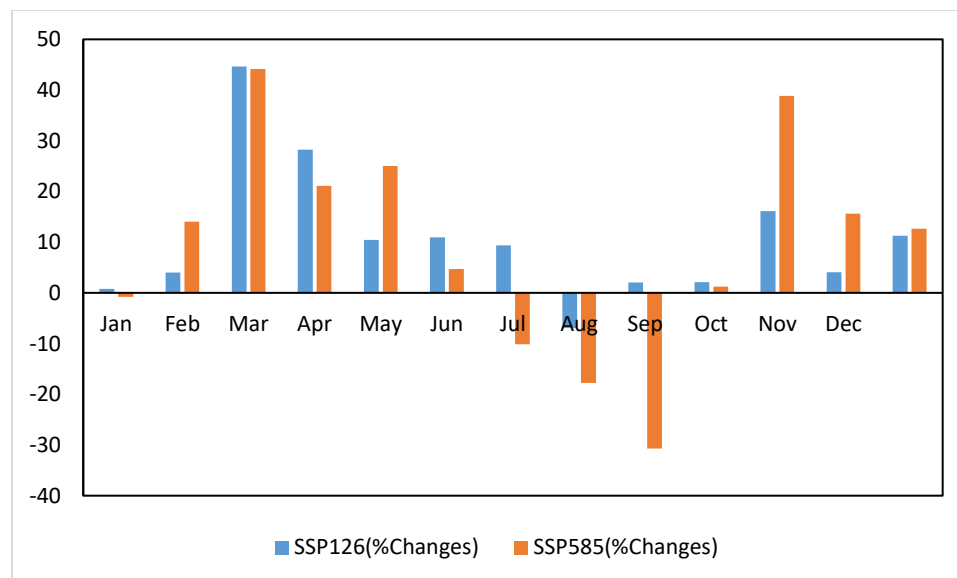
GCM data from each model under the SSP126 and SSP585 scenarios were downscaled and bias-corrected using the QDM algorithm. Historical data from each model, along with observed daily precipitation, were used to train the QDM, which produced downscaled and bias-corrected data. The periods 1966–1998 and 1970–2002 were selected as calibration periods for the Karkheh Hydrosystem, while 1999–2014 and 2003–2014 were chosen for validation. MAE values for each model were calculated (Table 4). All downscaled and bias-corrected datasets from the four models demonstrated excellent performance with the QDM algorithm, as their MAE values were lower than those of the reference data, consistent with the results reported by Firoozi et al. (2024) [24] and Xavier et al. (2022) [51].

Table 4. MAE values for downscaled and bias corrected models and references models in Karkheh Hydrosystem

Karkheh

	Calibration		Validation	
	References	Simulated	References	Simulated
Can-ESM	37.43	1.906	1.814	39.48
ACCESS-ESM	45.49	1.906	1.818	49.33
MIROC6	42.05	1.943	1.815	42.28
ACCESS-CM2	42.530	1.976	44.42	1.819

362 Daily precipitation data from four CMIP6 models under SSP1-2.6 and SSP5-8.5 scenarios were
 363 downscaled and bias-corrected for the Karkheh Hydrosystem. Due to the high uncertainty model,
 364 the mean precipitation from all four models was used for analysis. Precipitation changes during
 365 the period 2026–2039 were compared with reference data from 1966–2018 for the Karkheh
 366 Hydrosystem. Figure 3 shows precipitation changes under the mean of the four models for SSP1-
 367 2.6 and SSP5-8.5 in the Karkheh Hydrosystem. The highest increase in precipitation under both
 368 SSP1-2.6 and SSP5-8.5 occurs in March, with a 44% increase, corresponding to rises of 13.9 mm
 369 and 13.7 mm, respectively, compared to the reference period. The largest decrease under SSP5-
 370 8.5 is 30.68%, and 6.14 mm, in September. Overall, precipitation under SSP1-2.6 and SSP5-8.5 in
 371 the Karkheh Hydrosystem is projected to increase by 11.25% and 12.8%, respectively, relative to
 372 the reference period.



373
 374 **Figure 3.** Precipitation changes under mean of four models of SSP126 and SSP585 in 2026-2039
 375 relative to references period in Karkheh Hydrosystem

376 Drought

377 After determining the precipitation distribution using the Kolmogorov-Smirnov test, the
 378 Standardized Precipitation Index (SPI) was estimated. A gamma distribution was fitted to the
 379 monthly mean precipitation in the Karkheh Hydrosystem. SPI was calculated for 3-, 6-, 9-, and

12-month timescales using observed data from 1966 to 2018. Figure 4 illustrates the SPI for these timescales in the Karkheh Hydrosystem. The SPI for the 3- and 6-month scales exhibits greater variability than the 9- and 12-month scales because long-term SPI considers consecutive wet and dry periods as a single drought event. The basin experienced severe droughts in 2000 and 2008, consistent with the findings of Kamali et al. (2017) [52]. According to the Mann-Kendall test, the SPI for the 6-, 9-, and 12-month scales shows a significant downward trend at the 1%, 5%, and 10% confidence levels. This indicates that drought has intensified recently due to a negative precipitation trend in the Karkheh Hydrosystem.

