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Statistical downscaling of climatic parameters using the XGBoost model: A study on temperature and relative humidity in arid regions

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statistical downscaling, XGBoost model, deep learning models, climate change

Abstract

Climate change and its effects on water resources and agriculture have made the accurate prediction of climatic parameters at the local scale even more necessary. General Circulation Models, due to their low spatial resolution, require downscaling for regional analyses. This study investigates the performance of the XGBoost machine learning model in the statistically downscaling of monthly mean temperature and relative humidity at the synoptic station of Qaen during the period from 1991 to 2015. In this research, the output of the ECMWF-ERA5 model, after correcting structural errors using the Chunk Mapping method,was used as input for the XGBoost model. The model's performance was evaluated using statistical criteria KGE, NSE, NRMSE, and R^2 in two phases: training and testing. The results indicated that the XGBoost model exhibited very good performance in downscaling mean temperature (with R^2 and NSE values close to one and low NRMSE in both phases) and acceptable performance for relative humidity. The model's stability in temperature simulation was evident, although there is a need for improvement in the model training process for relative humidity. The analysis of the distribution of simulated data showed that the model faces limitations in reproducing extreme temperature values (less than -10 degrees Celsius) and very high relative humidity (more than 80 percent), showing a greater tendency to simulate median temperature values. These findings are consistent with similar research in other parts of the world and confirm the high potential of XGBoost as an efficient tool in climate change studies, especially in arid regions.

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Introduction

Climate change is considered one of the most significant global challenges of the twenty-first century, with its effects on water resources, agriculture, and human settlements becoming increasingly evident (IPCC, 2021). To predict the future state of the climate, General Circulation Models (GCMs) are commonly used and reliable tools that provide climate information on a global scale. However, one of the main limitations of these models is their low spatial resolution, which leads to insufficient accuracy at regional or local scales, particularly for hydrological analyses or water resource planning. (Maraun et al., 2019; Chen et al., 2020; Fouladi Nasrabad et al., 2024).

To overcome this limitation, downscaling techniques are used. Downscaling is generally divided into two categories: dynamic and statistical. The dynamic method is based on high-resolution regional climate models, while the statistical method focuses on the relationships between large-scale variables and local variables (Trigila et al., 2015; Gutiérrez et al., 2019).

In this context, Statistical downscaling (SD) has been widely used in climate studies due to its lower computational resource requirements and high flexibility (Anandhi et al., 2018; Maraun et al., 2019). The fundamental assumption in SD is that the statistical relationships between GCM predictors and local variables remain stable in the future. Although this assumption may be violated under conditions of severe climate change, SD remains a valuable tool in producing local climate data (Maraun & Widmann, 2018).

Statistical techniques range from simple methods like linear regression to more complex methods such as artificial neural networks (ANN), support vector machines (SVM), and random forests (RF) (Okkan & Kirdemir, 2018; Nourani et al., 2019). In the past decade, with the expansion of data science, machine learning (ML) models have gained a special position in downscaling. These models are capable of modeling nonlinear and complex relationships between climatic variables and can outperform traditional methods (Reichstein et al., 2019; Giri et al., 2021).

Extreme Gradient Boosting (XGBoost) is a machine learning algorithm based on gradient boosting that sequentially improves the model's performance using decision trees as base learners. This algorithm, introduced by (Chen and Guestrin 2016), provides scalability for large datasets with features such as sparsity-aware algorithms for sparse data and weighted quantile sketching for approximate tree learning. XGBoost supports parallel processing to accelerate computations, regularization techniques to reduce overfitting, and automatic handling of missing data, making it suitable for complex tasks such as regression, classification, and ranking. In the field of water resources engineering, (Niazkar et al., 2024) reported that XGBoost outperformed traditional models in 74% of the 72 reviewed studies between 2018 and 2023. However, there are limitations such as dependence on the quality and quantity of data, inability to provide explicit mathematical equations due to its tree-based structure, and the need for fine-tuning of hyperparameters.

Downscaling climatic parameters to improve the spatial resolution of satellite data and numerical prediction models is essential, especially in hydrological applications and water resource management. XGBoost has increasingly been used in this field due to its ability to model complex nonlinear relationships. The systematic review by (Niazkar et al., 2024) examines the applications of XGBoost in water resources engineering and highlights its use in downscaling hydrometeorological variables, such as water storage, precipitation, and soil moisture.

One of the prominent studies is the research by (Ali et al., 2023), which used XGBoost to downscale data on groundwater storage anomaly (TWSA) from the Gravity Recovery and Climate Experiment (GRACE) from a resolution of 1 degree to 0.25 degrees in the Indus Basin Irrigation System (IBIS). This study showed that XGBoost outperformed artificial neural networks (ANN), achieving metrics such as Nash-Sutcliffe efficiency (NSE = 0.99), Pearson correlation (R^2 = 0.99), root mean square error (RMSE = 5.22 mm), and mean absolute error (MAE = 2.75 mm). The downscaled data was used to compute the Water Storage Deficit Index (WSDI) and Water Storage Deficit (WSD), enabling precise identification of drought periods between 2010 and 2016.

