Long term effect of climate change on rainfall in northwest Iraq

Research Article

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Abstract: Middle East, like North Africa, is considered as arid to semi-arid region. Water shortages in this region, represents an extremely important factor in stability of the region and an integral element in its economic development and prosperity. Iraq was an exception due to presence of Tigris and Euphrates Rivers. After the 1970s the situation began to deteriorate due to continuous decrease in discharges of these rivers, are expected to dry by 2040 with the current climate change. In the present paper, long rainfall trends up to the year 2099 were studied in Sinjar area, northwest of Iraq, to give an idea about its future prospects. Two emission scenarios, used by the Intergovernmental Panel on Climate Change (A2 and B2), were employed to study the long term rainfall trends in northwestern Iraq. All seasons consistently project a drop in daily rainfall for all future periods with the summer season is expected to have more reduction compared to other seasons. Generally the average rainfall trend shows a continuous decrease. The overall average annual rainfall is slightly above 210 mm. In view of these results, prudent water management strategies have to be adopted to overcome or mitigate consequences of future severe water crisis.

Keywords: Rainfall trend • GCM • ANN • Sinjar • Iraq

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1. Introduction

Middle East and North Africa (MENA region) are considered as arid to semi-arid regions where the average annual rainfall does not exceed 166 mm [1]. For this reason, the scarcity of water resources in the MENA region, and particularly in the Middle East, represents an extremely important factor in the stability of the region

and an integral element in its economic development and prosperity [2, 3]. Recent work indicates that the situation will be more severe in future [4, 5]. Climate change is one of the main factors responsible for the future water shortages expected in the region [6]. By the end of this century mean temperatures in the MENA region are projected to increase by 3°C to 5°C while precipitation will decrease by about 20% [7]. Water run-off will be reduced by 20% to 30% in most of MENA by 2050 [8] and water supply might be reduced by 10% or greater by 2050 [9].

Iraq until the 1970s was commonly considered rich in its water resources due to the presence of the Tigris

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and Euphrates Rivers. Syria and Turkey started to build dams on the upper parts of these rivers which caused a major decrease in the flow of the rivers [10]. Tigris and Euphrates discharges will continue to decrease with time and they will be completely dried up by 2040 [11]. In addition, future rainfall forecast showed that it is decreasing in Jordan which is Iraq's neighboring country [12–14].

In this paper, statistical downscaling models, constructed using Levenberg-Marquardt trained Artificial Neural Network (ANN), were used to evaluate long term rainfall amounts expected in the northwestern Iraq for four seasons (winter, spring, summer and autumn). Such information would help farmers and decision makers to take precautions to overcome or mitigate the expected severe water shortage.

2. Studied Region & Data

Sinjar District is a plain area located within Nineveh province in northwest Iraq (Figure 1). The whole area is locally referred to as Al-Jazirah (the area bounded by the Tigris and Euphrates Rivers north of Tharthar Lake). It is bordered from north and west by the international Iraq–Syria borders and the extension Province of Nineveh from the east and south. The population reaches 21,584. The most prominent terrain is Sinjar Mountain with highest peak that reaches an elevation of 1400 (m. s. l.) (cf. Figure 1). Rainfall is the main source of water for agricultural practices in Sinjar area despite the presence of some wells.

Rainfall records in Sinjar indicate that the average annual rainfall is about 303 mm. The rainy season extends from November to May. During this season, surface water flows in the valleys from Sinjar Mountain toward the Iraqi–Syrian border at the northern Sinjar Mountain, and flows to the extension Province of Nineveh at the southern Sinjar Mountain. The maximum monthly evaporation is usually recorded in July and could reach 563.4 mm, whereas the minimum is recorded in December and could reach 57.4 mm. The soil in the study area has low organic content and consists of sandy loam, silty loam and silty clay loam [15]. Fields observation indicates that, the catchment land use in Sinjar is one of three types: cultivated land, pasture land, and land covered by exposures of hard rocks. The cultivated land represents very good farming conditions (Figure 2) and has the ability to produce main crops such as wheat, barley and tobacco if water is available.

Suitable data are usually needed to understand and investigate the relationship between hydrology and

Figure 1. Sinjar area.

Figure 2. Farm in Sinjar area.

climate change. Two principal data sets were employed were used to establish such relation and to calibration and validate the daily rainfall models as well as simulating future rainfall.

First, rainfall data, one of the main components in the hydrological cycle which intimately linked with almost all aspect of climate, is needed. Rainfall data of highest quality is of primary importance for any hydrological calculations. The main rainfall data used here are the

daily observations obtained from the Iraqi Meteorological Office for the period 1961–2001.

