DESERT 2022, 27(1): 13-33
DOI: 10.22059/JDESERT.2022.88507

RESEARCH PAPER

Assessment of Climate Change Impacts on Extreme Precipitation Events in Lake Urmia Basin, Iran

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Received: 18 December 2021, Revised: 04 March 2022, Accepted: 18 May 2022

Abstract
Climate change is known as one of the fundamental challenges of mankind, which has affected all aspects of human life. The present study aimed to evaluate the changes in precipitation and predict extreme precipitation in Lake Urmia basin. For this purpose, we evaluated the indices associated with changes in precipitation of eight synoptic stations of Lake Urmia basin for three time periods, namely near (2021-2040), middle (2041-2060) and far future (2061-2080), under two scenarios (RCP4.5 and RCP8.5). Using the CanESM2 model, we compared these periods to the observational period (1986-2005). To this end, after examining the capability of the SDSM model in simulating the reference period climate (1986-2005), future daily precipitation was downscaled. Subsequently, using the RClimDex, extreme precipitation indices were calculated for future periods. The results of the spatial distribution of precipitation variations showed that the average precipitation increased in the following decades, based on both scenarios. Investigation of the changes in extreme indices also revealed that percentile indices (R95p and R99p), Rx1day, SDII, and PRCPTOT rose based on both scenarios and in most future periods; meanwhile, the Rx5day, CWD, and CDD were reduced compared to the baseline period. Among the threshold indices, R10 increased based on RCP4.5 and decreased based on RCP8.5 whereas R20 and R25 did not change significantly compared to the reference period. However, in the far future, all the indices, except for CWD, had a decreasing trend. Although there is a great deal of uncertainty concerning precipitation and extreme precipitation forecasting, the results of such research can be conducive to the future policy making of a country, such as risk assessment.
Keywords: Extreme precipitation indices, Forecasting, Trend analysis, SDSM model, Lake Urmia basin

Introduction

Today, human beings face major environmental problems and threats; one of the major and vital threats is climate change (Wang et al., 2015; Romm, 2018) and the leading cause of climate change is believed to be the accumulation of greenhouse gases in the atmosphere (IPCC, 2014). The most important characteristic of global climate change is the significant increase in the temperature and the uneven distribution of precipitation, which are limiting factors for sustainable development (Zhao et al., 2015; Dong et al., 2018). Precipitation is one of the key components of the climate system and indicates a strong relationship between the atmosphere, the hydrosphere, and the biosphere (Chen & Frauenfeld, 2014). Precipitation changes, as a result of future climate change, will severely affect environmental processes and the use of environmental resources, especially water resources (Jiang et al., 2016). In addition to the changes in the mean values, extreme values have also changed; the rate of change in the extreme values is more severe and obvious (Zhou and Ren, 2011). The Intergovernmental Panel on Climate Change (IPCC), in its third report in 2001, mentioned the probability of changes in extreme precipitation, especially at mid and high latitudes due to global warming (IPCC, 2001).

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The IPCC in its fourth report in 2007, reported that the average precipitation had increased in the tropics while in the middle latitudes, precipitation had decreased slightly compared to the annual average. Nonetheless, precipitation has been reported to increase in general in all parts of the world compared to its average level (IPCC, 2007; Donat et al., 2013; Westra et al., 2013). This panel in its fifth report in 2013 predicted that extreme precipitation events in the mid-latitudes and humid tropical regions will increase, both in terms of intensity and frequency until the end of the 21st century (IPCC, 2013).

Global warming has significant effects on extreme events, including precipitation and their Spatio-temporal changes. Therefore, it is essential to study the rate of precipitation changes in order to assess the vulnerability of different regions and predict future changes under climate change scenarios. In this regard, the set of extreme indices introduced by the European Climate Support Network (including 11 precipitation extreme indices) can be used for analyzing and surveying precipitation extremes. These indices were identified and introduced in 1998 by the Commission for Climatology (CCL) and the World Climate Research Program (WCRP) associated with the Climate Variability and Predictability (CLIVAR) project. It comprises an expert team on climate change detection, monitoring, and indices (ETCCDMI) to investigate and determine extreme indices (Frich et al., 2002; Klein Tank et al., 2009; Zhang et al., 2011). Since the early 21st century, the study of regional and global extreme values has been the focus of researchers, particularly precipitation in different parts of the world, such as Europe (Casanueva et al., 2014), the Middle East (Zhang et al. 2005), China (Song et al., 2015; Sun et al., 2016; Wang et al., 2017), Korea (Jung et al., 2011), Turkey (Abbasnia et al., 2019), Pakistan (Hussain & Lee, 2013), Philippines (Cinco et al., 2014), India (Pingale et al., 2014), Siberia (Degefie et al., 2014), the USA (Thibeault & Seth, 2014; Schoof & Robeson, 2016), Australia (Perkins et al., 2014; Jakob & Walland, 2016), Italy (Boccolari & Malmusi, 2013), and in Iran (Rahim Zadeh et al., 2009; Molanejad et al., 2014; Soltani and et al., 2015; Najafi & Moazami, 2016; Azizzadeh & Javan, 2018). Through analyzing the effects of climate change, it has been found that different regions experience different trends.

To investigate the effects of climate change on different sources in future periods, general circulation simulation models have been developed, which are capable of modeling climate-associated parameters over a long time using approved IPCC scenarios (Kilsby et al., 2007). These models are one of the most common and appropriate methods for studying the mechanism of past and future climate changes (Zhao et al., 2013). The major problem with these models is their low spatial resolution which cannot detect the effects of certain local conditions, such as topography and vegetation, on atmospheric variables like precipitation and temperature (Fung et al., 2011). The temporal and spatial resolution of the general atmospheric circulation models is low necessitates the use of tools and models for downscaling to transform these model outputs into local variables at the scale of observational stations (Graham et al., 2007; Salon et al., 2008). Downscaling methods are divided into two dynamic and statistical approaches for the analysis of regional hydrological trends. Statistical models are often utilized for downscaling climatic data (Fowler et al., 2007). One of the reasons behind using these models is their quick and easy performance compared to other models (Dibike et al., 2005). Some examples of different types of statistical downscaling models include SDSM, LARS-WG, CLIMGEN, SimCLIM, and MET & ROLL (Wilby et al., 2002).

The importance of climate change has led to the study of the effects of this phenomenon across the globe. Hashmi et al. (2011) compared LARS-WG and SDSM models for simulation and downscaling thunderstorms in the south of New Zealand watershed. Their results showed that both models are capable of simulating and predicting climate-associated parameters. Chen et al. (2012) employed both SDSM and SVM models for downscaling the precipitation in China's Hanjiang River basin. They indicated better performance of the SDSM model compared to that of SVM. Alexander and Arblaster (2017) investigated extreme precipitation based on radiation forcing scenarios and CMIP5 models. Based on their results, under the RCP4.5 and RCP8.5 scenarios, precipitation will increase slightly in the middle future. Ishida et al. (2017) examined the impacts of climate change in the Northern California region on the outputs of CCSM4, HadGEM2-ES, and MIROC5 models and RCP4.5 and RCP8.5 scenarios. Their results implied that precipitation in the future period would decrease. Mo et al. (2017), studying the effects of climate change on water resources in the north of China Plain, indicated that in the future, precipitation changes will be greater than temperature changes. Precipitation will increase slightly in the middle future and decrease in the far future. Oztopal (2017) investigated the extreme precipitation events using the RCM model based on the A1B scenario in Turkey. His research showed that extreme precipitation will increase soon in winter (2021-2060) and in the far future (2061-2100) in most parts of Turkey.

In Iran, Samadi et al. (2011) investigated the capability of SDSM to simulate climate-related predictors for climate detection in Khorasan province. They concluded that this model has a good ability to simulate predictions, such as the minimum and maximum temperatures and precipitation. Fakhri et al. (2012) examined the impact of climate change on the number of wet days with precipitation of over 2 mm in the Behesht Abad basin (northern Karoon). Their results revealed a 37% reduction in the total precipitation in the future. Nuri et al. (2014) used different downscaling models under scenario A2 for investigating the uncertainty of climatic parameters. The results of the model showed that it is possible to decrease the precipitation shortly and increase the precipitation in the future (in the middle and far future). Rashidian and Ebrahimi (2016) studied the climate change in Fars province during 2011-2030 using data simulation. They indicated that temperature and precipitation will increase by about 1 degree and 23.9%, respectively. Danesh et al. (2016) studied the impacts of climate change on Iran's water resources utilizing dynamic and statistical models and found that the increase in the temperature would raise evaporation, as a result of which precipitation and the risk of flood would increase. Detection and comparative evaluation of the effects of global warming and climate change on precipitation and the occurrence of climatic phenomena are of great necessity in view of climate variability in each region, including Iran. As reported in the summary of Iran's extreme Climatic Events (2012), the increase in extreme climate events and the need to raise awareness of such phenomena in the national scene have been addressed to reduce the consequences and adaptation to climate phenomena. Urmia Lake basin has experienced a severe decline in inflows over recent years, which has led to a decrease in water levels (Alesheikh et al., 2007; Shadkam et al., 2016). The continuation of this situation will bring this body of water and natural habitat with risks that will have serious socio-economic and environmental consequences (AghaKouchak et al., 2015). In addition to the current issues, climate change can also exacerbate the situation (Zarghami, 2011). Therefore, given the importance of global warming and climate change and the lack of comprehensive studies on modeling and predicting its effects on precipitation extreme events in Lake Urmia basin, the present research attempted to evaluate the extreme precipitation changes using the CanESM2 model over three future periods, namely 2021-2040, 2041-2060, and 2061-2080, based on SDSM statistical downscaling technique Our goal was to create programs to raise awareness about adaptation, prevention or preparedness against the effects of this climate phenomenon in a regional or local area.