Similarly, (Dong et al., 2023) used XGBoost to correct biases in numerical weather predictions (NWP) of the second version of the Global Ensemble Forecast System (GEFS V2). This study, conducted in seven different climatic regions of China, showed that XGBoost improves short-term rainfall predictions, especially in the winter season, and outperforms traditional methods such as empirical cumulative distribution function matching (EDCDFm). This method addressed the deficiencies of the NWP model by using multi-factor correction of deviations, enhancing the accuracy of predictions.

In addition, (Zhang and colleagues, 2023) used XGBoost for downscaling soil moisture data derived from satellites using the GNSS-R technique in the southern United States. This study improved the soil moisture data from SMAP (36 kilometers) to a resolution of 3 kilometers, providing valuable information for agricultural and hydrological applications at a local level. The study area, characterized by a humid subtropical climate and an annual rainfall of about 834.45 millimeters, benefited from this high-resolution data for better water resource management.

These studies demonstrate the adaptability of XGBoost in downscaling climatic parameters. The ability of this algorithm to manage nonlinear relationships and complex data has made it a powerful tool for generating high-resolution climatic data that is essential for water resource planning, agricultural management, and climate change adaptation strategies. However, the success of these applications depends on the quality of input data and the appropriate selection of independent variables, such as elevation, land cover type, and climatic data.

In the field of Iran's climate, numerous studies have focused on downscaling precipitation and temperature using machine learning algorithms, but they have often been limited to older methods such as ANN and SVM (Zare et al., 2021; Ghahreman et al., 2022; Daneshkhah et al., 2020). A review of available resources indicates that the application of XGBoost for downscaling climatic parameters in different climatic regions of Iran (arid and humid) has not yet been widely conducted and is considered a significant research gap (Parsa et al., 2023).

Based on this, the present study aims to fill this gap by examining the performance of the XGBoost model for downscaling climatic parameters of temperature and relative humidity, using the outputs of GCM models in an arid climate region. In this study, the performance of the XGBoost model in downscaling temperature and relative humidity parameters will be evaluated with a focus on statistical analyses, in order to accurately assess its capability in reproducing climatic variables.

Materials and Methods

Study Area

The synoptic station of Qaen is located in the watershed of the Shour River in Qaen. This watershed includes Qaenat County, covering an area of 2412/92 square kilometers, situated between 59 degrees 12 minutes to 59 degrees 14 minutes east longitude and 33 degrees 42 minutes to 33 degrees 45 minutes north latitude. Fig 1 shows the boundaries of the Shour River watershed of Qaen. This watershed has an average elevation of 1420 meters above sea level and an average long-term annual rainfall of 173 millimeters, characterized by a dry climate (AkbariMotlagh et al., 2016). The Shour River of Qaen is the largest river in Qaenat County, flowing into the Khaf salt marsh. Its length is 100 kilometers, with a source elevation of 1420 meters and a drainage elevation of 600 meters, and its overall course is towards the northeast. This river is formed by the confluence of the Koohe Baz and Shakhan rivers, located 200 kilometers southeast of Qaen. Fig 1 shows the location of the Qaen synoptic station in the watershed, and Table 1 presents the specifications of the Qaen synoptic station.

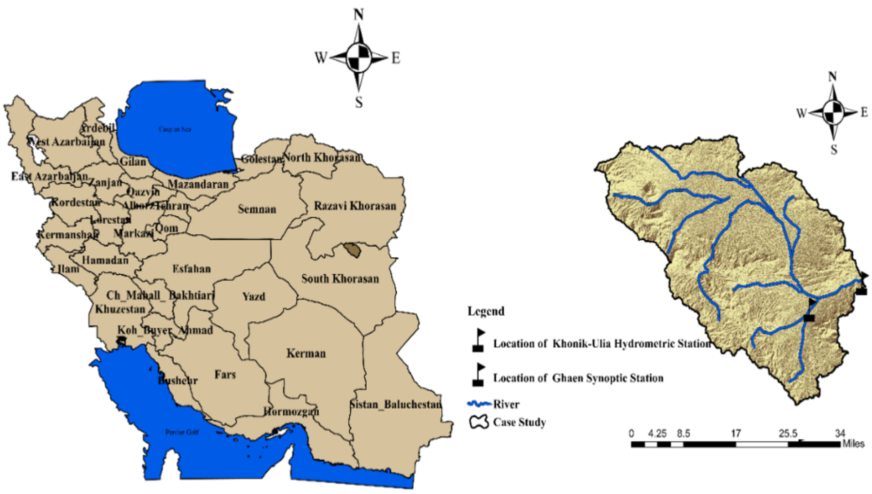


Fig 1. Study area

Table 1. Specifications of Ghaen synoptic station

Height meters	Utmx	Utmy	Longitude	latitude	Ghaen Synoptic Station
1446	702935	3734721	59-11-00	33-43-00	

Research Implementation Stages

This research was conducted with the aim of investigating the efficiency of machine learning models in downscaling climatic parameters of temperature and relative humidity on a daily scale at the synoptic station of Qaen. For extracting large-scale features, data from the ECMWF-ERA5 general circulation model was utilized. The model’s performance evaluation was carried out in two stages: training and testing, based on the Kling-Gupta Efficiency (KGE), Nash-Sutcliffe

Efficiency (NSE), Normalized Root Mean Square Error (NRMSE), and the coefficient of determination R^2. The packages xgboost, scikit-learn, and numpy were used for model implementation and data processing.

