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Environmental water demand assessment under climate change conditions

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Abstract Measures taken to cope with the possible effects of climate change on water resources management are key for the successful adaptation to such change. This work assesses the environmental water demand of the Karkheh river in the reach comprising Karkheh dam to the Hoor-al-Azim wetland, Iran, under climate change during the period 2010–2059. The assessment of the environmental demand applies (1) representative concentration pathways (RCPs) and (2) downscaling methods. The first phase of this work projects temperature and rainfall in the period 2010–2059 under three RCPs and with two downscaling methods. Thus, six climatic scenarios are generated. The results showed that temperature and rainfall average would increase in the range of 1.7–5.2 and 1.9–9.2%, respectively. Subsequently, flows corresponding to the six different climatic scenarios are simulated with the unit hydrographs and component

flows from rainfall, evaporation, and stream flow data (IHACRES) rainfall-runoff model and are input to the Karkheh reservoir. The simulation results indicated increases of 0.9–7.7% in the average flow under the six simulation scenarios during the period of analysis. The second phase of this paper's methodology determines the monthly minimum environmental water demands of the Karkheh river associated with the six simulation scenarios using a hydrological method. The determined environmental demands are compared with historical ones. The results show that the temporal variation of monthly environmental demand would change under climate change conditions. Furthermore, some climatic scenarios project environmental water demand larger than and some of them project less than the baseline one.

Keywords Environmental water demand · Climate change · Uncertainty · RCP · Change factor downscaling · Regression downscaling · Karkheh basin

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Introduction

The drying of wetlands, the reduction of river streamflow, and the associated degradation of ecosystems due to human overuse of water resources have become commonplace, especially in arid and semiarid regions. The environmental water demand is a key factor determining the proper functioning of riverine ecosystems and associated wetlands. The environmental water demand, or environmental demand, for short, is the rate of water inflow necessary for the proper

physical, chemical, and biological functioning of an aquatic ecosystem. This flow rate may vary seasonally. It is essential under these circumstances of water over-exploitation to assess the environmental demands of water bodies and dependent ecosystems. There are several methods that are applied to the calculation of environmental demand in rivers. Tharme (2003) surveyed 207 applications of environmental demand studies in 44 countries which are categorized in four major groups including (1) hydrological, (2) hydraulic rating, (3) habitat simulation, and (4) holistic methods. Each method proposed for determining the environmental demand of rivers has advantages and disadvantages according to the complexity and amount of required data. On the one hand, there are relatively simple and inexpensive hydrological methods that rely on flow time series, and the other hand, there are holistic methods that require extensive data and are costly to implement. Therefore, there is no generally preferred accepted method for evaluating the environmental demand. Hydrological methods are the simplest and most inexpensive way to determine the environmental demand, and they do not require considerable fieldwork. Hydraulic rating methods are designed to be applied in rivers that have a single defined channel (Linnansaari et al. 2012), and they require some field study data. Despite the fact that habitat simulation methods are more precise than hydrological and hydraulic methods, they are time consuming and costly. Also, they involve substantial biological data. Holistic methods consider several different aspects of river flow conditions. As a result, they need comprehensive data sets and expert opinions to evaluate the environmental demand. Therefore, they are generally time consuming and expensive to implement (Linnansaari et al. 2012). Among the commonly applied environmental demand determination methods are the physical habitat simulation (PHABISM) (US Fish and Wildlife Service (FWS), 1970s), the Tennant method (Tennant 1976), the Tessman method (Tessman 1980), the range of variability approach (RVA) (Richter et al. 1997), the Building Block Method (BBM) (King and Louw 1998), and Downstream Response to Imposed Flow Transformation (DRIFT) (King et al. 2003).

Tennant (1976) proposed 10, 30, and 60% of average annual flow to maintain river at minimum, good, and excellent level for aquatic life condition, respectively. Despite the fact that the Tennant method is a commonly applied hydrological method, it was not proposed for arid and semiarid regions. PHABISM, which is the

widely used of habitat simulation method, was developed by the US Fish and Wildlife Service. PHABISM simulates the relation between river flow and the physical condition of aquatic ecosystems. Therefore, in addition to hydrological data, it requires a hydraulic and ecological database (Milhous et al. 1989). DRIFT is a holistic method, which was developed in South Africa by King et al. (2003). It includes four main modules which are (1) biophysical, (2) sociological, (3) scenario development, and (4) economic module (Arthington et al. 2003). The output of DRIFT is scenarios that indicate how river flow changes affect environmental riverine conditions. Holistic methods require broad data in various fields; thus, they are time consuming and costly to implement. Reinfelds et al. (2004) proposed a hydraulic method to determine the minimum environmental demand in perennial gravel-bed rivers. They suggested the 50th flow duration percentile as the minimum environmental demand for perennial rivers that have high degree of variability. Kashaigili et al. (2007) suggested that 21.6% of the mean annual flow in Ruaha river, Tanzania, estimates its environmental demand.

The threats of contemporary climate change affected by greenhouse gas emissions have been summarized by the Intergovernmental Panel on Climate Change (IPCC 2014). The awareness of such climate threats has led to an international covenant for the reduction of fossil fuel use in an attempt for climate stabilization. Middle East countries, including Iran, are vulnerable to climate change (Jamali et al. 2012). Many other studies have reported climate change effects on water resources the world over.

Qian and Zhu (2001) reported climate change effects in parts of China. Dust storms in northern China, flow reduction in the downstream reach of the Yellow river, and changes in drought and wetness conditions were among the adverse impacts identified by Qian and Zhu (2001). Thodsen (2007) evaluated climate change effects on Danish rivers in the period 2071–2100. The results showed that the mean annual precipitation and evapotranspiration would increase by 7 and 12%, respectively. Githui et al. (2009) evaluated the potential climate change effects on the runoff of the Nzoia Catchment which is tributary to Lake Victoria in Africa. The climate change projections estimated precipitation increasing between 2.4 and 32.2% under various scenarios which lead to changes of runoff in the range of 6–115%. Ashofteh et al. (2013) studied river inflow to the

Aidoughmouh reservoir located in East Azerbaijan, Iran. This study showed a 0.7% decrease in mean annual runoff. Ngoc et al. (2016) showed that river flow in central Vietnam during wet and dry seasons might be increased by 200% and decreased by 7–30%, respectively, under climate change conditions.

Reservoirs are major regulators of river flow. The determination of the environmental water demand downstream of reservoirs is key to supporting a dependent and vulnerable ecosystem, as exemplified in Iran, where riverine ecosystems and wetlands have been severely affected by declining river inflow. Contemporary climate change may exacerbate conditions in riverine ecosystems and wetlands already stressed by river flow regulation and diversions. The assessment of climate change effects on such vulnerable aquatic environment entails several tasks, such as (1) developing greenhouse gas emission scenarios, (2) implementing general circulation models (GCMs), (3) downscaling methods of GCM outputs to drive regional hydrologic models, and (4) implementing rainfall-runoff models (Oyebode et al. 2014). Wilby and Harris (2006) stated that the major sources of climate change uncertainty predictions in decreasing order of importance are (1) GCMs' climatic simulations, (2) downscaling methods, (3) hydrological models' structure, (4) hydrological model parameterization, and (5) estimation of emission scenarios. Burlando and Rosso (2002) estimated the reduction of runoff by climate change in the Arno river runoff, Italy. Minville et al. (2010) simulated climate with five GCMs and two emission scenarios to estimate hydrologic variables in 2020, 2050, and 2080 in the Québec region, Canada. Results indicated that seasonal temperature would increase by 1–14 °C, and the seasonal precipitation might change between –9 and 55%. The latter authors estimated that GCM climatic simulations were the most important determinant of the hydrologic simulation results.

Previous studies addressed may impact areas for contemporary climate change. Yet, the issue of environmental water demands affected by climate change has not been given in-depth research attention. This paper's objectives are the determination of the Karkheh river environmental demand under climate change conditions and the assessment of the sources of climate change uncertainty on the estimation of the environmental water demand. To accomplish these objectives, the output of the CanESM2 large-scale climate model simulated under three representative concentration pathways (RCPs) (2.6, 4.5, and 8.5) is applied to temperature and rainfall

projection in the period 2010–2059 for the Karkheh river basin. The large-scale GCM output is downscaled with the change factor and regression approaches. Thus, six climatic scenarios are created in this paper's analysis. The identification of unit hydrographs and component flows from rainfall, evaporation, and stream flow data (IHACRES) rainfall-runoff model is herein implemented to project runoff for each scenario. Subsequently, the monthly environmental flow demand corresponding to each scenario is calculated with the RVA method. Figure 1 presents the flowchart of this paper's methodology.