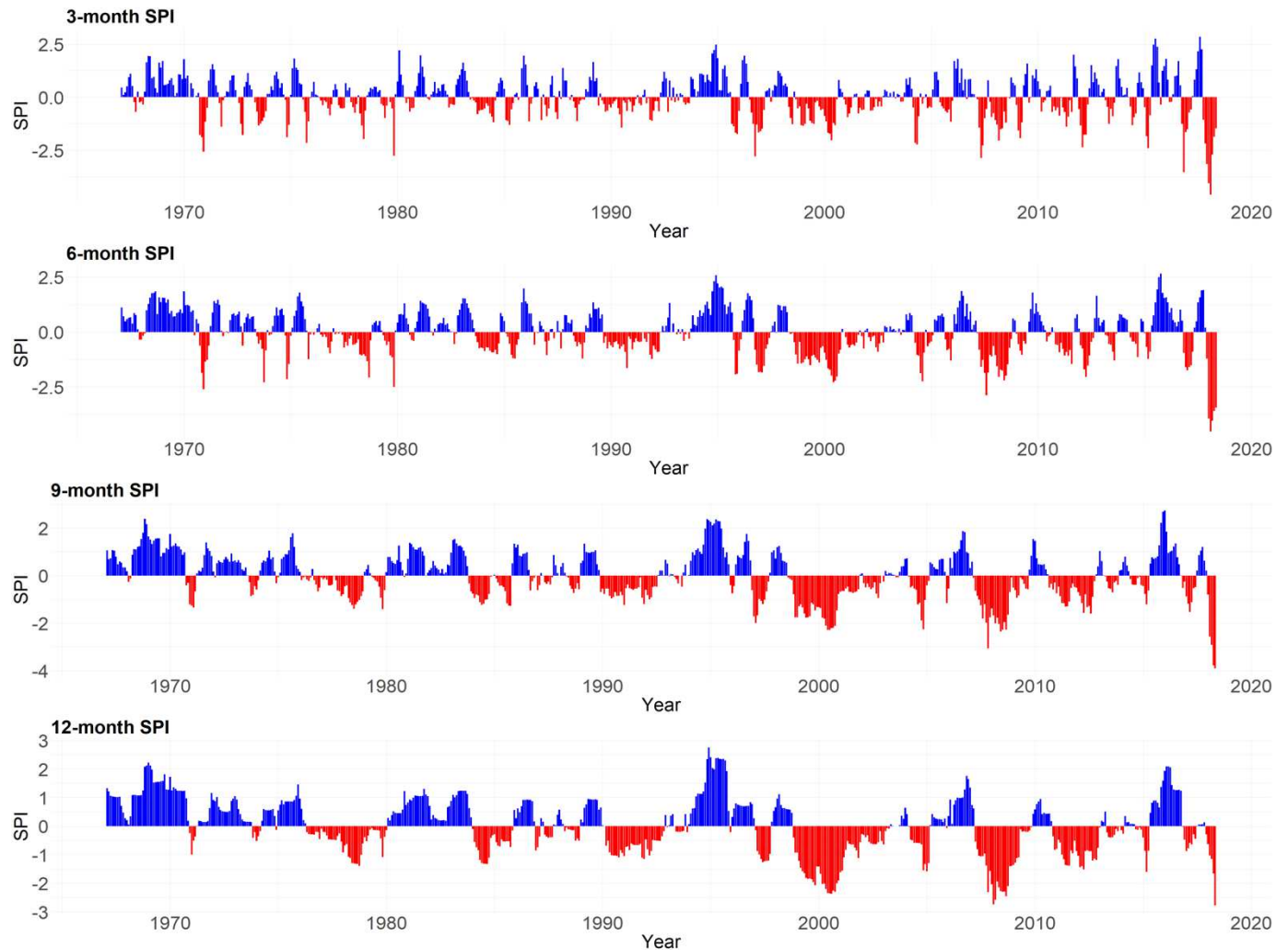
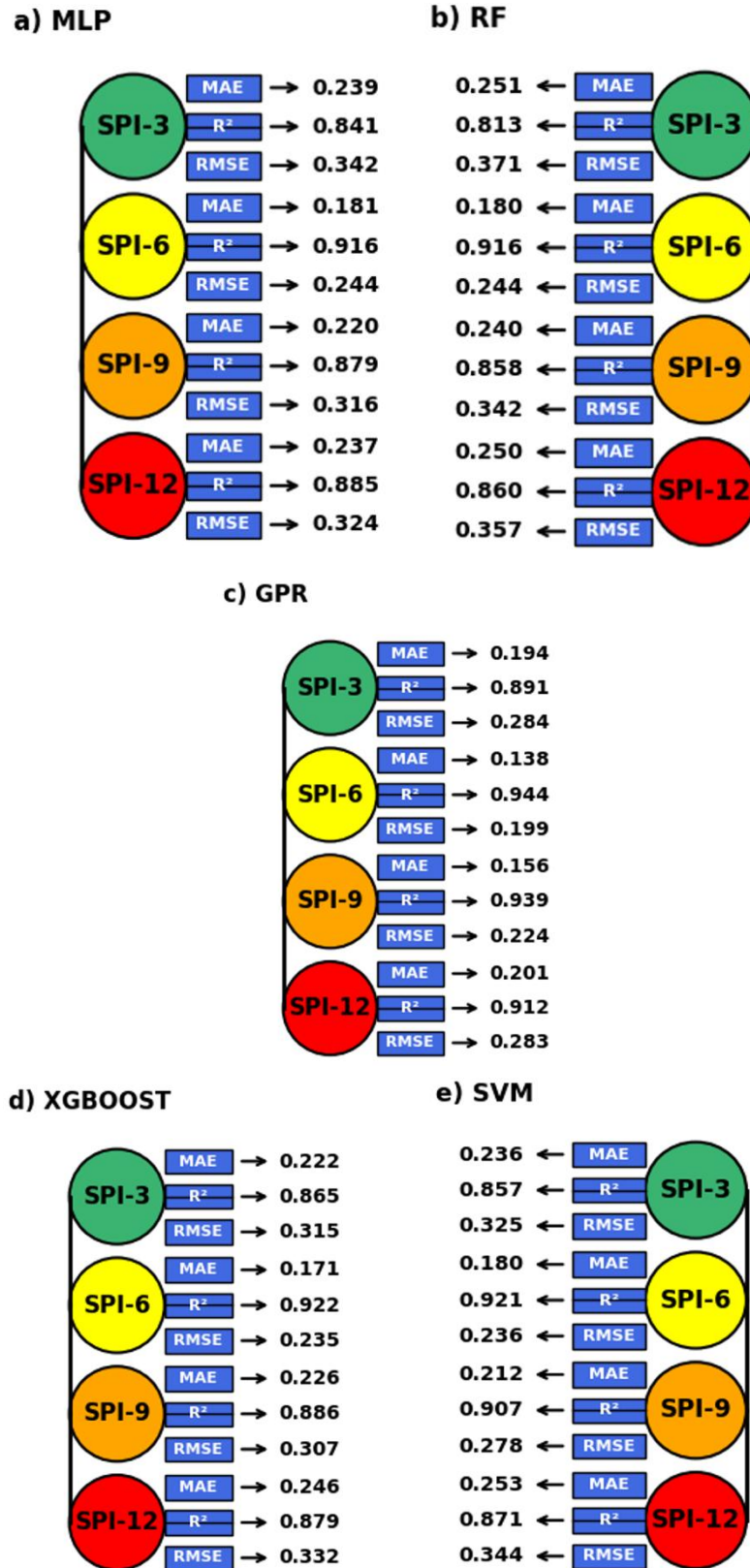


Figure 4. SPI for 3, 6, 9, and 12- month scale in Karkheh Hydrosystem (1966-2018)

Evaluation of Model Accuracy in Drought Forecasting (2026–2039)

The evaluation of five machine learning models, including GPR, XGBoost, SVM, MLP, and RF, for forecasting the Standardized Precipitation Index (SPI) drought index across four time-scales (3, 6, 9, and 12 months) revealed that the GPR model consistently outperformed the others. GPR achieved the highest coefficient of determination (R^2) at the 6-month scale (0.944), as well as strong performance at the 3-month (0.891), 9-month (0.939), and 12-month (0.912) scales. It also

recorded the lowest error values (RMSE and MAE) across all scales, establishing it as the best-performing model (Figure 5c). This superiority is attributed to the Bayesian and kernel-based nature of GPR, which enables highly accurate modeling of complex nonlinear relationships. The XGBoost model demonstrated very good performance at the 3- and 6-month scales ($R^2 = 0.865$ and 0.922 , respectively), ranking as the second-best model (Figure 5d). This highlights the strong capability of gradient-boosted tree-based algorithms in capturing short- and medium-term patterns. However, its accuracy declined at the 9- and 12-month scales ($R^2 = 0.886$ and 0.879 , respectively), suggesting that XGBoost requires more precise tuning and additional training data for reliable long-term predictions. The SVM model exhibited stable and acceptable performance across all scales, with an average R^2 of 0.889 , and particularly strong results at the 9-month scale ($R^2 = 0.907$), ranking it third (Figure 5e). This indicates the effectiveness of nonlinear kernels in drought forecasting. Nevertheless, SVM's limitations include the need for precise parameter tuning and time-consuming training. The MLP model showed moderate performance at short-term scales (3 and 6 months) but improved significantly at the 12-month scale, achieving an R^2 of 0.885 and ranking second after GPR, outperforming both XGBoost and SVM (Figure 5a). This suggests that the deep architecture of neural networks with multiple hidden layers is well-suited for identifying long-term patterns and complex nonlinear relationships in climatic data. These findings align with previous studies by Rezaeian-Zadeh and Tabari (2012) [53], Lee et al. (2013) [54], and Prabowo et al. (2024) [55], which demonstrated that neural network models perform better in long-term drought forecasting than in short-term predictions. The Random Forest model, despite acceptable performance (average $R^2 = 0.862$), exhibited the weakest results across all scales (Figure 5b). Analysis of the time scales indicates that the 6-month scale, which yielded the highest accuracy across all models, is the optimal scale for drought forecasting. Overall, the results confirm that the GPR model, by providing the highest accuracy and lowest error across all scales, is the most effective model for drought forecasting in the Karkheh Hydrosystem (Figure 6). This conclusion is consistent with findings from Pand et al. (2025) [56], Karbasi et al. (2022) [57], Ghasemi et al. (2021) [37] and Oruc et al. (2024) (38), which also reported the superior performance of GPR compared to other models.



