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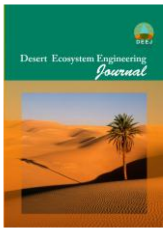

Investigating Short to Long-term Effects of Ground-based Agents on Dust Pollution Variations in Iranian Arid and Semi-arid Regions

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Abstract

This study sought to investigate change patterns in the standardized surface soil moisture (SSM), standardized land surface temperature (SLST), and standardized normalized difference vegetation index (SNDVI) in Iranian arid and semiarid regions using the Mann-Kendall test. To this end, the temporal response of dust occurrences to terrestrial factors variations in 1, 3, 6, 9, and 12-month time-series was identified at different lag times using the cross-correlation (CC) method. The standardized dust concentration (SDC) in dusty days was also considered as a criterion for evaluating the performance of dust storms during the study period (2010-2018). The study's results indicated dust storms' decreasing and increasing trends from 2010 onwards in Iran's arid and semiarid regions, respectively. Moreover, the trend of SSM changes was found to be significantly positive at different time series (Z>+1.96) in both regions. A similar trend was also observed for SNDVI in long-term series across the study areas. However, while the SLST variations showed meaningful positive trends in the arid regions at various time series (Z>+4.5), it only showed a significant positive trend in the 1-month series (Z=+2.12) in semi-arid regions.

Furthermore, according to the strongest CC values, the temporal response of dust storms to changes in vegetation, LST, and SM occurred at 6, 12, and 3-month time series with different time lags in arid regions. Nonetheless, the temporal responses of dust events to vegetation and LST variations in the semi-arid regions were found at 12-month time series with a 1-month and 5-month time lags, respectively.

Keywords: Air Pollution, Land Surface Temperature, Dust Concentration, Vegetation, Soil Moisture.

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1. ntroduction

Drylands are mainly characterized by low atmospheric precipitation (Morin et al., 2020), where the soil moisture content and the vegetation conditions are influenced by low rainfall rate (Mohamadi et al., 2018; Yang et al., 2018). Land surface temperatures may also affect dust events by influencing vegetation. Numerous studies have examined the relationship between such variables, reporting various results (Ferreira and Duarte, 2019; Kumar and Shekhar, 2015; Nega et al., 2019; Pal and Ziaul, 2017). For instance, some studies have reported that the type of dust particles has dual effects on the land surface temperature which is largely dependent on the content of suspended particles (Hereher, 2017; Luo et al., 2019). However, while the accumulation of sulfate-containing particles with solar radiation emission leads to a decrease in the Earth's surface temperature, black carbon particles increase the Earth's surface temperature by absorbing solar radiation (El-Gammal et al., 202).

Any increase in the frequency and severity of dust events can represent severe destruction of lands by the wind, probably resulting in reduced horizontal visibility (HV) and air quality deterioration in different areas (Chen et al., 2017; Karagulian et al., 2019; Querol et al., 2019). Therefore, HV indicates the concentration of dust particles in the atmosphere and the relative severity of dust storms (Furman, 2003; Zhao et al., 2013). Thus, dust concentration (DC) can be measured for different regions by applying different experimental functions and the horizontal visibility recorded by meteorological observers in the synoptic stations (Ebrahimi-Khusfi et al., 2020b).

Recently, the Moderate Resolution Imaging Spectroradiometer (MODIS) time series has an impressive role in monitoring land surface temperature (LST) and vegetation cover across different regions of the world (Aguilar-Lome et al., 2019; Bokaie et al., 2019; Chappell et al., 2019; Khandan et al., 2018; Meng et al., 2019; Rankine et al., 2017; Testa et al., 2018). The soil moisture and ocean salinity (SMOS) were also aimed to retrieve topsoil moisture with high temporal resolution (Ebrahimi-Khusfi et al., 2018). Unlike costly and time-consuming ground-based surveys, remote sensing data can help significantly save sampling time and costs (Effati et al., 2019; Navalgund et al., 2007; Wang and Qu, 2009; Yue et al., 2015). Therefore, in this study, land products of MODIS time series and SMOS-IC were utilized to obtain three important physical properties of the ground surface including the LST, normalized difference vegetation index (NDVI), and surface soil moisture (SM). The high correlation of LST (Duan et al., 2019), NDVI (Geng et al., 2014; Jafari et al., 2017), and SM-SMOS products (Ebrahimi-Khusfi et al., 2018; Jackson et al., 2011) with in situ measurements has been proven in many previous studies, which indicate their good ability to investigate these terrestrial characteristics. For this reason, they have been used to analyze their relationship with DC in the arid regions of Iran. The DC was calculated using the method proposed by Shao et al. (2003) to measure the activity of dust events in the arid and semi-arid regions of Iran.

Considering the fact that soil erosion may occur simultaneously with terrestrial and/or climatic changes or after a time lag, identifying the behavior of soil against changes in these driving forces plays an important role in mitigating their adverse effects. Although numerous studies have been carried out on the relationship between climatic parameters and climate response to dust events, the temporal dust events' response to changes in physical properties of the earth's surface has been under-researched. Therefore, as to the best of our knowledge, no attempt has yet been made to investigate this issue in Iranian arid and semi-arid regions, the current study south to do so using a combination of terrestrial and remotely sensed time series.

In addition, the influence of the ground-based factors' variations on dust storms has not been examined by previous studies in terms of the standardized dust concentration's (SDC) time series, standardized land surface temperature (SLST), standardized soil moisture (SSM), and standardized normalized difference vegetation index (SNDVI) at various time lags. Therefore, the main goals of this study were to (i) analyze the trend of changes in SDC, SNDVI, SLST, and, SSM from 2010 to 2018; (ii) determine the relationship between SDC-SNDVI, SDC-SLST, and SDC-SSM at different lag times; and (iii) determine the short and long-term effects of soil properties on dust pollution across Iran's arid and semi-arid regions.

2. Study Areas

The study areas included arid and semi-arid regions extending from the eastern to the southwestern borders of Iran (Fig.1b). It should be noted that about 87 million km^2 of Iran is covered by arid lands, mainly extended in the eastern parts of Iran. According to the satellite data obtained for this region, the average soil moisture, vegetation, and LST from 2010 to 1028 were 0.05, 10%, and, 15.5°C, respectively. Semi-arid region covers about 38% of Iran's area. According to the remotely sensed data for this region of Iran, long-term average values of vegetation, SM, and LST were 0.08, 18% and 14.8° C, respectively.

