Investigating relationship between soil moisture, hydro-climatic parameters, vegetation, and climate change impacts in a semi-arid basin in Iran

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Abstract

Climate change can alter soil moisture with subsequent effects on water resources and vegetation growth. This study aims to understand the interactions and quantify the impact of climate change on soil moisture and vegetation in the Urmia Lake basin, Iran. The ERA-5 precipitation and temperature, GLDAS soil moisture, and MODIS NDVI monthly time series were used for 2001–2018. The MK test and Pearson correlation revealed the seasonal and monthly precipitation, and NDVI displayed insignificant trends, but the positive trend of temperature was observed in the cold season. At a depth of 0–10 cm, the monthly soil moisture trend indicated the highest negative trends occurring during April–May, while the lowest negative trends were in winter between December and January. Also, time-lagged (0, 1, and 2 months) correlation analysis showed soil moisture and climatic parameters of each month with short time-lagged (0 and 1 month) mostly presented significant correlations, but mid-time-lagged (2-months) correlations were not found significant with precipitation. Results showed that temperature played a more critical role than precipitation in soil moisture distribution within the study area. Investigating the impact of climate change on soil moisture by ensembles of AOGCM models under the different RCPs showed that soil moisture is influenced by temperature increasing.

Keywords Climate change · Soil moisture · correlations · Urmia Lake basin

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Introduction

The soil moisture is one of the most important drivers of the ecosystems that, in association with land surface temperature, near-surface temperature, and water availability, influence vegetation cover (Chen et al. 2014; Boke-Olén et al. 2018). Soil moisture varies in time and place and impacts the strong effect on the terrestrial system (Wang and Qu 2009; Seneviratne et al. 2010). Under future climate scenarios in many areas, with increasing demand for evaporation due to rising temperatures, the soil moisture deficiency increases, and the role of soil moisture in climate change is significant (Dirmeyer et al. 2013; Meng et al. 2018). Also, the vegetation is significantly affected by climate change and increasing temperature (Saha et al. 2018; Potić et al. 2017). Soil moisture distribution is greatly affected by precipitation regime and temperature incorporation with vegetation and soil types (D'Odorico et al. 2000; Feng and Liu 2015). The precipitation directly affects soil moisture, while the temperature is indirect, which controls the soil moisture by evapotranspiration. The balance between precipitation and evaporation can lead to soil

moisture (Wang et al. 2018). In multiple studies, soil moisture has been investigated with the climatic variables, soil parameters, and vegetation cover across the world (Wang et al. 2018, 2019). Due to the interaction of the soil moisture and other affective variables, some studies tried to explore the role of soil moisture as a controlling factor on vegetation cover (Chen et al. 2014). For example, Engstrom et al. (2008) and West et al. (2018) have utilized remotely sensed data to examine vegetation change by using the spatial patterns of the soil moisture. It is noted that the vegetation cover affects temporal and spatial soil moisture by varying soil infiltration and reducing evaporation (Zucco et al. 2014; Ouyang et al. 2018; Yang et al. 2018; Wang et al. 2019). Niu et al. (2015) showed that the different vegetation cover could control soil moisture in the semi-arid region of China. Moreover, it concluded that temporal fluctuations of soil moisture in lands with a different cover are not typically consonant with the precipitation due to the aridity sequence. Generally, the number of soil moisture observation data is minimal due to the specific geographical and climate conditions and lengthy harvesting process and difficulty measuring (Wilson et al. 2003; Cai et al. 2017; Zeng et al. 2015). Over the past years to now, different remote sensed-based products of soil moisture in temporal coverage and post-processing are accessible and can be an alternative to soil moisture as observational data (Boke-OleÂn et al.,2018; Meng et al.,2018). Generally, remote sensing data and reanalysis data of soil moisture show better performance than station data due to greater regional connectivity and coverage (Legates 2000; Park et al. 2017). The ability of this data has been considered in many types of research. Cai et al. (2017) made use of GLDAS (Global Land Data Assimilation System) data version 2.0 from 1961 to 2011 provided by the National Centers for Environmental Prediction (NCEP) of the National Oceanic and Atmospheric Administration (NOAA). Cai et al. (2017) used this data to investigate soil moisture characteristics in Eastern China. Despite differences between GLDAS and observational data, they found that GLDAS data almost reflect the true characteristics of soil moisture in eastern China and show that precipitation and temperature had positively and negatively correlated with soil moisture in different seasons. Meng et al. (2018) examined the European Space Agency (ESA) Climate Change Initiative (CCI) soil moisture product and the observed precipitation in the Tibetan Plateau to evaluate the capability of the ESA dataset to investigate the relation of precipitation changes and soil moisture changes. The results displayed that except in the west part of the Tibetan Plateau, soil moisture increases depend on precipitation in many parts of this region. The SMAP soil moisture dataset (Soil Moisture Active Passive), NASA's environmental monitoring satellite, has been assessed in the Simineh-Zarrineh in the North West of Iran. The evaluation shows a good correlation between samples as ground-based observations and the SMAP soil moisture

products (Maleki et al. 2019). Based on studies, it can be concluded that there is a close and mutual relationship between hydro-climatic parameters, and soil moisture is important for the indicator in drought monitoring in the agricultural sector and water resource management. Urmia Lake basin is one of the important basins of Iran which faces a scarcity of water resources. It is sensitive to climate change, and the issue of water resources management has always been considered (Malekian and Kazemzadeh 2016). Furthermore, although drought is not an unusual phenomenon in Iran, this basin has continuously faced long-term severe droughts (Shokoohi and Morovati 2015). Several studies have been carried out to investigate the hydro-climatic parameters change such as precipitation (P), temperature (T), and NDVI (Normalized Difference Vegetation Index) in the Urmia Lake basin (Khazaei et al. 2016; Ghale et al. 2017; Tootoonchi et al. 2020). So far, a comprehensive study has been conducted to investigate the interaction of these parameters with soil moisture as an important parameter of Integrated Water Resources Management (IWRM) in this basin. This may be due to insufficient data on soil moisture. Soil moisture data in Iran are not comprehensive enough and are generally incomplete and highly dispersed. So, it is not possible to study long-term changes. Hence remote sensing and reanalysis data can be a good alternative to investigate the change of this hydro-climate parameter and its interaction with other parameters. Global Land Data Assimilation System (GLDAS) is one of these source data for soil moisture, and in several studies, the GLDAS soil moisture dataset was applied as soil moisture reference (Kim and Choi 2015; Li et al. 2015; Park et al. 2017). GLDAS is a global high-resolution land surface simulation system produced by assimilation of the satellite observation data and the ground observation data (Cai et al. 2017). There are also limitations in the spatial distribution of observational precipitation and temperature at different elevations as other effective hydro-climate parameters in the study area that have also been mentioned by Akbari et al. (2019) in the Urmia lake basin water balance study. So, as different studies have demonstrated, satellite-based and reanalysis datasets are a possible solution to estimate these parameters (Wang et al. 2020). In this study, due to the limitation in different hydro-climate parameters, GLDAS reanalysis data are used to obtain soil moisture data. Also, precipitation and temperature have been obtained from the ERA-5 (ECMWF Reanalysis v5) reanalysis dataset. The MOD13 (MODIS Vegetation Index Products)-Gridded Vegetation Index has been used as NDVI Index. The role of soil moisture in the hydrological cycle of the Urmia Lake basin in this study is attempted to investigate soil moisture change and relevance on precipitation, temperature, and vegetation cover. Thus, assessing soil moisture change will help us improve our conception of climate variability in the Urmia Lake basin.

Materials and methods

Study area

Urmia Lake basin area is about 51758 km2 in 35° 40′–38° 30′ N and 44° 07′–47° 53′ E of northwestern Iran (Figure 1) (Javadian et al. 2019). Urmia Lake basin is one of Iran's inner-catchments, including significant rivers such as the Ajichay, Zarinehroud, Siminehroud, Gadarchay, Brandooz, Shahrchay, Nazluchay, Mahabad, Rozechay, Ghalechay, and Zulachay rivers (Akbari et al.,2019). The range of elevation changes in the Urmia Lake basin ranges from about 1275 to 3707 m above sea level. This extensive topography has caused climate variations in the basin. The maximum and minimum temperatures vary from 46.5 to −37.5 °C. Minimum rainfall of about 250 occurs on the edge of the lake, and maximum occurs in the south and around 700 mm. The origin of these rainfalls is the air fronts that enter Iran from Europe and the colder regions and affect the basin from the north and northwest. The mean annual precipitation is around 340 mm and means an annual temperature close to 12 °C in this basin (Akbari et al.,2019).

