International Journal of Latest Research in Engineering and Management" (IJLREM)
ISSN: 2456-0766
www.ijlrem.org Volume 2 Issue 5 ǁ October. 2018 ǁ PP 01-13

Statistical Downscale climate change data from the HadCM3 models on precipitation for Iraq.

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ABSTRACT: *For over three decades, Iraq has suffered from climate variability and desertification. Rainfall rates have decreased with abnormal high-temperature degrees, recurrence of dust storms has been increasing and many agricultural areas have turned into barren land. Future water availability is mainly influenced by the impacts of climate changes on meteorological data. Future climate projected by General Circulation Models (GCMs) presents averaged values in large scales. Therefore, downscaling techniques are usually needed to transfer GCM-derived climate outputs into station-based values. In this study, a statistical downscaling model is investigated and its applicability in generating daily precipitation series. The results presented in this report have indicated that it is feasible to link large-scale atmospheric variables by GCM simulations from Hadley Centre 3rd generation (HadCM3) outputs with daily precipitation at a local site. Statistical Downscaling Model (SDSM) was applied using three set of data; daily precipitation data for the period 1961-1990 and 1971-2000 corresponding to 12 stations located in Iraq. The future precipitation for 12 stations of Iraq were projected for three future periods 2020s, 2050s, and 2080s from the Hadley Centre Climate Model (HadCM3) under different scenarios (A2a and B2a) using statistical downscaling model (SDSM).The model was calibrated and validated against daily data by using 70% of the data for calibration, and the remaining 30% for validation. Thereafter, the calibrated model was applied to downscale future scenarios of HadCM3 predictors. The aim of this study is to test a commonly-used weather generator, namely SDSM, at 12 sites in Iraq and to generate the future projection of daily precipitation.*

KEYWORDS: *Statistical downscaling; Projections; Precipitation; Iraq*

I. INTRODUCTION

Climate change can lead to severe impacts on different major sectors of the world such as water resources, agriculture, energy and tourism (Osman et al., 2014). Several studies have reported that the Middle East region may face more aridity due to temperature increase and rainfall decrease (Al-Rijabo and Salih, 2013; Bilal et al., 2013; Zakaria et al., 2013; Osman et al., 2014; Azooz and Talal, 2015). Iraq is located in the southwestern part of the Asian continent and extended between latitudes 29.5°–37.22°N and longitudes 38.45°–48.45°E (Hashim *et al.*, 2013). Iraq has the climatic zone between continental and subtropical. Winters are usually cool to cold, with an average daily temperature that reaches 16 °C and drops to 2 °C at night. Summers are dry and extremely hot, over 43 °C during July and August but drop to 26 °C at night (Zakaria *et al.*, 2013). The continental climate in Iraq is described as hot, dry summers and cool, wet winters, with north-westerly prevailing winds. Most of the rainfall occasionally occurred by the fluctuation of storm weather in the Mediterranean region during the winter, as it moves towards the east and across the northern Iraq (Kashef Al-Kataa, 1982). To develop strategies and to make informed decisions about the future water allocation for different sectors and management of available water resources, planners need information about the impacts of climate changes on meteorological parameters (usually in terms of watershed scale precipitation and temperature) that can directly be used by the hydrologic impact models. Atmosphere-ocean coupled Global Climate Models (GCMs) are the main source tools used to simulate present and future climate of the earth under different climate change scenarios. However, the course scaled GCM projections (usually grids of 10^4–105 km^2) cannot be applied directly in hydrologic studies at regional scales. The objectives of this study are to investigate the ability of statistical downscaling model in reproducing the meteorological parameters (i.e. precipitation) and, hence, to analyze the impact of future climate changes (2011-

2099) on precipitation in several station of Iraq. The outcomes from this study would help decision makers and researchers in better future planning for the water resources in Iraq and help in finding ways and means to minimize the effect of climate change on the inhabitants and the environment.

II. STUDY AREA AND DATA DESCRIPTION:

Iraq is located; geographically in the East Mediterranean Region. Bound by South Anatolia in the north, Iran in the east and northeast, Syria and Jordan in the west; it opens on the Saudi Arabia, Kuwait and the Gulf at the south. The total population in Iraq in 2017 is about 37.139.519. Iraq is composed of 18 Governorates. Twelve sites were selected across Iraq to represent as much as possible major climatic regions in the country (Fig. 1). As such, the selected stations extend from the north to the south of the country where most of the agricultural and urban areas are present. The investigated stations are Baghdad, Kirkuk, Mosul, Sulaymaniyah , Najaf, Nasiriyah, Al-Hay , Basra, Zakho, Erbil, Salah ad Din and Khanaqin. The observed data of those stations were obtained from Iraqi National Meteorological Organization and seismology. The data availability is listed in Table 2 with their corresponding mean annual precipitation. The observed daily rainfall data of the stations Kirkuk, Mosul, Baghdad, Nasiriyah, Najaf , Al-Hay, Basra and Khanaqin were available for the period 1961–1990. While, for the remainder stations (Sulaymaniyah, Zakho, Erbil and Salah ad Din) the data were from 1971–2000. For better understanding of the climate behavior in those stations, the mean monthly precipitation was depicted as shown in (Fig.2). As it can be seen from the figure, the mean monthly precipitation of the twelve stations over the respective period ranged from 140-20 mm in January to zero in the summer months (Jun, July, August) and September.