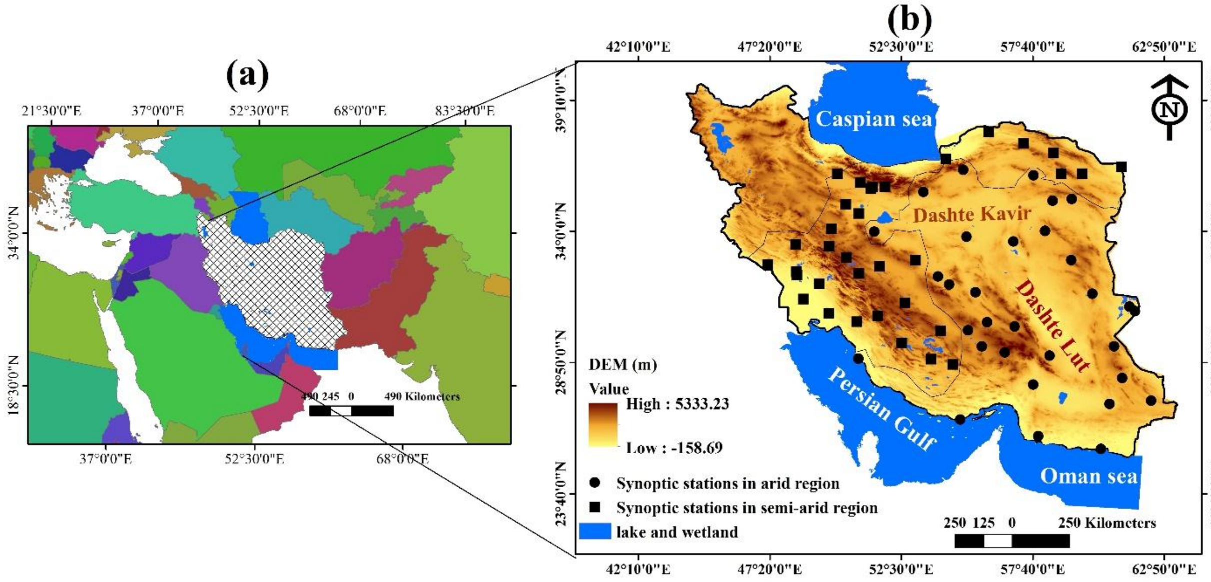

Figure (1): The geographical location of (a) Iran in Southwest Asia, and (b) the study areas in Iran

3. Material and methods

3.1. Data sets

To analyze the dust events' response time to changes in terrestrial factors, it is necessary to collect long-term data sets on terrestrial variables and on a variable representing the wind erosion events. This study used the dust concentration (DC) criteria to analyze such events in Iran's arid and semiarid regions from 2010 to 2018. To this end, the hourly horizontal visibility (km), surface wind speed (m/s), and wind erosion events' codes were used for the days when dust storms took place in the vicinity of weather stations throughout the study period, whose data were obtained from the Iranian Meteorological Organization (IRIMO). The data sets on soil moisture (SM), land surface temperature (LST), and normalized vegetation difference index (NDVI) were collected from the SMOS-IC and MODIS satellite imageries during the study period (2010 to 2018).

Moreover, the study used monthly products of global SMOS-IC for the study period to monitor soil moisture in the study areas. The

SMOS is one of the earth observation satellites developed by Institute National de la Recherché Agronomic, launched in November (2009) to retrieve soil moisture from the land surface (< 5cm) in the global scale with an unbiased root-mean-square error (ubRMSE) less than 0.04 cm^3/cm^3 (Van der Schalie et al., 2016). Considering the fact that the SMOS satellite's local overpass time is 06:00 AM/PM for ascending/descending passes, and that study areas' sand-dust storms often occur in the afternoon, evening overpasses SM was used. All the monthly NDVI and LST images were obtained from https://earthdata.nasa.gov. Finally, the two products were re-gridded in EASE 2.0 to be compared with SMOS-IC SM.

3.2. Dust concentration (DC) Calculation

Representing changes in dust events across different regions, DC is computed according to equations (1) and (2) for Middle Eastern countries (Shao et al., 2003):

$$Y = 3802.29 \times X^{-0.84} \qquad H_v < 3.5 \text{ km} \tag{1}$$

$$Y = \exp(-0.11X + 7.62) \qquad H_v \geq 3.5 \text{ km} \tag{2}$$

where X refers to the horizontal visibility in km, and Y stands for dust concentration in $\mu g/m^3$.

3.3. Standardized time series preparation

In this study, the standardized dust concentration (SDC), standardized soil moisture (SSM), standardized normalized difference vegetation index (SNDVI), and standardized land surface temperature (SLST) were computed based on the method proposed by McKee et al. (1993). Finally, the average moving values of SDC, SSM, SLST, and SNDVI time series were calculated at various time scales (1, 3, 6, 9, 12-monthly) from 2010 to 2018 for all synoptic stations and the regional scale (arid region and semi-arid region) using DIP software.

3.4. Mann- Kendall (M-K) test

The non-parametric Mann-Kendall test is usually used for exploring trends in various time series of different features (Kendall, 1975; Mann, 1945). In the present study, the M-K test was used to analyze the changes in vegetation, land surface temperature, soil moisture, and dust concentration. For the data series (v), the S statistic was calculated according to the following equation.

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \operatorname{sgn}(v_j - v_i), \qquad \operatorname{sgn}(v_j - v_i) = \begin{cases} 1 & if \quad v_j - v_i > 0 \\ 0 & if \quad v_j - v_i = 0 \\ -1 & if \quad v_j - v_i < 0 \end{cases} \tag{3}$$

Based on the Z values (Mann-Kendall coefficient), the change trend of time series can be identified. In this case, Z-values>0 and <0 show an upward and a downward trend in the study time series, respectively.

3.5. Correlation analysis

Cross-correlation is a useful technique for evaluating statistical correlations between two sets of data at different time lags (Lee et al., 2006a). For different input data sets, the cross-correlation function relates to the thump reaction. In the asymmetrical cross-correlation function, the output signal is affected by the output signal. Response time is defined as the delay associated with the maximum correlation function (Lee et al., 2006b). At a given lag time, the cross-correlation is calculated using equation (4)(McCoy and Blanchard, 2008).

$$R_{cc(m)} = \frac{n * \sum V_1 V_2 - \sum V_1 \sum V_2}{\sqrt{n * \sum V_1^2 - (\sum V_1)\left[n * \sum V_2^2 - (\sum V_2)\right]}} \tag{4}$$

In the above equation, *Rcc* denotes the cross-correlation coefficient at lag time t; t refers to the time lag between study time series; n^* shows the number of overlapping data; V_1 refers to the SSM, SNVI, and SLST series; V_2 is the SDC series. Of note, if Rcc values are larger than standard error, the correlation amounts with a specified lag time are significant at the 5% confidence level (Lee et al., 2006b).

4. Results and discussion

4.1. Changes trend analysis

Figures (2-5) illustrate the time series of SDC, SSM, SNDVI, and SLST in Iran's arid and semi-arid regions, whose trend changes are presented in Table (1).

