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Application of Maximum Entropy Model and Remote Sensing Technique to predict susceptible areas to dust storms in Isfahan Province, Iran

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ABSTRACT

Aims: This study modeled sensitive areas to dust storms in Isfahan province, which is sensitive to successive droughts and dust storms because of its climatic conditions and proximity to the desert. It used meteorological codes related to dust, AOD values, and the Maximum Entropy model (MaxEnt).

Materials & Methods: 200 occurrence points of dust were determined using dust meteorological codes and AOD values of MODIS sensor, Terra satellite (2011-2022). Ten parameters, including temperature, rainfall, albedo, altitude, slope, land use, enhanced vegetation index (EVI), normalized difference moisture index (NDMI), normalized difference salinity index (NDSI), and frequency percentage of erosive wind seed, were considered dust-predictive factors. Finally, the MaxEnt model was utilized to model dust susceptibility. The model's performance was specified using the AUC value, and the importance of each influential factor was identified using the Jackknife test.

Findings: The findings indicated that areas susceptible to dust are mainly bare lands, salt lands, and poor rangeland located chiefly in the north, northeast to parts of the east and southeast of the province, and the central parts towards the southwest of Isfahan Province. According to the results, the MaxEnt model, with AUC=0.72, efficiently modeled susceptible areas to dust storms in Isfahan Province.

Conclusion: This study's central conclusion is that the MaxEnt model performed well in mapping susceptible areas to dust in Isfahan Province. The results can help decision-makers identify areas prone to dust storms.

Keywords: AOD; Dust Storm; MaxEnt; Spatial Modeling; Susceptibility.

CITATION LINKS

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Introduction

As a climatic component in arid and semi-arid regions [1], the dust storm is considered one of the most critical environmental problems worldwide [2]. Several factors, such as vegetation cover, wind speed, soil features, and climatic parameters, are responsible for wind erosion and dust storms [3]. The dust storm has affected much of Iran as a global challenge due to its arid and semi-arid climate. In other words, due to particular environmental conditions, such as lack of rainfall, limited density of vegetation cover, and improper harvesting of water sources, many parts of Iran are prone to dust storms [4]. A dust storm is a severe challenge to sustainable production and land management. Therefore, it is necessary to combat this phenomenon, especially in developing countries like Iran, so that the severity of this phenomenon can be reduced and its spread can be prevented by providing appropriate management methods. In recent years, climate fluctuations have significantly affected various sectors, including agriculture, natural resources, and water. In this regard, investigating the effect of climate on secondary phenomena, including dust, which occurs due to changes in meteorological parameters, has also been considered. Precipitation, temperature, and wind speed are the most important climatic factors that contribute to the occurrence of dust storms [5]. In addition to climatic factors, improper human activities such as land use change [6] and destruction of vegetation [7] also lead to this phenomenon. The difficulties caused by dust storms are often due to an insufficient need for more knowledge about sensitive areas to this event. Therefore, to overcome this phenomenon and offer proper management, specifying the areas sensitive to dust storms and the role of effective parameters in the phenomenon is urgent. Modeling, which is often expressed in the form of mathematical relationships or conceptual models, is one of the appropriate tools for decision-making and predicting environmental and natural phenomena [8]. Machine learning (ML), which can be used for prediction, is programming to optimize a function using previous data and experiences. One of the common machine learning algorithms is the maximum entropy model (MaxEnt), whose basis is the principle of maximum entropy. Numerous studies have been done to assess and model dust sources and sensitive areas to this phenomenon using machine learning techniques. In a study, several machine-learning models were compared to identify susceptible areas to dust production. Its discoveries demonstrated that the RF and MDA models were the best algorithm for predicting dust sources. It also concluded that altitude was the most crucial factor in all employed models [8]. Dust sources were identified on the Chinese Loess Plateau using the support vector machine and convolutional neural network. The results illustrated that big geochemical data sets coupled with machine learning can trace sources [9]. In another study, dust sources were determined using hybridized machine-learning algorithms. The outcomes of this study showed that the hybridized ANFIS-DE model was efficient for specifying dust sources [10]. Also, in another study, the WOE, FR, and RF algorithms were applied to detect dust sources and map susceptible areas. The outcomes showed that all three models had an acceptable performance and Rf owned the best efficiency [11].

Even though all previous studies utilized machine learning algorithms to determine dust sources or areas prone to dust storms, no study assessed the efficiency of the MaxEnt model in identifying susceptible areas to dust storms in Isfahan Province. Therefore, this model was used in the

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current study to specify regions prone to dust in Isfahan Province and determine its performance.

Isfahan Province is one of Iran's most significant geographical regions prone to successive droughts, land degradation, and dust storms because of its specific conditions, low precipitation, and nearness to the desert [12]. Therefore, diagnosing sensitive areas in the province exposed to dust is urgent. In this study, spatial modeling of sensitive areas to dust storms in Isfahan Province was done using the AOD values of the MODIS and Maximum Entropy model. Generally, the goals of the current study were: 1) spatial modeling of susceptible areas to dust, 2) specifying the efficiency of the MaxEnt model, and 3) identifying the importance of predictive factors in modeling. The results of this research can be helpful for managers and decision-makers in better identifying the areas prone to dust storms.

