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ORIGINAL STUDY

Forecasting Future Precipitation in Basrah City, Iraq Using the Statistical Downscaling Model (SDSM)

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ABSTRACT

Accurate rainfall predicting has become for securing managing water resources, chiefly in light of escalating climate crises. Basrah is among the Iraqi cities most vulnerable to these changes, as climate fluctuations are clearly impacting water availability and hydrological sustainability indicators in the region. The results of this study, through using the Statistical Downscaling Model (SDSM), indicate that the future precipitation was predicted for Basrah Governorate/Iraq up to 2085. Future precipitation projections were developed under group of Representative Concentration Pathway (RCP) scenarios which RCP (2.6, 4.5, and 8.5). The CanESM2 global climate model was used to generate large-scale atmospheric predictors for the statistical downscaling process, and daily precipitation from the Hay Al-Hussein meteorological station in Basrah were used for the period 1980–2025. The model was calibrated to find the optimal parameters for the period 1980 to 2012 and then verified for the period 2013–2025. In calibration, the coefficient of determination (R^2) and the Nash-Sutcliffe efficiency (NSE) were 0.905 and 0.810, respectively. However, in validation, values of R^2 and NSE were 0.874 and 0.844, respectively. These values confirm reliability model. The results indicated that a decrease in annual precipitation was noticed for the three future scenarios for three periods: 2035s, 2055s, and 2075s. The outputs of the model can be utilized for sustainable water resource planning for Basrah Governorate.

Keywords: Basrah city, Climate change, Statistical downscaling model, CanESM2, Precipitation forecasting

1. Introduction

Recently, the climate system of the Earth has changed dramatically compared to past decades due to rising temperatures and shifts in rainfall patterns, which have changed the hydrological cycle [1]. These changes are essentially attributed to human activities in the post-industrial era and the increasing use of fossil fuels in particular, where the energy

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sector is responsible for more than 70% of the global Greenhouse Gas (GHG) emissions released into the atmosphere [2]. These gases act as a thermal blanket, trapping long wave radiation that is emitted to space and enhancing the natural greenhouse effect. This effect is considered the main source of global climate change and has wide-ranging impacts on ecosystems, the economy, and humans [3]. Climate change has spatial and temporal characteristics and is not uniformly distributed across the globe. Drylands are among the most fragile to climate change [4]. These areas are environmentally sensitive and are already facing water scarcity problems and will experience an increase in desertification, a greater frequency and severity of drought, and higher water variability [5]. Iraq, in the Middle East, is considered one of the most vulnerable countries to climate change impacts [6]. The literature shows that a significant increase in annual mean temperatures is observed across the country and a significant lower in precipitation, mainly in the southern and central parts of Iraq [7, 8].

Rising temperatures and declining precipitation will impose double pressure on water and food security in Iraq in the short and long term, the water deficit is expected to reach 11×10^9 m^3 meters by 2035, with the Tigris and Euphrates rivers expected to dry up by 2050. In addition, the production of strategic crops is may be decreasing due to of Iraq losing 1000 km^2 of agricultural land annually [9].

This trend is particularly pronounced in the Middle East region, where annual rainfall in the Middle East is foreseen to decrease 20% by the 2050s.

Jordan has recorded a significant decrease in its cumulative annual rainfall of 10% across its governorates, while simultaneously experiencing a notable increase in average temperatures of one degree Celsius [10]. Saudi Arabia has experienced rainfall 40% decrease in rainfall in its northern regions, especially in the Tabuk region, over the past two decades. Saudi Arabia has also witnessed an increase in mean temperatures of 2 °C to 3 °C [11].

Among these affected regions are southern Iraq areas, in particular the Basrah Governorate. Basrah is geographically situated at the confluence of the Tigris and Euphrates rivers. Therefore, the governorate is a center for water and climate stress [12]. Several local studies demonstrated the continuous decline and increase in precipitation and temperature, respectively in Basrah, in addition to the deteriorating water quality and the increasing salinity levels in the Shatt al-Arab River, which is due to the decreasing volume of water from the upstream flow and the increased intrusion of salty water from the Arabian Gulf [13]. This situation increased the environmental, economical, and social problems facing the governorate. It was reported that more than 94% of the population in the southern governorates of Iraq were affected by displacement due to water scarcity, and this problem is expected to deteriorate with the increasing Iraq population from 40 million to 80 million by 2050 [14]. One of the big problems facing the strategic planners and water resources planners is the uncertainty in predicting the future climate due to the uncertainty in future emission scenarios and the possibility of a wide range of scenarios [15]. General Circulation Models (GCMs) have been used as the primary tool for modeling the Earth's climate system and for future predictions [16]. GCMs are a set of three-dimensional numerical models that describe the physics and chemistry of the land, atmosphere, ocean, and ice. However, a significant drawback of GCMs is their spatial resolution, which is very large (e.g., 250 km × 250 km) [17]. This is why they are unable to provide the local-scale climate characteristics and topography-induced weather patterns that are important for regional impact studies [18].

In general, to resolve the issue of resolution mismatch between GCM outputs and the observation records, a downscaling procedure is often used to transform the large-scale variables of GCM outputs into local-scale climate data [19]. The downscaling techniques are classified into two groups: dynamical downscaling and statistical downscaling. Dynamical downscaling employs a limited-area, high-resolution regional climate model nested within a coarse resolution GCM; this method is, however, computationally intensive and expensive [20]. On the other hand, statistical downscaling establishes an empirical relationship between the large-scale atmospheric variables (predictors) simulated by GCM and the local-scale surface variables (predictands) obtained from the observational station data. The statistical downscaling approach is relatively computationally efficient and allows for the fast generation of multiple climate change scenarios for a particular site [21, 22]. The Statistical Downscaling Model (SDSM) is a widely used and extensively applied and validated statistical downscaling tool in climate change impact studies [21]. The SDSM used to generate daily time series of local climate variables [24]. SDSM has been found to be a powerful tool for linking large-scale climatic variables with the local observational data, which in turn improves the performance of temperature and precipitation models, particularly for the arid and semi-arid regions.