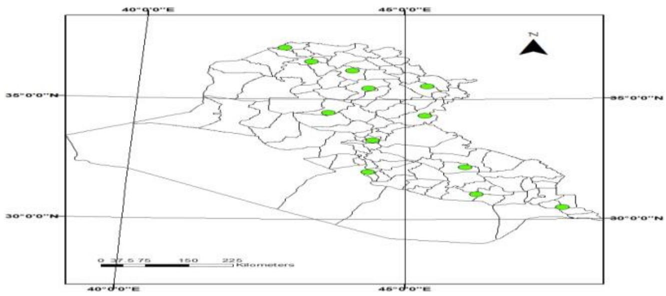

Fig. 1 Geographic map of Iraq with locations of 12 meteorological stations.

Table 1 Location details of the twelve stations in Iraq
Table 1 presents a detail description about the locations of the investigated stations.

Station	Latitude	Longitude	Altitude(m)	Area(km^2)	Population
Bagdad	33º 18´ N	44º 24´ E	34	204.2	7.665
Basra	30º 31´ N	47º 47´ E	5	181	2.15
Erbil	36°11′28″N	44°0′33″E	390	197	852,500
Al-Hay	32°10′ N	46°03′E	20	----	84,800
Najaf	32° N	44°20′00″E	60	28,824	1,389,500
Nasiriyah	31°03′ N	46°16′E	9	12,900	860,200
Zakho	37°08′37 N	42°40′54.88″E	440	----	350,000
Sulaymaniyah	35º 33´ N	45º 25´E	882	20,144	1.256
Salah ad Din	34°27′ N	43°35′E	-----	24,751	1.408
Khanaqin	34°20′ N	45°23′E	183	----	150,000
Mosul	36.34° N	43.13°E	223	180	664,221
Kirkuk	35°28′ N	44°19′0″E	350	9,679	850 787

Table 2 Description of data availability for the twelve stations used in the study

Station	Period	Mean annual precipitation (mm)
Baghdad	1961-1990	31.1
Basra	1961-1990	31.3
Erbil	1961-1990	11.8
Al-Hay	1971-2000	60.8
Najaf	1961-1990	8.12
Nasiriyah	1961-1990	9.5
Zakho	1961-1990	60
Sulaymaniyah	1961-1990	10.7
Salah ad Din	1971-2000	52.9
Khanaqin	1971-2000	34.6
Mosul	1971-2000	50.2
Kirkuk	1961-1990	25.5

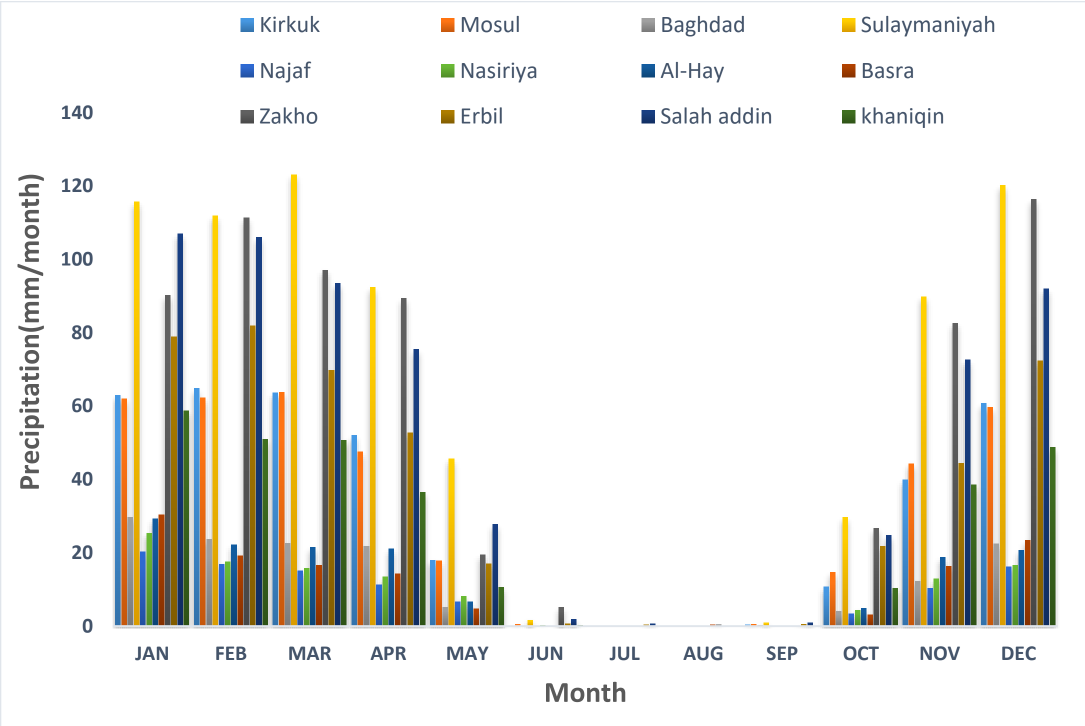

Fig.2 Monthly precipitation at weather stations for the baseline period (1961–1990) and (1971-2000).

The 26 predictors of NCEP/NCAR (National Center for Environmental Prediction/ Atmospheric Research) reanalyzed predictors with grid resolution 2.5°×2.5° were freely downloaded from:

(https://www.esrl.noaa.gov/psd/data/reanalysis/reanalysis.shtml). The HadCM3 climate model of the Canadian model for the A2 and B2 scenarios with grid resolution (2.5° x 3.75°) were obtained from a Canadian Centre for Climate Modelling and Analysis: (http://climate scenarios.canada.ca/?page=pred-canesm2) for the periods of 1961–2001 and 1961–2099 (Table 3). These predictors are assigned in zip file format and have three files inside; NCEP_1961-2001, H3A2a_1961-2099, and H3B2a_1961-2099, this technique was used especially as an input in SDSM model. The normalized predictors are only available for HadCM3 and CanESM2 in such a form that can be downloaded according to the coordinates of the study area and used directly for SDSM.

