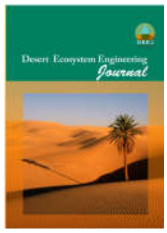
DEEJ (2023) 12 (10) 25-38

University of Kashan

Desert Ecosystem Engineering Journal

Journal homepage: http://deej.kashanu.ac.ir



Investigating the Best Representative Dust Activities Index, Its Spatial-Temporal Changes, and Its Relationship with Environmental Factors in Iranian Dry Areas

Ebrahimi-Khusfi[1]*, Zohre, Ebrahimi-Khusfi[2], Mohsen, Mirakbari, Maryam[3]

Received: 14/10/2023 Accepted: 24/12/2023

Abstract

The current study primarily sought to select the best index for elaborating on dust activities, analyze the temporal and spatial changes of the index's trend, and examine the relationship of the index with environmental factors in Iranian dry regions. To this end, the study examined the data collected on dust concentration, dust storm index, the number of dusty days (NDD), the pollution caused by dust storms, and the frequency of all dust events over a period of 18 years (2001-2018) using the MODIS-aerosols optical depth (AOD) product. Moreover, Pearson's correlation coefficient was used to analyze the correlation between the indices and AOD data sets. On the other hand, the trend of the best index annual changes in twenty-eight Iranian urban areas was analyzed using the Mann-Kendall method. Also, the most important environmental factors controlling dust activities in high-risk areas were identified using the random forest model. The results of the study indicated a strong correlation between NDD and AOD in Iranian dry regions ($r= 0.7$; $p\text{-value}= 0.001$). It was also found that the trend of NDD's annual changes significantly increased in Torbat Heydarieh, Nehbandan, and Anar ($Z>+1.96$). However, the trend significantly decreased in Chabahar and Iranshahr ($Z>|-1.96|$. Generally, the results indicated an insignificant decreasing trend of annual NDD changes across the entire Iranian arid regions from 2001 to 2018 ($Z= -0.45$). on the other hand, the random forest model suggested that air pressure and wind speed exerted the greatest influence on dust activities that occurred in Iran's high-risk area throughout the study period. Therefore, it could be argued that the findings of this study can help better monitor dust events and reduce their environmental risks in Iranian dry areas.

Keywords: Dust Events, Number of Dusty Days (NDD), Mann-Kendall Test, Environmental Factors, Machine Learning.

1. Department of Environmental Science and Engineering, Faculty of Natural Resources, University of Jiroft, Jiroft, Iran; Zohreebrahimi2018@ujiroft.ac.ir
2. Department of Geography, Faculty of Humanities and Social Sciences, Yazd University, Yazd, Iran
3. Postdoctoral Researcher, Faculty of Geographical Sciences and Planning, University of Isfahan, Isfahan, Iran

DOI: 10.22052/JDEE.2023.253732.1095

1. Introduction

As atmospheric phenomena that occur in many dry regions of the world (Ghafarian et al., 2022), dust event is considered one of the main factors that contribute to land degradation in such regions (Du et al., 2022). On the other hand, dust aerosols exert an adverse influence on climate change (Kok et al., 2023), agriculture (Ahmadzai, 2023), solar photovoltaic performance (Lay-Ekuakille et al., 2018; Nordine et al., 2023), and global radiation budget (Chauhan et al., 2023).

There are several indicators to measure the activity of dust events, which include Dust Storm Index (DSI) (O'Loingsigh et al., 2014), Dust Concentration (DC) (Shao & Wang, 2003), pollution of dust storm index (PDSI) (Jebali et al., 2021), number of dusty days (NDD) (Natsagdorj et al., 2003), and frequency of dust events (FDE) (Alizadeh-Choobari et al., 2016) which they have been used for different purposes in some researches.

Considering the fact that the difference between the parameters used in calculating the aforementioned indicators may affect the accuracy of the results obtained from the analysis of dust activities in different regions, it is necessary to identify the best indicator for assessing dust activities in areas that are sensitive to dust phenomenon. Therefore, as the issue has not been investigated in Iranian dry regions, this study sought to address it with special attention. To this end, the study considered the aerosols' optical depth (AOD) as its main criterion for evaluating the aforementioned ground-based indices (which are calculated using dust data recorded in synoptic stations). In other words, many studies have used AOD as an appropriate remote sensing tool to measure aerosols' activity and atmospheric dust (Mohammadpour et al., 2022; Omidvar et al., 2022), seeking to understand how it reacts to environmental drivers (Namdari et al., 2022; Sujitha et al., 2022).

It is very important to identify the most important environmental factors that control the dust activities in dry areas of the world. Recently, the good performance of machine learning models, especially tree-based tree models such as random forest (RF), has been confirmed in some dust studies (Berndt et al., 2021; Ouedraogo et al., 2022; Souri & Vajedian, 2015). Having introduced the best representative index for dust activities in Iranian dry regions, the current study applied the random forest (RF) model to identify the main important factors affecting dust activities in areas that are vulnerable to dust events. In other words, the relationship between environmental factors and the best dust index for Iranian dry areas was investigated using the RF model. In this regard, the main goals of the study could be stated as follows:

1. Introducing the best representative index for dust activities in Iranian dry areas based on the index's strongest correlation with aerosol optical depth (AOD) data sets.
2. Analyzing spatio-temporal changes of the best dust activities index in Iran's dry areas throughout the study period.
3. Determining the main factors controlling dust activity in areas more sensitive to this phenomenon using the RF model.

2. Study area

The study area of the current research is the dry areas of Iran, which are mainly located in the eastern half of this country and has an area of about 838000 square kilometers. The extent of dust prone areas in this region is about 601909 km^2. Based on the climatic parameters recorded for the selected stations in the mentioned period, the long-term average of air temperature, rainfall, relative humidity, and wind speed in the arid regions of Iran are 27.1°C, 107.3mm, 34.4%, and 3.1 m/s respectively.