General Circulation Models of the Atmosphere

ECMWF-ERA5 serve as important tools for climate prediction and understanding global changes. The ECMWF-ERA5 model is one of the climate prediction models that provides large-scale data for downscaling precipitation. This model is commonly used in climate studies due to its availability and global coverage (Wang et al., 2021). The ECMWF-ERA5 data includes various parameters such as sea level pressure, temperature, relative humidity, and wind speed, which are used as inputs for downscaling models. These parameters are generally used as predictor variables in climatic downscaling models (Sheikh Rabei et al., 2021).In Table 2, the relevant information and specifications regarding 23 parameters of the ECMWF-ERA5 used in this research are provided.

XGBoost model

The Extreme Gradient Boosting (XGBoost) algorithm has been selected as an advanced machine learning model for the statistical downscale of precipitation. XGBoost is suitable for this study due to its ability to model complex nonlinear relationships and its high accuracy in spatiotemporal predictions (Chen, and Guestrin., 2016). XGBoost uses an ensemble of weak decision trees and achieves a strong model by gradually optimizing them. The mathematical relationships in XGBoost are based on the loss function and gradient optimization, which is expressed as follows:

$$L = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \quad (1)$$

In which $l(y_i, \hat{y}_i)$ is the loss function, $\hat{y}_i$ is the model's prediction, and $\Omega(f_k)$ is the cost of each tree. In this relationship, $l(y_i, \hat{y}_i)$ is typically represented by the squared error function, which $(y_i - \hat{y}_i)^2$. $\Omega(f_k)$ also includes two main components: $\gamma T + \frac{1}{2}\lambda||w||^2$,where γ is the cost for each node, T is the number of nodes, λ is the regularization coefficient, and w is the weight of each node (Chen & Guestrin, 2016).

Evaluation criteria

The KGE, NS, NRMSE, and R^2 criteria are widely used in hydrological studies to assess the accuracy of models. These criteria help us evaluate the accuracy of the model's predictions in comparison

Table 2. Specifications of 23 parameters of standardized ECMWF-ERA5 models

Number	Predictor	Description	Acronym Type	Level (hpa)
1	Mean sea level pressure	Mslp	Circulation	Surface
2	Wind speed	p1_f		1000
3	Zonal wind component	p1_u		1000
4	Meridional wind component	p1_v		1000
5	Relative vorticity of true wind	p1_z		1000
6	Divergence of true wind	p1_zh		1000
7	Air temperature at 2 m	temp	Temperature	Surface
8	Specific humidity	shum	Humidity	1000
9	Precipitation	prcp		Surface
10	Wind speed	p5_f	Circulation	500
11	Zonal wind component	p5_u		500
12	Meridional wind component	p5_v		500
13	Relative vorticity of true wind	p5_z		500
14	Divergence of true wind	p5_zh		500
15	Specific humidity	shum	Humidity	500
16	Geopotential	p500	Circulation	500
17	Wind speed	p8_f		850
18	Zonal wind component	p8_u		850
19	Meridional wind component	p8_v		850
20	Relative vorticity of true wind	p8_z		850
21	Divergence of true wind	p8_zh		850
22	Specific humidity	shum	Humidity	850
23	Geopotential	p850	Circulation	850

with observational data. Next, detailed explanations regarding each of these criteria will be provided.

KGE:

This metric is defined based on three components: scale error, distribution error, and delay error, and is calculated as follows:

$$KGE = 1 - \sqrt{(r-1)^2 + (\alpha-1)^2 + (\beta-1)^2} \tag{2}$$

In which r is the correlation coefficient, α is the ratio of variances, and β is the mean of the relative values (Gupta et al., 2009). The ideal value for KGE is close to 1.

NS:

This criterion is calculated as follows:

$$NS = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \tag{3}$$

where y_i are the observed data, $\hat{y}_i$ are the predicted data, and $\bar{y}$ is the mean of the observed data (Nash & Sutcliffe, 1970). The ideal value for NS is between 0 and 1, with values close to 1 indicating high accuracy of the model.

NRMSE:

This criterion is calculated as follows:

$$RMSE = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}}{\bar{O}} \tag{4}$$

where y_i are the observed data and $\hat{y}_i$ are the predicted data, $\bar{O}$ and is the mean of the observed data. (Willmott & Matsuura, 2005). The ideal value for NRMSE is close to 0.