Data sources

Monthly precipitation and temperature series were collected from 9 synoptic stations of the Iran Meteorological Organization from 2001 to 2018 (Figure 1) and used to validate the reanalysis dataset of ECMWF (European Centre for Medium-Range Weather Forecasts). In this study, ERA-5 data (precipitation and temperature), which are fifth-generation reanalysis from European Center for Medium-Range Weather Forecast, are utilized in 0.25° resolution from 2001 to 2018. NASA Global Land Data Assimilation System (GLDAS) uses advanced land surface modeling and data assimilation techniques to ingest satellite- and ground-based observational data. The output data of this hydrology model are presented in four land surface models: Noah, Catchment, the Community Land Model (CLM), and the Variable Infiltration Capacity (VIC) (Rui and Beaudoing 2018). In this study, the GLDAS model used is Noah. The monthly 0.25-degree spatial resolution soil moisture dataset at depths of 0–10 cm and 10–40 cm is derived from the Goddard Earth Sciences Data and Information Services Center for 2001–2018. NDVI monthly series is obtained from MOD13C2 Version 6-gridded vegetation indices in a 0.5-degree resolution. The Normalized
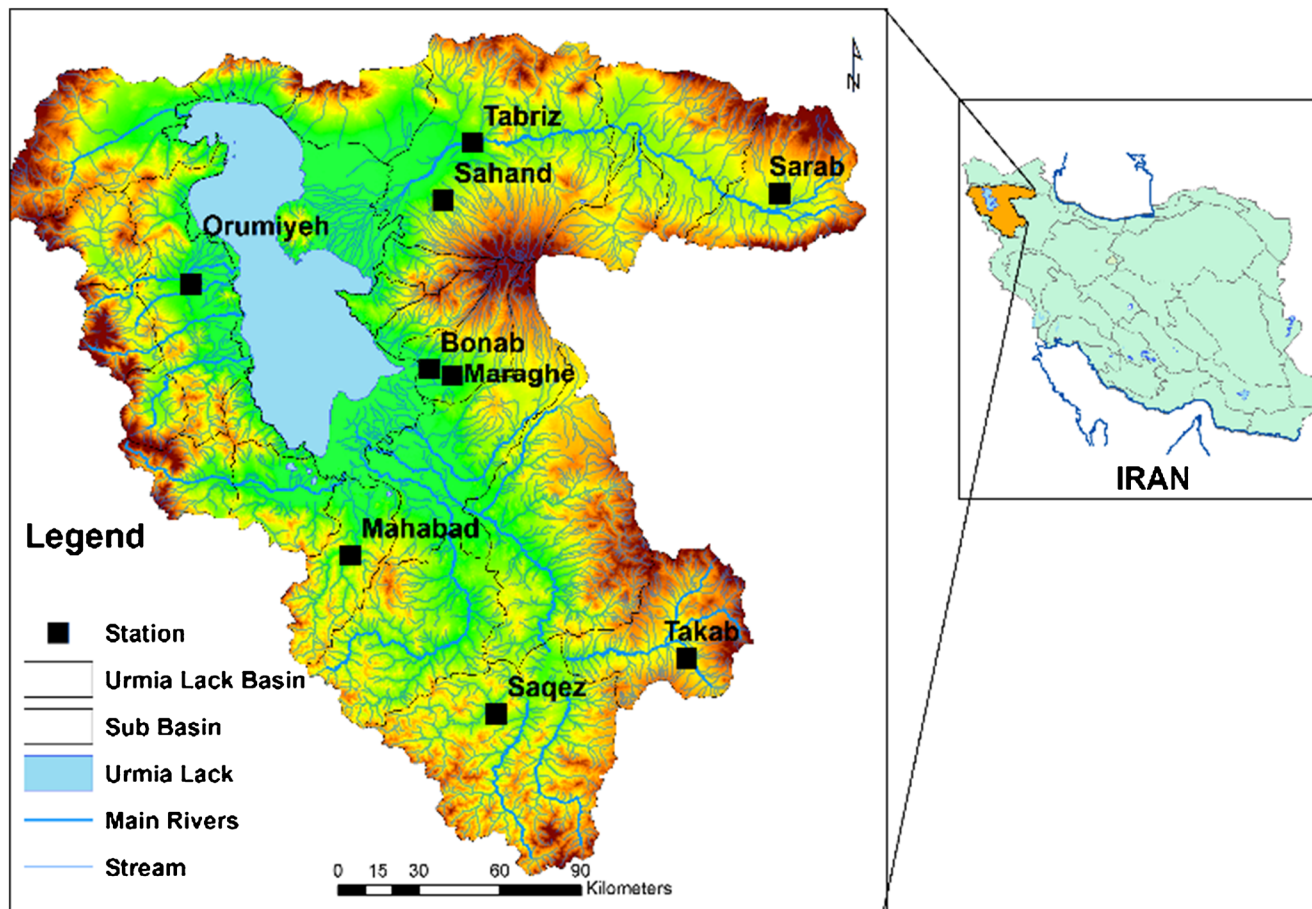

Fig. 1 Location of the study area in the northwest of IRAN

Difference Vegetation Index (NDVI) was developed by Rouse et al. (Rouse Jr et al. 1973). This index is one of the most common, most natural, and most fit indices known in vegetation studies. It has a simple computational process and has the best dynamic power compared to other indices. This index is most sensitive to vegetation changes and is less sensitive to climate and soil effects, except where vegetation is low. NDVI time series can be assessed by a range of sensors (West et al. 2018). NDVI has been widely applied in different studies (Shen et al. 2017; Zhang et al. 2017). NDVI values vary from −1 to 1. The values less than 0.1 correspond to unvegetated land, and the values greater than 0.2 correspond to low, moderate, and dense vegetation (for more details, follow Didan et al. (2015); Al-Doski et al. (2013)).

For change detection of hydro-climatic parameters in future CMIP5 (Coupled Model Intercomparison Project phase 5) dataset in the address, ftp://gdo-dcp.ucllnl.org/pub/dcp/archive/cmip5/ Global Mon / BCSD is used. Eventually, all the data were transferred to monthly temporal resolution and 0.5*0.5 spatial resolution to adjust the data.

Data analysis

Mann-Kendall (MK) trend test

There are a large number of statistical tests that are used for trend detection. One of the most convenient and practical statistical tests is Mann-Kendall's rank statistic test. It is applied to analyze climatic time series and climatic change detection in climatological and climate change studies (Bonfils 2012). Mann-Kendall rank test belongs to non-parametric tests, and the normal distribution of data is not required (Zaman et al. 2015). A more thorough description can be found in Sneyers (1990). In Equation (1), Kendall's S-statistic, variance, and Z can be calculated as follow:

$$s = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sgn(x_j - x_k)$$

$$sgn(x) = \begin{cases} +1 \ if \ (x_j - x_k) > 0 \\ 0 \ if \ (x_j - x_k) = 0 \\ -1 \ if \ (x_j - x_k) < 0 \end{cases}$$

$$var(s) = \frac{n(n-1)(2n-5) - \sum_{i=1}^{m} t_i(i)(i-1)(2i-5)}{18}$$

$$Z = \begin{cases} x = \frac{s-1}{\sqrt{var(s)}} \\ x = \frac{s+1}{\sqrt{var(s)}} \end{cases} \begin{cases} if \ s > 0 \\ if \ s = 0 \\ if \ s < 0 \end{cases}$$

$$|Z| = Z_{1/2}$$

where n is the number of time series observations and x_j and x_k are two time series of observational data, while $i=1, 2, 3, \ldots$ to $n-1$ and $j=i+1, i+2, i+3, \ldots. n$. Each x_k is as a reference

point in time series and all x_j is compared by that. t_i is the number of ties for t^{th} value, and m is the number of tied values. In this test, the null hypothesis (H_0) showed no trend; the alternate hypothesis (H_1) was a trend. If $|Z| > Z_{1/2}$ (H_0) is rejected and means there is a statistically significant trend. The critical value of a value of 0.05 from the standard normal table is 1.96 (McBean and Motiee 2008. Ahmad et al. 2015). In this study, significant level is $\alpha = 5\%$ (or 95% confidence intervals) for a two-sided probability.

Statistical analysis

The Pearson correlation coefficient (CC) is applied to investigate the relationships between the principal variables. This statistical index has no units and displays the score of agreement representing the linear correlation level, which ranges from −1 to 1, where a positive value shows a positive correlation and a negative value means the negative correlation (Wang et al. 2019). Soil moisture has vertical variations at different depths (ZHANG et al. 2003; Cai et al. 2017), and generally, soil moisture is affected by precipitation, but this effect can be delayed by 1 or 2 months (Zhu et al. 1996; Cai et al. 2017). So, in this study, to check the monthly correlation of variables and soil moisture, time-lagged correlation analysis (1 and 2 months) is examined. Initially, soil moisture data were obtained from the monthly GLDAS dataset at two depths of 0–10cm and 10–40 cm. Spatial distribution maps are plotted in different months to determine the extent and trend of moisture changes at different depths. Data on precipitation and temperature variables were obtained from the ERA-5 dataset. The performance of these data is evaluated with monthly temperature and precipitation observation data.

$$r = \frac{cov(sm, f)}{\sqrt{cov(sm)} * \sqrt{cov(f)}} \quad (2)$$

Here, sm is soil moisture, and f is climatic parameters and NDVI (Eq. 2).