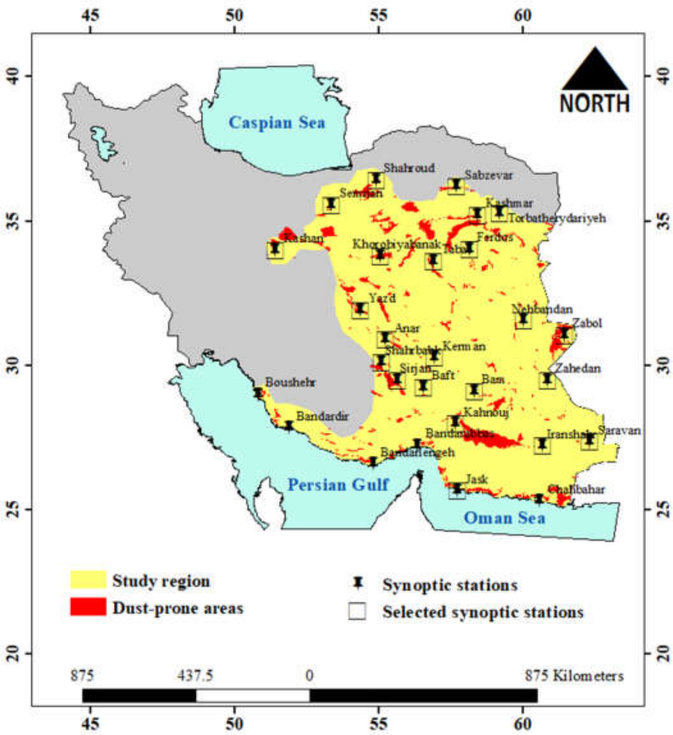


Figure (1): Geographical distribution of synoptic stations and dust-prone regions in dry areas of Iran

3. Data Sets and Methodology

The long-term weather observations and satellite data sets were used to investigate the objectives of the current research. The weather observations used in the study were three-hour recordings of horizontal visibility (HV) <10km, dust codes (06 to 09, 30 to 35, and 98), daily recorded data concerning the minimum temperature (Tmin), maximum temperature (Tmax), rainfall (Ra), relative humidity (RH), wind speed (WS), air pressure (Pr), and evaporation (ET). These data were acquired from Islamic republic of Iran meteorological organization (IRIMO). There are 28 synoptic stations in this region of Iran that have the same statistical period length with AOD data (2001-2018), but among them, 5 stations were excluded due to deficiency of AOD data. Finally, the 23 synoptic stations were selected to investigate the first two objectives of the current research. It is worth mentioning that after choosing the best dust activities index, analysis of their temporal and spatial changes was performed based on the recorded information for all synoptic stations.

Moreover, the satellite data used in the study were AOD, land surface temperature (LST), and normalized difference vegetation index (NDVI) time series which were obtained for the years 2001-2018 from 'https://earthdata.nasa.gov/' at daily, eight-day, and sixteen-day time scales, respectively**.** All the satellite data belonged to the MODIS sensor.

The monthly mean values of all data sets were calculated using the arithmetic mean method for monthly and annual time scales. Three-hour recordings of HV and dust events were also used to calculate the representative indices of dust activities in the mentioned time scales as explained below.

3.1. The calculation of Dust concentration (DC)

In this research, at first, mean monthly values of HV were calculated using the arithmetic mean method based on three-hour observations of HV recorded for all dust events in 23 selected synoptic stations. Then, equation (1) and equation (2) were used to calculate the monthly DC ($\mu g.m^{-3}$) in the HV<3.5 km and ≥3.5 km, respectively (Shao & Wang, 2003).

$$Monthly\ DC = 3802.29 \times monthly\ HV^{-0.84} \qquad for\ HV < 3.5km \qquad (1)$$

$$Monthly\ DC = \exp(-0.11HV + 7.62) \qquad for\ \ HV \geq 3.5km \qquad (2)$$

The average DC values in each year of the study period (2001-2018) were calculated for all synoptic stations using the arithmetic mean of DC in 12 months. Finally, the yearly DC values were applied to calculate the long-term DC values in each station.

3. 2. The calculation of Dust storm index (DSI)

This index proposed by O'Loingsigh et al. (2014) to measure wind erosion and dust storm activities, which is calculated as follows:

(1) The total number of local dust events (LDE: codes 07 to 09), moderate dust storms (MDS: codes 30 to 32, and 98), and severe dust storms (SDS: codes 33 to 35) for each month was calculated based on the maximum daily code recorded for these events.
(2) The monthly DSI values were calculated by multiplying the number of LDE, MDS, and SDS by 0.05, 1, and 5, respectively.
(3) The yearly DSI values were calculated for all synoptic stations based on the sum of DSI values in 12 months.

3. 3. The calculation of Pollution of dust storm index (PDSI)

The PDSI was proposed by Jebali et al. (2021) to elaborate on the pollution caused by dust storms with both internal and external origins. The steps for calculating the index are the same as those presented for DSI. However, the calculation formula of the index differs from that of the DSI in the following terms: (1) in addition to the events with the codes mentioned above, external events (code 06) are also considered in calculating the MDS; and (2) the LDE, MDS, and SDS are counted based on the frequency of all codes corresponding to each dust event.

3. 4. The calculation of Frequency of all dust events (FADE)

The FADE is another indicator to measure the activity of sand and dust storms. In this work, monthly values of the FADE for all study stations were calculated based on the total number of three-hour events recorded in each month. The annual FADE values were calculated by summing FADE values in all months of each year in the selected stations.

3. 5. The calculation of Number of dusty days (NDD)

In this study, the number of dusty days per month was calculated by counting the days when at least one of the local, moderate or severe dust events occurred. The annual NDD values were also obtained by summing the NDD values in 12 months of each year for all synoptic stations located in arid regions of Iran.

Finally, the mean annual values of DC, DSI, PDSI, NDD, and FADE for dry regions of Iran were calculated based on the average values of these indices in all selected synoptic stations located in arid region of Iran. Among the mentioned indices, DSI and NDD were calculated only by considering internal dust events and the other three indices were calculated by considering all dust events (internal and external); Therefore, it is also possible to find out whether the impact of external events should be considered in the analysis of the dust activities across dry areas of Iran or not.

3. 6. Determining the best representative index of dust activities

To determine the best representative index of dust activities for dry areas of Iran, Pearson's correlation coefficient (r) was used (Equation 3; Sedgwick, 2012). This coefficient was used to analyze the intensity and direction (negative or positive) of the correlation of dust indices with the AOD data sets during the study period. The index that had the highest correlation with AOD, was introduced as the best index.

$$r = \frac{\sum(xi-\bar{x})(yi-\bar{y})}{[\sum(xi-\bar{x})^2 \sum(yi-\bar{y})^2]^{0.5}} \qquad (3)$$

In the mentioned equation, x and y are independent and dependent variables, respectively. In the current research, dust indices were considered independent variables, and AOD was considered a dependent variable. $\bar{x}$ refers to the mean of the values of the x-variable and $\bar{y}$ indicates the mean of the values of the y-variable.