Materials and Methods

Study Area

Lake Urmia, which is the focal point for the accumulation of surplus surface currents on the consumption of all the rivers in the closed Urmia basin, is approximately 5750 km^2 in the middle of the northern part of the basin. This lake has been registered as a protected environmental heritage by the United Nations on account of its unique ecological environment (Soudi et al., 2017). Lake Urmia is the 20th largest and the second supersaturated salt lake in the world. Its catchment area accounts for about 3.2% of the total area of Iran (Hassanzadeh et al., 2012). Urmia Lake watershed, with an area of about 51800 km^2, is located between 35° 10' to 38° 30' N and 44° 14' to 47° 53' E in the northwestern Iran (Figure 1). The precipitation changes in the Urmia Lake catchment area are 220 to 450 mm and the average rainfall is 310 mm. Rainfall increases from the central part of the basin to the peripheral highlands. In this basin, the average rainfall was reported to decrease by about 9.2% and the average maximum temperature increased by about 0.8 °C (Delju et al., 2013). One of the major problems in this area is the decrease in the water level of Lake Urmia over the recent years, which seems to have affected climate change in addition to the construction of numerous dams and the expansion of gardens and agriculture (Zarghami, 2011; Jalili et al., 2012; Khazaei et al., 2019). Shadkam et al. (2016) reported that the discharge of rivers leading to the lake decreased by over 40%. Currently, the lake's water level has decreased by over 6 meters from the peak, and nearly 3 meters from the ecological level (Tourian et al., 2015). Therefore, this catchment for the northwestern Iran is of particular importance such that it necessitates effective and expeditious policymaking for the future. So far, research has been conducted on the future status of rainfall and runoff in Lake Urmia basin using different models (Zamani Nuri et al., 2013; Razmara et al., 2013; Goudarzi et al., 2015; Sobhani et al., 2016;; Emami and Koch, 2018; Sanikhani et al., 2018; Nourani et al., 2019). Nevertheless, there are no studies on the variation of the extreme precipitation indices in this basin.

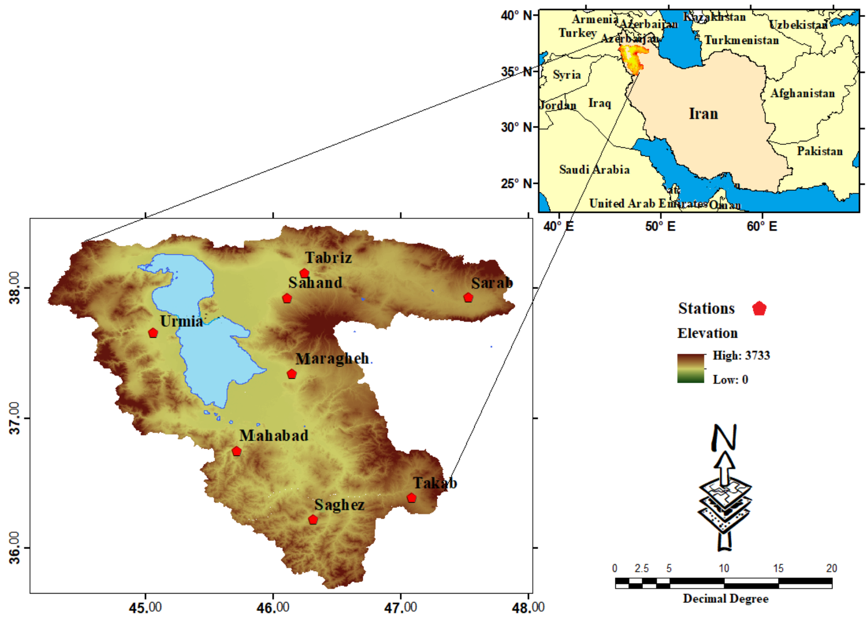


Figure 1. Geographic locations of Lake Urmia basin in Iran

Data

In this study, two sets of data were used to provide an overview of the changes in extreme precipitation indices in the stations of Lake Urmia basin:

1- Daily precipitation observational data of eight synoptic stations in the basin with long-term and reliable statistics, which were acquired from the I.R. of IRAN Meteorological Organization (IRIMO). These data focus on the period 1986-2005. The period 1986–2000 was selected as the model calibration period and 2001–2005 was the validation period. High-quality, reliable, long-term climatic data with the daily (or higher) temporal resolution are needed for evaluating extreme events (Klein Tank et al., 2009); thus, in the first step, the data quality and homogeneity control were investigated. Herein, the data were controlled in terms of quality using the RClimDex software package. In this software, prior to calculating the indices, the data are controlled with the software and incorrect information, such as negative precipitation, is checked. The missing data are then identified (Zhang & Yang, 2004). The daily data were also homogenized based on a two-step regression test via RHtests software (Wang & Feng, 2010).

2- Large-scale atmospheric daily data, including NCEP forecasters, during the same period of observation and output of the CanESM2 general circulation model related to the next three periods of 2021-2040, 2041-2060, and 2061-2080 and under RCP4.5 and RCP8.5 scenarios were extracted from the Canadian Climate Data Center Web site and downscaled via the SDSM model at the station scale. Figure 1 and Table 1 represent the distribution of the used meteorological stations and the characteristics of the stations, respectively.

Table 1. List of the stations with altitude, latitude, and longitude in Lake Urmia basin

Station	Altitude (m)	Latitude (N)	Longitude (E)
Mahabad	1500	36° 46´	45° 43´
Maragheh	1477.7	37° 24´	46° 16´
Urmia	1316	37° 32´	45° 05´
Saghez	1552.8	36° 14´	46° 16´
Sahand	1641	37° 56´	46° 07´
Sarab	1682	37° 56´	47° 32´
Tabriz	1361	38° 05´	46° 17´
Takab	1765	36° 23´	47° 7´

Methods

Extreme precipitation indices

To study the changes of precipitation extreme indices in Lake Urmia basin, we utilized 11 extreme precipitation indices introduced by ETCCDMI. Table 2 lists these indices. In general, they can be divided into five groups, as mentioned in the following (Alexander et al., 2006).

Percentage indices: Precipitation indices in this group show a decrease in precipitation over the 95th percentile (R95p) and 99th percentile (R99p) and one-year extreme precipitation events.

Absolute indices: A minimum of 1-day precipitation (RX1day) and maximum of 5-day precipitation (RX5day) belong to this category.

Threshold indices: They are characterized as indices that measure the number of days when precipitation is more than or equal to a threshold. Among the 11 extreme precipitation indices, this category comprises the number of heavy precipitation days exceeding 10 mm (R10), the number of very heavy precipitation days exceeding 20 mm (R20), as well as the number of the heaviest precipitation days exceeding 25 mm (R25).

Periodic indices: These indices measure the wet and excessively dry periods during the growing season or normal periods and include the indices related to continuous dry days (CDD) and continuous wet days (CWD).

Other indices that do not fit into any of the above-mentioned groups: This category includes the annual wet day precipitation (PRCPTOT) and the simple daily intensity index (SDII).

All these indices are estimated via RClimDex software which is developed for calculating the temperature and extreme precipitation indices. It extracts these indices and calculates their gradient based on the thresholds defined for each index (Zhang and Yang, 2004).