424 **Figure 5.** The accuracy and rank chart of the models over SPI-3, SPI-6, SPI- 9, and SPI-12

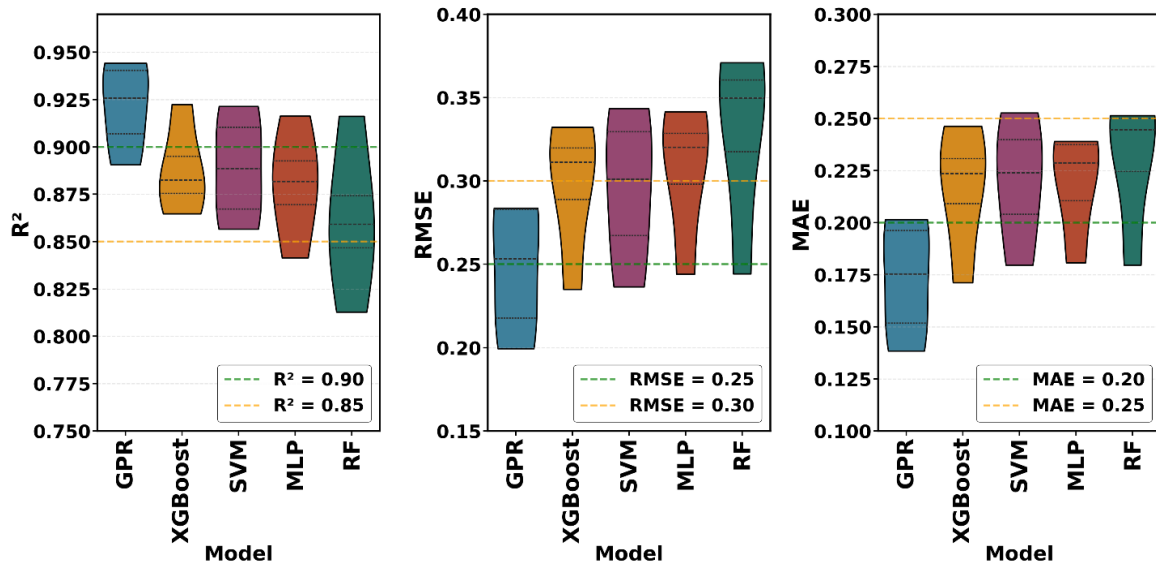


Figure 6. Mean distribution of model evaluation metrics

SPI Drought Forecasting under the SSP1-2.6 and SSP5-8.5 Scenarios for the Period 2025–2039

SPI-3 drought forecasting

The SPI-3 index represents the three-month precipitation status of the Karkheh Hydrosystem, where positive values indicate wet periods and negative values indicate drought conditions. The trend of drought variations under the SSP126 and SSP585 scenarios is presented in Figure 7. Based on statistical analysis and an overall comparison of the scenarios (Figure 8), the mean SPI-3 under the SSP126 scenario is 0.102, and under the SSP585 scenario, it is 0.108 both indicating normal climatic conditions with a slight tendency toward wetter conditions. These values suggest that, on average, the Karkheh Hydrosystem will experience normal conditions under both scenarios, and the difference of 0.006 units between the two scenarios is statistically negligible and insignificant. However, the range of variation reveals fundamental differences; under SSP126, SPI-3 fluctuates from -0.859 to +1.282, while under SSP585, it varies from -0.983 to +1.673. This difference of 0.124 units in the minimum and 0.391 units in the maximum indicates that the pessimistic scenario not only brings more severe droughts but also experiences much more intense wet periods, significantly increasing the range of climatic fluctuations. The standard deviation under SSP126 is 0.466, and under SSP585, it is 0.555; the difference of 0.089 units indicates greater variability and higher climatic instability in the pessimistic scenario. Under the SSP126 scenario, out of a total of 268 months studied, 115 months (42.85%) exhibited negative SPI values, indicating drought conditions, while 153 months (57.15%) had positive or zero SPI values, representing normal to wet conditions. Under the SSP585 scenario, 112 months (41.70%) experienced drought, and 156 months (58.30%) had normal or wet conditions. This 1.15% difference suggests that despite greater variability in the pessimistic scenario, the percentage of drought occurrence is slightly lower than in the optimistic scenario. This may be attributed to an increase in extreme precipitation events under SSP585. In other words, the increased variability under SSP585 is

predominantly skewed toward more intense wet periods, thereby reducing the number of dry months. The analysis of different SPI classes indicates that, in both scenarios, drought occurs only in the mild category (SPI between 0 and -1). No instances of moderate drought (SPI between -1 and -1.5), severe drought (SPI between -1.5 and -2), or extreme drought (SPI less than -2) were observed. Notably, the Karkheh Hydrosystem, over the three-month period and under both climate scenarios, is not expected to experience severe droughts; all droughts will be mild and manageable. Furthermore, under SSP126, 42.9% of months experienced mild drought, while 57.1% were normal to wet. Under SSP585, 41.7% of months experienced mild drought, and 58.3% were normal to wet, indicating a relative similarity in drought class distribution between the two scenarios. Examination of the SPI-3 time series reveals distinct seasonal patterns, with summer months (June to September) tending toward negative SPI values and winter to early spring months (December to April) tending toward positive SPI values. This seasonal pattern is consistent across both scenarios. The highest positive SPI value under SSP126 occurred in January 2032, reaching +1.282, while under SSP585, it also occurred in January 2032 but reached +1.673, indicating a concurrent severe wet event in both scenarios at the beginning of 2032. The lowest negative SPI value under SSP126 was recorded in September 2036 at -0.859, and under SSP585 in September 2032 at -0.983, indicating a mild drought event in early autumn under both scenarios. Notably, under SSP126, SPI-3 values never exceed +1.282 or fall below -0.859, whereas under SSP585, SPI-3 reaches +1.673 and -0.983, indicating greater intensity of extreme events in the more pessimistic scenario. Specifically, during 2031 to 2033, the SSP585 scenario experiences a relatively severe wet period with SPI values above 1.5 in several months, while under SSP126, this period exhibits lower intensity (maximum +1.282). Additionally, during 2036 to 2038, both scenarios experience a relatively prolonged drought period, with intensities reaching -0.859 under SSP126 and -0.983 under SSP585. Annual analysis of the data shows that in both scenarios, the years 2031 and 2032 had the highest positive SPI values (indicating wet conditions), while the years 2036 and 2037 had the lowest negative SPI values (indicating drought conditions). Under SSP1-2.6, 2032 with a mean SPI of approximately 0.40 and 2036 with a mean SPI of approximately -0.25 were the wettest and driest years, respectively. Under SSP5-8.5, 2032 with a mean SPI of approximately 0.50 and 2036 with a mean SPI of approximately -0.30 were the wettest and driest years, respectively. This pattern indicates that in both scenarios, 2032 is projected as a high-precipitation year and 2036 as a low-precipitation year, but the intensity of these events is greater under the more pessimistic scenario.

Based on a detailed analysis of SPI-3 data, the Karkheh Hydrosystem is not expected to experience severe droughts over the three-month period; all droughts are projected to be mild. However, drought conditions are anticipated in approximately 42% of the months (about five months per year), highlighting the need for sustainable water resource management and planning to address short-term droughts. Under the pessimistic SSP585 scenario, despite greater fluctuations and more intense wet events, the number of dry months decreases, potentially posing fewer challenges for agricultural and drinking water supplies. However, this scenario increases the risk of floods and extreme precipitation events. Conversely, the optimistic SSP126 scenario, characterized by lower

fluctuations but more dry months, implies a higher likelihood of recurrent droughts and prolonged water stress. Therefore, it is essential to plan for both types of extreme events floods and droughts simultaneously, as decisions cannot rely solely on climate scenarios. Given that over 57% of months are expected to have normal to wet conditions, there is a favorable opportunity for water storage during wet periods and consumption management during dry periods, which can significantly reduce the vulnerability of the Karkheh Hydrosystem to climatic fluctuations.