Case study

The Karkheh river basin is located in western Iran between longitudes 46° 23' and 49° 12' east and between latitudes 31° 40' and 35° 00' north. The general topographic slope declines from north to south. Figure 2 shows the location of the Karkheh basin. The total area of the basin equals 51,604 km², 55% of which is mountainous. Minimum and maximum average temperatures equal 12.22 and 36.0 °C, respectively, and minimum and maximum rainfall equal 0.0 and 44.20 mm, respectively (Table 1).

The Hoor-al-Azim wetland is the discharge portion of the basin, which is located on the border between Iran and Iraq. The major water supply to the Iranian section of the wetland is the Karkheh river. The area of the wetland is almost 118,000 ha under normal conditions. Yet, the lack of water supply, which has fallen below the environmental demand, has reduced the Iranian portion of the wetland by about one half. The minimum yearly environmental demand of the Hoor-al-Azim wetland has been estimated to be about 1271×10^6 m³ based on ecological considerations.

Data and methods

Climate change considerations

Climate change is a long-term terrestrial-atmospheric-oceanic complex phenomenon of global reach caused by natural processes and by human-induced actions such as the emission of greenhouse gases by burning fossil fuels. Climate change is reflected in many ways such as modification of (i) the temporal and spatial

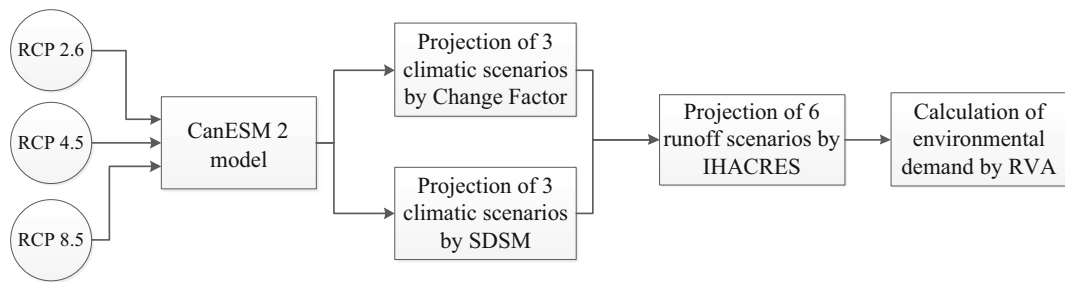


Fig. 1 Flowchart of this paper's methodology

distribution of rainfall and its form (solid and liquid), (ii) the pattern of natural disasters related to hydrological conditions such as floods and droughts, (iii) streamflow characteristics, and (iv) evapotranspiration, and in general, new trends in the global climate. A key factor needed to predict future climate conditions and to mitigate and adapt is the future concentration of greenhouse gases as affected by human activities. The IPCC's Fourth Assessment Report (AR4, IPCC 2007) issued 40 greenhouse gas emission scenarios in its Special Report on Emissions Scenarios (SRES). These scenarios were categorized into four main groups, namely, A1, A2, B1, and B2, each of which projected the emissions of greenhouse gases until year 2100 on the basis of rates of population growth, economic development, and environmental protection throughout the world. The IPCC (2014) (Intergovernmental Panel on Climate

Change 2014) issued four new scenarios named RCPs of future emissions of greenhouse gases. These are the RCP 2.6, RCP 4.5, RCP 6, and RCP 8.5 concentration pathways. These four pathways lay out four different climatic conditions depending on future atmospheric greenhouse gas concentrations on the basis of economic activities, energy sources, population growth, and other social factors by year 2100. The climatic conditions are expressed in terms of the radiative forcing (RF) in units of watts per square meter of the Earth's surface (W/m^2). General information about the RCPs is listed in Table 2 (see also Fujino et al. 2006; Riahi et al. 2011; Thomson et al. 2011; Van-Vuuren et al. 2011; Wayne 2013).

This study relies on the outputs of the Canadian CanESM2 large-scale climate model under emission scenarios RCPs 2.6, 4.5, and 8.5 to forecast temperature and rainfall by 2010–2059 in the Karkheh river basin,

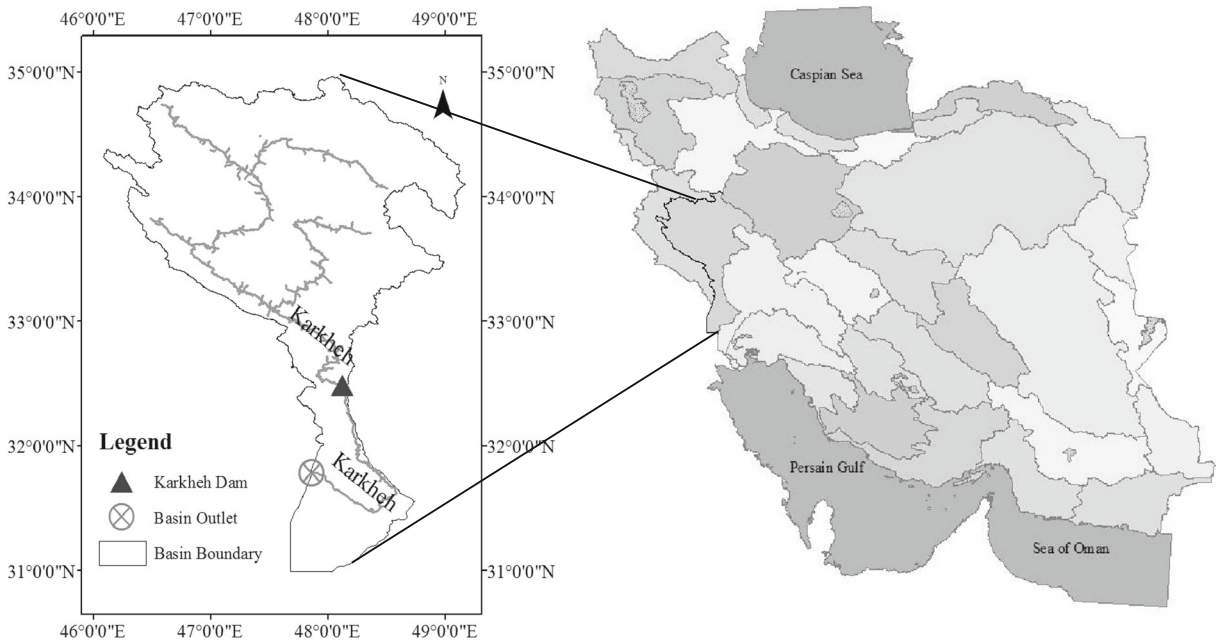


Fig. 2 Location map of the Karkheh basin

Table 1 Monthly average temperature and rainfall in Karkheh basin in the baseline period (1980–2009)

Variable	Month											
	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
Temperature (°C)	12.22	13.91	18.17	23.65	29.89	34.31	36.00	35.24	31.62	26.07	19.48	13.91
Rainfall (mm)	43.46	35.87	30.07	19.62	7.11	0.18	0.00	0.11	0.70	8.12	28.89	44.20

located in Iran. The climate model outputs were downloaded from the www.ccds-dscs.ec.gc.ca website. The resolution of the CanESM2’s predictions in the atmosphere and the ocean is listed in Table 3.

GCMs are complex, large-scale, numerical models implemented to simulate future climatic conditions (Wilby and Harris 2006; and many others). GCMs are based on the physical processes governing the transient states of the earth’s atmosphere, oceans, and continents. GCMs’ outputs must be downscaled to render them useful for basin-scale analysis. The downscaling may be achieved with (1) statistical methods that are based on empirical relations between large-scale climatic variables and regional-scale variables, or with (2) dynamic methods that rely on regional climate models (RCMs) that are nested within GCMs and simulate climate variables with a higher spatial resolution. The change factor and regression methods are applied in this work to forecast temperature and rainfall within the study region.

