



Long-term spatiotemporal variations in satellite-based soil moisture and vegetation indices over Iran

Elham Fakharizadehshirazi^{1,2} · Ali Akbar Sabziparvar² · Sahar Sodoudi¹

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Abstract

Soil moisture plays a crucial role in vegetation growth. However, the long-term influence of soil moisture on vegetation growth was not sufficiently understood in many regions, especially in developing countries, due to the lack of ground measurements. Remote sensing data provide a promising way to overcome this limitation. In this study, a long-term spatiotemporal variation in remote sensing surface soil moisture (SSM) and vegetation indices (VIs) and their relationship during 1988–2015 were analyzed over Iran. Trend-free pre-whitening Mann–Kendall test was applied for the detection of the trends in soil moisture and VIs time series. Also, the validity of the “dry gets drier, wet gets wetter” (DGDWGW) paradigm was examined throughout the country. Finally, the consistency between SSM and vegetation indices trends was investigated using homogeneity Chi-squared test. The results showed that the monthly average of the SSM over 45% of Iran is lower than $0.15 \text{ m}^3/\text{m}^3$. Seasonal average of SSM is 0.17 and $0.12 \text{ m}^3/\text{m}^3$ in spring and winter, respectively. On average, monthly SSM trends are downward in 70% of Iran, which 30% of those is statistically significant. Over the past 28 years, about 50% and 35% of Iran got drier with rates of 0.24×10^{-2} (spring) and 0.78×10^{-3} (summer) m^3/m^3 per year. According to DGDWGW paradigm examining, 14% of Iran follows the DGDWGW paradigm. Summer and spring normalized difference vegetation index (NDVI) and enhanced vegetation index values are less than 0.1 in about 45% and 65% of the areas, respectively. The NDVI values are decreased in 40% of Iran in the last 28 years, of which half of those are statistically significant. SSM trends were consistent with vegetation indices using a homogeneity test. About 45% of SSM trends agree in sign with NDVI values. Life zone in the Southeast of Iran is arid desert scrubs, and in this area with sparse vegetation cover, mixing the spectral of soil and vegetation causes a serious problem in vegetation indices representing therefore the prominent mismatch between SSM and vegetation indices trends which were observed in Southeast of Iran.

Keywords Soil moisture · Normalized difference vegetation index · Remote sensing · Nonparametric · Mann–Kendall test · Trend-free pre-whitening

Introduction

Soil moisture plays a significant role to control the interactions of the hydrosphere, biosphere, and atmosphere (Li et al. 2016a; Wagner et al. 1999). This important water storage component has a direct influence on plants, animals, and microorganisms (Li et al. 2015) and plays a major role in exchanging energy between the air and the soil (Li et al.

2014; Li et al. 2017). It also affects surface albedo (Sugathan et al. 2014), soil temperature regime (Lehnert 2014), plants growth (Wagner et al. 2003), and vegetation restoration (Brevik et al. 2015; Li et al. 2016b; Niu et al. 2015; Yu et al. 2015). Also, soil moisture information as a proportionate factor can be considered as a reliable index for monitoring agricultural quality and yield anomalies (Dorigo et al. 2015).

Due to the importance of soil moisture analysis, many researchers investigated the changes in soil moisture patterns based on different datasets, i.e., reanalysis data (Albergel et al. 2013; Sheffield and Wood 2008; Wilson 2013; Zhu and Lettenmaier 2007), satellite data (Dorigo et al. 2012; Feng and Zhang 2015; Kuenzer et al. 2008; Liu et al. 2012; Wagner et al. 2014), and in situ observation (Robock et al. 2005). In many regions without reliable

✉ Ali Akbar Sabziparvar
swsabzi@basu.ac.ir

¹ Department of Earth Science, Institute of Meteorology, Freie Universität Berlin, Berlin, Germany

² Water Engineering Department, Faculty of Agriculture, Bu Ali-Sina University, Hamedan, Iran

in situ observation of soil moisture, remotely sensed datasets are useful tools to assess soil moisture and their changes over large areas (Jiao et al. 2016). Prior to the availability of global satellite-based soil moisture datasets, it is difficult to conduct a long-term evaluation due to the lack of ground measurement soil moisture data. The climate change initiative (CCI) soil moisture dataset of the European Space Agency (ESA) is the longest satellite-based soil moisture dataset that has been recently used in many studies (e.g., An et al. 2016; Li et al. 2015; Wang et al. 2016; Zheng et al. 2016). Rahmani et al. (2016) analyzed the soil moisture over a time series throughout Iran by using ESA CCI satellite and reanalysis data.

In recent decades, significant drying or wetting trends were observed in many regions, which caused serious social, ecological, and environment difficulty (Change 2007; Chou et al. 2013; Dai 2011; Dai 2013; Donat et al. 2016; Feng 2016; Greve et al. 2014). The “dry gets drier, wet gets wetter” (DGDWGW) paradigm has been confirmed in a global moisture trend analysis (Cayan et al. 2010; Chou et al. 2009, 2013; Feng and Zhang 2015; Liu and Allan 2013). Feng and Zhang (2015) studied the global moisture trends by using satellite soil moisture over the past 28 years (1989–2015) and showed that only 15.12% of the land areas followed the DGDWGW paradigm, whereas 7.8% followed the opposite pattern. Greve et al. (2014) found that only 10.8% of the global land surface adapted to DGDWGW pattern and 9.5% followed the opposite pattern.

In semiarid regions, soil moisture decreasing has a negative effect on vegetation growth (Zribi et al. 2010). Positive relationships between soil moisture and vegetation indices (VIs) were found in Senegal (Cissé et al. 2016), China (Wang et al. 2016, 2017), Australia (Chen et al. 2014; Liu et al. 2017), East Africa (McNally et al. 2016; Wu et al. 2016), African Sahel (Ahmed et al. 2017), Ukraine (Ghazaryan et al. 2016), and Sub-Saharan and Southern Africa (Jamali et al. 2011). However, in some water-limited regions despite the negative soil moisture trends, no corresponding trend in normalized difference vegetation index (NDVI) was found (Dorigo et al. 2012). The positive relation between soil moisture and vegetation is controlled by the vegetation type and vegetation density (Feng 2016; McNally et al. 2016). Stranger correlation was found between soil moisture and NDVI in densely vegetated areas in East Africa in comparison with sparsely vegetated areas (McNally et al. 2016). Also, Huber et al. (2011), Davidson et al. (2012) and Mapa (1995) claimed that vegetation has a negative effect on soil moisture trend in dry and low-density vegetated regions and has a positive effect in wet and high-density vegetated regions. Evapotranspiration causes these effects. Expansion of vegetation increases evapotranspiration in drylands that mitigates soil moisture, but in wet and high-density vegetated regions, vegetation stores a higher quantity of rain in

soil compensating for the consumption of evapotranspiration water.