4. Analysis of dust activities' spatio-temporal changes in Iranian dry areas based on the best dust index

This study prepared the spatial distribution map of dust occurrences according to the selected dust index using the inverse distance weighting (IDW) interpolation method in ArcGIS10.4.1 software. To this end, the study used long-term average values of the best index collected from all synoptic stations. This method has already been used in previous studies to prepare a spatial distribution map of dust events (Ghafarian et al., 2022; Zhao et al., 2022). On the other hand, the trend of annual changes in the selected dust index throughout the study period (2001-2018) was investigated by the Mann-Kendall test both at local (synoptic stations) and regional scales (Iranian arid regions). According to the test, if the S value (equation 4) is not significantly different from zero, no trend could be proven; otherwise, the trend will either be upward or downward. Moreover, the zero hypotheses of the test indicate randomness and the absence of any trend in the data series. However, the verification of any of the hypotheses (i.e., the rejection of the null hypothesis) indicates the existence of a trend in the data series. The Mann-Kendall test statistic (Z) for a time series x1,x2,...,xn is calculated using equations (5) to (6) (Kendall, 1975; Mann, 1945).

$$S=\sum_{k=1}^{n-1}\sum_{j=k+1}^{n}\operatorname{sgn}(x_j+x_k) \qquad \operatorname{sgn}(x)=\begin{cases}+1 & x>0\\ 0 & x=0\\ -1 & x<0\end{cases} \tag{4}$$

$$\begin{cases} Z=\dfrac{S-1}{(\operatorname{var}(S))^{\frac{1}{2}}} & if \quad S>0\\ 0 & if \quad S=0\\ \dfrac{S+1}{(\operatorname{var}(S))^{\frac{1}{2}}} & if \quad S<0\end{cases} \tag{5}$$

$$Var\,(S)=\{n(n-1)(2n+5)\} \tag{6}$$

where j and k are the order of observations, sgn(x) is the sign function, and n is the number of observations. Statistical significance was considered at $p<0.05$.

4.1. Determining environmental factors controlling dust activities

After analyzing the spatial distribution of dust activities based on the best- selected index, more sensitive areas to dust storms were identified. Then, the most important factors influencing the changes in dust activities across the areas were ranked using the random forest model. Before the modeling process, collinearity analysis was performed on nine environmental variables (Tmin, Tmax, Ra, Pr, RH, ET, WS, LST, and NDVI) using the tolerance coefficient ($TC=1-R^2$). Accordingly, X-variables with the $TC<0.1$ were excluded and the remaining variables with the $TC>0.1$ were used for modeling (Midi et al., 2010). This model can be utilized for various purposes such as regression, classification, and determining the importance of X-variables. In the present study, this model was used to rank the variables controlling dust activities based on their relative importance. To determine the relative importance of controlling variables, a random forest model is first fitted to the data. During this process, the out-of-bag error at each point is calculated and averaged for a forest. After training the data set entered into the model, the values of each variable are permuted among the training data and the mentioned error is recalculated on the shuffled data set. In the next step, the difference of the error for before and after the permutation is calculated and the relative importance of the variable is determined and normalized by the standard deviation of the obtained differences (Breiman, 2001). In fact, variables which that generate small values for this score are less important than features that generate larger values, and vice versa. In this study, collinearity analysis and modelling process were respectively performed in the SPSS20 and the R studio software (Version 1.1.463).

5. Results and discussion

5. 1. Comparing dust indices and choosing the best dust index for Iranian dry regions

Table 1 shows the average values and standard deviation of the dust indices collected from the twenty-three synoptic stations in Iranian dry areas throughout the 2001-2018 period.

Table (1): The mean and standard deviation of the dust indices in the selected synoptic stations during the study period (2001-2018)

	DC		DSI		PDSI		NDD		FADE	
Synoptic station	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Anar	723.84	179.88	1.84	1.90	37.73	27.30	17.33	7.80	64.78	39.97
Baft	75.89	86.45	0.04	0.06	0.56	1.08	0.78	1.13	1.67	2.29
Bam	529.64	278.57	0.71	1.45	12.37	18.53	5.50	5.17	22.33	22.19
Ferdos	485.44	195.00	0.71	0.46	6.25	11.92	12.00	6.64	23.72	18.78
Iranshahr	991.88	167.52	5.00	2.38	28.85	36.58	74.61	28.92	146.28	84.16
Jask	1089.57	80.46	6.49	2.93	17.13	8.26	116.72	39.62	268.17	110.03
Kahnouj	658.52	474.96	1.53	2.49	17.39	17.39	8.89	6.47	29.44	26.27
Kashan	357.97	332.29	0.92	1.77	18.71	19.82	4.17	5.29	23.33	24.72
Kashmar	391.19	156.11	0.55	1.18	6.38	7.09	4.44	2.31	12.33	8.99
Kerman	676.21	185.79	0.89	0.49	19.39	13.19	12.56	4.44	39.50	21.33
Khur-va-biyabanak	652.80	170.37	0.61	0.30	73.84	51.44	11.17	3.76	90.83	52.71
Nehbandan	737.37	170.58	3.28	3.53	117.76	155.09	28.72	22.08	177.33	192.08
Sabzvar	649.14	128.92	1.22	0.61	3.63	3.02	19.11	7.25	29.28	16.56
Saravan	926.33	114.38	2.41	0.79	35.52	35.41	46.11	14.22	124.61	54.50
Semnan	279.48	234.91	0.19	0.37	8.92	14.68	1.72	1.94	10.56	14.78
Shahrbabak	499.10	117.85	1.78	2.68	3.19	2.94	11.67	3.51	19.50	8.81
Shahroud	162.30	154.42	0.06	0.06	1.71	2.99	1.17	1.21	3.50	4.73
Sirjan	299.46	224.02	0.18	0.22	7.92	15.57	3.56	4.34	13.78	21.02
Tabas	900.30	160.29	2.00	1.29	9.61	15.41	27.11	9.81	40.22	22.28
Torbatheydariyeh	424.98	264.11	0.59	0.53	3.83	3.23	11.72	10.50	20.72	18.90
Yazd	985.75	90.00	2.59	2.01	114.25	72.95	31.28	9.15	160.78	80.09
Zabol	1102.13	92.51	39.28	20.90	67.15	42.06	166.06	19.30	364.83	207.68
Zahedan	1047.78	78.22	5.86	3.18	141.14	101.27	70.56	10.54	287.94	105.14

The values presented in Table (1) show that in terms of DC, DSI, NDD, and FADE, Zabol station, and in terms of PDSI, Zahedan station had the highest dust activities in arid regions of Iran during the study period (2001-2018). Mean ±standard deviation values of DC, DSI, NDD, and FADE in the Zabol were 1102.13 ±92.51 ($\mu g.m^{-3}$), 39.28±20.90, 166.06±19.30, and 364.83±207.68, respectively. The mentioned statistics for PDSI in Zahedan station were 141.14±101.27.

