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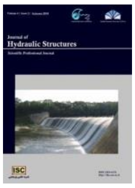

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Using the IHACRES model to investigate the impacts of changing climate on streamflow in a semi-arid basin in north-central Iran

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Abstract

Understanding the variations of streamflow of rivers is an important prerequisite for designing hydraulic structures as well as managing surface water resources in basins. An overview of the impact of climate change on the streamflow in the Hablehroud River, the main river of a semi-arid basin in north-central Iran, is provided. Using the LARS-WG statistical downscaling model, the outputs of HadCM3 general circulation model under the IPCC SRES A1B, A2, and B1 emission scenarios were downscaled to a finer spatial scale and the daily precipitation and temperature time series over the period of 2011-2030 for the study area were obtained. Results showed that the study area would experience a decline in precipitation (8.2% on average). The IHACRES rainfall-runoff model was then calibrated in the study area. Based on the fit statistics in calibration and validation phases, the overall performance of the developed model was judged to be satisfactory. The calibrated hydrological model was driven by the downscaled rainfall and air temperature data to project the effect of changing climate on the outflow of the basin under study. Results showed that, with some exceptions in June, July and August, all emission scenarios predict a decrease in the long-term monthly average outflow of the Hablehroud Basin. The outflow reduction in winter, spring, summer, and autumn had an average value of 25.7, 14.3, 1.9, and 48.8%, respectively. It was also observed that if climate change would occur in the basin, monthly flows associated to each return period would decrease.

Keywords: SRES scenarios, downscaling, conceptual rainfall-runoff model

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1. Introduction

Trends in meteorological variables associated with climate change may affect the quantity

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and quality of existing water supplies. In Iran, a mostly semi-arid country with limited water resources, food security mostly depends upon the availability and reliability of surface and ground water resources. In countries like Iran, quantifying the impact of the phenomenon of climate change on valuable and scarce water resources is an important issue. While an increasing trend in global river discharge due to global warming was reported by Labat et al. [1], the fifth assessment report of IPCC (the Intergovernmental Panel on Climate Change) stated that there is low evidence for global river streamflow increasing during the 20th century.

Simulating the climate change impacts on meteorological variables such as rainfall, solar radiation, and air temperature is a prerequisite to make predictions about the possible trends in streamflow due to climate change. GCMs (General Circulation Models), which also recognized as Global Climate Models, mathematically represent physical processes in the atmosphere, oceans, land surface, and the frozen water part of the Earth system. Generally, GCMs have a spatial resolution of 250 to 600 km, which is too coarse to project the impact of climate change at small spatial scales. The output of a GCM can be downscaled using either a dynamic model (i.e. a high-resolution regional climate model) or through statistical downscaling [2]. It is worth noting that dynamic models for downscaling the output of GCMs are based on solving the sophisticated differential equations governing the circulation of atmosphere, meaning that dynamic models are not commonly used and need lots of time to run. A variety of methods, from simple scaling procedures to more sophisticated regression models and weather generators, have been successfully applied to statistically downscale GCMs outputs [3-5].

The impact of climate change on river streamflow can then be simulated utilizing an appropriate hydrological model, and statistically downscaled projections of meteorological variables to drive the model. Since the early sixties, various physically-based and conceptual models such as SLURP [7], SHE [8], SWAT [9], IHACRES [10], and VIC [11] have been developed to simulate the hydrology of watersheds. Data-driven models such as time series models, regression models, and artificial intelligence based models basically do not consider the physics of the phenomenon under study and are alternatives to physically-based or conceptual models. There are numerous studies in the literature [12-26] in which different types of hydrological models have been successfully employed to model the effects of climate change on the water balance of watersheds. Among different models, IHACRES is a simple lumped rainfall-runoff model which employs just temperature and precipitation as input data to simulate the outflow of watersheds. Comparing to other models, this simple model produces reasonable results. Hosseini et al. [27] used the IHACRES model to estimate the effect of changing climate on the outflow of the Sufichay Basin, northwestern Iran, and concluded that there is a considerable difference between GCMs under emission scenarios A2 for the period of 2046-65. Lotfirad et al. [28] successfully used the IHACRES model to simulate daily streamflow in the Navrood Basin, northern Iran. Their results showed that IHACRES is a reliable model to simulate the runoff with reasonable accuracy.

The objective of the present study is to examine the impacts of projected climate change on the outflow of the semi-arid Hablehroud Basin, Tehran Province, north-central Iran, using a lumped conceptual rainfall-runoff model and a statistical weather generating tool. The climate projection used in this study was based on the HadCM3 general circulation model under the SRES (Special Reports on Emissions Scenarios) A1B, A2, and B1 emission scenarios.