Table 2. Definitions of the used precipitation indices

Index	Descriptive name	Definition	Units
PRCPTOT	Wet-day precipitation	Yearly total precipitation based on moist days	mm
RX1day	Maximum 1-day precipitation	Yearly maximum 1-day precipitation	mm
RX5day	Maximum 5-day precipitation	Yearly and monthly maximum 5-day precipitation	mm
R95	Very wet day	Yearly precipitation when RR N95th percentile of the 1982–2012 daily precipitation	mm
R99	Extreme very-wet day	Yearly precipitation when RR N99th percentile of the 1982–2012 daily precipitation	mm
SDII	Simple daily intensity index	Mean precipitation on moist days	mm/d
R10mm	Number of heavy precipitation days	Yearly count of days when RR ≥ 10 mm	day
R20mm	Number of very heavy precipitation days	Yearly count of days when RR ≥ 20 mm	day
R25mm	Number of the heaviest precipitation days	Yearly count of days when RRS 25 mm	day
CWD	Continuous wet days	Maximum number of continuous moist days	day
CDD	Continuous dry days	Maximum number of continuous dry days	day

SDSM downscaling Model

Wilby et al. (2002) first developed the SDSM statistical model. This model is based on multivariate regression and the statistical relationship between the observed or predicted variables with large-scale variables (atmospheric) or the predictor is evaluated based on partial correlation. Atmospheric variables in the SDSM model are about 26 variables selected based on the correlation coefficient (Hassan et al., 2014). The SDSM workflow consists of two parts; the first part is establishment of a statistical relationship between atmospheric variables and observational variables and determination of the atmospheric variables required for climate generator, including quality control and data transformation, screening of forecaster variables, model calibration, and climate generator (application of observational data for prediction); the second part is simulation of future time series of observational variables using the predicted data from GCMs and the parameters generated in the first part (Chen et al., 2012). In this study, among the CMIP5 series general circulation models, we used the second version of the Canadian Earth System Model or CanESM2 provided by CCCma[†]. The CanESM2 model is an upgraded version of general circulation models called Earth System Models (ESMs). ESMs try to consider the most influential components of the Earth system on climate in their modelling structure. On the contrary to the specific reporting of the emission scenarios used in the CMIP3 models, the Fifth Assessment Report (AR5) uses representative concentration pathway scenarios that are presented in Table 3. The new emission scenarios are based on the radiative forcing level by 2100 AD. This series contains four scenarios, namely RCP2.6, RCP4.5, RCP6, and RCP8.5 (Van Vuuren et al., 2011). In the present work, two scenarios of RCP4.5 and RCP8.5 were employed, which represent the intermediate and the most pessimistic scenario, respectively (Moss et al., 2010).

Criteria of Evaluation of the model results

Prior to using the outputs of climate models in each study, the predictions of these models should be compared with the observed data. To investigate the prediction accuracy of the CanESM2 model, we compared the simulated model values in the study areas with measured

[†] - Canadian Center for Climate Modeling and Analysis

precipitation data for the 1986-2005 (reference period) using RMSE and the mean of the absolute error (MAE) (Jolliffe and Stephenson, 2012).

Table 3. Emission scenarios: representative concentration pathway in various greenhouse gases (Van Vuuren et al., 2011)

Scenario	Radiative forcing	Co2 (ppm)
RCP2.6	Top in radiative forcing at 3 W/m2 followed by a decrease	**490 ppm CO2 tantamount before 2100 and then decrease**
RCP4.5	Fixation without overshoot pathway to 4.5 W/m2 after 2100	**650 ppm CO2 tantamount at fixation after 2100**
RCP6	Fixation without overshoot pathway to 6 W/m2 after 2100	**850 ppm CO2 tantamount fixation after 2100**
RCP8.5	Increased radiative forcing pathway leading to 8.5 W/m2 by 2100	**1370 ppm CO2 tantamount by 2100**

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

$$MAE = \frac{\sum_{i=1}^{N}|S_i - O_i|}{N} \quad (2)$$

where S_i is the precipitation estimated by the model, O_i is the observed precipitation amount, and N is the total number of the observations. The RMSE shows the mean deviation of the simulated values from the measured values that indicate the confidence of the model. The proximity of RMSE and MAE values to zero implies better simulation. Ideally, if the simulated and measured values are equal, the numerical values of RMSE and MAE will be zero. These methods have been used as an appropriate method for comparison and validation in several studies (Ly et al., 2010).

Results and Discussion

SDSM Model Capability Evaluation

In the SDSM model, the daily precipitation data of basin stations are qualitatively controlled and transformed if necessary. In this study, the fourth root conversion for the stations was used due to the non-normal distribution of the daily precipitation data and also because of the better fit of the model. Following qualitative control and data transformation, the best large-scale observational predictor variables (NCEP) were selected and entered into the model. From the 26 available predictor variables, we selected the best variables for each station using the graph of dispersion and the correlation between predictor variables and the partial correlation coefficient between the predictor and predictor variables (Table 4). The results showed that in the majority of stations, the closest correlation belonged to the mean temperature at 2 m (temp), the horizontal velocity at 500 hPa (p5_u), the average sea level pressure (MSLP), and the geopotential altitude at 850 hPa (p850).

Table 4. Selected NCEP predictors to statistically downscale the daily precipitation of Lake Urmia basin

Station	Predictor variable	Station	Predictor variable
Urmia	(p8_zh) ،(shum) ،(temp)	Sahand	(p8_z) ،(temp)
Tabriz	(p5_u) ،(p8_f) ،(temp)	Mahabad	(p5_u) ،(p8_v) ،(temp)
Takab	(s850) ،(p5-v)	Maragheh	(p850) ،(mslp) ،(temp)
Sarab	(mslp) ،(p850) ،(temp)	Saghez	(p5_u) ،(temp)

After calibrating the model for the reference period using the selected predictive variables, the precipitation data were produced for the validation period and the scenario was generated. For model validation, the observational and simulated precipitation data from NCEP data were extracted and compared. Figure 4 illustrates the correspondence of the mean and variance of the observational monthly precipitation with the simulated precipitation by the NCEP model during the validation period. According to Figure 2, the difference in the value of the series in the stations was negligible and that the pattern of the changes in the mean of these statistics was well simulated throughout the year. Given the fact that the actual performance of the SDSM model in precipitation microscopy is based on the accuracy criteria calculated during the validation period, the results of this evaluation are presented below (Table 5). Lower values of MAE and RMSE represents a more efficient model. The results in Table 4 also show that the predicted precipitation in the stations of the Lake Urmia basin did not have a significant difference with the observed data and the estimations of the model in this area were close to the reality. Overall, the results indicated the satisfactory performance of the model in the stations of Lake Urmia basin.

Table 5. Evaluation of SDSM capacity for the simulated precipitation during the verification period (2001-2005)

Station	Urmia	Tabriz	Takab	Sarab	Saghez	Sahand	Maragheh	Mahabad
MAE	1.25	1.09	1.32	1.06	1.91	0.98	1.31	1.76
RMSE	2.96	2.5	2.8	2.26	3.08	1.21	2.9	3.02