In Iraq, to analyze the climate change conditions, several studies have been carried out either by conducting trend analysis of the historical climate data or directly applying the simulated data from the low-resolution GCM.

In 2022, SDSM was used to assess the efficiency of stormwater drainage networks, linking large-scale climatic variables with the local observational data in Basrah. It showed that annual rainfall amounts in 2099 would decrease by 12.2 %, 10.4%, and 8.3 % in the worst (rcp8.5), middle (rcp4.5), and best(rcp2.6) scenarios, respectively, when compared to the base date (1979–2018) [25].

In 2024, SDSM was applied to predict the precipitation in Wadi Houran in Iraq until 2100. The data on daily precipitation were used from the Al-Rutba station from 1990 to 2020, the data of the predictor was used from CanEsM2. Three scenarios of climate were used rcp2.6, rcp4.5, and rcp8.5. The data confirm that rainfall rates will be lowering by 32%, 35% and 37% in the 2020s, 2050s, and 2080, respectively, according to the worst scenario rcp 8.5 [4].

Therefore, this study seeks to project future precipitation in Basrah Governorate using the SDSM based on outputs from the CanESM2 global climate model.

2. Material and methods

2.1. Study area

Basrah Governorate, situated in the southeast of Iraq, is considered an economic and geographical key for Iraq. Its latitude and longitude are 29°13' and 31°29' N, and 46°60' and 48°60' E, respectively. It is bounded by Iran from the east and Kuwait from the south and shares borders with the governorates of Maysan, Dhi Qar, and Muthanna (see Fig. 1). It has an area of about 19,070 km^2 [26]. The Shatt al-Arab river valley and the extensive marshlands are the most prominent geographical features of this region.

The climate of Basrah is classified as a hot desert climate (BWh based to the Köppen classification). The average annual precipitation during the last three decades is about 264 mm/yr., occurring mainly between October and May. No rain falls during the three months in summer starting from June to August, and the mean temperature varies between 47 °C (August) and 8 °C (January). The mean relative humidity is about 69 % and means wind speed is 2.7 m/s [28]. The topography of the governorate is generally flat and of low elevation; hence, it is more vulnerable to climatic and hydrological impacts, especially sea-level rise and saltwater intrusion from the Arabian Gulf.

Fig. 1. Location of study area, Basrah Governorate, southern Iraq [27].

2.2. Data used

The analytical framework of this study is built upon a combination of observed station data and large-scale climate model outputs to ensure a robust and comprehensive analysis.

2.2.1. Observed data (Predictand)

Daily precipitation is used as the predictand variable. The observed daily precipitation data was collected from the Hay Al-Hussein meteorological station (HAMS) within the study area (Basrah Governorate). The predictand dataset covers the baseline period 1980 to 2025, including observed data and the required projected data to form a complete time series dataset to train and test the downscaling model. This station-based dataset is used as the base to train and test SDSM. The temporal database series were examined to ensure accuracy for the period (1980 to 2025). The standard protocol for program inputs, code –999, was used for any missing values. This code skips any missing values to ensure the results are unbiased [23].

2.2.2. GCM and reanalysis data (Predictors)

Predictors were selected based on their statistical relationship with precipitation using correlation and partial correlation analysis:

1. NCEP/NCAR Reanalysis Data: Daily data for large-scale predictors from NCEP and NCAR reanalysis dataset was used for the training and validation periods (1961 to 2005). The NCEP/NCAR reanalysis data is one of the best reanalysis datasets used to calibrate and validate SDSM [23].
2. CanESM2 GCM Data: The predictors for future prediction were taken from the second-generation CanESM2, which is a global climate model developed by the Canadian Centre for Climate Modeling and Analysis and can downloaded from the website https://climate-scenarios.canada.ca/?page=pred-canesm2 [29]. The model output files are in grid format and have a spatial resolution of approximately 2.8° x 2.8° latitude-longitude. The grid box that is closest to the study region was considered.

2.2.3. Future emission scenarios

The three RCPs of the IPCC's Fifth Assessment Report were used for future projection of precipitation. The RCPs are:

- **RCP 2.6:** A "peak-and-decline" or optimistic scenario, it represents a stringent mitigation pathway, aiming to limit global warming to below 2 °C [30].
- **RCP 4.5:** An intermediate stabilization scenario, it assumes the implementation of policies to curb GHG emissions [31].
- **RCP 8.5:** A high-emissions or "business-as-usual" scenario characterized by continuously rising GHG emissions throughout the 21st century. It represents a future with high population growth and continued reliance on fossil fuels [30].

Future projections were generated for three 20-year time slices: 2035s period: represents the duration from 2026 to 2045, 2055s period: represents the duration from 2046 to 2065, and 2075s period: represents the duration from 2066 to 2085, and compared against the baseline period (1980–2012).

2.3. Statistical downscaling model (SDSM)

SDSM used to evaluate the effects of climate change on a local scale by downscaling the data from GCM [23]. It is a hybrid model that combines a multivariate linear regression with a stochastic weather generator. The model develops a transfer function between atmospheric large scale circulation patterns, in the form of a series of predictor variables (mean sea level pressure, geopotential height, specific humidity, etc.), and predictands (precipitation, temperature, etc.) at a site-specific scale. The transfer functions are then used to generate a synthetic series of daily data at the site of interest, given a series of large scale predictor variables for a future time period. The interface of SDSM model program allows the user to perform a series of operations that include data quality control, screening of predictor variables, automatic model calibration, generation of weather series, and statistical analysis of results [24]. The model is able to simulate both unconditional variables (i.e., temperature), as well as conditional variables (i.e., precipitation), which requires an intermediate variable to occur (i.e., if precipitation > 0.5 then a wet day occurs). Table 1, shown all the variables used as NCEP predictors.

2.4. Methodology

The research procedure is organized as a multi-staged framework, which is presented in the flowchart in Fig. 2. This framework provides a systematic workflow between data collection and the projection of future climate conditions.

Table 1. Predictor variable codes and descriptions in the NCEP dataset used by SDSM [33].

