University of Birjand

Water Harvesting Research Vol. 6, No. 1, Spring & Summer 2023, Original Paper p. 109-121

10.22077/JWHR.2023.6956.1115

Evaluation of SMDI Drought Index Changes Using Data and Scenarios of Climate Change Model

Mostafa Yaghoobzadeh[a&e*], Mokhtar Salehi Tabas[b], Davood Akbari[c], Farhad Azarmi Atajan[d&e]

[a]Associate Professor, Department of Water Engineering, University of Birjand, Birjand, Iran.
[b]MSc in Water Resources, Department of Water Engineering, University of Birjand, Birjand, Iran.
[c]Associate Professor, Department of Remote Sensing Division, Surveying and Geomatics Engineering, University of Zabol, Zabol, Iran.
[d]Assistant Professor, Department of Soil Engineering, University of Birjand, Birjand, Iran.
[e]Research Group of Drought and Climate Change, University of Birjand, Birjand, Iran.

[*]Corresponding Author, E-mail address: m.yaghoobzadeh@birjand.ac.ir
Received: 15 October 2023/ **Revised**: 01 December 2023/ **Accepted**: 23 December 2023

Abstract

Drought begins with a lack of rainfall and depending on its duration and severity, Drought can affect parameters such as soil moisture, volume of surface and subsurface water, and human and ecosystem activities. For this purpose, in this research, by using the estimated soil moisture data by the SWAP model and the data of the fifth climate change report, agricultural drought was determined by using of the soil moisture deficit index for the future period (2020-2039) and then they compared with the base period (1992-2011). The results showed that the climatic parameters such as minimum temperature, maximum temperature and precipitation have increased in the future period compared to the base period. The RCP8.5 scenario has estimated the temperature is higher and the precipitation is lower compared to the RCP4.5 scenario. Moisture changes at a soil depth (30 cm) showed that the percentage of soil moisture increases slightly for each scenario in the future period (2020-2039) compared to the base period (1992-2011). The presence of error values of R^2=0.81, NS=0.79 and RMSE=0.02 showed that there is a high correlation between the measured and observed results of soil moisture obtained from calibration and validation of the SWAP model. The results show that calculated SMDI drought index values in the future period (2020-2039) for RCP4.5 scenario has higher than the RCP8.5 scenario, and the predicted SMDI value for the future period is higher than the base period. The results of SMDI drought index uncertainty under RCP4.5 and RCP8.5 scenarios showed that CanEsm2 model has the most certainty and IPSL models have the least certainty compared to other models. The results of this research determined that drought can be estimated in the future by using the vegetation model.

Keywords: GCM model, LARS-WG model, Moisture deficit index, SWAP model, Uncertainty.

1. Introduction

It is very necessary to carry out research related to climate change in order to prepare as much as possible to adapt to this phenomenon and also to reduce the damage costs caused by climate change (Mohammadi and Taghavi, 2005). The most important difference between drought and other natural disasters is that, firstly, drought starts slowly, and secondly, in addition to the area where the drought occurred, neighboring areas are also affected. The adverse effects of this phenomenon in all sectors such as water resources, agriculture, environment and society are gradually revealed (Jalali et al., 2013). The lack or decrease of soil moisture and evapotranspiration can in the fields indicate drought better than precipitation. In examining climate change over the coming decades, the fourth report of the Intergovernmental Panel on Climate Change shows that summer dryness intensified in the late 20th century, which is expected to continue into the 21st century (IPCC, 2007).

There are many definitions of `drought. One of the comprehensive definitions of with global acceptance has grouped droughts into four meteorological, agricultural, hydrological and socio-economic categories (Moasaedi et al., 2016). Meteorological and agricultural droughts are more important than the other. Meteorological drought which in many sources is named as climatic drought as occurs due to the lack or decrease of rainfall over a time period. Agricultural droughts are the result of a lack of soil moisture, which occurs due to the disruption of the balance between water supply and its loss through evapotranspiration (Yaghoobzadeh, 2015).

Drought indicators, as one of the most important parts of the drought monitoring system, are a determining factor in monitoring the drought situation and helping the decision-making process in drought management (Sohrabi et al., 2008). The SMDI index was first introduced by Narasimhan and Srinivasan (2005). They used to indicate the agricultural drought of soil moisture deficit index and evapotranspiration deficit index. The input data was obtained with the SWAP model by simulating soil moisture during growth season and the necessary data to calculate evapotranspiration. Due to the lack of soil moisture data, they used the vegetation index to calibrate the model results. The coefficient of explanation equal 0.75 between the results of the soil moisture deficit index and the evapotranspiration deficit index with the yield of sorghum and wheat crops during the critical weeks of the crop growth seasons shows the high accuracy of these two indices in showing drought. Guo et al. (2023), Watson et al. (2022), and Fang et al. (2021) calculated the pattern of spatial and temporal distribution of agricultural drought with the SMDI index.

Chen et al. (2023) investigated the effect of agricultural drought on the yield of winter wheat and Yao et al. (2022) investigated the effect of agricultural drought on the yield of spring wheat, spring and summer corn. They used the Standardized Precipitation Evapotranspiration Index (SPEI) and Soil Moisture Deficit Index (SMDI) at time scales of 1 to 9 months at 108 and 98 sites in China, respectively. They also used DSSAT-CERES-Wheat/Maize models to simulate crop yield and soil moisture. These researchers found the SMDI index for determining agricultural drought to be more effective than the SPEI index. Also Hu et al. (2022) compared two drought indices in determine the impact of drought on spring wheat. They determined that the SMDI index can show drought changes better than SPEI index.