Materials & methods

Study Area

Isfahan Province, with an area of nearly 107017 km2 (6.4% of Iran's area), is located between 30° 43′ to 34° 30′ N and 49° 38′ to 55° 31′ E in central Iran (Figure 1). The mean annual precipitation of this Province is between 40 mm and more than 800 mm, and its mean annual temperature varies from 10 °C to 20 °C (Iran Meteorological Organization). According to the Torrent White method, the climate of Isfahan Province is dry in 58.73% of its area (eastern, northeastern, and sub-central parts of the Province), semi-arid in 28% of its area (central and northern parts of the Province), and humid and semi-humid in 13.27% of its area (western and southern parts of the Province).

Methodology

Dust occurrence points were identified using AOD values to model susceptible

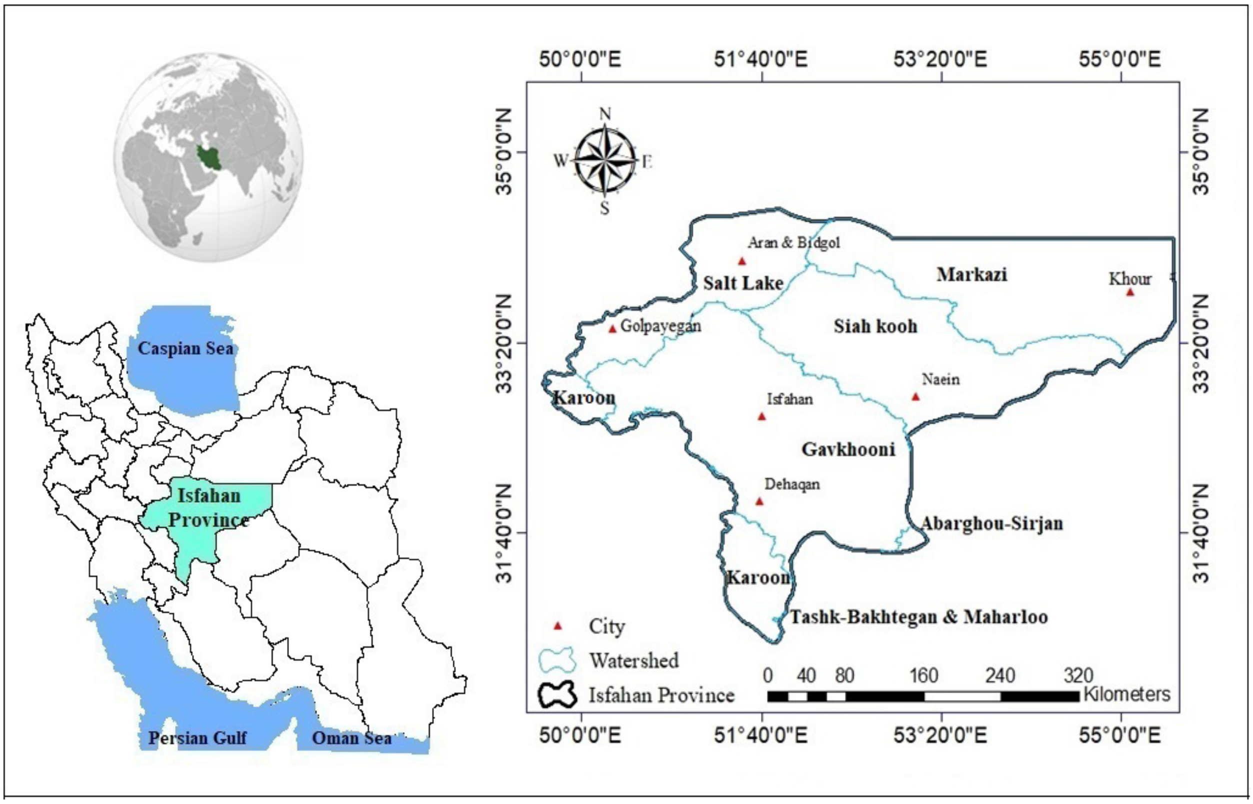

Figure 1) Location of Isfahan Province, Iran.