Code	Description	Code	Description
mslp	Mean pressure of sea level	p8_f	Velocity of airflow at 850 hPa
P_f	Airflow velocity close to surface	p5_f	Velocity of airflow at 500 HPa
r500	Humidity at 500 hPa	p8_z	Vorticity at 850 hPa
p8_v	Component of velocity meridional at 850 hPa	p_v	Component of velocity meridional close to surface
p_z	Vorticity close to surface	p8th	Direction of wind at 850 hPa
p_th	Direction of wind close to surface	p8zh	Divergence at 850 hPa
p_zh	Divergence close to surface	p500	Height of geopotential at 500 hpa
P5_u	Component of velocity zonal at 500 hPa	p850	Height of geopotential at 850 hpa
P8_u	Component of velocity zonal at 850 hPa	temp	Mean temperature at 2 m height
p5_v	Component of velocity meridional at 500 hPa	shum	Specific humidity close to surface
p5th	Direction of wind at 500 hPa	p5_z	500 hPa vorticity
rhum	Relative humidity close to surface	p_u	Component of velocity zonal close to surface
p5zh	Deviation at 500 hPa	r850	Humidity at 850 hPa

The key steps were as follows:

A. Data Preparation and Quality Control: The daily observed precipitation time series from HAMS (1980 to 2025) and the large-scale predictors from NCEP (1961 to 2005) and CanESM2 (1961 to 2100) were prepared. A quality control procedure was employed to check for gaps or outliers. Since precipitation data are mostly skewed, a fourth-root transformation was adopted to the daily series of precipitation to normalize the data, which enhances the regression model [4]. Missing data treatment was performed by identifying gaps in the daily precipitation record and filling them using linear interpolation between adjacent observations where gaps were short ($\leq$3 days), or by long-term monthly mean substitution for longer gaps. Data quality control involved systematic identification and removal of erroneous entries, including negative precipitation values and unrealistic outliers exceeding three standard deviations from the monthly mean Homogeneity testing was conducted using the Standard Normal Homogeneity Test (SNHT) to detect any in homogeneities in the observed sequence of precipitation that could grow from shift in instrumentation, translated station, or observational practices. The results confirmed the homogeneity of the series over the study period.

B. Screening of predictor variables: The "Screen Variables" function in SDSM was used to identify the most appropriate large-scale predictors for downscaling daily precipitation in Basrah. The function involves scatter plots, correlation matrix, and partial correlation, and between the predictand (rainfall) and 26 available NCEP predictors. The predictors were selected according to their correlation strength and statistical significance (p-value < 0.05).

C. Model calibration: The model was calibrated using observed daily precipitation data and NCEP predictor variables for the period 1980–2012. During the calibration process, the model develops a set of multiple linear regression equations between the selected predictors and transformed precipitation data. Since precipitation is a conditional process (it does not occur every day), the model was set to "conditional" which models the occurrence and amount of precipitation separately. The ordinary least squares (OLS) optimization algorithm was used to determine the regression parameters.

D. Model validation: The calibrated model was validated using an independent dataset for the period 2013–2025. The model simulated a synthetic weather series using NCEP predictors for the given period, which was compared with the observed precipitation

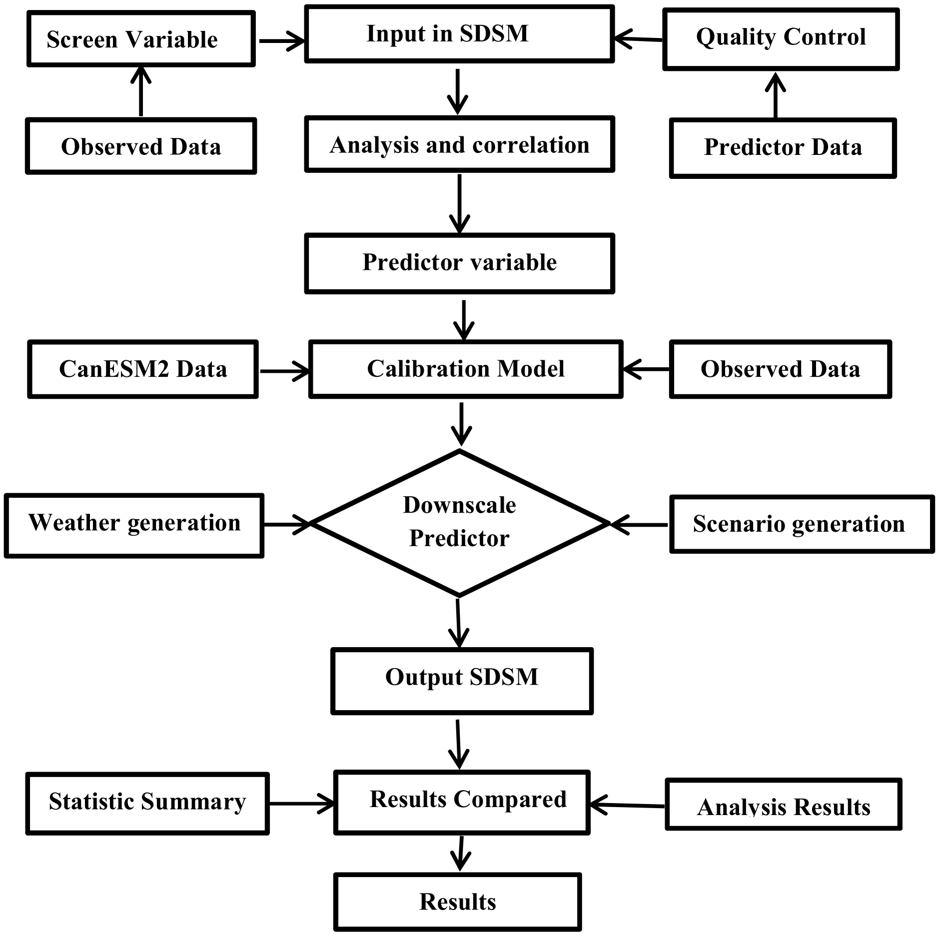

Fig. 2. Flowchart illustrating the methodological steps for climate downscaling using SDSM.

data. This step is important to evaluate the model's capability to reproduce the statistical properties of the local climate outside the calibration period.