In the context of investigating the effect of climate change on drought, Delghandi et al. (2023) investigated the effect of climate change on the intensity, duration and amount of drought in Semnan region using SPI and RDI indices, and Helmi and Shahidi (2023) evaluated the impact of drought on the quality of surface water resources, in Kashfroud River, Iran using SPI and SPEI indices. In the context of the effect of climate change on soil moisture, Hauser et al. (2016) evaluated the mutual effect of soil moisture and climate change by using of the CESM model and fifth report data. Their results indicate the importance of moisture change and its effect on soil temperature. Ramazani Etedali et al. (2011) in order to determine the drought index of soil moisture deficit and compare this index with other drought indices such as percentage of normal index, deciles index, standard precipitation index and Chinese Z index simulated soil moisture by using the AquaCrop model during 1982-2008 at Qazvin station, Iran. Their results showed that the highest value of soil moisture deficit index occurred in 1994 with a value equal 2.7 and the lowest value occurred in 1997, 1999 and 2008 with a value equal -1.5.

In a research, Dubrovsky et al. (2009) two drought indices, Palmer's relative drought severity index and relative standard precipitation index were introduced, which were obtained by recalibrating Palmer's drought severity indices and standard precipitation with measurement data. They used these two indicators to assess the effects of climate change on future drought in the Czech Republic. Their results showed that Palmer's drought severity index shows drought better because it is not solely dependent on rainfall. Also, the scenarios of global climate models (GCM) in the standard precipitation index predict an increase in precipitation and in the Palmer drought severity index, an increase in precipitation and temperature in the future. Chan et al. (2021) assessed the impact of climate change on drought events in a Danish agricultural catchment under the RCP8.5 emission scenario by three different drought indices covering soil moisture, groundwater and river flow deficit. They used SMDI index to determine soil moisture drought, SGDI index for groundwater drought, and SDI index for river flow drought. These indices are based on the results of a hydrological model that is fed by the outputs of fine-scale climate models from 16 Euro-CORDEX climate models (GCM-RCMs), while taking into account the uncertainties among the climate model predictions. The hydrological model showed satisfactory ability in modeling historical drought characteristics. The results of future forecasts showed that the intensity and frequency of droughts have increased until the end of the century.

Shin and Jung (2014) developed the IWMM irrigation water management model based on the genetic algorithm in order to reduce the severity of drought in irrigated lands. In their study, the SWAP model simulates the soil moisture and the degree of dryness in two states of irrigation and rain is determined by the drought index of soil moisture deficit. Based on the results of the agricultural drought index of soil moisture deficit, the IWMM model was determined water management at the right time and amount of water for irrigation. Wondie and Terefe (2016) showed that during the study period (1901-2014) in the north and northwest part of Ethiopia a trend of decreasing rainfall and increasing temperature compared to other parts of the country and drought was observed by using the calibrated Palmer drought severity index in the three times during 1941-1950, four times in 1951-1960, five times in 1980-1990, twice in 1991-2000 and three times in 2001-2010.

Considering that few research has been done regarding the estimation of agricultural drought in the future, therefore in this research has been tried by using the simulated soil moisture data by the SWAP model and climate change data, agricultural drought determined using of the drought index of soil moisture deficit for the future period and compared with the base period. Also in this research the uncertainty of climate change models and scenario were determined.

2. Materials and Methods

2.1. Case study

The study area in this research include the Neyshabur plain which located in between 58º-13´ to 59º-30´ east longitude and 35º-40´ to 36º-39´ north latitude and the total area equal 7300 square kilometers. The climate of the region is semi-arid and dry and the mean temperature is 12 ºC, and the annual rainfall in the plain is 292 mm. In order to evaluate the methods of determining evapotranspiration, the corn field data of Faroub village has been used (Fig1).

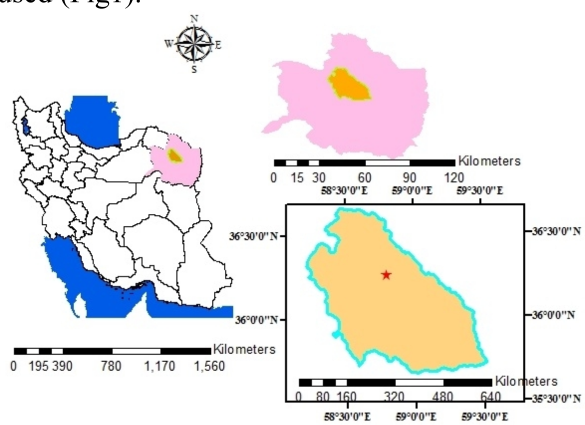


Fig. 1. Location of study area in Iran

In this research Faroob farm located in Neishabur Plain used to simulate the soil moisture in the base period (1992-2011) and future (2020-2039). The characteristics of corn planting and harvesting are shown in table 1. Also, the physical and chemical properties of the soil and the chemical properties of the farm water are shown in tables 2 and 3, respectively.

Table 1. Planting and planting specification used in the experimental farm

Planting date		Harvest data	
AD data	Julius Day	AD data	Julius Day
2008/6/28	180	2008/10/15	289

2.2. Research method

In this research the SWAP model and the soil, agricultural and meteorological data were used to simulate the soil moisture data in soil depth of 0-30 cm. In the next step, to ensure of moisture simulation results, the results of the SWAP model were calibrated and validated with the measured moisture data of the crop for 2008 and 2009. The crop studied in this research is corn which was planted in July and harvested crop in October. After ensuring the accuracy of SWAP model results, soil moisture was simulated by SWAP model for the base period of 1992-2011. Daily meteorological scenarios for the future period were predicted by using of six models of AOGCM model and the RCP4.5 and RCP8.5 scenarios. The ratio of the monthly values of the meteorological parameters of the 2020-2039 period compared to the base period was estimated to determine the amount of soil moisture in the future period by using of climate change scenarios and GCM models.