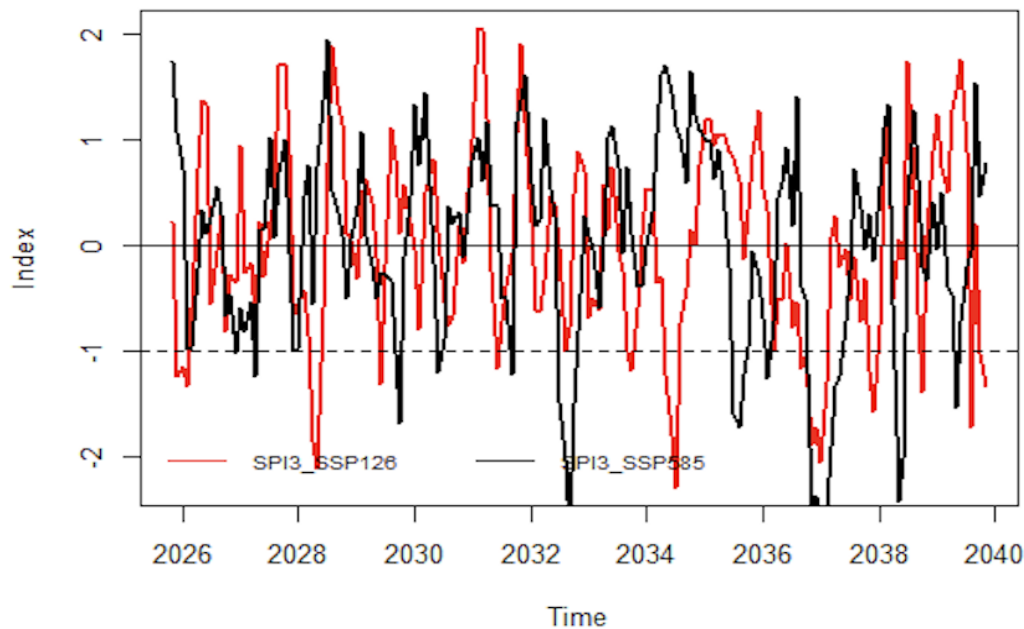


Figure 7. Temporal trend of SPI-3 under SSP126 and SSP585 scenarios

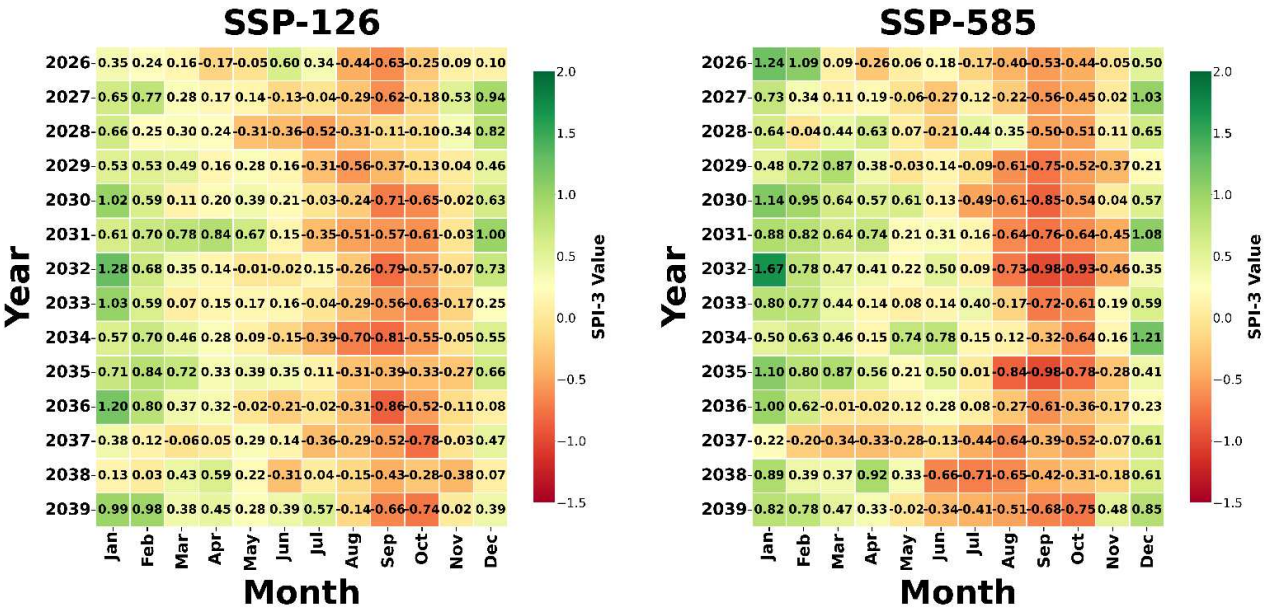


Figure 8. Temporal (annual-monthly) distribution of SPI-3 under SSP126 and SSP585 scenarios

SPI-6 drought forecasting

Based on the data from Figures 9 and 10, the mean SPI-6 under the optimistic SSP1-2.6 scenario is 0.186, while under the pessimistic SSP5-8.5 scenario, it is 0.193. Both values indicate normal climatic conditions with a tendency toward wetter conditions. These values have increased compared to the 3-month period, reflecting the positive effect of precipitation accumulation over longer time scales. The range of variation under SSP1-2.6 spans from -0.593 to +1.125, whereas under SSP5-8.5, it ranges from -0.879 to +1.388, indicating a wider fluctuation range in the pessimistic scenario. The differences of 0.286 units in the minimum and 0.263 units in the maximum demonstrate that the pessimistic scenario results in more intense extreme events on both the dry and wet ends. The standard deviation under SSP1-2.6 is 0.367, compared to 0.478 under SSP5-8.5, with a difference of 0.111 units, indicating greater variability and higher climatic instability in the pessimistic scenario. Under the SSP126 scenario, out of 268 months studied, 102 months (38.1%) exhibited negative SPI values, indicating drought conditions, while 166 months (61.9%) showed positive or zero SPI values, corresponding to normal to wet conditions. Under the SSP585 scenario, 88 months (32.8%) experienced drought, and 180 months (67.2%) had normal or wet conditions. This difference of 5.3 percentage points reflects a notable reduction in drought occurrence in the pessimistic scenario compared to the optimistic one. In other words, with the increased variability under SSP585, more intense wet events have become more frequent, and the number of dry months has decreased substantially. Additionally, comparison with the 3-month aggregation period shows that drought percentages in both scenarios have declined (from approximately 42% to 38% and 33%, respectively), indicating improved precipitation conditions with longer aggregation periods. The analysis of different SPI classes reveals that, in both scenarios, drought occurs only in the mild category (SPI between 0 and -1). No cases of moderate drought (SPI between -1 and -1.5), severe drought (SPI between -1.5 and -2), or extreme drought (SPI less than -2) are observed. Notably, the Karkheh Hydrosystem, over the six-month period and under both climate scenarios, will not be affected by severe droughts; all droughts will be mild and manageable. Under SSP126, 38.1% of months experienced mild drought, while 61.9% were normal to wet. Under SSP585, 32.8% of months experienced mild drought, and 67.2% were normal to wet, indicating improved conditions even in the more pessimistic scenario. Under SSP1-2.6, the highest positive SPI value occurred in April 2031, reaching +1.125, while the lowest negative SPI value was recorded in September 2034 at -0.593. Under SSP5-8.5, the highest positive SPI value occurred in March 2035, with a value of +1.388, and the lowest negative SPI value occurred in November 2032, at -0.879. These values indicate a more intense wet event in the pessimistic scenario (an increase of 0.263 units) and a more severe drought (an increase of 0.286 units) compared to the optimistic scenario. Notably, in both scenarios, wet periods predominantly occur in spring and winter, whereas drought periods mainly occur in summer and autumn. Under SSP5-8.5, the years 2031 to 2035 experience a relatively prolonged wet period, with SPI values exceeding 1 in several months; this period is more intense than under SSP1-2.6, which has a maximum SPI of 1.125. Additionally, under SSP1-2.6, the years 2033 to 2034 experience a mild drought period, with negative SPI values around -0.5. Annual data analysis

reveals that, in both scenarios, the years 2031 and 2035 exhibited the highest positive SPI values (indicating wet conditions), while the years 2032 and 2036 showed the lowest negative SPI values (indicating drought conditions). Under SSP126, 2031 had the wettest conditions with a mean SPI of approximately 0.45, and 2034 was the driest year with a mean SPI of about -0.05. Under SSP585, 2035 was the wettest year with a mean SPI of around 0.55, and 2032 was the driest with a mean SPI near -0.10. This pattern suggests that the pessimistic scenario (SSP585), characterized by increased intensity of wet events in 2035, experiences wetter conditions overall, whereas the optimistic scenario (SSP126) exhibits relatively more balanced conditions. The overall trend in both scenarios indicates a gradual increase in SPI from 2026 to 2039, reflecting improving precipitation conditions throughout the study period (Figures 9).