Second, atmospheric variables data, which act as triggers for the rainfall are needed. These variables are used for constructing the rainfall model which subsequently used to simulate the future rainfall. Two sets of atmospheric variables are needed, observed variables set (also called re-analysis) which is used with the observed rainfall data to build the rainfall models, and the corresponding GCM variables set which is used as inputs in the built rainfall model to simulate future rainfall. Both atmospheric variables data sets have to be normalised with respect to their 1961–1990 means and standard deviations to account for any bias from the GCM. The normalisation process ensures that the distributions of observed and GCM-derived predictors are in closer agreement than those of the raw observed and raw GCM data. These two data sets are described below:

A. Reanalysis data

Reanalysis data provide baselines or climate reference for future climate projections. The data set used in this paper was obtained from the US National Centre for Environment Predictions (NCEP/NCAR) [16]. NCEP reanalysis dataset provides contemporaneous gridded data which is usually considered the best global climate circulation representation of the current state of the earth system. The NCEP data originally produced at a resolution of 2.50×2.50 , was re-gridded to conform to output of the GCM and was considered adequate for the present purpose of building the rainfall downscaling model. The re-gridded data corresponds to the grid box covering Singar District, for the period 1961–2001, was then selected in used in this study.

B. Climate Model Data

With provision for the simulation of the effects of anthropogenic emissions, climate models are an important tool for providing future climate information [17]. The GCM data sets used in this study were obtained from the Canadian Climate Impacts Scenarios Group. Data set from HadCM3 (GCM) with grid resolution of 2.50×3.750 is used to provide future climate scenarios for three future periods 2020s (2010–2039), 2050s (2040–2069) and 2080s (2070–2099); as the HadCM3 GCM is widely used for such purposes and its data was easy to obtain. Since climate projections are related to emission uncertainty, different climate scenarios, defined by Nakicenovic et al. [18], are used by the Intergovernmental Panel on Climate Change (IPCC) to account for the uncertainty of future anthropogenic carbon emissions. Both the A2 and B2 emission scenarios are employed here. The A2

scenario [38] assumes continuous increase in population and economic development is regionally oriented and per capita economic growth and technological changes are more fragmented and slower relative to other scenarios. The B2 scenario [38] emphasis is on local solutions to economic, social, and environmental sustainability. In this scenario it is assumed that the world is continuously increasing global population at a rate lower than A2, intermediate levels of economic development, and less rapid and more diverse technological change than in the B1 and A1 scenarios. This scenario is oriented toward environmental protection and social equity; it focuses on local and regional levels.

3. Methodology

GCMs are the main tools to predict large scale climate variations at seasonal and inter-annual scales, but they are usually not successful in reproducing higher order statistics and extreme values. Furthermore, they cannot be adapted for impact-oriented applications at regional scale because of their relatively coarse resolution of typically several hundred kilometers [19]. For bridging the gap between the scale of GCM and required resolution for practical applications, downscaling provides climate change information at a suitable spatial scale from the GCM data.

In this study a downscaling approach has been used to obtain local scale rainfall at Sinjar area in two steps. First selecting the suitable climate variables (predictors) and second developing the rainfall model.

3.1. Model Predictors

For downscaling rainfall, the selection of appropriate predictors is one of the most important steps in a downscaling exercise. The predictors are chosen by the following criteria: (1) they should be skillful in representing large-scale variability that is simulated by the GCMs and are readily available from archives of GCM outputs and reanalysis data sets; (2) they should strongly correlate with the surface variables of interest/predictands, i.e. they should be statistically significant contributors to the variability in rainfall; (3) they should represent important physical processes in the context of the enhanced greenhouse effect [20, 21]. The stepwise regression has been used for purpose of this process in order to select the parsimonious model as it would generally not be useful to include all predictors in the final model. The stepwise selection procedure is a combination of forward selection and backward

elimination after adding one predictor to the subset or excluding one predictor from the subset. In this process, the observed daily predictors (climatic variables), which come from NCEP data, are selected from a range of candidate predictors that correlated with daily rainfall data for each winter(JFD), spring(MAM), summer(JJA) and autumn(SON) season.

3.2. Rainfall Model

The daily single-site rainfall downscaling model used in this study is ANN which has been recently used in many single or multisite daily rainfall generation as well as downscaling applications [22–24]. ANNs is an example of regression statistical downscaling methods and has potential for complex, nonlinear, and time varying input-output mapping and rely on empirical relationships between local-scale predictands and regional-scale predictor(s). Although the weights of an ANN model are similar to nonlinear regression coefficients, the unique structure of the network and the nonlinear transfer function associated with each hidden and output node allows ANNs to approximate highly nonlinear relationships. Therefore the interest in ANNs is nowadays increasing [25].