Table 2. Soil physical and chemical characteristics of experimental farm

depth (cm)	EC of saturation extract (dS/m)	pH	PWP	FC	Bulk density (gr/cm^3)	Soil texture	Clay (%)	Silt (%)	Sand (%)
0-30	1.06	8	7.3	20.1	1.51	Silt-Loam	18	52	30

Table 3. Water chemical characteristics used in experimental farm

EC (dS/m)	pH	SAR	Cations (meq/lit)				Anions (meq/lit)			
			Ca^{++}	Mg^{++}	Na^{+}	K^{+}	Cl^{-}	Hco_3^{-}	Co_3^{2-}	So_4^{2-}
0.6	7.9	3.5	3.5	1	3.5	1.1	2.5	2.8	0	1

2.3. SWAP model

The SWAP model is a physically based one-dimensional model to simulate vertical transport of water flow, solute transport, heat flow and crop growth at the field scale level (Van Dam et al., 2013). It requires inputs including management practices and environmental conditions to compute a daily soil water balance and crop growth. The major processes taken into account are phonological development, assimilation, respiration and ET. SWAP uses Richard's equation to simulate vertical soil water movement in variably saturated soils.

$$\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial z}\left[K(\theta)\left(\frac{\partial h}{\partial z}+1\right) - S(h)\right] \quad (1)$$

where θ is volumetric soil moisture (cm^3/cm^3), t is time (hr), z is soil depth to the ground surface (cm), $K(\theta)$ is hydraulic conductivity (cm/h) and h is hydraulic load (cm). In SWAP model, the analytical functions provided by Van-Gnochten and Moalem are used to define the soil hydraulic functions with the following equation.

$$\theta = \theta_{res} + \frac{\theta_{sat} - \theta_{res}}{\left(1 + |\alpha h|^{n}\right)^{m}} \quad (2)$$

where θ_{sat} is saturated volumetric moisture (cm^3/cm^3). θ_{res} is residual volumetric moisture (cm^3/cm^3), α is air inlet suction (cm/1), and m and n are experimental factors, respectively. By having the amount of moisture in each suction, the unsaturated hydraulic conductivity of the soil can be obtained by using Mueller's equation.

$$k(\theta) = k_{sat} S_e^{\lambda}\left[1 - (1 - S_e^{n/n-1}\right]^2 \quad (3)$$

$$S_e = \frac{(\theta - \theta_{res})}{(\theta_{sat} - \theta_{res})} \quad (4)$$

where K_{sat} is hydraulic conductivity of soil saturation (cm/d), λ is dependent factor of hydraulic conductivity changes to suction changes, and S_e is saturation ratio.

To evaluate the accuracy of methods, root mean square error (RMSE, Eq.5), R^2(Eq.6), and Nash–Sutcliffe (NS, Eq.7) were used as follow (Yaghoobzadeh, 2022).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i - x_m)^2}{n}} \quad (5)$$

$$R^2 = \frac{\sum_{i=1}^{n}(x_m - \overline{x_m})^2}{\sum_{i=1}^{n}\left(x_i - \overline{x_m}\right)^2} \quad (6)$$

$$NS = 1 - \frac{\sum_{i=1}^{n}(x_i - x_m)^2}{\sum_{i=1}^{n}\left(x_m - \overline{x_m}\right)^2} \quad (7)$$

where in these equations, x_i is the predicted values, x_m is the measured values, n is number of used samples and $\overline{x_m}$ is average value of observed parameter. The R^2 index shows the dispersion ratio between the predicted and measured values (Yaghoobzadeh, 2022).

2.4. Scenarios and models

Currently, GCM models are the important tools for generating data for climate change scenarios. The Intergovernmental Panel on Climate Change (IPCC) has used scenarios called RCP in compiling its fifth report. The RCP scenarios include a strict reduction scenario (RCP 2.6), two intermediate scenarios (RCP 4.5, RCP 8.5) and a pessimistic scenario (RCP 8.5) with very high greenhouse gas production (IPCC, 2013). The characteristics of the models and scenarios used in this research are presented in Table 4.

Table 4. Models and scenarios characteristics used in this research

Emission scenarios	**Model name**	**Founder country**	**Horizontal resolution (latitude×longitude, degree)**
RCP 4.5 & RCP 8.5	Canesm2	Canada	1.25×1.875
	GFDL	America	2.5×2
	MIROC	Japan	1.77×2.81
	IPSL	France	1.875×3.75
	Csiromk-3.6	Australia	1.8×1.8
	GISS-ES-R	America	2×2

It is not possible to directly use from the output climate predictors of GCM models in connection with some simulation models such as the SWAP model which used in this research. The output of these predictors are monthly data, while the SWAP model requires daily weather time series. For this reason, the output of GCM models need different downscaling techniques. To generate daily and downscaling climate data, LARS-WG random weather generator was used for precipitation and temperature variables. The LARS-WG downscale model is one of the most up-to-date and challenging scientific topics in the world in the topics of climate change. Investigating GCM models, scenarios presented in scientific assemblies and predicting the future changes based on climate change scenarios are among the basic needs of climate change related research. LARS-WG model is one of the models that can investigate these changes and perform simulations for the future (Semenov, 2009)

2.5. Soil Moisture Deficit Index (SMDI)

SMDI is based on the daily soil moisture for one year, and soil moisture data is the only climatic factor used and necessary. These soil moisture data are calculated with the use of the moisture simulator model for the base period and SMDI index is obtained. Also with use of table 5, the status of agricultural drought can be evaluated by this index (Narasimhan and Srinivasan, 2005).

Table 5. Classification of drought severity by soil moisture deficiency index (Yaghoobzadeh, 2015).

Drought classification	SMDI amounts
Extremely Wet	< 4
Very wet	3 - 3.99
Moderate humidity	2 - 2.99
Mild humidity	1 - 1.99
Early wet period	0.5 - 0.99
Normal	-0.49 - 0.49
Early dry period	-0.5 – (-0.99)
Mild drought	-1 – (-1.99)
Moderate drought	-2 – (-2.99)
Severe drought	-3 – (-3.99)
Very severe drought	-4 >

In order to simulate the soil moisture for the future and base period, the SWAP model should be calibrated and validated with using the measured data of soil moisture. The calibration process was done using the data of the first year of cultivation and validation process was done using the data of the second year of cultivation during the growth period.

3. Results and Discussion

3.1. Verification of SWAP model

The results of validation of the simulated values of soil moisture during the corn growth period are shown in Figure 2. The correlation coefficient equal 80% between the measurement and simulation values of soil moisture at a soil depth of 30 cm indicated the good accuracy of the SWAP model in simulating soil moisture (Table 6). Nepal et al. (2021) in their research pointed to the good performance of the SMDI index in drought determination. Leper et al. (2021) also found the importance of determining soil moisture as a determining factor of drought in their research. The results of Chen et al. (2023) also showed that the DSSAT-CERES model performed well in simulating winter wheat pollination date, maturity date and yield and soil moisture (R^2 coefficient between 0.64 and 0.97).