The results of the study indicated that the use of different indicators to identify areas with more dust pollution did not lead to totally similar results. Therefore, to determine an index that can better show the activity of such events in Iranian arid regions, the average values of DC, DSI, PDSI, NDD, and FADE were calculated separately based on the indices obtained from the twenty-three synoptic stations during the study period. Figure 2 (a –e) shows the annual changes of the indices in Iranian dry regions from 2001 to 2018 compared to the temporal changes of AOD.

According to the results presented in Figure (2), the average values of DC, DSI, PDSI, NDD, and FADE across the dry areas were reported as 636.8$\mu g.m^{-3}$, 3.4, 32.7, 29.9, and 85.9 from 2001 to 2018, respectively, and their standard deviation values were found to be 57.7, 1.1, 11.4, 3.9, and 23.2, respectively. Figure 2 also suggested that while the DSI and NDD had a decreasing slope during the study period, the DC, PDSI, and FADE experienced an increasing slope during the same period.

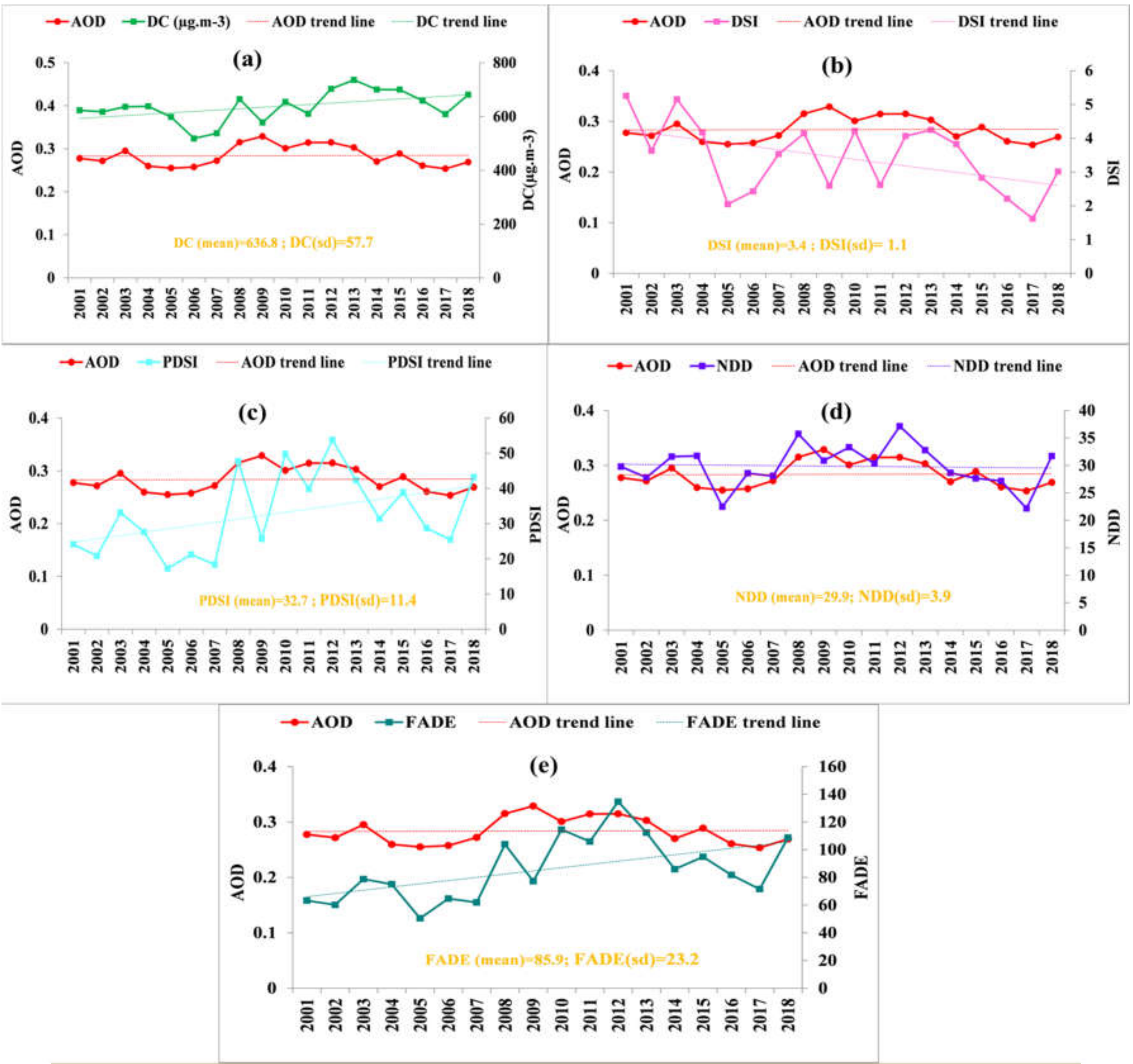


Figure (2): Dust indices and their statistical characteristics in Iranian dry areas (2001-2018)

In total, based on the two indicators of DSI and NDD, the dust activity across the arid regions of Iran was decreasing while their activities was increasing during the study period based on the other three indicators. Therefore, considering that the distribution of dust indices and AOD data sets were normal (Sig>0.05; Table 2); Pearson's correlation coefficient (r) was applied to analyze the relationship between all study dust indices and AOD data series and to determine the best dust index in the study area.

Table (2): The results of One-Sample Kolmogorov-Smirnov Test for dust indicators

Parameters	AOD	DC (μg.m-3)	DSI	NDD	PDSI	FADE
Kolmogorov-Smirnov Z	0.786	0.389	0.502	0.561	0.592	0.534
Sig. (2-tailed)	0.567	0.998	0.963	0.911	0.875	0.938

Table (3): Pearson's correlation coefficients between dust indicators and AOD in Iranian dry areas during the study period (2001-2018)

Correlation coefficient and p-values	DC	DSI	NDD	PDSI	FADE
r	0.27	0.33	0.70**	0.63**	0.63**
p-value	0.28	0.19	0.001	0.005	0.005

*. Correlation is significant at the 0.05 level.
**. Correlation is significant at the 0.01 level

According to the obtained results, no significant correlation was observed between DC-AOD (r= 0.27; p-value= 0.28) and DSI-AOD (r= 0.33; p-value= 0.19). However, the stronger correlations (at the 0.05 and 0.01 level) were observed between NDD-AOD (0.7; p-value= 0.001), PDSI-AOD (r= 0.63; p-value= 0.005), and FADE-AOD (r= 0.63 ; p-value= 0.005) (Table 3).