Results

Validation ERA-5 dataset

In Figure 2, the scatterplots of ERA-5 precipitation and temperature data versus observational data are shown for the nine stations separately. Also, the retrieve R^2 and Root Mean Square Error (RMSE) are displayed. The statistical comparison shows that linear correlations for temperature are more potent than precipitation. The R^2 values of temperature are mostly close to 0.99 or 1, and the RMSE is from 0.77 to 2.47. The linear correlations value of precipitation range
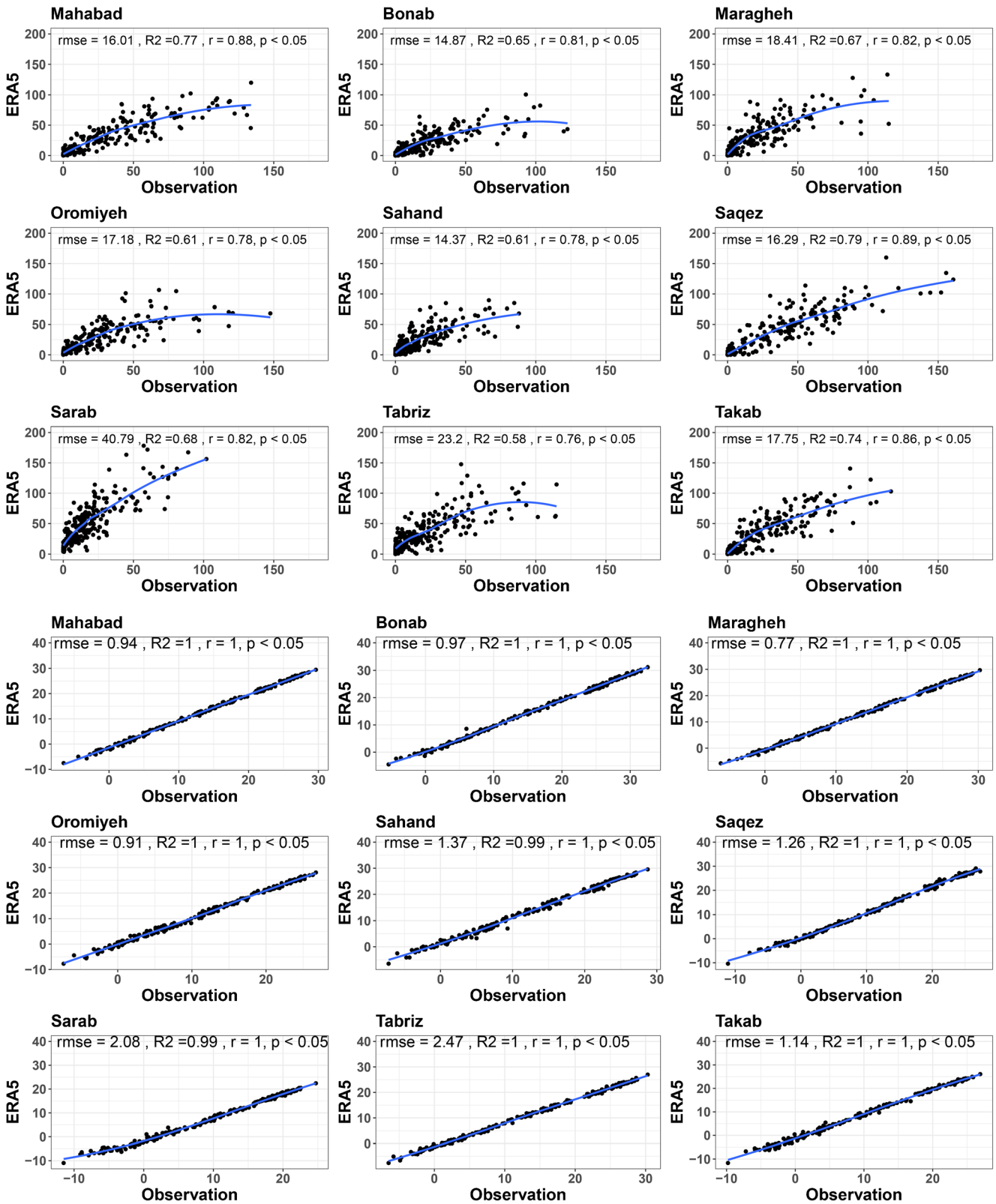
Figure 2. Scatterplots of ERA-5 precipitation (up) and temperature (down) data versus observational data for 2001–2018 separately

from 0.58 to 0.79 for all stations, and the RMSE values show a wide range of precipitation. The magnitude of the RMSE values compared to the observed rainfall data with the reanalysis and remotely sensed data is not an unexpected point and has been observed in several case studies, for example, Razei and Sotoudeh (2017) and Katiraie-Boroujerdy et al. (2019). In the study area, generally, this issue occurs due to the complex topographic.

Spatial and temporal characteristics of climatic variables, soil moisture, and NDVI

Figure 3 reveals mean monthly climatic variables, soil moisture spatial, and NDVI temporal distribution from 2001 to 2018 in the Urmia Lake basin. Figure 3 a presents a variation of mean monthly precipitation, ranging less than 20 to rather than 70 mm in the study area. The minimum precipitation appeared in the middle of the basin and the edge of the Urmia lake, as long as the maximum appeared in the eastern and western borders of the basin and rising by elevation due to orographic precipitation. According to Figure 3a, the precipitation distributed throughout all months, and low precipitation was observed from June to September. Generally, more precipitation occurs during the winter, autumn, and spring. The spatial distribution of temperature is given in Figure 3b and ranged from −5 to 25 °C in other months. Temperature in the plain of the study area, which is scattered in the basin, is higher than high altitude areas on the mountains region in the boundary of the basin. The temporal investigation of temperature presents a strong consistency between the temperature and the precipitation map. It shows that the most considerable amounts of temperature occur in low precipitation months of June, July, and August. They are associated with the climate of the study area, and wet and cold months are in winter and spring. As given in Figure 3 c and d, both soil moisture 0–10 cm and 10–40 cm have a robust monthly distribution. The soil moisture 0–10 cm ranges from less than 10 to 40 ($m^3\ m^{-3}$), and the range of less than 30 up to 120 ($m^3\ m^{-3}$) belongs to soil moisture 10–40 cm. The spatial distribution of mean annual soil moisture (0–10 cm and 10–40) is similar to the precipitation. The temporal distribution shows that the most of the monthly moisture corresponds with the wet season of the year, observed in winter and spring, and shows a seasonal cycle of increase from November to May versus a decreasing cycle from June to October. The slope of soil moisture is increasing from June to October due to increased evaporation from the soil surface.

Compared to the distribution of soil moisture coupled with the precipitation distributed, soil moisture distributions are homogeneous with precipitation patterns. Also, soil moisture response to precipitation rate change is asserted by Javadian et al. (2019), in the Urmia Lake basin. Moreover, the spatial patterns of soil moisture in different depths are similar in monthly and seasonal distribution, which was reported by Cai et al. (2017) in a semi-arid region. The spatial distribution

of NDVI (Figure 3e) shows that vegetation over the central region is much dense than in other regions. The temporal distribution of NDVI is in harmony with precipitation and temperature variations, especially in spring and summer. Moderate T and soil moisture coupling with a sufficient amount of precipitation provide high NDVI in the growing season of the study area spatially in May and June. Referred to Barlow et al. (2016), temporal variability of vegetation is related to the distribution of climatic variables in the study area as the middle-east, and monthly variation of NDVI is almost in line with the region's growing season.

Trend analysis

The Mann-Kendall test for trends detection in the monthly and seasonal average of climatic variables, soil moisture, and NDVI is shown in Figure 4. Monthly and seasonal precipitation trends from 2001 to 2018 are given in Figure 4a. As can be seen, an increasing trend in May, June, and July is notable, and in January, February, and March, decreasing trends are considerable. In other months, trends are quite slight and do not alter significantly during the whole term. In seasonal precipitation except for autumn, in other seasons, almost high variations are observed. The trend of temperature in monthly and seasonal scales is shown in Figure 4b. The monthly trend showed a slight upward trend from May to August and is partly close to the study of Malekian and Kazemzadeh (2016).