Change factor method

An approach to downscale statistically GCM projections is by means of the change factor method. It is based on the ratio of a GCM future-year prediction to baseline-year prediction and multiplying such ratio by the observed climatic variable (for rainfall variable) in a baseline period to calculate predicted, future, and climatic variables. The change factor method applies

differences to temperature. In this case, the method calculates the difference between future-year and baseline-year temperature predictions and adds those differences to observed data in the baseline period to predict future temperatures (see Loáiciga et al. 2000; Loáiciga 2003; Ahmadi et al. 2015). Among the variety of simulated climatic variables predicted from the implementation of the CanESM2 model, we chose temperature and rainfall variables to simulate the rainfall-runoff process at the basin scale in the period of time 2010–2059 using as baseline years 1980–2009. The change factors for temperature and rainfall at monthly time scale are calculated respectively by Eqs. (1) and (2):

$$\Delta T_i = (\bar{T}_{GCM,fut,i} - \bar{T}_{GCM,base,i}) \tag{1}$$

$$\Delta R_i = \left(\frac{\bar{R}_{GCM,fut,i}}{\bar{R}_{GCM,base,i}} \right) \tag{2}$$

in which ΔT_i and ΔR_i are change factors for temperature and rainfall for the i th month of the year, respectively; $\bar{T}_{GCM,fut,i}$ and $\bar{R}_{GCM,fut,i}$ are long-term means of simulated temperature and rainfall, respectively, by the GCM in future years for the i th month; and $\bar{T}_{GCM,base,i}$ and $\bar{R}_{GCM,base,i}$ are long-term means of simulated temperature and rainfall, respectively, by the GCM for the i th month in the baseline and observation periods.

Table 2 RCPs’ characteristics

Name	Radiative forcing	Increasing mean annual temperature (°C) (2046–2065)	Increasing mean annual temperature (°C) (2081–2100)
RCP 2.6	3 W/m ² before 2100, declining to 2.6 W/m ² by 2100	1 (0.4–1.6)	1 (0.3–1.7)
RCP 4.5	4.5 W/m ² post 2100	1.4 (0.9–2.0)	1.8 (1.1–2.6)
RCP 6	6 W/m ² post 2100	1.3 (0.8–1.8)	2.2 (1.4–3.1)
RCP 8.5	8.5 W/m ² in 2100	2 (1.4–2.6)	3.7 (2.6–4.8)

Table 3 CanESM2's characteristics

GCM	Resolution in the atmosphere		Resolution in the ocean	
	Latitude	Longitude	Latitude	Longitude
CanESM2	2.7906°	2.8125°	0.9303–1.1407°	1.4062°

The change factors are applied to observed temperature and rainfall as expressed by Eqs. (3) and (4), respectively:

$$i = 1, 2, 3, \dots T_i = T_{obs,i} + \Delta T_i^i \tag{3}$$

$$i = 1, 2, 3, \dots R_i = R_{obs,i} \times \Delta R_i \tag{4}$$

in which T_i and R_i are temperature and rainfall predictions under climate change in future years for the i th month, respectively, and $T_{obs,i}$ and $R_{obs,i}$ are the observed temperature and rainfall for the i th month, respectively.

Regression downscaling method

The regression downscaling approach is based on empirical relations between regional predicted variables and regional predictor(s) (Wilby et al. 2002). The statistical downscaling method (SDSM) is a regression-based downscaling proposed by Wilby et al. (2002) for the assessment of regional climate change. Regression downscaling has five steps: (1) screening of variables: in this step, suitable predictor(s) are chosen; (2) model calibration: in which multiple linear regressions are developed and a model structure is determined; (3) synthesis of observed data: that enables the verification of calibrated models; (4) generation of scenarios: in which ensembles of synthetic weather series are produced; and (5) analysis of scenarios (Wilby et al. 2002).

Table 4 Calibrated parameters values of the IHACRES model

Parameter	Value
c	0.000016
l	0
p	1
τ_w	22
f	1.5
T_r	20

This paper applies the SDSM version 4.2.9 to predict necessary climatic data at the monthly time scale.

Flow simulation

Runoff is simulated with the IHACRES model in the time interval 2010–2059 following the projection of temperature and rainfall. IHACRES is a conceptual model that produces runoff by applying temperature and rainfall as inputs in two steps: (1) nonlinear module and (2) linear module. In step (1), the effective rainfall is estimated where temperature and rainfall are the model inputs (Eqs. (5), (6), and (7)). Step (2) simulates streamflow Q from the effective rainfall with a linear module (Eq. (8)) (Croke and Jakeman 2008). The simulation equations for effective rainfall, soil moisture, and the drying rate are as follows, respectively:

$$t = 1, 2, 3, \dots u_t = [c(\varphi_t - l)]^p \times R_t \tag{5}$$

$$t = 1, 2, 3, \dots \varphi_t = R_t + \left(1 - 1/\tau_t\right) \varphi_{t-1} \tag{6}$$

$$t = 1, 2, 3, \dots \tau_t = \tau_w \exp[0.062f(T_r - T_t)] \tag{7}$$

in which u_t = effective rainfall, R_t and T_t = input rainfall and temperature, φ_t = soil moisture index, τ_t = drying rate, c = mass balance parameter, l = soil moisture index threshold, p = nonlinear response term, τ_w = reference drying rate, f = temperature modulation, and T_r = reference temperature. Runoff is calculated with the following equation:

$$t = 1, 2, 3, \dots Q_t = a^q Q_{t-1} + b^q (u_{t-1}) + a^s Q_{t-1} + b^s (u_{t-1}) \tag{8}$$

where Q_t and Q_{t-1} = runoff at times t and $t - 1$, respectively, and a^q , b^q , a^s , and b^s = parameters of the linear module (Ashofteh et al. 2013).

The IHACRES rainfall-runoff model was applied to simulate streamflow with the projected temperature and

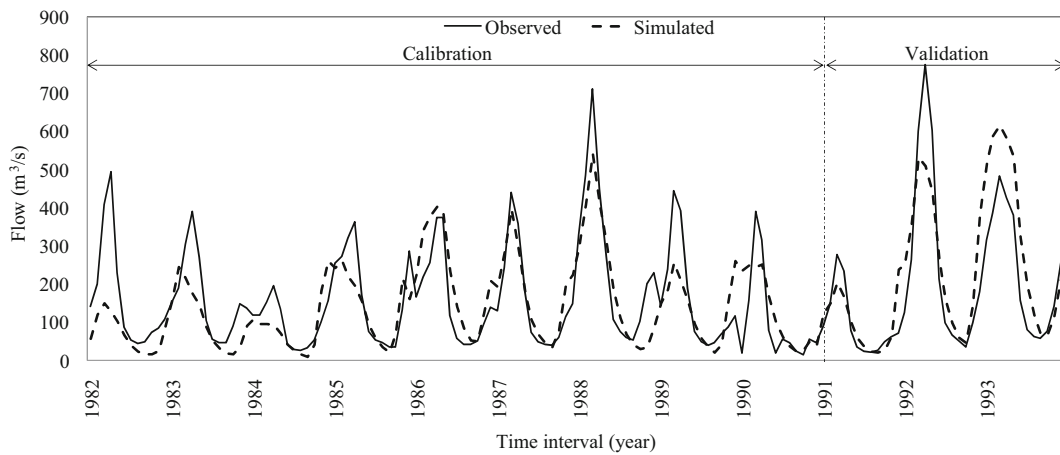


Fig. 3 Comparison of observed and simulated flow time series for the calibration and validation periods

rainfall. IHACRES is a lumped, continuous, and conceptual hydrological model that requires monthly temperature and rainfall data as driving inputs. Monthly data in 1982–1990 and 1991–1993 for the Karkheh river basin were applied for calibration and validation of the IHACRES model, respectively. The model calibration step estimated optimal parameters for the IHACRES model, which are described in past studies, listed in Table 4.

The IHACRES model performance in calibration and validation and the differences between observed and simulated time series are presented in Fig. 3. Model performance was measured with two criteria, namely, relative bias (RB) and the Nash-Sutcliffe efficiency (NSE) index, given by Eqs. (9) and (10), respectively:

$$RB = \frac{\sum_{t=1}^T (Q_{ot} - Q_{Mt})}{\sum_{t=1}^T Q_{ot}} \tag{9}$$

$$NSE = 1 - \frac{\sum_{t=1}^T (Q_{ot} - Q_{Mt})^2}{\sum_{t=1}^T (Q_{ot} - \bar{Q}_o)^2} \tag{10}$$

in which RB = relative bias, Q_{ot} = observed flow in month t , Q_{Mt} = simulated flow by the IHACRES model

Table 5 Performance indices for IHACRES rainfall-runoff model

	RB (%)	NSE
Calibration interval (1982–1990)	11.48	0.6
Validation interval (1991–1993)	-18.88	0.7

in month t , NSE = Nash-Sutcliffe efficiency index, and \bar{Q}_o = average of the observed flow. The calculated values of the efficiency indices are shown in Table 5 for calibration and validation intervals separately.

