The effect of climate change on the maximum temperature in Southwest Iraq using HadCM3 and CanESM2 modelling

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Abstract

In the twenty-first century, climate change has become a major environmental threat specifically for regions which are already dry. The identification and assessment of climate change in the future are therefore paramount for suitable environmental planning in order to adapt to and decrease its impact. In this research, changes in the maximum temperature in Iraq over the period 2020–2099, were generated by two general circulation GCM models, HadCM3 and CanESM2, based on emission scenarios A2, B2, RCP2.6, RCP4.5, and RCP 8.5. After checking the ability of the Statistical Downscaling Model (SDSM) to generate climatic data based on the period 1979 to 2018, the daily maximum temperature was downscaled for the period 2020–2099 in seven meteorological stations in Iraq. The results of the uncertainty analysis show the maximum temperature generation using the CanESM2 model with emission scenario RCP 2.6, having the best performance among all stations. The results also show an increase in maximum temperature of between 0.3 and 1.2 °C across all stations by the end of the twenty-first century. This increase in the maximum temperature impacts water resources due to increased evaporation from surface water, causing water scarcity. Changes in the maximum temperature show more of an increase using the HadCM3 model when compared with CanESM2, for all stations in Iraq.

Keywords Climate change · Statistical downscaling model · Maximum temperature changes · RCP scenarios · SDSM

1 Introduction

In arid/semiarid areas in the Middle East, climate change is an unexpected and intricate phenomenon attributed to human activity and greenhouse gas emissions. Changes in the temperature in humid and arid areas have been observed in most parts of the world but changes of temperature in dry regions are of concern as these will speed up the desertification process. Climate change can affect groundwater resources in a number of ways, both directly and indirectly. Changing precipitation patterns and increasing temperatures will directly impact groundwater discharge, recharge, storage and general water levels. In addition to this, a rise in sea levels, demand for water for irrigation and changes in vegetation cover can

affect groundwater quality and quantity indirectly. Higher temperatures will lead to increased evaporation and plant transpiration rates which mean drier soil, this in turn leading to higher losses of soil moisture and groundwater recharge [1].

The Intergovernmental Panel on Climate Change (IPCC) states that they expect an increase in temperature of between 1 and 3.5 °C due to an increase in greenhouse gases, by the end of this century [2]. This pattern of global warming is expected to increase through the twenty-first century under all representative concentration pathways (RCPs). This is likely to be due to increased greenhouse gas emissions because of intensified levels of manufacturing [3]. The impact of climate change on groundwater resources is probably even more serious due to increased

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potential evapotranspiration (ETP) and decreased precipitation, both of which may lead to more intensive groundwater abstraction in the future [4–6]. Shahid et al. [7], researching in northwest Bangladesh, reported that higher temperatures lead to increased evapotranspiration which offsets the advantage of increased precipitation, and therefore, no appreciable change in groundwater recharge. Essink et al. [8] studied the effects of climate change on coastal groundwater systems in the Netherlands and reported that future increases of salt load due to an increase in sea levels, will cause salinization of shallow groundwater and reduce the total volume of fresh groundwater. Abbasnia and Toros [3] studied future maximum temperatures changes applying CGCM3 modeling to emission scenarios A2, B1, and A1B using the (SDSM) model in seven study stations in Iran over 2041–2070 and 2071–2099. The results predicted an increase in average maximum temperature of between 0.3 and 3.5 °C at all selected stations in Iran. Other research has shown that climatic parameters, such as average annual global temperature, have increased between 0.3 and 0.6 °C since the late nineteenth century, this expected to increase between 1 and 3.5 °C over the next 100 years [9]. Samper et al. [10] assessed the impact of climate change on mean annual recharge in the Plana de La Galera aquifer in Spain, reporting that groundwater recharge will decrease by 23% during 2020–2050 and 27% during 2069–2099, compared to 1960–1990. Hassan [11] studied the effect of climate change (temperature and precipitation) on groundwater recharge in the Western Desert of Iraq in the Umm er Radhuma unconfined aquifer, using WetSpass as a modeling approach. Climate data for the period 2020 to 2099 were generated using HadCM3 modeling applied to emission scenarios A2 and B2. The results revealed an increase in average temperatures and an increase in annual precipitation by 5.4% and 3.19%, for A2 and B2 scenarios, respectively. The average annual groundwater recharge is predicted to decrease by 16% for both scenarios in the next century.