In these months, the rising temperature trend confirms the increasing precipitation trend due to temperature in extreme precipitation in the region due to environmental conditions. The analyses of the seasonal trend of temperature also indicate the increasing temperature in summer compared to other seasons, which is expected due to the monthly temperature changes in the warm months of the year. The soil moisture trend in different depths is shown in Figure 4 c and d. The soil moisture in 0–10cm and 10–40cm showed a relatively significant decreasing trend in most months. Remarkably, the downward trend of soil moisture in wet months is more intense. Most of the months present a significantly decreasing trend at the 5% level and indicate soil moisture change in the study area. The soil moisture variations of 10–40 cm are more severe in February and March than at a depth of 0–10 cm. The seasonal trends of soil moisture show Winter and spring seasons, which have the highest rainfall in the study area and have the highest downward trend in soil moisture. Winter and spring seasons, which have the highest rainfall in the study area, are coupling with the highest decrease in soil moisture, which specifies the dependence of soil moisture on precipitation. With a downward trend of precipitation in winter, the soil moisture trend is significantly decreasing. This result is considered a decline in soil moisture in the west of china by Cia et al. (2017) and in surface soil moisture over 1991–2009 in West and Central Australia (Chen et al. 2014). Figure 4 e
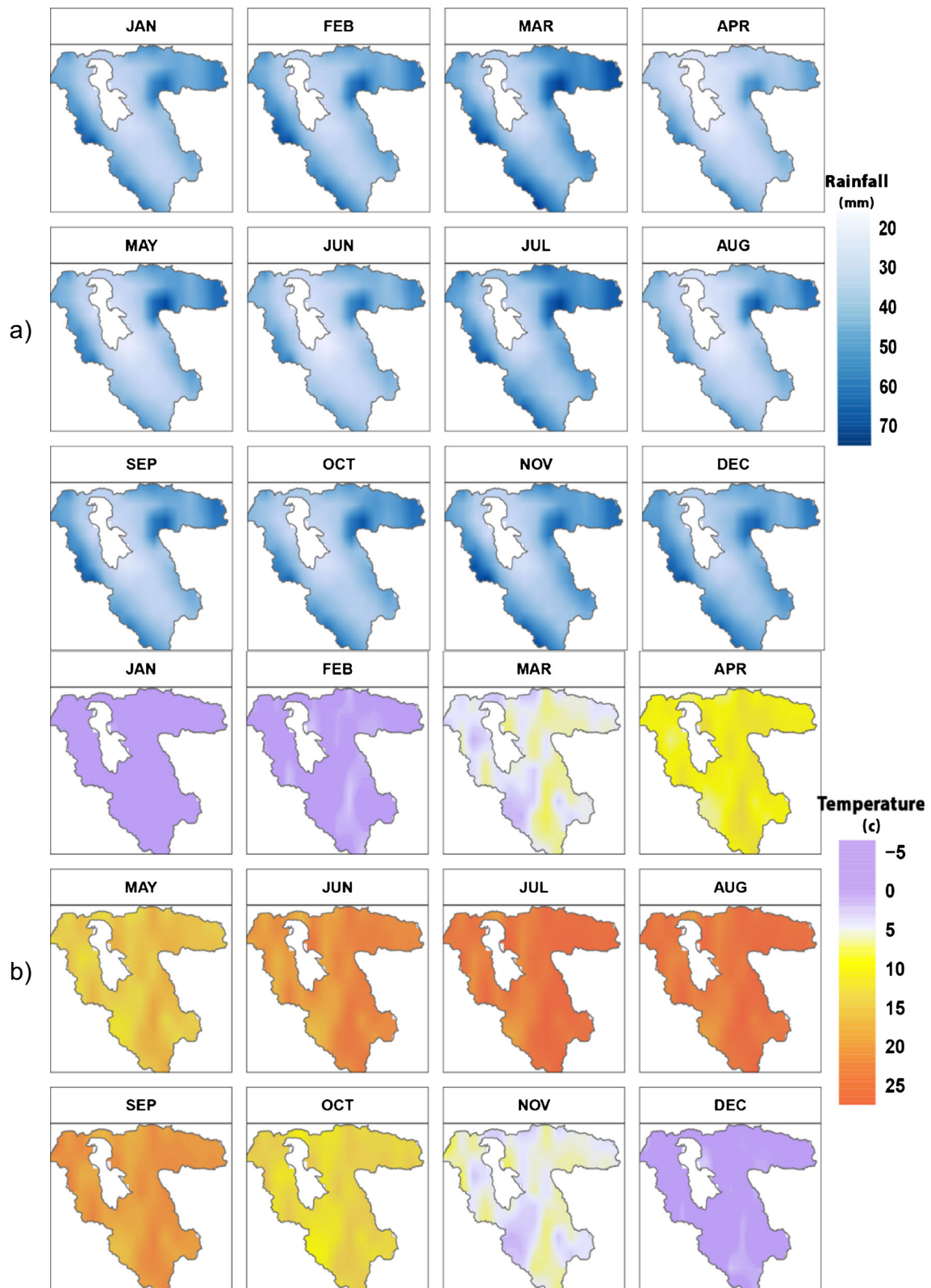
Figure 3 Spatial and temporal patterns of monthly mean: **a** precipitation in mm, **b** temperature in °C, **c** soil moisture in different depth 0–10 cm, **d** 10–40cm in m^3 m^{-3}, and **e** NDVI 2001–2018.
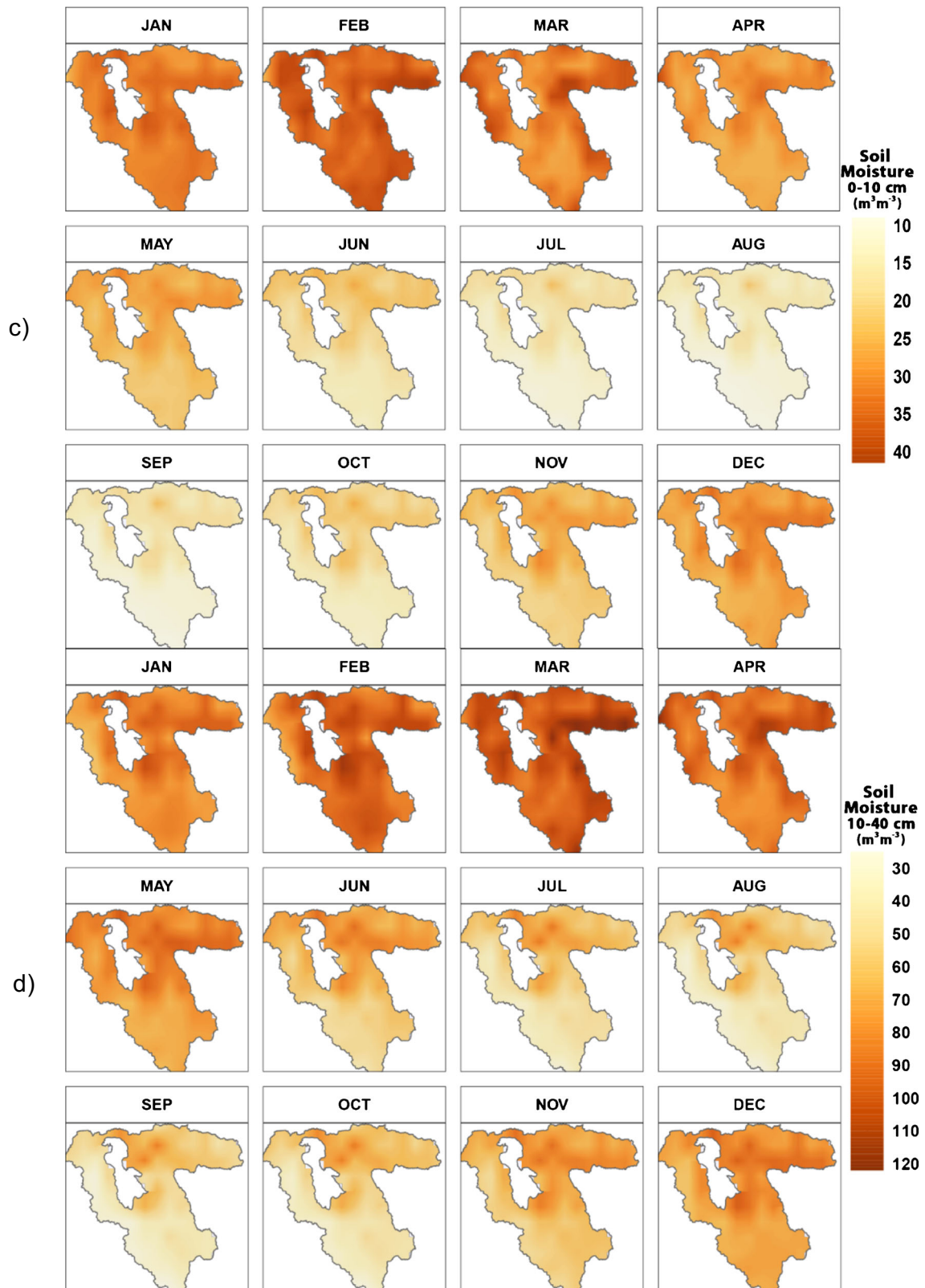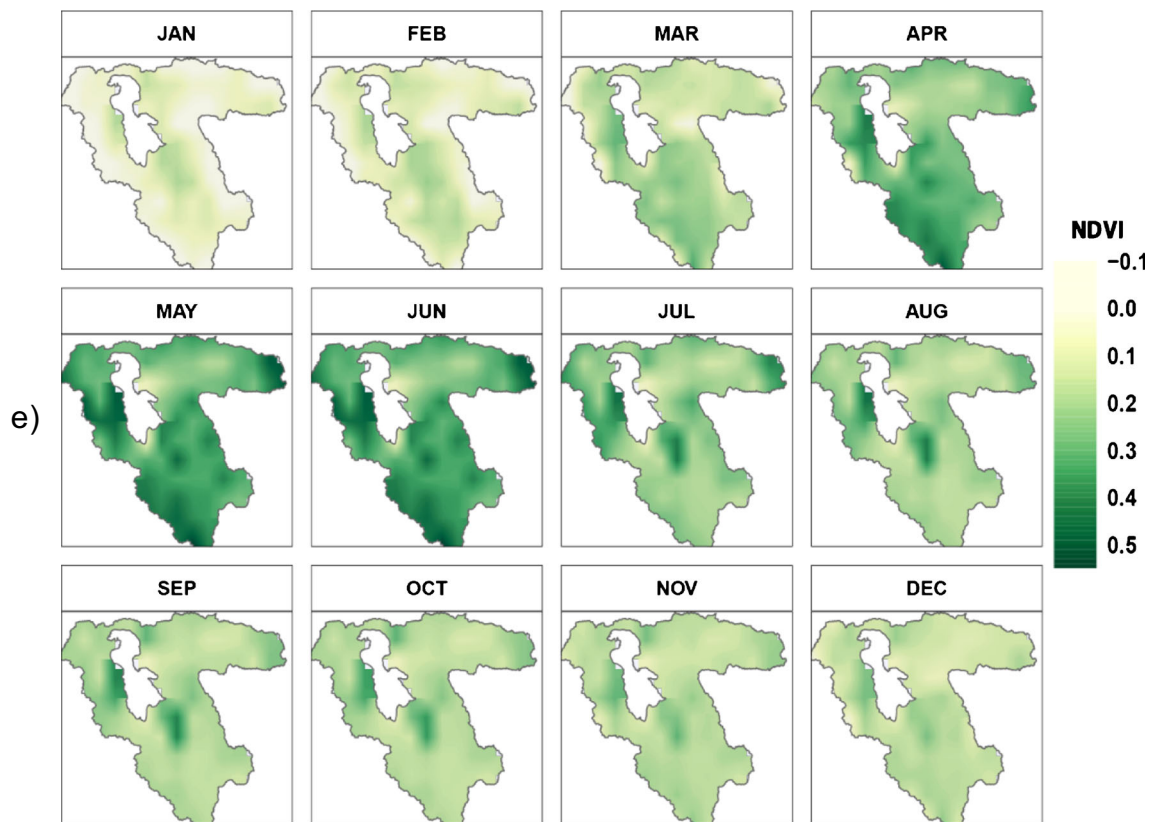
Fig. 3 continued.