The model simulates rainfall wet and dry day at each location and is formulated to reproduce the temporal structure of the observed rainfall record in the simulations. On a given day, the model simulates rainfall at Sinjar station conditional on selected atmospheric variables for each season.

3.2.1. ANN Model Structure

The multi-layer feed forward ANN (MLF-ANN) (see Figure 3) consists of multiple simple processing nodes, or neurons, assembled in different layers (input, hidden, output). Each node computes a linear combination of the weighted inputs including a bias term from the links feeding into it. The assumed value of these inputs is transformed using a certain activation function; either linear or non-linear. The output obtained is then passed as input to other nodes in the following layer. One important requirement for this activation function is that it must map any input to a finite output range, usually between 0 and 1 or -1 and 1 [26]. Several different activation functions can be used, in this study, the linear (output layer) and log-sigmoid (hidden layer) have been selected which are commonly used. Figure 1 shows a typical three layer MLF, the output y (rainfall) of a network with n inputs, k log-sigmoid nodes in the hidden

Figure 3. Multilayer feed forward ANN.

layer and one linear node in the output layer is given by:

$$y = \sum_{j=1}^k W_j^{(2)} Z_j + b^{(2)} \quad (1)$$

$$Z_j = f \left(\sum_{i=1}^m W_{ij}^{(1)} + b_j^{(1)} \right) = \frac{1}{1 + \exp \left(- \sum_{i=1}^m W_{ij}^{(1)} + b_j^{(1)} \right)} \quad (2)$$

where X_i corresponds to the i^{th} input (selected climatic variables), $W_j^{(2)}$ and $b^{(2)}$ ($W_{ij}^{(1)}$ and $b_j^{(1)}$) are the weights and biases from the output (hidden) layers, f is the the log-sigmoid transfer function.

3.3. Training of MLF-ANN

The training of ANN simply means estimation of the model parameters which are the weights and number of hidden neurons. The main objective behind all ANN training algorithm is to minimise a certain error function, E . The quantity E , usually the Mean Square Error, measures the difference between the observed (O) and predicted (S) values for a data with size (n) [28] and can be expressed as:

$$E = \frac{1}{n} \left(\sum_i^n (O(i) - S(i))^2 \right) \quad (3)$$

For MLF-ANN, with more than one layer of weights (as in Figure 1), the error function will typically be a highly non-linear function of weights. As consequence of non-linearity, it is not in general possible to find an analytical

solution for the minimum of the E . Instead, it is necessary to consider algorithm that involves a search through the weight space consisting of a succession of steps.

Different algorithms involve different techniques to define the weight. The training technique most widely used in literature is the backpropagation algorithm in which the error is then back propagated through the network and weights are adjusted as the network attempts to decrease the prediction error by optimising the weights that contribute most to the error. This process is repeated many times with many different hidden neurons pairs until a sufficient accuracy for all data sets has been obtained. There are different backpropagation algorithms, however in the present application, Levenberg-Marquardt approach (LM) has been applied and that distinguish the current paper from the conventional ANN algorithms used. The LM algorithm which was independently developed by Kenneth Levenberg and Donald Marquardt [28, 29] provides a numerical solution to the problem of minimizing a nonlinear function. It is usually more stable and more reliable than any other backpropagation techniques, and was designed to speed up the training process [30, 31]. LM is based on the approximation of the Gauss-Newton method and introduces another approximation to the Hessian matrix, H defined as:

$$H = J^T J + \mu I \quad (4)$$

where μ is always positive, called combination coefficient, I is the identity matrix, J is the Jacobian matrix and can be computed through a standard backpropagation technique that is much less complex than computing the Hessian matrix. The Jacobian contains the first derivatives of the ANN errors with respect to weights. So the update rule of the LM algorithm can be presented as:

$$W_{k+1} = W_k - (J^T J + \mu I)^{-1} J^T e \quad (5)$$

3.3.1. Model Evaluation techniques

Part of daily rainfall within the period 1961–2001 was used for verification processes for each of the winter, spring, summer and autumn models. The performances of the developed ANN models were evaluated mainly based on:

1. The correlation coefficient (R) has been widely used to evaluate the goodness-of-fit of hydrologic and hydrodynamic models [32]. This is obtained by performing a linear regression between the ANN-predicted values (S) and the targets for n

observations (O), being defined as,

$$R = \frac{\sum_i^n (O - \bar{S})(S - \bar{S})}{\left(\sum_i^n (S - \bar{S})^2 \sum_i^n (O - \bar{S})^2 \right)^{\frac{1}{2}}} \quad (6)$$

A case with R equals to 1 refers to a perfect correlation and the predicted values are either equal or very close to the target values, whereas there exists a case with no correlation between the predicted and the target values when R is equal to zero. Intermediate values closer to 1 indicate better agreement between target and predicted values [32].

