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Investigating the effect of land cover on dust spatial distribution in Southern Khuzestan province

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ABSTRACT

Aims: This research investigates the impact of land cover on dust distribution in the southern part of Khuzestan province in the period of 2000 to 2018.
Materials & Methods: We used the Landsat 7 and 8 satellite data in 2000, 2009, and 2018 to extract land cover. The land cover map was prepared using the decision tree classification. Aerosol data was extracted using the aerosol optical depth index from the Modis Terra and Aqua sensors. Finally, the relationship between land cover changes and dust index was analyzed.
Findings: The results of land cover maps showed a 5% decrease in rangeland cover; a 4.3% increase in salt marshes area; and, a 0.2% decrease in water bodies. The results also showed that the maximum aerosol index in 74% for Hindijan, Ahvaz, and Bandar Mahshahr. The maximum value of this index has increased in recent years. The highest percentage of land-use changes between 2000 and 2018 are bare lands to saline lands, rangelands to bare lands, and bare lands to croplands, respectively. We believe that salt lands by an increase in area by 68195 ha are the main cause of the increase in dust storms in the study area.
Conclusion: Our results confirm the need to reconsider land use management and restore the basic functionality of the region's ecosystems to prevent the occurrence of grave consequences of aerosol accumulation in the atmosphere.

Keywords: Aerosol optical depth; Landsat; Modis; Decision tree classification.

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Introduction

Dust event, as a climatic phenomenon, occurs in all climatic conditions and cause adverse social, economic, environmental, and commercial damages, especially in arid areas where it can disrupt human activities such as agriculture, transportation, industries, social and medical services [1]. The large volume of particles transported to the troposphere affects the energy balance, which in turn affects the weather condition and climate of the area. The importance of investigating dust storms is due to their role in erosion and sedimentation, as when they occur, they result in a sharp reduction of visibility to less than one kilometer [2]. The amount of dust has been intensified by some human factors including land use changes in recent years [3, 4].

Land-use change is regarded as an important factor in altering global environments [5]. Today, remote sensing techniques have facilitated land use change analysis, where the required maps can be retrieved at any time and spatial scales at unprecedented speed and extent [6]. The Aerosol Optical Depth (AOD) is one of the important parameters in the study of dust events. One way to determine the aerosol optical depth is to use remote sensing imageries [7]. The AOD index is dimensionless and indicates the degree of inhibition of light beams in the atmosphere due to the absorption and dispersion of aerosols in the path of light. AOD refers to the distribution of dust aerosols in the atmosphere [8].

Xu et al. [9] studied the temporal and spatial changes of the AOD index in the Yangtze Delta from 2000 to 2011 and examined the effect of land use and land cover changes on this index. The results showed that the increase in the AOD index in urban areas with high human activities is more than in rural areas with forest covers. He et al. [10] examined the AOD index in China from 2002 to 2015 and concluded that the highest AOD occurs in industrial and economically developed regions and the lowest in underdeveloped regions and villages located in western and northeastern China. Zhang et al. [11] used Geographic Weight Regression (GWR) to identify the spatio-temporal relationships between AOD and the factors affecting it. Socio-economic factors such as population, vegetation, altitude, and land use were also examined. Land use simulation with 89.76% accuracy showed that residential areas expansion and deforestation are the main land-use changes affecting AOD. Karam et al. [12] examined changes in land cover and AODs in 2000 and 2016 in the northwestern part of Central Iran. The results showed that during the study period, the barren lands and rangelands decreased and desert areas and salt marshes increased. Also, the spatiotemporal distribution of dust on saline land-uses in deserts and desert areas has been high in both years.

Khuzestan Province in Iran is known for its high concentration of aerosols and dust. This hazardous event has impacted the people of the area as well as the industries, transportation services, and medical services among others. Since Khuzestan has witnessed the considerable land-use change over the past decades, we believe that it has resulted in the elevation of dust concentration in the area. Therefore, awareness of long-term changes in land cover and use is very important and fundamental. This research investigates the impact of land cover and land-use on dust distribution in the southern part of Khuzestan province in the period of 2000 to 2018.

Materials & Methods

Study Area

Khuzestan province in the southwest of Iran with an area of 63,355 sq. Km^2 includes a mountainous area in the western and northern parts, as well as the marginal hills and the great plain of Khuzestan. The study area, located in the south of Khuzestan province, includes the cities of Ahvaz, Ramhormoz, Bandar Mahshahr, Omidieh, and Hindijan with an area of 15503 sq. Km^2, between 30° 00' and 31 30N and 48° 00' and 50 30 E (Figure 1).