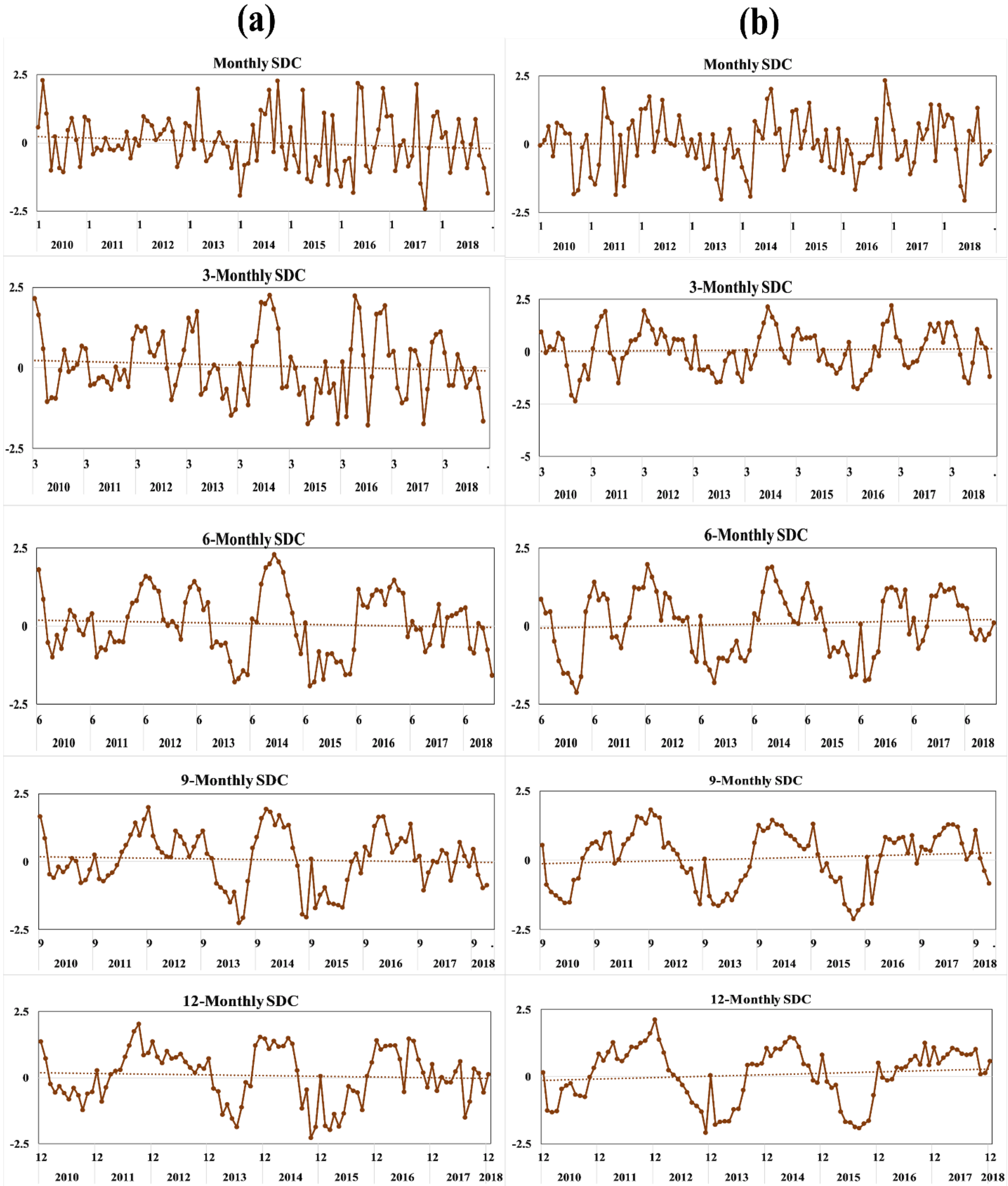

Figure (2): Standardized time series of dust concentration (SDC) in Iran's (a) arid regions and (b) semi-arid regions from 2010 to 2018

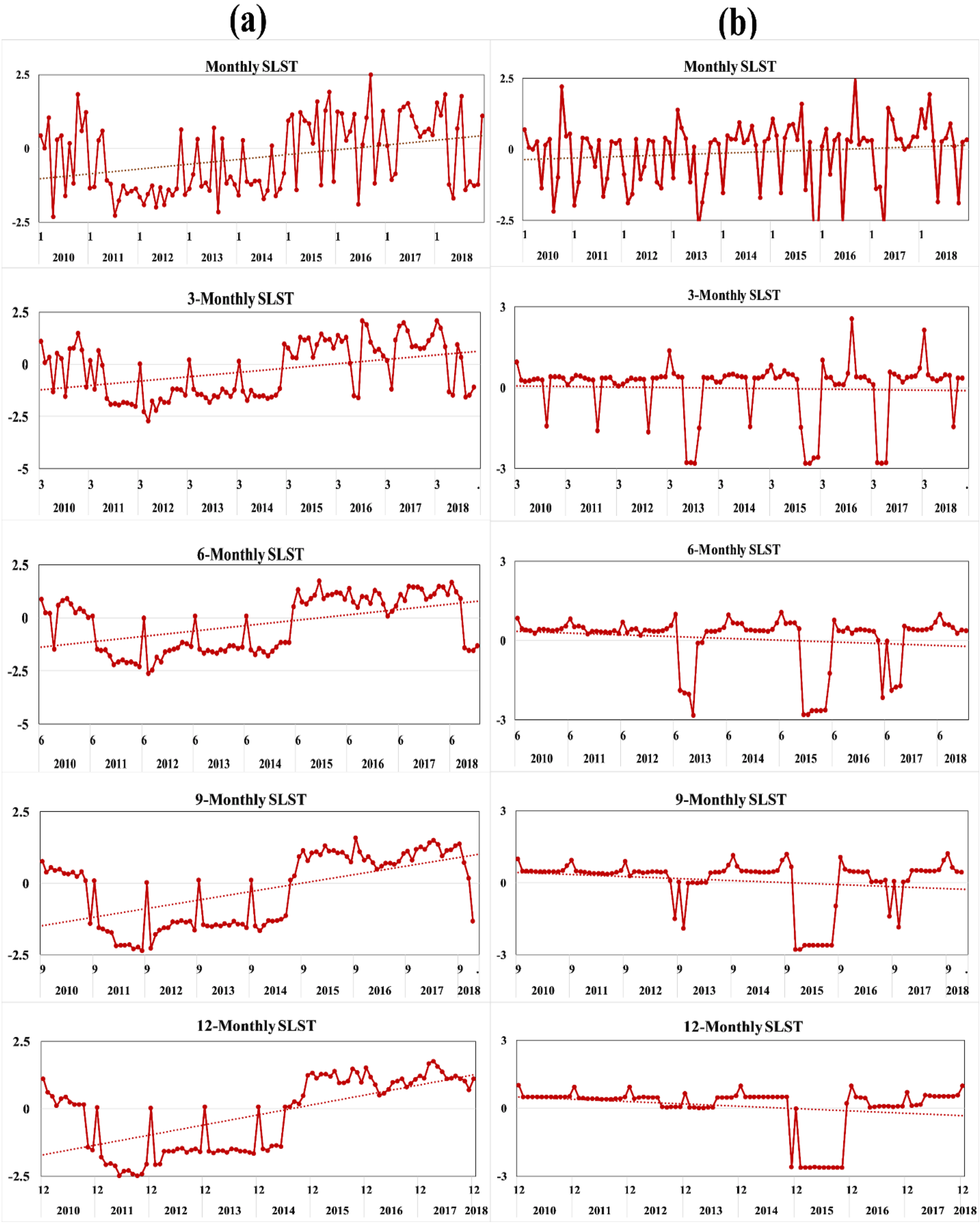

Figure (3): Standardized land surface temperature (SLST) time series in Iran's (a) arid regions and (b) semi-arid regions from 2010 to 2018