2. Root Mean Squared Error ($RMSE$) for n observations [33] is defined as,

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (O_i - S_i)^2}{n}} \quad (7)$$

ANN responses are more precise if $RMSE$ close to (0).

3. Nash -Sutcliffe coefficient. The range of this coefficient lies between 1 (perfect fit) and $-\infty$. An efficiency of lower than zero indicates that the mean value of the observed time series would have been a better predictor than the model. The statistical index of model efficiency (Nash and Sutcliffe, 1970) is used,

$$Nash = \frac{\sum_{i=1}^n (O_i - S_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2} \quad (8)$$

4. Bias. The optimal value of the Bias coefficient is (0); with low values indicate accurate model simulation. Positive values indicate underestimation and negative values indicate overestimation [34] and can be represented by,

$$Bias = \frac{\sum_{i=1}^n (O_i - S_i) \cdot 100}{\sum_{i=1}^n (O_i)} \quad (9)$$

Furthermore, other visual plots to compare the observed and simulated rainfall amount by the ANN on seasonal basis are also considered

3.4. Results and Discussions

Downscaling models are developed following the methodology described in Section 3. The results and discussion are presented in this section.

3.5. Potential Predictor Selection

The most relevant probable predictor variables necessary for developing the downscaling models for the four seasons (winter, spring, summer and autumn) have been selected based on stepwise regression process. The results in Table 1 show the selected predictors together with significance of their correlations with rainfall in each season in terms of zero correlation and partial correlation (correlation of each predictor with the rainfall but take the effect of the other predictors). The most dominant predictor is the relative humidity at 850 hpa for the four seasons which reveals significance between 0.00–0.021 less than 0.05. The vorticity at 850 hpa and relative humidity at 500 hpa are ranked second for all seasons except the summer and spring. Other climate variables have also been considered as important (see Table 1) with a significance of 0.00–0.045, although the relative small correlation ranged between 0.038–0.351 for zero correlation and 0.058–0.0256 for partial correlation. In general 7 predictors were found to have a significant relation with the rainfall for winter and spring, and 6 predictors for autumn while the summer shows only 4 predictors. Table 2 shows definition of each climate variable that has been used.

3.6. Model Performance

The selected climatic variables are provided as inputs to the regression downscaling model together with the observed rainfall as output. For purpose of this study, 90% of the rainfall amount data, the period 1961–2001, was considered as training set and 5% as validation set with additional 5% as test set after the training is stopped. Data in each of these sets were selected randomly. The validation set was used during the training to avoid the problem of overfitting. If the ANN is trained without stopping criteria (early stopping), then it begins to overfit, and the mean-square error begins increasing from its minimum. Without the early stopping method, data that have high complexity typically produce high variance when the training is terminated. The rainfall model has been applied using MATLAB 7.110.

Results of the different statistical properties of the observed and simulated rainfall model as defined in previous section are tabulated in Table 3 in terms of correlation coefficient (R), root mean squared error

Figure 4. Average monthly rainfall of the observed & the simulated during calibration and validation periods (1961–2001).

Figure 5. Average monthly wet days of the observed & the simulated during calibration and validation periods (1961–2001).

(RMSE), Nash coefficient and Bias. The results of statistical parameters analyses indicated good model simulation for rainfall because of the relatively high R and Nash coefficient above 80% and 65%, respectively, for daily rainfall for all seasons. The RMSE and bias are relatively considered a bit high as it would not expect the model to replicate the exact daily sequences found in observations in an arid region.

Figure 4 shows comparisons of the observed and ANN estimated month-wise mean rainfall. Examination of Figure 4 shows that the calibrated model has reproduced the seasonal values quite well (during calibration and verification period). The model has slightly underestimated the mean monthly rainfall for January, February, March and December and overestimated May and September, while for the other months the model was in good agreement with the observed. Hence the observed and the estimated annual rainfall are equal.

Further, examination of Figure 5 in terms of average monthly wet days, reveals that only for a few months

Table 1. Definition of the selected climate variable.