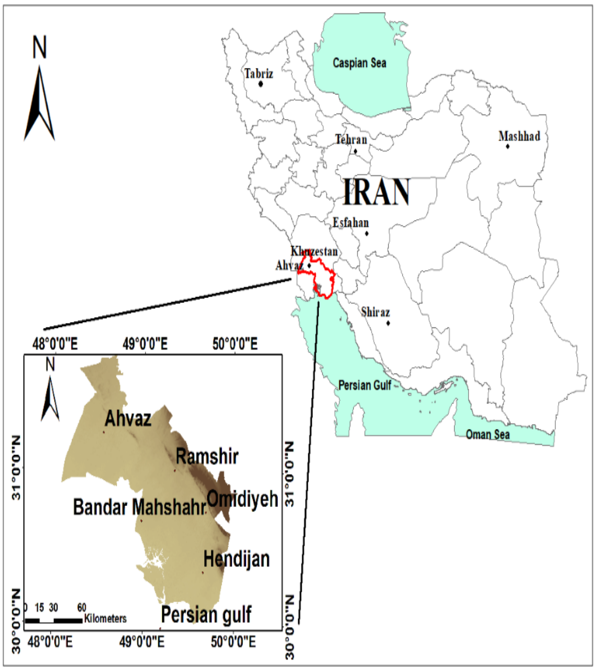

Figure 1) The location of the study area in Khuzestan Province and Iran.

Data Analysis

Land-use classification

In this research, two types of data have been used. The Landsat satellite imagery data was used to extract land cover maps for the years, 2000, 2009, and 2018. Due to the size of the study area, 2 images were used to cover the entire area, which can completely cover the study area, including the cities of Ahvaz, Ramhormoz, Bandar Mahshahr, Omidieh, and Hindijan. Finally, by mosaicking, the obtained images, the complete image of the study area was obtained. The images used are provided in Table 1.

Table 1) The Landsat images used for land-use classification in the study area.

Year	Satellite	Sensor	Resolution	No	Date
2000	Landsat 7	ETM	30 m	2	2000-03-19
2009	Landsat 8	ETM	30 m	2	2009-3-12
2018	Landsat 8	OLI	30 m	2	2018-3-13

Images were radiometrically and geometrically corrected in Envi Software. Since satellite images often contain geometrical distortions, they cannot be directly used for measurements. Therefore, they require geometric corrections for compensating the effects of ground curvature, topography, and train correction. Radiometric correction is the conversion of digital numbers in satellite images to reflectance values. When using multiple sensors, radiometric correction is essential [13]. Geometric Correction was conducted using the nearest neighbor method with the Round Mean Squared Error (RMSE) error of smaller than 0.4 pixels. RMSE is calculated as in Eq. (1):

$$RMSE = \frac{\sqrt{r_i^2}}{n} \qquad \text{Eq. (1)}$$

Where r_i is the pointwise error and n is the total number of control points.

We used the Bidirectional Reflectance Distribution Function (BRDF) function for compensating for the effects of atmospheric and topographic interferences. Histogram Equalization was used for adjusting the brightness of the images. The land-use classification was conducted using the Maximum Likelihood Method and Decision Tree Method (DT). The decision tree methodology is a commonly used method for establishing systems based on multiple covariates for developing prediction algorithms for a target variable. This method classifies a population into branch-like segments that construct an inverted tree with a root node, internal nodes, and leaf nodes [14]. For more information on the decision tree method, see [15] and Figure 2.