E. Scenario generation: Once the model was successfully validated, the calibrated model was used to generate future daily precipitation scenarios. The model was forced with downscaled predictor variables from the CanESM2 for the three RCP scenarios (2.6, 4.5, and 8.5). Twenty ensemble members were generated for each scenario to incorporate the stochastic uncertainty in the downscaling process. The final projections were created for the future time slices: 2035s, 2055s, and 2075s.

2.5. Performance evaluation

A set of statistical indicators were computed to compare the observed and predicted time series of daily precipitation, in the calibration and validation stages, using the coefficient of determination, R^2, and the Nash-Sutcliffe Efficiency, NSE. In addition, the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) were also calculated to further strengthen the performance evaluation and provide a comprehensive assessment of model accuracy [34].

- **(R^2):** provides an indication of the proportion of variance of the observed data that is explained by the simulated data, whose values range between 0 and 1 (perfect agreement).
- **(NSE):** is a statistical tool which provides the relative value of variance of the errors to variance of the data of observed time series; NSE ranges from $-\infty$ to 1 (perfect agreement), with NSE = 0, meaning that the predictive accuracy of the model is similar to the accuracy of the mean of the observations.
- RMSE: it measures the quadratic mean of the discrepancies between observed and simulated datasets, the lower values refers to the best performance model.
- MAE: represents the arithmetic average of the absolute magnitudes of the deviations between observed and predicted values. The lower values refer to the best performance model.

The goodness of fit was evaluated according to the ranges of the coefficients of determination and Nash-Sutcliffe Efficiency presented in Table 2, which are commonly adopted in hydrological and climatological applications.

Table 2. Criteria for evaluating model performance based on R^2 and NSE values [35, 36].

Performance Rating	NSE	R^2
Unsatisfactory	$NSE \leq 0.50$	$R^2 < 0.5$
Satisfactory	$0.50 < NSE \leq 0.65$	$0.5 \leq R^2 \leq 0.6$
Good	$0.65 < NSE \leq 0.75$	$0.7 \leq R^2 \leq 0.75$
Very good	$0.75 < NSE \leq 1.00$	$0.8 \leq R^2 \leq 1.0$

3. Results

3.1. Selection of predictor variables

In the downscaling, the first step is the selection of the atmospheric variables that are expected to have the most significant and the most physically reasonable relationship with the predictand, in this case, the daily precipitation. The predictor screening tool in SDSM was used to screen the 26 NCEP variables for the predictors having the highest partial correlation coefficients (P. r) and lowest p -values with the observed daily precipitation at HAMS. A p -value of 0.05 or less was chosen as the criterion for rejecting the null hypothesis and concluding that the correlation is statistically significant.

Four predictor variables were found to be the most effective in controlling the precipitation rate over Basrah. These variables are: r500, p500, mslp, and p5th. The selected predictors and their corresponding P. r and p -values are given in Table 3. These variables are related to moisture availability, atmospheric stability, and large scale pressure systems, which are the major controllers of the precipitation.

Table 3. Selected predictor variables and their statistical significance for downscaling precipitation in Basrah.

Predictor Parameter	Partial r (P.r)	p-value (P)
r500	0.350	0.003
p500	–0.312	0.015
mslp	0.083	0.002
p5th	0.320	0.007

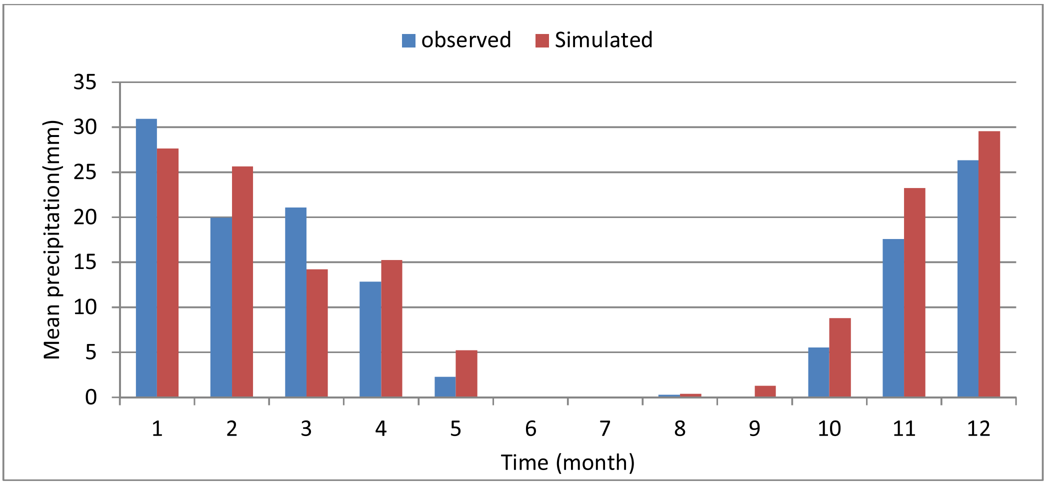

Fig. 3. Calibration results: Comparison of mean monthly observed and simulated precipitation (1980–2012).

3.2. Model performance: Calibration and validation

For the future projections to be trustworthy, SDSM was subjected to rigorous calibration and validation. The model was calibrated for the period 1980 to 2012 and then validated for the period 2013 to 2025.

3.2.1. Calibration (1980–2012)

In the calibration process, SDSM captured the observed monthly precipitation very well. Fig. 3 compares the mean monthly observed precipitation and the mean monthly simulated precipitation. It correctly predicted higher precipitation during the winter months; and near-zero precipitation during the summer months. Although there was a slight over prediction in February and slight under prediction in January, overall, the agreement was very good.

The scatter plot (Fig. 4) shows the results of the correlation analysis for the calibration period. The R2 was computed to be 0.905, indicating that more than 90% of the observed precipitation variance was explained by the model. The NSE was computed to be 0.810. Both statistics were ranked as “Very good” according to the classification given in Table 2, giving high confidence in the calibrated model parameters. To assess the risk of overfitting, the calibrated model was subsequently applied to an independent validation dataset; if the model had been overfit, a marked deterioration in performance metrics would be expected during validation. The high performance retained in the validation stage (see Section 3.2.2) therefore provides evidence against overfitting.