The results also showed that the NDD, PDSI, and FADE could explain the dust storm activities in the dry areas better than the other two indicators. Considering that the NDD had a strongest correlation with the optical depth of aerosols., it was chosen as the best index for analyzing the spatial and temporal changes of dust storms activities in the study area. In the analysis of the relationship between a ground-based index called DSI and several satellite indices with AOD for the stations around Horulazim wetland, it was shown that less than 20% of AOD changes can be explained by DSI and about 50% of these changes can be explained by satellite indices (Poordehghan Ardekani et al., 2022). Therefore, the findings of these researchers about the relationship between DSI-AOD confirm the findings of this research.

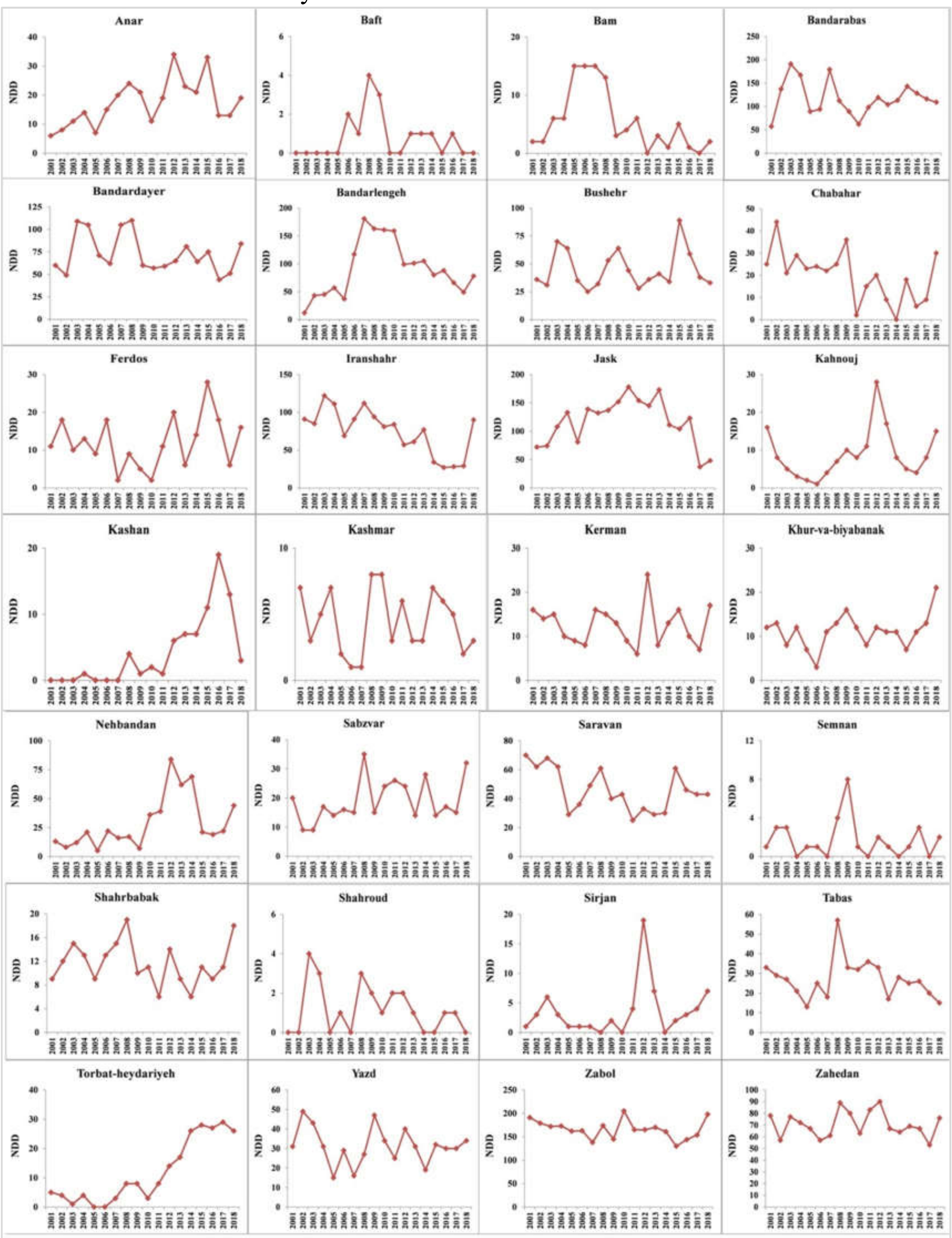


Figure (3): The annual NDD values in the synoptic stations located in the arid regions of Iran from 2001 to 2018

5.2. The analysis of dust activities' spatio-temporal changes in Iranian dry areas based on the best dust index

As explained in the methodology, after selecting the best representative index of dust events, spatio-temporal changes of these events were analyzed based on the selected index in all stations located in the study region. In the studied urban areas, Zabol, Bandar Abbas, Bandarlangeh and Jask had the worst air quality in 2010, 2003, 2007 and 2010, respectively, with 205, 191, 181, 178 and 122 dusty days (Figure 3). In order to understand more about the spatial changes of dust activities in the study area, the spatial distribution map of dust activities in dry regions of Iran were prepared based on the long-term mean values of the NDD in 28 stations using the IDW method, and the trend of annual changes in the NDD for all stations was determined using the Mann-Kendall test, which the results are summarized in figure 4.

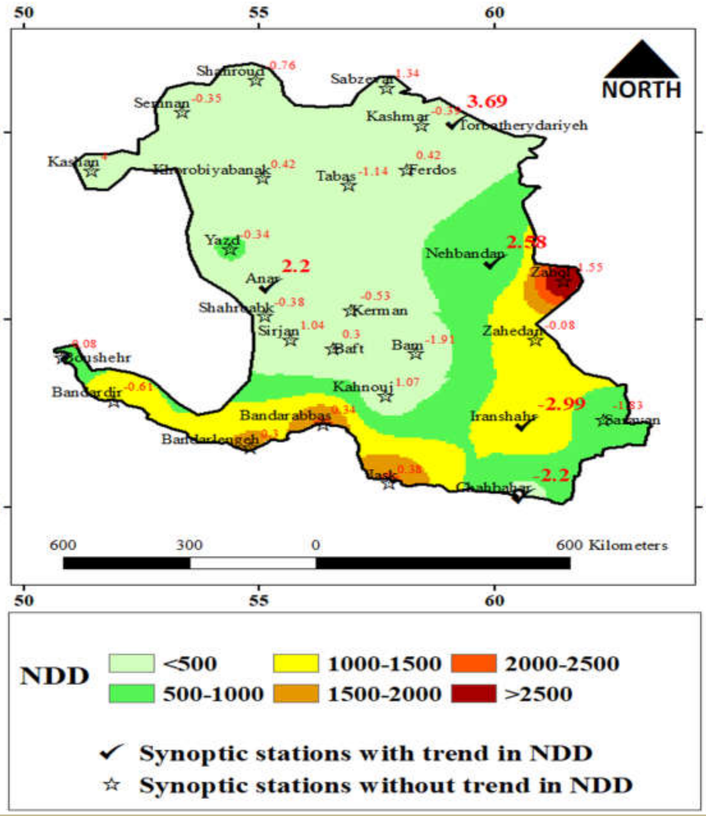


Figure (4): The Spatio-temporal changes of the number of dusty days (NDD) in Iranian dry areas during 2001-2018 (Mann-Kendall statistic values were marked in red at each station)