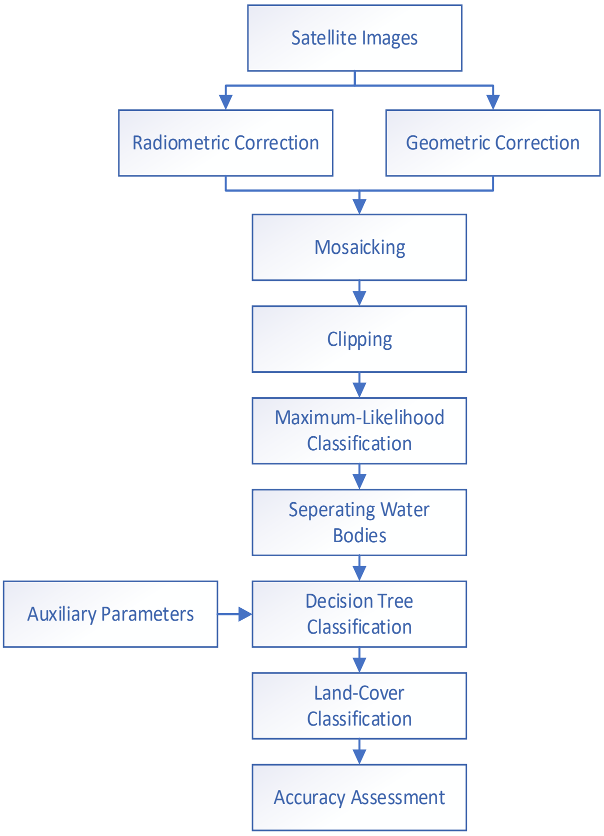

Figure 2) Flowchart of the Decision Tree Land Cover Classification Algorithm.

Since the DT method requires auxiliary data, we used the Brightness Temperature Index which is calculated as Eq. (2):

$$L_{(\lambda)} = L_{\min(\lambda)} + \left(L_{\max(\lambda)} - L_{\min(\lambda)} \right) Q_{dn}/Q_{max} \quad \text{Eq. (2)}$$

Where $L_{(\lambda)}$ is the at-sensor spectral radiance, Q_{max} represents the maximum DN value (255), Q_{dn} is the DN value of the target pixel of the Landsat image, $L_{\max(\lambda)}$ is the maximum at-sensor spectral radiance for $Q_{dn} = 255$ and $L_{\min(\lambda)}$ is the minimum at-sensor spectral radiance for $Q_{dn} = 0$ [16].

Normalized Difference Vegetation Index (NDVI) which is calculated as Eq. (3):

$$NDVI = \frac{(NIR-Red)}{(NIR+Red)} \quad \text{Eq. (3)}$$

Where NIR is the near-infrared and Red is the Red band of the satellite image.

And, the Normalized Difference Water Index (NDWI) which is calculated as Eq. (4):

$$NDWI = \frac{(Green-NIR)}{(Green+NIR)} \quad \text{Eq. (4)}$$

Where Green and NIR are the green and near-infrared bands of the satellite image.

Dust aerosol optical depth (AOD)

The data for this section was extracted from Modis Aqua Sensor, Level 2 Collection 6 with a spatial resolution of 3 km for the years 2000 to 2018. Land cover was used as an independent variable for dust analysis, which includes agricultural uses, grasslands, urban areas, water areas, saline, and bare lands with a resolution of 30 meters. A description of the data used is summarized in Table 1.

Validation

Validation was done using the Overall Accuracy and the Kappa Index. Overall accuracy indicates the proportion of all the reference sites correctly estimated. This index ranges between 0 and 100% (as the perfect classification). The Kappa index is calculated as Eq. (5):

$$k = \frac{\Pr(a)-\Pr(e)}{1-\Pr(e)} \quad \text{Eq. (5)}$$

Where Pr(a) represents the observed agreement, and Pr(e) represents chance agreement. Kohen Kappa ranges between 0 and 100 where values above 0.6 indicate moderate agreement between the observations and estimated values and values above 0.9 indicated perfect agreement. Observations were obtained for the monitoring stations of the study area under code 0.7 for the daily aerosol optical depth (AOD) index. The corresponding AOD values were also obtained from MODIS aqua and Terra platforms from Nasa Portal (https://worldview.earthdata.nasa.gov).

Findings

Land-use changes

In this study, to study and evaluate land cover changes in the southern region of Khuzestan province, Landsat 7 and 8 satellite images for the years 2000, 2009, and 2018 were used and the relationship between land cover changes and MODIS dust index was evaluated. In this regard, using the DT method, six land cover categories including croplands, rangelands, residential areas, water bodies, saline lands, and bare lands were identified. The validation results showed that the accuracy of classification, based on the Kappa index for the years 2000, 2009, and 2018 are 0.87, 0.85, and 0.89, respectively which indicates high conformity levels.