III. DOWNSCALING OF GCM OUTPUTS USING SDSM MODEL

Description of SDSM : Downscaling of climate data to local level was done by SDSM software, which was downloaded freely from http://www.sdsm.org.uk. It was used to develops quantitative relationship between the large scale GCM (predictor) and local surface variables (e.g. rainfall and temperature), which are observed data from ground meteorological stations, based on multiple regression technique. Reanalysed atmospheric dataset obtained from National for Environmental prediction (NCEP) together with observed data were used for model calibration and validation. The HadCM3 predicators for A2a and B2a scenarios were obtained from Prof. Wilby at Loughborough University, UK. The most commonly used predictor variables for the NCEP and HadCM3 GCM experiment are listed in Table 3. These were inputs into the SDSM model.

Table 3 NCEP and HadCM3 predictors which used in SDSM downscaling method

No	Notations	predictor full name	No	Notations	predictor full name
1	ncepmslp	mean sea level pressure	14	Ncepp500	500 hpa geopotential
2	Ncepp5-f	500 hpa wind speed	15	ncepp850	850 hPa geopotential
3	Ncepp5-u	500 hpa U-component	16	ncepp-f	1,000 hpa wind speed
4	Ncepp5-v	500 hpa V-component	17	ncepp-u	1,000 hPa U-component
5	Ncepp5-z	500 hpa vorticity	18	ncepp-v	1,000 hPa V-component
6	Ncepp5th	500 hpa wind direction	19	ncepp-z	1,000 hpa vorticity
7	Ncepp5zh	500 hpa divergence	20	ncepp-th	1,000 hpa wind direction
8	Ncepp8-f	500 hpa wind speed	21	ncepp-zh	1,000 hpa divergence
9	Ncepp8-u	850 hpa U-component	22	Nceppr500	500 hPa relative humidity
10	Ncepp8-v	850 hpa V-component	23	Ncepr850	850 hPa relative humidity
11	Ncepp8-z	850 hpa vorticity	24	nceprhum	1,000 hPa relative humidity
12	Ncepp8th	850 hpa wind direction	25	ncepshum	1,000 hpa specific humidity
13	Ncepp8zh	850 hpa divergence	26	nceptemp	temperature at 2m

In SDSM, some suitable predictors from the atmospheric predictors are selected through a multiple linear regression model, utilizing the combination of the correlation matrix, partial correlation, P value during the selection of predictors. There are two kinds of optimization methods: (1) ordinary least squares (OLS) and (2) dual simplex (DS). The OLS produces comparable results with DS and is also faster than DS (Huang et al. 2011). There are three kinds of sub-models—monthly, seasonal, and annual—that comprise the statistical/empirical relationship between the regional-scale variables (temperature and precipitation), and large-scale atmospheric variables. Annual sub models drive the same kind of regression parameters for 12 months and the monthly sub-model represents 12 regression equations, giving different calibrated parameters for each of the 12 months. There are also two kinds of sub-models, conditional and unconditional; any of them can be used according to the local-scale variables. The conditional sub-model is used for variables such as precipitation and evaporation (Wilby et al. 2002; Chu et al. 2010). Most of the time, precipitation data is not distributed normally, but in the case of temperature, the data is distributed normally. SDSM can transform the data to make it normal before using the data in regression equations (Khan et al. 2006). For example, Khan et al. (2006) and Huang et al.

(2011) used the fourth root for precipitation to render it normal before using it in a regression equation. The major steps adopted for downscaling of maximum, minimum temperatures and precipitation involve: (1) quality check, transformation, screening of probable predictors. (2) calibration the model using station scale predictands data with the selected predictors of NCEP/NCAR. (3) generation of present and future time series for predictands from the gridded datasets of NCEP/NCAR and GCMs, and (4) statistical analysis of downscaled projected predictands at each individual station. The various steps followed in the present study for downscaling and scenario generation are shown in **(**Fig 3).