2. Materials and methods

2.1. Basin under study and data

The Hablehroud Basin is located in the eastern part of Tehran Province, north-central Iran (Fig. 1). The main river of the basin, the Hablehroud River, rises in the Alborz Mountain Range and flows generally south-westward, discharging into Garmsar County and the Kavir Desert (Fig. 2).

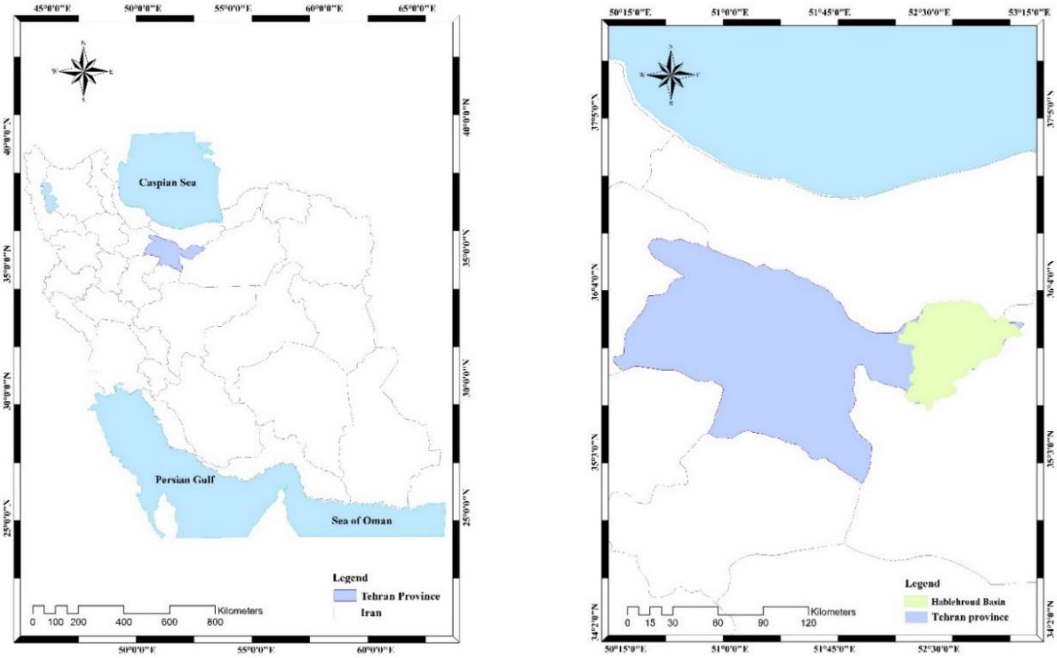

Figure 1. Map of Iran and the location of the Hablehroud Basin.

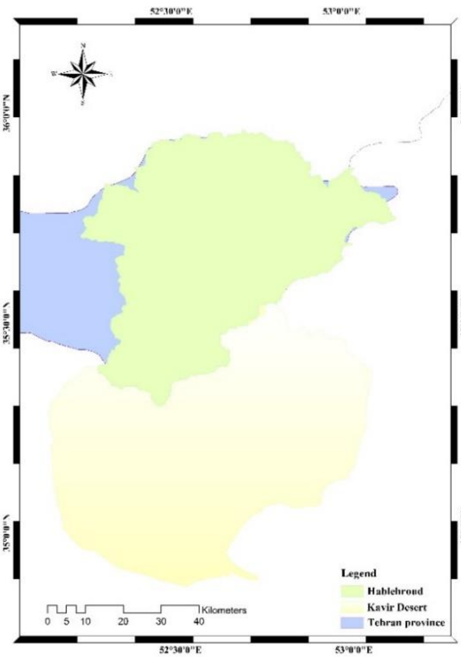

Figure 2. The river system of the Hablehroud.

The Hablehroud River has a length of 119.5 km, a drainage basin of 3261.2 km2, and an average daily discharge of 7.73 m3/s for the period of 1998-2012. The regime of its principal tributaries, the Firuzkuh and the Namroud, is combined rain-fed/snow-fed. The Hablehroud River is the main sources of domestic (4.94×106 m3/year), industrial (3.64×106 m3/year) and agricultural (248.3×106 m3/year) water supply in the area. Based on the climate classification system of Köppen-Geiger [29], the climate of the Hablehroud Basin is mid-latitude arid (BWk) in the south, and mid-latitude semi-arid (BSk) in the north (B: arid; W: desert; S: steppe; k: cold). Meteorological data are recorded at sixteen weather stations throughout the basin (Fig. 3).