Table 6. Evaluation of simulated and measured soil moisture values

R^2	RMSE	NS	Soil depth (cm)
0.81	0.02	0.79	0-30

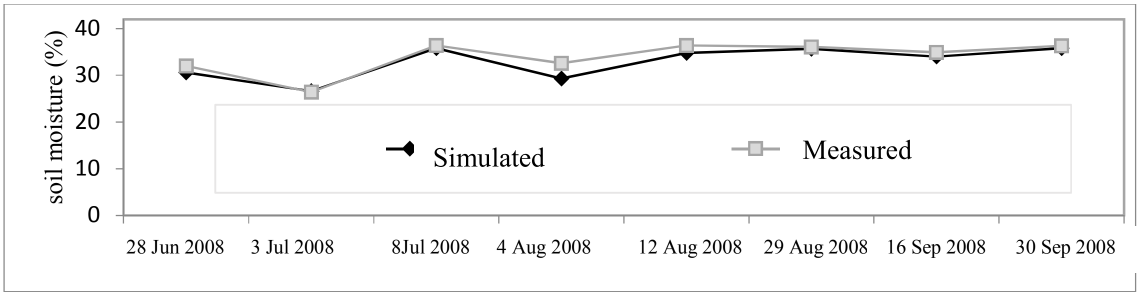


Fig. 2. Comparison of simulated and measured soil moisture data during maize growth

3.2. Climatic data under future climate change conditions

Six GCM models were used in combination with two emission scenarios RCP4.5 and RCP8.5 to generate climate data and determine their changes in the future period. Climatic parameters used in this research are minimum, maximum temperature and precipitation, which are one of the most important factors affecting soil moisture. Table 7 shows the mean daily values of climate parameters in the base and future periods for GCM models in the RCP4.5 scenario. This table shows that the minimum temperature, maximum temperature and precipitation for most GCM models will increase in the future period compared to the base period. In order to compare the models in estimating of climatic parameters of the future period compared to the base period, the highest and lowest increase in minimum temperature is related to IPSL and GFDL models, respectively, and the highest and lowest increase in maximum temperature and precipitation is related to CanEsm2 and Csiromk-3.6 models, respectively. Also, the GFDL and GISS-ES-R models have estimated the maximum temperature values in the future period to be lower than the base period, and the MIROC model has estimated the amount of precipitation in the future period to be equal to the base period. In the research os Sayari et al. (2013), similar to the results of this section, a slight increase in precipitation, maximum and minimum temperature is evaluated for the future years. Yaghoobzadeh (2015) also found a higher correlation between the SMDI index and the SPI index than the ETDI index in their results for the basic and future periods.

Table 7. Daily average values of climate parameters in the base and future periods for GCM models under two scenario of RCP4.5

Models	Minimum temperature	Maximum temperature	Precipitation
baseline	6.80	22.08	0.63
Canesm2	8.31	23.39	0.79
GFDL	7.92	21.37	0.75
MIROC	8.73	22.27	0.63
IPSL	8.78	22.57	0.71
Csiromk-3.6	8.45	22.21	0.65
GISS-ES-R	8.19	21.54	0.74

Table 8 shows the mean daily values of climate parameters in the base and future periods for GCM models in the RCP8.5 scenario. According to this table, the minimum, maximum temperature and precipitation for most GCM models will increase in the future period compared to the base period. In order to compare the models in estimating the climatic parameters of the future period compared to the base period, the highest and lowest increase in minimum temperature respectively related to MIROC and GISS-ES-R models, the highest and lowest increase in maximum temperature respectively related to CanEsm2 and GFDL models and the highest and lowest increase in precipitation respectively related to GISS-ES-R and IPSL models were considered. Also, the GISS-ES-R model and the Csiromk-3.6 model have estimated the amount of precipitation in the future period to be lower than the base period.

Table 8. Daily average values of climate parameters in the base and future periods for GCM models under two scenario of RCP8.5

Models	Minimum temperature	Maximum temperature	Precipitation
baseline	6.80	22.08	0.63
Canesm2	8.55	23.70	0.74
GFDL	8.49	22.15	0.66
MIROC	8.95	22.57	0.71
IPSL	8.83	22.56	0.64
Csiromk-3.6	8.63	22.54	0.62
GISS-ES-R	8.41	21.82	0.78

3.3. The effect of climate change on the SMDI index in the base and future periods

In order to simulate and estimate of agricultural drought by using of SMDI index, the results shows the trend of soil moisture deficiency during the crop growth period from the first week after growth to the week in which the plant is harvested. Therefore, the severe lack of soil moisture in one week may be compensated or adjusted by the week in which irrigation took place or rainfall occurred. Table 9 shows the minimum, maximum and mean values of annual SMDI in the base and future period for six GCM models and two scenarios RCP4.5 and RCP8.5. Based on this table, for both RCP4.5 and RCP8.5 scenarios, the mean annual SMDI values estimated by all six models are within the range of the normal state to the early wet period state. Also, the highest and lowest mean annual SMDI values are respectively related to IPSL and GFDL models for RCP4.5 scenario and Csiromk-3.6 and CanEsm2 models for RCP8.5 scenario.