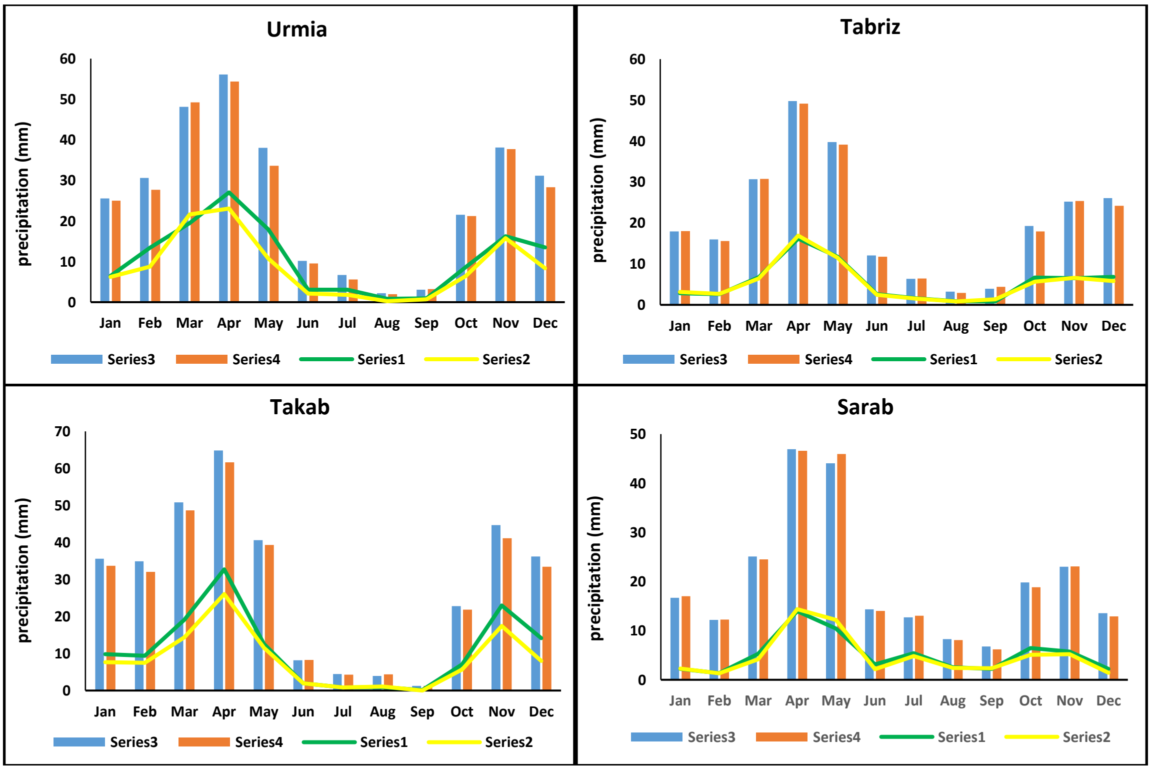
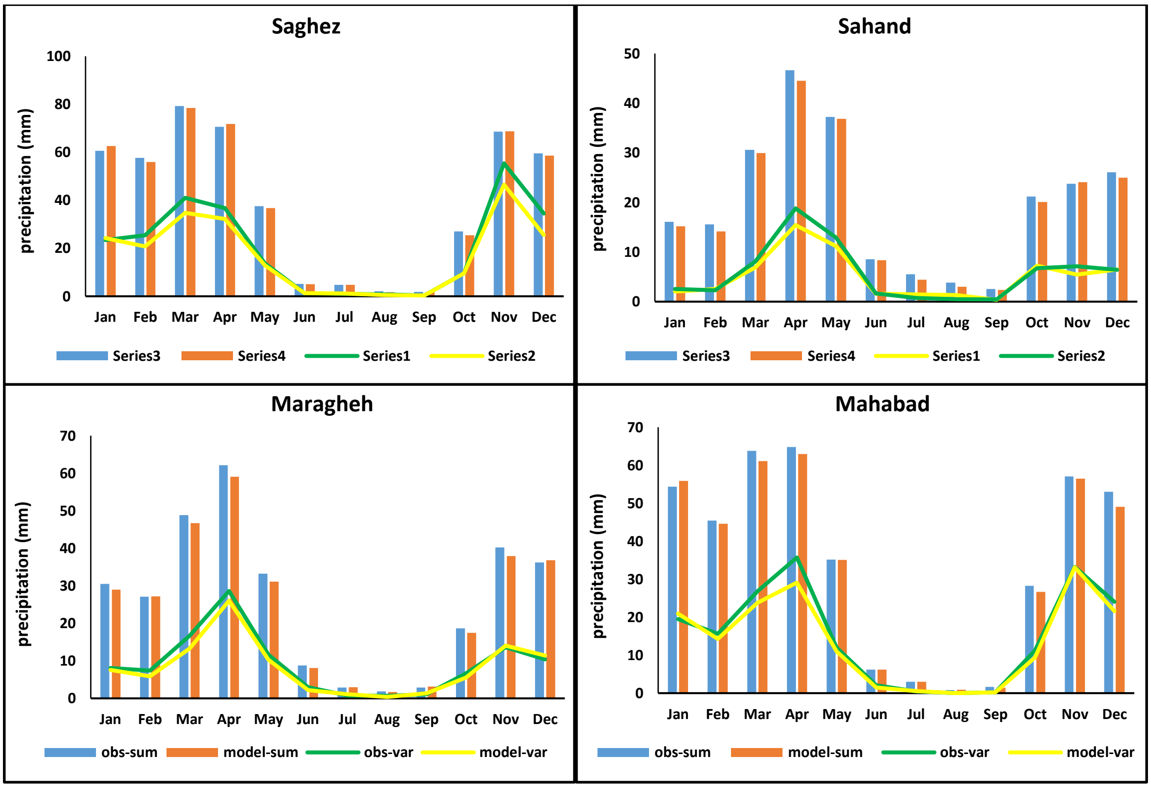


Figure 2. Comparison of the mean and variance of the monthly observed and simulated precipitation via NCEP model



Continued Figure 2. Comparison of the mean and variance of the monthly observed and simulated precipitation via NCEP model

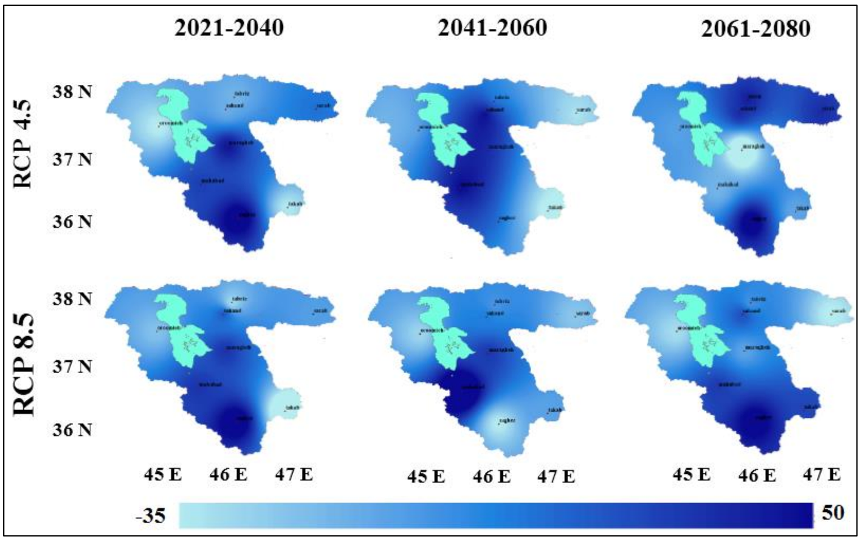


Figure 3. Spatial distribution of the predicted precipitation changes using CanESM2 based on RCP4.5 and RCP8.5 in future periods in Lake Urmia basin

Changes in the predicted extreme precipitation indices with SDSM model

After generating precipitation for the periods of 2021-2040, 2041-2060, and 2061-2080 under the RCP4.5 and RCP8.5, the mean extreme precipitation indices of the stations under study were calculated for the reference period and the future period. Figures 4 to 8 depict extreme precipitation indices of Lake Urmia basin stations via CanESM2 model output under two RCP4.5 and RCP8.5 emission scenarios over three forthcoming periods of 2020-2040, 2060-2041 and 2080-2080 compared to the reference period (1986-2005).

Changes in the predicted absolute precipitation indices

Based on RCP4.5, the 1-day maximum precipitation index (Rx1day) was predicted to increase in the Urmia Lake basin over the three periods compared to the reference period. This increase was by 1.8, 2, and 1 mm for the whole basin, respectively. Based on the RCP8.5 scenario in the first period, the Rx1day index would increase in half of the basin. However, on average, this index increases in the entire basin by 2.4 mm compared to the reference period; this increase also reaches 13 mm in Saghez. In the second and third periods, this index rises in all the basin stations, except for Urmia and Saghez, with an average increase of about 0.9 and 1.9 mm. In general, it could be concluded that in Lake Urmia basin, 1-day maximum precipitation index will increase during the coming periods; yet it will not be significant. Based on RCP4.5, the Rx5day index decreases in all the three periods compared to the base period. This decrease was estimated to be high (about 5 mm) in the first period (2021-2040); meanwhile, it gradually decreased to 3.6 and 3.2 mm in the second and third periods, respectively. The RCP8.5 predicted a decline in the Rx5day in all the three future periods for most of the basin stations; the average of this decrease for the entire basin during the next three periods was found to be 3.2, 3.4, and 3.5 mm, respectively (Figure 4). Overall, in Lake Urmia basin, the maximum 5-day precipitation index decreases over the future periods. However, the Rx5day indicated the continuity of cyclonic systems or instability in multi-day periods; therefore, it is a suitable indicator for flood investigation. Given the fact that in Lake Urmia basin, the amount of this index will decrease in the future, it could be concluded that the potential for floods and the resulting damage in the region will be reduced.