R²:

This criterion is calculated as follows:

$$R^2 = \left(\frac{\sum_{i=1}^{n} (y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})}{\sqrt{\sum_{i=1}^{n} (y_i - \bar{y})^2 \sum_{i=1}^{n} (\hat{y}_i - \bar{\hat{y}})^2}} \right)^2 \tag{5}$$

where y_i represents the observed data, $\hat{y}_i$ represents the predicted data, $\bar{y}$ is the mean of the observed data, and $\hat{y}_i$ is the mean of the predicted data (Cohen et al., 2013). The ideal value for R^2 ranges from 0 to 1, with values close to 1 indicating high accuracy of the model.

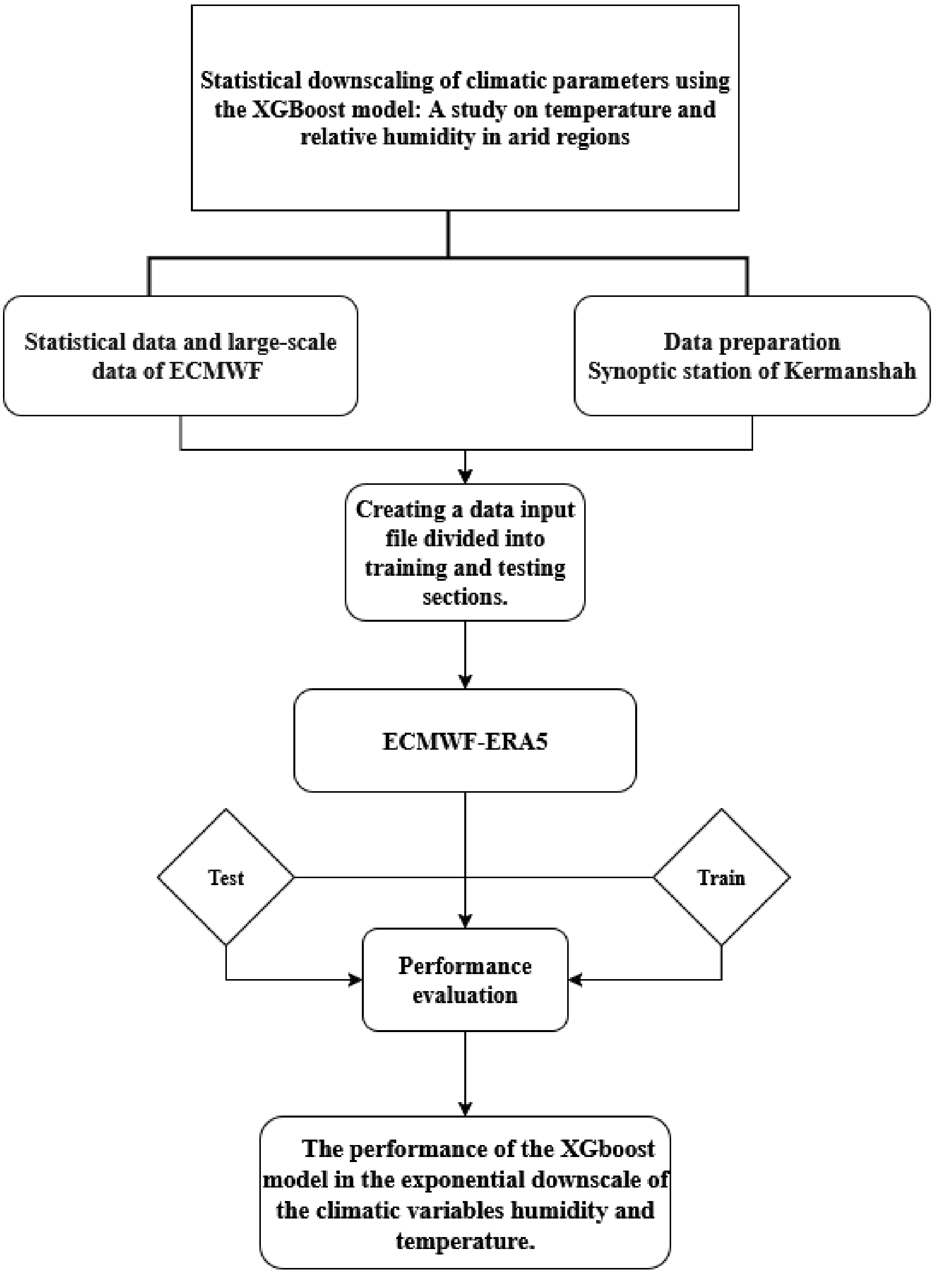


Fig2. Step diagram

Results and Discussion

In order to evaluate the performance of the XGBOOST model in the statistical downscale of the climatic parameters of relative humidity and mean temperature at the synoptic station of Qaen, first, the necessary observational data (relative humidity and monthly mean temperature of Qaen synoptic station) for the period from 1991 to 2015 were collected, and preprocessing operations were performed on it. Then, the ECMWF-ERA5 model data were downloaded from the website https://