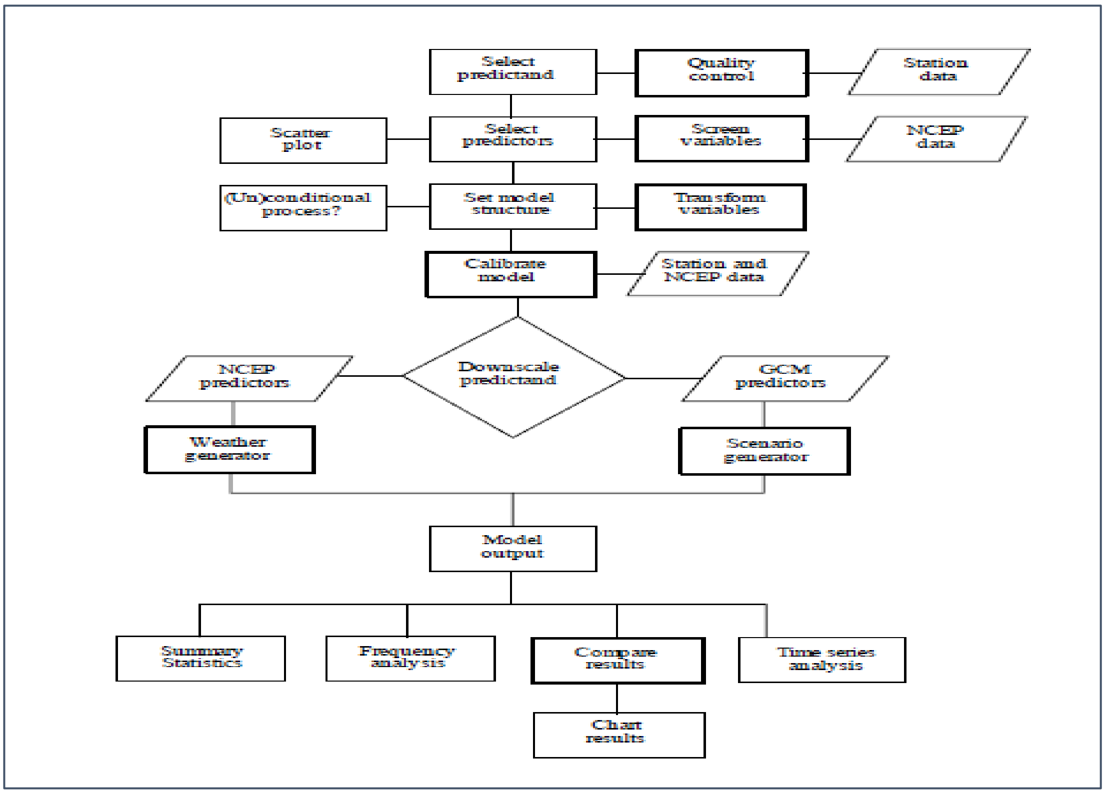

Fig. 3 Flow chart showing steps involved in downscaling and scenario generation (modified after Wilby and Dawson 2007)

Screening of probable predictors: Identifying empirical relationships between gridded predictors (such as mean sea level pressure) and (such as station precipitation) is central to all statistical downscaling methods. The main purpose of the 'Screen Variables' operation is to assist the user in the choice of appropriate downscaling predictor variables. This remains one of the most challenging stages in the development of any statistical downscaling model since choice of the predictors largely determines the character of the downscaled climate scenario (Wilby et al. 2002). The choice of predictors can be different for various geographical regions depending on the properties of the predictor and the predictand to be downscaled (Anandhi et al. 2009). In order to consider predictor-predictand relationship for all months in a year, annual analysis was used. Conditional process was selected for precipitation, where amounts depend on weteday occurrence and unconditional process for temperature. In selection of predictor predictand relationship, the default values were significance level of $p < 0.05$ and partial correlation of r ±1 (Wilby and Dawson, 2007). The predictor variables were selected based on the explained variance and correlation between predictor-predictand relationships being analysed in SDSM 5.2. Therefore, sets of predictor variables which have p-value (0_ p _0.05) were taken as best-correlated predictors with individual predictand. Due to variation of SDSM performance in different geographical locations, it is advised not to limit the performance level on explained variance.

Calibration and validation: The model calibration take specified predictand along with a set of predictor variables and computes parameters of multiple regression equation through optimization algorithm (either simplex or ordinary least square). Then the model structure is specified as conditional for temperature and unconditional for precipitation. In the case of conditional model structure, where direct process between regional forcing and local weather is assumed, the sub models are selected in monthly, seasonal or annual analysis. By selecting one of these model types, the model decides how the regression parameters should be developed (for example, if a model type of monthly is selected, then the model develops one regression equation for the whole months and if annual model type is selected again one regression equation is developed for the whole one year and so on). In this study, the annual model was selected to evaluate the output for all months in a year. The 30 years observed data was divided into two periods. The period (1961-1981) and (1971-2000) of daily data was used for model calibration and the period (1982-1990) and (1992-2000) was used for model validation. The conditional sub-model was applied for precipitation with fourth root transformation. Optimization of the best fit was achieved by OLS. Validation is required as a subsequent process to calibration. Daily dataset for the period of 1982–1990 and 1992-2000 was selected for the validation of each predictand (precipitation). Validation of SDSM was carried out by comparing the average generated twenty ensembles of synthetic weather series using NCEP-reanalysis data used for calibration of the model with those counterparts from the observations.

Downscaling future climate: In this study, the calibrated model was used in further analysis i.e. assessing future climate changes on temperature and precipitation over three periods by downscaling the A2 and B2 scenarios predictors obtained from the HadCM3 model. To achieve that, the built-in SWG was employed to generate 20 ensembles of future predictands. Ultimately, the downscaled future climate change predictands in the 2020s (2011–2040), 2050s (2041–2070), and 2080s (2071–2099) were compared with those in the baseline period (1961–1990). The reasons behind using period from 1961 to 1990 as baseline are attributed to the facts that this period is long enough to define local climate because it is likely to have dry, wet, cool, and warm periods, therefore, the length of 30 years period is recommended by the IPCC for use as a baseline period (Gebremeskel et al. 2005). In addition, it has been utilized in most climate change studies (Huang et al. 2011). The anomaly of monthly precipitation was obtained from the percentage change of average 20-ensemble future predictand with respect to the baseline period monthly average.

SDSM Performance Evaluation: In order to evaluate the SDSM performance with respect to the observed precipitation data, the following three statistical model performance evaluations measures were applied. The R^2 value indicates the correlation between the observed and simulated values, and E measures how well the plot of the observed against the simulated.

Coefficient of Determination (R^2)

It was given by (Krause and Boyle 2005) as shown in (Eq. 1) is a measure used to determine the variability in observed data that the model could capture it.

$$R^2 = \frac{(\sum[X_i - X_{av}][Y_i - Y_{av}])^2}{\sum(X_i - X_{av})^2 \sum(Y_i - Y_{av})^2} \quad (1)$$

Nash–Sutcliffe Coefficient (NSE)

The NSE is a dimensionless model evaluation statistic where the relative magnitude of the residual variance is determined in comparison to the observed variance (Nash and Sutcliff 1970):

$$E = 1 - \frac{\sum_{i=1}^{n}(X_i - Y_i)^2}{\sum_{i=1}^{n}(X_i - Y_{av})^2} \quad (2)$$

Root Mean Square Error (RMSE)

The RMSE is an error index type of model evaluation statistics (dimensional). The closer value to zero, the better model performance (Singh et al. 2004).