Predictors	JDF			MAM			JJA			SON		
	sig	Zero-order	Partial correlation	sig	Zero-order	Partial correlation	sig	Zero-order	Partial correlation	sig	Zero-order	Partial correlation
p_8z	.003	.143	.087	.000	.205	.139	-	-	-	.001	.067	.095
r850	.000	.252	.138	.000	.247	.256	.021	.045	.067	.000	.268	.250
P_v	.000	.325	.193	-	-	-	-	-	-	.000	.201	.212
P_f	-	-	-	-	-	-	-	-	-	.000	.132	.140
p_8f	.000	.351	.140	-	-	-	-	-	-	-	-	-
r500	.000	.332	.112	.000	.275	.122	.000	.154	.149	-	-	-
p_5th	.000	-.240	-.109	-	-	-	-	-	-	-	-	-
p_z	.003	.073	.086	-	-	-	-	-	-	-	-	-
p_5z	-	-	-	-	-	-	-	-	-	.002	.068	-.088
p_5u	-	-	-	.000	-.060	-.140	-	-	-	-	-	-
p_8v	-	-	-	.000	.237	.174	-	-	-	-	-	-
p_5f	-	-	-	.000	.065	.107	-	-	-	-	-	-
shum	-	-	-	.001	.096	.100	-	-	-	-	-	-
rhum	-	-	-	-	-	-	.000	.105	.123	-	-	-
p_8th	-	-	-	-	-	-	.045	.038	.058	-	-	-
p850	-	-	-	-	-	-	-	-	-	.000	-.126	-.131

* sig: significant level which is < 0.05 for significant correlation

Table 2. Definition of the selected climate variable.

Code	Variable
r500	Relative humidity at 500 hpa
r850	Relative humidity at 850 hpa
P5_u	Zonal velocity at 500 hpa
p_z	surface vorticity
p5_z	500hpa vorticity
P8_z	850 hpa vorticity
rhum	Near surface relative humidity
p_8f	Surface airflow strength
P_f	Surface airflow strength
P_5f	500hpa airflow strength
p_v	Surface meridional velocity
p_8v	850 hpa meridional velocity
p850	850 Geopotential height
shum	Near surface specific humidity
P8_th	850 hpa wind direction

(February, June, July and August), ANN simulated monthly mean almost equally or below that of the observed data. For all other months of the year, the model has overestimated the wet days.

It has been noticed that summer months were modelled better than the other seasons and that could be due to

Table 3. Statistical properties of ANN downscale model during calibration and validation periods.

Coefficient	JFD	MAM	JJA	SON
R	0.84	0.81	0.84	0.85
RMSE	3.33	2.53	0.22	1.63
Nash	0.69	0.66	0.70	0.71
Bias	-13.41%	-12.16%	-3.76%	-9%

a low skewness characteristic of the rainfall during this period.

Another comparison for ability of ANN to reproduce the observed rainfall is the quantile-quantile plot shown in Figure 6 between the observed and simulated daily rainfall for the period 1961–2001. It can be seen in this figure that the ANN model follows the 45° line for all daily rainfall amounts, suggesting the ANN model is closer to the observed rainfall distribution. There are outliers for the ANN model for high rainfall amount, but not for low amounts in winter and spring seasons, which shows that low amounts are better simulated than high amounts, while the summer and autumn are more or less maintain the same distribution.

Moreover, uncertainty in simulation of future extreme values using the ANN approach needs to be taken into consideration. For instance, if an event was not

Figure 6. Quantile $\hat{\leftrightarrow}$ Quantile plot for observed & simulated daily rainfall for (a) winter (b) spring, (c) summer and (d) autumn during calibration and validation periods (1961-2001).

represented in the observed climate then it is unlikely to be represented in the future climate. So the ANN extremes performance produced from the observed NCEP predictors was validated by comparing them with the observed extremes. Extreme values, corresponding to specific return periods were estimated with a standard frequency analysis using Generalised Extremes Value Distribution (GEV) [35] (cf. Figure 7). ANN was able to reproduce the winter extremes properly while overestimate the daily extremes for the other seasons specially the autumn.

In general there are some differences between the observed daily rainfalls and those simulated by the ANN, but the overall performance of the downscaling model for the calibration and validation phases at daily and monthly level is deemed satisfactory.

The final structures of the ANN used in building the models are shown in Figure 8. The suitable size and structure of ANN in terms of hidden neurones and weight were selected during the training process. It can be deduced from the network structures that the ANN modelling approach employs a larger number of

neurons in the hidden layer in winter, spring and autumn and sometimes two hidden layers (12-20 neurons). This larger number of neurons in the hidden layer generally contributes to the accuracy of the model. In contrast, the summer model network uses smaller numbers of neurons in the hidden layer (one layer of 4 neurons).

3.7. Future Rainfall Projection

To incorporate the change in climate, one needs to calculate the relative change in daily mean wet and dry series lengths from the GCM output (HADCM3) of the control period (1961-1990) and future time-period. From the bar chart of downscaled predictand (Figure 9), it can be observed that rainfall is projected to decrease in future for the A2 and B2 scenarios. The patterns of rainfall in the future are relatively the same for both scenarios although the B2 scenarios projected more reduction than the A2 scenario. This is because among the scenarios considered, the scenario A2 has the highest concentration of atmospheric carbon dioxide (CO_2). Generally a greater reduction is anticipated in the 2080s for most of the

Figure 7. Return period-return level relationship of observed & simulated extremes rainfall for (a) winter (b) spring, (c) summer and (d) autumn during calibration and validation period (1961-2001).