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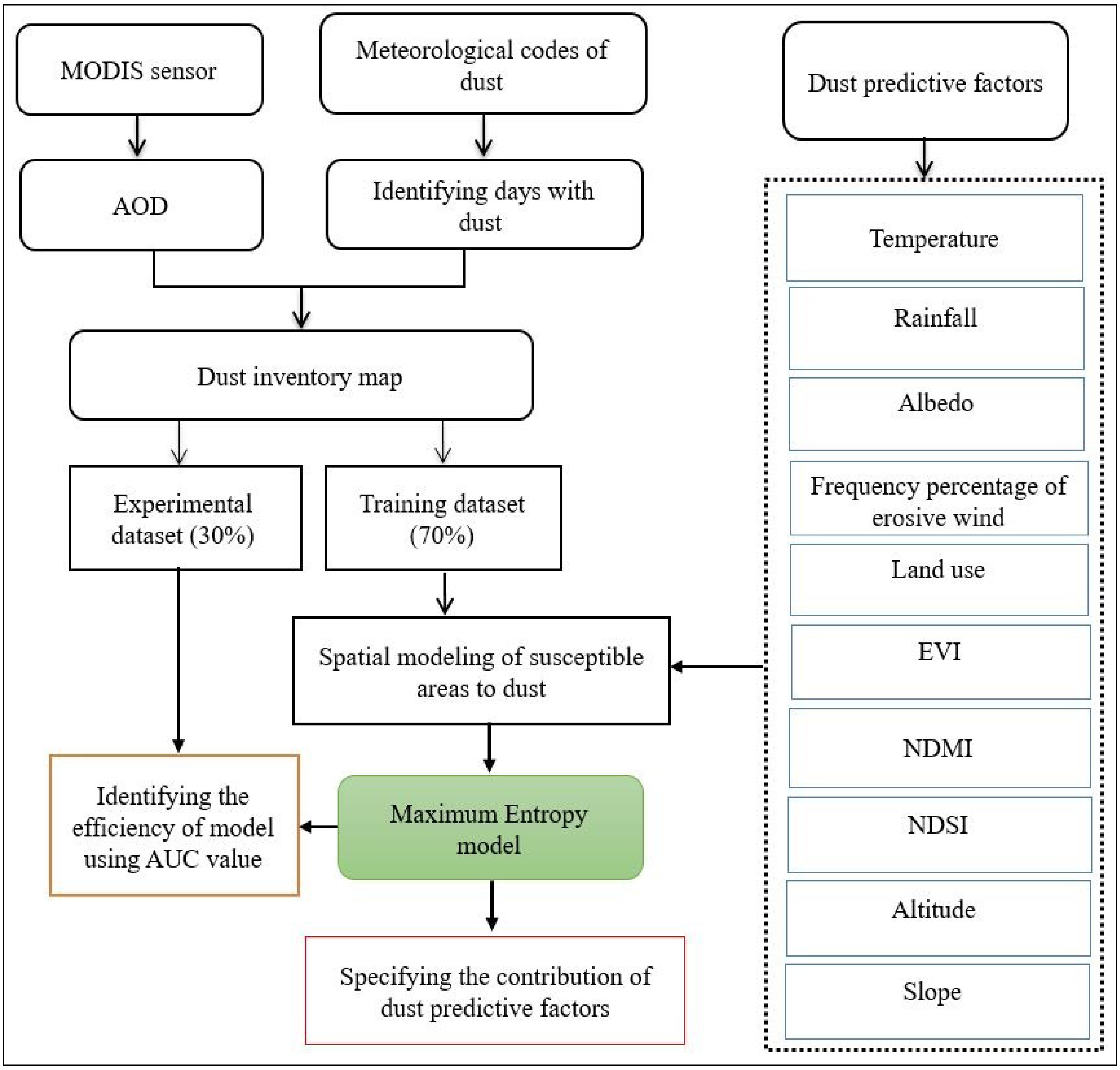

Figure 2) Methodology of the current research.

areas to dust in Isfahan Province spatially. Ten parameters of temperature, land use, rainfall, slope, frequency percentage of erosive wind, altitude, albedo, vegetation index, soil surface moisture index, and soil salinity index were determined as predictive factors. Maps of all predictive factors were prepared employing ArcGIS software. The correlation among the factors was determined utilizing the variance inflation factor (VIF). Using the MaxEnt model, spatial modeling of susceptible areas to dust was done, and the importance of predicting factors in modeling was specified using the jackknife test. Finally, using the value of the area under the ROC curve (ROC-AUC), the model's efficiency was determined. The methodology is briefly shown in Figure (2).

Dust inventory map

Meteorological codes assigned to dust were utilized to prepare the dust inventory map. According to the World Meteorological Organization (WMO) definition, 11 codes have been defined for dust among the various meteorological phenomena codes. After recognizing the days of dust occurrence during 22 years (2001-2022), the aerosol optical depth (AOD) values were obtained

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from the MODIS sensor, Terra satellite. After determining the maximum AOD value in 22 years and its conformity with the detachment, transport, and sediment map of the province (Natural Resources and Watershed Management office of Isfahan Province), the AOD values were divided into two classes based on the natural break method in ArcGIS. The high class of this index, which was related to areas with the highest AOD value, were considered prone areas to dust, and the rest of the Province with a low class of AOD value was not influenced by dust. Finally, in the sites with the occurrence of dust storms, 200 points were randomly selected for modeling (Figure 3).

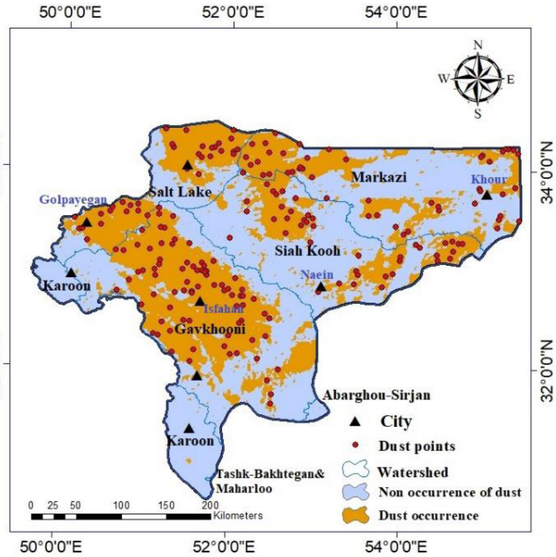

Figure 3) Dust inventory map of Isfahan Province based on AOD value.