3.2.2. Validation (2013–2025)

In the validation process, the ability of the model to predict the data not used for calibration was examined. The results are presented in Fig. 5, which compares the mean monthly observed and simulated precipitation for the 2013 to 2025 period. The model performed well in simulating the monthly precipitation distribution for the 2013 to 2025 period. It correctly predicted the dry and wet seasons and the magnitude of monthly

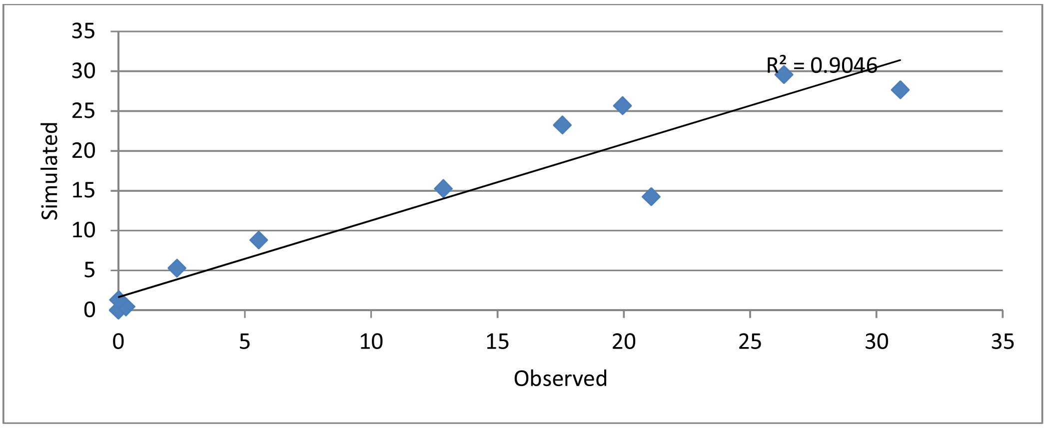

Fig. 4. Correlation analysis for the calibration period, showing a strong relationship between simulated and observed monthly precipitation ($R^2 = 0.905$).

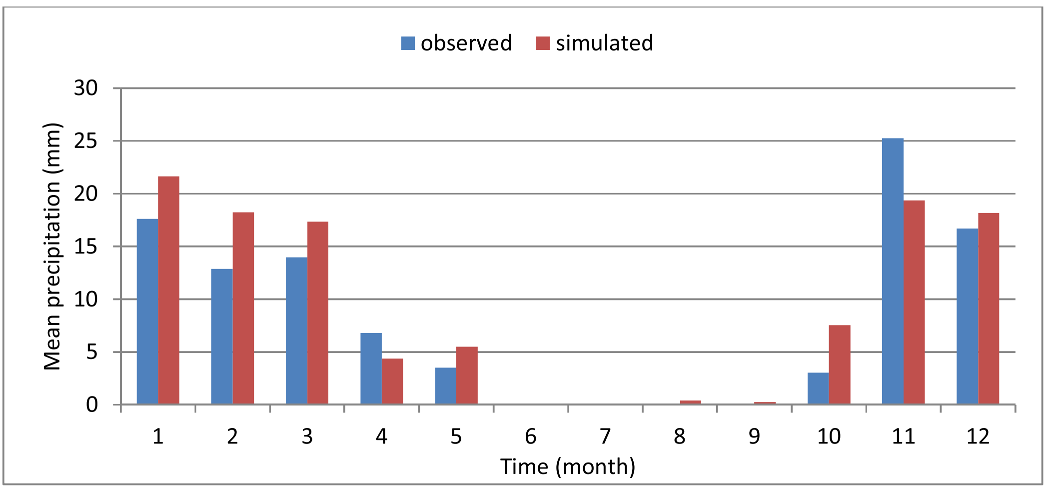

Fig. 5. Validation results: Comparison of mean monthly observed and simulated precipitation (2013–2025).

precipitation, although there was some over prediction in January and some under prediction in November.

The correlation analysis for the validation period (Fig. 6) yielded an R^2 value of 0.874 and an NSE value of 0.844. These results, both rated as "Very good," confirm that the model is robust and that the relationships established during calibration hold true for an independent period. This successful validation provides a strong basis for using the model to generate credible future precipitation scenarios. Model uncertainty arises primarily from the choice of GCM predictors, the statistical transfer functions embedded in SDSM, and the inherent uncertainty of future emission scenarios. These sources of uncertainty are acknowledged, and the use of three distinct RCP scenarios in this study partially addresses the emission-pathway uncertainty by providing a range of possible future precipitation trajectories.

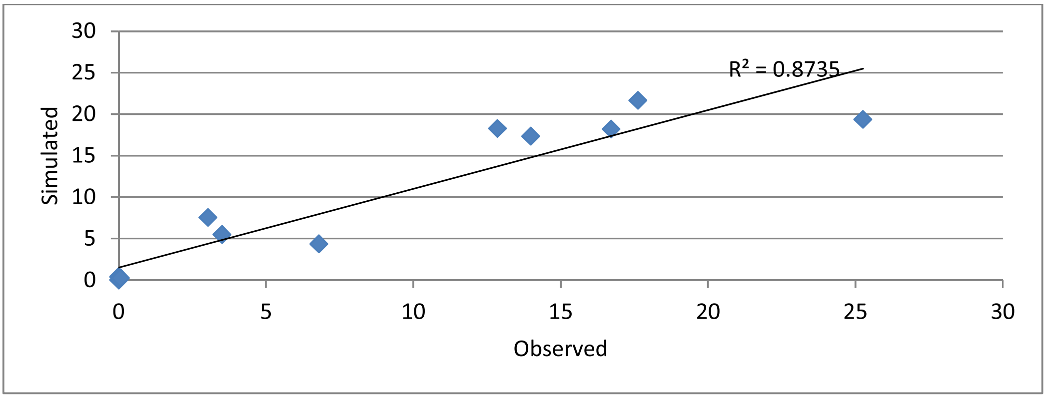

Fig. 6. Correlation analysis for the validation period, confirming the model's predictive accuracy ($R^2 = 0.8735$).