Fig. 3 continued.

shows the monthly and seasonal trends of NDVI. Generally, NDVI trends same as temperature and precipitation are slight approximately in most months, except April.

Regarding trends in the NDVI series, the tendency to an upward trend in April, May, June, and July is more extreme, and a slightly increasing trend is shown in other months. Chen et al. have reported a slight upward trend in the NDVI time series. 2014 as a result of research in the arid land of Australia. The seasonal trend pattern shows that seasonal trends of NDVI did not changed and are similar to those reported earlier for temperature.

## Effects of precipitation, temperature, and vegetation on soil moisture and time-lagged effects

Statistical correlation of precipitation and soil moisture

Figure 5 a displays Pearson's correlation for mean soil moisture in 0–10cm and 10–40cm depth and mean precipitation in the study area. The spatial distribution of soil moisture-precipitation correlation ranges from −0.2 to +0.1 and shows a pattern of negative to positive correlations in different altitude regions in the study area. The effect of precipitation on soil moisture is predominantly positive in mid-elevation and low-elevation areas in direction mode, and mildly positive

correlations around 0.1 occurred in the depth of 0–10 cm, which explains that the effect of rainfall on soil moisture is not dominant, especially at depths (10–40). In the mode of time-lagged, the correlation between precipitation and soil moisture with time-lagged of 1 or 2 months has been investigated. In 1-month time-lagged, the positive correlations considered in the depth of 0–10 and the number of gridded that show moderate correlations in depth of 10–40 decreased. In a 2-month lagged time mode, the correlation coefficient in depth of 10–40 declines. Results show that 0–10 cm soil moisture is affected directly by precipitation, and a negative correlation occurs predominantly in 2 months lagged precipitation. In the depth of 10–40cm, the effects of precipitation decrease by increasing lagged though in 2-month lagged time. Positive correlations are more potent than the depth of 0–10 due to water infiltration conditions and affect soil moisture. Overall, it resulted in the effect of precipitation on soil moisture that is weak. Some studies had a comparative result and mildly positive and negative relationships have been reported between precipitation and soil moisture (Yang et al. 2018).