Predictive Factors

According to various studies carried out in this field and the availability of data, ten factors including temperature, rainfall [10], frequency percentage of erosive wind [13], slope, altitude [8], albedo, land use [14], Enhanced Vegetation Index (EVI) [15], Normalized Difference Salinity Index (NDSI) [16], and Normalized Difference Moisture Index (NDMI) were selected as dust predictive factors. Wind is one of the most significant factors for aeolian erosion, and it can move sand and dust at different altitudes because of its speed and uplift. Land use shows the intensity of anthropogenic factors and the ability for soil and land degradation and, consequently, dust occurrence. Topographic factors such as aspect altitude are essential in soil evolution and, as a result, its susceptibility to degradation and distribution. The amount of rainfall and temperature also determines soil moisture and the intensity of vegetation cover directly, which influence dust storms. Considering that the difference in surface reflection and the creation of convective currents can lead to wind production, the albedo factor has been considered as a predictive factor in this research to investigate its role in the occurrence of dust phenomenon.

The data of the synoptic stations of the Iran Meteorological Organization were used to prepare the map of meteorological factors (temperature, precipitation, and frequency percentage of erosive wind). Maps of albedo, EVI, NDSI, and NDMI were prepared utilizing remote sensing and ArcGIS. The basic map of Iran's forest, range, and watershed management was used to create the land use map. Altitude and slope maps were also obtained from DEM.

Maps of albedo, EVI, NDSI, and NDMI were prepared utilizing remote sensing data and ArcGIS based on Eq. (1-3). The zoning of temperature, rainfall, and frequency percentage of erosive wind, done using the IDW method in ArcGIS software, showed low rainfall and high temperature in the northern, northeastern, eastern, and central parts of the Province. The highest frequency percentage of erosive winds can be seen in the central, south, southwest, and parts of the north of the Province (Figure 4).

According to the albedo map, the earth's highest surface reflection is related to the eastern areas, parts of the north of the

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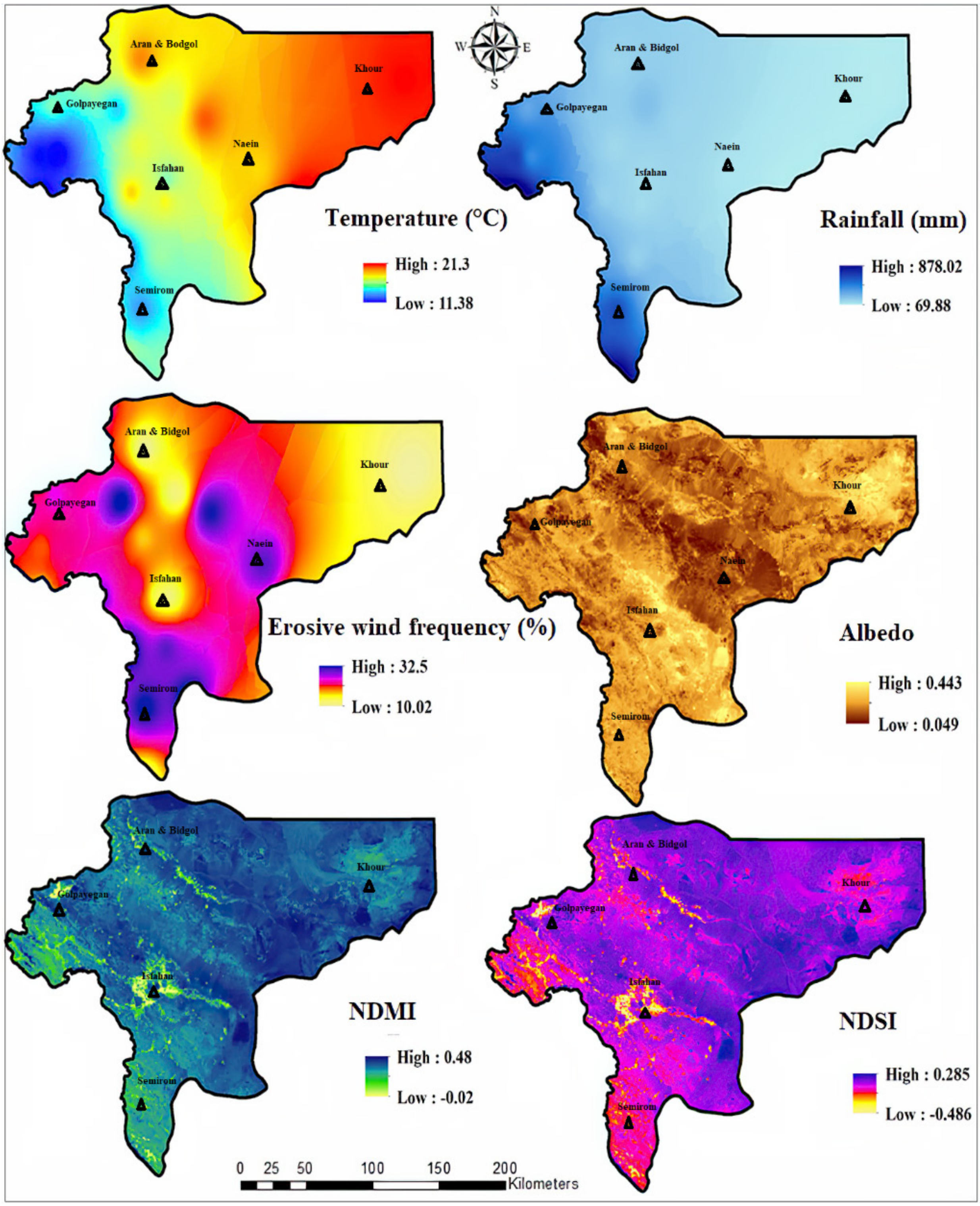