climate-scenarios.canada.ca/ and the performance of the XGBOOST model was evaluated using each of the ECMWF-ERA5 models at the Qaen synoptic station using the evaluation criteria NRMSE, NS, R^2, and KGE in two parts: training and testing. It is worth mentioning that the observational data and 23 parameters of each ECMWF-ERA5 model were entered into a single Excel file and then divided into training and testing sections in a ratio of 70 to 30 in the code. Additionally, the parameters of the XGBOOST model were calibrated using the RandomizedSearchCV method and with the RMSE objective function. Table (3) shows the values of the evaluation criteria for the training and testing sections of the relative humidity and mean temperature parameters.

Table 3. values of the evaluation criteria in the training and testing section of relative humidity and mean temperature parameters

(Evaluation criteria)		(Temperature)		(Relative humidity)	
		Train	Test	Train	Test
Ghaen Synoptic	NRMSE	2.88	3.82	8.87	12.62
	R^2	0.98	0.97	0.90	0.88
	NS	0.97	0.95	0.81	0.67
	KGE	0.94	0.91	0.78	0.68

Analyzing the values of evaluation metrics from two perspectives, the percentage changes of the metrics in both training and testing sections, and examining the metric values in these two sections provide precise information and analyses. The examination of the percentage changes of the metrics indicates the stability and effective training of the model, while the evaluation of the metric values allows for judgment regarding the model's performance adequacy. Therefore, considering the above table, the small percentage changes in the evaluation metrics during training and testing indicate the stability and effective training of the model, and the very desirable values of the evaluation metrics signify the extraordinary performance of the XGBOOST model in the statistical downscale of the temperature parameter. The analysis of the percentage changes in the evaluation metrics in the statistical downscale of the humidity parameter indicates a decline in model performance in the testing section and a need for better model training. However, based on the evaluation metric values, it can be stated that since the values of the NS, R^2, and KGE evaluation metrics fall within an acceptable range, the results of the model in the statistical downscale are satisfactory.

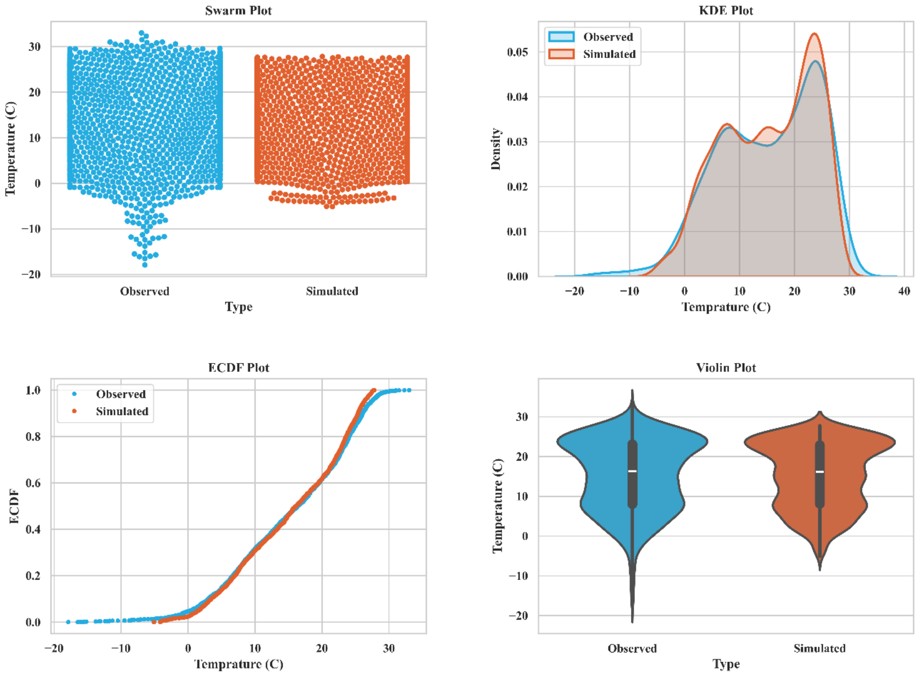


Fig 3. compares the distribution of observed and simulated temperature data using statistical charts (Swarm, KDE, ECDF, and Violin)