Environmental water demand

Rivers constitute essential water sources. The construction of dams, water diversions, river engineering, and contaminated discharges to rivers cause a variety of adverse impacts to rivers and dependent environments. It is essential to establish the environmental water demand to mitigate the negative effects of humans’ action on rivers and riverine ecosystems (Yin et al. 2015). This paper focuses on the environmental water demand, or, in short, environmental demand, which is herein defined as the flow required in a river reach to maintain functional riverine ecosystems. The operation of reservoirs to meet required downstream environmental demands is tackled in this work. Mazvimavi et al. (2007) proposed 30–60% of the mean annual runoff as environmental demand of

Table 6 Long-term projected average temperature (°C)

Time interval (year)	Climatic scenario					
	C-2.6	C-4.5	C-8.5	S-2.6	S-4.5	S-8.5
2010	25.02	24.99	25.00	25.67	25.58	25.65
2020	24.82	24.78	24.80	25.78	25.67	25.71
2030	25.04	25.01	25.02	25.77	25.77	25.72
2040	25.06	25.16	25.30	25.73	25.82	25.93
2050	24.86	24.96	25.10	25.76	25.85	26.07

Table 7 Long-term projected average rainfall (mm)

Time interval (year)	Climatic scenario					
	C-2.6	C-4.5	C-8.5	S-2.6	S-4.5	S-8.5
2010	193.88	198.42	204.76	227.16	260.45	254.80
2020	252.13	257.69	267.42	247.29	215.50	252.54
2030	191.59	195.25	202.75	239.76	230.25	235.57
2040	206.67	199.74	209.31	214.27	230.07	224.93
2050	271.08	206.67	274.48	262.11	236.85	210.53

perennial rivers in Zimbabwe. Liu et al. (2016) stated that 26% of blue water resources should be allocated to environmental demand in the Huangqihai river basin, China, to maintain a healthy riverine ecosystem. Richter et al. (1997) proposed the range of variability approach (RVA) for the statistical assessment of the ecological condition of a river flow regime that affects riverine ecosystems. The RVA method was developed for and has been applied to rivers where maintaining natural ecosystems and biodiversity is a main management objective. The RVA method seeks to achieve river management that maintains the Indicators of Hydrologic Alteration (IHA) (such as monthly river flow) within their ranges of natural variation. The variability of the IHA parameters is measured by their standard deviations (SD), or by their 25 and 75% quartiles. The RVA method requires at least a 20-year time series of river flow to estimate statistical parameters. Hydrologic simulation may be applied to make up for the shortage of hydrologic data.

The RVA method determines a specific range of river flow statistically and designates that range as the environmental demand. This study calculates the environmental demand in month k ($k = 1, 2, \dots, 12$) of a year by means of the 25 and 75% quartiles of the river flows of month k calculated over the previous 20 years of river flow data. Therefore, for example, the minimum and maximum environmental demands in January of year 2000 equal respectively the 25 and 75% quartiles of the January river flow calculated from data for years 1980 through 1999. The environmental demand for the other

months of year 2000 (or any other year being assessed) is calculated analogously. This study considers that the minimum bound of the environmental demand calculated with the RVA method meets a river's ecosystem functions. Based on these considerations, this study calculates the environmental demand with Eq. (11):

$$n = 1, 2, 3, \dots, De_{nk} = Q1_{nk} \quad (11)$$

In which De_{nk} = environmental demand of month k , $k = 1, 2, \dots, 12$, for all n years, an $Q1_{nk}$ = the 25% quartile of river flow in month k calculated from river flow data in the previous $n = 20$ years.

Results and discussion

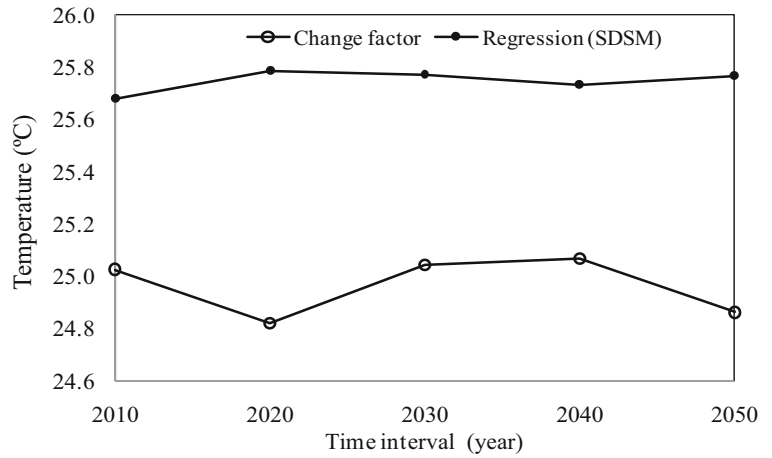
Six climatic scenarios for temperature and rainfall in the study region were produced by applying the RCPs 2.6, 4.5, and 8.5 and the change factor and regression downscaling methods (the latter herein denoted by SDSM) in periods 2010–2019 (designated by 2010), 2020–2029 (designated by 2020), 2030–2039 (designated by 2030), 2040–2049 (designated by 2040), and 2050–2059 (designated by 2050). The six scenarios are named C-2.6, C-4.5, C-8.5, S-2.6, S-4.5, and S-8.5, in which “C” and “S” are indicative of the change factor and SDSM methods, respectively, and the numbers are related to the RCPs. The long-term means of temperature and rainfall are calculated and listed in Tables 6, 7, and 8, respectively.

It is seen in Table 6 that temperature changes in the period 2010–2050 calculated with the change factor method varying. Thus, in 2010–2020, the mean temperature declines and it increases until 2040, followed by a decline through 2050. The mean temperature changes calculated in the period 2010–2050 applying the downscaling SDSM method exhibit a general ascending trend. In general, the predicted mean temperature with the SDSM method is higher than that predicted with the change factor method. Figure 4 graphs the temperature predictions associated with the RCPs. The graphs shown in Fig. 4 affirm that the SDSM method predicted the temperature to exceed those calculated with the

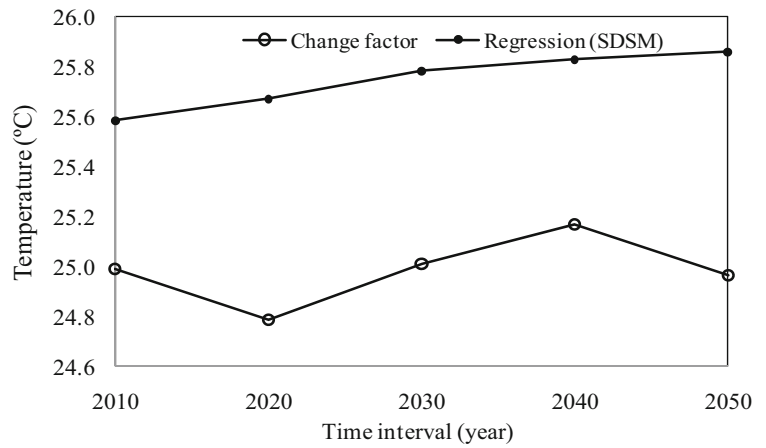
Table 8 Average monthly environmental demand of Karkheh river for six climatic scenarios

Climatic scenario	C-2.6	C-4.5	C-8.5	S-2.6	S-4.5	S-8.5
Environmental demand (m ³ /s)	76.90	77.27	78.69	105.51	108.94	115.99

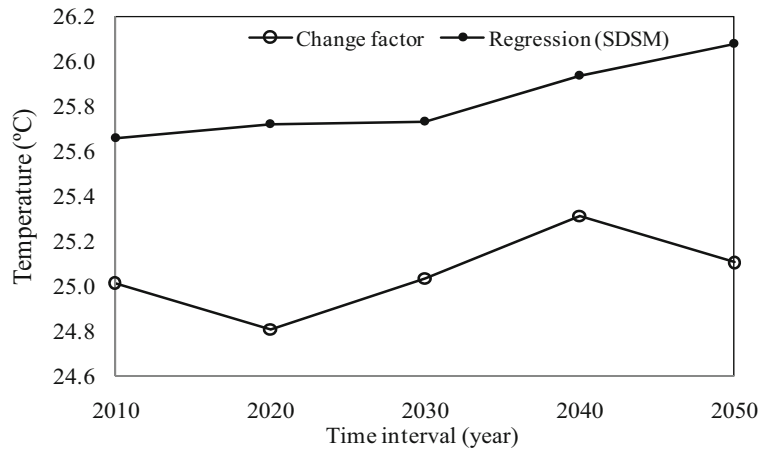
Fig. 4 Projected mean temperature in future periods under **a** RCP 2.6, **b** RCP 4.5, and **c** RCP 8.5