Based on a detailed analysis of SPI-6 data, the Karkheh Hydrosystem is not expected to experience severe droughts over the six-month period; all droughts are projected to be mild. The drought occurrence is approximately 38% under SSP1-2.6 and about 33% under SSP5-8.5, indicating a reduction in drought frequency compared to the three-month period. Although the pessimistic SSP5-8.5 scenario involves greater fluctuations and more intense wet events, it significantly reduces the number of dry months and may create more favorable conditions for agriculture and drinking water supply. However, it also increases the risk of floods and extreme precipitation events. Conversely, the optimistic SSP1-2.6 scenario, characterized by lower fluctuations and more dry months, entails a higher likelihood of recurrent droughts and prolonged water stress. Since approximately 62% to 67% of months exhibit normal to wet conditions, there is a favorable opportunity for water storage during wet periods and effective consumption management during dry periods. Furthermore, the significant reduction in drought occurrence over the six-month period compared to the three-month period suggests that using the SPI-6 index for medium-term water resource planning is more efficient, as it filters out short-term fluctuations and provides a more realistic representation of climatic conditions. Planning for both types of extreme events floods and droughts simultaneously is essential. The adoption of adaptive strategies and continuous monitoring of drought indices is recommended to mitigate risks associated with climate change.

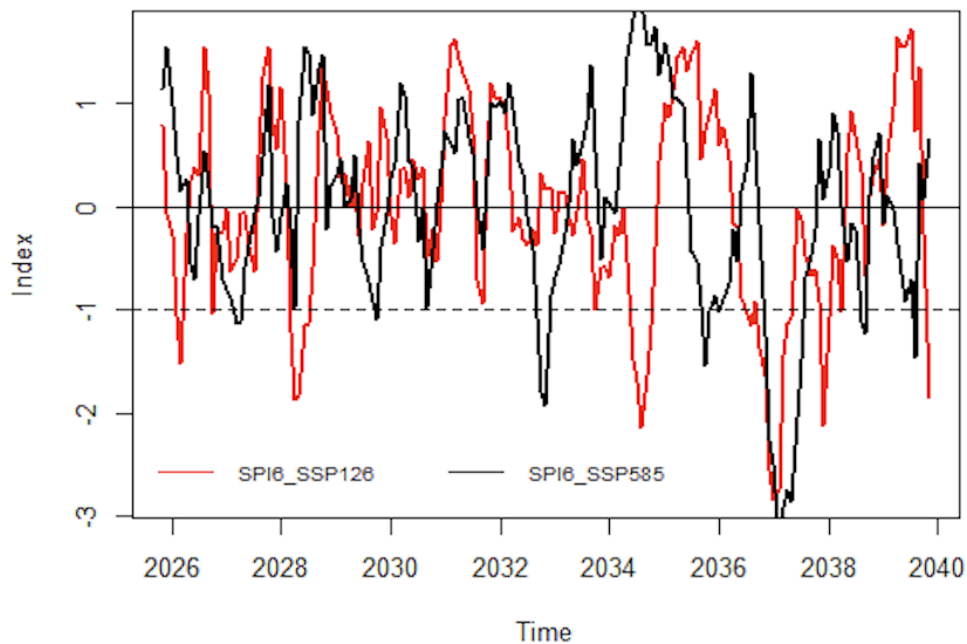


Figure 9. Temporal trend of SPI-6 under SSP126 and SSP585 scenarios

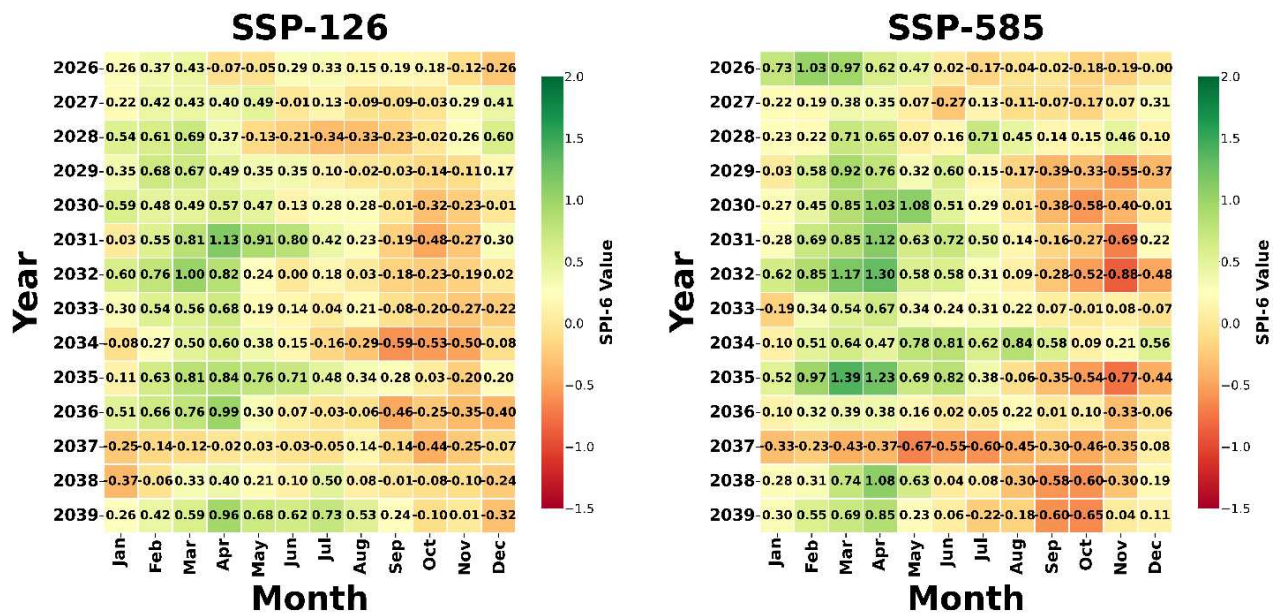


Figure 10. Temporal (annual-monthly) distribution of SPI-6 under SSP126 and SSP585 scenarios

SPI-9 drought forecasting

At a general glance, the trend of drought variations for SPI-9 is presented in Figure 11. The mean SPI-9 under the optimistic SSP1-2.6 scenario is 0.363, while under the pessimistic SSP5-8.5 scenario, it is 0.370. This represents a considerable increase compared to the 3- and 6-month periods and indicates wetter conditions in the Karkheh Hydrosystem over longer time scales. This