Sansom and Renwick [12] evaluated the impact of future climate change, finding that it can cause both floods and droughts. Using general circulation models (GCMs) to estimate climate change in New Zealand, they found an increase in rainfall due to increases in rainfall frequency because of climate change. Evans [13] studied the prediction of future climate change in the Middle East with 18 global climate models as used by the Intergovernmental Panel on Climate Change (IPCC). This study concluded that the temperature would rise by 1.4 °C by mid-century and 4 °C by the end of the century and that there would be lower precipitation in Turkey, Syria, Northern Iraq, Northeastern Iran, and the Caucasus. Osman [14] studied the effect of climate change on rainfall in the dry areas of Iraq using seven Global

Climate Models (GCMs) for three time periods: 2011–2030, 2046–2065, and 2080–2099. The results suggested that the annual mean rainfall would decrease for most regions by the end of the twenty-first century.

The output generated by general circulation models (GCM's) can be used to understand the effects of global warming and climate change in the future. Lemke et al. [15] found that global temperatures will increase between 2 and 4.5 °C over the next 80 years using these models. However, because GCM model spatial and temporal resolution is a generalized estimation, downscaling is important to produce local parameters from observation stations [16]. The statistical downscaling model (SDSM) suggested by [17] is considered a suitable tool for the statistical downscaling of both current and future climate data. Therefore, in this research, changes in maximum temperatures in Iraq over the period 2020–2099 due to global warming are to be predicted using an SDSM model based on output from two GCM's, the Hadley Center for Climate Prediction and Research (HadCM3) and the Canadian Earth System Model Second Generation (CanESM2) under the existing scenarios A2, B2, RCP 2.6, RCP 4.5, and RCP 8.5.

2 Study area

Geographically, Iraq sits in a semiarid/arid region of the Middle East. The study area, the southwest of Iraq, is notable for its vastness. It extends from the west to the southern points of Iraq, comprising approximately 265,736 km², forming about 64% of Iraq. It is located between latitude 29° 10'–34° 55' N and longitudes 38° 80'–48° 50' E. The study area has average minimum and maximum temperatures of 17.3 °C and 31.4 °C, respectively. In this study, in order to assess temperature change, seven meteorological stations, namely Karbala, Ramady, Rutba, Nukhayb, Salman, Samawah, and Zubair, were used as climatic representatives of the study area, as shown in Fig. 1. The most important groundwater aquifers in Iraq are located in the study area, e.g., Al-Dibdiba unconfined aquifer which extends from the center to the far south in the study area. It depends on rainfall recharge which is related to changes in temperatures [18]. There are also many open-surface reservoirs in the center of the study area such as Al-Tharthar Lake and Al-Razazah Lake as well as multiple natural marshes located in southern Iraq.

3 Materials and methods

3.1 Analysis of data

To calculate changes in maximum temperatures, the SDSM model was applied to statistically downscaled output from

Fig. 1 The study area within Iraq and the local meteorological stations used

the Global Climate Model (GCM). Downscaling involves building relationships between atmospheric information on a global scale as predictors, and climate information on a regional scale as predicted [19]. As such, to generate the probability of local maximum temperature changes at a selected station, two datasets are used:

1. Daily maximum temperature data were provided by the Organization for Meteorology and Seismology in Iraq, from seven meteorological stations acting as climatic representatives in the study area (southwest Iraq) during the period of observation (1979 to 2018).
2. Daily global climatic parameters as predictors were taken from the Canadian Climate Change Scenarios Network. This data includes National Center of Environmental Predictions (NCEP) collected over the observational period, as well as output from HadCM3 and CanESM2 under existing scenarios for both current and future time periods (2020–2099). Two GCM data sets are used (presently HadCM3 and CanESM2) to downscale using SDSM model version 4.2 [19]. Table 1 shows the closer mesh boxes from the meteorological stations under study, these used to obtain GCM information from those specific grid cells. Table 2

Table 1 GCM coordinates at study station scale

GCM	Station	Karbala	Nukhayb	Ramady	Rutba	Salman	Samawah	Zubair
HadCM3	X:	12	12	12	11	12	12	13
	Y:	21	21	20	21	22	22	22
CanESM2	X:	16	17	17	16	17	17	18
	Y:	44	45	45	45	44	44	44

shows the GCM features used as SDSM model input [15].

3.2 Statistical downscaling model (SDSM)

The SDSM [17], was applied to downscale GCM output and generate climate data via multiple linear regression (MLR). The model structure in the SDSM is given in Fig. 2. To generate climatic variables across any period of time (annually, monthly, or seasonally), a multivariate linear regression model is built between independent variables (predictors on a global scale) and a dependent variable (predicted climatic parameters on a local scale) over the following stages:

3.2.1 Monitoring and screen variables

The main purpose of this step is to facilitate the choice of suitable downscaling predictor parameters. This stage is the most challenging in the process of any statistical downscaling simulation because the selection of predictors largely defines the shape of the downscaled climate scenario. For the current research, predictors were chosen dependent on the outcome of the correlation analysis (a correlation tested between predicted and predictors, this including a partial correlation, the analysis of the correlation matrix and scatter plot), used to identify the most suitable multiple regression model across all meteorological stations. Table 3 shows the partial correlation results between maximum temperature variables at each local station, and the selected predictors for both the HadCM3 and CanSM2 models.

Table 2 GCM features used as input of SDSM model

GCMs	SRES	Resolutions	Reference
HadCM3	A2, B2	2.5°×3.75°	Hadley Centre for Climate Prediction and Research, United Kingdom.
CanESM2	RCP2.6, RCP4.5, RCP8.5	2.79°×2.81°	Canadian Centre for Climate Modeling and Analysis (CCCma).

Fig. 2 Structure of SDSM Version 4.2 for climatic scenarios generation

3.2.2 Calibration and validation

Data for the period 1979 to 2018 were used for the validation and calibration model. Different statistical indicators were used to assess the accuracy of the validation stage in the SDSM. The results of the multivariate regression model were compared to the observed data for each station at baseline. The prediction model was validated using the coefficient of determination (R^2), root-mean-square error (RMSE), and mean bias error (MBE). R^2 is a measure of relativity, its best value equal to one (Eq. 1). RMSE is the standard deviation of

the residuals (prediction errors) and is equal to zero if the predictions of model correspond very well with the observations (Eq. 2). The MBE represents the error estimation of modeling. It can be a negative or positive value but the best value is equal to zero (Eq. 3).

$$R^2 = \frac{\sum_1^n P_i O_i}{\sqrt{\sum_1^n P_i^2 \sum_1^n O_i^2}} \quad (1)$$

Table 3 Partial correlations between the maximum temperatures at all local stations through the period of observation with the selected predictors, using both HadCM3 and CanESM2 models