Iran is located in the arid and semiarid region, and evaluation of soil moisture and vegetation variations is a very important issue due to the shortage of water. Unfortunately, a detailed investigation of factors affecting soil moisture has not been reported so far. This work is aimed to detect the trend of surface soil moisture (SSM) to find out how it might affect vegetation indices over Iran.

In this research, which is based on satellite datasets, the geographical distribution of SSM and VIs was depicted throughout Iran and the long-term spatiotemporal patterns of SSM and VIs trends were analyzed, and then, the SSM trend is compared over the same period in VI trends in order to examine their consistencies. DGDWGW paradigm was also calculated to find the SSM trend pattern in semiarid and wet regions throughout Iran. The other goal of this research is to determine the performance of ESA CCI soil moisture and VIs in semiarid areas. ESA CCI soil moisture data were widely used globally, but few in Iran. Two VIs [NDVI and enhanced vegetation index (EVI)] were applied in the present study. The NDVI is the longest VIs datasets available. However, it is highly sensitive to soil background and atmospheric effects, while the EVI is much less sensitive to them.

Materials and methods

Study area

Iran with an area of 1,648,195 km² is located between the latitudes of 25° and 40°N and the longitudes of 44° and 62°E (Fig. 1). The Alborz and Zagros mountain ranges are stretched in the North and West of Iran (Mahmoudi 2014). There are two salted flat deserts in Iran: the Dasht-e Kavir

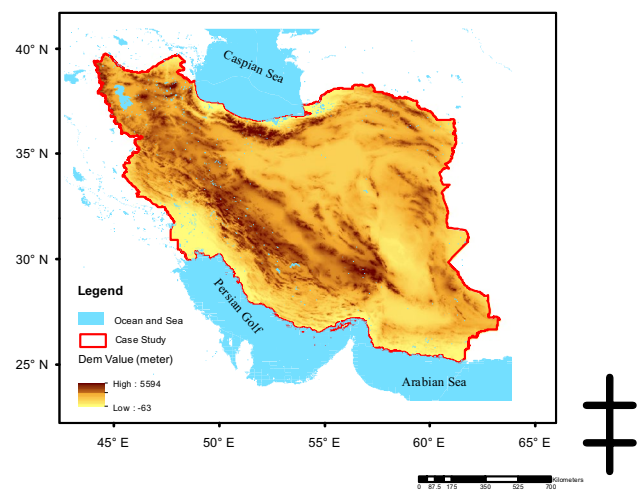


Fig. 1 Geographical location of study area

in Central Iran and the Dasht-e Lut in the East. Iran is surrounded by the Caspian Sea in the North and Persian Gulf and Oman Sea in the South. The long-term average of annual precipitation throughout Iran is 250 mm, varying between 50 mm in the desert and 1600 mm on the Caspian coast. Minimum and maximum temperatures of Iran are -20 to $+50$ °C, respectively (Araghi et al. 2015). The low precipitation and high temperature in most regions of Iran are due to the correspondence of arid and semiarid climate over 80% of its area.

Iran contains six main life zones including Hyrcanian humid forests, Zagros semiarid and humid forests, humid grasslands, semiarid scrub grasslands, arid desert scrubs, and arid desert. The widest zone is arid desert scrubs, which are located in the Central, East, and Southeast part of Iran. Hyrcanian humid forest is found in the South of the Caspian Sea (Sanjerehei 2014). Large parts of Iran are dominated by Irano-Turanian floristic elements phytogeographically (Akhani et al. 2013). Based on physiognomic types, most parts of Iran (35%) are covered by desert life zone which includes scrub (30.4%), steppe (18.7%), forest (10.2%), woodland (5.6%), and tundra (0.14%) life zones (Sanjerehei 2014).

Datasets

Soil moisture

The European Space Agency Climate Change Initiative Soil Moisture (ESA CCI SM, v04.3) data at the spatial resolution of 25 km were produced by combining active and passive microwave satellite observations. The active dataset was produced by the University of Vienna, based on the observations from the C-band scatter meter on board the European Remote Sensing Satellites (ERS-1 and ERS-2) and the Meteorological Operational Satellite (MetOp—A). The passive dataset was produced by the Vrije University Amsterdam in collaboration with NASA, which was based on the observations from the scanning multichannel microwave radiometer (SMMR), the special sensor microwave/image (SSM/I), the tropical rainfall measuring mission microwave imager (TRMM TMI), and the advanced microwave scanning radiometer—earth observing system (AMSR-E) (Feng and Zhang 2015). In the present study, ESA surface soil moisture data from 1988 to 2015 were analyzed on a monthly and seasonal scale, i.e., spring (March, April, and May; MAM) and summer (Jun, July, August; JJA).

Vegetation indices (VI) dataset

Two satellite NDVI sources [global inventory monitoring and modeling system (GMMS) and moderate resolution imaging spectroradiometer (MODIS)] and MODIS-EVI

were applied to investigate vegetation changes over Iran. The GIMMS NDVI dataset version 3gv₁ which was derived from NOAA AVHRR (advanced very high resolution radiometer) data (Pinzon and Tucker 2014) at a resolution of 8 km from 1988 to 2015 and the MODIS NDVI and EVI at a resolution of 0.05-degree from 2000 to 2015 was applied. MODIS vegetation indices are monthly (MOD13C2, V006) product in which the MOD13A2 product (1 km) is used to produce these monthly vegetating indices products (Didan 2015). The spring and summer VIs time series were calculated by averaging the observations within these seasons.

Trend analysis

In this study, a nonparametric Mann–Kendall test, which has been widely used in detecting climate time series trends [e.g., (Liu et al. 2011; Sheffield and Wood 2008)], was applied to do trend analysis. It should be noted that in order to mitigate the effect of serial correlation on the Mann–Kendall test, trend-free pre-whitening (TFPW) which was proposed by Yue et al. (2002) was considered. In addition, the Thiel–Sen method was applied for determining the slope value of the significant trends.

Mann–Kendall test (MK test)

In this research, a rank nonparametric test developed by Mann (1945) and Kendall (1975) was used. To detect linear or nonlinear trends, the MK test is superior (Hisdal et al. 2001; Wu et al. 2008). In this test, the null hypothesis(H_0) is nonexistence and alternative hypothesis (H_1) is the existence of a trend in the time series. The MK test statistic s and the standardized test statistic Z_{MK} are calculated as follows:

$$s = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(X_j - X_i) \tag{1}$$

$$\text{var}(s) = 1/18 \left(n(n-1)(2n+5) - \sum_{i=1}^m t(t-1)(2t-5) \right) \quad \text{if } x > 10 \tag{2}$$

$$\begin{cases} Z = \frac{s-1}{\sqrt{\text{var}(s)}} & \text{if } s > 0 \\ Z = 0 & \text{if } s = 0 \\ Z = \frac{s+1}{\sqrt{\text{var}(s)}} & \text{if } s < 0 \end{cases} \tag{3}$$

where X_j and X_k are the sequential data values of the time series in the years j and k , n is the size of the time series, t is the number of ties, and m is the number of tied values. Positive and negative values of Z_{MK} indicate increasing and decreasing trends, respectively.

