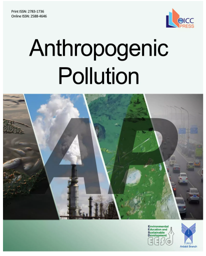

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Comparing random forest and regression models for dust storm assessment in Kermanshah Province, Iran

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Abstract:

Identifying dust sources is essential for effective management. This study employs remote sensing and machine learning techniques, specifically Random Forest Model (RFM) and Multiple Linear Regression (MLR), to identify dust production areas in Kermanshah province from 2000 to 2020. The results indicate that the Random Forest Model (RFM) outperforms Multiple Linear Regression (MLR). Specifically, the accuracy of the RFM, with a correlation coefficient of 0.900, is significantly higher than that of the MLR, which has a correlation coefficient of 0.840. Furthermore, the Root Mean Square Error (RMSE) for the RFM was 5.59, whereas for the MLR it was 7.05, confirming the superiority of the RFM's accuracy. Key factors influencing dust production include elevation, erosion, soil moisture, land cover, geology, daytime land surface temperature, and NDVI. The western and southwestern regions have been identified as hotspots for dust production. These findings can assist policymakers in effectively allocating resources and managing dust-related issues. Hazard zoning maps will facilitate the identification of areas requiring immediate intervention.

Keywords: Dust sources; Random forest model; Multiple linear regression; Remote sensing technique; Kermanshah

1. Introduction

Dust storms, both natural and human-induced, pose significant environmental and health challenges globally (Salvador et al., 2024; Williams and Samara, 2023). Their economic, health, and ecological impacts necessitate urgent attention to mitigate their effects and promote sustainable development. Given the documented devastating impacts on human health, particularly cardiovascular and respiratory well-being, and the exacerbation of pre-existing conditions, a deeper understanding of the factors influencing dust storm intensity is crucial (Kai Kong et al., 2024; Wang et al., 2024). In recent decades, the frequency and intensity of dust storms have increased, driven by land degradation, soil disturbances, climate change, and human activities (Salvador et al., 2024). This trend is notably significant in the Northern Hemisphere, especially in the Middle East and Southwest Asia (Awadh, 2023; Mahmoudi and Ikegaya, 2023). Understanding the complex interplay of these factors is the first step towards effective mitigation strategies.