Table 9. Mean values of annual SMDI for six GSM models in the base and future periods under two scenarios of RCP4.5 and RCP8.5

Models	Emission scenarios					
	RCP 8.5			RCP 4.5		
	Mean	Maximum	Minimum	Mean	Maximum	Minimum
Canesm2	-0.408	3.99	-3.70	-0.017	3.704	-3.824
GFDL	0.060	3.091	-3.410	-0.397	3.998	-3.521
MIROC	-0.206	2.904	-3.428	-0.086	3.108	-3.708
IPSL	-0.186	2.876	-3.139	0.811	3.893	-3.995
Csiromk-3.6	0.063	3.759	-3.450	0.703	3.233	-3.998
GISS-ES-R	-0.257	3.186	-3.384	0.376	2.840	-3.998
Baseline	-0.679	3.546	-3.598	-0679	3.546	-3.598

3.4. Investigating the uncertainty of GCM models in estimating of soil moisture

To investigation the uncertainty of GCM models in soil moisture estimation, the range of annual soil moisture changes for six GCM models under two scenarios RCP4.5 and RCP8.5 is shown as Figure 3. In order to compare the models in the RCP4.5 scenario, due to the low thickness of the band, most of the models have good and acceptable certainty, except for the GISS-ES-R model which has less certainty with a large thickness of the band. In the RCP8.5 scenario, all models have good and acceptable certainty. However, the IPSL model has the highest certainty due to the lower thickness of the band, and the GFDL and GISS-ES-R models have the lowest certainty compared to other models due to the greater thickness of the band. On the other hand, the soil moisture values in the future period compared to the base period are estimated to be lower for all models and under both RCP4.5 and RCP8.5 scenarios.

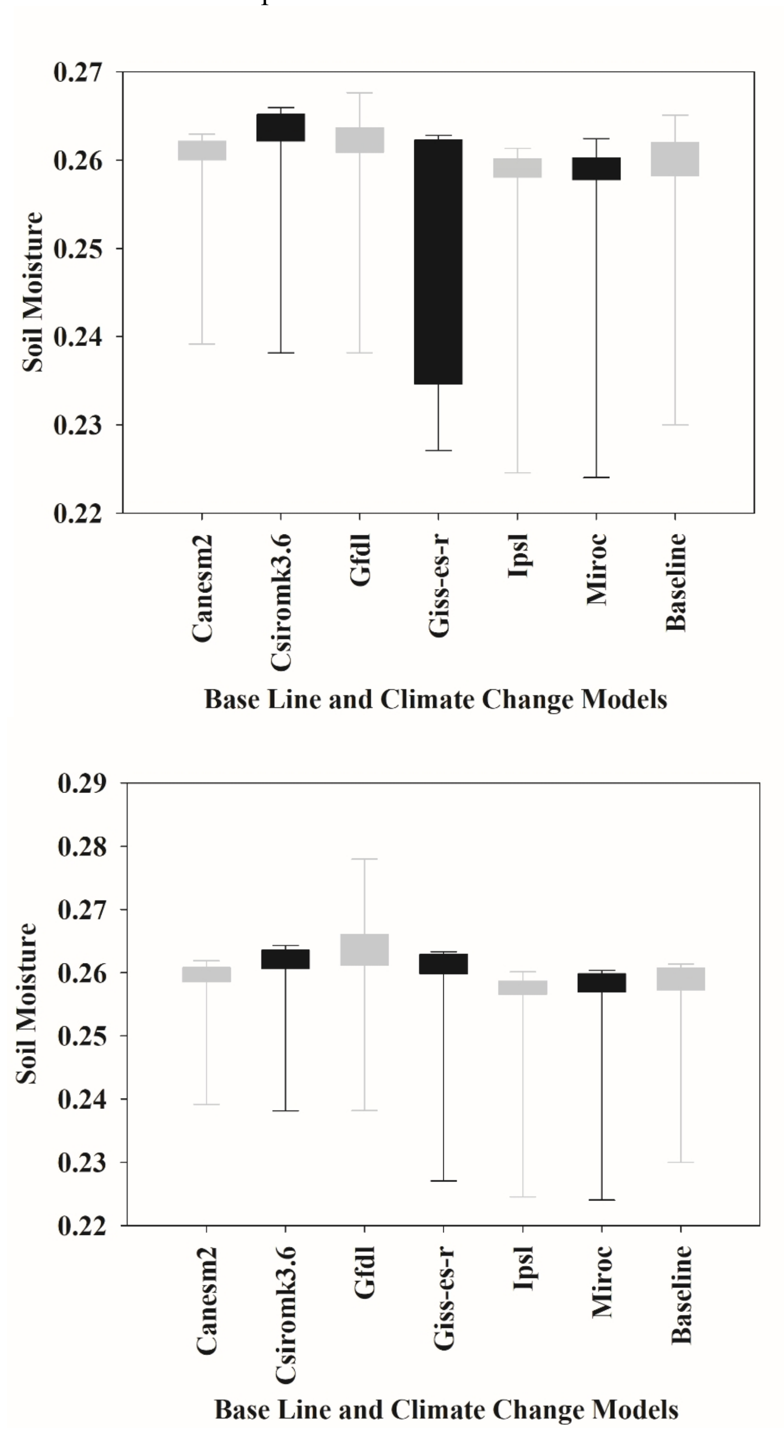
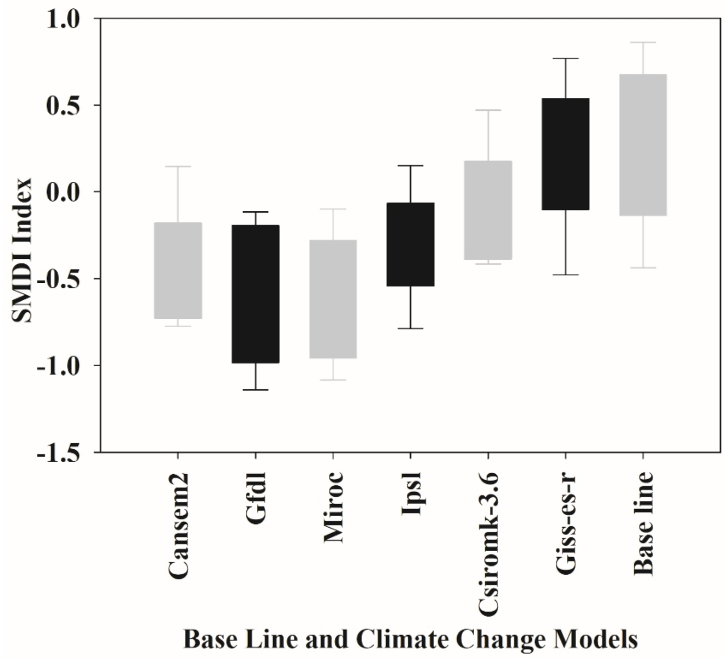