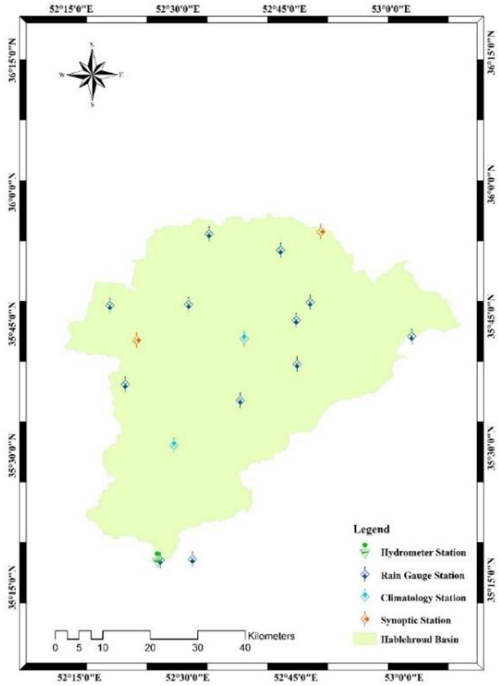

Figure 3. Location of meteorological stations and hydrometric gauging station.

The areal averages of the observed weather data were obtained using the Thiessen polygon method and the time series of daily precipitation as well as daily maximum and daily minimum air temperature over the period of 1995-2010 were prepared for the study area. Discharge of the Hablehroud River is recorded at a gauging station located at the basin outlet. Data used in the present study extracted from the databases of IMO (Iran Meteorological Organization), and Tehran Regional Water Authority. Characteristics of the stations used in the present study is given in Table 1. Flow characteristics of the hydrometric station located at the outlet of the basin is presented in Table 2.

Table 1. The stations that are located in the Hablehroud Basin.

Station	***Latitude (degree)***	***Longitude (degree)***	***Altitude (meters)***	***Type***
Ali Abad	35.78	52.52	2100	Rain gauge
Amiriyeh	35.78	52.80	1995	Rain gauge
Anzeha	35.60	52.63	1665	Rain gauge
Bonkooh	35.30	52.43	995	Rain gauge, Hydrometric

Davar Abad	35.22	52.49	852	Rain gauge
Firouzkooh	35.75	52.77	1910	Rain gauge
Gandab	35.72	53.03	2366	Rain gauge
JelizJand	35.88	52.73	2500	Rain gauge
Lazoor	35.92	52.57	3100	Rain gauge
Najafdar	35.78	52.33	2400	Rain gauge
Namroud	35.72	52.65	1950	Rain gauge
Pirdeh	35.67	52.77	2300	Rain gauge
Saeed Abad	35.63	52.37	2100	Rain gauge
Namroud	35.72	52.65	1810	Climatology
Simin Dasht	35.53	52.50	1440	Climatology
Firouzkooh	35.92	52.83	1975	Synoptic
Firouzkooh (Poll.)	35.72	52.40	2986	Synoptic

Table 2. Flow characteristics in Bonkooh hydrometric station.

Upstream Area (Km^2)	*Long term annual flow (cms)*	*Maximum observed annual flow (cms)*	*Minimum observed annual flow (cms)*
3261.2	7.73	13.4	3.00

2.2. IHACRES

IHACRES, which stands for "Identification of unit Hydrographs And Component flows from Rainfall, Evapotranspiration and Streamflow", was first developed by Jakeman et al. [30]. IHACRES tries to avoid issues such as data acquisition and parameter estimation, which are associated with physically-based rainfall-runoff models [31]. A non-linear module for converting observed rainfall into excess rainfall, and a linear module for converting the estimated excess rainfall into river discharge are the main components of the IHACRES model. The first module is a lumped conceptual model while the second module is basically a data-driven technique. Various versions of the non-linear module are available [32–35]. In IHACRES, excess rainfall, u_k, could be estimated as follows [36]:

$$u_k = \begin{cases} s_k{}^p r_k, & r_k > l \\ 0, & r_k \le l \end{cases} \tag{1}$$

where r_k is the observed rainfall at the time k; p is the exponential loss parameter; l is a streamflow threshold value for rain; and s_k is a wetness index which is defined as follows:

$$s_k = \frac{r_k}{c} + \left[1 - \frac{1}{\tau_w \exp\left[(20 - t_k)f\right]}\right] s_{k-1} \tag{2}$$

where c is a response parameter which is selected in a way to ensure that the mass-balance of the basin is conserved; τ_w is a time parameter for the decline in s_k; t_k is the observed temperature at the time k(°C); and f is a parameter for the modulation of temperature.