increase in the mean suggests that the accumulation of precipitation over nine months has amplified the positive effects of seasonal rainfall, shifting normal conditions toward mild wetness. The difference of 0.007 units between the two scenarios remains negligible; however, the range of variation under SSP1-2.6 spans from -0.725 to +1.679, whereas under SSP5-8.5, it ranges from -1.124 to +1.951. This indicates a notable expansion of the fluctuation range in the pessimistic scenario. The differences of 0.399 units in the minimum and 0.272 units in the maximum demonstrate that the pessimistic scenario brings more intense extreme events on both the dry and wet sides. The standard deviation under SSP1-2.6 is 0.423, compared to 0.588 under SSP5-8.5, with a difference of 0.165 units, indicating much greater variability and higher climatic instability in the pessimistic scenario compared to the shorter time scales (Figure 12). Percentages reveals that under the SSP126 scenario, out of 268 months studied, 54 months (20.2%) exhibited negative SPI values indicative of drought conditions, while 214 months (79.8%) showed positive or zero SPI values, representing normal to wet conditions. In contrast, under the SSP585 scenario, 68 months (25.6%) experienced drought, and 200 months (74.4%) had normal or wet conditions. This 5.4 percentage point increase indicates a significant rise in drought occurrence under the pessimistic scenario compared to the optimistic one, which contrasts with the trends observed over the 3- and 6-month periods. In other words, over the 9-month scale, the pessimistic scenario with increased drought intensity during certain periods has led to a higher number of dry months. Comparisons with shorter time scales show that drought percentages in both scenarios have decreased sharply (from approximately 42% in SPI-3 to about 20–25% in SPI-9), reflecting a substantial improvement in precipitation conditions with longer aggregation periods. The analysis of different SPI classes reveals that under the SSP126 scenario, all droughts are classified as mild (SPI between 0 and -1), with no occurrences of moderate or severe drought. In contrast, under the SSP585 scenario, in addition to mild droughts (24.4%), there were 2 months (1.2%) of moderate drought (SPI between -1 and -1.5), indicating an intensification of drought conditions in the pessimistic scenario. Notably, over the 9-month period, the Karkheh Hydrosystem under the optimistic scenario is completely free from moderate drought, whereas under the pessimistic scenario, low-intensity moderate drought does occur. Specifically, under SSP126, 20.2% of months experienced mild drought and 79.8% were normal to wet; under SSP585, 24.4% experienced mild drought, 1.2% moderate drought, and 74.4% were normal to wet. Under SSP1-2.6, the highest positive SPI value occurred in July 2039, reaching +1.679, while the lowest negative SPI value was recorded in March 2037 at -0.725. Under SSP5-8.5, the highest positive SPI value occurred in June 2035, with a value of +1.951, and the lowest negative SPI value occurred in August 2037, at -1.124. These values indicate a more intense wet event in the pessimistic scenario (an increase of 0.272 units) and a more severe drought (an increase of 0.399 units) compared to the optimistic scenario. Notably, under SSP5-8.5, the years 2035 to 2039 experience a very intense wet period, with SPI values exceeding 1.5 in several months (including June 2035 with an SPI of 1.95 and July 2039 with an SPI of 1.68), whereas under SSP1-2.6, this period exhibits lower intensity. Additionally, in both scenarios, the years 2036 and 2037 experience a mild to moderate drought period, with intensity reaching -1.12 under SSP5-8.5,

621 compared to a limit of -0.72 under SSP1-2.6 (Figure 12). Annual analysis of the data reveals that,
622 in both scenarios, the years 2035 and 2039 exhibited the highest positive SPI values (indicating
623 wet conditions), while the years 2036 and 2037 showed the lowest negative SPI values (indicating
624 drought conditions). Under SSP126, 2039 was the wettest year with a mean SPI of approximately
625 0.70, and 2037 was the driest year with a mean SPI of about -0.10. Under SSP585, 2035 was the
626 wettest year with a mean SPI of around 0.80, and 2037 was the driest year with a mean SPI of
627 approximately -0.30. This pattern suggests that the pessimistic scenario experiences more intense
628 wet events during 2035–2039, resulting in wetter conditions overall; however, the drought in 2037
629 is also more severe. The overall trend in both scenarios indicates a gradual increase in SPI from
630 2026 to 2039, reflecting a significant improvement in precipitation conditions over the study
631 period, with this improvement being more pronounced under the pessimistic scenario.

632 Based on a detailed analysis of SPI-9 data, the Karkheh Hydrosystem over the nine-month period
633 is predominantly characterized by normal to wet conditions, with droughts occurring mainly as
634 mild events. The drought percentage under SSP1-2.6 is approximately 20%, while under SSP5-
635 8.5 it is about 26%, indicating a significant reduction in drought frequency compared to the 3- and
636 6-month periods. However, in the pessimistic scenario, two months of moderate drought occur,
637 suggesting an increased risk of more severe drought over longer time scales. Despite greater
638 fluctuations and more intense wet events, the pessimistic SSP5-8.5 scenario actually increases the
639 number of dry months and introduces moderate drought, potentially posing greater challenges for
640 agricultural production and drinking water supply. In contrast, the optimistic SSP1-2.6 scenario,
641 characterized by lower fluctuations and only mild drought, offers more stable conditions for water
642 resource management. Given that approximately 75% to 80% of months experience normal to wet
643 conditions, there is a favorable opportunity for water storage during wet periods and effective
644 consumption management during dry periods. Moreover, due to the significant reduction in
645 drought severity over the nine-month period compared to shorter time scales, using the SPI-9 index
646 for long-term water resource planning is the most effective approach. This index effectively filters
647 out seasonal fluctuations and provides a more accurate representation of climatic trends. Planning
648 for both types of extreme events floods and droughts simultaneously is essential. Given the
649 emergence of moderate drought conditions in the pessimistic scenario, special attention to drought
650 management during critical periods is strongly recommended.

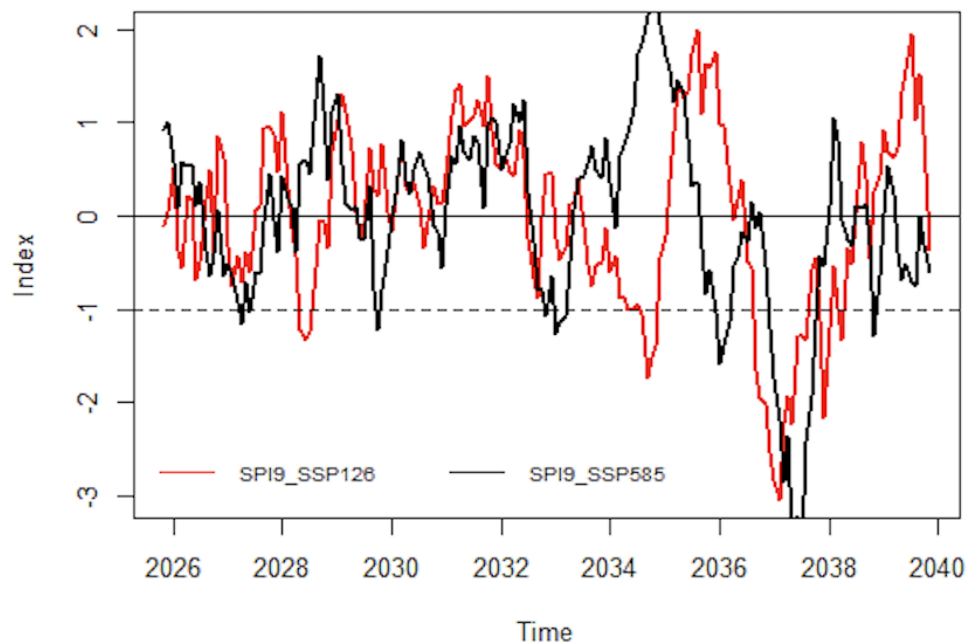


Figure 11. Temporal trend of SPI-9 under SSP126 and SSP585 scenarios

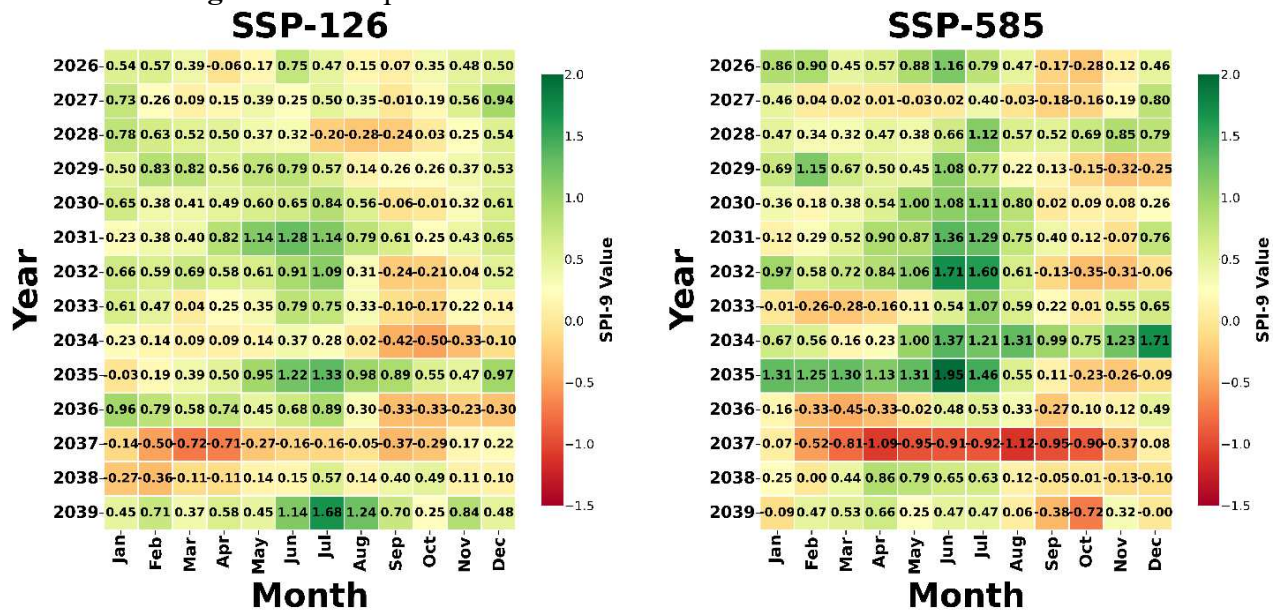


Figure 12. Temporal (annual-monthly) distribution of SPI-9 under SSP126 and SSP585 scenarios