It was determined that in 2018 the largest area belongs to the bare land class with 76.8% of the total area, followed by croplands with 10.5%. According to land cover maps, the highest rate of changes between 2000 and 2018 is related to rangeland cover by -5% and saline lands by +4.3%. Likewise, shrinkage of 0.2% of water bodies indicates a significant reduction in soil moisture and higher dust emission rates. The results also showed that in the study area, the maximum dust index in 74% of the images is related to the cities of Hindijan, Ahvaz, and Bandar Mahshahr. The findings also showed that the highest percentage of land use changes between 2000 and 2018 are related to bare lands to saline lands, grasslands to bare lands, and bare lands to croplands, respectively. For the details on land-use changes visually and statistically see Figure 3 and Tables 2 and 3.

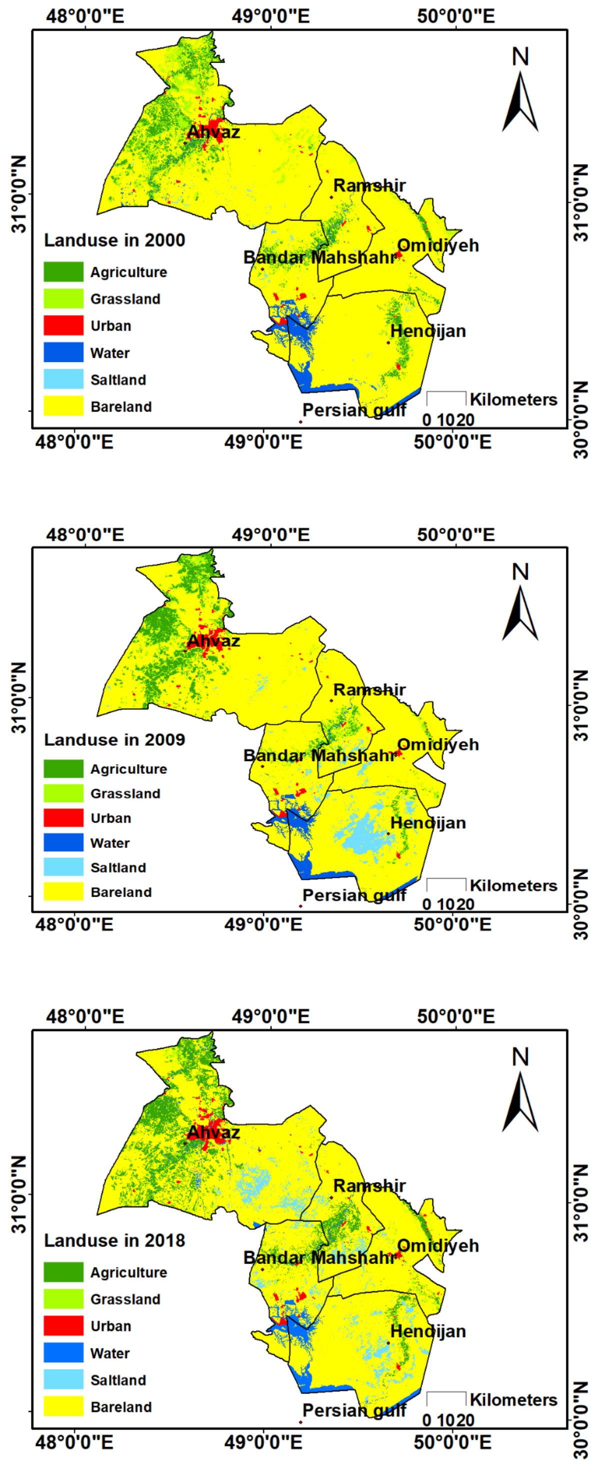

Figure 3) Land-use changes in the study area over time.

AOD Changes

The changes in AOD values over the study period are provided in Figure 4. According to the obtained results, in almost 74% of the images, the highest amount of AOD was

Table 2) Areal changes in different land-use classes in the study area.

	2000		2009		2018		Diff.	
Land-use	Area (ha)	%	Area (ha)	%	Area (ha)	%	Area (ha)	%
Cropland	106444	6.9	113849	7.4	161188	10.5	55744	3.6
Rangeland	113566	7.3	81101	5.2	34960	2.3	-78606	-5
Residential	22838	1.5	26817	1.7	31120	2	8282	0.5
Water Bodies	59403	3.8	47611	3	55995	3.6	-3408	-0.2
Salt Lands	6851	0.5	61238	4	75046	4.8	68195	4.3
Bare lands	1241119	80	1219605	78.7	1190912	76.8	-50207	-3.2

Table 3) Results of the land-use classifications' validation based on the kappa and overall accuracy indices.