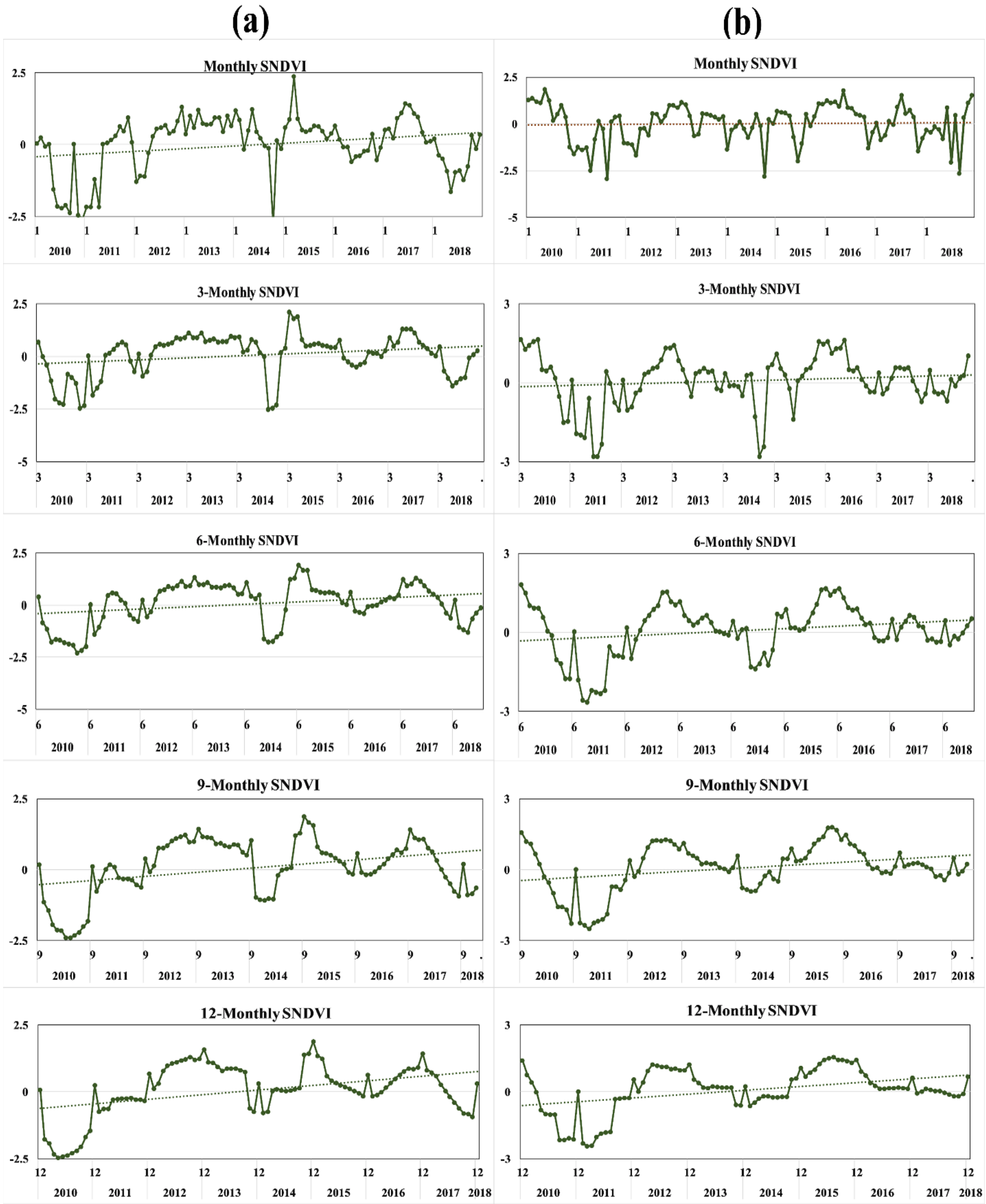

Figure (4): Standardized normalized difference vegetation index (SNDVI) time series in Iran's (a) arid regions and (b) semi-arid regions from 2010 to 2018