Figure 8. Structure of ANN models for (a) winter (b) spring, (c) summer and (d) autumn.

Figure 9. Future monthly average rainfall for different time slices for A2 scenario (upper) and B2 scenario (lower) compared with control period.

Figure 10. Seasonal average daily rainfall for different future time slices for A2 scenario (upper) and B2 scenario (lower) compared with control period. The vertical error bars indicate the standard deviation.

Figure 11. Average annual rainfall for A2 scenario (upper) and B2 scenario (lower) compared with control period. Linear trend indicates that there is a significant downward trend.

months and can be up to 96% and 58% as in June of the A2 and March of the B2 scenarios, respectively. December experiences a very slight increase in the 2020s for both scenarios and the same trend was obtained for January in the 2050s.

Moreover, seasonal pattern of the average daily rainfall for different future time slices for the A2 and B2 scenarios in Sinjar area are also projected as shown in Figure 10. All the seasonal models consistently projected a drop in the daily rainfall for all future periods (black dots) with the summer expected to have more reduction compared to the other seasons as it is considered to be almost dry by the end of the 21st century in both tested scenarios. A drop of up to 34%, 45% and 30% for winter, spring and autumn, respectively, can be detected for the A2 scenario by the 2080s, while the B2 scenario projected a maximum drop of up to 34%, 30% and 33%. The vertical bar chart shows the standard deviation of the rainfall and confirms that rainfall will be less variable and skewed due to the reduction of daily rainfall amount.

Using a simple linear trend approach [36], the gradient and variance of the resulting regression of the hydrological series with respect to time is used to check the possible trends in the rainfall series for the period 1961–2099. Using the Wald test, the significance of trend gradient is tested based on a normally distributed assumption. Figure 11 shows the series plots and their trend lines for the average annual rainfall for the Sinjar station. The

Figure 12. Average monthly wet days for A2 scenario (upper) and B2 scenario (lower) compared with control period.

rainfall trend shows a significant downward for the A2 and B2 scenarios ($\alpha < 0.05$) which confirm that climate change in the Sinjar area affects the rainfall pattern in a negative way, especially in the 2080s.

Figure 12 indicates that, there is an appreciable change in the number of wet days by the 2080s for months January, February and March in both scenarios with about 10%–40% decrease in the wet days, while rest of the months experience a slight drop in all future periods. No changes in summer months are noticed as they are anticipated to be almost dry; however, a tendency of dryness extending to September is also observed (Figure 12).

Figure 13 and Figure 14 show a comparison of PDF estimates of GEV distribution for the current and projected daily annual extremes rainfall amount in the Sinjar area, which reveal a change in the shape of the distribution. The ANN model shows some increase in the extremes event of the 2020s for the A2 scenarios (the tail of the distribution is shifted more to the right compared with the control period), while the other future period PDFs for the same scenario relatively maintains the shape of distribution (Figure 13). The B2 scenario shows mixed results for changes in the distribution of extremes event (Figure 14). The ANN model shows a decrease in the extreme amounts for the three future periods, while the model also projects an increase in the low rainfall amounts in the 202s and 2050s, and a decrease in the 2080s (the

tail of distribution is shifted to the left) for the chosen GCM.

The ANN model is sensitive to the temporal changes in climatic variables, as it uses temporal features as well as point values in defining rainfall distribution. This may make the model very sensitive to small changes between scenarios, leading to different projections.

In summary, it is evident that the average rainfall trend shows a continuous decrease. Similar trends have also been observed before in some studies in the region [39], which confirm the results obtained in the present study. The overall average annual rainfall is envisaged to be slightly above 210 mm. This will keep this area below the average annual rainfall limit of 300 mm required to maintain crop growth [37]. Both scenarios (A2 and B2) showed that about 83% of the years having rainfall less than 300 mm. However, the distribution of the dry years varies with time (Figure 15). In this figure there is a very slight increase of the average annual rainfall until the 2060–70s followed by a sharp decrease towards the 2099.