Statistical correlation of temperature and soil moisture

The various correlation strengths of the soil moisture in 0–10cm and 10–40cm depth with temperature are given in
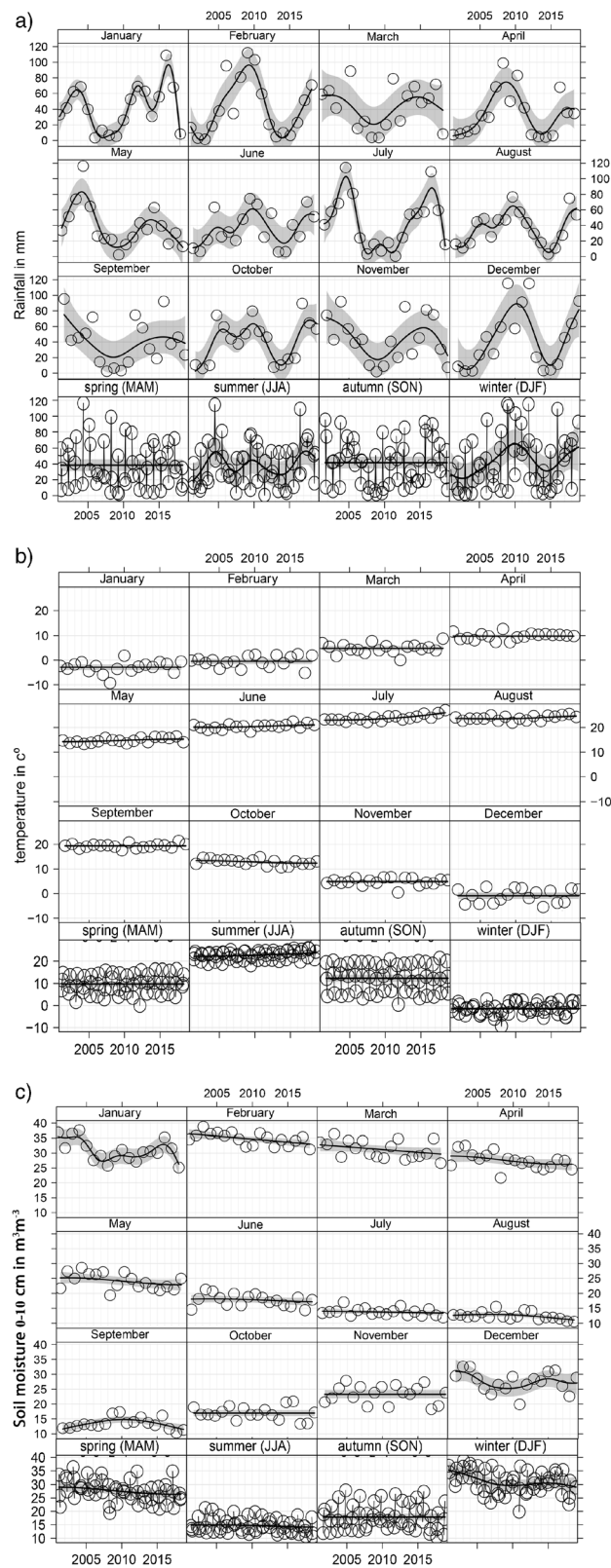
Figure 4 Monthly and seasonal trend of **a** precipitation, **b** temperature, **c** soil moisture 0–10cm, **d** soil moisture 10–40cm, and **e** NDVI 2001–2018, significant at *P*<0.001 level
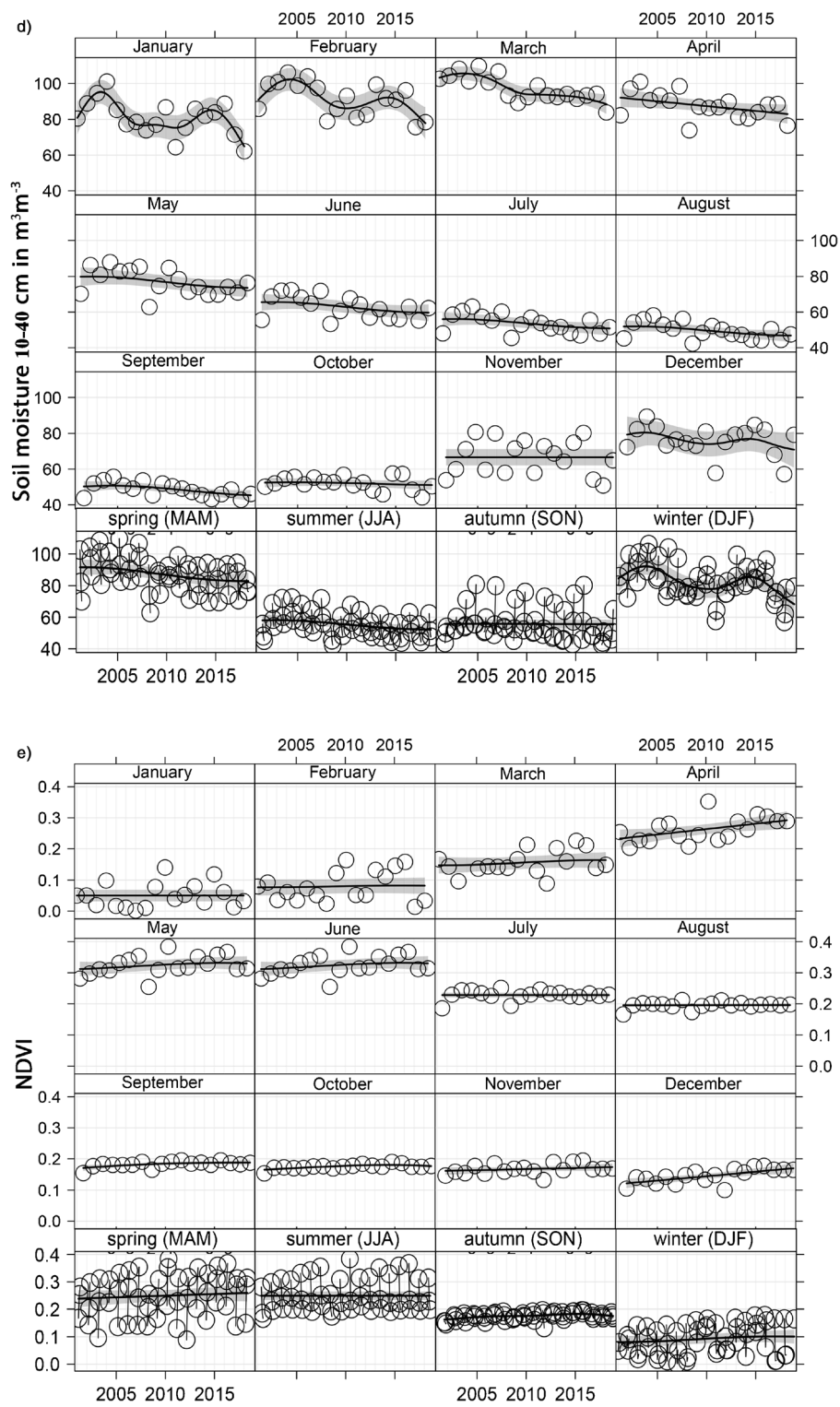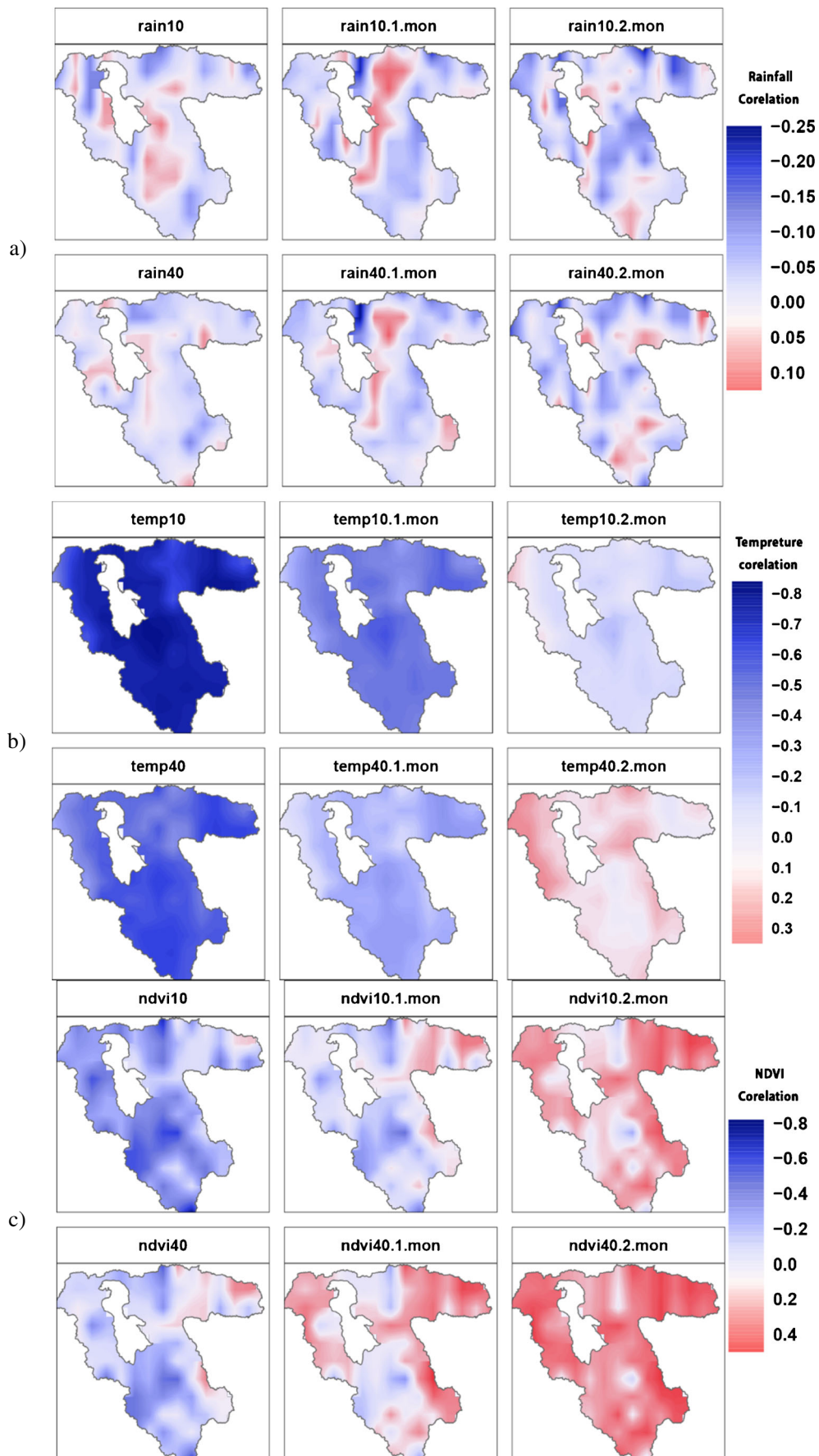
Fig. 4 continued.

◀ **Figure 5** Spatial pattern of Pearson correlation: **a** precipitation and soil moisture 0–10 and 10–40, **b** temperature and soil moisture 0–10 and 10–40, and **c** NDVI and soil moisture 0–10 and 10–40 bottom. Panel left, no-lagged; panel middle, 1 month lagged; and panel right, 2 months lagged. The P values are significant in < 0.01.

Figure 5b. The correlation exhibits that the soil moisture and temperature are correlated very weak to moderate in different time-lagged modes and different depths. Direct correlation between temperature and soil moisture shows bad effects of temperature on soil moisture. It means that the sensitivity of soil moisture is weak into the change of temperature in the mode of 0-month lagged time. In other words, the highest negative relationship between soil moisture and an average temperature of 2 m was observed at 0–10 m depth. In this mode, the negative correlation decreases in depth of 10–40. Also, lagged time effects of temperature on soil moisture show which 1-month and 2-month antecedent temperatures have been affected on soil moisture insufficient to moderate in the study area. Increasing the time delay to 1 month increases the amplitude of temperature impact at both depths. By increasing the time delay to 2 months, the effect rose again, and the correlation increased. Also, the extreme correlation was considered in the evaluation relation of temperatures with soil moisture in different depths in a region of China by Wang et al. (2018).