If $|Z| \leq Z_{\alpha/2}$, the null hypothesis is rejected and it means a significant trend exists in the time series. For 10% significant level, the value of $Z_{\alpha/2}$ is equal to 1.68.

Thiel–Sen slope

Thiel–Sen slope (Sen 1968; Thiel 1950) is proposed for estimating the magnitude of the slope of the trend of the MK test. This slope is calculated as follows:

$$\beta = \text{Median} \left[\frac{X_j - X_i}{j - i} \right] \quad \text{for each } i < j \quad (4)$$

where β is the estimated magnitude of the trend slope.

TFPW method

The data must be independent to apply the nonparametric tests. Serial correlation leads to an increase in the probability of significant trend detection and the rejection of the null hypothesis, while the null hypothesis is actually true. Therefore, the lag-one autoregressive serial correlation was calculated and the pre-whitening procedure was used to remove significant autocorrelation from a time series by means of the trend-free pre-whitening or TFPW procedure. The TFPW procedure provides a better performance to identify the significance of the trends for autocorrelated data than the other methods (Yue et al. 2003, 2002; Zhang and Lu 2009). In this research, before applying the MK test, the TFPW procedure was used to the SSM and VIs time series with significant autocorrelation (at 10% significant level) to remove the effect of serial correlation. The trend-free pre-whitening Mann–Kendall (TFPW-MK) procedure has four steps as follows:

Step 1: Removing the trend from the series (x_i) with the assumption of linearity as:

$$x'_i = x_i - (\beta \times i) \quad (5)$$

where β is Sen—Slope.

Step 2: Using pre-whitening to remove the autoregression process (AR) from the de-trended series (x'_i) as:

$$y'_i = x'_i - r_1 \times x'_{i-1} \quad (6)$$

where r_1 is the lag-1 serial correlation coefficient.

Step 3: Combining the removed trend (x'_i) and the residual (y'_i) series as:

$$y_i = y'_i + x'_i \quad (7)$$

Step 4: Finally, the MK test was used to blended series (y_i) to assess the significance of the trend.

DGDWGW paradigm

To find the soil moisture trend pattern in arid and wet regions, the DGDWGW paradigm (Feng and Zhang 2015) was calculated as follows:

$$\text{DGDWGW} = \frac{S_{\text{drierdry}} + S_{\text{weterwet}}}{S_{\text{land}}} \quad (8)$$

where S_{drierdry} and S_{weterwet} are areas of drier in dry regions and wetter in wet regions, respectively, and S_{land} is the whole area of the study. In this study, the areas with average monthly SSM equal and less than $0.15 \text{ m}^3/\text{m}^3$ were treated as drylands.

Consistency between SSM and VIs trends

To test consistency between SSM and VIs trends, homogeneity Chi-squared (χ^2_{homog}) statistic was applied (Gilbert 1987).

$$\chi^2_{\text{homog}} = \chi^2_{\text{total}} - \chi^2_{\text{trend}} = \sum_{j=1}^M Z_j^2 - M\bar{Z}^2 \quad (9)$$

$$Z_j = \frac{S_j}{[\text{var}(S_j)]^{1/2}} \quad (10)$$

$$\bar{Z} = \frac{1}{M} \sum_{j=1}^M Z_j \quad (11)$$

S_j is the Mann–Kendall trend statistic for j th variable (SSM and VI). M is the number of variables. χ^2_{homog} has a Chi-squared distribution with $M - 1$ degrees of freedom (df).

In case χ^2_{homog} exceeded the critical value for the Chi-squared distribution with $M - 1$ freedom degree, the null hypothesis, H_0 , of homogeneous trends over time (trends in the same direction and of the same magnitude) was rejected. In that case, the Kendall test is not meaningful. In case χ^2_{homog} did not exceed the critical value in the Chi-squared tables, the calculated value of $\chi^2_{\text{trend}} = M\bar{Z}^2$ was referred to the Chi-squared distribution with one freedom degree to test for a common trend in SSM and VIs.

Results and discussions

Monthly and seasonal variations in SSM from 1988 to 2015

Monthly and seasonal SSM maps over Iran indicate that December, January, February, and March are the wettest and July to September are the driest months (Fig. 2). Spatial distribution of SSM in plant growing seasons (spring and summer) for the period 1988–2015 is illustrated in Fig. 3. The spatial pattern of seasonal SSM is almost the same as the monthly map. The difference in Northern provinces SSM content in the spring and summer is not significant (Fig. 3). In most of the regions in Iran, except for the Northern region, it has no sufficient moisture to grow, which resulted in an irrigation demand for agriculture during these seasons. Figures 2 and 3 show that the wettest areas are located in the Northern, Northeastern, and Western parts and the driest areas are located in the Southeast and Central parts of Iran, in which land cover is arid deserts in Central and arid desert scrubs in Southeast parts. Dense forest of high-quality timber, Elburz Range forest steppe (Hircanian humid forests zone), is located in the South of Caspian Sea with high SSM content. Zagros forest (Zagros semiarid and humid forests zone) is also located in high SSM content regions (West parts of Iran). Seasonal averages of SSM in Iran are 0.17 and 0.12 m³/m³ in spring and winter, respectively. Monthly mean SSM in about 35% and 30% of Iran is in 0.1–0.15 and 0.25–0.35 m³/m³ classes (Fig. 4). Throughout the country, the spatial or temporal of SSM is consistent with rainfall, which occurs mainly in November to May (Hosseini-Moghari et al. 2018; Javanmard et al. 2010).

Long-term trends of monthly and seasonal SSM

Predominantly, in the most parts of the country, the SSM trends were generally negative at both monthly and seasonal scales; a few upward trends were found in the West and North parts sporadically (Figs. 5 and 6). The most prominent wetting is observed in November (Fig. 5). As Javari (2016) showed significant increasing trends by 1.064 mm/month for November, the most probability for increasing soil moisture in November is a positive precipitation trend. Some parts of the country have white color in Figs. 5 and 6, in particular in cold months, because in ESA CCI soil moisture data, ice cover, snow cover, and a large fraction of water coverage were masked and soil moisture retrievals in these surfaces are not statistically meaningful. On average, 70% of Iran shows negative SSM trends over the past 28 years, which is mostly located in

the Center and Southeast regions of Iran. Land covers are arid deserts and arid desert scrubs in the decreasing trend areas. The reason for this decreasing trend of SSM can be attributed to the decreasing trend in precipitation and increasing trend in temperature throughout Iran (Tabari and Talaei 2011a, b). The significant trends account for about 30% of Iran (Fig. 7). Rahmani et al. (2016) also found that the Center and Southeast regions of Iran got severely drier in the last decade.