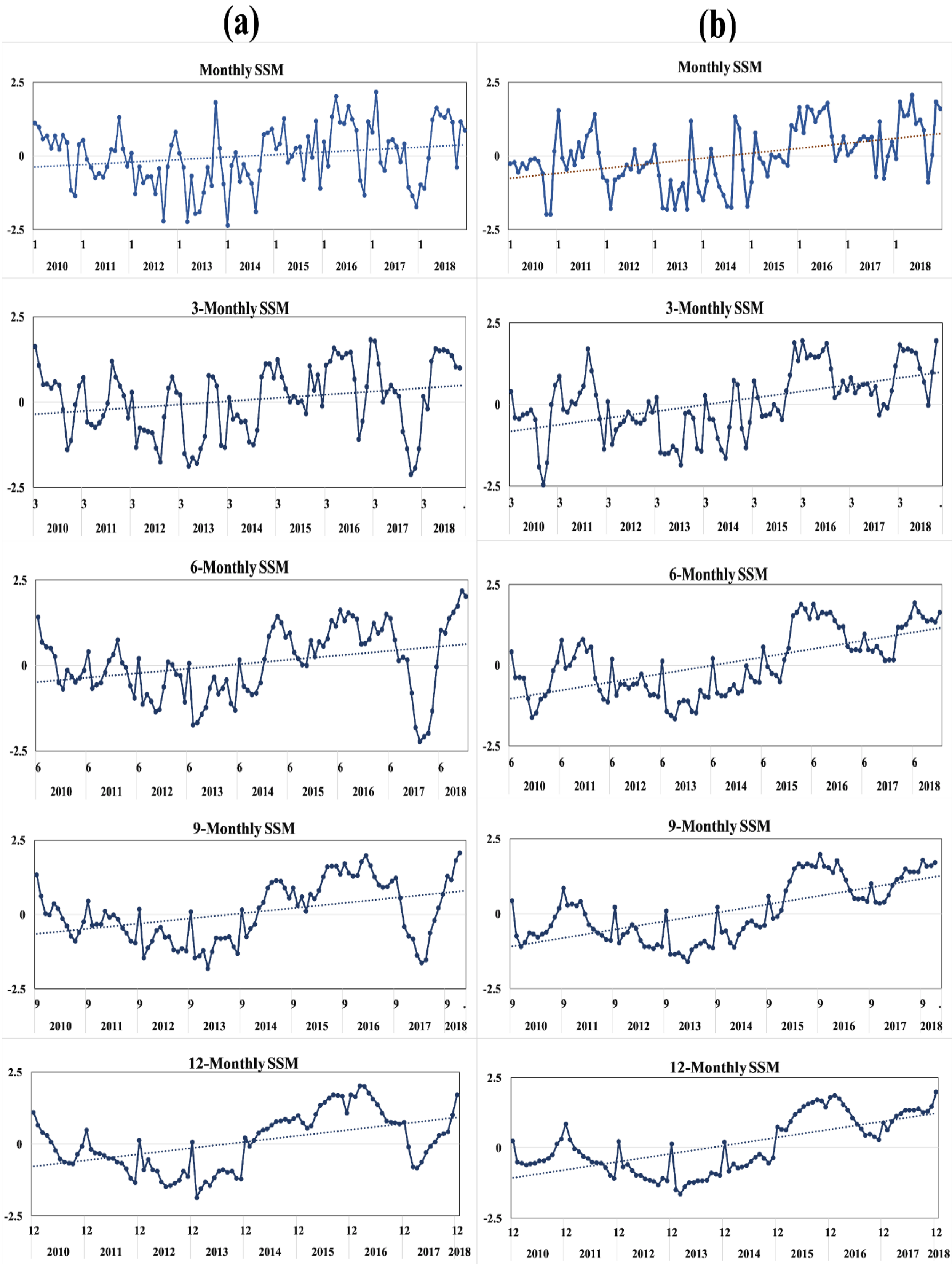

Figure (5): Standardized soil moisture (SSM) time series in Iran's (a) arid regions and (b) semi-arid regions from 2010 to 2018

Table (1): Results of trend analysis of the study's variables in Iranian arid and semi-arid regions based on the Mann-Kendall test

Study regions	Time Series	1 Monthly	3 Monthly	6 Monthly	9 Monthly	12 Monthly
Arid regions	SDC	-1.42	-0.66	-0.24	-0.1	-0.26
	SSM	2.56*	3.26*	3.98*	3.88*	4.63*
	SLST	4.54*	4.97*	6.01*	6.99*	6.97*
	SNDVI	1.30	1.65	1.99*	2.24*	2.87*
Semi-arid regions	SDC	0.2	0.51	0.74	1.08	1.31
	SSM	5.23*	5.71*	6.34*	6.50*	5.85*
	SLST	2.12*	-1.48	-0.12	-0.97	-1.60
	SNDVI	0.58	1.14	1.53	2.23*	2.99*

Z- value > +1.96 and <-1.96 represent upward and downward trends respectively. *Indicates significant level at α<0.05

As shown in Fig. 2a, the trend of SDC changes at different time series (1 to 12 monthly) in Iran's dry regions has been decreasing from 2010 to 2018. It should be noted that the trends of changes in dust events, climatic and terrestrial parameters depend on the length of the statistical period under study and the study areas. For instance, dust concentration in Iran suggests a decreasing trend during 1990-1999 and 2000-2008. However, from 2009 to 2018, DC has decreased again (Ebrahimi-Khusfi et al., 2022). Moreover, it has recently been reported that the optical depth of aerosols has decreased in Iran since 2010 (Yousefi et al., 2021).

Considering the fact that Iran is largely covered by arid regions and that recent studies have shown a decreasing trend for dust pollution throughout the past decade, it can be said that the results found in the current study are partially confirmed. However, Iran's semi-arid regions were found to have been experiencing a moderate increase in DC events at all the time series investigated in this study except for the 12-month series (Fig. 2b), which could be attributed to the opposite change trends at the local scales (incremental changes at some stations and decreasing changes at other stations), eventually leading to a weak insignificant trend on the regional scale. In other words, compared to the arid regions, a similar trend was observed for the semi-arid regions only at the long-term series. Furthermore, the results of the Mann-Kendall test (Table 1) indicated that the trend of SDC changes was insignificant in both study areas (Z<±1.96; α>0.05). As a whole, this result does not mean that dust events are not affected by climatic or ground forces, as has been shown in many previous studies (Kamal et al., 2019; Khusfi et al., 2020). Therefore, due to the high importance of the wind erosion phenomenon, even minor changes should not be ignored. Identifying the factors that influence these changes and detecting the temporal response to their variations can prevent the growing trend of dust storms and improve soil and air quality.

The obtained results of changes trend analysis in the terrestrial variables of the arid and semi-arid regions showed that all three variables of SNDVI, SSM, and SLST had an increasing trend since 2010 in most of the time series (Fig. 3 (a,b), Fig 4 (a,b) and Fig 5(a,b); Table 1). The SSM and SLST values increased significantly in the short to long time series in the arid regions of Iran (Z_{SSM}>+2.5; Z_{SLST}>+4.5; α<0.05). However, SNDVI increased considerably in the long-term series (Z>+2.2; α<0.05). It was also observed a similar trend for semi-arid regions in the study time series of SSM (Z>+5.2; α<0.05) and in the 9- to 12-monthly series of SNDVI (Z>+2.2; α<0.05) while an insignificant decreasing trend was found in time series of SLST (Z<-1.96; α<0.05) except in the one-monthly SLST data set (Z=+2.12; α<0.05).

These results are partly indicative of improved ground conditions in both study areas, especially in the arid regions of Iran, as reported in recent research for some regions of the country (Ebrahimi-Khusfi et al., 2020a; Nateghi et al., 2018). Based on our results, it is anticipated that the erosion response caused by wind force to changes in ground variables will show different results concerning different time series, which will be discussed in more detail in the next section.

4.2. Temporal response of wind erosion to terrestrial variables variations

This study investigated the temporal relationship between changes at different SDC time series (as an indicator of the activity of wind erosion events) and alterations in the SNDVI, SLST, and SSM data sets with and without various lag times (lag= 1 to 12 months, and lag=0, respectively) to identify the first significant relationship established between the study variables, and to determine the moment when the strongest meaningful relationship was established at different time series.

It should be noted that the first significant cross-correlation time (FSCT) represents the first reaction of wind erosion to alteration in the studied ground variable. In other words, the FSCT indicates the onset of wind erosion and dust generation events induced by the changes in terrestrial factors. However, the strongest cross-correlation coefficient (SCC) reveals when the wind erosion activity in the study areas has been strongly influenced by changes in the physical properties of the earth's surface. Figs. 6 (a and b) to 8 (a and b) show the cross-correlation coefficients between the SDC and the SLST, SSM, and SNDVI at the intended time series in Iran's arid and semi-arid regions, respectively. Moreover, Table (2) summarizes the effect of terrestrial variables' time on wind erosion occurrence in arid and semi-regions.

Table (2): Temporal response of wind erosion to the influence of terrestrial variables in Iran's arid and semi-arid regions based on the FSCT and SCC at different time series.