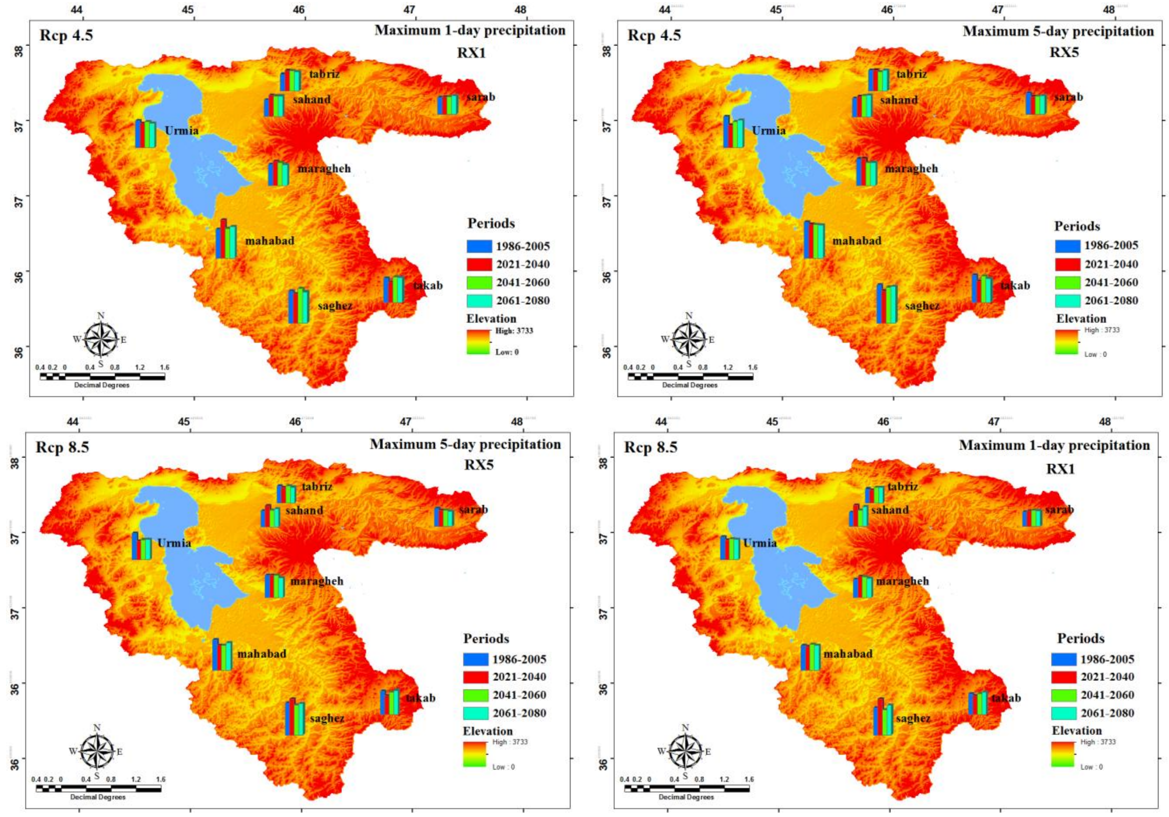


Figure 4. Comparison of the predicted absolute precipitation indices with the SDSM model over the next three periods compared to the base period (1986-2005) based on RCP4.5 and RCP8.5 scenarios

Changes in the predicted percentile precipitation indices

The index of very wet days, based on RCP4.5 during the first period, increased in most of the basin stations; the average increase in the basin was 3 mm, which reached 18 mm at Maragheh. The RCP4.5 scenario in the second and third periods predicted an increase of R95p for the entire basin, which was 7.6 and 4.5 mm, respectively. The increasing trend of this index was also observed based on RCP8.5, which was 5.8, 3.4, and 6.6 mm for the next three periods, respectively (Figure 5). According to RCP4.5, the index of extreme very wet days (R99p) in the first period increased in half of the stations and decreased in the other half. In the second and third periods, this index increased in most of the stations, by 3.2 mm and 0.1 mm, respectively. The RCP8.5 scenario for the majority of the basin stations in the next three periods predicted an increase of R99p. On average, this increase for the entire basin in the three periods was 2.5, 2.2, and 2.2 mm, respectively, compared to the reference period (Figure 5). Generally, in Urmia Lake basin, the percentile precipitation indices increased over the coming periods.

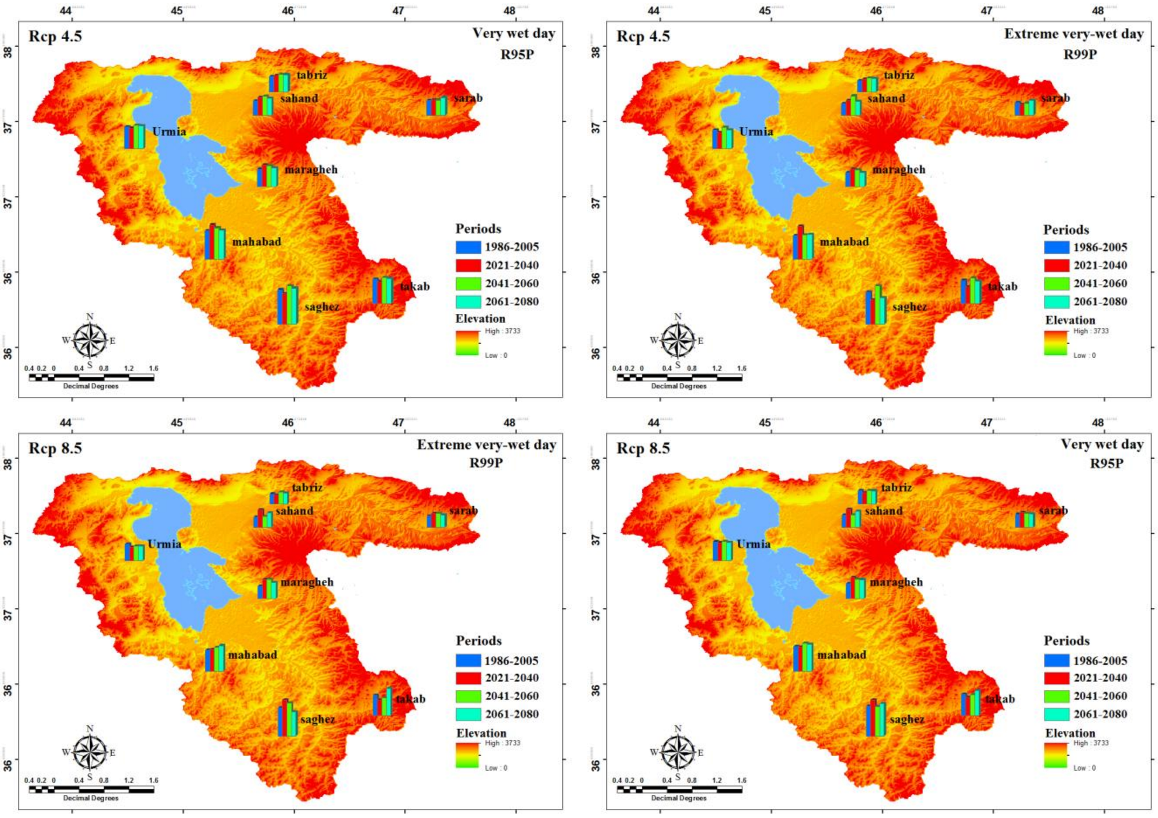


Figure 5. Comparison of the predicted percentile precipitation indices with the SDSM model over the next three periods compared to the base period (1986-2005) based on RCP4.5 and RCP8.5 scenarios

Changes in the predicted threshold precipitation indices

RCP4.5 predicted an increment in the number of heavy precipitation days (R10) compared to the base period for most of the basin stations in the first and second periods, with an average increase by 0.2 and 1 day, respectively. According to this scenario and in the third period, this index decreased in most of the basin stations and reached 0.3 days. Based on RCP8.5, the R10 index decreased in the majority of the basin stations in all the three periods by 0.4, 0.5, and 0.2 days compared to the base period, respectively (Figure 6). The number of very heavy precipitation days (R20) based on RCP4.5 in the first period increased in half of the stations and decreased in the other half. In the second and third periods, this index did not change much compared to the reference period. The RCP8.5 scenario for most of the basin stations in the first and second periods predicted a decrease of R20, averaging 0.2 days for the entire basin in both periods compared to the reference period. In the third period, this index did not change significantly compared to the reference period. The number of the days with precipitation equal to or greater than 25 mm (R25) declined during the second period under the RCP4.5 scenario, with a very small decrease by about 0.1 days. In the first and third periods, the index did not change remarkably compared to the reference period. According to RCP8.5 in the first and second periods, this index remained unchanged compared to the base period, but increased in most of the basin stations in the third period. On average, this increase was estimated to be 0.2 days for the Lake Urmia basin (Figure 6). In general, we predicted that R25 in Lake Urmia basin will not be significantly different from the reference period.