The negative trend of soil moisture is vulnerable to desertification, especially in the Center and Southeast of Iran, where rainfall is less than 150 mm. Desertification can lead to the destruction of the land, the degradation of natural habitats, and the loss of land bio-potential. Therefore, it should be combated (e.g., using oil mulch, revegetation, and windbreaks) mainly in the Southeast of Iran.

In spring and summer, 50% and 37% of the study area got drier over the past 28 years (Fig. 7) by 0.24×10^{-2} and 0.78×10^{-3} m³/m³ per year, respectively. The results are consistent with the study of Dorigo et al. (2012). They carried out SSM trend analysis in global scale and demonstrated drying trends in the Southern USA, Central South America, Central Eurasia, Northern Africa, and the Middle East, Mongolia and Northeast China, Northern Siberia, and Western Australia.

DGDWGW paradigm

The DGDWGW paradigm was assessed over Iran (Table 1). The highest and lowest values (50% and 0.9%) appear in September and January, respectively.

Monthly mean DGDWGW is 14%, meaning 14% of the area follows the DGDWGW pattern (Table 1). Iran has a hot and dry climate, and the SSM is less than 0.15 m³/m³ in most parts; therefore, the first part of DGDWGW paradigm (DGD) is meaningful for Iran but the other part, WGW, makes no sense. The highest values of DGDWGW which occurs in September as a dry and hot month indicated the role of temperature is also highlighted on decreasing moisture from the soil from the past to now. This fact is supported by the global warming studies which have been done over Iran (Tabari et al. 2011).

Spatial distribution and trend analysis of the vegetation indices

In this study, spatial distribution and trend analysis of two vegetation indices: NDVI (GIMMS and MODIS) and MODIS-EVI were analyzed. Since the three datasets had the same behavior, regional maps of GIMMS NDVI and its trends are presented as vegetation indices representation (Fig. 8). Minimum values of VIs are observed in the Central provinces, and in the Southeast of the country in arid deserts

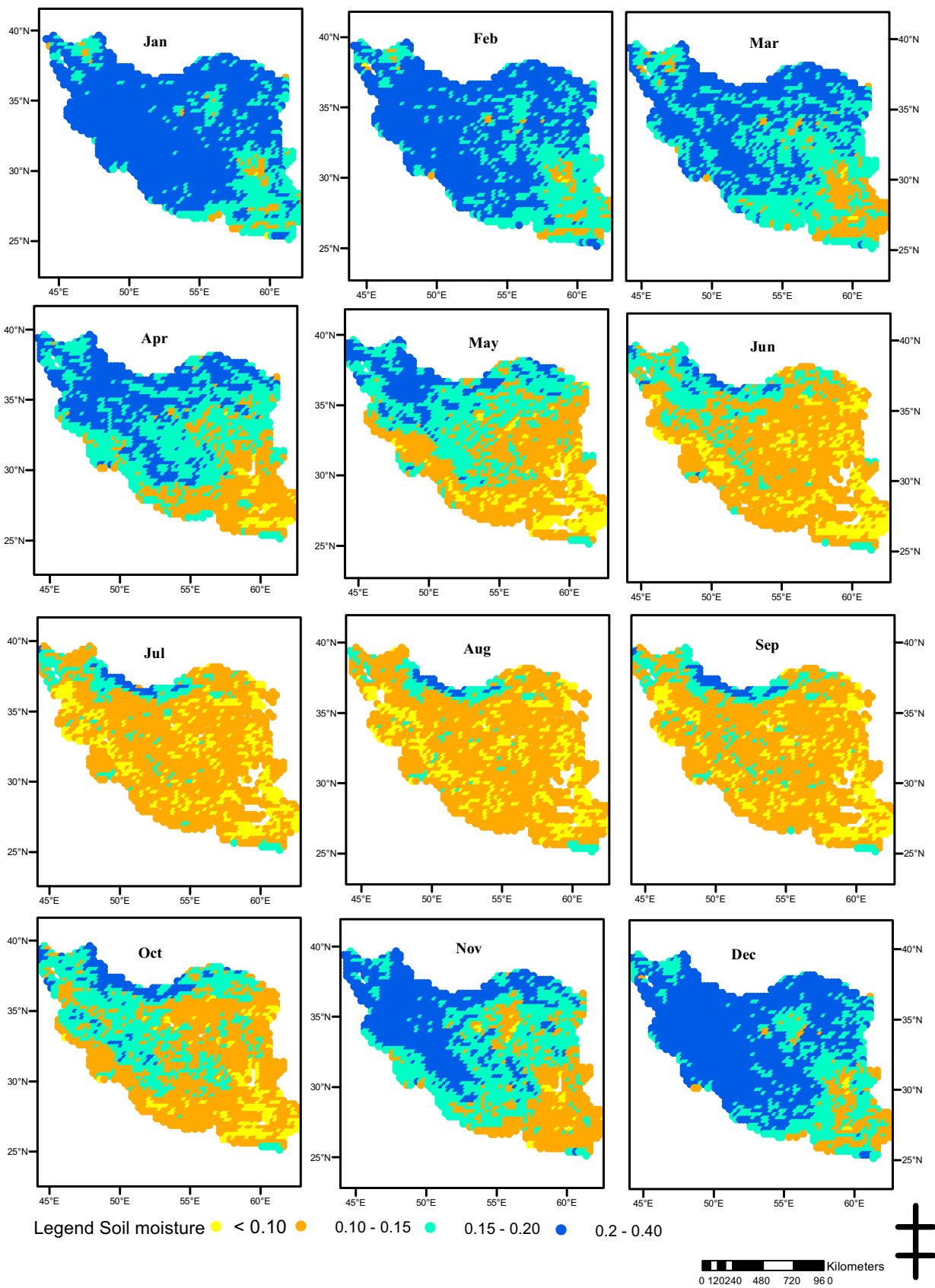


Fig. 2 Spatial patterns of the monthly mean soil moisture (m^3/m^3) over Iran from 1988 to 2015