4. Conclusions

Two emission scenarios proposed by the Intergovernmental Panel on Climate Change (A2 and B2) were used to study the long term rainfall trends up to the year 2099 in the Sinjar area in northwestern Iraq. ANN was used to build a climate-aware model to provide a suitable spatial scale using GCM data. In general 7 predictors were found to have a significant relation with the rainfall for the winter and spring seasons and 6 predictors for the autumn while the summer season shows only 4 predictors. All seasonal models consistently projected a drop in the daily rainfall for all future periods with the future summer expected to have more reduction in rainfall compared to the other seasons as it is predicted to be dry by the end of the 21st century under both emission scenarios considered.

The results also indicates that, there is an appreciable change in the number of wet days by the 2080s for months January, February and March in both scenarios with a decrease of about 10%–40% in wet days, while the rest of the months experiences a slight drop in rainfall in all future periods. No changes are noticed in summer months as they are considered almost dry, however, a tendency of dryness extending to September is also observed. Generally the average rainfall trend shows a continuous decrease. The overall average annual rainfall is envisaged to be slightly above 210 mm. Both annual models showed that about 83% of the years having rainfall less than 300 mm. However, the distribution of dry

Figure 13. Probability density function distribution (pdf) of (a) control period compared with the future period for (b) 2020s (c) 2050s, (d) 2080s of annual extremes events for A2 scenario.

Figure 14. Probability density function distribution (pdf) of (a) control period compared with the future period for (b) 2020s (c) 2050s, (d) 2080s of annual extremes events for B2 scenario.

Figure 15. Change of average annual rainfall with time.

years varies with time. In view of the results obtained in this study prudent water management strategies have to be adopted to overcome or mitigate this expected severe water shortage crisis

References

- [1] Al-Ansari N. A., Water resources in the Arab countries: Problems and possible solutions. UNESCO International conf. (Water: a looming crisis), Paris, 1998, 367-376
- [2] Naff T., Conflict and water use in the Middle East, in Roger R. and Lydon P. (Ed.), Water in the Arab World: Perspectives and Prognoses, Harvard University, 1993, 253-284
- [3] Al-Ansari N. A., Applied surface Hydrology, Al al-Bayt University Publication, 2005
- [4] Bazzaz F., Global climatic changes and its consequences for water availability in the Arab World, in Roger R. and Lydon P. (Ed.), Water in the Arab World: Perspectives and Prognoses, Harvard University, 1993, 243-252
- [5] Voss K., Famiglietti J., Lo M., de Linage C., Rodell M. and Swenson S., Groundwater depletion in the Middle East from GRACE with implications for transboundary water management in the Tigris-Euphrates-Western Iran region, Water Resources Research 49, 2013, 904-914
- [6] Al-Ansari N. A., Management of Water Resources in Iraq: Perspectives and Prognoses, J. Engineering 5, 2013, 667-684
- [7] Elasha B. O., Mapping of Climate Change Threats and Human Development Impacts in the Arab Region, United Nations Development programme, Arab Human Development Report (AHDR), Research Paper Series, <http://www.arab-hdr.org/publications/other/ahdrps/paper02-en.pdf>. Last accessed 22/12/2013
- [8] IPCC (Intergovernmental Panel on Climate Change), "Climate Change, Climate Change Impacts, Adaptation and Vulnerability", Cambridge University Press, 2007
- [9] Milly P. C. D., Dunne K. A and Vecchia A. V., Global Patterns of Trends in Streamflow and Water Availability in a Changing Climate. Nature, 2005, 438, 347-350
- [10] Al-Ansari N. A., Knutsson S., Toward Prudent Management of Water Resources in Iraq. Journal of Advanced Science and Engineering Research, 2011, 1, 53-67
- [11] UN, Water Resources Management White Paper, United Nations Assistance Mission for Iraq, United Nations Country Team in Iraq, 2010, 20
- [12] Al-Ansari N. A., Salameh E. and Al-Omari I., Analysis of Rainfall in the Badia Region, Jordan, Al al-Bayt University Research paper No. 1, 1999, 66
- [13] Al-Ansari N. A., Al-Shamali B. and Shatnawi A., Statistical analysis at three major meteorological stations in Jordan, Al Manara Journal for scientific studies and research 12, 2006, 93-120
- [14] Al-Ansari N. A., Baban S., Rainfall Trends in the Badia Region of Jordan, Surveying and Land Information Science 65, 2005, 233-243
- [15] Rasheed H., Mohammad E. and Awchi T., A field study on influence of initial moisture content on infiltration function. J. Al-Rafidain Engineering 2, 1994, 1-10
- [16] Kalnay E., Kanamitsu M., Kistler R., Collins W., Deaven D., Gandin L., Iredell M., Saha S., White G., Woollen J., Zhu Y., Leetmaa A., Reynolds B., Chelliah M., Ebisuzaki W., Higgins W., Janowiak J., Mo K. C., Ropelewski C., Wang J., Jenne R. & Joseph D., The NCEP/NCAR 40-Year Reanalysis Project. Bulletin of the American Meteorological Society 77, 1996, 437-471
- [17] Wheeler H. S., Progress in and prospects for fluvial flood modelling. Philosophical Transactions: Mathematical Physical and Engineering Sciences 360, 2002, 1409-431
- [18] Nakicenovic N., Davidson O., Davis G., Grübler A., Kram T., Lebre La Rovere E., Metz B., Morita T., Pepper W., Pitcher H., Sankovski A., Shukl P., Swart R., Watson R., Dadi Z., Emissions Scenarios. A Special Report of the Intergovernmental Panel on Climate Change. Cambridge University Press; 2000,