## Statistical correlation of NDVI and soil moisture

The average correlation coefficient of NDVI and soil moisture over the study period is shown in Figure 5c. The different patterns of correlation of NDVI and soil moisture in various time-lagged suggested that vegetation has a considerable influence on soil moisture in lagged time and from the surface to deep. Chen et al. (2014) note this relation. This figure reveals that vegetations are positively correlated to soil moisture at different time lags. The number of grid points that show a positive correlation increased by extending ranges of lagged time from 1 to 2 months. Yang et al. (2018) mention the effect of vegetation on soil moisture

Responses of soil moisture to climate change

The same as other regions in the world, the Urmia Lake basin is affected by climate change, and the hydrological cycle has accelerated. Many studies conclude that by climate change effects, precipitation reduced, and temperatures increased in this basin. The change in two main climatic parameters suggested that soil moisture is influenced. As the trends investigated in Figure 4, a slightly decreasing trend in precipitation and soil moisture has been observed, and air temperature exhibits a slightly increasing trend in the whole study period.
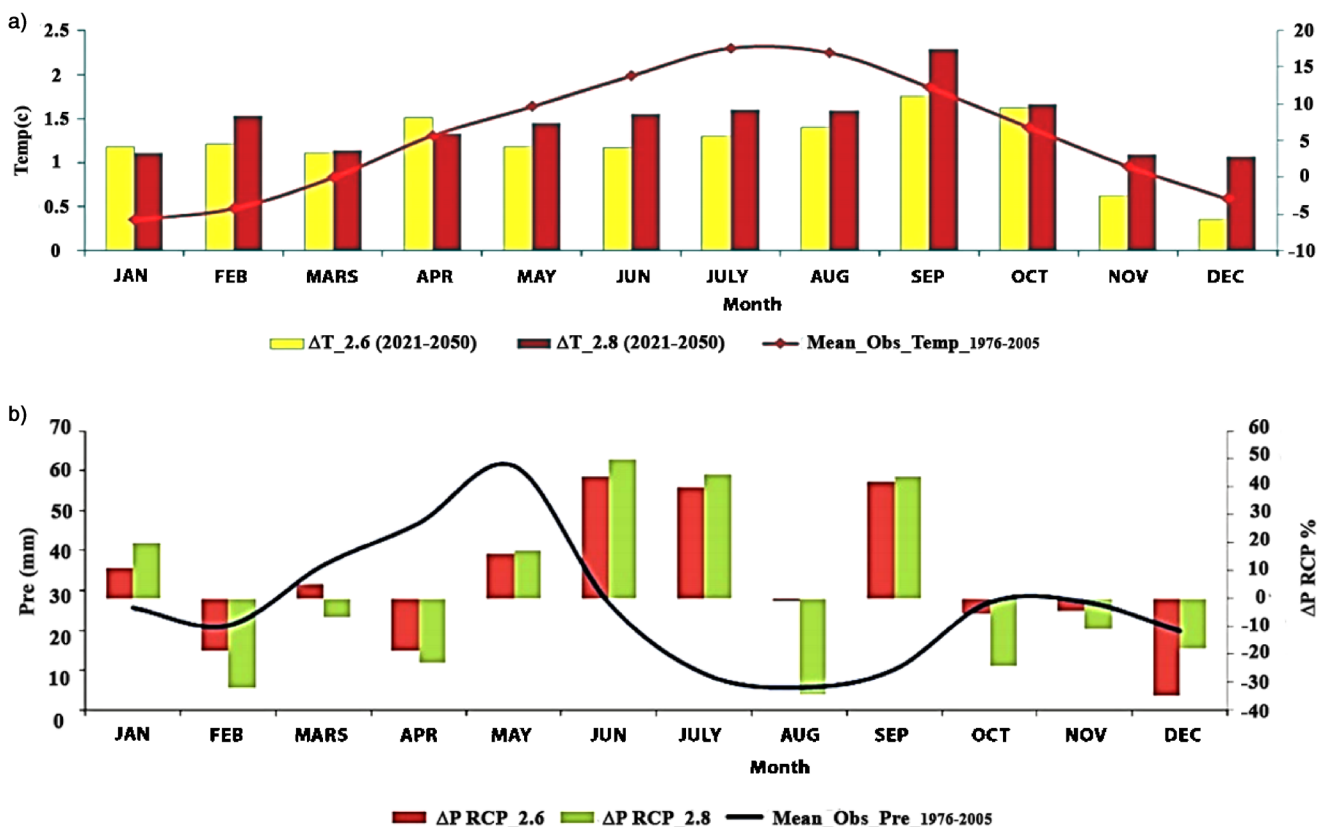
Figure 6 Monthly distribution of observational data and future change scenario of temperature (**a**) and precipitation in percentage (**b**) for different RCPs, the 2050s.
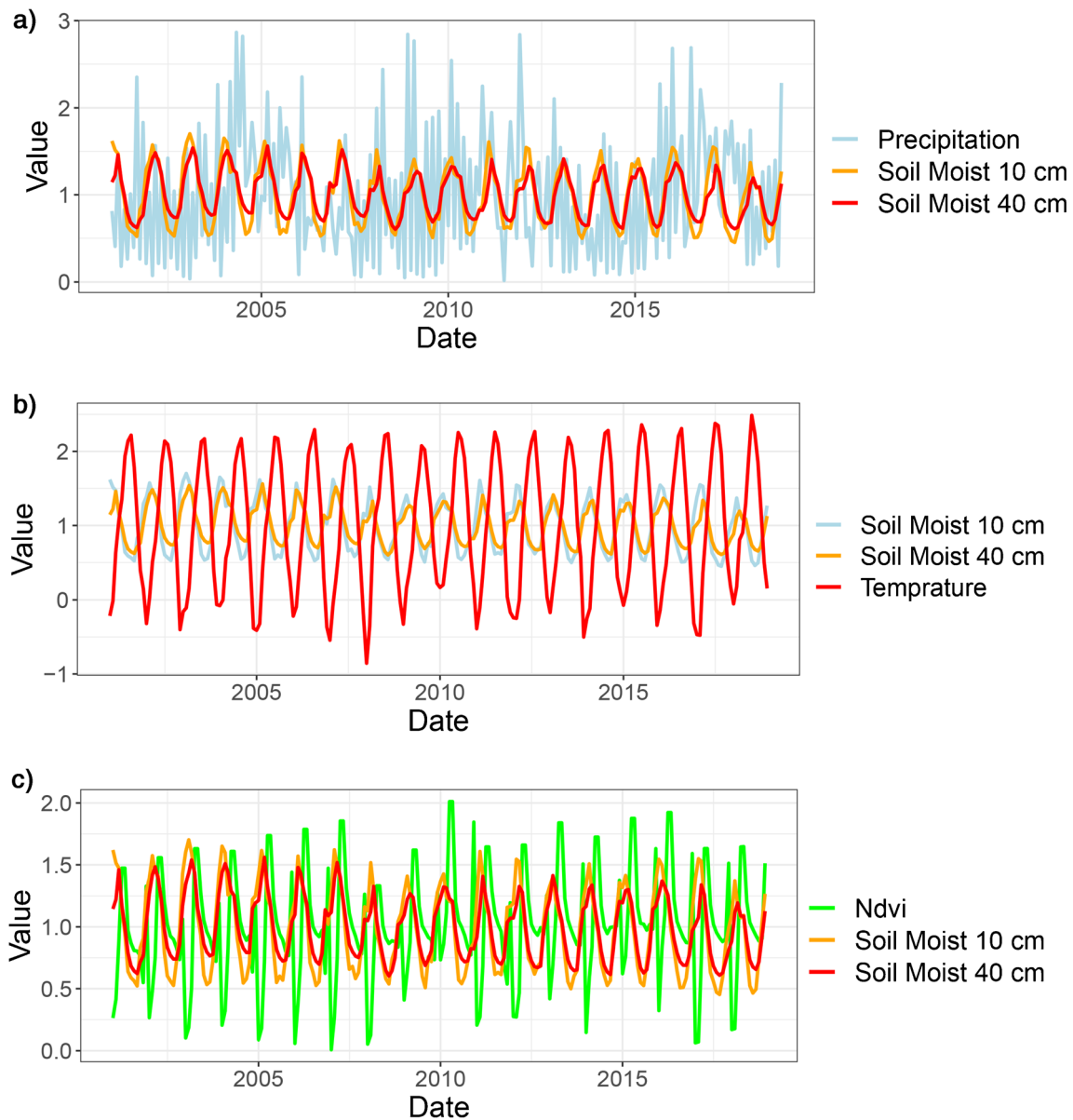
Figure 7 Time series of climatic variable

According to Figure 5b, in none-lagged time mode, air temperature and soil moisture showed negative coupling, but the positive coupling is considerable in the lagged time mode. This reinforces the possibility that soil moisture decline is affected by temperature raising and the slight changing precipitation. The results of future temperature and precipitation prediction under the representative concentration pathway (RCP) 2.6 and 8.5 scenarios by CMIP5-AOGCM (Coupled Model Intercomparison Project Phase5- Atmosphere-Ocean General Circulation Model) ensemble model CSIRO-Mk3-6-0, CCSM4, and HadGEM2-ES the 2050s are shown in Figure 6. This figure reveals a slightly decreasing trend in precipitation and an increasing trend in temperature for the basin over future periods. Since the precipitation change in the future is not very big (Figure 6b) and its effect on soil

moisture is weak by the result of this research, it may be statistically pointless to investigate the future effects. However, as a result, the Urmia Lake basin will experience a decrease in soil moisture, resulting from the increase in temperature.