Fig. 3. Box plot of mean values of annual soil moisture in the base and future periods under two scenarios of RCP4.5 (top) and RCP8.5 (bottom)

3.5. Investigating the uncertainty of GCM models in estimating the SMDI drought index

In assessing the certainty of GCM models in estimating the weekly SMDI index, the range of weekly SMDI changes for six GCM models under the two scenarios of RCP4.5 and RCP8.5 is shown as Figure 4. According to the bandwidth of the models in the figure, the higher the bandwidth have the less certainty. In order to compare the models in the weekly SMDI estimation, the IPSL and GFDL models under the RCP4.5 scenario and the CanEsm2 and IPSL models under the RCP8.5 scenario have the highest and lowest certainty respectively. The changes range of annual SMDI index values for six GCM models under two RCP4.5 and RCP8.5 scenarios is shown as Figure 5.



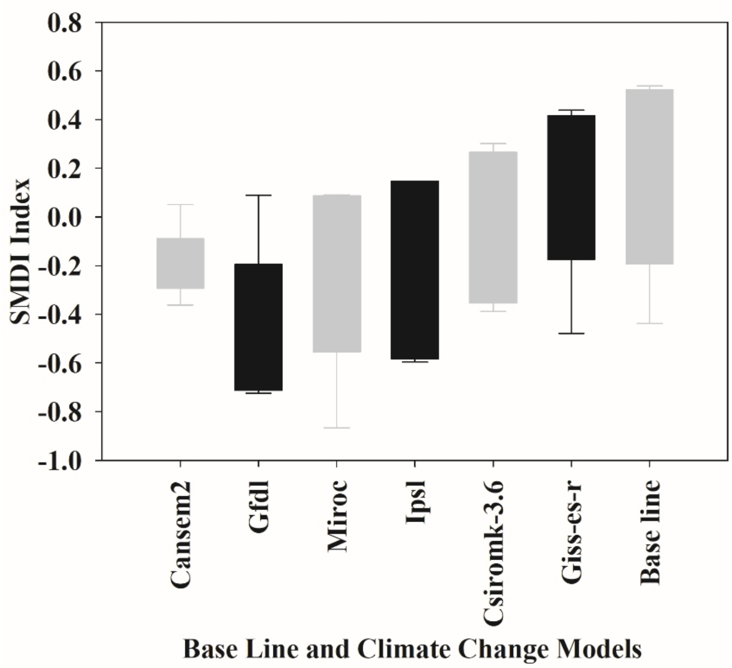


Fig. 4. Box plot of mean values of weekly SMDI in the base and future periods under two scenarios of RCP4.5 (top) and RCP8.5 (bottom)

In order to compare the models, the CanEsm2 and IPSL models has the most and least certainty respectively under the RCP4.5 scenario, but the MIROC and GISS-ES-R models has the most and least certainty respectively under the RCP8.5 scenario in estimating the annual SMD index.

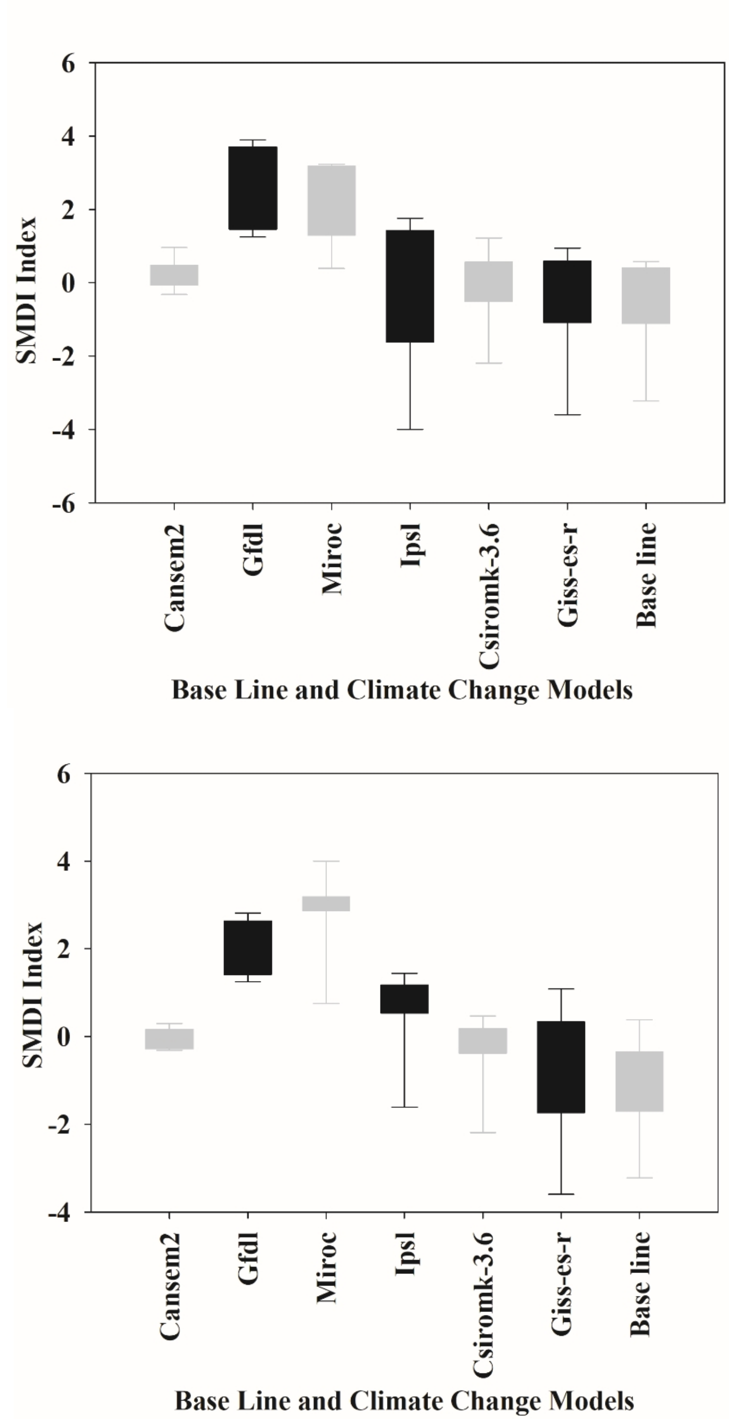


Fig. 5. Box plot of mean values of annual SMDI in the base and future periods under two scenarios of RCP4.5 (top) and RCP8.5 (bottom)