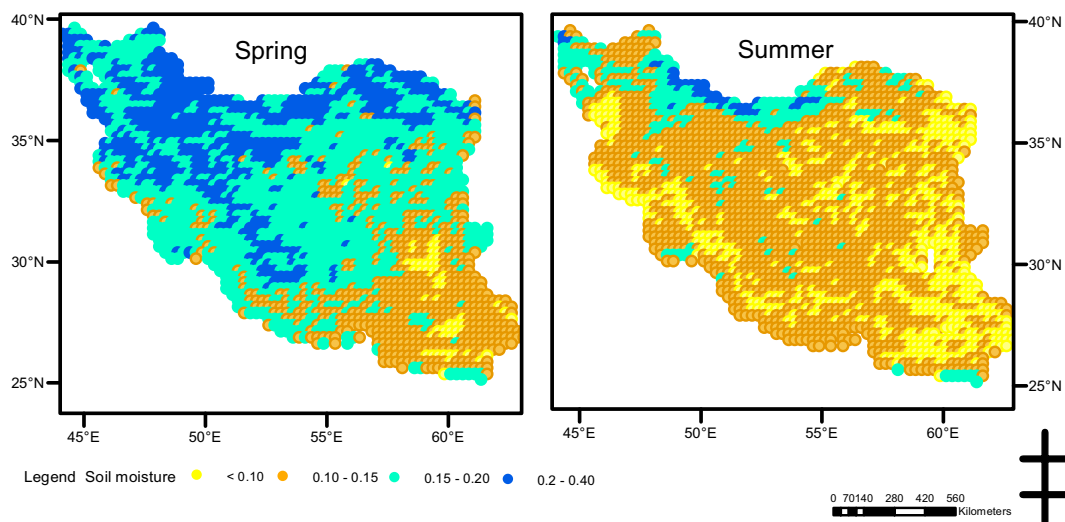


Fig. 3 Spatial patterns of the seasonal mean soil moisture (m^3/m^3) over Iran from 1988 to 2015

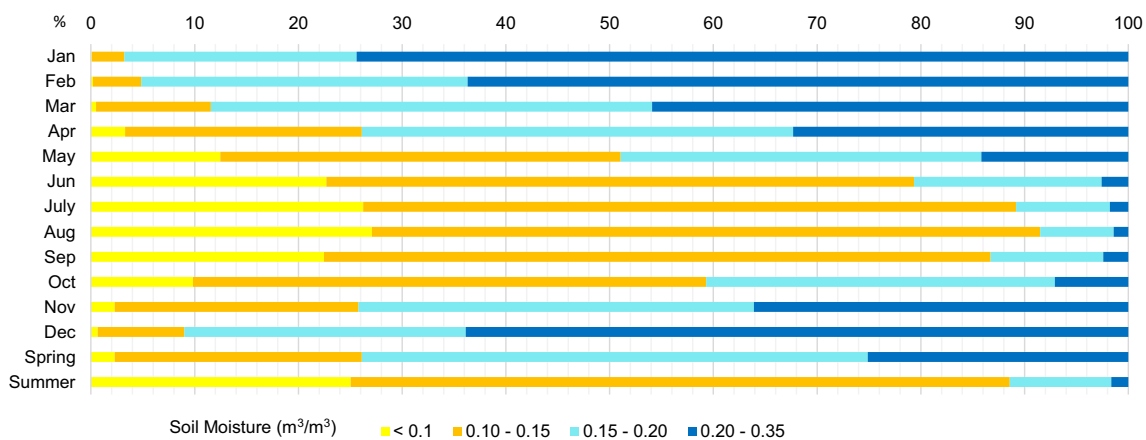


Fig. 4 Frequency distribution of soil moisture (%)

and arid desert scrubs zones, the greenest parts are located in the South of Caspian Sea in the North of Iran in Hircanian humid forests zone (Fig. 8a, b). GIMMS and MODIS NDVI trends are negative in Central parts and positive in the North and Southeast, but not significant in all areas (Fig. 8c, d). This pattern is also confirmed with EVI trends.

NDVI and EVI are less than 0.1 in about 45% (summer) and 65% (spring) of the areas (Fig. 9). Comparing the MODIS and GIMMS NDVI, distribution pattern, value, and behavioral trends over Iran are almost the same. Approximately 40% and 30% of the areas are covered by the positive trends in GIMMS and MODIS NDVI time series, respectively, that are most widespread in the Southeast and Northwest of Iran, while negative trends covered about 20% of areas observed in Central parts and Western sides of Iran (Fig. 10). The results of the current study are in line with the study of Faramarzi et al. (2018), who investigated NDVI

changes in a semiarid rangeland in Western Iran and also found a decreasing trend in vegetation cover.

Consistency between SSM and VIs Trends

GIMMS NDVI (1988–2015) was applied to compare the SSM and vegetation changes through time. According to the results, approximately 45% of SSM trends agree in sign with NDVI. Applying a consistency test between SSM and NDVI reduced this percentage. Significance of consistency in the trend between SSM and NDVI was done over the same period using the homogeneity test (Gilbert 1987). Regarding the consistency test, SSM trends are consistent with NDVI and EVI trends in about 45% (summer) and 50% (spring) of Iran. Of those, approximately 35% and 40% are the same sign in spring and summer (Fig. 11). Also, the MODIS NDVI and EVI trends are compared with the SSM trends.