Predictor	Model	Description	Karbala	Nukhayb	Ramady	Rutba	Salman	Samawah	Zubair
mslp	Had	Mean sea level pressure	0.025	0.03	0.005	0.018	0.091	−0.011	−0.109
mslp	Can		−0.07	−0.065	−0.024	0.015	−0.095	−0.096	−0.029
P500	Had	Geopotential height(500 hPa)	0.029	−0.041	−0.056	−0.045	0.126	0.023	0.109
P500	Can		0.122	−0.027	−0.029	0.047	0.033	0.027	0.025
P850	Had	Geopotential height(850 hPa)	−	−	−	−	−0.123	−0.003	−
P850	Can		0.02	−	0.002	−0.039	0.062	0.062	0.005
temp	Had	Mean temperature at 2 m	0.397	0.375	0.18	0.836	0.348	0.324	0.396
temp	Can		0.245	0.39	0.305	0.282	0.217	0.228	0.28
P8-u	Had	Zonal velocity(850 hPa)	−0.009	−	−	−	−	−	−
P5-u	Had	Zonal velocity(500 hPa)	−	−	−	−	0.04	−	0.055
p-zh	Had	Surface divergence	0.338	0.332	−	−	−	−	−
p-z	Had	Surface vorticity	−	−	−	−	−	−	−0.084
P8tzh	Had	Vorticity(850 hPa)	−	−	−	−	−	−	0.044
S500	Can	Specific humidity(500 hPa)	−0.164	−	−	−	−	−	−
rhum	Had	Near-surface relative humidity	−	−0.185	−0.278	−0.066	−0.116	−	−
P5-u	Can	Zonal velocity(500 hPa)	−	0.108	−	−	−	−	−
shum	Had	Surface Specific humidity	−	−	0.272	−	−	−	−
shum	Can		−	−	−	−0.074	−	−	−
R500	Had	Relative humidity (500 hPa)	−	−	−	−0.149	−0.235	−0.16	−
R500	Had	Relative humidity (850 hPa)	−	−	−	−	0.017	−0.144	−
P8th	Had	Wind direction(850 hPa)	−	−0.026	−	−	0.038	−	−
P5th	Can	Wind direction (500 hPa)	−	−	−	−	−	−	0.111

$$RMSE = \sqrt{\frac{\sum_1^n (P_i - O_i)^2}{n}} \quad (2)$$

$$MBE = \frac{\sum_1^n (P_i - O_i)}{n} \quad (3)$$

where P_i is the daily value of predicted; O_i the daily value of observation and n the total number of data.

3.2.3 Generation of climatic scenarios

The GCMs were developed using different scenarios for potential emissions in the future. This was to compensate for fluctuations in human activity that can affect climate change. More than 40 scenarios related to emissions were considered by IPCC [20] in the Special Report on Emission Scenarios (SRES), a report which examined quantity of greenhouse gas emissions, development of technology, land use, land cover, and other human activities. A1F1, A1T, A1,

A2, A1B, B1, and B2 can be considered as the most important emissions scenarios [20]. With this in mind, an SDSM model was generated with climate scenarios for the future, these a function of alterations regarding local variables. At this stage of the research, and considering statistical calibration and regression equations between several global scale predictors parameters, e.g., maximum temperature at all stations through baseline interval (1979–2018), a statistical down-scaling operation will be carried out on the GCM output (HadCM3 and CanESM2) under different emissions scenarios (A2, B2, RCP 2.6, RCP 4.5 and RCP 8.5). A time series of daily maximum temperatures at local stations, will be modeled and generated as applicable to the study time frame.

3.3 Analysis of uncertainty

In climate change studies, there are several modeling uncertainties which need to be taken into account in the quest for dependable results [21]. When calculating climate change,

there are two major sources of uncertainty, the first attached to the dynamic structure of GCMs and their computational operations. With the passing of time, and because of increasing accuracy and quality of GCM output, this type of uncertainty gradually decreases. The second is attached to the quantity of greenhouse gas emissions [22]. In this research, calculate the weight for all scenarios, the mean observed temperature is used (Eq. 4).

$$W_{ij} = \frac{\frac{1}{\Delta T_{ij}}}{\sum_{i=1}^n \frac{1}{\Delta T_{ij}}} \quad (4)$$

where W_{ij} is the weight given to each scenario across models (j), ΔT_{ij} the variance between the average generated maximum temperatures in future decades from the average observational maximum temperatures for every day (i), and n the total number of model scenarios. Consequently, dependent on the range of weight which is connected with the GCM output, the assemble scenario was generated to gain a global scenario of maximum temperature changes at all local stations in Iraq (Eq. 5).