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(X_i - Y_i)^2}{n}} \quad (3)$$

IV. RESULTS AND DISCUSSION

Screening of predictors : The best-correlated predictor variables were selected for each station's predictands (precipitation) and are listed in Table 4 along with their corresponding p-value and partial r. These variables were then used for calibration of the SDSM. However, for the case of precipitation, the correlation (partial r) for individual predictand and sets of predictors was not satisfactory (it is satisfactory when partial r is ±1). This is due to its conditional behavior of precipitation where there is an intermediate process between the regional forcing and local weather (e.g., precipitation amount depends on wet/dry-day occurrence. As it can be seen in Tables 4, the driving parameters on precipitation with significance level p <0.05 were varied (Table 4). In other words, "Shum", "p500", "p5_u" and "ptemp" were the most effective parameters on precipitation at all stations. These parameters are associated and highly correlated to precipitation occurrence because their synchronous variation is dependent to the saturated phase of water vapour in the air (Hessami et al. 2008). The significant deriving parameters were subsequently used in the SDSM calibration.

Table (4): Significantly effective HadCM3 predictors for precipitation screening

station	Predictor	P.r	P	station	Predictor	P.r	P
Baghdad	mean sea level pressure 500 hpa U-component 500 hpa vorticity 500 hpa geopotential mean temperature at 2m	0.053 -0.012 -0.022 -0.003 -0.186	0.0001 0.0000 0.0000 0.0010 0.0000	Erbil	mean sea level pressure 500hpa geopotential height 500 hpa U-component 1hpa specific humidity 500 hpa wind direction temperature at 2m	- 0.001 -0.404 0.098 -0.301 -0. 18 0.120	0.000 0.000 0.000 0.000 0.000 0.000
Basra	500 hpa U-component 500 hpa geopotential 1 hpa specific humidity 850hpa geopotential height 850 hpa vorticity temperature at 2m	0.08 0.0411 -0.092 -0.126 0.034 0.004	0.0000 0.0019 0.0000 0.0002 0.0000 0.0003	Kirkuk	1hpa meridional velocity 500hpa geopotential height 850hpa meridional velocity 850hpa geopotential height 850hpa divergence specific humidity at 850 hpa mean temperature at 2m	0.054 -0.007 -0.04 -0.88 -0.015 0.125 -0.015	0.0000 0.0009 0.0211 0.0004 0.0000 0.0002 0.0007
Zakho	mean sea level pressure 500 hpa U-component 500 hpa V-component	-0.087 0.049 -0.82 0.103 -0.34 -0.064	0.0002 0.0000 0.0000 0.0002 0.0011 0.0042	Salah ad Din	500hpa geopotential height 500 hpa U-component	0.005 0.004 -0.107 -0.124 0.216	0.0006 0.00011 0.0000 0.0122 0.0043

	850 hpa vorticity 1hpa specific humidity 500 hpa geopotential				500 hpa divergence 850 hpa vorticity temperature at 2m		
Al-Hay	500 hpa vorticity 500 hpa wind direction 850hpa geopotential height 1hpa specific humidity temperature at 2m	-0.107 -0.156 0.075 -0.403 0.67	0.0000 0.0002 0.0034 0.0002 0.0017	Mosul	1hpa meridional velocity 1hpa vorticity 500hpa vorticity 500hpa geopotential height 850hpa meridional velocity 850hpa vorticity 850hpa geopotential height specific humidity at 850 hpa	0.001 0.098 -0.124 -0.014 0.005 -0.205 0.001 -0.078	0.0052 0.0110 0.0000 0.0000 0.0002 0.0018 0.0000 0.00001
Khanaqin	mean sea level pressure 850 hpa U-component 500hpa vorticity 500hpa geopotential height 1hpa specific humidity mean temperature at 2m	-0.005 0.104 -0.54 -0.013 0.109 -0.012	0.00 0.0346 0.0004 0.000 0.0341 0.000	Sulaymaniyah	850hpa geopotential height 850hpa divergence 850 hpa vorticity 1hpa specific humidity 500 hpa U-component 850 hpa V-component	-0.002 0.108 0.130 -0.86 0.0270 0.031	0.0000 0.0104 0.0404 0.0023 0.0000 0.0012
Najaf	mean sea level pressure 500hpa geopotential height specific humidity at850hpa 500 hpa V-component	-0.106 -0.328 0.001 -0.125	0.0000 0.0000 0.0000 0.0000	Nasiriyah	mean sea level pressure 500 hpa V-component mean temperature at 2m	-0.134 0.066 0.235	0.0000 0.0114 0.0012

Calibration and validation: The 30 years baseline (observed) data was used for calibration (1961-1981), (1971-1991) and validation (1982-1990), (1992-2000) of SDSM. According to Wilby and Dawson (2004), in conditional model, there is an intermediate process between regional forcing and local weather (e.g.,local precipitation amounts depend on wet/dry day occurrence). As indicated in the previous studies above, this is hardly captured well in SDSM. Therefore, downscaling for precipitation is problematic than temperature (Hassan 2011). The results of calibration and validation are illustrated in Tables 5 and 6, respectively.