The linear module of IHACRES treats a basin as a combination of two parallel components (or stores), one for quick flow, $x_k^{(q)}$, and one for slow flow, $x_k^{(s)}$ [37]. So, the streamflow at time k can be written as follows:

$$q_k = x_k{}^{(q)} + x_k{}^{(s)} \tag{3}$$

$$x_k^{(q)} = \exp(\frac{-\Delta}{\tau_q}) x_{k-1}^{(q)} + v_q \left[1 - \exp(\frac{-\Delta}{\tau_q}) \right] u_k \quad (4)$$

$$x_k^{(s)} = \exp(\frac{-\Delta}{\tau_s}) x_{k-1}^{(s)} + v_s \left[1 - \exp(\frac{-\Delta}{\tau_s}) \right] u_k \quad (5)$$

where Δ is the time step; τ_q and τ_s are, respectively, the decay time constants for the quick and slow stores; and v_q and v_s are, respectively, the relative volumetric throughputs for the quick and slow components of flow ($v_s = 1 - v_q$). The linear module has only three parameters (τ_q, τ_s and v_s), making a total of eight parameters for the model (the five parameters of the non-linear module are p, l, τ_w, c and f). A flowchart showing how the model simulates the outflow of a basin is presented in Fig. 4.

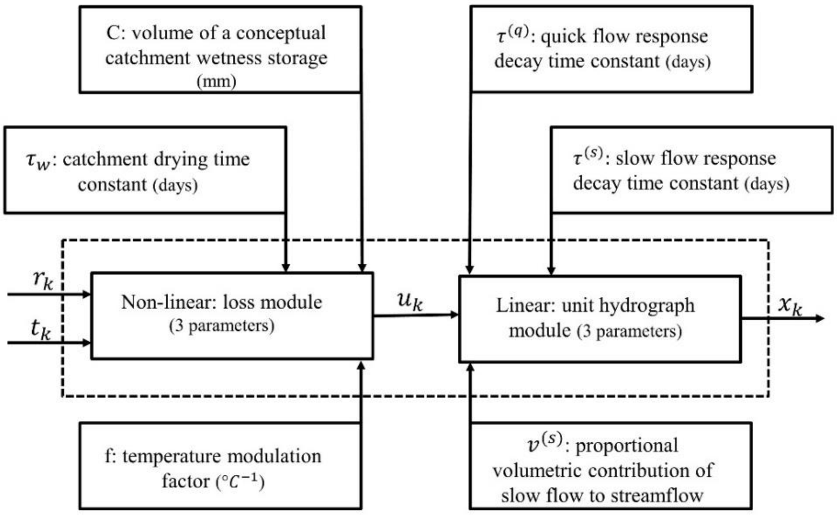

Figure 4. The flowchart of the IHACRES model.

In the present study, IHACRES was calibrated based on daily mean temperature, rainfall, and discharge data. Different periods for calibration and validation were considered and examined. Finally, the model was calibrated over a period from 1/1/2002 to 12/31/2004, and validated over a period from 1/1/2006 to 12/31/2010.

2.3. LARS-WG

LARS-WG [38] is a stochastic simulator for generating time series of weather data (rainfall, air temperature (maximum and minimum), and solar radiation) at single weather stations. LARS-WG can be used for simulating observed weather data, as well as for generating time series under future climate conditions. LARS-WG utilizes exponential probability distribution functions to model the temporal distances between wet and dry days, as well as rainfall depth on wet days. In LARS-WG, air temperature (both minimum and maximum) and radiation are considered as stochastic variables conditioned on the time series of wet days and dry days.

LARS-WG 5.5, a release of LARS which includes 15 general circulation models, was utilized in the present study. Among the existing GCMs, HadCM3 (the Hadley Centre Coupled Model, version 3), which has a surface grid with a spatial resolution of 2.5(latitude)×3.750(longitude), was used. For HadCM3, predictions are available for three IPCC emission scenarios (A1B, A2 and B1), as well as three periods (2011-2030; 2046-2065; 2080-2099).

2.4. Model evaluation

The accuracy of forecasts was assessed using RMSE (Root Mean Square Error), RSR (RMSE-Standard deviation Ratio), the Nash-Sutcliffe model efficiency coefficient (NS), and Percent BIAS (PBIAS). These statistics are defined as follows:

$$\mathrm{RMSE}=\sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_{i(obs)}-y_{i(for)})^2} \tag{6}$$

$$\mathrm{RSR}=\frac{\sqrt{\sum_{i=1}^{m}(y_{i(obs)}-y_{i(for)})^2}}{\sqrt{\sum_{i=1}^{m}(y_{i(obs)}-\bar{y}_{for})^2}} \tag{7}$$

$$\mathrm{NS}=1-\frac{\sum_{i=1}^{m}(y_{i(obs)}-y_{i(for)})^2}{\sum_{i=1}^{m}(y_{i(obs)}-\bar{y}_{for})^2} \tag{8}$$

$$\mathrm{PBIAS}=\frac{\sum_{i=1}^{m}(y_{i(obs)}-y_{i(for)})}{\sum_{i=1}^{m}y_{i(obs)}}\times 100 \tag{9}$$

where the subscripts "obs" and "for" stand, respectively, for observed and forecasted; and m is the number of all observed data.