$$SRE_{\text{Assemble}} = \sum_{j=1}^n (\Delta T_{ij} \times W_{ij}) \quad (5)$$

Table 4 Calibration results of downscaled models during the basic observation period (2001–2018)

Stations	Models	MBE	RMSE	R ²
Karbala	HadCM3	−0.0113	3.46	0.905
	CanESM2	0.0106	3.45	0.905
Nukhayb	HadCM3	−0.0003	3.25	0.906
	CanESM2	−0.0016	3.25	0.906
Ramady	HadCM3	−0.0104	3.38	0.901
	CanESM2	0.0022	3.34	0.912
Rutba	HadCM3	0.0086	3.54	0.880
	CanESM2	−0.0029	3.53	0.880
Salman	HadCM3	−0.0008	3.35	0.901
	CanESM2	−0.0066	3.36	0.901
Samawah	HadCM3	0.0013	3.36	0.911
	CanESM2	0.0061	3.39	0.910
Zubair	HadCM3	−0.0034	3.18	0.918
	CanESM2	0.0298	3.21	0.917

4 Results and discussion

In this research, after checking the capability of SDSM, two GCM outputs, HadCM3 and CanESM2, were used to down-scale maximum temperature data for the study period at selected stations in Iraq. Table 4 shows the cross-over results of the validation models for the climate variables, using the statistical indexes determination coefficient (R^2), RMSE and MBE. The ranges of R^2 , RMSE and MBE were 0.880–0.918, 3.18–3.54, and 0.0298–0.0013, respectively. The results of the cross-validation confirm that the final developed regression models have acceptable accuracy and can predict expected maximum temperatures in the future when using global-scale climate parameters as independent parameters.

Table 5 shows the probability weight, calculated according to Eq. 4, regarding the ability of both models, HadCM3, and CanESM2, to generate maximum temperatures in the future. As shown in Table 5, the results show the maximum temperatures generation by CanESM2 under the scenario of emissions RCP 2.6, gives the best performance over all stations because it has the greatest probability weight.

Figure 3 shows the results of increasing maximum temperatures, at all selected stations, obtained for the period 2020–2099, based on each model scenario. There are increases in the maximum temperature at all stations. HadCM3 found the lowest maximum temperature increase for scenario B2 at Rutba station, located in the west of Iraq, the greatest maximum temperature increases under scenario A2, at Zubair and Samawah stations located in the south of Iraq. CanESM2 found the lowest maximum

Table 5 The probability weight of all model scenarios regarding maximum temperature generation in the study period (2020–2099)

Model/SRES	HadCM3		CanESM2		
	A2	B2	RCP2.6	RCP4.5	RCP8.5
Karbala	0.15	0.17	0.3	0.22	0.14
Nukhayb	0.11	0.13	0.34	0.26	0.16
Ramady	0.15	0.17	0.3	0.22	0.14
Rutba	0.16	0.2	0.3	0.21	0.13
Salman	0.19	0.24	0.25	0.19	0.12
Samawah	0.14	0.16	0.3	0.23	0.15
Zubair	0.14	0.16	0.3	0.23	0.15

Fig. 3 Simulation range of increases in annual maximum temperatures under different model scenarios, **a** HadCM3, **b** CanESM2 between 2020 and 2099

temperature increase under scenario RCP 2.6 at Rutba and Nukhayb stations, both located in the west of Iraq, the greatest maximum temperature increase using scenario RCP 8.5 at Samawah station, located in the south of Iraq. The results show an increase in maximum temperature of between 0.3 and 1.2 °C across all stations in the future. The HadCM3 model found higher increases in maximum temperatures in comparison with CanESM2.

Figure 4 shows a comparison between average monthly temperatures observed over the period 1979–2018, and predicted values by scenarios A2, B2, RCP 2.6, RCP 4.5, and RCP 8.5, for both HadCM3 and CanESM2 for 2020–2099. The maximum increases in average monthly maximum temperature were observed for July, August and September, the summer season. Minimum increases were observed for January and December, the winter season, across all stations. The maximum increment was observed at Zubair Station where the temperature is predicted to be between 45 and 50 °C while the minimum increment was observed at Rutba Station where the temperature is predicted to be 40 °C.