SPI-12 drought forecasting

The mean SPI-12 under the optimistic SSP1-2.6 scenario is 0.597, while under the pessimistic SSP5-8.5 scenario it is 0.617. This represents a considerable increase compared to shorter time scales (3, 6, and 9 months) and is the highest mean among all periods. This increase indicates that the Karkheh Hydrosystem experiences wetter conditions over longer time scales, as the positive effects of seasonal precipitation accumulate over the course of a year (Figure 13). The difference

of 0.020 units between the two scenarios suggests slightly wetter conditions in the pessimistic scenario, although this difference is negligible. However, the range of variation under SSP1-2.6 spans from -0.934 to +1.891, while under SSP5-8.5 it ranges from -1.791 to +2.778, indicating a substantial expansion of the fluctuation range in the pessimistic scenario. The differences of 0.857 units in the minimum and 0.887 units in the maximum represent the largest disparities among all time scales, showing that over the 12-month period, the pessimistic scenario results in much more intense extreme events on both the dry and wet ends. The standard deviation under SSP1-2.6 is 0.558, compared to 0.749 under SSP5-8.5, with a difference of 0.191 units. This indicates the highest variability among all periods and reflects severe climatic instability in the pessimistic scenario (Figure 14). Under the SSP126 scenario, out of 268 months studied, 38 months (14.3%) exhibited negative SPI values, indicating drought conditions, while 230 months (85.7%) showed positive or zero SPI values, corresponding to normal to wet conditions. Under the SSP585 scenario, 35 months (13.1%) experienced drought, and 233 months (86.9%) had normal or wet conditions. This difference of 1.2 percentage points suggests a slight reduction in drought occurrence in the pessimistic scenario compared to the optimistic one, consistent with the 3- and 6-month periods but differing from the 9-month period. Comparison with previous time scales reveals that drought percentages in both scenarios have reached their lowest levels (approximately 42% in SPI-3 to about 13–14% in SPI-12), reflecting a significant improvement in precipitation conditions with longer aggregation periods (Figure 14). An examination of different SPI classes reveals fundamental differences between the two scenarios. Under the SSP126 scenario, all droughts fall within the mild category (SPI between 0 and -1), with 14.3% of months experiencing mild drought and 85.7% classified as normal to wet. No cases of moderate, severe, or extreme drought are observed. In contrast, under the SSP585 scenario, the distribution is as follows: 86.9% normal to wet, 8.9% mild drought, 3.6% moderate drought (SPI between -1 and -1.5), and 0.6% severe drought (SPI between -1.5 and -2). This distribution indicates that over the 12-month period, the pessimistic scenario not only includes moderate drought (6 months) but also severe drought (1 month), reflecting a significant increase in the risk of severe droughts over longer time scales. Meanwhile, the optimistic scenario remains entirely free of moderate and severe drought (Figure 14). Examination of the SPI-12 time series reveals distinct patterns and long-term fluctuations. Under SSP1-2.6, the highest positive SPI value occurred in December 2031, reaching +1.891, while the lowest negative SPI value was recorded in July 2037 at -0.934. Under SSP5-8.5, the highest positive SPI value occurred in March 2035, with a value of +2.778, and the lowest negative SPI value was in July 2037, at -1.791. These values indicate a significantly more intense wet event in the pessimistic scenario (an increase of 0.887 units) and a more severe drought (an increase of 0.857 units) compared to the optimistic scenario. Notably, under SSP5-8.5, the years 2034 to 2036 experience an extremely severe wet period, with SPI values exceeding 2 in several months (including March 2035 with an SPI of 2.78 and December 2034 with an SPI of 2.49), whereas under SSP1-2.6, this period shows a maximum SPI of 1.89. Additionally, in both scenarios, the years 2037 and 2038 experience a relatively severe drought period, with intensity reaching -1.79 under SSP5-8.5 (severe drought) and limited to -0.93 under SSP1-2.6 (mild drought) (Figure 14).

Annual data analysis reveals that, in both scenarios, the years 2031 and 2035 exhibited the highest positive SPI values (indicating wet conditions), while the years 2037 and 2038 showed the lowest negative SPI values (indicating drought conditions). Under SSP126, 2031 had the wettest conditions with a mean SPI of approximately 0.90, and 2037 was the driest year with a mean SPI of about -0.30. Under SSP585, 2035 was the wettest year with a mean SPI of around 1.40, and 2037 was the driest with a mean SPI near -0.70. This pattern suggests that the pessimistic scenario, characterized by increased wet event intensity during 2034–2036, experiences significantly wetter conditions; however, the drought in 2037 is also considerably more severe, reaching the severe drought category. The overall trend in both scenarios indicates a gradual increase in SPI from 2026 to 2039, reflecting a substantial improvement in precipitation conditions over the study period. Nevertheless, this trend is accompanied by more intense fluctuations in the pessimistic scenario (Figure 14).

Final Conclusion and Management Implications: Based on a detailed analysis of SPI-12 data, the Karkheh Hydrosystem over the twelve-month period is predominantly characterized by normal to wet conditions. In the optimistic scenario, droughts are only mild, whereas in the pessimistic scenario, moderate droughts (lasting six months) and severe droughts (lasting one month) also occur. The drought percentage in both scenarios has reached its lowest level (approximately 13–14%), indicating a significant improvement in precipitation conditions over longer time scales. The pessimistic SSP585 scenario, despite exhibiting intense fluctuations and extreme wet events (SPI above 2), slightly reduces the number of dry months but introduces moderate and severe droughts, which is highly significant from a management perspective. This finding suggests that climate change under the pessimistic scenario not only dramatically increases the intensity of wet periods but also raises the risk of severe droughts. In contrast, the optimistic SSP126 scenario, characterized by lower fluctuations and only mild droughts, offers more stable conditions for water resource management and minimizes the risk of extreme events. Given that approximately 85% to 87% of months experience normal to wet conditions, there is a favorable opportunity for water storage during wet periods and consumption management during dry periods. The use of the SPI-12 index for long-term and strategic water resource planning is considered the most efficient approach, as it eliminates seasonal fluctuations and provides a realistic picture of climatic trends. Considering the emergence of severe droughts in the pessimistic scenario, special attention to drought management during critical periods and the design of early warning systems to cope with extreme events are essential. Furthermore, planning for both types of extreme events extreme floods and severe droughts simultaneously, while accounting for existing uncertainties, is recommended to reduce the vulnerability of the Karkheh Hydrosystem to climate change.