Figure 4) Predictive factors for susceptible areas to dust storms.

province, and the central and southeastern parts. The slope map of the Province was classified into five classes, and the class of 0-5% occupied the largest area of the Province. The study area's north, northeast, and east regions have the lowest altitude and the highest salinity in the entire Province, mainly poor rangeland, salt land, and bare land.

Based on the NDMI, which can identify

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water stress in the early stages, the highest amount of soil surface moisture, about 0.48, is allocated to agricultural lands and rangelands with good quality, and the lowest is assigned to the north, northeast, and east parts.

$$EVI = 2.5 * ((p_{NIR} - p_{RED}) / ((p_{NIR}) + (C1 * Red) - (C2 * p_{BLUE}) + L)) \quad \text{Eq. (1)}$$

where NIR/red/blue are partially atmosphere-corrected surface reflectances, L is the canopy background adjustment that addresses non-linear, differential NIR and red radiant transfer through a canopy, and C1 and C2 are the coefficients of the aerosol resistance term, which uses the blue band to correct for aerosol influences in the red band. The coefficients adopted in the MODIS-EVI algorithm are; L=1, C1 = 6, C2 = 7.5, and G (gain factor) = 2.5.

$$NDMI = (B5 - B6)/(B5 + B6) \quad \text{Eq. (2)}$$

$$DSI = (B4 - B5)/(B5 + B4) \quad \text{Eq. (3)}$$

where B5 and B6 are the near-infrared and the short wavelength infrared bands of band 6, and B4 is the red spectral band, respectively.

Correlation Between Predictive Factors

The high correlation between predictive factors in modeling can reduce the model's accuracy. There are different methods to check the linear correlation between predictive factors, and in most cases, each of these methods confirms the others. One of the widely used methods for detecting the presence of collinearity is the variance inflation factor (VIF). The VIF illustrates how much the estimated coefficients' variance is swelled compared to the condition that the estimated parameters are not linearly correlated. In other words, VIF indicates how much a predictive factor changes under the influence of other predictors (Eq. 4). Usually, a VIF > 10 is considered an index of multicollinearity [17]. In the present study, we applied the RStudio software to identify the correlation among predictive factors based on the VIF.

$$VIF_I = \frac{1}{1 - R_j^2} \quad \text{Eq. (4)}$$

where R_j^2 is the R-squared value gained by regression of the jth predictive factor on the rest of the factors.

Modeling Sensitive Areas to Dust

The maximum entropy model was used to determine susceptible areas to dust in Isfahan Province, Iran. Some 70% of the dust occurrence points were randomly selected to train the model, and 30% were considered the test data set.

This model, proposed by Berger et al. (1996) for the first time, is connected to the maximization principle and probability theory [19]. The maximum entropy principle indicates that the distribution with the most entropy is the best distribution for modeling. In the current study, this method realizes the possible distribution (Π) of dust occurrence upon the set of locations X in Isfahan Province. If $\Pi(x)$ defines the possible distribution of the target and is an accidental cell in the study area, the possibility that dust occurred at location X is illustrated as $P(y=1|X)$, which is calculated using Eq. (5) (Bayes' rule):

$$P(y = 1|X) = \frac{P(y = 1)P(X|y = 1)}{P(X)} = \frac{P(y=1)\Phi(X)}{1/|X|} \quad \text{Eq. (5)}$$

where $P(y=1)$ is the spread of dust occurrence, and |X| is the number of dust events in Isfahan Province.

Π (x) that is measured based on the maximum entropy principle is an

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exponential distribution (Gibbs possible distribution.) If n predictive factors are considered. The Gibbs possible distribution can be determined as:

$$q_\lambda(x) = \frac{1}{Z_\lambda(x)} = \exp\left(\sum_{i=1}^{n} \lambda_i f_i(x)\right) \quad \text{Eq. (6)}$$

$$Z_\lambda(x) = \sum_y \exp\left(\sum_i \lambda_i f_i(x.y)\right) \quad \text{Eq.(7)}$$

where $Z_\lambda(x)$ is a normalization stable vector, and λ_i demonstrates a vector of the predictive factors' weights. The difference between log-likelihood ($\Psi(\lambda)$) and the regularization is measured as follows:

$$\Psi(\lambda) = \frac{1}{m}\sum_{i=1}^{m} \ln(q_\lambda(X_i)) - \sum_{j=1}^{n} \beta_j |\lambda_j|$$

Eq. (8)

where β_j is the regularization parameter for predictive factor.