3.3. Future precipitation scenarios

Following the successful calibration and validation, SDSM was used to project future daily precipitation for Basrah up to 2085 under three scenarios. The results were analyzed for three future time slices: 2035s (2026–2045), 2055s (2046–2065), and 2075s (2066–2085), and compared with the baseline period (1980–2012).

3.3.1. Projections under RCP 2.6

Under the optimistic RCP 2.6 scenario, a general decrease in monthly precipitation is projected compared to the baseline, particularly during the core rainy season from November to March (Fig. 7). For instance, in January, the baseline precipitation of nearly 27 mm is projected to decrease in all future periods. A similar declining trend is observed for December. The summer months (June-September) are projected to remain extremely dry, consistent with the baseline climate. This scenario suggests that even with strong global mitigation efforts, Basrah is likely to face a drier future.

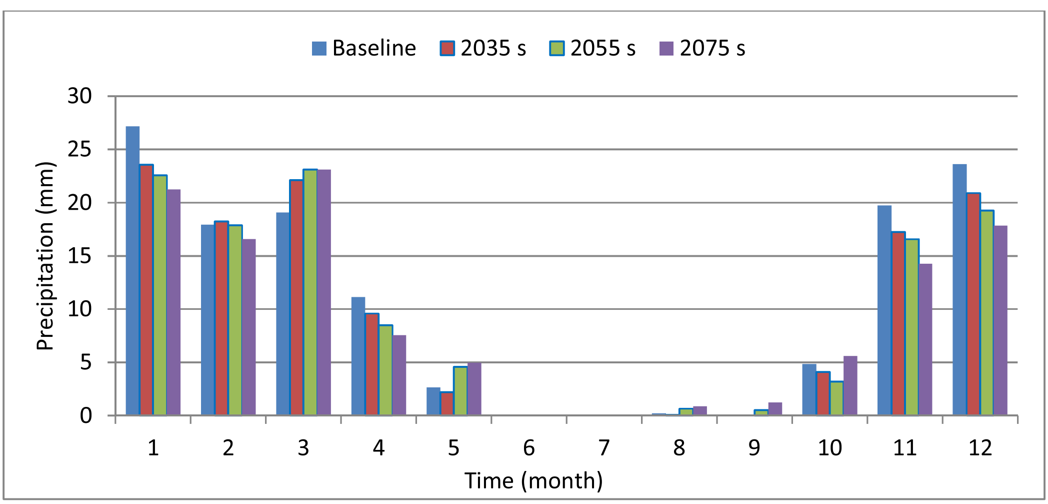

Fig. 7. Projected mean monthly precipitation for future periods (2035s, 2055s, 2075s) compared to baseline with the RCP 2.6 scenario.

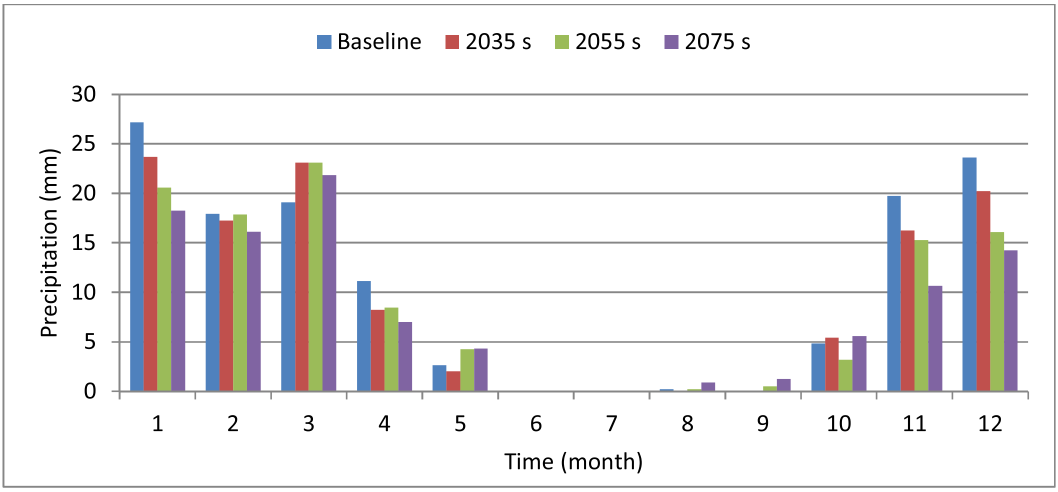

Fig. 8. Projected mean monthly precipitation for future periods (2035s, 2055s, 2075s) compared to baseline with the RCP 4.5 scenario.

3.3.2. Projections under RCP 4.5

The worst-case results are those for RCP 4.5 scenario (Fig. 8).The reduction in precipitation in winter is pronounced. The monthly maximum values are well below the baseline for all future horizons, and the reduction worsens in time. For example, for the 2075s horizon, the modeled values of monthly precipitation for November, December, and January are significantly reduced, which may indicate the tendency for a more arid climate, with an already short and weak rainy season.

3.3.3. Projections under RCP 8.5

The most pessimistic scenario of RCP 8.5 yields the most critical results (Fig. 9). A noticeable reduction in the precipitation during the winter season can be observed. In