Regions	Variables	Time series	1 Monthly	3 Monthly	6 Monthly	9 Monthly	12 Monthly
Arid regions	**SDC-SLST**	FSCT (p<0.05)	**-0.22***	-0.21*	Ns	Ns	-0.22*
		Lag (month)	**5**	4			0
		SCC (p<0.05)	-0.22*	-0.21*	Ns	Ns	**-0.32***
		Lag (month)	5	4			**2**
	SDC-SSM	FSCT (p<0.05)	**-0.2***	Ns	Ns	Ns	Ns
		Lag (month)	**1**				
		SCC (p<0.05)	**-0.2***	Ns	Ns	Ns	Ns
		Lag (month)	**1**				
	SDC-SNDVI	FSCT (p<0.05)	Ns	Ns	**-0.22**	Ns	Ns
		Lag (month)			**0**		
		SCC (p<0.05)	Ns	Ns	**-0.28**	Ns	Ns
		Lag (month)			**1**		
Semi-arid regions	**SDC-SLST**	FSCT (p<0.05)	**+0.29***	+0.32*	+0.42*	+0.5*	+0.58*
		Lag (month)	**1**	0	0	0	0
		SCC (p<0.05)	+0.29*	+0.32*	+0.42*	+0.5*	**+0.58***
		Lag (month)	1	0	0	0	**0**
	SDC-SNDVI	FSCT (p<0.05)	**-0.22***	-0.22*	-0.23*	-0.41*	-0.4*
		Lag (month)	**0**	3	0	0	0
		SCC (p<0.05)	-0.22*	-0.29*	-0.44*	-0.58*	**-0.6***
		Lag (month)	0	4	6	4	**5**

Ns means non-significant and * indicates significant at 95% confidence level. Red numbers show the best response of wind erosion to terrestrial factors based on the FSCT and SCC

The study's findings indicated a negative relationship between changes in the standardized dust concentration's (SDC) values and standardized land surface temperature (SLST) at most time series in arid regions (Fig.6a). In this regard, Rayegani et al. (2020) reported that LST played a key role in identifying the dust storm sources and that a considerable decrease in LST was observed in areas with a high frequency of dust events, confirmed by the AOD data sets. However, the current study found such a relationship to be significant all the time series except for the 6 and 9-month time series. Also, the first and strongest cross-correlations were observed at 1-month time series with a five-month lag ($R_{cc\ (lag5)} = -0.22$; $p<0.05$) and 12-month time series with a two-month lag ($R_{cc\ (lag\ 2)} = -0.32$; $p<0.05$), respectively (Fig.6a and Table 2).

The correlation between the SDC and SLST was mostly positive and significant in semi-arid regions at different time series (Fig.6b). Moreover, the first cross-correlation between these variables was found at monthly time series (R cc=+0.29; $p<0.05$) with a 1-month lag. In addition, the highest cross-correlation value was found for 12-month time series with one lag time (Fig6.b and Table 2; R cc=+0.58; $p<0.05$). The above-mentioned results indicated that the effect of LST's long-term changes on the dust events in Iranian dry and semi-dry lands was more than its short-term changes. The results also suggested the dual behavior of land surface temperature fluctuations on the soil erosion at two different Iranian climatic zones, which could be due to different compositions of dust particles and their ability to absorb and reflect solar radiation in various regions (El-Gammal et al., 2012).

On the other hand, in arid regions, the relationship between SSM and SDC was only meaningful at the 1-month time series with a one-month lag time (Fig. 7a, Table 2; $R_{cc\ (lag\ 1)} = -0.2$; $P<0.05$). in this regard, considering the fact that soil moisture affects wind erosion and dust particles' release by affecting the velocity of wind erosion threshold friction (Koohizadeh et al., 2021), Yousefi et al. (2021) reported that an increase in soil moisture from 2010–2018 led to the decreased depth of aerosol optical in Iran. Therefore, as SSM and SDC variations suggested increasing and decreasing trends in Iran's arid regions, respectively (Table 1, Fig 2a), it could be concluded that while the increase in soil moisture's content did not simultaneously affect the emission of dust particles, its cumulative and short-term effect could prevent the emission of dust particles in those areas with a one-month delay.

The inverse impact of soil moisture fluctuations on wind erosion events has also been confirmed by some previous studies (Munkhtsetseg et al., 2016; Zambrano-Cruzatty et al., 2019), which is consistent with the results found by the present study. Furthermore, it was found that alterations in SM across semi-arid regions had no significant effect on wind force-induced soil erosion in recent years. However, although the volume of soil moisture's changes was higher in semi-arid regions (Fig. 5b) than in arid lands (Fig 5. a), this terrestrial driving force did not have any significant effect on DC variations over the regions. Therefore, the direct relationship between these parameters can either be attributed to the prevailing unstable atmospheric conditions or the import of dust particles from other regions (Khusfi et al., 2020), suggesting the insufficient ability of the SMOS-SM datasets to explain the relationship between SSM and SDC in semi-arid regions and its relatively acceptable ability to explain the relationship at short time series in Iranian arid regions.