Assessing the Efficiency of the Model

Assessing the model's efficiency is essential in modeling and simulation [20]. Validation is used in all modeling and simulation methods to determine the efficiency and acceptability of the results [21]. The current study used 30% of dust occurrence points and the ROC curve to validate the model results. The AUC, an area under the ROC curve, is one of the most common validation methods used in modeling to evaluate prediction models [22]. The AUC values vary between zero and 1, and the closer the values are to 1, the better the model's efficiency is (Table 1).

Table 1) AUC values interpretation [23].

AUC values	Test quality
0.5 – 0.6	Poor (Unsatisfactory)
0.6 – 0.7	Average (Satisfactory)
0.7 – 0.8	Good
0.8 – 0.9	Very good
0.9 - 1	Excellent

Specifying the Importance and Contribution of Predictive Factors

The model specified the importance and contribution of predictive factors in modeling using the jackknife test. This test determines the role of each factor in modeling and its effect without considering the interaction of other factors.

Findings

Predictive Factors' Correlation

The result of the VIF test is presented in Table (2). Based on the results of this section, the VIF values for the predictive factors are below 10, which does not create a problem for modeling in terms of correlation and colinearity of the factors.

Table 2) VIF values for all predictive factors.

Predictive factors	VIF values
Temperature	1.9
Rainfall	1.5
Slope	2.2
Erosive wind speed	1.7
Albedo	1.6
Altitude	2
EVI	6
NDSI	2.5
NDMI	2.1
Land use	3.2

Modeling Sensitive Areas to Dust

Figure (5) presents the zoning map of dust-prone areas. Based on the findings, the low-altitude and flat parts of the north, northeast to parts of the east and southeast of the Province, and the central areas towards the southwest of Isfahan Province are susceptible to dust.

Figure (5) also shows the classification map of susceptible areas to dust. According to this map, very high, high, and medium susceptibility classes are related to the north, northeast to parts of the east and southeast, and the central areas toward the southwest of the Province.

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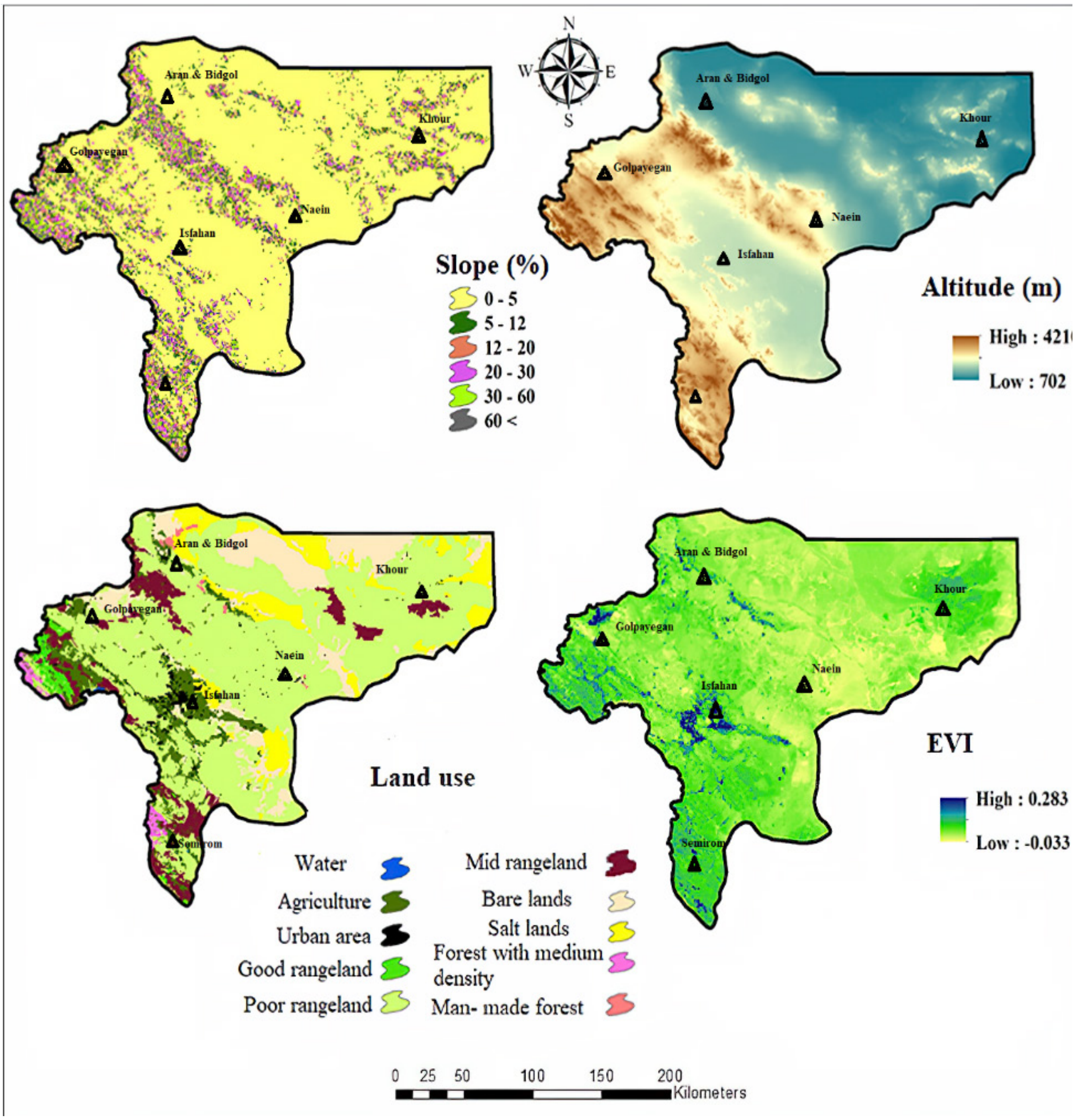