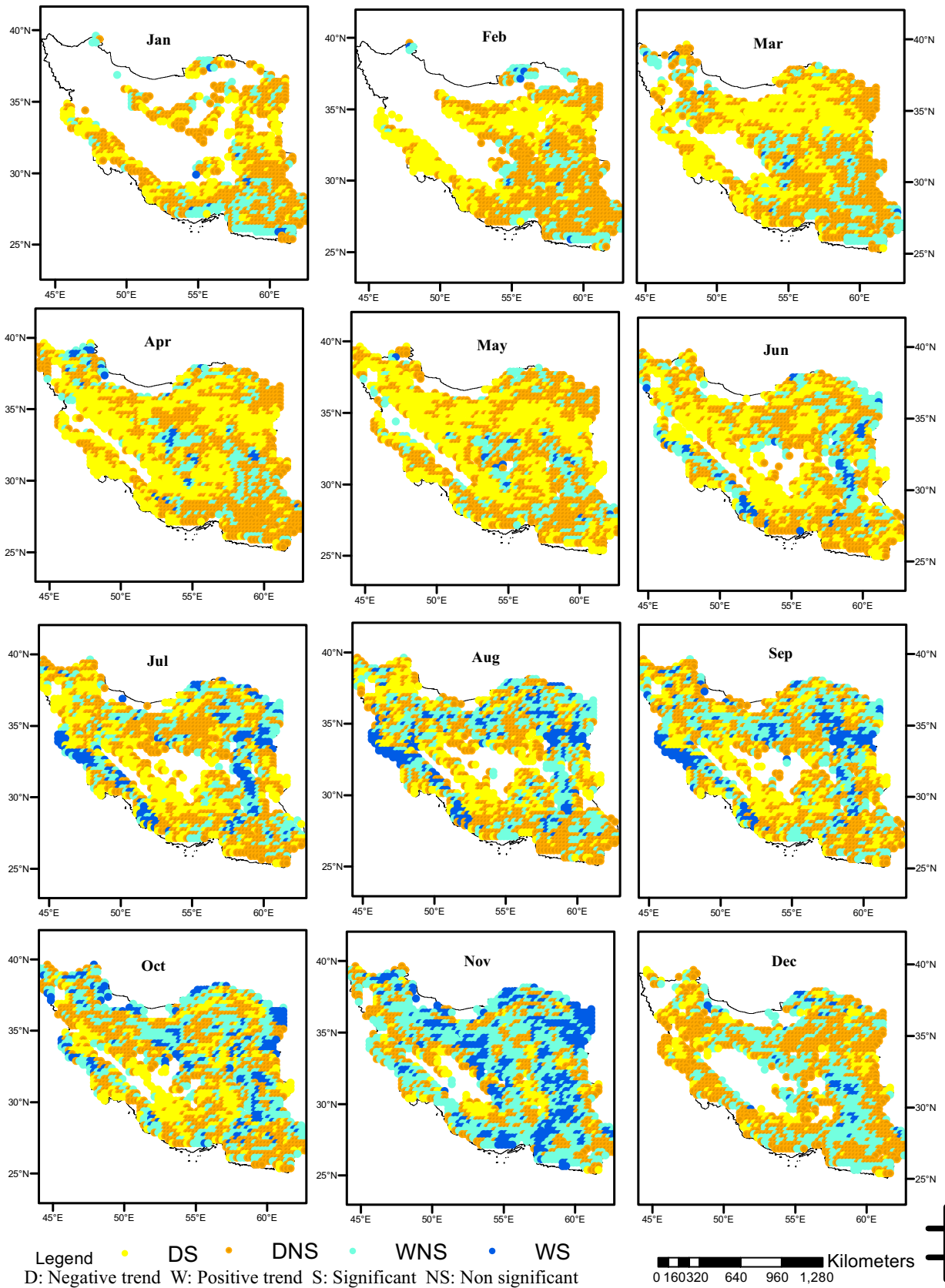


Fig. 5 Monthly trends of surface soil moisture over Iran (1988–2015)

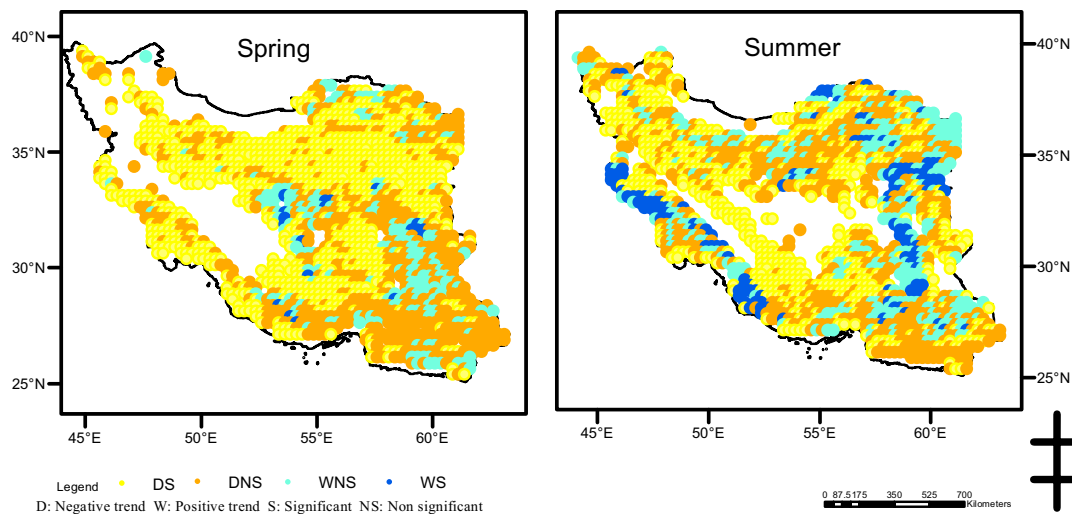


Fig. 6 Seasonal trends of surface soil moisture over Iran (1988–2015)

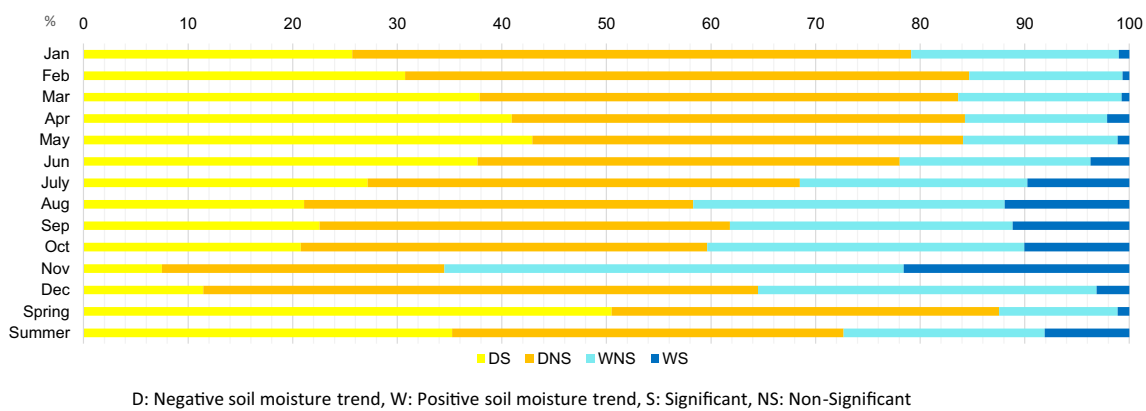


Fig. 7 Percentage of areas in different cases of soil moisture trend

Table 1 DGDWGW paradigm over Iran (%)

Months	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
%	0.9	3.1	1.5	4.6	24.6	27.0	24.4	19.5	50.5	11.7	5.9	1.7

The results almost are the same as GIMMS NDVI. With respect to the results, 40% (spring) and 45% (summer) of the SSM trends agree in sign with MODIS NDVI. These values are 40% and 47% for EVI. After the consistency test, about 10% of these values were reduced. Decreasing SSM caused the decreasing vegetation index and vice versa (Ahmed et al. 2017; Cissé et al. 2016; Ibrahim et al. 2015; Jamali et al. 2011; Owe et al. 1993; Yang et al. 2014) because water availability is a determining factor in vegetation growth. Based on the present research results, in 45% of areas SSM and VIs trends had a positive relationship.