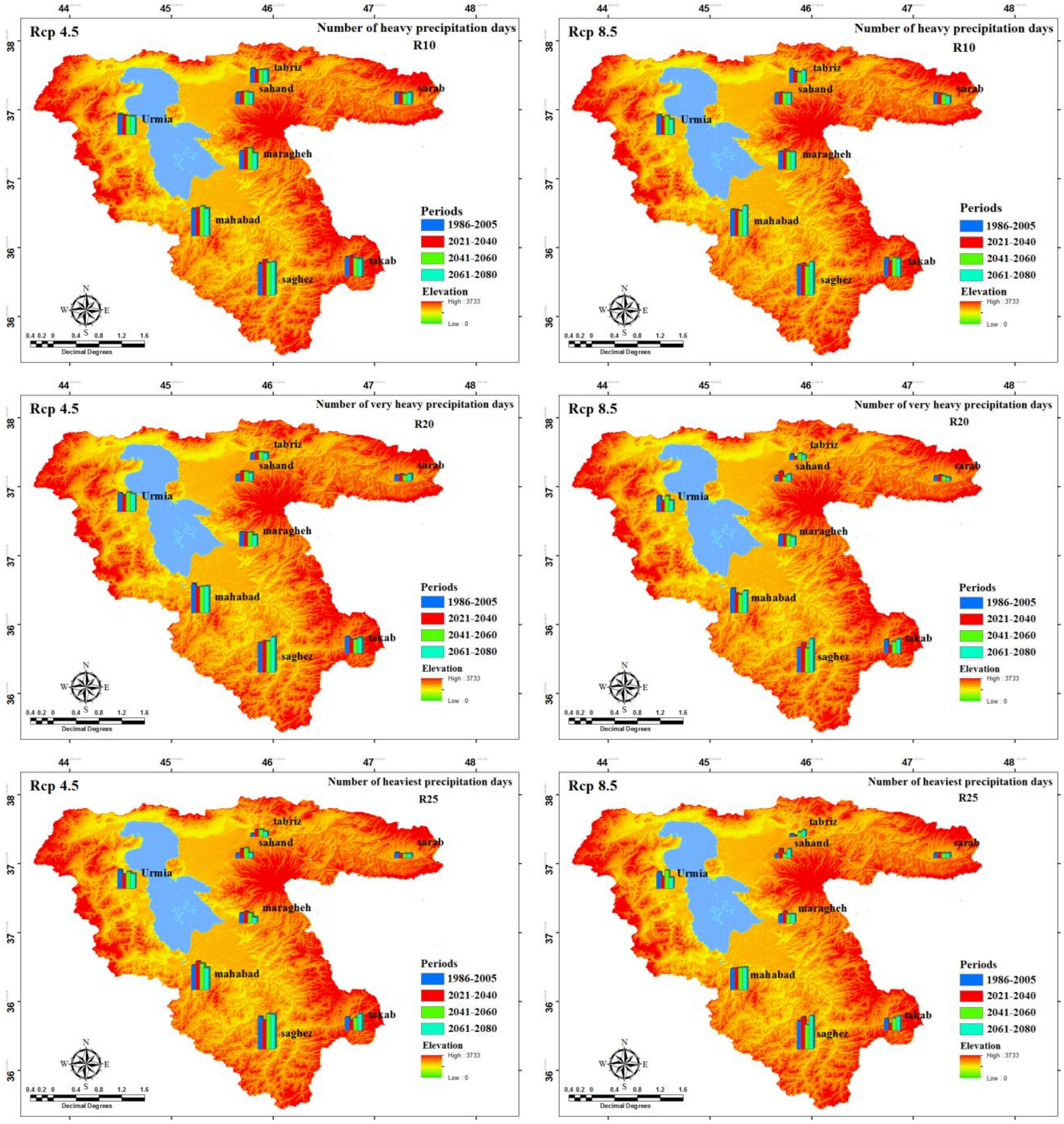


Figure 6. Comparison of the predicted threshold precipitation indices with the SDSM model over the next three periods compared to the base period (1986-2005) based on RCP4.5 and RCP8.5 scenarios

Changes in the predicted periodic precipitation indices

According to RCP4.5, the number of consecutive dry days (CDDs) in all the three future periods decreased in all the stations. On average, the amount of CDD in the first period (2021-2040) decreased by about 11 days, but gradually increased to 12.8 and 13.8 days in the second and third periods, respectively. Based on this scenario, the Sahand, Tabriz, and Sarab will experience the highest rate of CDD reduction over the three periods, ranging from 20 to 22 days, respectively. Based on the RCP8.5 scenario, the CDD index in all the stations also decreased in all the three periods, averaging about 14, 15.6, and 12 days, respectively. According to RCP4.5 scenario, the number of consecutive wet days (CWD) decreased throughout the basin in all the three future periods, with a decrease by 1.1, 0.9, and 1.1 days, respectively, compared to the reference period. The RCP8.5 scenario also predicted a decrease in the CWD for the entire basin over the next three periods compared to the reference period, averaging about 1.1, 0.9, and 1.1 days, respectively (Figure 7).

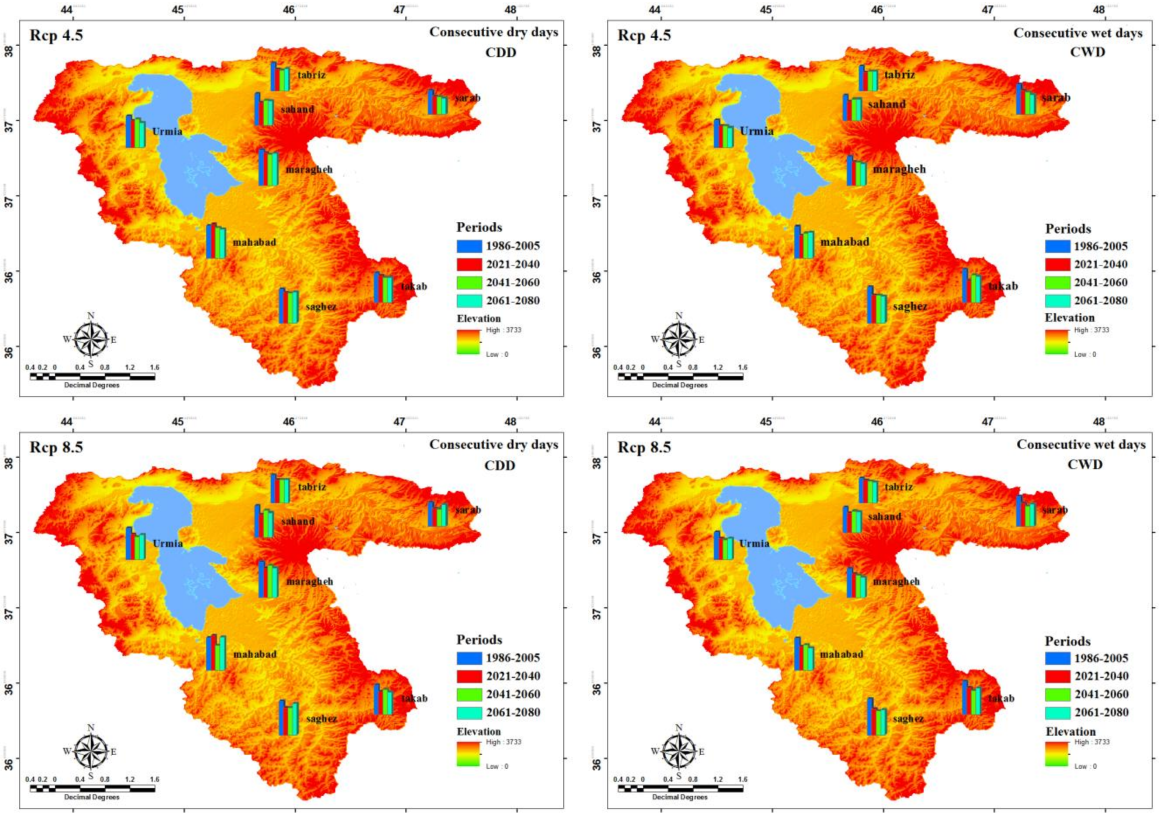


Figure 7. Comparison of the predicted periodic precipitation indices with the SDSM model over the next three periods compared to the base period (1986-2005) based on RCP4.5 and RCP8.5 scenarios

Changes in other predicted extreme precipitation indices

The total annual moist day precipitation index (PRCPTOT) increased according to RCP4.5 in all the three periods in all the stations b 25.6, 31, and 20.7 mm compared to the reference period, respectively. In the first and third periods, Saghez and in the second period, Maragheh were predicted to experience the highest increase of this index (between 50 and 55 mm). The RCP8.5 scenario also predicted an increase in PRCPTOT for all the basin stations the periods. It will increase by 18.4, 11.5, and 23.1 mm, respectively, compared to the reference period. According to this scenario it has a good relationship, in the first and third periods, Saghez and in the second period, Maragheh will experience the highest increase in this index (between 25 and 77 mm)

(Figure 8). The results of the downscaling of the CanESM2 model based on the RCP4.5 and RCP8.5 scenarios showed a slight increase in the Simple Daily Precipitation Intensity Index (SDII) in all the three future periods; accordingly, the amount of this increase in the whole basin was between 0.1 and 0.2 mm. The most significant increase in this index was observed in Saghez and Maragheh (between 0.3 and 0.8 mm) (Figure 8).