(a)



(b)



(c)

change factor method. The maximum temperature difference obtained with SDSM and the change factor

method is observed in 2050, in which the temperature prediction by SDSM is about 3.7% higher than that

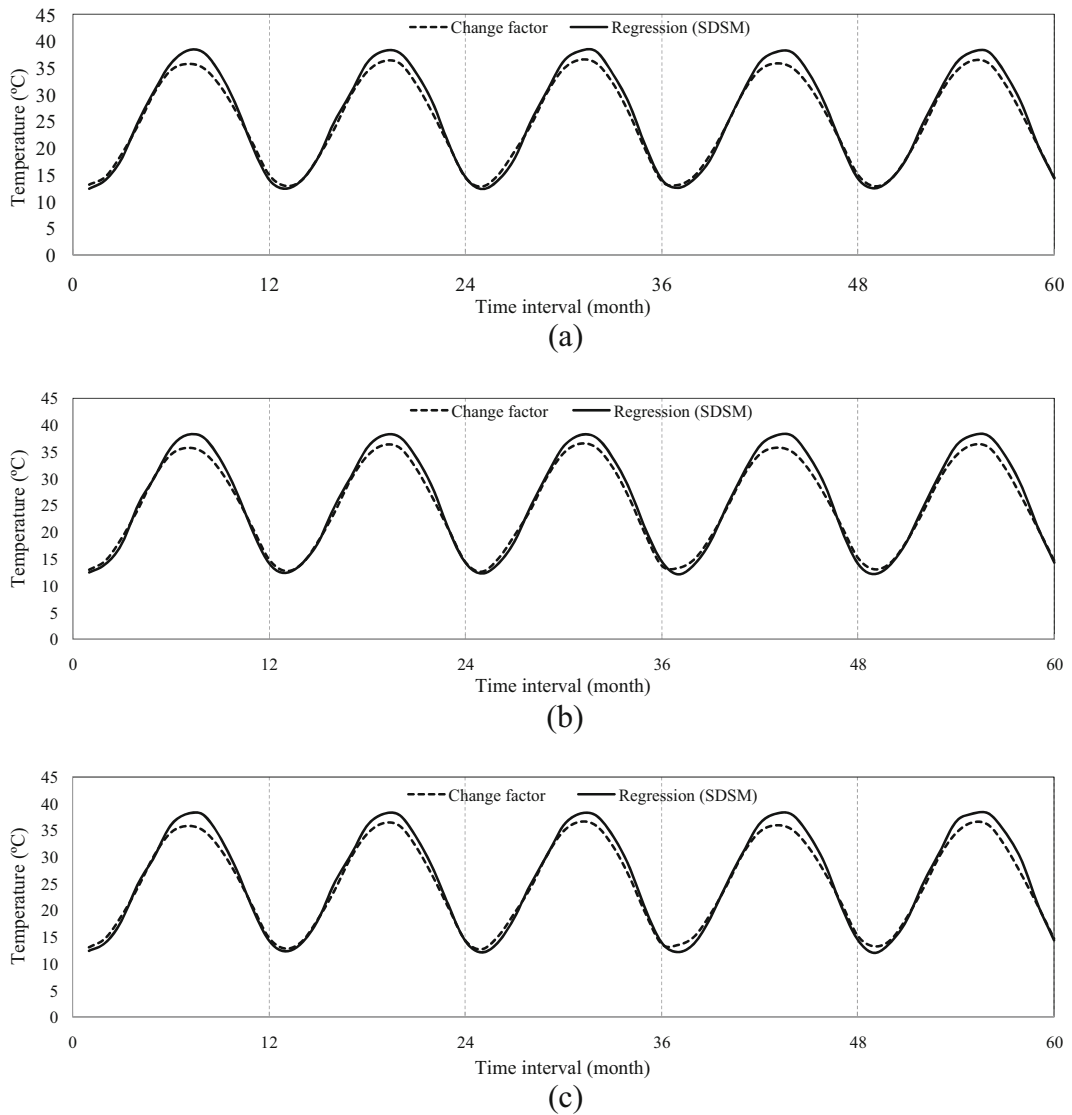


Fig. 5 Comparison of the mean monthly temperature projected with two downscaling methods under **a** RCP 2.6, **b** RCP 4.5, and **c** RCP 8.5

Fig. 6 Changes of projected long-term mean temperature relative to the baseline period

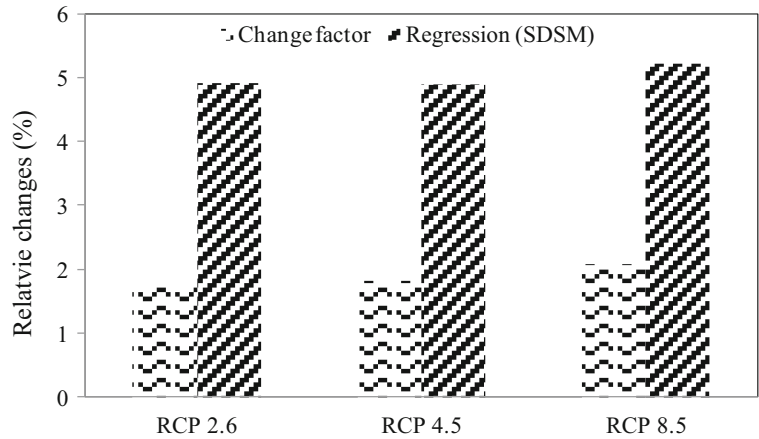
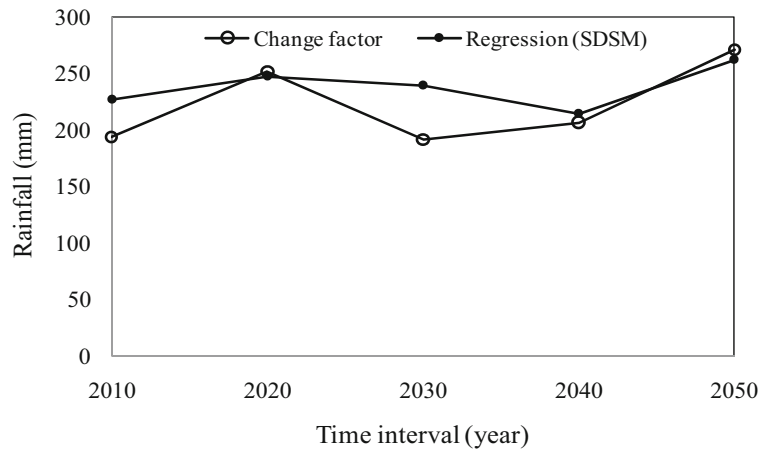
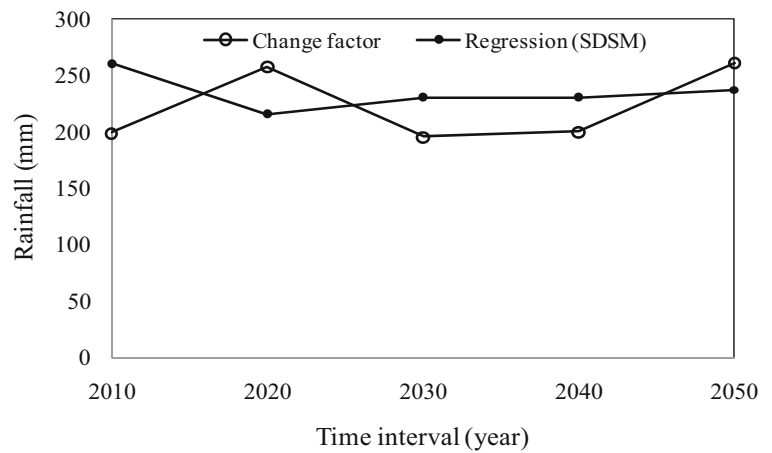