Satellite	Sensor	Kappa Index	Overall Accuracy
Landsat 7	ETM	0.87	89%
Landsat 8	ETM	0.85	88%
Landsat 8	OLI	0.89	92%

found in the cities of Hindijan, Ahvaz, and Mahshahr port.

The results also showed an increase in the AOD in recent years. Based on the results, the years 2001, 2003, 2006, 2008, 2013, and 2016 had the worst condition in terms of aerosols. However, there seems not to be a regular pattern in the distribution of AOD values over the years which is perse a function of wind patterns and weather events. Most winds of the area blow from south and southwest and hence it pushes the aerosols more towards the north-eastern to south-eastern sections of the area.

Discussion

This research has been conducted to evaluate aerosols in the southwestern part of Iran using remote sensing and local observations. We used the annual changes in AOD values obtained from MODIS images along with the changes in land-use classes to identify what elements have impacted dust emissions in the area. Successful application of MODIS data in dust storm evaluation has been reported in many cases such as Mirzaei *et al.* [17], Jebali *et al.* [18], and Bakhtiari *et al.* [19] among others.

Land-use change is believed by many researchers to be the main cause of dust emissions [20-22]. We found that rangelands have shrunk in the area by more than 5%. Reduction in vegetation cover and soil protective cover could result in higher rates of dust emission [23, 24]. Dust emission itself could affect normal vegetation photosynthesis and further degrade local vegetation cover in a vicious cycle [25, 26]. We also found a ~4.3% increase in the area of salt marshes and saline lands. Saline lands which are the result of the conversion of rangelands and croplands are the main source of salt particles in the aerosols [27]. The same has happened in the case of Urmia Lake in Iran over the last decade where the retreat of the main body of the lake and the generation of saline lands has resulted in severe salt storms [28, 29]. Salt particles could result in the pollution of the nearby areas and further expansion of saline lands as well as salty dust storms [30]. Approximately 0.2% of the water bodies of the area have been lost over the past two decades. The loss of water bodies could result in soil moisture deficit, vegetation degradation, and higher numbers of dust storms [31].