3. Results

The fitted parameters for the IHACRES model are shown in Table 3. The loss parameter (p) and the rain threshold value (l), were considered, respectively, one and zero. These values are recommended in the literature, so in the present study, the values of one and zero was considered for these two parameters. The model error measures (RMSE, RSR; NS, and PBIAS) in calibration and validation phases are shown in Table 4.

Table 3. Fitted parameter values for the IHACRES model.

Parameter	*Value*
Decay time constant for the quick store ($\boldsymbol{\tau_q}$, day)	49.34
Decay time constant for the slow store ($\boldsymbol{\tau_s}$, day)	717.06
Relative volumetric throughput for the quick store ($\boldsymbol{v_q}$, dimensionless)	0.399
Relative volumetric throughput for the slow store ($\boldsymbol{v_q = 1 - v_s}$, dimensionless)	0.601
Time parameter for the decline ($\boldsymbol{\tau_w}$, day)	2
The response parameter ($\boldsymbol{c}$, 1/mm)	0.0023
Temperature modulation parameter ($\boldsymbol{f}$, 1/^{0}C)	3.14

Table 4. IHACRES fit statistics.

Phase	*RMSE (m^3/s)*	*RSR*	*NS*	*PBIAS (%)*
Calibration period	1.67	0.61	0.63	0.49
Validation period	1.80	0.66	0.55	3.10

The results presented in Table 4 show satisfactory results; the RMSE values are reasonably small, the RSR values are less than 0.70 (or 70%) and the NS values are greater than 0.50. In general, river flow simulation can be judged as satisfactory, if the model NS is greater than 0.5 and RSR ≤ 0.7 [39]. Based on the calculated RMSE, RSR, and NS values in both phases of calibration and validation, the overall performance of the calibrated model is judged to be satisfactory. The PBIAS values are also small (0.49 and 3.1%) which shows that in general, IHACRES neither clearly overestimates nor underestimates the daily discharge in the basin under study. Fig. 5 illustrates the daily observed rainfall and the excess rainfall estimated by the non-linear module of the calibrated IHACRES model. Fig. 6 shows the comparison of the daily observed and forecasted discharges over the periods of calibration and validation. As seen, while the overall fit for the periods of calibration and validation is satisfactory, pick flows that occur in response to high rainfalls, are underestimated.

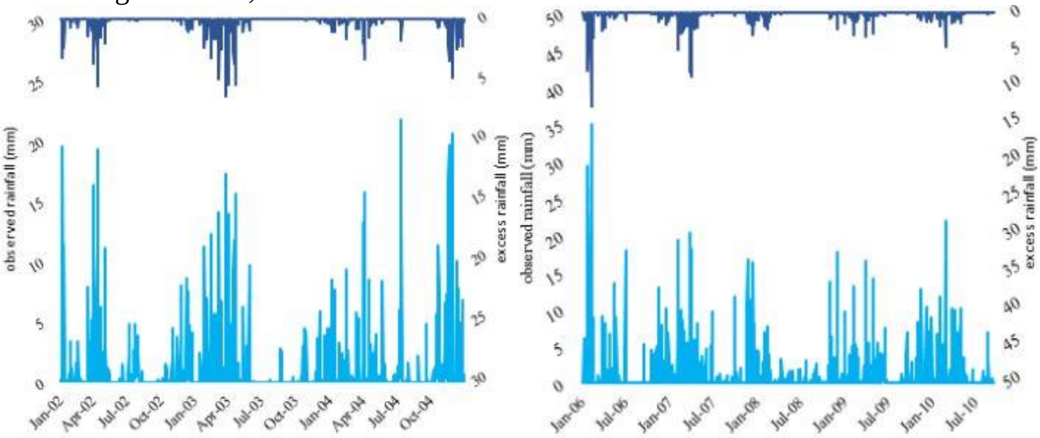

Figure 5. Observed rainfall and the excess rainfall estimated by the IHACRES model.