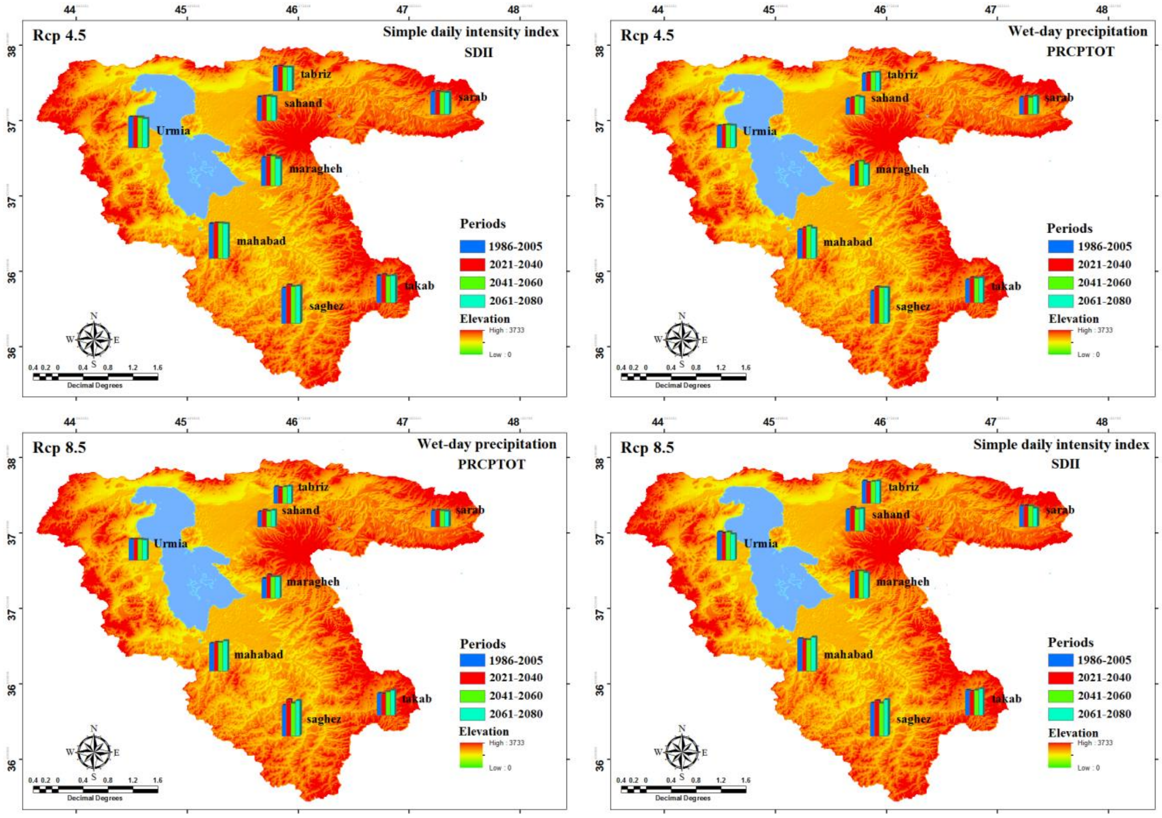


Figure 8. Comparison of the PRCPTOT and SDII indices predicted with the SDSM model over the next three periods compared to the base period (1986-2005) based on RCP4.5 and RCP8.5 scenarios

Trend analysis of the predicted precipitation extreme indices

After prediction of the extreme indices for future periods in the stations of Lake Urmia basin, the trend of these indices was determined utilizing the Mann-Kendall test. Table 6 demonstrates the results of the Mann-Kendall test according to the RCP4.5 scenario. During 2021-2040, the CDD, R20, R25, R95p, R99p, Rx1day, and SDII indices showed an increasing trend in most of the studied stations; only the trend of R95p and R99p indices was decreasing and significant in Mahabad station. The trend of CWD, R10, and PRCPTOT indices was increasing in half of the basin stations and decreasing in the other half. Only PRCPTOT had a significantly decreasing trend in Sarab and the trend of R10 in Urmia significantly increased. The Rx5day index also showed a decreasing trend in most of the basin stations; however, this trend was not significant in any of the stations. In the period of 2041-2060, the CDD index in most of the basin stations had a decreasing trend. Moreover, Rx5day increased in half of the stations and a decreased in the other half; meanwhile, none of these trends were significant. The rest of the precipitation indices revealed an increasing trend in most of the stations, but only the R95p trend in Tabriz station was significant. In the majority of the basin stations in the period of 2061-2080, R10 and Rx5day had an increasing trend while R25 had a decreasing trend; nonetheless, these trends were not significant in any of the stations. The other indices (CDD, CWD, R20T, R95p, R99p, Rx1day, PRCPTOT, and SDII) were increasing in half of the stations and decreasing in the other half. Among these indices, only CWD and R95p indices in Mahabad were decreasing and significant.

Table 6. Mann-Kendall test statistic for the predicted extreme precipitation indices via SDSM model with RCP4.5

STATION	PERIOD	RX1	RX5	R10	R20	R25	CDD	CWD	R95	R99	SDII	PRCPTOT
Urmia	2021-2040	-0.88	-0.30	2.05*	0.37	-0.50	-0.32	0.14	0.16	-1.40	0.23	**0.42**
	2041-2060	0.94	1.20	0.00	-0.10	0.79	1.27	0.91	0.06	1.06	0.65	**-0.36**
	2061-2080	0.36	0.55	-0.56	-0.50	-0.40	0.94	-0.07	-0.1	1.07	0.46	**-0.75**
Tabriz	2021-2040	0.62	-0.68	-0.36	0.48	0.88	0.10	-1.09	0.10	0.27	0.65	**-0.55**
	2041-2060	0.36	0.55	0.60	1.07	0.76	-0.29	0.49	2.30*	0.07	1.60	**1.07**
	2061-2080	0.49	0.94	-0.8	0.00	0.70	0.29	1.68	0.00	0.50	0.16	**0.00**
Takab	2021-2040	0.68	0.81	0.29	0.63	0.60	0.16	0.22	1.36	0.56	0.20	**0.88**
	2041-2060	0.29	-0.55	0.40	-0.70	0.35	-0.03	0.22	-1.10	0.00	-0.85	**-0.10**
	2061-2080	-1.40	-1.46	0.16	-0.70	-1.00	-0.91	-0.25	-1.00	-1.70	-0.13	**0.03**
Sarab	2021-2040	-1.27	-0.03	-1.60	-1.40	-1.00	0.72	-0.07	-1.10	-1.40	-1.88	**-2.17***
	2041-2060	-0.36	-0.36	-0.50	0.57	0.00	-0.36	-1.11	-0.40	0.00	-0.10	**-0.94**
	2061-2080	-1.01	-0.81	0.13	-0.80	-0.60	-1.59	1.81	0.030	-0.90	-0.16	**-0.16**
Saghez	2021-2040	1.14	-0.16	-0.50	-0.50	0.00	0.68	0.34	-0.60	0.64	-0.13	**-0.16**
	2041-2060	0.00	0.03	0.68	-0.90	0.13	0.49	-0.14	-0.30	-0.60	0.16	**0.16**
	2061-2080	-1.65	0.55	0.91	0.07	-0.20	-1.75	0.00	-0.10	-1.40	0.07	**0.03**
Sahand	2021-2040	0.36	0.75	0.30	0.55	0.71	1.79	-1.39	0.32	0.00	0.58	**0.16**
	2041-2060	0.36	0.49	-0.50	0.51	0.45	-0.01	1.56	0.10	0.34	0.23	**0.16**
	2061-2080	0.23	0.75	0.33	0.00	0.63	0.49	0.92	0.62	0.80	0.13	**1.52**
Maragheh	2021-2040	1.20	0.88	0.82	1.21	0.82	-1.10	0.35	0.72	1.22	1.01	**1.59**
	2041-2060	1.65	0.55	0.40	0.37	0.23	-1.72	0.36	1.27	0.04	0.20	**0.55**
	2061-2080	1.27	0.55	-0.90	1.34	1.24	1.56	0.00	0.97	1.22	-0.07	**-0.36**
Mahabad	2021-2040	-1.52	-1.20	-0.90	-1.80	-1.30	-0.55	-0.91	2.00*	2.10*	-1.53	**-1.65**
	2041-2060	0.03	-0.16	0.40	0.37	0.23	1.62	0.38	0.19	0.70	0.20	**0.55**
	2061-2080	-1.72	-1.01	0.53	-1.20	-1.10	-0.10	-2.12*	-2.20*	-1.60	-0.55	**-0.03**

** Trend at a 99% confidence level and * Trend at 95% confidence level

Table 7 shows the results of the Mann-Kendall test for the predicted precipitation extreme indices according to the RCP8.5 scenario. In the period of 2021-2040, Rx1day, R20, R95p, R99p, and SDII indices in most of the studied stations increased. In the R99p index, there was a significant trend in Sarab and Mahabad. The CDD, CWD, and PRCPTOT indices also showed a decreasing trend in the majority of the stations, with the CWD trend in Urmia and the PRCPTOT trend being significant in Mahabad; the CWD trend in Urmia and the PRCPTOT trend in Mahabad were significant. The Rx5day, R10, and R25 indices had an increasing trend in half of the stations and a decreasing trend in the other half. The R10 trend in Mahabad and the R25 trend in the Sarab were significant. During 2041-2060, the trend of the R10 index in most of the stations was decreasing, but the decrease was not significant in any of the stations. The trend of CWD, R20, R95p, and R99p indices were increasing in half of the stations and decreasing in the other half. The other extreme indices had an increasing trend in most of the stations; PRCPTOT in Tabriz station and the CDD trend in Sarab were significant. In the third period (2061-2080), the CWD index in the majority of the stations increased, which was significant only in Sarab station. There was also a significantly decreasing trend in this index in Takab. The trend of CDD and Rx1day indices was rising in half of the stations and descending in the other half; the trend of CDD rose and declined significantly in Maragheh and Urmia, respectively. The trend of other indices in this period was decreasing, which was not significant in any of the stations.