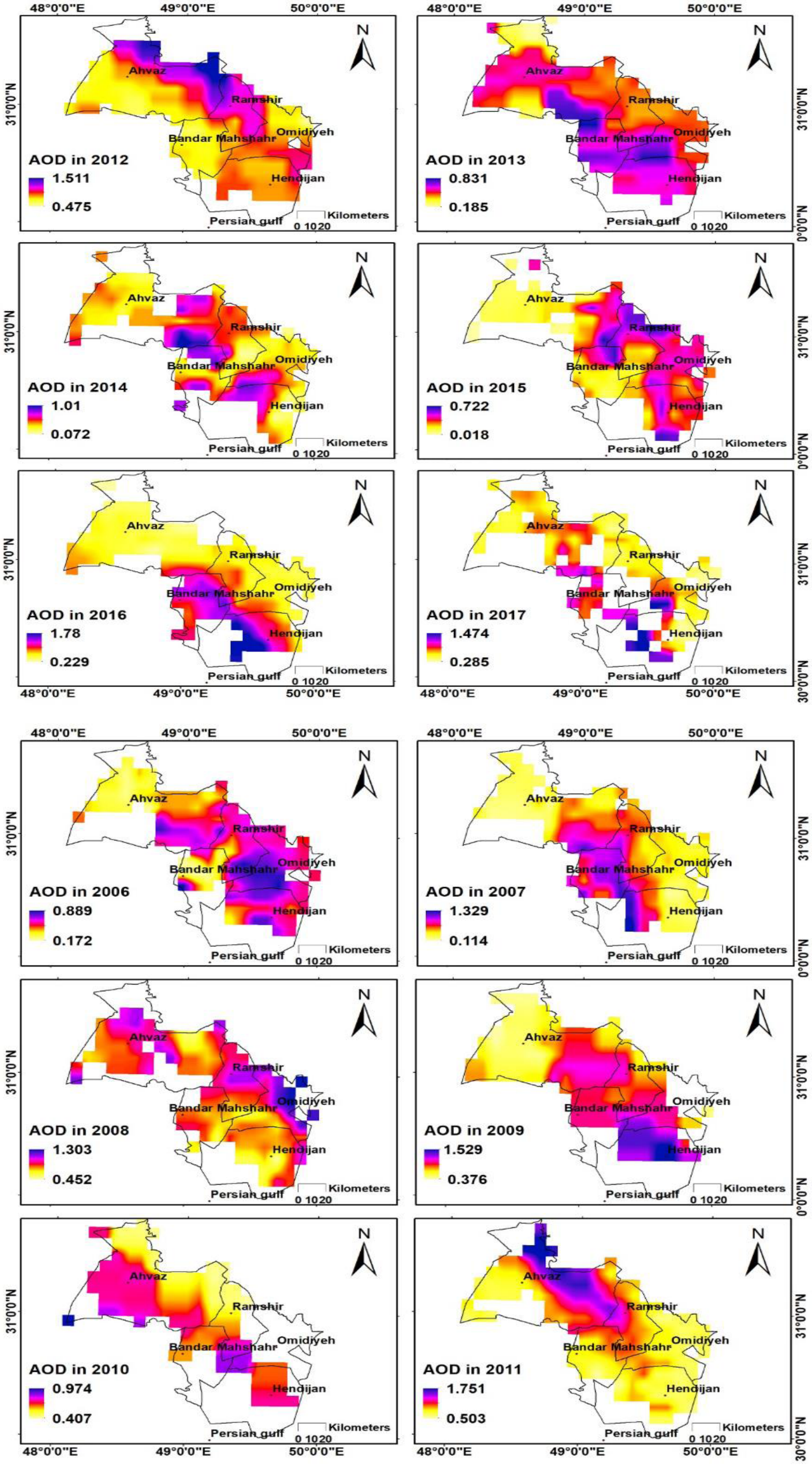

Figure 4) Time series of the AOD values in the study area.