Table (5): Statistical performance of precipitation modeling during calibration

Station name	***RMSE***	***R^2***	***NSE***
Baghdada	0.77	0.69	0.71
Basrah	0.84	0.67	0.70
Erbil	0.95	0.60	0.53
Al-Hay	0.39	0.61	0.77
Khaniqin	0.34	0.56	0.86
Kirkuk	*0.44*	0.61	0.70
Mosul	0.36	0.50	0.66
Najaf	0.49	0.73	0.60
Nasiriya	0.73	0.73	0.72
Salah ad Din	0.37	0.51	0.73
Zakho	0.47	0.50	0.80
Sulaymaniyah	**0.34**	**0.71**	**0.77**

Table (6): Statistical performance of precipitation modeling during validation

Station name	**RMSE**	**R^2**	**NSE**
Baghdada	0.79	0.54	0.68
Basrah	0.57	0.61	0.66
Erbil	0.83	0.73	0.86
Al-Hay	0.77	0.80	0.64
Khaniqin	1.01	0.82	0.76
Kirkuk	*0.37*	0.53	0.69
Mosul	0.39	0.77	0.87
Najaf	0.74	0.65	0.80
Nasiriya	0.86	0.66	0.74
Salah ad Din	0.88	0.89	0.67
Zakho	0.54	0.50	0.86
Sulaymaniyah	**0.45**	**0.62**	**0.66**

Tables 5 and 6 list the statistical evaluation performances of precipitation predictand during the calibration and validation, respectively. It can be noticed from Table 5 that the RMSE, R^2, and NSE were less than 0.95 mm, greater than 0.73, and greater than 0.86, respectively across all the stations during the calibration. According to this evaluation, it can be judged that the observed and the modelled data were consistent. In other words, the SDSM were sufficiently capable to reproduce the observed Tmin data. During the validation period, the values of RMSE, R^2, and NSE were less than 1.01 mm, greater than 0.89, and greater than 0.86 across all the stations, respectively (Table 6).

Downscaling future climate scenarios : After the statistical downscaling model performance has been checked, the GCM simulations from HadCM3 SRES A2 and B2 scenarios of represent future climate is used to generate synthetic daily precipitation series. The SDSM model developed for each site was used to predict future daily precipitation in the sites for the periods of 2011-2040 (near future), 2041-2070 (medium future), and 2071-2100 (far future) depended on the A2 and B2 scenarios generated from HadCM3. The best way of evaluating the characteristics of change in precipitation pattern is the annual statistics. Fig4 shows projected change of annual precipitation for stations for three future periods. The change in climate was calculated by subtracting rainfall values of the future period from baseline period. Monthly change in rainfall shows that, there is decrees in rainfall in all months As it can be noticed, that the annual precipitation in Baghdad was projected to negatively change by -15%, -22% and -11% by A2 and -23%, -28%, -10% by B2 during 2020s, 2050s and 2080s, respectively with respect to the baseline period.

The average annual rainfall was projected to decrease in Basra station by -6%, and -8.1% and -15% by A2 and -8%, -18%, -25% by B2 during 2020s, 2050s and 2080s, respectively (Fig. 4).
With respect to the precipitation, the average annual rainfall in Erbil station will change by -9%, -18% and -21% by A2 and -10%, -20%, -16% by B2 during 2020s, 2050s and 2080s, respectively(Fig 4).
The projected change in the average annual rainfall for Zakho station was projected to change by -10% and -12%, -33% by A2 and 12%, -20%, -28%by B2 during 2020s, 2050s and 2080s, respectively (Fig.4).
The average annual rainfall for Selamaniyah station will likely decrease by -40% and -22%, -33% by A2 and -15%, -18%, -38% by B2 during 2020s, 2050s and 2080s, respectively (Fig 4).
The average annual rainfall for Salah ad Din station was projected to decrease by -10%, -22% and -33% by A2 and -15%, -18%, -38% by B2 during 2020s, 2050s and 2080s, respectively (Fig 4).
The average annual rainfall for Mosul station was projected to decrease by -12% and 1%, -1% by A2 and -15%, 4%, -5% by B2 during 2020s, 2050s and 2080s, respectively (Fig 4).
For Khaniqin station the average annual rainfall will change by -11% and -20%, -15% by A2 and -10.58%, -27.99%, -33% by B2 during 2020s, 2050s and 2080s, respectively (Fig 4).
In Kirkuk station, the average annual rainfall was projected to slightly decrease by 5.32% and -7.1%, -1.8% by A2 and 5.87%, -10.96%, -11% by B2 during 2020s, 2050s and 2080s, respectively (Fig 4).