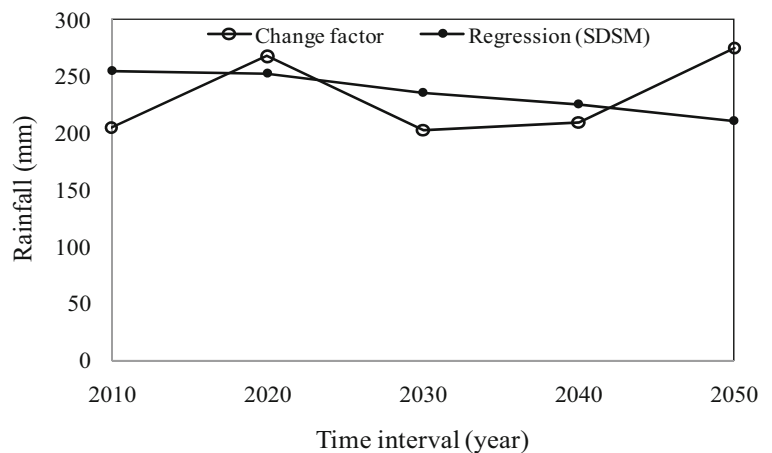
Fig. 7 Projected mean rainfall in future periods under **a** RCP 2.6, **b** RCP 4.5, and **c** RCP 8.5



(a)



(b)



(c)

obtained with the change factor method under RCP 8.5. On the other hand, the minimum temperature difference

between the two downscaling methods occurs corresponding to the RCP 4.5 in 2010, in which the

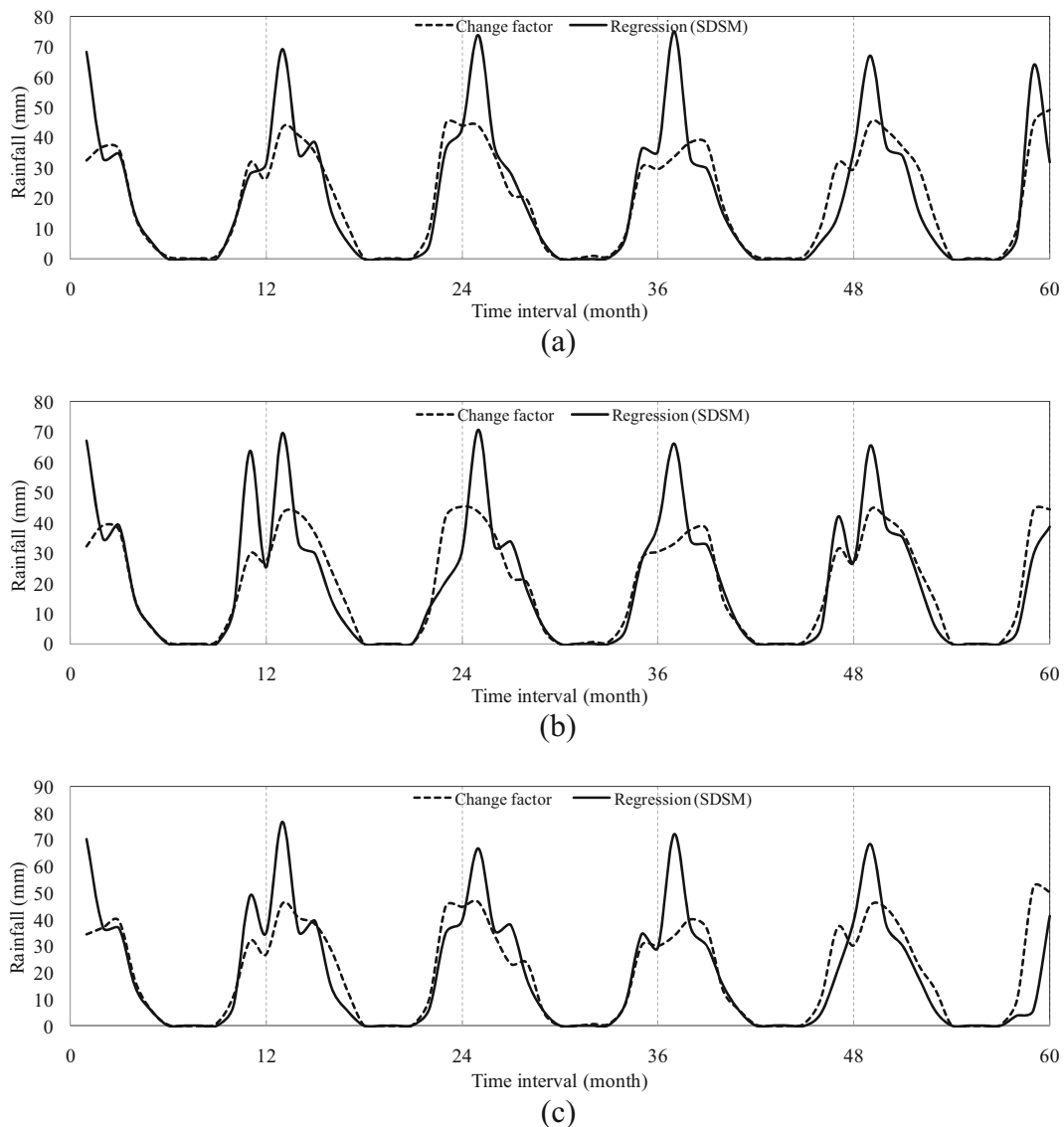


Fig. 8 Comparison of mean monthly rainfall projected with two downscaling methods under **a** RCP 2.6, **b** RCP 4.5, and **c** RCP 8.5

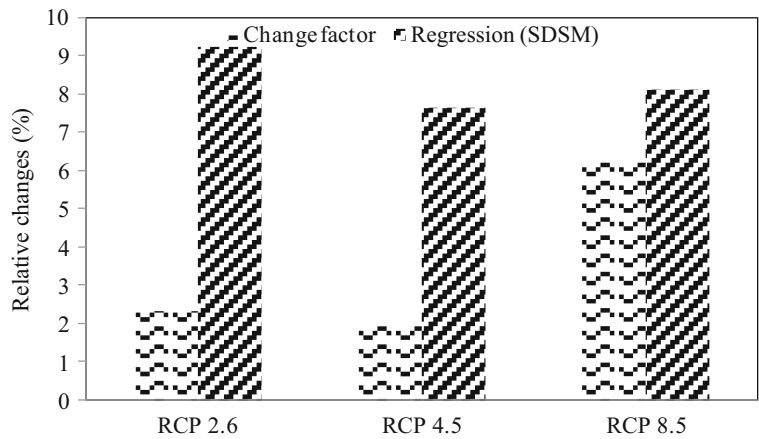
temperature predicted by SDSM is about 2.3% than that calculated with the change factor method. Thus, the difference between temperature values predicted by the change factor and SDSM methods increases over time. This means that the effect of downscaling uncertainty increases over time.

Figure 5 depicts the predicted average monthly temperature in the periods starting in 2010, 2020, 2030, 2040, and 2050. It is seen in Fig. 5 that the mean monthly temperature calculated by SDSM with all RCPs and in most months (particularly in July, August, and September (summer)) exceeds the temperature calculated with the change factor method.

Figure 6 depicts the projected temperatures associated with the RCPs and downscaling methods relative to the temperature in the baseline period 1980–2009. The largest and smallest temperature changes correspond to RCP 8.5 and SDSM (S-8.5), which is about 5.2%, and to RCP 2.6 with the change factor method (C-2.6), which is about 1.7%.

Tables 7 and 8 and the graphs of Fig. 7, which depict the predicted mean annual rainfall in periods 2010, 2020, 2030, 2040, and 2050, establish that the rainfall trend in future periods is increasing under RCP 2.6 with both downscaling methods (Fig. 7a). RCP 4.5 exhibits increasing and constant trends of predicted rainfall by

Fig. 9 Projected changes of long-term mean rainfall relative to the baseline period



the change factor and SDSM methods, respectively (Fig. 7b). The values of predicted mean rainfall by the two downscaling methods under RCP 8.5 exhibit opposite trends in future periods: they are decreasing and increasing by the SDSM and change factor methods, respectively (Fig. 7c). This is a source of uncertainty in the results introduced by conflicting rainfall predictions by the two downscaling methods under the same RCP.