The NDD's spatial distribution map indicated that during the study period, the total number of dusty days was less than 500 days in the northwest and the northeast of the study area. However, the number exceeded 500 days in the south and southeast regions of the study area during the same period. According to the NDD map, Zabul was identified as the dustiest city among Iranian arid regions, with its NDD being greater than 2500 days throughout the study period. In general, based on the reclassified NDD map, it was found that the southeastern and southern areas of the study area were more sensitive to dust storms than the central, northwestern, and northeastern areas. The high sensitivity of the southeastern regions, especially the cities of Zabol and Zahedan, to the wind erosion and dust storms has been proven in some past studies (Ebrahimi-Khusfi et al., 2020; Mesbahzadeh et al., 2020), which can confirm the findings of the present study. In most of the cities located in these areas, which were identified as high-risk areas in this study, the contribution of dust events with internal origin was higher than those with external origin (Figure. 5). In general, on a regional scale, 55.4% of the dust events were of internal origin and 45.6% of them were of external origin. This can be one of the reasons why NDD performed better than indices such as DC, PDSI and FADE, which include external events in their calculation. Although the calculation of DSI is done only based on internal dust events, this index is presented based on Australian weather conditions and the constant coefficients considered for its parameters (LDE, MDS, and SDS) may not be suitable for Iranian conditions. Although the DSI is calculated only based on internal dust events, but the weights used in its calculation are defined based on Australian conditions, and these weights may not be suitable for Iran's climatic conditions. Therefore, this seems to have led to a weak correlation of DSI- AOD compared to NDD-AOD, despite the fact that both indices are calculated based on internal dust events.

Moreover, the results of the Mann-Kendall test suggested an insignificant decreasing trend of NDD's annual changes in the dustiest station (Zabul) throughout the study period (Z= -1.55). In general, out of the synoptic stations investigated in this study, only two stations, namely Iranshahr (Z= -2.99) and Chabahar (Z= -2.2), experienced significant decreasing changes in NDD, and three other stations, that is, Torbat Heydarieh (Z= 3.69), Anar (Z= 2.2), and Nehbandan (Z= 2.58) underwent significant increasing changes in terms of the NDD throughout the study period (2001-2018). The Mann- Kendall's statistic obtained for the entire study area was -0.45, indicating that the trend of changes in NDD in the regional scale during the years 2001 to 2018 was decreasing and insignificant. The average value of NDD in dry areas of Iran was about 30 days (Figure 2d), with the highest number of dusty days occurring in 2012 (37 days) and 2008 (35 days) and the lowest in 2005 and 2017 (27 days). Modarres & Sadeghi (2018), in a part of their research, showed that during the years 2001 to 2010, the change trend of NDD had an increase trend, which is consistent with the findings of the current research for this period of time.

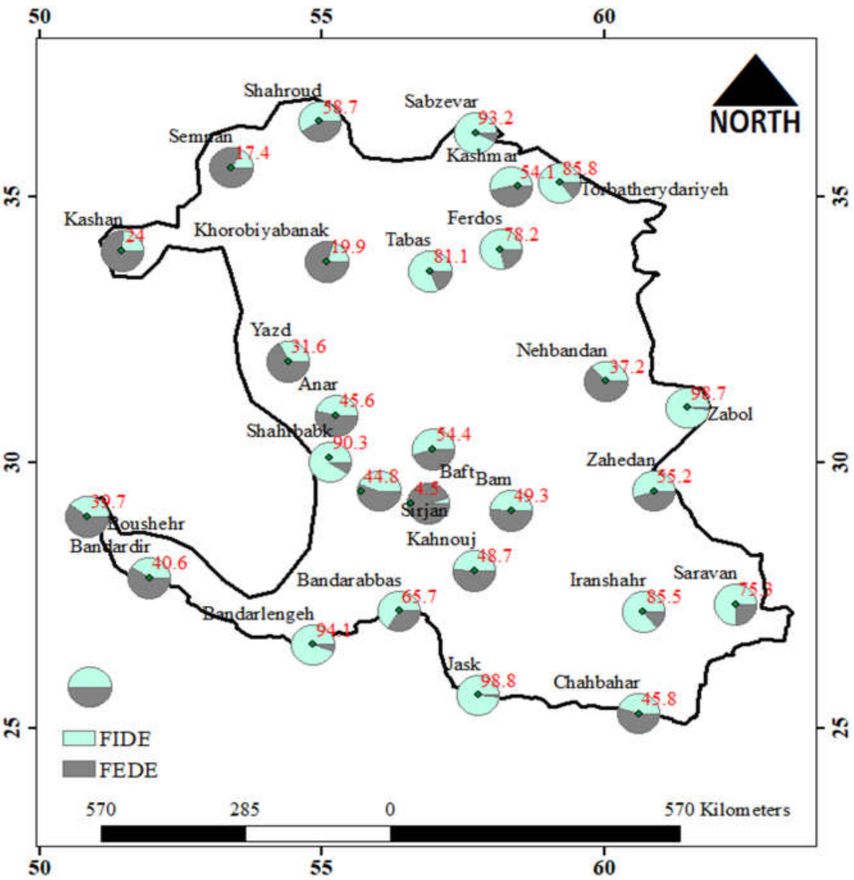


Figure (5): The frequency of internal dust events (FIDE%) and the frequency of external dust events (FEDE%) in the synoptic stations of Iranian arid regions

5. 3. Main factors controlling dust activities in high-risk areas of dry regions of Iran

In this stage of the current research, collinearity analysis was performed on the average values of nine environmental variables in areas more sensitive to dust storms. After removing highly correlated variables (TC<0.1) in 4 steps (Figure.6), the main variables were identified. They were rain, Pr, RH, WS, LST, and NDVI (TC>0.1) and were determined their relative importance using the RF model. The results showed that two important factors affecting NDD changes in high-risk areas of Iran were long-term changes in air pressure (RI= 5.90) and wind speed (RI= 1.89). After that, the land surface temperature (RI= 1.7), relative humidity (RI= 0.73), rainfall (RI= 0.70), and vegetation cover (RI= 0.59) have played the most effective role in changing NDD and air quality in this region. Recently, Temperature, WS, RH, and Pr are selected to model and optimize dust concentration estimation (Luan et al., 2023). The strong relationship between the LST and the dust emission is also been proven in the study conducted by Ma et al. (2020), which can indicate the high importance of these factors in dust studies and confirm the findings of this research. Jazmurian area as an area with high dust production potential is located in the high-risk area of dry areas of Iran. According to the reports of Dolatkordestani et al. (2022), four factors of vegetation cover, elevation, wind speed and rainfall are introduced as the main factors controlling dust activity in this region, which is largely consistent with the findings of the present study.