3.6. Uncertainty analysis of emission scenarios

In the following the uncertainty of emission scenarios in the estimation of the SMDI index was investigated. Six GCM models were used to show the changes range in RCP4.5 and RCP8.5 emission scenarios in SMDI index estimation. Figure 6 shows the range of weekly and annual SMDI changes under two RCP4.5 and RCP8.5 scenarios.

According to the figure 6 for the weekly SMDI index, the certainty of the RCP8.5 scenario is higher than the RCP4.5 scenario and the base period. On the other hand, the RCP8.5 scenario estimates the weekly SMDI index values less than the base period and the RCP4.5 scenario. For the changes range of annual SMDI index values, the two RCP4.5 and RCP8.5 scenarios have equal certainty with the base period due to the same thickness of the band.

Also the RCP4.5 scenario estimates the annual SMDI index values less than the base period and the RCP8.5 scenario**.**

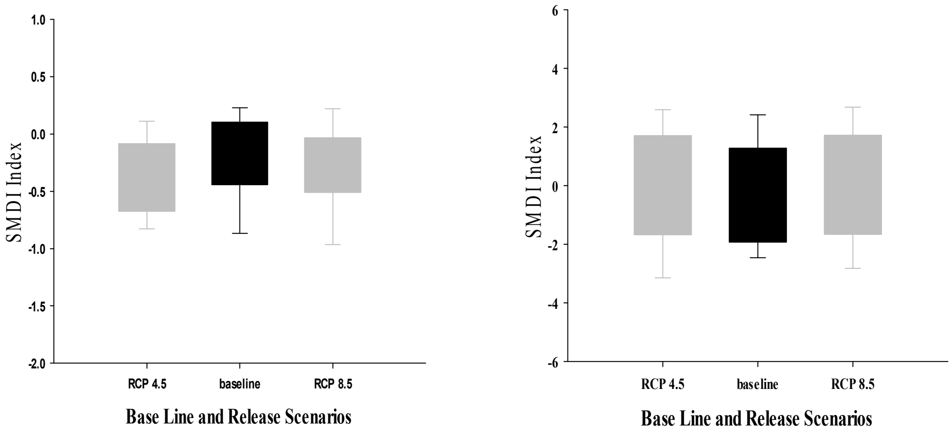


Fig. 6. Box plot of average values of weekly (right) and yearly (left) SMDI in the base and future periods under two scenarios of RCP4.5 and RCP8.5

4. Conclusion

In this research, to generate soil moisture data in the future period (2020-2039) compared to the base period (1992-2011), six GCM models were used under the influence of two emission scenarios of RCP4.5 and RCP8.5. In order to downscaling the daily climate data, the LARS-WG model was used and the climate parameters for the future period were predicted. Then, by using of the SWAP model, the soil moisture values at the soil depth of 30 cm were determined. The soil moisture changes at the soil depth of 30 cm showed that the percentage of soil moisture in the future periods of 2020-2039 will increase slightly compared to the base period for two scenario. Then SMDI values were obtained. The results of the calculated SMDI values for the future period (2020-2039) shows a higher average of SMDI index for RCP4.5 scenario than the RCP8.5 scenario which shows that the average soil moisture is higher. However, the highest and lowest SMDI values are in the RCP4.5 scenario and both scenarios show the normal moisture condition for the future period (2020-2039) and the amount of SMDI index predicted for the future period is higher than the base period. Certainty results of SMDI drought index showed that under RCP4.5 scenario have the highest and lowest certainty for CanEsm2 models and IPSL and GFDL models respectively, but under RCP8.5 scenario, CanEsm2 and MIROC models have the highest certainty and IPSL and GISS-ES-R models has the least certainty compared to other models. Uncertainty can be done with other methods of uncertainty that in this research was used of the simple box plot method due to the small number of climate change models.

5. Disclosure statement

No potential conflict of interest was reported by the authors.

6. References

Chan, S.S., Seidenfaden, I.K., Jensen, K.H., & Sonnenborg, T.O. (2021). Climate change impacts and uncertainty on spatiotemporal variations of drought indices for an irrigated catchment, *Journal of Hydrology*, 601, 126814.

Chen. X., Li, Y., Yao, N., Liu, D.L., Javed, T., Liu, C., & Liu, F. (2020). Impacts of multi-timescale SPEI and SMDI variations on winter wheat yields, *Agricultural Systems, 185,* 102955.

Delghandi, M., Joorablou, S., & Ganji, N.Z. (2023). The impact of climate change on severity, duration, and magnitude of drought using SPI and RDI in the Semnan region, *Journal of Drought and Climate Change Research*, *1*(1), 1-18. (In Persian)

Dubrovsky, M., Svoboda, M.D., Trnka, M., Hayes, M.J., Wilhite, D.A., Zalud, Z., & Hlavinka, P. (2009). Application of relative drought indices in assessing climate-change impacts on drought conditions in Czechia. *Theoretical and Applied Climatology, 96*(1-2), 155-171.

Fang, B., Kansara, P., Dandridge, C., & Lakshmi, V. (2021), Drought monitoring using high spatial resolution soil moisture data over Australia in 2015–2019, *Journal of Hydrology*, 594, 125960.

Guo, Y., Zhang, J., Li, K., Aru, H., Feng, Z., Liu, X., & Tong, Z. (2023). Quantifying hazard of drought and heat compound extreme events during maize (Zea mays L.) growing season using Magnitude Index and Copula, *Weather and Climate Extremes*, 40, 100566.