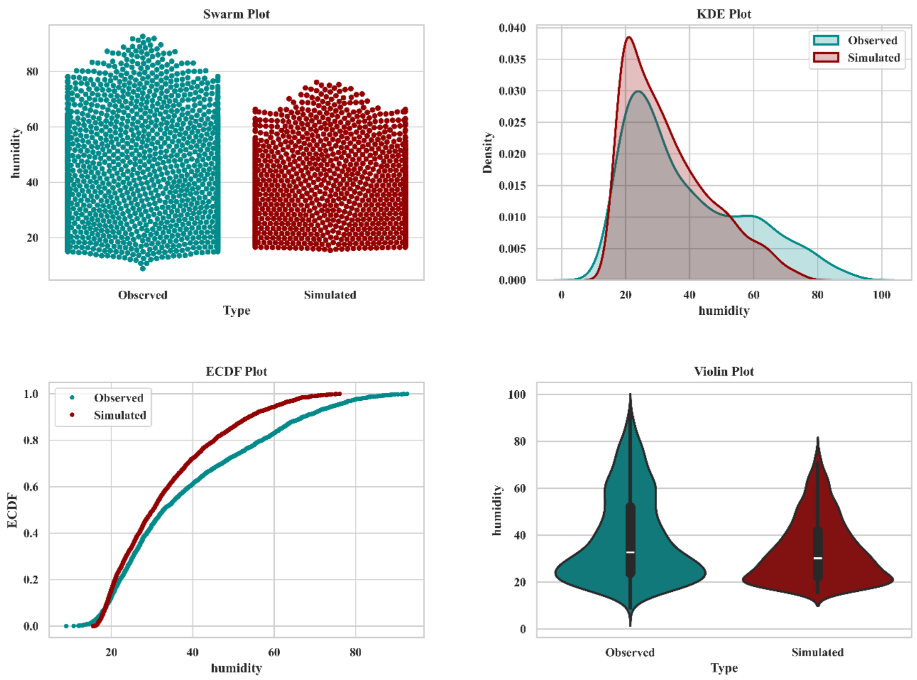


Fig 4. compares the distribution of observed and simulated relative humidity data using statistical charts (Swarm, KDE, ECDF, and Violin).

Review and analysis of the distribution of observed and simulated relative humidity and temperature data.

Comparison of temperature and relative humidity values between observed and simulated data (SWARM chart)

The Swarm Plot is a type of scatter plot used to display the distribution of classified data. In this plot, data points are arranged such that they do not overlap, making the structure of the distribution and the density of points clearly visible. In these plots, the data points related to the two categories of 'observational' and 'simulated' are displayed separately and without overlap. According to Figure 3 (temperature parameter), the spread of data in both groups is almost uniform. A notable point is the model's unwillingness to simulate values lower than -10 degrees Celsius. Comparing the relative humidity values between observed and simulated data shows that the model has not performed well in simulating high humidity values (above 80 percent) and is more focused on simulating values between 20 and 80 percent.

Comparison of the continuous distribution between observed and simulated data (KDE plot):

The KDE (Kernel Density Estimation) chart shows a continuous estimate of the probability density function of continuous variables. This chart reveals the shape of the data distribution without using a histogram, allowing for accurate comparison of multiple distributions. The normalized density function for temperature data shows that both time series have a bimodal pattern, but the peak of the simulated data distribution is more pronounced at higher temperature values (around 25 degrees Celsius) compared to the observed data. Additionally, the distribution of simulated data is skewed towards higher positive temperatures, and the density in regions below zero is lower than that of the actual data. The normalized density function for the relative humidity parameter indicates that the simulated data has a significant concentration in the humidity range of about 20%. In contrast, the observed data has a more uniform range with a long tail on the high humidity side (over 60%). This observation suggests that the model has difficulty in reproducing high humidity levels (above 60 percent).

Comparison of cumulative temperature distribution in both datasets (ECDF chart):

The ECDF chart displays the empirical cumulative distribution function. This chart shows the proportion of data that is less than or equal to a certain value, thus providing an accurate representation of the cumulative structure of the data. The ECDF chart of observed and simulated temperatures indicates a general similarity in the distribution structure of the data. However, differences are observed in the temperature range of -10 to -20 degrees Celsius, whereby the simulation model does not cover this interval. This point signifies that the model tends to produce more median temperature values. Examining the difference between the cumulative distributions of observed and simulated relative humidity data indicates that the simulated data have a steeper slope in the low relative humidity regions, demonstrating a concentration of data at lower values (below 60%). In contrast, the observed data have a gentler slope.