Discussion

Hydroclimate parameters are varying regionally and are in complex interaction together. Hence the investigation of the change and relation of precipitation, temperature, and NDVI against soil moisture may help explain the water cycle of the study area. Since the study area is one of the momentous regions of water resources management in Iran and always

was studied in different terrestrial sectors in recent years. However, soil moisture changes and the relationship between soil moisture and other climate parameters were less has considered. So, in this research, it is attempted to the assessment of the role of change in climatic variables and NDVI on soil moisture and investigate the correlation of soil moisture time series of GLDAS data at 0–10cm and 10–40cm with precipitation, temperature, and NDVI index over recent 2 decades. Based on scientific literature, GLDAS as a reanalysis soil moisture dataset generally is associated with uncertainty, but in some areas, the observed data of soil moisture is rare, is helpful, and is useful to help to investigate the correlation of soil moisture with climate variable (Cia et al., 2017). In order to calculate both the Mann-Kendal test as a non-parametric test and Pearson coloration and their significances across the study area, ERA-5 reanalysis data products (monthly temperature and precipitation) of ECMWF are used for coherent regional coverage. At first, the performance of ERA-5 reanalysis data products was evaluated against rain gauge data over the Urmia Lake basin from 2001 to 2018. The performance ERA-5 reanalysis datasets were significant and suggested that ERA-5 is applied to study gridded precipitation and temperature in the Urmia Lake basin.

The trend analysis indicated that a downward trend of monthly soil moisture is more robust than a slight monthly precipitation trend. The significant upward trend in monthly temperature exhibited an increase in temperature in the warm month. Also, the upward trend of NDVI is represented in April to July (growing season), and in other months, NDVI

trend is slight. The investigation correlation coefficient of mean monthly temperature, NDVI, and soil moisture showed that the correlation coefficient of precipitation is not as strong as others. The role of temperature on soil moisture distribution and the amount is more vital than precipitation. The effects of temperature increasingly become strong by the increasing time lag. This pattern was reported by Barlow et al. (2016).

The precipitation and surface soil moisture (0–10) correlation goes more negative by increasing lagged time. Inversely, positive correlations are more by increasing lagged time and increasing deep soil moisture(10–40cm). Overall, precipitation usually influences intense soil moisture (10–40cm) by the time lag, and its effects are extended in surface soil moisture in a short time. Time series change of GLDAS soil moisture and precipitation (Figure 7a) also shows that increases in soil moisture concur with precipitation increases. However, increases in intense soil moisture do not coincide with precipitation, which agrees with the correlation result. This result is in contrast to the impacts of temperature on soil moisture. Figure 7 b reveals a pattern of where temperature rises soil moisture drop. Though, in some areas, such as the arid region and semi-arid regions such as China, precipitation efficiency is more notable than the temperature (Yunqian Wang et al. 2019). The coldness of our study area may cause this contradiction. In the Urmia Lake basin, most precipitation occurs during the cold months, so the effect of temperature on soil moisture levels increases and partly strengthens precipitation. An enormous time lag pattern is seen in NDVI and soil moisture in Figure 7c, which is in harmony with them. This result

Figure 8 Summary of Pearson correlation coefficients between soil moisture and climatic indices in straight months, one lagged month, and two lagged months.
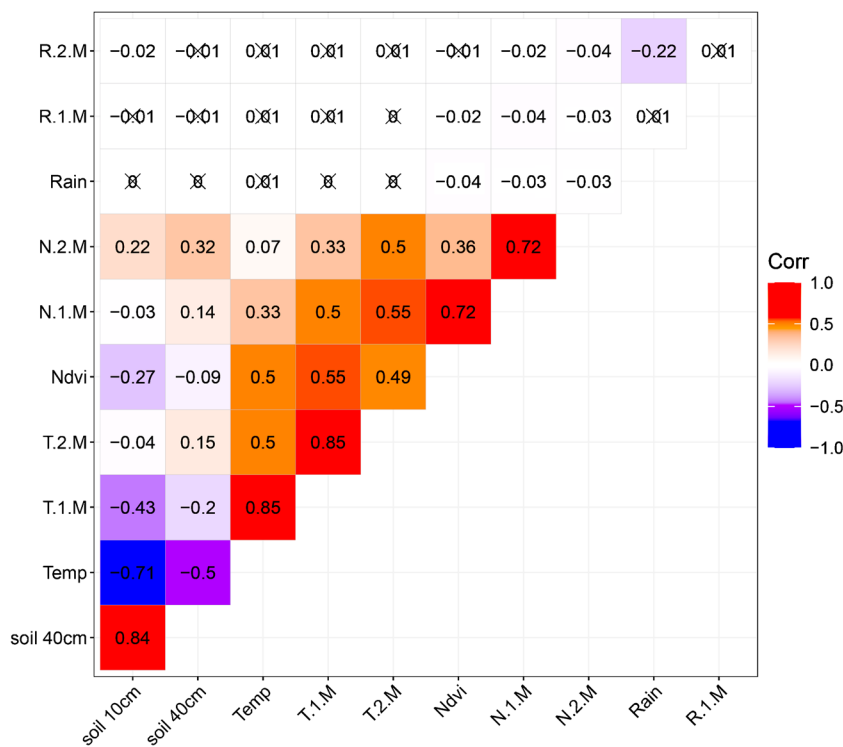
shows that soil moisture is so sensitive to climate variables, and the change of these climatic parameters affects soil moisture as a critical element of the water cycle. Figure 8 shows a significant matrix which reveals soil moisture is significantly correlated with temperature and NDVI in a different time lag. It is noted that the correlation of precipitation with soil moisture is not significant.

Conclusions

In this research, the GLDAS Noah soil moisture dataset was used to study the response of soil moisture to climatic variables and NDVI on the Urmia Lake basin and investigate the changes of soil moisture under climate change. According to the result derived from this work, (1) spatial distribution of soil moisture is similar to precipitation, and the soil moisture displayed a specific monthly pattern, from December to March. (2) Investigating the trends analysis showed monthly precipitation not accompanied by a significant trend. The soil moisture trend in most of the month was decreasing slightly. The upward trend is considered in summer, and temperature and NDVI have been slightly rising for some months. (3) The statistical correlation shows that temperature positively affected cold months and adverse effects in a warm month on soil moisture. Moreover, the temperature played a more critical role than precipitation in soil moisture distribution within the study area. Investigation of future climate showed by increasing temperature affected future soil moisture. According to the result of the CMIP5 ensemble, soil moisture will be influenced by the change of the future temperature. The relation of soil moisture with precipitation, temperature, and NDVI showed less resilience to climate change. Hence, soil moisture will change as a potential factor of water resources in the future, influencing water balance and water resource management policies and planning the study region that needs more attention.

Data Availability The datasets analyzed during the current study are available in the ERA-5-ECMWF dataset repository (ERA-5|ECMWF), and stationary data are available in IRIMO and NASA Global Land Data Assimilation System (GLDAS).

Code availability The software was used in this study was R, which has been using as a programming language and free software for statistical computing and graphics.

Declarations

Ethics approval 1) This material is the authors' original work, which has not been previously published elsewhere.

2) The paper is not currently being considered for publication elsewhere.

3) The paper reflects the authors' research and analysis wholly and truthfully.

4) The paper properly credits the meaningful contributions of co-authors and co-researchers.

5) The results are appropriately placed in the context of prior and existing research.

6) All sources used are correctly disclosed (correct citation). Copying of text must be indicated as such by using quotation marks and giving proper reference.

(Chen et al. 2014) All authors have been personally and actively involved in substantial work leading to the paper and will take public responsibility for its content.

The violation of the ethical statement rules may result in severe consequences.

I agree with the above statements and declare that this submission follows Solid-State Ionics' policies outlined in the guide for authors and the ethical statement.

Consent to participate I am a corresponding author; on behalf of the other authors, I declare that we are satisfied with participating in the research.

Consent for publication I am a corresponding author; on behalf of the other authors, I declare that we are pleased to publish this valuable journal research.

Conflict of interest The authors declare no competing interests.

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