The most prominent disagreement between SSM and VIs trends can be seen in the Southeast of Iran in arid

desert scrubs zone. SSM is reduced in the Southeast of Iran. In addition to negative SSM trend, precipitation trend (1975–2014) is also negative in the Southeast of Iran (Javari 2016). In spite of reducing rain and SSM in the Southeast, VIs trends are positive. In order to evaluate the accuracy of VIs data, ground measurement is needed, but there is no comprehensive vegetation data dealing with all regions of Iran. Sanjerehei (2014) showed, according to the physiognomic types, the Southeast of Iran is covered by a desert life zone, which is dominated by an arid desert scrubs zone. Sanjariehei (2014) compared the life zones and the current land cover of Iran and found that most parts of scrub and steppe life zone converted to poor

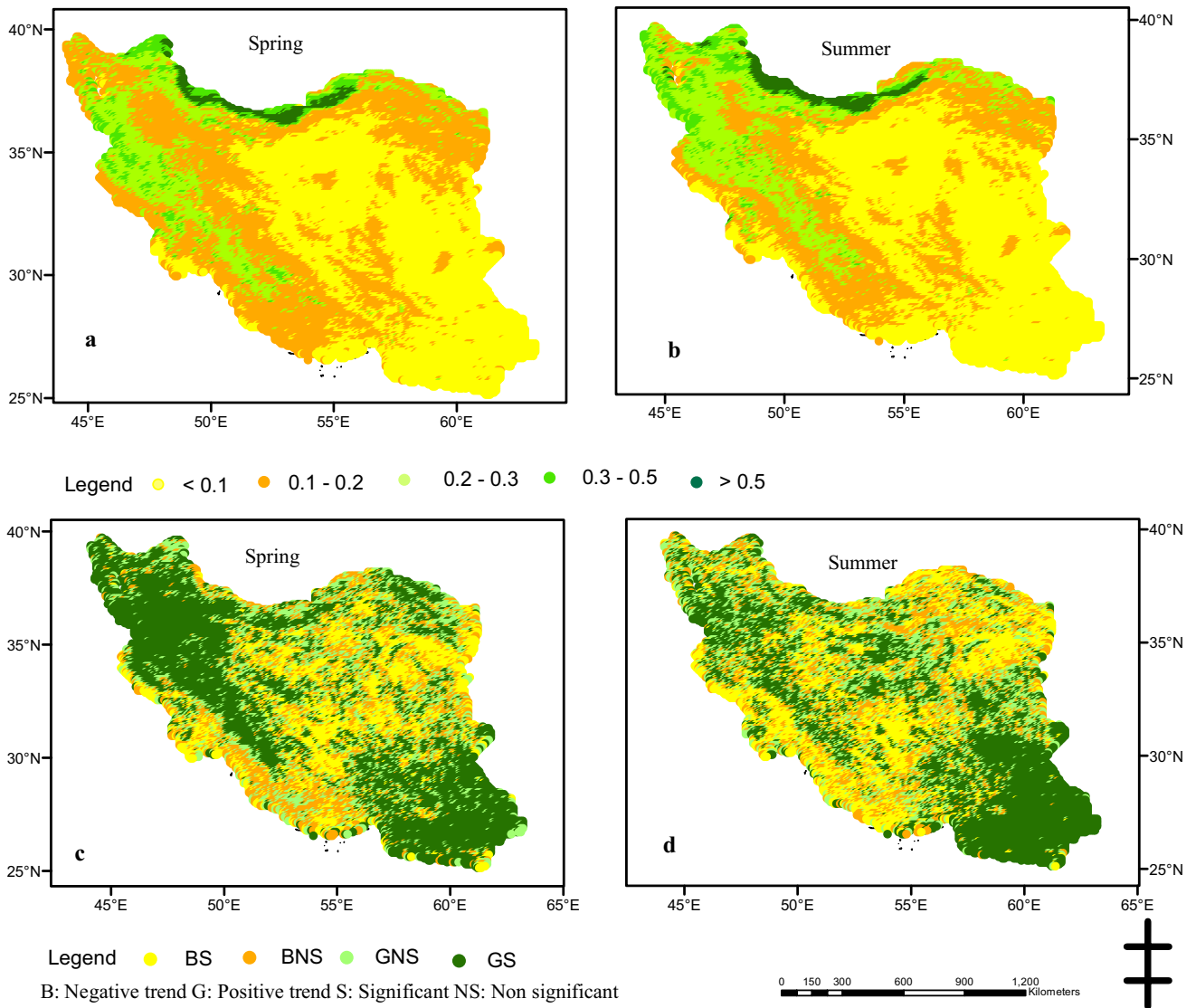
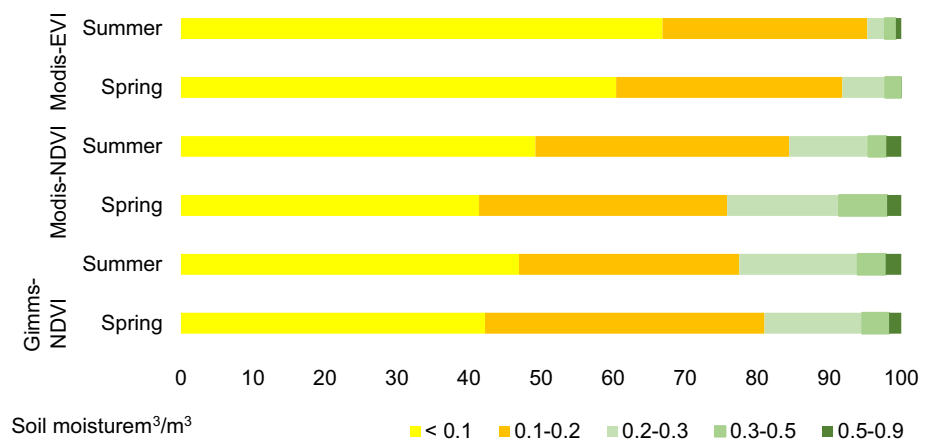


Fig. 8 a Mean NDVI—spring, b mean NDVI—summer, c trend of spring NDVI, d trend of summer NDVI over Iran (1988–2015)

Fig. 9 Seasonal frequency distribution of VI (%)