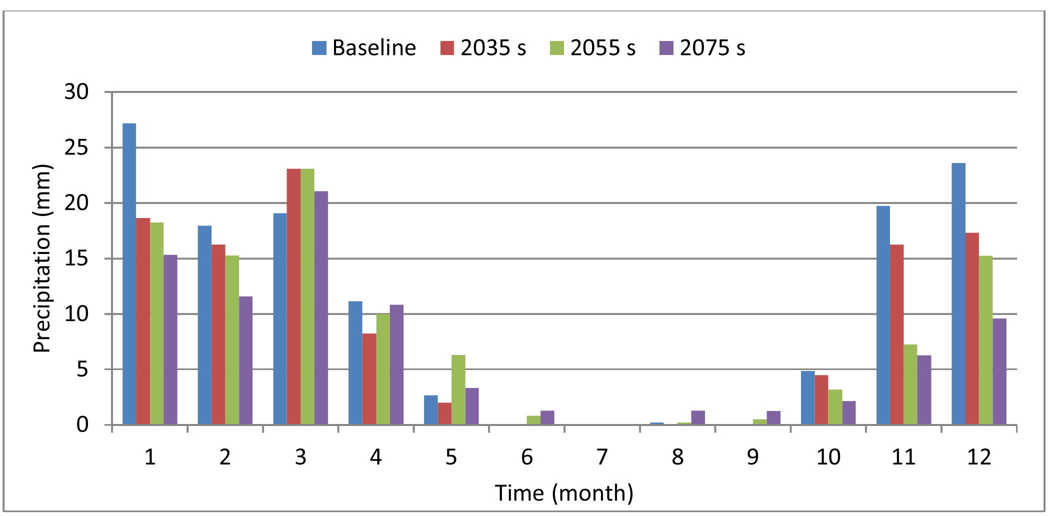

Fig. 9. Projected mean monthly precipitation for future periods (2035s, 2055s, 2075s) compared to baseline under the RCP 8.5 scenario.

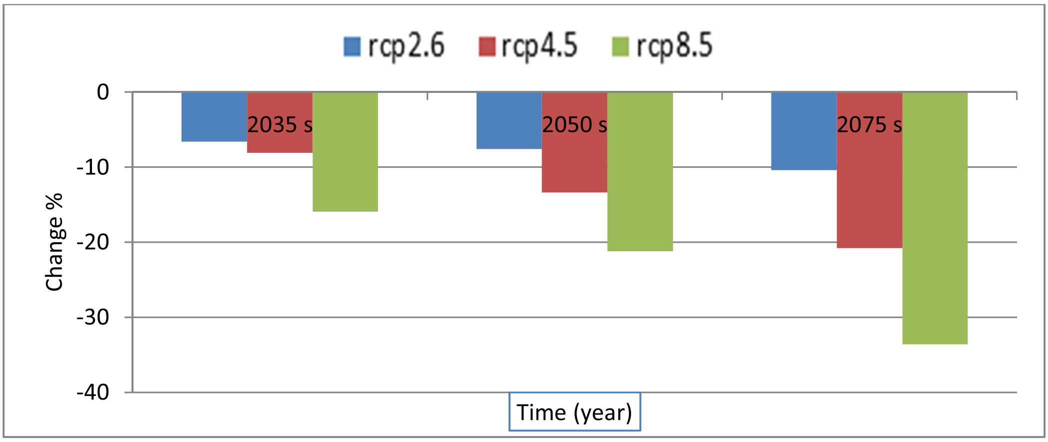

Fig. 10. Projected percentage change in mean annual precipitation for future periods under RCP 2.6, RCP 4.5, and RCP 8.5 scenarios relative to baseline.

all the future horizons, the monthly maximum value of the projected precipitation was found to be less than that of the base period and the reduction in the precipitation become more critical as the time progresses. For example, the precipitation for the three months starting from November to January in the 2075s time horizon was found to be significantly reduced, which may indicate that in the future Basrah may experience an arid climate with a much shorter and weaker rainy season.

3.4. Annual precipitation change

Fig. 10 shows the percent change of the mean annual precipitation for all scenarios and horizons. There is a systematic trend towards an increasingly more arid climate. Under different scenarios of yearly precipitation, we observed:

- Under **RCP 2.6**, projected to decrease by 6.6% in the 2035s, 7.6% in the 2055s, and 10.4% in the 2075s.
- Under **RCP 4.5**, the decrease is more significant, with reductions of 8.1% (2035s), 13.4% (2055s), and 20.8% (2075s).
- Under **RCP 8.5**, the projected decline is the most severe, with decreasing by 15.9% (2035s), 21.2% (2055s), and a substantial 33.6% by the 2075s.

The RCP8.5 scenario shows the largest variability in projected precipitation compared with the moderate scenarios. Specifically, the percentage reduction in annual precipitation under RCP8.5 (33.6% by the 2075s) is approximately 3.2 times greater than under RCP2.6 (10.4% by the 2075s) and 1.6 times greater than under RCP4.5 (20.8% by the 2075s), clearly demonstrating the strong dependency of future precipitation decline on greenhouse gas emission pathways. These results collectively indicate that Basrah is on a trajectory towards a significantly drier climate, with the severity of the change directly linked to the global emissions pathway.

4. Discussion

This study has focused on downscaling the future precipitation changes over Basrah Governorate, which is one of the climate change hotspots, by employing SDSM. The results stages of SDSM indicate that the model performance is "Very good" for the Basrah area because both R^2 and NSE are greater than 0.87 and 0.81, respectively. This reflects that the empirical relationships established between the local precipitation and large-scale atmospheric predictors are powerful, and consequently, it can be trusted the future changes predicted by SDSM. The results obtained here with regard to the suitability of SDSM to be used in an arid environment are in line with the results from other previous studies performed in the same region of the Middle East, such as that carried out in the Iraqi Western Desert [4], Fars Province (Iran) [37] and some other locations in the Middle East [7, 8], who also obtained satisfactory performance in using SDSM for the downscaling of precipitation. The future precipitation generated under three scenarios showed an overall similar signal, albeit with a clear declining trend in the annual precipitation of Basrah during 21st century, which is found to be dependent on the climate scenario. The reduction in the precipitation ranged from a small percentage of 10.4 % in the 2075s under RCP2.6 scenario to 33.6 % under RCP 8.5. These results are in good agreement with the climate projections for the Middle East that also predicted a hotter and drier region in the future [6, 9]. For example, a study carried out in the Iraqi Western Desert by using the CanESM2 model showed that the annual precipitation is expected to be decreased, where the decline reached up to 37 % under the RCP 8.5 scenario by the end of the century [4]. A reduction in precipitation of Basrah (southern Iraq) by 10.4 % to 33.6 % suggests an increase in aridity of the region during the 21st century, and this is particularly important in the light of the already water stressed situation in the area due to a reduction in the Tigris and Euphrates river inflows, high evaporation losses, and high saltwater intrusion in the Shatt al-Arab [13]. The reduction in the local precipitation will add extra pressure to the water crisis in the Basrah area. Firstly, it will contribute to a reduction in the direct recharge to the local surface and shallow groundwater resources, which provide a minor portion of the water supply to agriculture and drinking water. Secondly, it will contribute to the reduction in the river inflows from the Tigris and Euphrates rivers, and this, in turn, will add extra pressure to the water resources in the Basrah area, as the region is suffering from severe water scarcity and salt water intrusion. Furthermore, the increase in temperature projected for the region [8]. Compared with previous regional studies on precipitation in southern Iraq, the findings of this study are broadly consistent. Wadi et al. [25] found that annual rainfall in Basrah would decrease by 12.2% under RCP8.5 by 2099 using SDSM, which aligns with change in direction of projected that study, though the magnitude differs due to different time horizons and baseline periods. Similarly, Al-Mukhtar and Qasim [7] projected significant precipitation declines across Iraq using SDSM, consistent with our findings. At the broader Arabian Gulf scale, climate projections consistently indicate a trend towards decreased precipitation and increased aridity under all RCP scenarios [8]. The results obtained here reinforce these regional findings, providing additional local-scale evidence of precipitation decline in one of the most climate-vulnerable areas of Iraq.