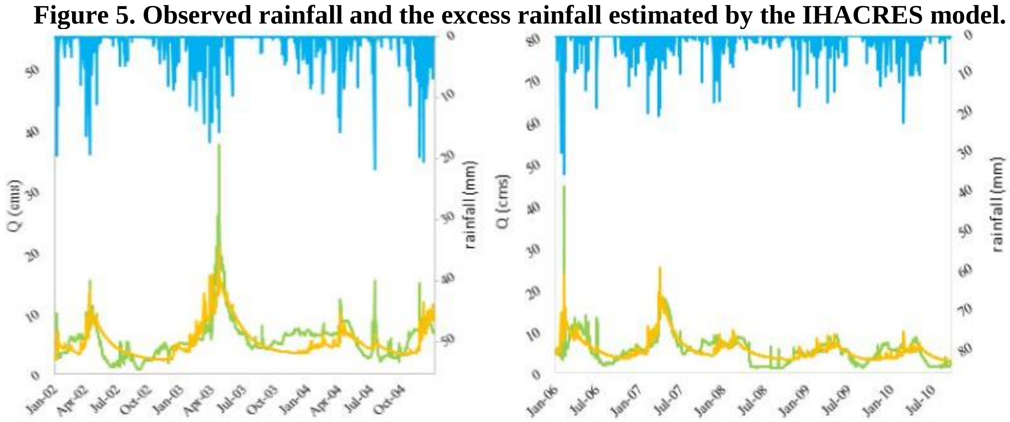

Figure 6. Observed daily flows at the basin outlet (the green line), and the IHACRES output over the periods of calibration (left) and validation (right).

Using the LARS-WG model and the HadCM3 data, the downscaled daily precipitation and temperature (maximum and minimum) data over the period of 2011-2030 under IPCC emission scenarios (A1B, A2 and B1) were simulated for the study area. To handle the uncertainty in the simulated meteorological variables, the procedure described by Gohari et al. [40] and Zamani et al. [41] was followed in the present study. Two hundred years of daily data were generated using LARS-WG. The generated time series was then broken into 10 twenty-year blocks and the average daily values were calculated. In Figures 7 to 9, the simulated long-term monthly averaged precipitation and temperature over the period of 2011-2030 are compared against the trends that are already observed over the period of 1995-2010.

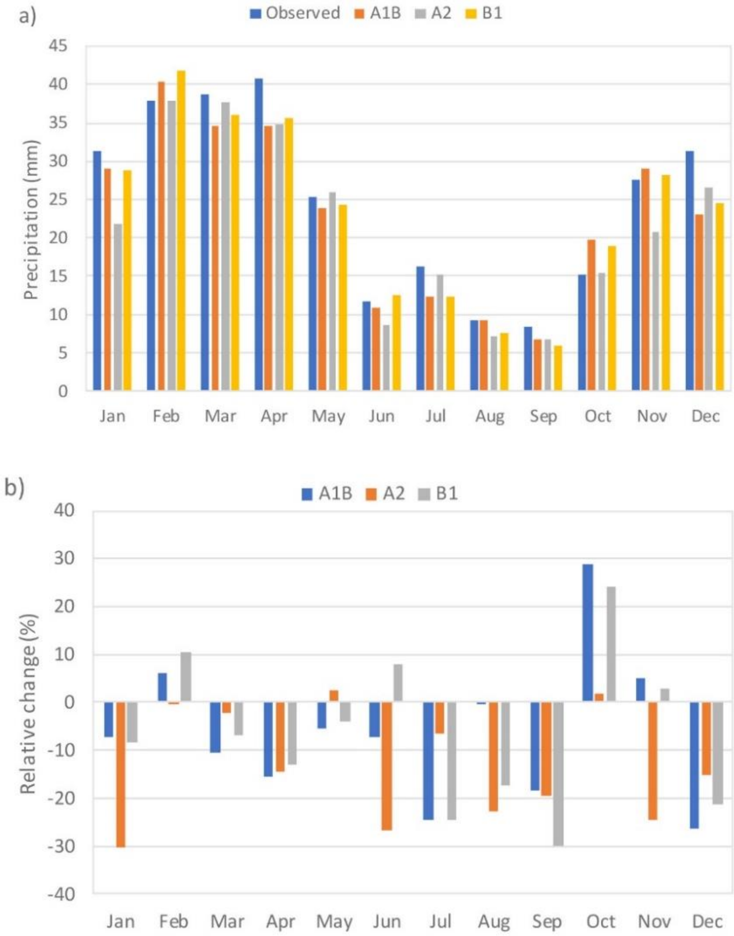

Figure 7. Impact of climate change on precipitation in the Hablehroud Basin.