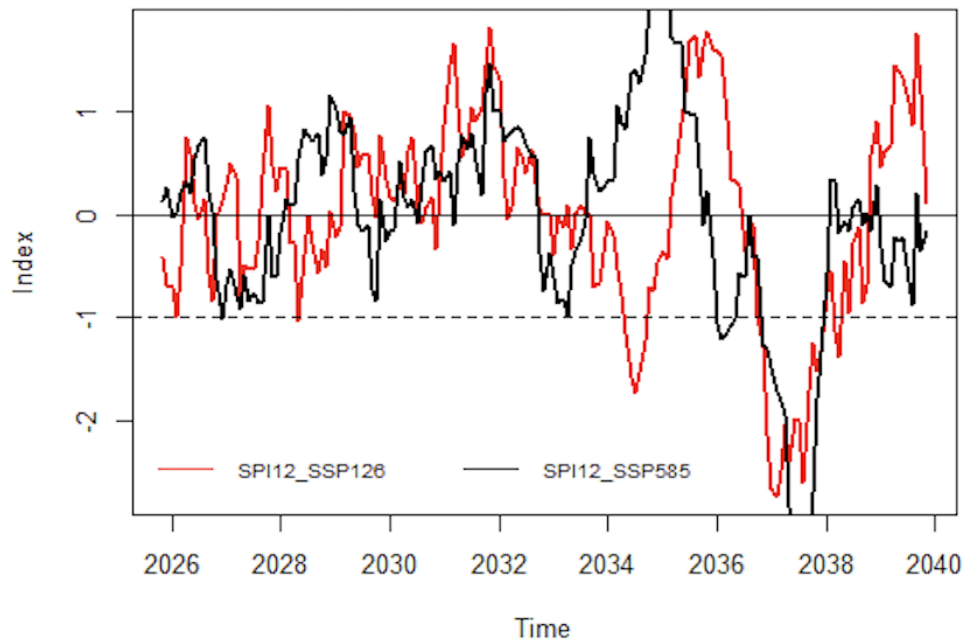


Figure 13. Temporal trend of SPI-12 under SSP126 and SSP585 scenarios

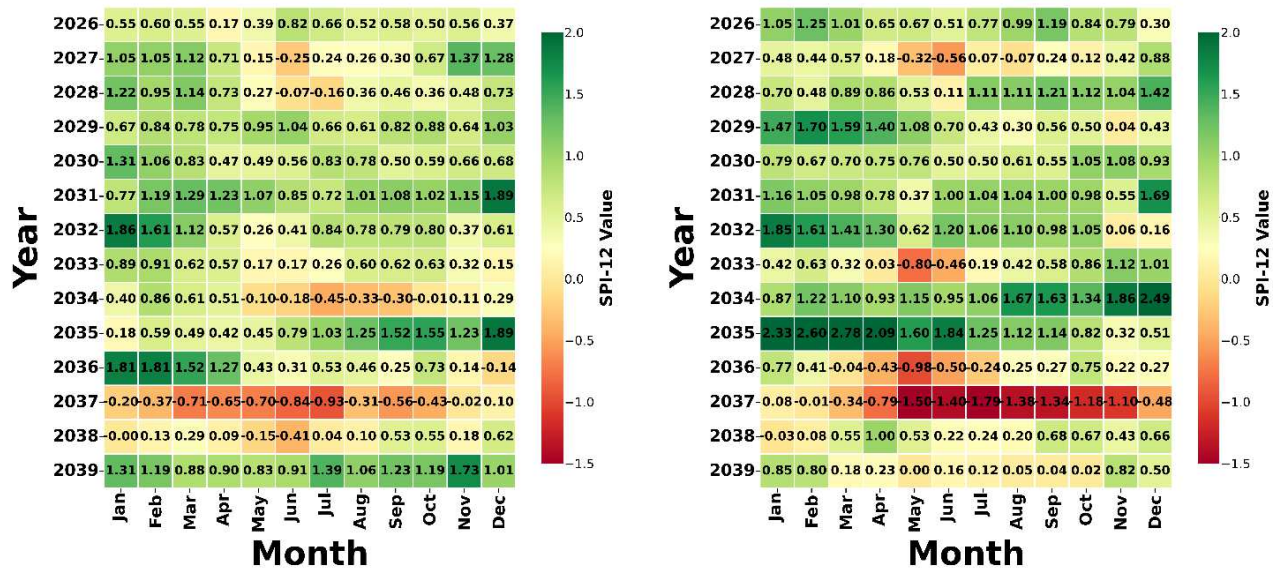


Figure 14. Temporal (annual-monthly) distribution of SPI-12 under SSP126 and SSP585 scenarios

Conclusion

Accurate drought forecasting is critically important as one of the fundamental challenges in water resources management, especially in semi-arid regions such as the Karkheh Hydrosystem. This study aimed to evaluate the performance of five machine learning models Gaussian Process Regression (GPR), XGBoost, Support Vector Machine (SVM), Multilayer Perceptron (MLP), and Random Forest and to analyze drought forecasts under two climate scenarios, SSP126 and SSP585,

for the period 2026–2039. The results indicated that the GPR model, which provided the highest accuracy and lowest error across all time scales, was the best-performing model. Additionally, the 6-month time scale, which yielded the highest accuracy across all models, was identified as the optimal scale for drought forecasting. Analysis of the Standardized Precipitation Index (SPI) forecasts revealed that as the time scale increases, the percentage of drought decreases and conditions tend toward wetter periods. However, the intensity of extreme events under the pessimistic SSP585 scenario is significantly greater than under the optimistic SSP126 scenario. For example, at the 12-month scale, the SSP585 scenario leads to severe drought, whereas the SSP126 scenario experiences only mild drought. Overall, the optimistic SSP126 scenario, characterized by lower fluctuations and mild drought, provides more stable conditions for water resources management. In contrast, the pessimistic SSP585 scenario, with an increase in extreme events, necessitates integrated planning to address both floods and droughts simultaneously. Based on these findings, the use of the GPR model and the 6-month time scale is recommended as the primary drought forecasting tool for medium-term water resources planning in the Karkheh Hydrosystem. Designing an early drought warning system based on this model can facilitate timely notifications to managers and stakeholders. Furthermore, developing water consumption management programs during dry periods and enhancing water storage during wet periods guided by SPI forecasts and with particular attention to the pessimistic scenario in long-term planning is essential to mitigate severe droughts and sudden floods. For future research, it is suggested to incorporate complementary climatic variables such as temperature, evapotranspiration, soil moisture, and runoff alongside precipitation to improve forecasting accuracy. Employing ensemble approaches and multi-modeling techniques can help reduce uncertainty. Additionally, the use of deep neural networks and transfer learning is recommended to enhance long-term forecasts. Investigating the impacts of land-use changes and population growth on water demand and drought intensification, as well as evaluating the performance of the GPR model in other watersheds with different climates to assess the generalizability of the results, are also advised. Moreover, examining the influence of large-scale climatic phenomena such as the El Niño–Southern Oscillation (ENSO) and the North Atlantic Oscillation (NAO) on drought in the Karkheh Hydrosystem, along with conducting socio-economic studies to assess drought impacts and evaluate the cost-benefit of management measures, can contribute to improving drought mitigation strategies. Implementing these recommendations will significantly enhance sustainable water resources management in the Karkheh Hydrosystem and reduce vulnerability to climate change.

Limitations

Despite the valuable findings of this study, several limitations should be considered. One of the most significant limitations is the exclusive use of precipitation data to calculate the SPI index. Complementary climatic variables such as temperature, evapotranspiration, and soil moisture also significantly influence the severity and duration of droughts. Their exclusion from the modeling results in an incomplete representation of climatic conditions. Additionally, the limited number of synoptic stations (only three) in the Karkheh Hydrosystem does not adequately capture the spatial variability of precipitation, making it uncertain to generalize the results across the entire basin.

Moreover, although four CMIP6 models were used, incorporating a larger number of climate models or employing multi-model ensemble approaches could have reduced the uncertainty, as each climate model has distinct strengths and weaknesses. Despite these limitations, the study's results provide a valuable foundation for water resource management and drought mitigation planning in the Karkheh Hydrosystem and offer useful guidance for future research in this field.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data supporting the findings of this study are available upon request. To obtain access to the data, please contact the corresponding author.

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CRediT authorship contribution statement

MN.J: Writing–Original Draft, Writing-Review and Editing, Conceptualization, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Resources, Project administration. S.A: Writing-Review and Editing, Methodology, Software, Validation, Formal analysis, Resources, Formal analysis. B.B: Writing-Review and Editing, Formal Analysis, Investigation. Z.A: Writing-Review and Editing, Formal Analysis, Investigation. M.K: Formal Analysis, Investigation, Project Administration.

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