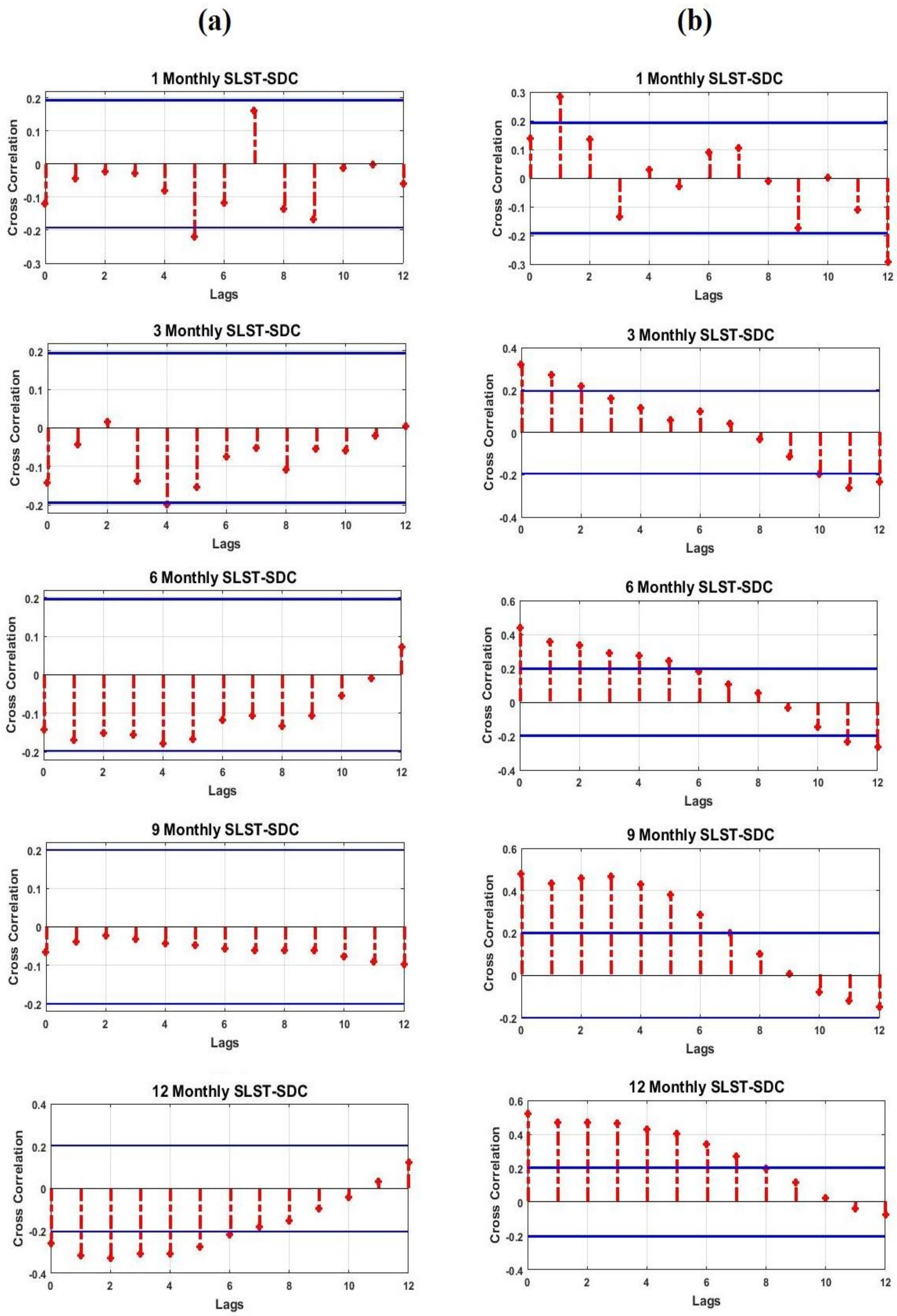

Figure (6): The cross-correlation coefficients between the SLST and SDC time series in (a) arid regions and (b) semi-arid regions of Iran (2010-2018)

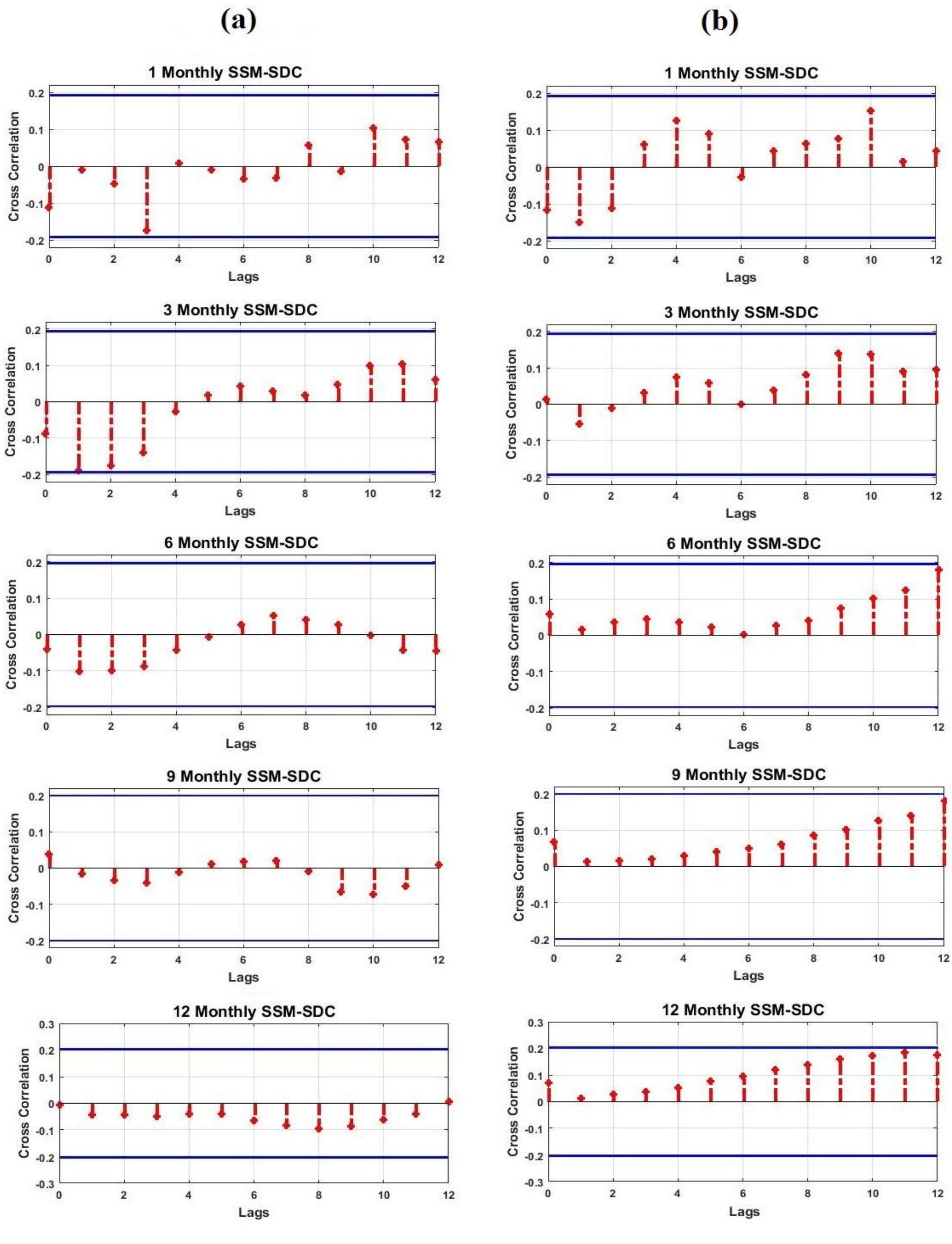

Figure (7): The cross-correlation coefficients between the SSM and SDC time series in (a) arid regions and (b) semi-arid regions of Iran (2010-2018)

As shown in Fig. 8a and Table 2, the significant effect of vegetation improvement on the reduction of dust concentration in arid regions was merely observed at 6-month time series with zero and one-month lag ($R_{cc\ (lag\ 0)}$ = -0.22; $R_{cc\ (lag\ 1)}$ = -0.28; P<0.05).

While this study's findings showed a dramatic response to vegetation variations at 6 to 12-month time series in all the time lags (Fig.8b), it was found that according to the FSCT, wind erosion events and soil erosion changes occurred without any time lag ($R_{cc\ (lag}$

$_{0)}$ = -0.22; p<0.05) in Iran's semi-arid regions (Fig. 8b, Table 2). Moreover, based on the SCC between SNDVI and SDC, it was found that long-term vegetation changes with a 5-month lag had the greatest impact on dust concentration variations in Iranian semi-arid regions ($R_{cc\ (lag\ 5)}$ = -0.6; p<0.05). In other words, the highest dependence of dust events on vegetation variations was observed about 5 months after the long-term variations in the NDVI over the region. The inverse linear relationship between soil erosion and vegetation has also been reported by previous studies (Azoogh and Jafari, 2018; Kergoat et al., 2017; Sofue et al., 2018), which is consistent with the current study's findings.