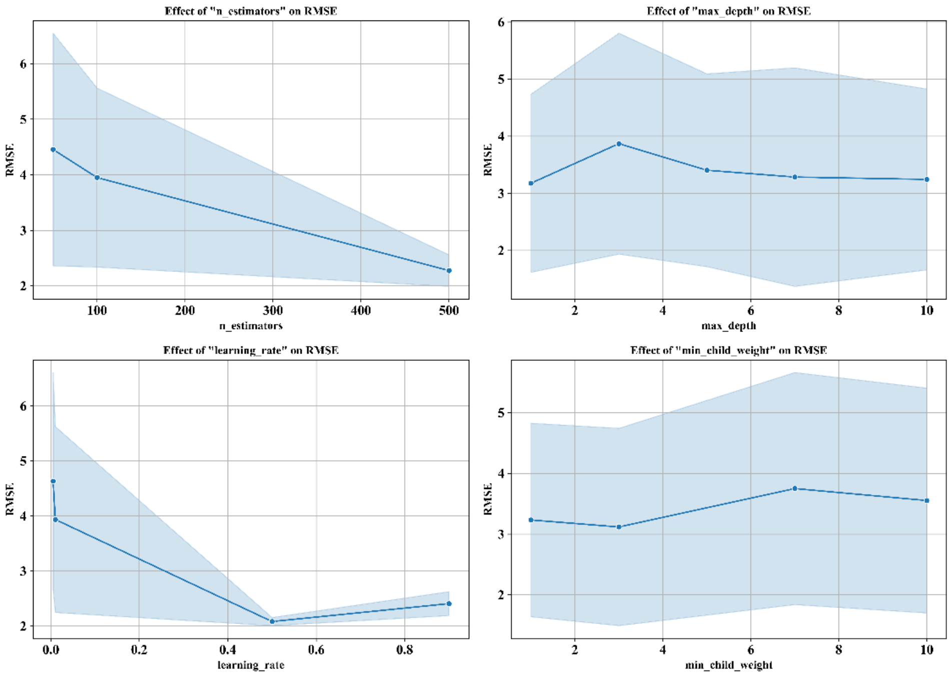
Examination of density structure and robust statistics in two data groups (villion chart):

The violin plot is a combination of a boxplot and KDE that, in addition to displaying descriptive statistics (median, quartiles, and range), also shows the probability distribution of the data with a smoothed density. This plot clearly illustrates that despite the similarity of the mean and median in both datasets, the density distribution has a wider range in the observed temperature and possesses longer tails. Particularly in the extreme temperature regions, observations show more variability, which is less pronounced in the simulated data. This issue may result from excessive smoothing in the downscaling process. Examining the density structure and robust statistics of the relative humidity parameter shows that the distribution range in the observed data is wider than in the simulated data. Moreover, the tails in the observations are longer. The median and mid-quartiles in the two groups are positioned almost similarly, but the kernel density in the simulated data shows more concentration in the 20 to 40 millimeter range. This concentration may result from excessive smoothing or failure to consider climatic variability in the downscaling model.

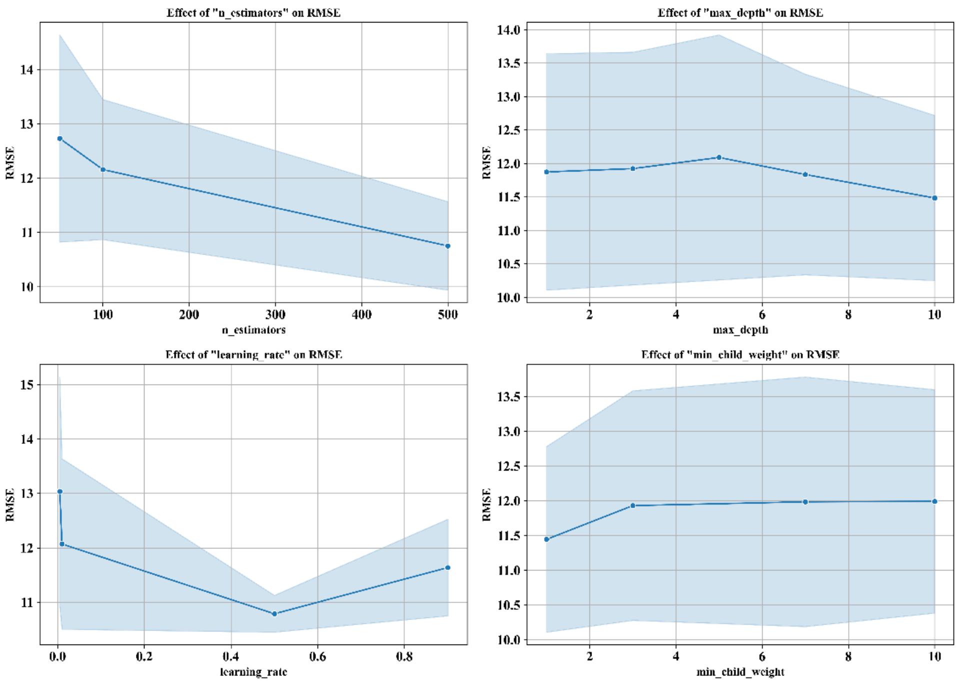
Sensitivity Analysis of the XGBOOST Model in Downscaling of Climate Parameters: Focusing on Model Structure and Input Climate Characteristics

In this study, in order to improve the accuracy and reliability of the climate downscaling model based on the XGBOOST algorithm, sensitivity analysis was performed based on the internal parameters of the machine learning model using the CRROS validation method and separately for each of the climate variables temperature and relative humidity.

Figure (4) shows the results of the sensitivity analysis of the XGBoost model parameters separately for the climate variables temperature and relative humidity.



Temperature



Relative Humidity

Fig 5. Results of sensitivity analysis of XGBoost model parameters by climate variables: relative humidity and mean temperature.