Figure 4) Predictive factors for susceptible areas to dust storms.

The high susceptibility class occupied the most area of the Province with 28.66%, followed by medium (23.61%) and very high classes (22.36%), as shown in Table 3.

The Maximum Entropy Model's Efficiency

The AUC value, considered to validate the model efficiency, demonstrated that the MaxEnt model with AUC= 0.72 performed well in identifying susceptible areas to dust in Isfahan Province (Figure 6).

Table 3) The area percentage of various classes of dust susceptibility.

Classes	Values
Very low	12.61
Low	12.73
Medium	23.61
High	28.66
Very high	22.36

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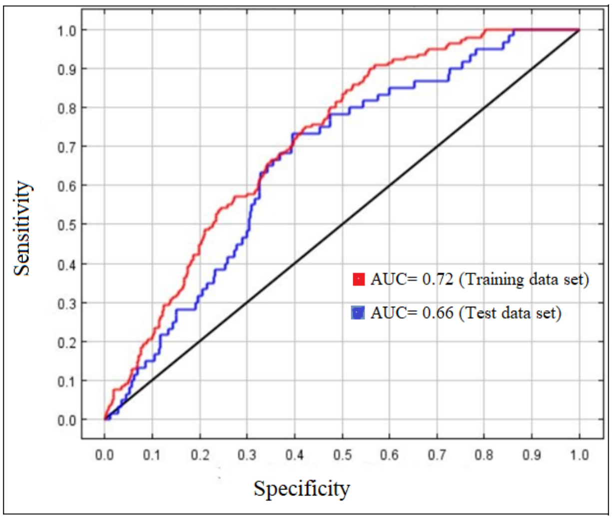

Figure 6) The value of the area under the ROC curve for assessing the model's efficiency.

The Importance of Predictive Factors

The results of the Jackknife test showed that rainfall was the most significant factor in modeling susceptible areas to dust in Isfahan Province, followed by temperature, land use, NDSI, and NDMI (Figure 7). Rainfall, which has the most beneficial information, provides the most benefit when used alone. However, rainfall also declines the benefit when removed, as it appears to have the most data that can be absent in the other factors.

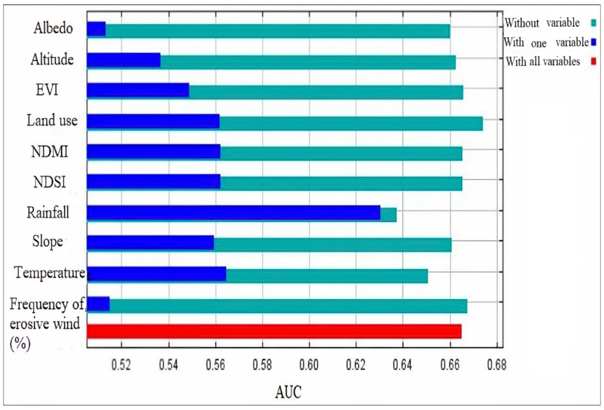

Figure 7) The importance of predictive factors in modeling based on the Jackknife test.

Discussion

Because of its location and climatic conditions, Isfahan Province is prone to dust storms. Therefore, studies that identify dust-prone areas and the centers of this phenomenon in this Province are necessary. In the present research, the maximum entropy model identified susceptible areas to dust.

Based on Figure (5), the flat parts of the north, northeast to parts of the east and southeast, and the central areas towards the southwest of Isfahan Province are vulnerable areas to dust. These areas, mainly with a 0-5% slope class, have the lowest rainfall and the highest temperature. The main land uses of these areas include salt lands, bare lands, and poor rangelands. In most of these areas, EVI had its lowest value, and NDSI had its highest value. The highest amount of NDMI, with a value of 0.4, was allocated to agricultural lands and rangelands of good quality in the south, southwest, and west parts of the province. According to the values of this index, it can be concluded that the entire Province of Isfahan is under tension in terms of soil moisture. Based on the conditions prevailing in the vulnerable areas, it can be mentioned that low rainfall, poor vegetation cover, and expansion of salt and bare lands can be among the factors affecting dust, consistent with several studies' results [24, 25]. In other words, the reduction of vegetation cover, as the result of natural factors such as a decrease in rainfall or anthropogenic factors like land use change, will lead to more sensitivity of susceptible areas to dust storms.