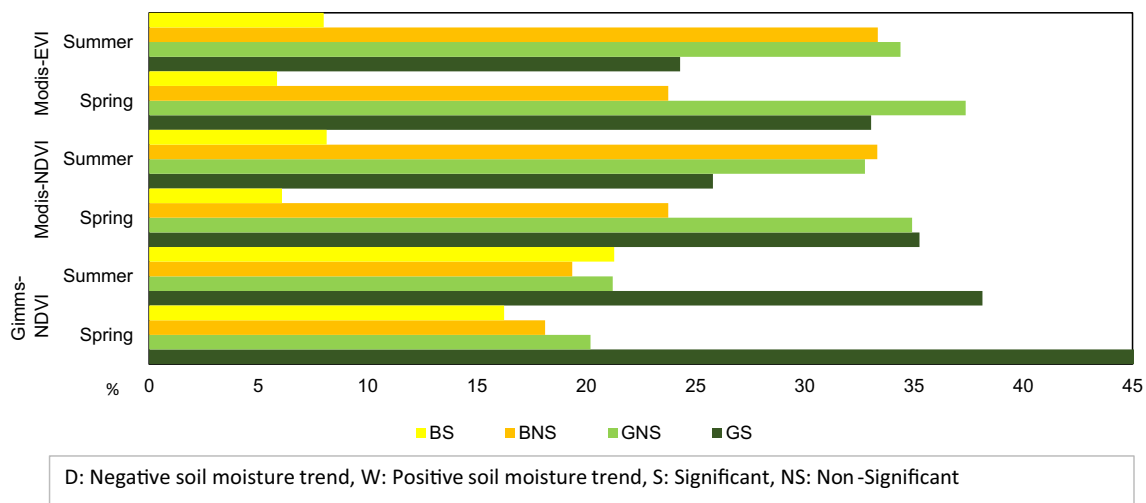


Fig. 10 Percentage of areas in different cases of VI trend

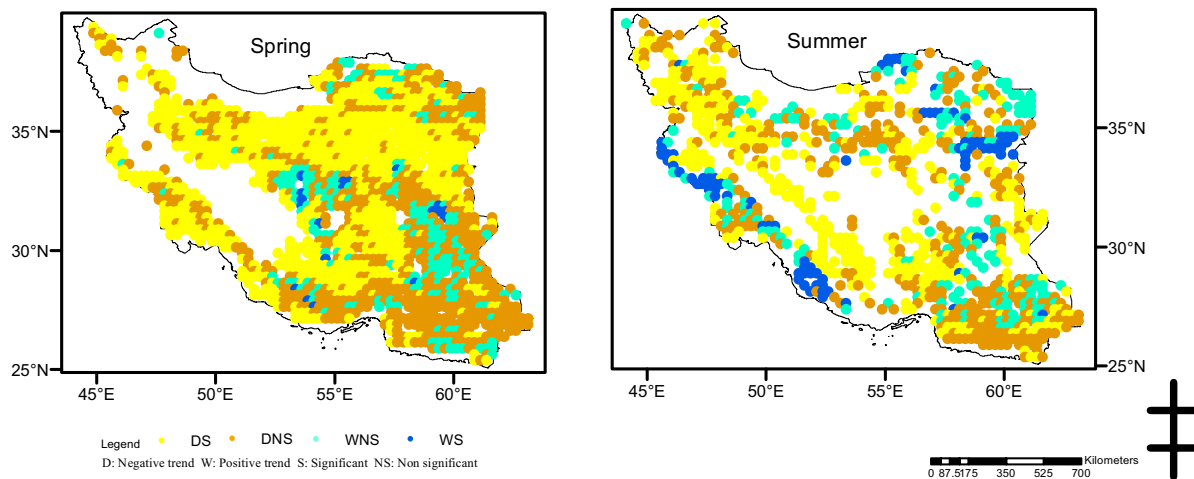


Fig. 11 Trends in soil moisture that agree significantly ($P=0.1$) with trends in GIMMS NDVI (1988–2015)

rangeland with less ecologically valuable land covers. Another available vegetation information in long time slice is local farmer observations. According to the local farmer records, vegetation cover has decreased. Based on Sanjarihei (2014) study and the local farmer observations, increasing NDVI in the Southeast of Iran is hardly acceptable. In semiarid areas, soil-vegetation spectral is mixed and causes the most serious soil-related problem in vegetation indices interpreting (Huete and Tucker 1991; Jeong et al. 2011; Karnieli et al. 1996; Lu et al. 2003; Montandon and Small 2008). Eastman et al. (2013) also did the trend analysis of global GIMMS–NDVI only for the area with NDVI more than 0.15; they masked the areas with NDVI less than 0.15. Barati et al. (2011) have compared the accuracy of spectral vegetation indices in sparse vegetated areas and found NDVI is not proper in arid areas. The

Southeast of Iran is an arid sparsely vegetated area where the NDVI and EVI values are less than 0.1; therefore, the most probable reason for inconsistency between SSM and VIs trends in some parts of Iran in particular in the Southeast is the low value of VIs in these parts.

There are so many parameters having an impact on SSM and VIs, which range from natural to human-dominated ones, e.g., soil type, elevation, slope, aspect, vegetation type, microclimate, land use pattern, and irrigation. Iran landforms lead to variations in topography and have different plant spaces, climate, precipitation amount, air temperature, etc., which have an impact on SSM and VIs. Therefore, the assessment of the relationship between SSM and VIs is very complicated. Further multi-scale studies are required by using land use and soil characteristics.

Conclusion and outlook

Satellite-based data are the necessary choice for studying the soil condition in Iran, where there is a lack of ground measurements. As the first attempt in Iran, this study investigated the long-term remote sensing SSM and VIs and examined the consistency of SSM and VIs trends. SSM trend was found negative (declining) in most parts of Iran. As a result, 50% (spring) and 35% (summer) of Iran have experienced drier conditions during the past 28 years. The results of this study confirm the negative influences of global warming on desertification, which is also reported by Dorigo et al. (2012) and Qiu et al. (2016).

In 45% of the country, SSM trends agree well in sign with the NDVI variations. However, by applying the consistency test, this agreement is reduced to 35%. Despite the SSM reduction, vegetation indices have been increased in sparse vegetated areas, in particular in Southeast of Iran. Since the spectral of soil and vegetation in such areas are mixed, vegetation assessment using satellite-based VIs in sparse vegetated areas should be done with more care and attention.

Soil erodibility is linked to land surface elements such as soil moisture and vegetation cover (Abulaiti et al. 2014; Ishizuka et al. 2012; Kimura et al. 2009). Vegetation cover can quench dust outbreaks (Han et al. 2011; Kimura et al. 2009), and wind erosion decreases with increasing soil moisture (Ishizuka et al. 2012). Therefore, long-term negative trends of SSM and VIS in Iran have to be considered for environmental management in order to control the desertification and soil erosion.

The relationship between SSM and NDVI is very complicated since the vegetation type, land cover, and vegetation density play a crucial role. In order to get more accurate results, further works are required by using detailed ground land cover, land use, regional precipitation regimes, vegetation density, and soil properties.

Unfortunately, a few unpublished case study projects (unpublished) have been done over Iran to investigate the effects natural and human-made factors affecting soil moisture. Most of the published works (case study; one or two sites) have been focused on soil quality, soil fertility, and soil chemical components (e.g., Abaslou and Abtahi 2008; Akbari et al. 2014; Eghdami et al. 2019; Jalali and Khanlari 2014).

Consequently, there is a need to conduct new works for evaluating the integrated impacts of natural and man-made on soil moisture variations in country scale.

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