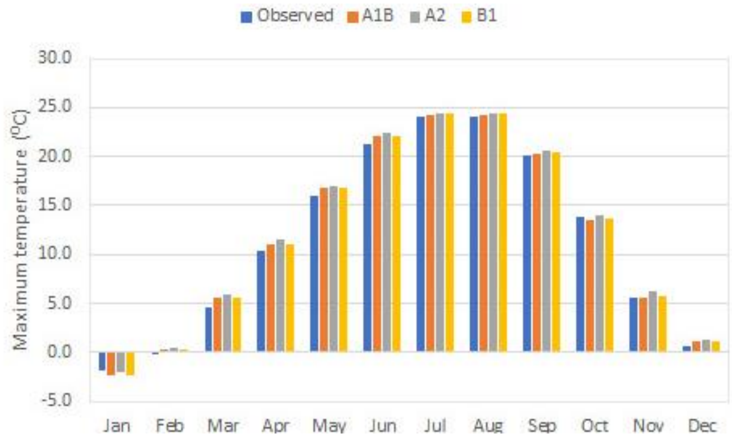

Figure 8. Impact of climate change on maximum temperature in the Hablehroud Basin.

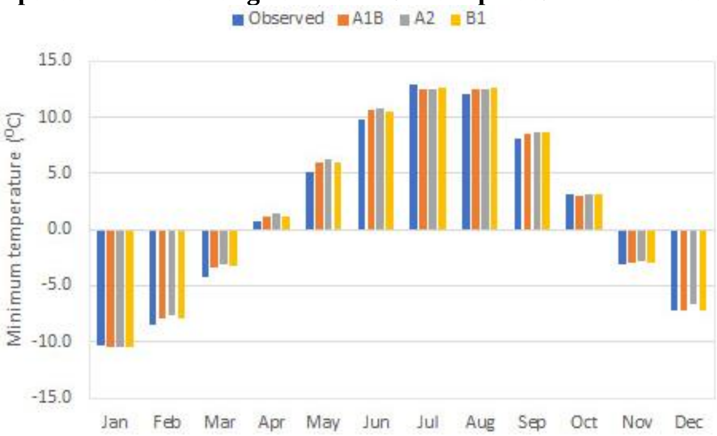

Figure 9. Impact of climate change on minimum temperature in the Hablehroud Basin.

It was seen that, with some exceptions, the study area would experience a decline in precipitation (Fig 7b). Precipitation varies between -9.5 mm to 4.4 mm (-30.5% in January for A2 scenario, to +28.9% in October for A1B scenario) with an average of -2.0 mm (-8.2%). In the case of maximum and minimum temperature, while all months experience some changes, major changes occur in February, March, and December for maximum temperature, and form February to June for minimum temperature. Maximum temperature varies between -0.4 to 1.3 0C in different scenarios with the highest occurring in March for A2 scenario. Minimum temperature varies between -0.4 to 1.2 0C in different scenarios with the highest also occurring in March for A2 scenario.

The calibrated IHACRES model was driven over the period of 2011-2030 by statistically downscaled rainfall and temperature data from HadCM3. The results are presented in Fig. 10. This figure suggests that, with some exceptions in June, July and August, all scenarios predict a decrease in the long-term monthly average outflow of the Hablehroud Basin. The decreases in streamflow of the Hablehroud River could be quite large, even as large as 62% (in November for A2 scenario). The outflow reduction in winter, spring, summer, and autumn has an average value of 25.7, 14.3, 1.9, and 48.8%, respectively. Major changes occur from October to December. The results of our study are similar to Zamani et al [42], showing a decreasing flow trend in most months of the year in future periods.