Hauser, M., Orth, R., & Seneviratne, S. (2016). Investigating soil moisture-climate interactions with prescribed soil moisture experiments: an assessment with the Community Earth System Model (version 1.2). *Geoscientific Model Development*, 10(4), 1665-1677.

Hejazizadeh, Z., & Parvin, N. (2007). Rainfall Modeling and Forecasting Using SARIMA Models and Drought Monitoring Using BMI Index and PDRI Index of Urmia Lake Watershed. *Journal of Geographical Research*, 1(87), 97-124. (In Persian)

Helmi, M., & Shahidi, A. (2023). The using of SPI and SPEI indices in evaluating the effect of drought on quality of surface water resources (Case study: Kashafroud river), *Journal of Drought and Climate Change Research*, *1*(1), 83-96. (In Persian)

Hou, M., Yao, N., Li, Y., Liu, F., Biswas, A., Pulatov, A. & Hassan, I. (2022). Better Drought Index between SPEI and SMDI and the Key Parameters in Denoting Drought Impacts on Spring Wheat Yields in Qinghai, China. *Agronomy*, *12*, 1552.

IPCC-TGICA. (2007). General guidelines on the use of scenario data for climate impact and adaptation assessment. In: Carter TR (Eds.), Intergovernmental Panel on Climate Change, Task Group on Data and Scenario Support for Impact and Climate Assessment.

Jalali, L., Bazrafshan, J., & Tavakoli, A.R. (2013). Evaluation of Soil Moisture Deficiency Index (SMDI) in Agricultural Drought Monitoring (Case Study: Maragheh). The First National Conference on Agricultural Sciences, Payame Noor University West Azerbaijan, West Azerbaijan, Iran, 18-19 September 2013. (In Persian)

Leeper, R.D., Petersen, B., Michael A., Palecki, M.A. & Diamond, H. (2021). Exploring the Use of Standardized Soil Moisture as a Drought Indicator, *Journal of Applied Meteorology and Climatology*, *60*, 1021-1033.

Masaedi, A., Mohammadimoghaddam, S., & Coqueby, GH. (2016). Determination of drought characteristics based on RDI drought identification index and its variation in different time zones and periods. *Journal of Soil and Water Conservation Research*, *23*(6), 27-52. (In Persian)

Mohammadi, H., & Taghavi, F. (2005). Trend of Temperature and Precipitation Indicators in Tehran. *Geographical Space Scientific-Research Quarterly*, *38*(1), 151-171. (In Persian)

Narasimhan, B., & Srinivasan, R. (2005). Development and evaluation of Soil Moisture Deficit Index (SMDI) and Evapotranspiration Deficit Index (ETDI) for agricultural drought monitoring. *Agricultural and Forest Meteorology*, *133*(1-4), 69-88.

Nepal, S., Pradhananga, S., Shrestha, N. K., Kralisch, S., Shrestha, J. P., & Fink, M. (2021). Space–time variability in soil moisture droughts in the Himalayan region. *Hydrology and Earth System Sciences*, *25*(4), 1761-1783.

Ramazanietedali, H., Lyaghat, A.M., & Parsinejad, M. (2011). Survey of Agricultural Drought Status Based on Soil Moisture in Qazvin Province. The First National Conference on Meteorology and Agricultural Water Management, Pardis Agriculture and Natural Resources, University of Tehran, Tehran, Iran. (In Persian)

Sayari, N., Bannayan, M., Alizadeh, A., & Farid, A. (2013). Using drought indices to assess climate change impacts on drought conditions in the northeast of Iran (case study: Kashafrood basin). *Meteorological Applications*, *20*(1), 115-127.

Semenov, M. A. (2009). Impacts of climate change on wheat in England and Wales. *Journal of the Royal Society Interface*, *6*(33), 343-350.

Shin, Y., & Jung, Y. (2014). Development of irrigation water management model for reducing drought severity using remotely sensed soil moisture footprints. *Irrigation and Drainage Engineering, 140*(7), 04014021.

Sohrabi, R., Sohrabi, A.H., & Arab, D.R. (2008 October). *Investigation of drought monitoring indices from the perspective of evolution, nature and performance and suggesting an index selection process appropriate to the conditions of the regions.* The Third Water Resources Management Conference, Tabriz University, Tabriz, Iran, 14-16 October 2008. (In Persian).

Van Dam, J. C., Huygen, J., Wesseling, J. G., Feddes, R. A., Kabat, P., Van Walsum, P. E. V., ... & Van Diepen, C. A. (1997). *Theory of SWAP version 2.0; Simulation of water flow, solute transport and plant growth in the soil-water-atmosphere-plant environment* (No. 71). DLO Winand Staring Centre.

Watson, A., Miller, J., Künne, A., & Kralisch, S. (2022). Using soil-moisture drought indices to evaluate key indicators of agricultural drought in semi-arid Mediterranean Southern Africa. *Science of the Total Environment*, *812*, 152464.

Wondie, M., & Terefe, T. (2016). Assessment of drought in Ethiopia by using self-calibrated Palmer Drought Severity Index. *Irrigation and Drainage Engineering, 7*(2), 108-117.

Yaghoobzadeh, M. (2015). Simulation of Soil Evapotranspiration and Transpiration to Evaluate Agricultural Drought for Basic and Future Periods Using Remote Sensing Technique. PhD Thesis on Irrigation and Drainage, Faculty of Water Engineering, Chamran martyr of Ahwaz University, Ahwaz, Iran. (In Persian)

Yaghoobzadeh, M. (2022). Selecting the best general circulation model and historical period to determine the effects of climate change on precipitation, *IDŐJÁRÁS/Quarterly journal of the Hungarian meteorological service*, *126*, 247-265.

Yao, N., Yi Li, Y., Liu, Q., Zhang, S., Chen, X., Ji, Y., Liu, F., Pulatov, A., & Fenge, P. (2022). Response of wheat and maize growth-yields to meteorological and agricultural droughts based on standardized precipitation evapotranspiration indexes and soil moisture deficit indexes, *Agricultural Water Management*, *266*, 107566.