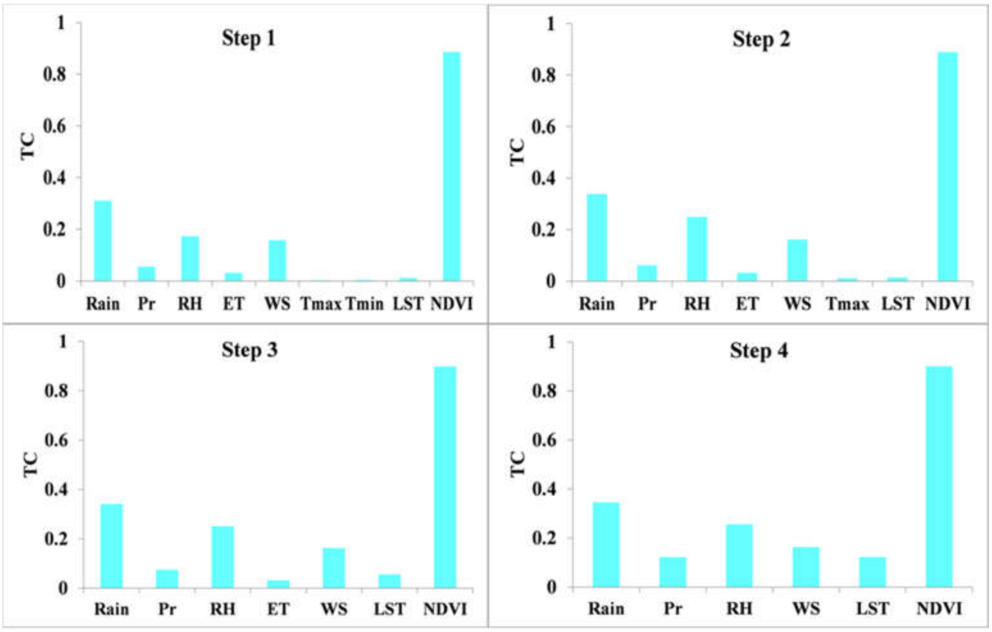


Figure (6): Collinearity analysis results of factors controlling dust activities in high-risk areas of arid regions of Iran

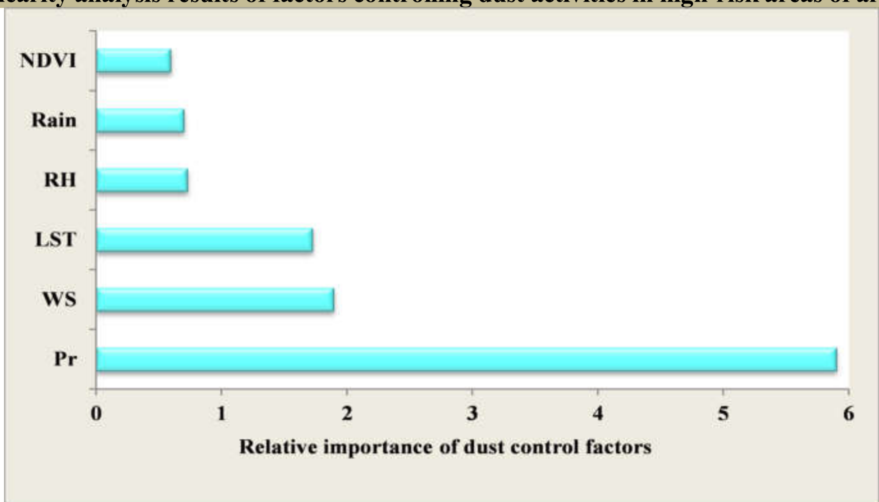


Figure (7): Relative importance of factors controlling dust activities in high-risk areas of arid regions of Iran

6. Conclusion

Dust events are one of the main factors contributing to land degradation in Iranian dry regions. Therefore, it is necessary to evaluate their changes based on a suitable criterion and identify the most important factors affecting them in different regions. This study found a strong correlation between NDD and AOD, thus recommending the latter to be used as a ground-based index for analyzing temporal-spatial changes of dust events in other regions. According to the NDD, the southeastern and southern areas of Iran were identified as areas with higher dust activities. Moreover, in most of the cities located in high-risk areas, the contribution of internal dust events was higher than that of the external dust events in the regions.

On the other hand, air pressure, wind speed, land surface temperature, relative humidity, rainfall, and vegetation were identified as the most important environmental factors controlling dust activities in high-risk areas, respectively.

The results of the current study could thus be useful to increase our knowledge concerning the most important factors controlling dust activities, especially in the high-risk areas of Iran. Moreover, the findings of the study can be used to provide suitable solutions to better control and manage aeolian hazards in areas with more dust activity in Iranian dusty areas.

Acknowledgments

This research was supported by the University of Jiroft under grant NO: 4812-00-3, and the authors appreciate the educational and research vice-chancellor of the university.