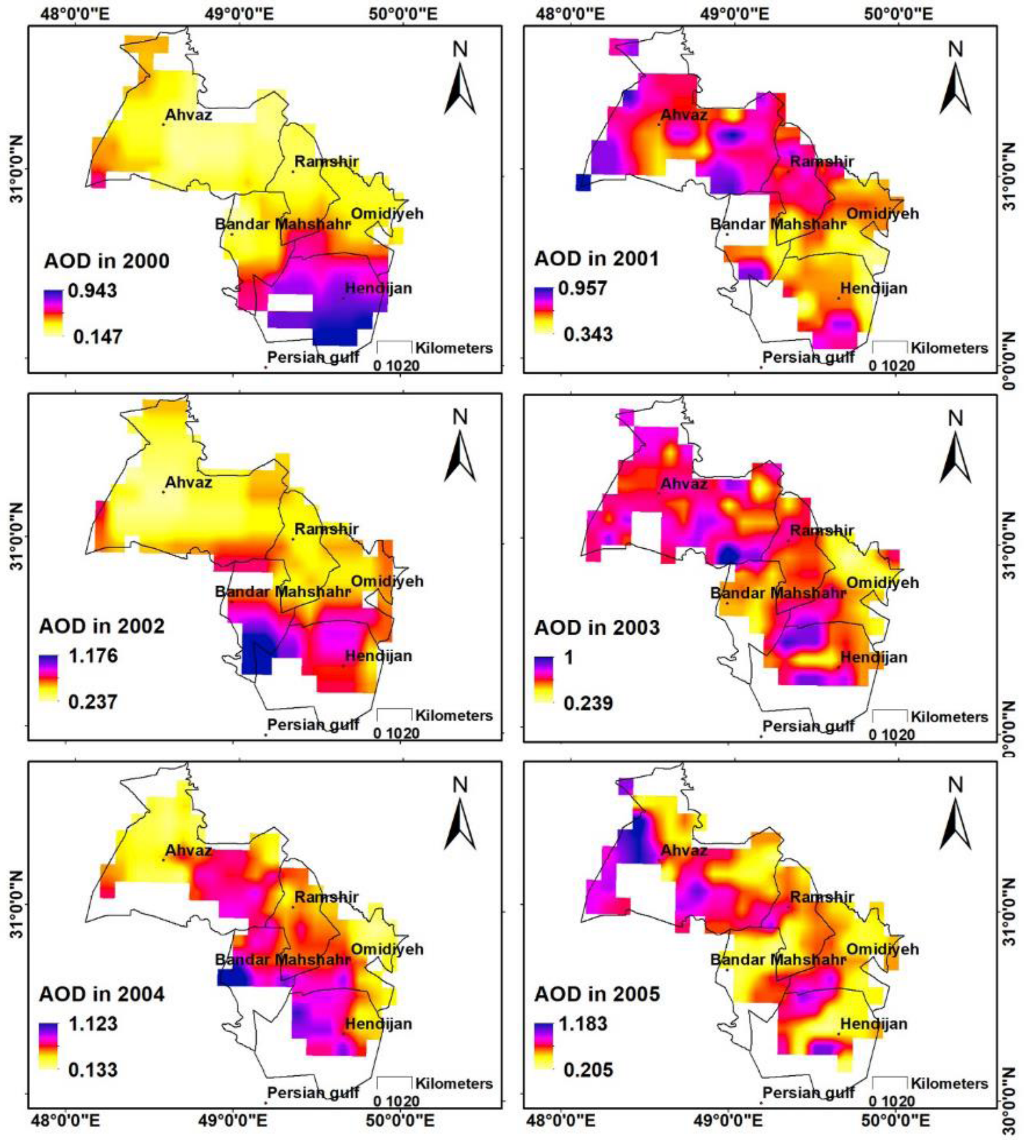

Figure 4 continued) Time series of the AOD values in the study area.

As for the AOD index, we found an increasing trend in the number of dusty days in our study area. The same has been reported in Broomandi *et al.* [32], Soleimani *et al.* [33], and Javadian *et al.* [34] among others. Apart from the land-use changes in the area which is the main reason behind dust emission, we believe that recent droughts over the past decade have played a major role in increasing the number of days with reported dust storms. Droughts by impacting vegetation cover on one hand and reducing soil moisture on the other results in soil sensitivity to detachment by the wind [34]. The increasing frequency of drought and the corresponding increase in dust storms have been reported by several authors such as McTainsh *et al.* [35] who evaluated aridity, drought, and dust storms in Australia over 1960–84; Middleton [36] who evaluated the effect of drought on dust production in the Sahel; Al Ameri *et al.* [37] who evaluated drought severity and increased dust storm frequency in the Middle East: a case study from the Tigris–Euphrates alluvial plain, central Iraq, a very close area to our site. Droughts' increasing frequency is believed by many researchers to be the direct impact of climate change.

For instance, Adib and Marashi [38], Adib *et al.* [39], Dehcheshmeh and Ghaedi [40], and Arami *et al.* [1] believe that climate change will impact drought severity, extent, duration, and frequency along with the following dust storms in Khuzestan Province of Iran. Dust storms are also a function of wind speed. Since most winds in the study area blow from the west, southwest, and southern directions, dust accumulation is higher in the central to eastern parts of the area. However, since wind pattern is expected to change in the future in response to climate change and higher numbers of extreme wind speeds are expected, higher frequencies of dust storms could be expected for the area as identified by Seidl *et al.* [41].

Conclusion

In conclusion, it seems that dust storms are increasingly hitting Khuzestan Province and given the relentless pressure of climate change and the resulting drought events, future events will be more extensive and severe. We have found that land-use change is also in favor of more dust storms and atmospheric aeolian concentration in the area. The results we have obtained show that salt lands have expanded in the area by almost 68195 ha. At the same time, rangelands have shrunk in area by 78606 ha in favor of agricultural areas, salt lands, and residential areas. The area of water bodies has also shrunk by 3408 ha in favor of salt lands which we believe to be the main local sources of dust emission.

Proper land use planning and management could ameliorate dust storms' severity and bring more favorable health-related outcomes. Dust concentration is more concentrated around the major cities of the Khuzestan Province including Ahvaz, Mahshahr, and Hendijan, and when combined with the industrial particles could become a serious public health issue. Most dust sources in the area are in the vicinity of populated cities and therefore urgent measures are required for fixing the land cover of these sources such as biological, or physiochemical measures such as organic mulching. Finally, the results of our manuscript could help authorities in the province to have a better understanding of dust storms, their causes, extension, severity, and future projection. In light of this understanding, the measures will be directed towards the area's hotspots and root causes of dust storms.

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Ethical Permission

The author confirms that the research is conducted in line with all University, legal and ethical standards

Authors' contributions

All data collection, curation, analysis, drafting, and proofreading were done by the main single author.

Conflicts of interest/Competing interests

The authors have no conflicts of interest to declare that are relevant to the content of this article.

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