Figure 5 gives a comparison of average annual temperatures observed between 1979 and 2018, and predicted values using scenarios A2, B2, RCP 2.6, RCP 4.5 and RCP 8.5

as per HadCM3 and CanESM2, between 2020 and 2099. The largest increase in average maximum temperature is expected at Samawah and Zubair stations, the minimum increase at Rutba Station. HadCM3 using scenarios A2 and B2, predicted a larger increase than CanESM2 under RCP 2.6, RCP 4.5 and RCP8.5 scenarios across most stations. Figure 6 shows the distribution of average annual changes in maximum temperature under every model scenario over the period 2020–2099. The results from all models under different scenarios show that the maximum temperature will continue rising until the end of the century. The largest increase in average maximum temperature is observed in southern Iraq, an area which has a more arid climate in comparison to the west where the minimum increase is observed. HadCM3 using A2 and CanESM2 using RCP 8.5, predict the highest increases in temperature. A2 focuses on economic growth and increasing population, while RCP 8.5 represents maximum population growth, low technological expansion in combination with high energy use, and subsequent emissions throughout the twenty-first century.

Fig. 4 Comparison between average monthly temperatures observed over 1979–2018, and values predicted by A2, B2, RCP 2.6, RCP 4.5, and RCP 8.5 scenarios using HadCM3 and CanESM2 between 2020 and 2099, **a** Karbala, **b** Samawah, **c** Nukhayb, **d** Salman, **e** Ramady, **f** Zubair, **g** Rutba

Fig. 5 Comparison between average annual temperatures observed between 1979 and 2018, and values predicted by scenarios A2, B2, RCP 2.6, RCP 4.5, and RCP 8.5 by both HadCM3 and CanESM2 over the period 2020–2099

5 Conclusions

Climate change, specifically increasing temperature, is a growing global issue. In this research, two GCM output models, HadCM3, and CanESM2, using scenarios A2, B2, RCP 2.6, RCP4.5, and RCP8.5, were employed to examine the impact of climate change on increases in temperature over the period 2020 to 2099. The aim of downscaling was to predict future changes in maximum temperature, in order to estimate possible risks for the future from climate change. HadCM3 predicted higher

increases in comparison with CanESM2 across all stations. The maximum temperature is predicted to increase between 0.3 and 1.2 °C, over 2020–2099, in southwest Iraq at all study stations. This increase will impact water resources by increasing evaporation from surface water, this causing water scarcity. The maximum temperature predicted by CanESM2 under emission scenario RCP 2.6 has the best performance between all stations because it has the greatest probability weight. In geographic distribution terms, the most prominent maximum temperature increase is predicted at Samawah and Zubair stations which are located in the south of Iraq; the lowest maximum temperature increase is predicted at Rutba station which is located in the west of Iraq. The results also revealed that stations which are located in the more southern areas which have a drier climate, will encounter more serious problems related to the predicted increase in temperature. As these areas contain large and important groundwater aquifers for Iraq, this will cause a decrease in their recharge capacities in the future. It is recommended that countries in the region reduce greenhouse gas emissions by converting their energy sources to clean energy. The results of this study are limited by the set of data used. But the methodology, which has been developed and validated here, can predict the effect of climate change on temperature and be adopted for use in any region, worldwide. For future studies, could be used the results of this study to predicting the effects of this increase in temperature for groundwater recharge and surface water quantity and quality within study region. Also, it is can be creating a model for predicting the maximum temperature depending on the machine learning methods.

Fig. 6 Predicted distribution of average annual changes in maximum temperature by each model scenario over the period 2020 to 2099 **a** Observed, **b** A2, **c** B2, **d** RCP2.6, **e** RCP4.5, **f** RCP8.5

Compliance with ethical standards

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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