- Cambridge, UK
- [19] Von V., Heckl A., Impact of Climate Change on the Water Availability in the Near East and the Upper Jordan River Catchment. Phd Thesis, 2000. University of Augsburg, Germany
 - [20] Hewitson B. C., Crane R. G., Climate downscaling: techniques and application, *Clim Res* 7, 1996, 85-95
 - [21] Cavazos T. Hewitson B. C., Performance of NCEP variables in statistical downscaling of daily precipitation. *Clim Res* 28, 2005, 95-107
 - [22] Ojha, C.S.P., Goyal, M. K., Adeloje, A. J., Downscaling of Precipitation for Lake Catchment in Arid Region in India using Linea Multiple Regression and Neural Networks. *The Open Hydrology Journal* 4, 2010, 122-136
 - [23] Hoai N. D., Udo K., Mano A., Downscaling Global Weather Forecast Outputs Using ANN for Flood Prediction. *Journal of Applied Mathematics*, 2011, Article ID246286, 14 pages doi:10.1155/2011/246286
 - [24] Fistikoglu O., Okkan U., Statistical Downscaling of Monthly Precipitation Using NCEP/NCAR Reanalysis Data for Tahtali River Basin in Turkey. *J. Hydrol. Eng.* 16, 2011, 157-164 doi 10.1061/(ASCE)HE.1943-5584.0000300
 - [25] Coulibaly P., Dibike Y. B., Downscaling Precipitation and Temperature with Temporal Neural Networks. *J. Hydrometrology* 6, 2004, 483-496
 - [26] Lisboa P. G. J., *Neural Networks: current applications*, Chapman & Hall, New York, 1992
 - [27] Trigo R. M., Improving Metrological Downscaling Methods with Artificial Neural Network Models. PhD thesis, 2000 University of East Anglia
 - [28] Levenberg K., A method for the solution of certain problems in least squares, *Quarterly of Applied Mathematics* 5, 1944, 164-168
 - [29] Marquardt D., An algorithm for least-squares estimation of nonlinear parameters, *SIAM Journal on Applied Mathematics* 11, 1963, 431-441
 - [30] Jeong D.-I., Kim Y.-O., Rainfall-runoff models using artificial neural networks for ensemble stream flow prediction. *Hydrol. Process* 19, 2005, 3819-3835
 - [31] Yadav D., Naresh R., Sharma V., Stream flow forecasting using Levenberg- Marquardt algorithm approach. *IJWREE* 3, 2010, 30-40
 - [32] Legates D. R., McCabe G. J., Evaluating the use of goodness-of-fit measures in hydrologic and hydro-climatic model validation. *Water Resources Research* 35, 1999, 233-241
 - [33] Schaap M. G., Leij F. J., Database related accuracy and uncertainty of pedotransfer functions. *Soil Science* 16, 1998, 765-779
 - [34] Gupta H. V, Sorooshian S., Yapo P. O., Status of automatic calibration for hydrologic models: Comparison with multilevel expert calibration. *J Hydrologic Eng.* 4, 1999, 135-143
 - [35] Coles, S., *An introduction to statistical modeling of extreme values*, 2001, Springer, London
 - [36] Hannaford C. and Marsh T., An assessment of trends in UK runoff and low flows using a network of undisturbed basins, *International Journal of Climatology* 26, 2006, 1237-1253
 - [37] FAO, Improving Productivity of Dry land Areas. Committee on Agriculture (Ninth session), 1987, FAO, Rome. <http://www.fao.org/docrep/meeting/011/ag415e/ag415e04.htm#4.1>. Last accessed 22/12/2013
 - [38] IPCC. Special Report on Emission Scenarios Summary for policy makers. IPCC, Working Group III. Cambridge University Press. 2001
 - [39] Shabani, Farzin, Lalit Kumar, and Subhashni Taylor, Climate Change Impacts on the Future Distribution of Date Palms: A Modeling Exercise Using CLIMEX, *PLOS|ONE*, 2012, DOI: 10.1371/journal.pone.0048021