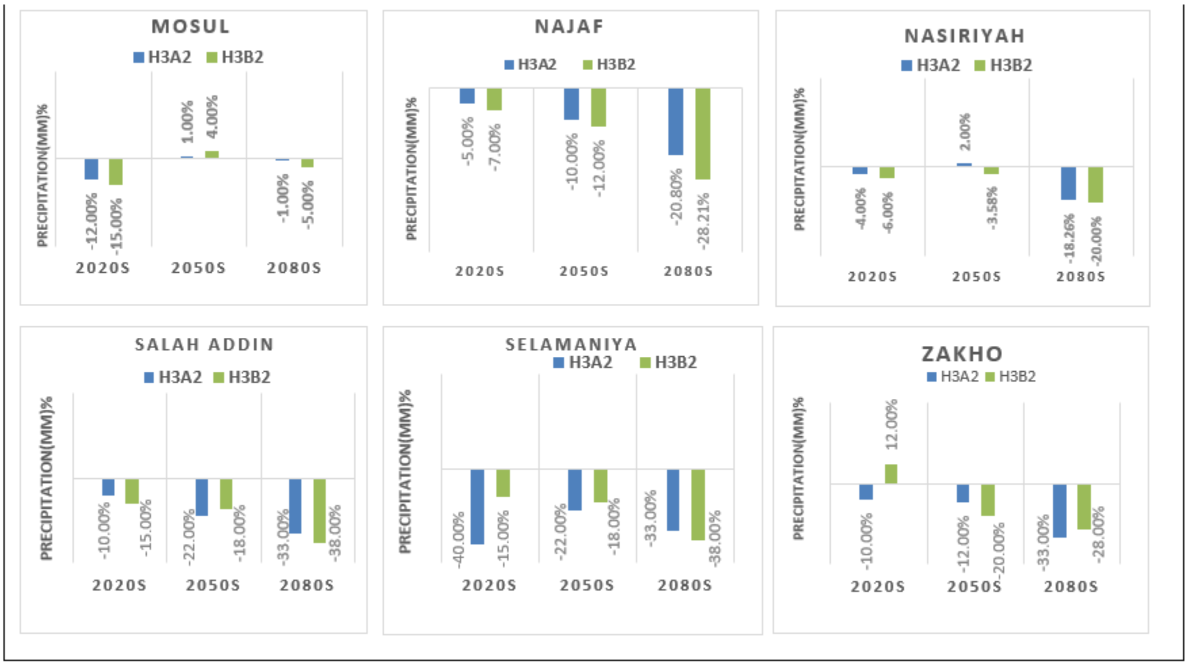

Fig. 4 Change in average annual rainfall in the future for H3A2 and H3B2 scenario.

V. DISCUSSION

Statistical Downscaling Model (SDSM) was applied using three set of data; observed daily precipitation for the period of 1961-1990 and 1971-2000, twelve station and NCEP re-analysis data composed of 26 daily atmospheric variables for the same period which are selected at grid box covering each of the stations considered . HadCM3 SRES A2 and B2 emission scenarios SDSM have used. NCEP reanalysis data of gridded large atmospheric variables as predictors and station data as predictands. The outcomes from this study pointed an decrease in precipitation across the country. The results show that the decrease in annual precipitation is more remarkable in the northern (Sulaymaniyah, Salah ad Din , Zakho and Khaniqin) stations than those the southern part of the country. The greatest decrease in annual precipitation was observed in Sulayrnaniyah at the end of 2020s under H3A2 and 2080s under H3B2. While, the lowest decrease was detected in Najaf, Basra and Nasiriya station. Though that the general trend tends towards a decrease in precipitation across the country, some stations like Kirkuk, Mosul and Al-Hay show a slight increase in the annual precipitation during the 2020s and 2050s, Respectively. Such as unforeseen trend is physically uninlerpretable especially that most of the surrounded stations show decreasing in the same periods. However, the uncertainty in measurements and modelling results could be the essential reasons behind.

VI. CONCLUSIONS

SDSM (hybrid of MLR and SWG based downscaling technique) is used to downscale and generate long-term (2011–2040, 2041–2070 and 2071–2099) future scenarios of climate variables (precipitation) from predictors of HadCM3 models. These future scenarios are generated under forcings of A2 and B2 emission scenarios. The annual sub-model of SDSM is found proficient in downscaling The calibrated model was then utilized to simulate future climatological parameters depended on the outputs of SDSM driven by GCMs under the climate change scenarios as established. Thus, the impacts of climate change on most stations of Iraq under the three scenarios were comprehensively analyzed.

The most notable conclusions of this present study can be summarized as follows: The future precipitation will grow more complex and uncertain; there were significant differences between A2 and B2. Overall, annual precipitation in Had3CM3 will apparently to decrease in the future. There is a clear trend of precipitation reduction in the study region. The findings obtained from this study can be of use to help policy makers in making decisions and planning for adaptation of impacts of climate changes. Moreover, the results can provide a support for better water resources management in Iraq.

ACKNOWLEDGEMENT

The Ministry of Higher Education and Scientific Research in Iraq is acknowledged for their support during the study.

REFERENCES

1 Abbasnia M, Tavousi T, Khosravi M (2016) Assessment of future changes in the maximum temperature atselected stations in Iran based on HADCM3 and CGCM3 models. Asia-Pac J Atmos Sci 52(4):371–377.

2 Al-Rijabo WI, Salih HM. 2013. Spatial and temporal variation of rainfallin Iraq. J. Appl. Phys. 5(4): 01–07.

3 Anandhi A, Shrinivas V V, Nanjundiah R S and Kumar D N 2009 Role of predictors in downscaling surface temperature to river basin in India for IPCC SRES scenarios using support vector machine; Int. J. Climatol. 29(4) 583–603

4 Azooz AA, Talal SK. 2015. Evidence of climate change in Iraq. J. Environ. Prot. Sustain. Dev. 1(2): 66–73.

5 Bilal DA, Al-jumaily KJ, Habbib EA. 2013. Air temperature trends in Baghdad, Iraq for the period 1941–2000. Int. J. Sci. Res. Publ. 3(9): 1.

6 Christensen J H, Machenhauer B, Jones R G, Sch¨ar C, Ruti P M, Castro M and Visconti G 1997 Validation of presentday regional climate simulations over Europe: LAM simulations with observed boundary conditions; Clim. Dyn. **13** 489–506.