The validation results (Figure 6) and Table (1) show that the Maxent model performs well for zoning dust-prone areas. The excellent performance of the Maxent model in predicting sand and dust storm sources in arid Central Asia was previously confirmed [26]. Other studies have also been done for the zoning of groundwater [27], flood-prone areas [28], and land degradation [29] using this model, which illustrated the excellent performance of the model. Also, according to Afshari and

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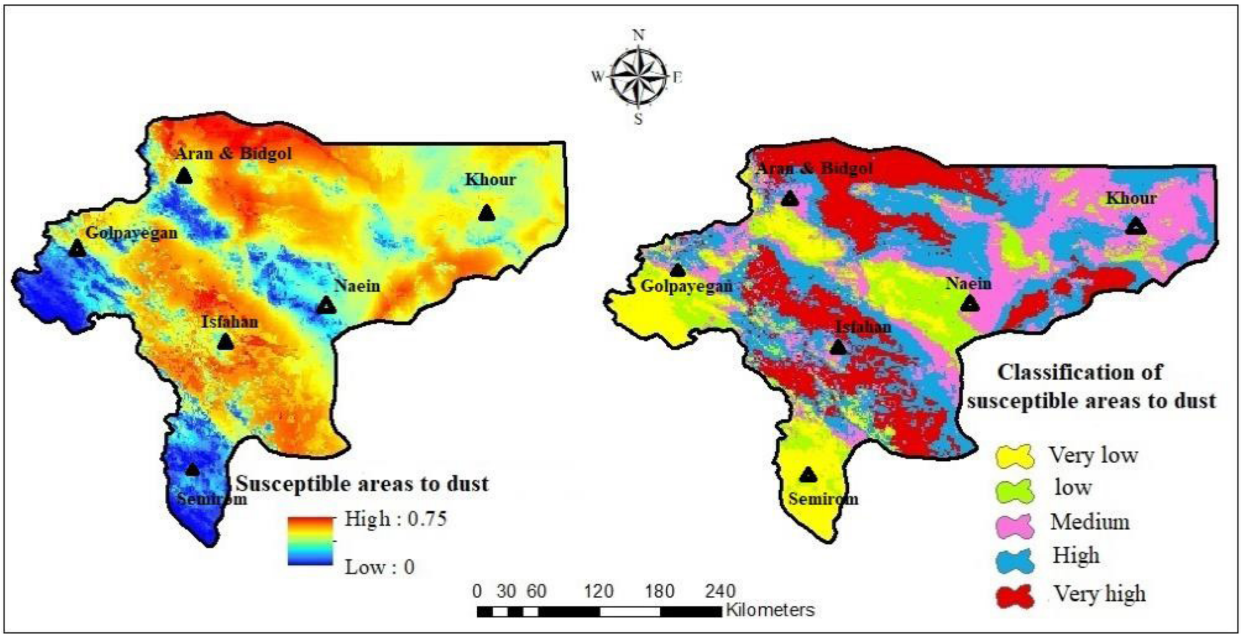

Figure 5) Zoning and classification maps of susceptible areas to dust.

Vali (2023), the AUC values of RF, BRT, CART, and SVM models were respectively 0.86, 0.82, 0.79, and 0.77 in assessing the effectiveness of machine learning algorithms in zoning areas prone to dust in Isfahan Province which showed the lower compatibility of the maximum entropy model compared to RF, BRT, SVM, and CART models [30].

According to the results of the Jackknife test (Figure 7), rainfall had the most critical role in modeling, followed by temperature. Considering the low amount of rainfall in areas prone to dust, it can be concluded that low rainfall can cause an increase in soil dryness, a reduction in vegetation, and, as a result, an increase in dust occurrence. This finding aligns with a study that indicated a direct relationship between drought and dust storms and showed that dust storms increased or decreased due to a rise or drop in drought intensity [11]. The lowest frequency of dust storms was recorded in regions with high rainfall values.

Since only winds with a speed of more than six $m.s^{-1}$, known as erosive winds, were used in the modeling, the wind was considered less important than other factors.

Conclusion

Dust is an important environmental issue that can cause global problems and disasters. This event has always been a menace to various ecosystems, economic improvement, and human health. The present study proposed applying the maximum entropy model in modeling susceptible areas to dust in Isfahan Province. The significant inference of this study is that the MaxEnt model had good efficiency in modeling susceptible areas to dust in the study area. It is recommended that this model be used in areas with different climates using various predictive variables to compare the model's efficiency under different climate types. In addition, it is also recommended that various statistical methods or machine learning models besides the MaxEnt model be applied to compare their efficiency.

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Authors' contributions: Majid Afshari is a Ph.D. student in desert control and management in the Department of Arid Land Management, Faculty of Natural Resources and Earth Sciences, University of Kashan, Kashan, Iran, and AbbasAli Vali is the supervisor of his thesis.

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