The impact of these projected changes on the food security, water management, and the agricultural sector as a major source of income of the majority of the rural people of the region will be very severe. Also, the prospect for the Mesopotamian Marshes (partially close to Basrah) will be very critical. The ecological integrity and sustainable livelihoods of communities of these marshes are dependent on sufficient freshwater supply and their degradation due to drier climate will likely to aggravate [6]. Moreover, socioeconomic impacts including water-related conflicts, poor water quality causing health problems, and migration will be exacerbated [14]. From a water resource management perspective, the projected precipitation declines necessitate immediate attention to adaptive management strategies. Policymakers and water authorities in Basrah should prioritize investments in water storage infrastructure, demand-side management, and climate-resilient agricultural practices. The development of integrated water management plans that account for future climate scenarios, as presented in this study, is essential for ensuring long-term water security and climate adaptation in the region.

So, it is necessary to provide an effective plan for the management of water and adapt with change of climate in Basrah area. In particular, the results from the scenarios of this study can be used by local and regional water authorities and decision-makers to: (i) shift from the current practices that mostly involved with crisis management to a longer-term planning based on these scenarios and (ii) evaluate the advantages and disadvantages of different adaptation options that could be adopted. These may include, for example, measures such as:

1. Improving water use efficiency by introducing advanced irrigation systems (e.g., drip irrigation), changing to drought-tolerant crops and reducing urban and industrial distribution losses;
2. Developing alternative sources of water such as desalination of Arabian Gulf seawater and reusing treated wastewater for irrigation and industrial applications;
3. Introducing integrated water resources management strategies that consider the whole river basin, encourage intersectoral integration and engage in transboundary negotiations to obtain its fair share of water resources; and
4. Enhancing climate monitoring and drought early warning systems by developing more effective monitoring systems to generate reliable and timely data for climate and water resources to better manage droughts.

Despite the novelty of the results of this study, we have to recognize that the data from only one GCM (CanESM2) is employed here. Although it is noted that CanESM2 performs well in this region [4, 8]. One limitation of this study is the use of a single global climate model (CanESM2). Using multiple climate models could reduce projection uncertainty and improve reliability, to represent the uncertainty of the projection. It would be ideal if we can consider more CMIP6 models to narrow down the range of the projection in the future. Moreover, the statistical approach employed in SDSM assumes that the relationship between the selected predictor variables and the predictands will persist into the future; this might not always be true. It would be beneficial to use the results of the dynamical downscaling and other more sophisticated statistical models for comparison and verification purposes.

5. Conclusions

In this research, SDSM was successfully employed to prognostication the future precipitation in Basrah Governorate, Iraq up to the year 2085. The model performed satisfactorily "Very good" during the calibration ($R^2 = 0.905$, NSE $= 0.810$) and validation ($R^2 = 0.874$, NSE $= 0.844$) phases, and thus the model was found to be adequate for the downscaling of the precipitation projections in this region. These results confirm that Basrah Governorate is highly susceptible to future precipitation decline, underscoring the urgent need for climate-adaptive water management strategies. The major outcomes of this research are as follows:

1. There is a statistically significant negative trend for the future projection of the annual total precipitation in Basrah Governorate under all three scenarios (RCP2.6, RCP4.5 and RCP 8.5).
2. The rate reduction in precipitation depends on the future global emissions pathway, and the RCP 8.5 is found to be the worst scenario with a total reduction of 33.6 % of

the total annual precipitation by the end of the 2075s period, however, under RCP 2.6 scenario, the future total annual precipitation is expected to be decreased by over 10%.

3. The reduction in the future annual total precipitation will occur during the wet season (from October to March) which is the wet season in the region and the main source of the water recharge for the natural water, and this will create a big deficit in the future water budget and will impact the agricultural sector, ecosystems and the water supply.
4. Provide an essential basis for local scientific evidence for decision-makers and water managers in Basrah Governorate, Iraq, in order to develop an adaptation strategy and to manage future water resources. To this end, the results of this study could be used in the future studies for a long-term planning of the available water resources, and to produce appropriate adaptation and mitigation measures.

Ultimately, the obtained results in this study show that the southern region of Iraq is highly vulnerable to climate change and there is a need for proper water management practices and to encourage more investments in water and climate resilient infrastructure. The results of this model can be used to produce an early warning for creating a long-term planning in to mitigate the expected environmental, economic, and social risks that might occur as a result of the future expected drought in the region. The results are expected to provide decision-makers with valuable information to develop reliable strategies for better management of climate adaptation, which will help in minimizing the environmental and socio-economic of future climate in this region.

Conflict of interest

The authors declare that they have no conflict of interest.

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Data availability

The data that support the findings of this study are available on request from the corresponding author.

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