Sensitivity analysis using the Cross Validation method can, in addition to examining the sensitivity of each parameter, also show the optimal range of each parameter. In such a way that the bandwidth indicates the changes in the error function value (Rmse) in each run assuming that the value of that parameter remains constant. Therefore, a greater bandwidth indicates greater changes in the error function and, as a result, a greater sensitivity of the model to that parameter. On the other hand, the line in the graph shows the changes in the error function with respect to the change in the parameter value. Therefore, the lower the error function value, the more optimized the value of that parameter. As a result, by examining these two analyses simultaneously, the optimal range of each parameter can be identified (the optimal range is located in a place with a low bandwidth and a minimum error function value.) Therefore, examining the sensitivity analysis graphs shows that the XGboost model has shown the greatest sensitivity to the parameters max_dept and min_Child in the exponential scaling of both climate variables of temperature and relative humidity because they have the greatest bandwidth compared to other parameters.

Therefore, considering the mentioned points, the results showed that the XGBOOST model, after optimizing the parameters using the RandomizedSearchCV method, had a very favorable performance in the statistical downscaling of the temperature parameter. This is confirmed by the desirable values of the evaluation metrics R^2, NS, and NRMSE in both the training and testing stages. The model's stability in the temperature section was evident due to the slight variations in the evaluation metrics between the training and testing sections. Regarding the relative humidity parameter, although the results indicated a drop in the model's relative performance in the testing section compared to the training section, suggesting the need for better model training, the values of the evaluation metrics still remained within an acceptable range and indicated the desirability of the statistical downscaling results for this parameter as well. The analysis of the distribution of the simulated data showed that the model faced limitations when simulating values of temperature below -10 degrees Celsius and very high relative humidity values (above 80 percent).

Additionally, the model shows a greater tendency to simulate median temperature values and has struggled with reproducing high relative humidities (above 60 percent). One of the reasons for the model's poor performance at these values is that the XGBoost model is a machine learning algorithm based on the boosting method, which uses a combination of decision trees for predictions. This model typically uses the MSE (Mean Squared Error) loss function by default for regression problems. However, this loss function may not be suitable for predicting extreme values, such as very low temperatures, and tends to favor learning median values. Therefore, by selecting an appropriate loss function, it can be expected that the model will perform better in learning rare events.

The successful performance of machine learning models, including XGBOOST, has been reported in studies of downscaling climatic parameters in various regions of the world. For instance, in a study in North Africa (a region with predominantly arid and semi-arid climate), machine learning models including XGBoost were used for downscaling hourly temperature of reanalysis products, and the results showed that these models significantly reduced the RMSE error compared to classical methods (El Htiti et al., 2023). This finding is consistent with the present study's results regarding the high performance of XGBOOST for temperature. Additionally, in another study in China, the performance of the XGBoost model in estimating soil temperature in different climatic regions was evaluated, and the results demonstrated its superiority over Random Forest (RF) and M5P models (Zhao et al., 2022).

This also affirms the high capability of XGBoost in modeling temperature-related variables. In the field of downscale modeling using XGBoost for multiple parameters, a study in China evaluated this model for correcting the bias of numerical weather predictions for daily precipitation and noted its satisfactory performance; the same research also mentioned the successful application of XGBoost for temperature (Guo et al., 2022). Although the present study does not directly address precipitation, the success of XGBoost in various climatic parameters indicates its broad potential.

One of the limitations of this study is the use of data from a single synoptic station. Although the Qaen station has been chosen as a representative of arid regions, examining the model's performance at other stations with different topographical and climatic characteristics in arid areas could lead to a more comprehensive understanding of the capabilities of the XGBOOST model. The observed limitation in this study regarding the simulation of extreme temperature and high humidity values has also been reported in some other machine learning studies. For example, it has been noted that machine learning models may struggle to generalize to environmental conditions that are not adequately represented in the training data (Ma et al., 2021b, as cited in Zhang et al., 2024). This could be one of the reasons for over-smoothing and the inability to fully reproduce observed range fluctuations. Additionally, as mentioned in the results, the model's performance for relative humidity has room for improvement; using more predictor variables or combining XGBOOST with other deep learning models could be explored in this regard. Future research may also investigate the impact of various climate change scenarios on the outputs downscaled by the XGBOOST model. Comparing XGBoost with other modern deep learning algorithms could provide new insights.

Conclusion

The XGBOOST model showed very good performance in the downscaling of average temperature and satisfactory performance in the downscaling of relative humidity at the synoptic station of Qaen (as a representative of dry areas). The results of this study are consistent with the findings of other research in Iran and worldwide that have used machine learning models for downscaling climatic parameters, confirming the high potential of XGBOOST as an efficient tool in this field, especially for dry areas. However, it is essential to pay attention to the limitations of the model in simulating extreme values and to strive to improve its performance for parameters like relative humidity, as well as to evaluate the model's performance in humid areas with different climates in future studies, which the authors of this research are currently undertaking, and results will be published in subsequent papers.

Resources

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