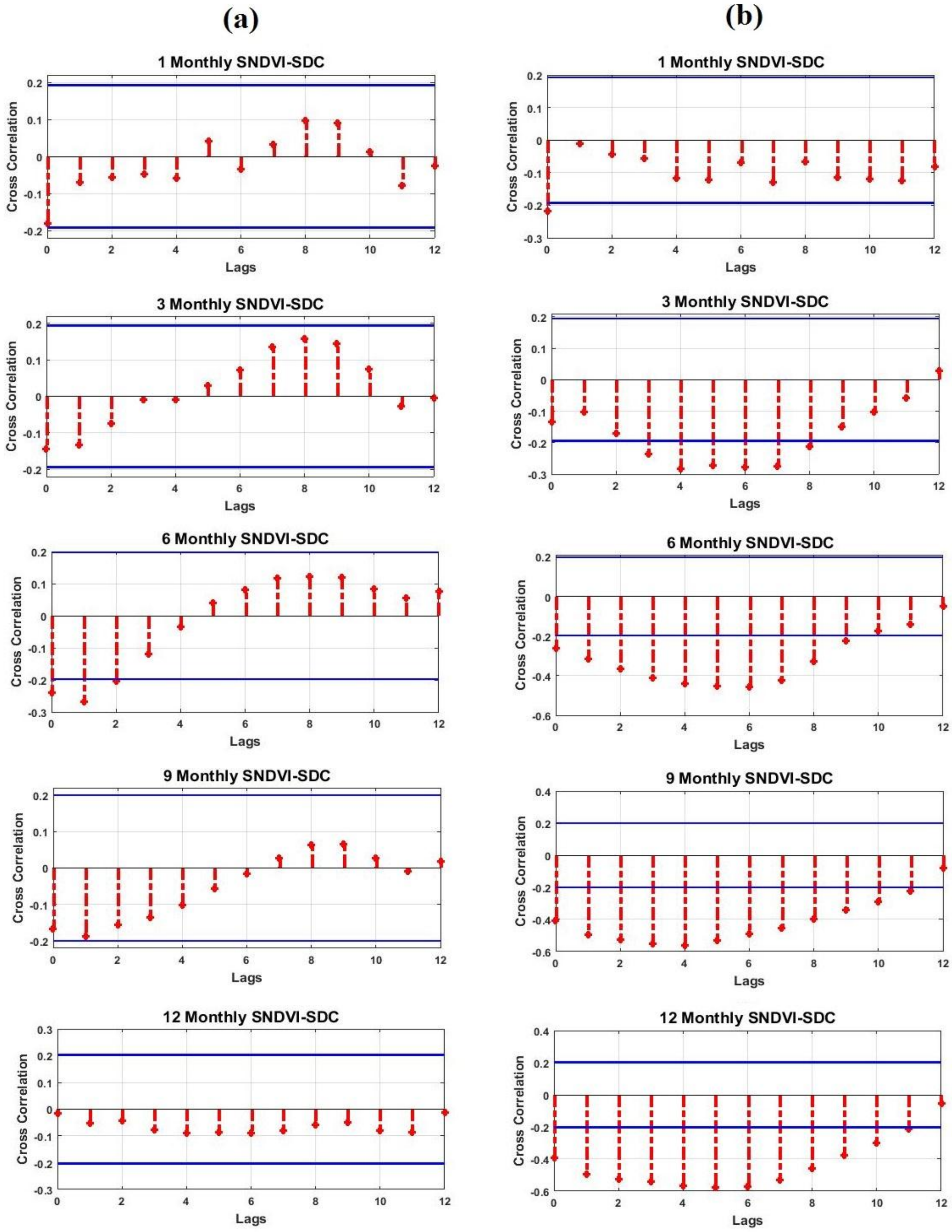

Figure (8): The cross-correlation coefficients between the SNDVI and SDC time series in (a) arid regions and (b) semi-arid regions of Iran (2010-2018)

Also, a comparison of maximum cross-correlation values showed that changes in land surface temperature in Iranian arid regions were more effective on wind erosion events than alterations in soil moisture and vegetation (Table 2). However, in semi-arid regions, the impact of vegetation variations on dust events was more than that of the fluctuations in the other two driving forces (Table 2). Although the current study did not attempt to evaluate the predictability of wind erosion based on physical characteristics of the earth's surface, it could be argued that soil moisture-based dust concentration is more difficult to predict than wind erosion in both study regions, which is in contrast with the findings reported by Kim et al. (2017), who used aerosol optical depth index to measure dust events instead of dust concentration data considered in this study.

As a whole, our results exhibited that the cross-correlation coefficients between terrestrial factors in the long-term series were often higher than the short-term series. In other words, the long-term effect of changes in the SLST and SNDVI was better to reveal the temporal behavior of the erosion caused by wind force to changes in the terrestrial agents. Also, the current study's results indicated that MODIS-NDVI products have been successfully able to show vegetation changes in both study areas, especially in semi-arid regions of Iran. One of the causes may be higher vegetation density in semiarid regions than in arid regions and better its reflectance in satellite images (Song et al., 2017; Tagesson et al., 2015).

5. Conclusion

In this study, the temporal behavior of wind erosion against changes in terrestrial agents across dry lands of Iran for the years 2010 – 2018 was investigated. To perform this, the standardized time series of LST, NDVI, SM, and DC were produced at different time scales with various time lags. The change trends in the SLST, SNDVI, SSM, and SDC and their relationships were evaluated using the Mann-Kendall test and cross-correlation method, respectively for one to 12-monthly time series at zero to 12-month time lags. For arid regions, the Mann-Kendall test results revealed a decreasing trend of wind erosion activity along with an increasing trend of all three terrestrial factors across these areas. However, for semiarid regions showed a weak increasing trend of wind erosion events along with an increasing change in vegetation and surface soil moisture. In this region of Iran, SLST variations showed the opposite trends at short- and long-term data sets. The strongest cross-correlation analysis revealed that the temporal response of the wind erosion to the changes in physical characteristics of the earth's surface varied in different Iranian climatic regions. In general, the most significant relationships were observed between the study variables in lagged time series. In this regard, according to the highest cross-correlation values, it was found that wind erosion occurred in response to long-term changes in land surface temperature and vegetation at 1 and 5-month lags, respectively, in semi-arid regions. It was also found that MODIS products performed well in displaying the NDVI and LST fluctuations in Iranian arid and semiarid regions, indicating that using LST and NDVI in dust concentration prediction appeared promising. Moreover, the relatively good performance of SMOS-SSM data sets in revealing changes in soil moisture and its relationship with dust concentration in arid regions was another important achievement obtained by the present study. As a whole, The findings of the study could help develop short and long-term plans to combat the desertification risks posed by wind force-induced soil erosion in Iran's arid and semi-arid regions of Iran.

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