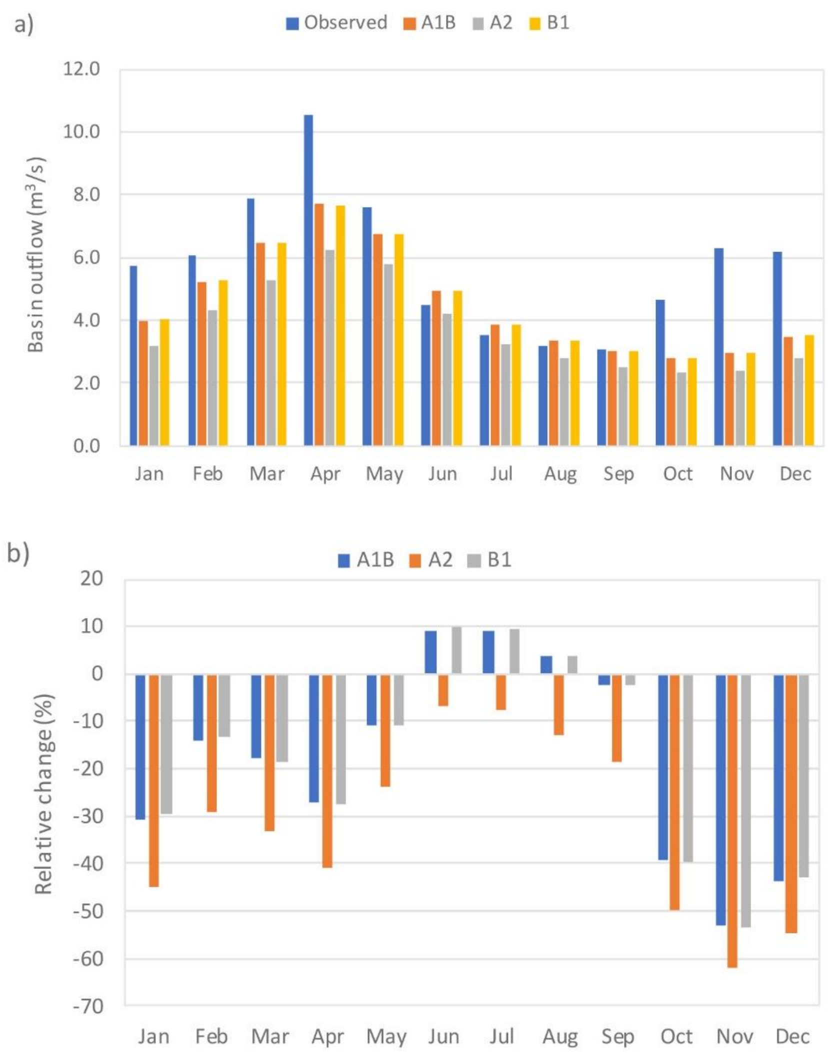

Figure 10. Impact of climate change on the streamflow in the Hablehroud River.

Tables 5 and 6, respectively, represent the probabilities of exceeding associated to monthly outflow of the Hablehroud Basin, in current situation and in the case of climate change (for A2 scenario). It is seen that for each probability, smaller values of outflow are calculated in the case of climate change. In the other words, for each return period, the basin would produce lower annual streamflow, if climate change would occur.

Table 5. Probabilities associated to the basin outflow in current situation.

The probability of exceeding (current situation)	***Monthly outflow (cms)***											
	Oct.	***Nov.***	***Dec.***	***Jan.***	***Feb.***	***March***	***April***	***May***	***June***	***July***	***Aug.***	***Sep.***
50	5.7	7.73	7.91	7.38	7.08	7.94	11.1	10.63	6.59	4.5	3.66	3.75

60	4.8	7.04	7.32	6.98	6.6	7.35	9.92	8.91	5.45	3.68	3.16	3.16
70	4.1	6.4	6.67	6.42	6.12	6.69	8.93	7.46	4.34	3.02	2.77	2.6
80	3.42	5.51	5.8	5.5	5.5	6.28	8.19	6	3.35	2.5	2.12	2.03
90	2.8	4.24	5.03	4.73	4.6	5.55	6.8	4.08	1.8	1.6	1.5	1.37

Table 6. Probabilities associated to the basin outflow in the case of climate change.

The probability of exceeding (current situation)	***Monthly outflow (cms)***											
	Oct.	***Nov.***	***Dec.***	***Jan.***	***Feb.***	***March***	***April***	***May***	***June***	***July***	***Aug.***	***Sep.***
50	1.85	2.93	2.78	2.71	2.17	3.17	4.31	3.7	2.68	1.46	1.2	1.34
60	1.87	2.38	3.14	2.91	2.21	2.78	3.81	3.07	1.83	1.27	1.07	1.01
70	1.71	2.44	2.22	2.83	2.32	2.91	2.87	2.51	1.83	1.33	1.16	0.94
80	1.45	1.87	1.91	1.79	2.21	2.48	2.83	2.09	1.24	0.94	0.92	0.9
90	1.02	1.45	1.99	1.99	1.82	1.75	2.18	1.25	0.62	0.66	0.51	0.53

4. Conclusion

Almost the total agricultural water in Garmsar County, north-central Iran, is supplied from the Hablehroud River. The Hablehroud Basin is currently under high pressure due to the growing demand for water. An understanding of the variability of the river flow is required, now and in the future, for the appropriate management of surface water resources. In the present study, the effect of changing climate on the river flow was investigated, using the LARS-WG model, the output of a general circulation model (HadCM3), and the IHACRES hydrological model. The study showed that the basin under study would receive less rainfall (8.2% on average) and the discharge of the main river would decrease (22.7% on average). Management options should be considered in order to alleviate the effects of changing climate on the main source of water supply in the study area.

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