References

2. Ahmadzai, H. (2023). The impact of sand and dust storms on agriculture in Iraq. *Middle East Development Journal*, 1-16.
3. Alizadeh□Choobari, O., Ghafarian, P., & Owlad, E. (2016). Temporal variations in the frequency and concentration of dust events over Iran based on surface observations. *International Journal of Climatology, 36*(4), 2050-2062.
4. Berndt, E., Elmer, N., Junod, R., Fuell, K., Harkema, S., Burke, A., & Feemster, C. (2021). A machine learning approach to objective identification of dust in satellite imagery. *Earth and Space Science, 8*(6), e2021EA001788.
5. Breiman, L. (2001). Random forests. *Machine learning, 45*(1), 5-32.
6. Chauhan, P. K., Kumar, A., Pratap, V., Chaubey, S. K., & Singh, A. K. (2023). Dust storm characteristics over Indo-Gangetic basin through satellite remote sensing. In *Atmospheric Remote Sensing* (pp. 373-392): Elsevier.
7. Dolatkordestani, M., Nosrati, K., Maddah, S., & Tiefenbacher, J. P. (2022). Identification of dust sources in a dust hot-spot area in Iran using multi-spectral Sentinel 2 data and deep learning artificial intelligence machine. *Geocarto International*(just-accepted), 1-14.
8. Du, H., Xue, X., Wang, T., Lu, S., Liao, J., Li, S., . . . Liu, X. (2022). Modeling dust emission in alpine regions with low air temperature and low air pressure–A case study on the Qinghai-Tibetan Plateau (QTP). *Geoderma, 422*, 115930.
9. Ebrahimi-Khusfi, Z., Mirakbari, M., Ebrahimi-Khusfi, M., & Taghizadeh-Mehrjardi, R. (2020). Impacts of vegetation anomalies and agricultural drought on wind erosion over Iran from 2000 to 2018. *Applied Geography, 125*, 102330.
10. Ghafarian, P., Kabiri, K., Delju, A. H., & Fallahi, M. (2022). Spatio-temporal variability of dust events in the northern Persian Gulf from 1991 to 2020. *Atmospheric Pollution Research, 13*(4), 101357.
11. Jebali, A., Zare, M., Ekhtesasi, M. R., & Jafari, R. (2021). Detection of areas prone to wind erosion and air pollution using DSI and PDSI indices. *Natural Hazards, 108*(1), 1221-1235.
12. Kendall, M. (1975). Rank correlation methods (4th edn.) charles griffin. *San Francisco, CA, 8*, 875.
13. Kok, J. F., Storelvmo, T., Karydis, V. A., Adebiyi, A. A., Mahowald, N. M., Evan, A. T., . . . Leung, D. M. (2023). Mineral dust

aerosol impacts on global climate and climate change. *Nature Reviews Earth & Environment*, 1-16.

14. Lay-Ekuakille, A., Ciaccioli, A., Griffo, G., Visconti, P., & Andria, G. (2018). Effects of dust on photovoltaic measurements: A comparative study. *Measurement, 113*, 181-188.
15. Luan, B., Zhou, W., Jiskani, I. M., & Wang, Z. (2023). An Improved Machine Learning Approach for Optimizing Dust Concentration Estimation in Open-Pit Mines. *International Journal of Environmental Research and Public Health, 20*(2), 1353.
16. Ma, M., Yang, X., He, Q., Zhou, C., Mamtimin, A., Huo, W., & Yang, F. (2020). Characteristics of dust devil and its dust emission in northern margin of the Taklimakan Desert. *Aeolian Research, 44*, 100579.
17. Mann, H. B. (1945). Nonparametric tests against trend. *Econometrica: Journal of the econometric society*, 245-259.
18. Mesbahzadeh, T., Salajeghe, A., Sardoo, F. S., Zehtabian, G., Ranjbar, A., Krakauer, N. Y., . . . Mirakbari, M. (2020). Climatology of dust days in the Central Plateau of Iran. *Natural Hazards, 104*(2), 1801-1817.
19. Midi, H., Sarkar, S. K., & Rana, S. (2010). Collinearity diagnostics of binary logistic regression model. *Journal of interdisciplinary mathematics, 13*(3), 253-267.
20. Modarres, R., & Sadeghi, S. (2018). Spatial and temporal trends of dust storms across desert regions of Iran. *Natural Hazards, 90*(1), 101-114.
21. Mohammadpour, K., Rashki, A., Sciortino, M., Kaskaoutis, D. G., & Boloorani, A. D. (2022). A statistical approach for identification of dust-AOD hotspots climatology and clustering of dust regimes over Southwest Asia and the Arabian Sea. *Atmospheric Pollution Research, 13*(4), 101395.
22. Namdari, S., Zghair Alnasrawi, A. I., Ghorbanzadeh, O., Sorooshian, A., Kamran, K. V., & Ghamisi, P. (2022). Time series of remote sensing data for interaction analysis of the vegetation coverage and dust activity in the middle east. *Remote Sensing, 14*(13), 2963.
23. Natsagdorj, L., Jugder, D., & Chung, Y. (2003). Analysis of dust storms observed in Mongolia during 1937–1999. *Atmospheric Environment, 37*(9-10), 1401-1411.
24. Nordine, S., Ziane, A., Dabou, R., Neçaibia, A., Rouabhia, A., Lachtar, S., . . . Boudjamaa, T. (2023). Technical and economic study of the sand and dust accumulation impact on the energy performance of photovoltaic system in Algerian Sahara. *Renewable Energy*.
25. O'Loingsigh, T., McTainsh, G., Tews, E., Strong, C., Leys, J., Shinkfield, P., & Tapper, N. (2014). The Dust Storm Index (DSI): a method for monitoring broadscale wind erosion using meteorological records. *Aeolian Research, 12*, 29-40.
26. Omidvar, K., Dehghan, M., & Khosravi, Y. (2022). Assessment of relationship between aerosol optical depth (AOD) index, wind speed, and visibility in dust storms using genetic algorithm in central Iran (case study: Yazd Province). *Air Quality, Atmosphere & Health, 15*(10), 1745-1753.
27. Ouedraogo, W. Y. S. B., Tiemounou, S., Djibo, M., Doumounia, A., Sanou, S. R., Sawadogo, M., . . . Zougmore, F. (2022). Application of Machine Learning Methods on Climate Data and Commercial Microwave Link Attenuations for Estimating Meteorological Visibility in Dusty Condition.
28. Poordehghan Ardekani, F., Tazeh, M., Kalantari, S., & Ebrahimi Khosfi, Z. (2022). Investigating the relationship between dustiness indices and the aerosols optical depth around the Horulazim wetland. *Journal of Arid Biome, 12*(1), 141-158.
29. Sedgwick, P. (2012). Pearson's correlation coefficient. *Bmj, 345*.
30. Shao, Y., & Wang, J. (2003). A climatology of Northeast Asian dust events. *Meteorologische Zeitschrift, 12*(4), 187-196.
31. Souri, A. H., & Vajedian, S. (2015). Dust storm detection using random forests and physical-based approaches over the Middle East. *Journal of Earth System Science, 124*(5), 1127-1141.
32. Sujitha, P., Santra, P., Bera, A., Verma, M.,

& Rao, S. (2022). Detecting dust loads in the atmosphere over Thar desert by using MODIS and INSAT-3D data. *Aeolian Research, 57*, 100814.

33. Zhao, X., Zhao, C., Yang, Y., Sun, Y., Xia, Y., Yang, X., & Fan, T. (2022). Distinct changes of cloud microphysical properties and height development by dust aerosols from a case study over Inner-Mongolia region. *Atmospheric Research, 273*, 106175.