7 Chu J, Xia J, Xu CY, Singh V (2010) Statistical downscaling of daily mean temperature, pan evaporation and precipitation for climate change scenarios in Haihe River, China. Theor Appl Climatol 99 (1):149–161. doi:10.1007/s00704-009-0129-6

8 Diaz-Nieto J, Wilby RL (2005) A comparison of statistical downscaling and climate change factor methods: impacts on low flows in the River Thames, United Kingdom. Clim Chang 69(2):245–268. doi:10.1007/s10584-005-1157-6

9 Elhakeem ,A and Elshorbagy,W AlNaser H and Dominguez F (2015) Downscaling Global Circulation Model Projections of Climate Change for the United Arab Emirates 1 15 DOI 10.1061 ASCE WR 1943 5452.0000507

10 Fowler HJ, Blenkinsop S, Tebaldi C (2007) Linking climate change modelling to impacts studies: recent advances in downscaling techniques for hydrological modelling. Int J Climatol 27 (12):1547–1578. doi:10.1002/Joc.1556

11 Gebremeskel S, Liu YB, de Smedt F, Hoffmann L, Pfister L (2005) Analysing the effect of climate changes on streamflow using statistically downscaled GCM scenarios. Int J River Basin Manag 2(4):271–280. doi:10.1080/15715124.2004.9635237.

12 Gebremeskel S, Liu YB, de Smedt F, Hoffmann L, Pfister L (2005) Analysing the effect of climate changes on streamflow using statistically downscaled GCM scenarios. Int J River Basin Manag 2(4):271–280. doi:10.1080/15715124.2004.9635237.

13 Giorgi,1990: Simulation of regional climate using a limited area model nested in a general circulation model. J. Climate, 3, 941-963.

14 Goyal MK, Burn DH, Ojha CSP (2012) Evaluation of machine learning tools as a statistical downscaling tool: temperatures projections for multi-stations for Thames River Basin, Canada. Theor Appl Climatol 108:519–534. doi:10.1007/s00704-011-0546-1

15 Hashim BM, Ajmi RN, Abduljabbar SA. 2013. Identification of dust sources in Iraq using meteorological surface data and satellite data. J. Environ. Sci. Eng. A2: 299–305.

16 Hassan, Z., Harun, S., 2011. Statistical downscaling for climate change scenarios of rainfall and temperature. In: United Kingdom-Malaysia-Ireland Engineering Science Conference 2011 (UMIES 2011).

17 Hessami, M., Gachon, P., Ouarda, T. B. M. J., St-Hilaire, A. (2008). Automated regression-based statistical downscaling tool. Environ Model Software, 23 (6), 813- 834. doi:10.1016/j.envsoft.2007.10.004

18 Huang J, Zhang J, Zhang Z, Xu C,Wang B, Yao J (2011) Estimation of future precipitation change in the Yangtze River basin by using statistical downscaling method. Stoch Env Res Risk A 25(6):781– 792. doi:10.1007/s00477-010-0441-9

19 Kashef Al-Kataa BA. 1982. Water science and applications. Ministry of Higher Education and Scientific Research, Baghdad University: Baghdad, 512.

20 Khan MS, Coulibaly P, Dibike Y (2006) Uncertainty analysis of statistical downscaling methods. J Hydrol 319(1–4):357–382. doi:10.1016/j.jhydrol.2005.06.035

21 Krause P, Boyle DP (2005) Advances in geosciences comparison of different efficiency criteria for hydrological model assessment. Adv Geosci 5(89):89–97. http://www.adv-geosci.net/5/89/2005/

22 OsmanY,Al-nasari N, Abdellatif M, Aljawad SB. 2014. Expected future precipitation in central Iraq using LARS-WG stochastic weather generator. Engineering 2014(6): 948–959.

23 Moriasi, D. N., Arnold, J. G., Van Liew, M. W., Bingner, R. L., Harmel, R. D., and Veith, T. L. (2007). "Model evaluation guidelines for systematic quantification of accuracy in watershed simulations". Transactions of the ASABE, 50(3), 885-900.

24 Najafi1,R and Kermani,M. Uncertainty Modeling of Statistical Downscaling to Assess Climate Change Impacts on Temperature and Precipitation, Earth Syst. Environ. (2017) 2:68,DOI 10.1007/s40808-016-0112-z

25 Nash JE, Sutcliff JV (1970) River flow forecasting through conceptual models, part I—adiscussion of principles. J Hydrol 10:282–290

26 Singh J, Knapp HV, Arnold JG, Demissie M (2004) Hydrologic modeling of the Iroquois river watershed using HSPF and SWAT. J Am Water Resour Assoc 41(2):343–360

27 Wetterhall F, Bárdossy A, Chen D, Halldin S, Xu C-Y (2009) Statistical downscaling of daily precipitation over Sweden using GCM output. Theor Appl Climatol 96(1):95–103. doi:10.1007/s00704-008-0038-0.

28 Wilby R L, Hay L E, Gutowski W J, Arritt R W, Takle E S, Pan Z, Leavesley G H and Martyn P C 2000 Hydrological responses to dynamically and statistically downscaled climate model output; Geophys. Res. Lett. **27(8)** 1199, doi: 10.1029/1999GL00607.

29 Wilby, R. L. and C. W. Dawson. (2002). SDSM-a decision support tool for the assessment of regional climate change impacts. Environmental Modelling and Software, 17(2), 145-157.

30 Wilby RL, Whitehead PG, Wade AJ, Butterfield D, Davis RJ, Watts G (2006) Integrated modelling of climate change impacts on water resources and quality in a lowland catchment: River Kennet, UK.J Hydrol 330(1–2):204–220. doi:10.1016/j.jhydrol.2006.04.033.

31 Wilby, R.L., Dawson, C.W., 2007. Statistical Downscaling Model (SDSM), Version 4.2. Department of Geography, Lancaster University, UK.

32 Xu C-Y (1999) Climate change and hydrologic models: a review of existing gaps and recent research developments. Water Resour Manag 13(5):369–382. doi:10.1023/a:1008190900459

33 Zakaria S, Al-Ansari N, Knutsson S. 2013. Historical and future climate change scenarios for temperature and rainfall for Iraq. J. Civil Eng. Archit. 7(12): 1574–1594.