Our results establish that the SDSM predicts higher temperature in almost all months and larger rainfall in most of months than the change factor method. This assertion is confirmed for predicted mean monthly rainfall by the graphs shown in Fig. 8, which establishes larger mean monthly predicted rainfall by SDSM compared with the rainfall predictions obtained with the change factor method especially in wet months when

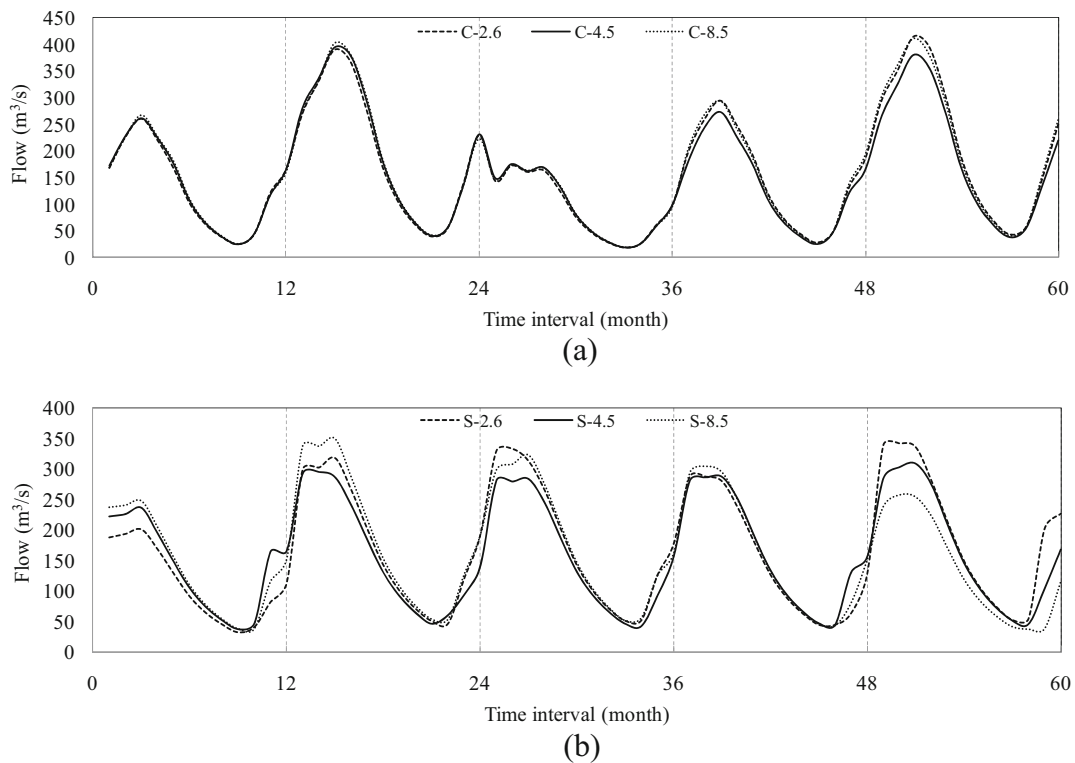


Fig. 10 Projected river flow time series by **a** change factor (scenarios C-2.6, C-4.5, C-8.5) and **b** regression (SDSM) methods (scenarios S-2.6, S-4.5, S-8.5)

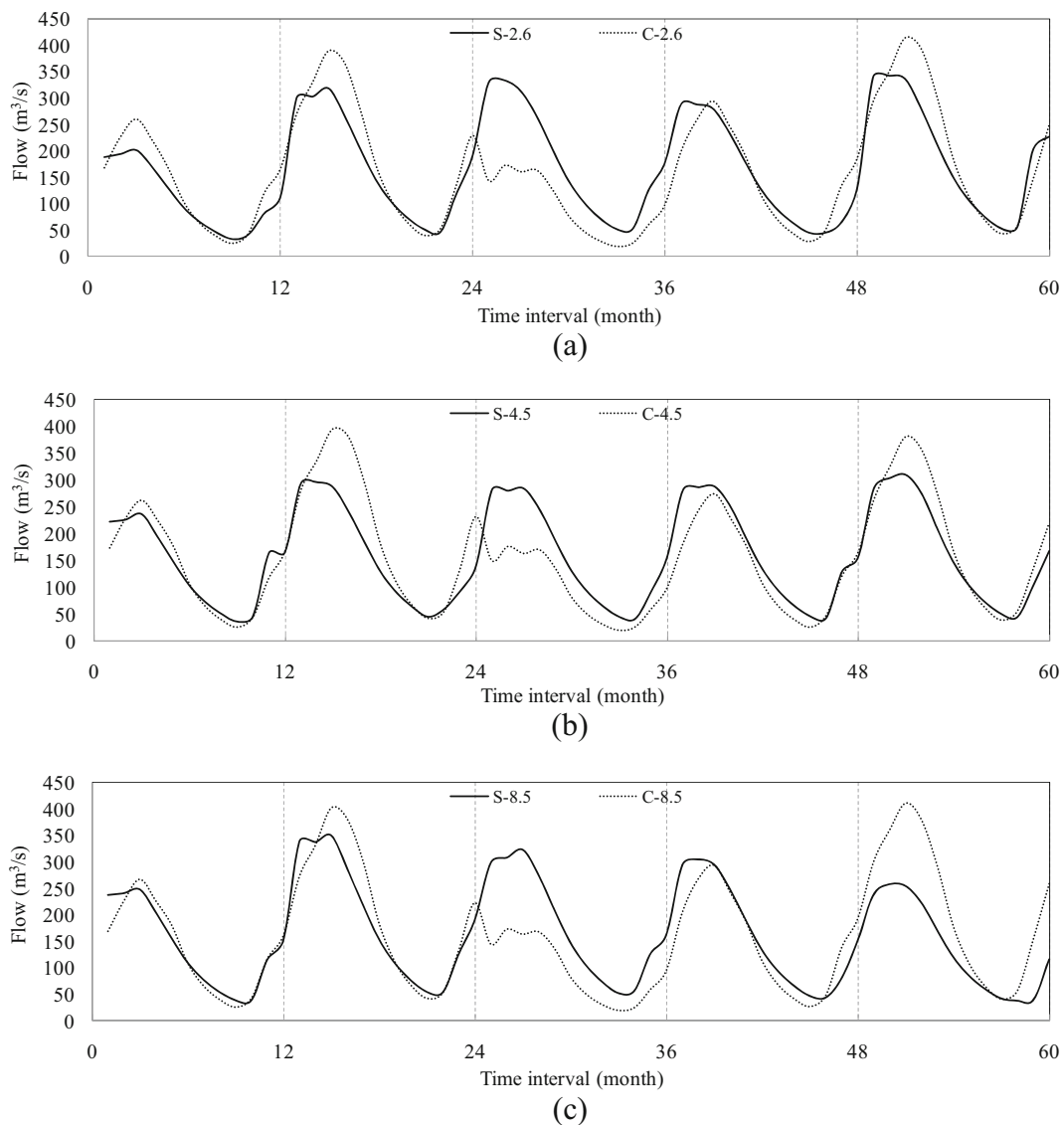


Fig. 11 Projected river flow time series under **a** C-2.6 and S-2.6, **b** C-4.5 and S-4.5, and **c** C-8.5 and S-8.5 scenarios

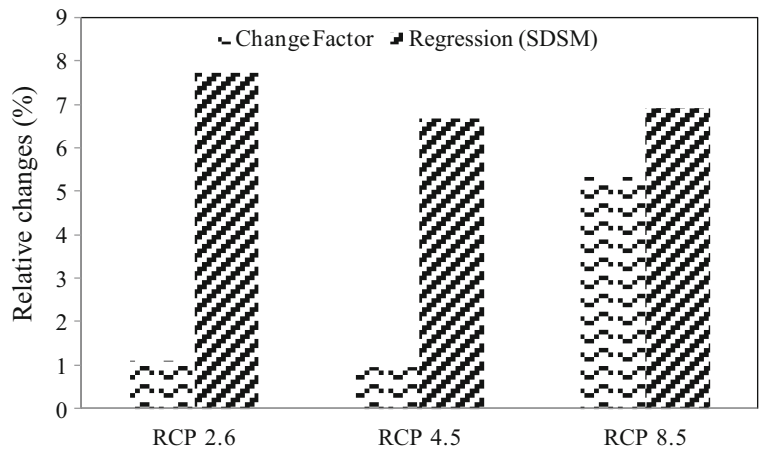
the peak values occurred. It is also seen in Fig. 8 that the rainfall predicted by both downscaling methods equals zero in the warm months. The rainfall predictions by the two downscaling methods differ from each other in wet and cold months.

Figure 9 presents graphs for the predicted rainfall in future periods (2010–2050 combined duration) and for the baseline period (1980–2009). The graphs in Fig. 9 establish that the average rainfall increases compared with the baseline years under all climatic scenarios. The maximum and minimum changes between predicted and baseline rainfall correspond to RCP 2.6 with the SDSM method

(S-2.6), which is about 9.2%, and to RCP 4.5 with the change factor method (C-4.5), which is about 1.9%.