Conclusion

Climate change is a global challenge whose effects vary on a local scale and according to the spatial characteristics of each region. Identification of extreme climate events is of particular importance to plan for mitigating negative effects and enhancing adaptation strategies on a spatial and temporal scale. The present study aimed to predict the effects of climate change on the extreme precipitation of Lake Urmia basin based on RCP radiation forcing scenarios and

CanESM2 general circulation model output. To downscale the outputs of CanESM2, we employed the SDSM model and after ensuring the capability of this model, the daily precipitation data for the future periods were downscaled under RCP4.5 and RCP8.5 scenarios. Subsequently, precipitation extreme indices were calculated for the studied stations. The results of previous papers also showed the capability of the SDSM model in downscaling precipitation data in Iran and Lake Urmia basin (Danesh et al., 2016; Davarpanah et al., 2021). Comparison of the future changes in precipitation maps to the reference period revealed that based on both scenarios, the basin average precipitation would increase in future periods. The results of some studies have also indicated the increase in precipitation due to downscaling of atmospheric general circulation models in Iran (Roshan et al., 2012; Mozafari et al., 2014; Khazaei, 2016; Keihanpanah et al., 2018). In a study conducted on Aidoghmoush basin in East Azerbaijan, Ashofteh and Massah (2009) concluded that in the 2050s, we will see increased precipitation mainly in the fall and winter. Ahmadi et al. (2018) estimated and determined the spatial pattern of water needs of apple trees in Iran, which mainly covers the cold regions of the country. They suggested that the rainy hotspots will be displaced in these areas. Furthermore, these results are consistent with those reported by Hafezparast and Pourkheirolah (2017), who confirmed the slight increase in precipitation in the future period based on the output of GCM models and RCP scenarios. Changes in precipitation will cause significant changes in the quality and quantity of water resources, which requires careful planning focusing on water resources use.

Table 7. Mann-Kendall test statistic for the predicted extreme precipitation indices via SDSM model with RCP8.5

STATION	PERIOD	RX1	RX5	R10	R20	R25	CDD	CWD	R95	R99	SDII	PRCPTOT
Urmia	2021-2040	-0.16	-1.33	0.26	0.34	-0.10	-0.49	-2.90**	0.29	0.89	-0.03	**-0.29**
	2041-2060	1.27	0.75	-0.16	-0.10	1.77	0.32	0.70	0.62	1.07	0.49	**0.00**
	2061-2080	-1.33	-1.33	-1.90	-1.30	-1.20	2.05*	0.42	-1.20	-0.10	1.69	**1.72**
Tabriz	2021-2040	0.03	-0.75	-0.26	-0.10	-0.20	-0.88	-0.30	0.52	-0.40	0.13	**-0.16**
	2041-2060	1.59	1.78	0.99	1.33	1.75	0.00	0.34	1.78	1.50	0.88	**2.30***
	2061-2080	0.55	0.75	0.00	0.91	0.86	0.10	-0.46	0.55	0.48	0.46	**0.16**
Takab	2021-2040	0.68	0.10	-0.70	0.00	0.84	1.20	-0.17	-0.30	1.19	0.16	**-0.94**
	2041-2060	2.30	1.46	-0.10	1.20	1.40	0.42	-0.96	0.97	1.88	0.75	**0.88**
	2061-2080	0.36	-0.10	-0.60	-0.20	-0.30	0.49	-2.42*	-0.70	-0.10	-0.62	**-0.55**
Sarab	2021-2040	1.20	0.42	1.91	1.23	2.20*	0.72	0.18	1.33	2.30*	1.85	**1.49**
	2041-2060	1.59	1.27	0.33	1.85	0.93	2.02*	-0.56	2.27*	1.43	1.79	**0.29**
	2061-2080	0.36	1.20	-0.70	0.15	0.93	-0.03	2.18*	-0.10	0.73	-0.62	**-0.55**
Saghez	2021-2040	1.52	0.94	1.12	1.35	1.85	-0.45	1.25	1.85	1.22	1.75	**1.91**
	2041-2060	-0.81	-0.68	-0.20	-0.70	-0.10	0.65	-1.73	-0.10	-1.30	-0.49	**-0.49**
	2061-2080	-0.94	-0.42	-0.62	0.00	-0.30	-0.81	1.30	-0.70	-0.30	-0.42	**0.00**
Sahand	2021-2040	1.07	1.52	1.02	0.10	0.49	-0.65	-0.60	0.65	1.49	1.37	**1.40**
	2041-2060	-0.68	0.36	0.30	0.00	0.23	0.13	1.63	-0.70	-0.10	-0.29	**0.62**
	2061-2080	-1.40	-1.40	-1.40	-1.60	-1.20	-0.33	1.37	-1.20	-0.97	-1.04	**-0.81**
Maragheh	2021-2040	0.10	-0.29	-0.30	-1.00	-0.80	-0.42	-1.02	-0.70	0.43	-0.07	**-0.94**
	2041-2060	0.23	0.03	-0.10	-0.20	-0.20	0.29	-0.90	-0.30	-0.10	0.33	**0.94**
	2061-2080	0.75	-0.62	1.10	0.94	0.91	-2.14*	0.00	1.30	0.64	1.04	**0.94**
Mahabad	2021-2040	-1.78	-1.33	-2.6*	-1.10	-0.70	0.91	0.00	-0.90	-2.00*	-1.95	**3.02****
	2041-2060	-0.42	-0.68	-0.36	-1.30	-1.70	0.32	0.07	-1.30	-0.80	-0.75	**-0.81**
	2061-2080	-1.46	-1.33	-0.20	-1.10	-1.00	0.58	0.51	-1.60	-1.10	-0.62	**-1.14**

** Trend at a 99% confidence level and * Trend at 95% confidence level

Precipitation extreme indices in Lake Urmia basin stations have shown different and uneven behaviors affected by the rising trend of global warming and climate change, and consequently inconsistency in the spatial and temporal distribution of precipitation. Herein, the changes in extreme indices also showed that percentile precipitation indices (R95p and R99p), Rx1day, SDII, and PRCPTOT increased based on both scenarios and in most future periods compared to the reference period. Meanwhile, the Rx5day, CWD, and CDD indices decreased compared to the reference period. Among the threshold precipitation indices, R10 rose based on RCP4.5 and declined based on RCP8.5 whereas R20 and R25 did not change significantly compared to the reference period.

Darand (2020) also studied the projected changes in precipitation indexes in Iran in the 21st century and reported that despite the differences concerning the rates between the GCM models, extreme precipitation events in Iran were generally projected to increase. There have not been many studies on extreme precipitation in Iran. A few papers have emphasized that the amount of precipitation in an area of low precipitation will be reduced and the amount of precipitation will be increased in an area of high precipitation (Molanejad et al., 2014). In spite of a great deal of uncertainty in terms of forecasting precipitation, particularly its extreme values (Sillmann et al., 2013; Kharin et al., 2013; Najafi and Hesami Kermani, 2017), in several developed countries, such results are taken into account in the future policy-making of these countries, like risk assessment and urban infrastructure design (Willems et al., 2012; Shrestha et al., 2017; Requena et al., 2019). Additionally, the compatibility of all activities with the minimum amounts of rainfall and its high fluctuations is an issue that should be considered in land use research; different land-use systems are required to be of the necessary flexibility according to this issue.

Acknowledgment
The authors gratefully acknowledge the project funding (grant No. 53/49) provided by Urmia Lake Research Institute, Urmia University, Iran.

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