River flow was simulated by applying IHACRES rainfall-runoff model once the temperature and rainfall projections were obtained. Simulated river flow under the RCPs with the change factor downscaling method (Fig. 10a) exhibits a clear similarity among the three RCPs, especially in periods 2010, 2020, and 2030. It reflects the relatively minor effect of the greenhouse concentration scenarios on the change factor downscaling method. The periods 2040 and 2050 exhibit slight differences between the scenarios. These differences are

Fig. 12 Changes of the long-term mean flow relative to the baseline period



accentuated in high-flow months. Thus, the uncertainty associated with the RCPs increases over time. In the latter two decades, the river flow values predicted with the C-2.6 and C-8.5 scenarios are greater than those obtained with C-4.5. This assertion holds true for the mean rainfall values predicted with these three scenarios.

The SDSM downscaling method (Fig. 10b) produced flow projections without a regular pattern of similarity or differences between them, except that the differences between projections tend to be more pronounced in wet months. This finding establishes that the SDSM method introduces high uncertainty in river flow predictions.

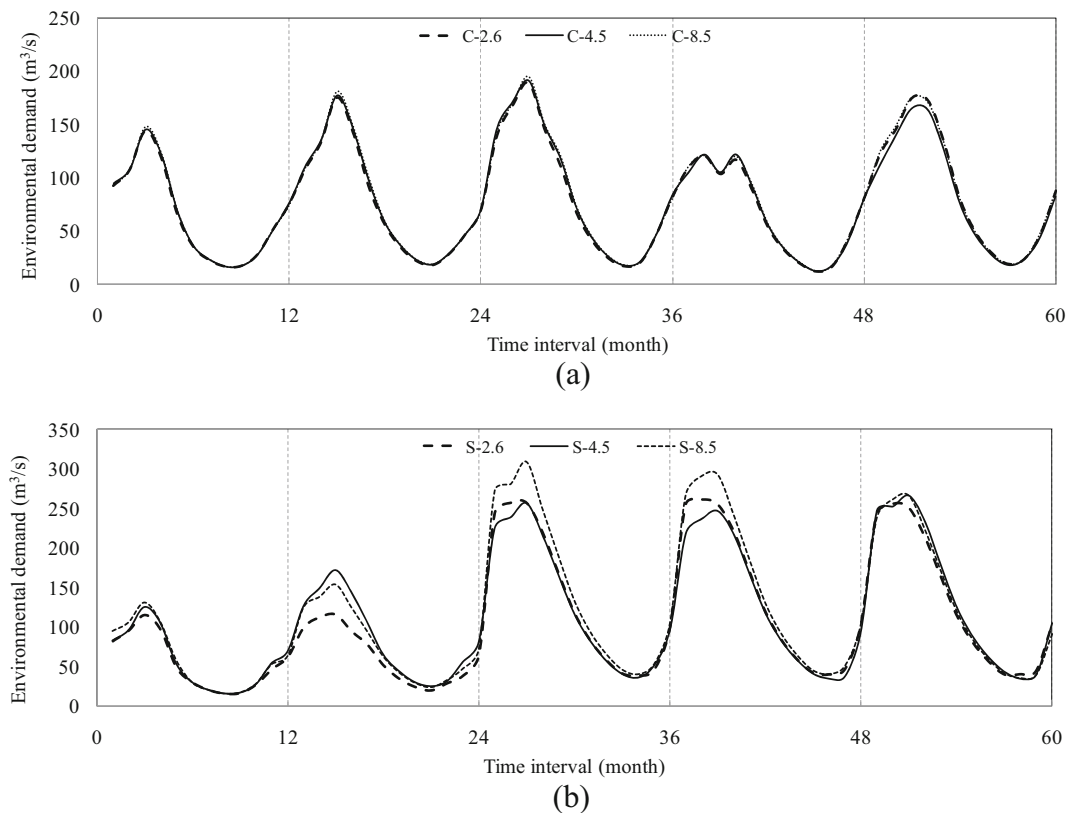


Fig. 13 Minimum environmental demand under six climatic scenarios calculated with **a** change factor and **b** regression (SDSM) method

Fig. 14 Average monthly minimum environmental demand under six climatic scenarios and baseline years

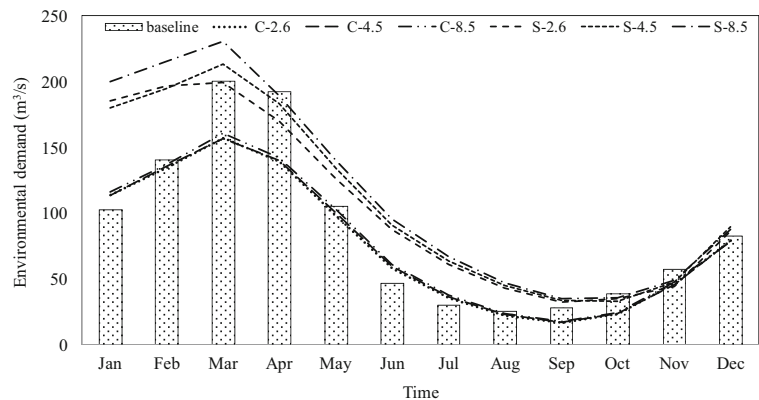


Figure 11 depicts the uncertainty associated with predictions of river flow by the two downscaling methods. The figure's graphs highlight the key role that uncertainty introduced by the downscaling method has on predicted river flow. This indicates that the uncertainties introduced by the choice of the downscaling method are more significant than that introduced by the RCP uncertainty.

Figure 12 shows the percentage change in the uncertainty of river flow prediction in relation to the baseline period, which is between 0.9 and 7.7% for the C-4.5 and S-2.6 scenarios, respectively.

The environmental demand for the Karkheh reservoir releases to the downstream Hoor-al-Azim wetland was determined with the RVA method under the six climatic scenarios of climate change conditions. The minimum environmental demand of any particular month in each of n years is equal to the 25% flow quartile for that particular month calculated over the 20 years immediately preceding year n in order to consider the hydrological regime changes. Figure 13a, b portrays the graphs of the monthly environmental demand under each climatic scenario corresponding to the change factor and SDSM methods, respectively. It is seen in Fig. 13a, b that the calculated series for minimum environmental demand under different greenhouse gas concentration scenarios exhibit similar trends. Therefore, it is concluded that the RCPs have no significant impact on the pattern of the 25% river flow quartile, and that the downscaling method is the controlling factor explaining the differences between river flow projections in the study area. The data plotted in Fig. 14 indicate that the largest and smallest monthly environmental demand would occur in March and September, respectively, in all climatic scenarios under climate change conditions. Also, it can be seen that the largest

difference between C and S scenarios occurs in January, February, and March (winter). This indicates that there is a wide range of uncertainty in the wet months. Furthermore, the monthly environmental demand under climate change conditions was compared with that of baseline period 1980–2009 in Fig. 14. Despite the fact that the largest monthly environmental demand occurs in the same month (March) in all six climatic scenarios and the baseline period, the smallest monthly environmental demand occurs in different months. The smallest monthly environmental demand occurs in August for the baseline period; however, it occurs in September for the six projected scenarios under climate change conditions.

Tables 7 and 8 list the estimated average monthly environmental demand under the six climatic scenarios entertained in this study. The monthly largest and smallest environmental demand estimates are projected by the S-8.5 and C-2.6 calculations as being 115.99 and 76.90 m^3/s , respectively. The data listed in Tables 7 and 8 shows that the average monthly environmental demand corresponding to the C-2.6, C-4.5, and C-8.5 predictions range between 10 and 12% below the baseline environmental demand of the river to the wetland, and for the other scenarios downscaled by SDSM the projections range between 20 and 32% above the baseline environmental demand. Clearly, the C-scenarios under climate change conditions suggest that environmental threats are likely in the next decades within the Karkheh basin/Hoor-al-Azim wetland ecosystem.

Conclusions

This study addressed climate change effects on climatic parameters and the hydrological regime in 2010–2059

within the Karkheh basin by generation of six climatic scenarios. The results indicate that the average temperature, rainfall, and river flow would increase compared to the baseline period (1980–2009). The climate change effects on the environmental water demand and its temporal variation were also assessed. It can be concluded that climate change might have potential effects on the environmental water demand regime that should be considered in the environmental assessment of the Karkheh basin to mitigate negative effects on its riverine ecosystems. The effects of two main uncertainty sources in climate change studies were determined. The uncertainties introduced by downscaling methods are more significant than the RCPs in the projection of climate change effects on the hydrologic regime.

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