Kermanshah Province, Iran, is a critical area for studying dust storms due to its proximity to Iraqi dust sources and the prevailing winds that transport particles into the region. Between 2002 and 2018, Kermanshah experienced 12,163 dust storm days-an average of 48.2 days annually per county (Hamzeh et al., 2021). The province's arid conditions, low rainfall, and human-induced changes, such as dam construction and altered land use, exacerbate the issue (Mahmoudi and Ikegaya, 2023; Parno et al., 2024). Dust storms in Kermanshah have severe consequences, including respiratory health issues, economic losses for farmers and livestock breeders, and increased social stress, leading to migration and reduced quality of life (Hamzeh et al., 2021). Effective dust storm management requires accurate modeling, prediction, and early warning systems (Mohammadpour et al., 2022; Yarmohamadi et al., 2023). Remote sensing is crucial for identifying dust sources (Alalam et al., 2024; Castellanos et al., 2024; Zhang et al., 2024), and integration with predictive models is essential. Machine learning models, particularly Random Forest (RFM) and Multiple Linear Regression (MLR), offer robust approaches for this task (Jia and Ye, 2023; Jain et al., 2023). We selected RFM due to its strengths in handling complex and highdimensional datasets, which is particularly relevant for our study considering the multifactorial influences on dust storm intensity. RFM also excels in reducing overfitting, thus providing robust predictions even in the presence of noise and irrelevant features. MLR complements RFM by offering a straightforward interpretation of linear relationships within the data. While RFM provides powerful predictions, MLR helps us validate these predictions by explicitly modeling the linear aspects of the relationships among variables. This dual approach ensures that our findings are grounded in both sophisticated machine learning techniques and understandable statistical relationships (Salah Eddine et al., 2024; Azlim Khan and Ahamed Hassain Malim, 2023). Studies conducted in Iran examine specific characteristics of dust storms. Jafari Dezfooli (2024) used GIS to analyze dust storms in Ahvaz, identifying 2021 as the year with the highest frequency. Pourhashemi et al. (2023) mapped the sensitivity of dust sources along the Iran-Iraq border using remote sensing and machine learning, declaring land use as the most influential factor. Azar Beyranvand et al. (2023) identified Tharthar Lake and the Hoor al-Azim marshes as critical dust sources affecting western Iran. Dargahian et al. (2023) traced foreign dust sources impacting southwestern Iran using MODIS images and the HYSPLIT model. Alizadeh et al. (2024) focused on identifying the sources and factors associated with the dust storm that occurred in Kermanshah from November 1 to 3, 2017. They utilized mid-range atmospheric data from the European Centre for Medium-Range Weather Forecasts (ECMWF) to determine dust transport pathways to the region: A northwest-southeast route passing over the deserts of Iraq and Syria. A second route from southwestern Iran, primarily originating from Kuwait, northern Saudi Arabia, and parts of Iraq. Mohammadpour et al. (2022) investigated the occurrence of dust in western Iran using horizontal visibility data and remote sensing. They found that the highest frequency of dust events occurred in the southern regions, such as Ahvaz and Bushehr, with an increasing trend of dust events from north to south across the study area. Ghafarian et al. (2022) analyzed the temporal and spatial variations of dust in Khuzestan province using satellite data. They discovered significant dust levels in areas like Ahvaz and Abadan, with a notable increase in dust levels moving from the southeast toward the western parts of the province. Other studies have explored broader aspects: Kim et al. (2024) improved PM10 forecasting using LSTM. Wang et al. (2024) noted a decreasing trend in DAOD over East Asia. Rafi and Rivas (2024) utilized satellite data and machine learning for quantitative dust analysis. Jalal and Mahdi (2024) identified transboundary dust sources in Iraq, while Attiya and Jones (2023) investigated the dust storm event in BaghdadPrior research into dust storm events has established a foundation for understanding these phenomena. Building on this, we innovate by utilizing advanced machine learning algorithms and optimizing parameters with the Grid Search method. Specifically, we will use Grid Search to fine-tune the hyperparameters of the Random Forest model, such as the number of trees, the maximum depth of the trees, and the minimum number of samples required to split an internal node. This parameter optimization allows us to maximize the model's predictive power and generalizability. We concentrate on comparing the performance of Random Forest and Linear Regression models to achieve accurate predictions of dust storm intensity. Although satellite images have been used to identify dust storms, further analysis is needed to assess the impact of factors such as temperature, humidity, and vegetation cover on storm intensity and their potential integration for better prediction accuracy.

Furthermore, the lack of analysis regarding temporal dynamics and seasonal patterns impedes a complete understanding. For instance, while previous research has acknowledged the role of land use, the precise quantification of its impact on dust storm intensity, considering seasonal variations, remains largely unexplored. Thus, exploring relationships between these variables can provide valuable insights for refining predictive models. Addressing these gaps is essential for advancing knowledge in disaster management related to dust storms and improving data analysis methods. By analyzing these dynamics and incorporating environmental variables, this research seeks to provide more accurate and actionable predictions for mitigating the impacts of dust storms in Kermanshah Province, ultimately contributing to developing more effective early warning systems and sustainable land management strategies.

2. Materials and methods

2.1 Study area

Kermanshah Province, covering an area of 24,640 km^2, is situated in the western part of Iran, with geographical coordinates ranging from 36° 32′ to 35° 15′ north latitude and 45° 24′ to 48° 30′ east longitude. The region experiences a dry and semi-arid climate influenced by Mediterranean moist fronts, with average rainfall between 400 to 500 millimeters, which decreases significantly in the western areas. Precipitation primarily occurs during fall and winter, greatly influencing the region's environmental conditions. Kermanshah shares a border with Iraq, making it susceptible to dust originating from the area (Zinatizadeh et al., 2017; Sheikh Ghaderi et al., 2023). Seasonal temperature variations are noteworthy, featuring cold winters and warm summers that affect the ecosystem. Winds, particularly the westerly and northwesterly breezes from nearby desert areas, process transports dust particles into Iran. Furthermore winds from the northeast (Siva) also contribute to dust events, making these occurrences notably frequent during the spring and summer months (Nazari et al., 2022; Sheikh Ghaderi et al., 2023).

Figure 2 illustrates the overall process of the research, which includes stages such as data collection, data processing, identification of variables affecting dust emission, and the use of machine learning models to predict dust sources. This flowchart depicts the different stages from data gathering to final analysis and evaluation of results.

In this study, we utilized MODIS satellite images from the Terra satellite covering the years 2000 to 2020 (Table 1). We concentrated on thermal infrared bands 11 (BT11) and 12 (BT12) for dust storm detection, as these bands are particularly sensitive to surface temperature variations and at-

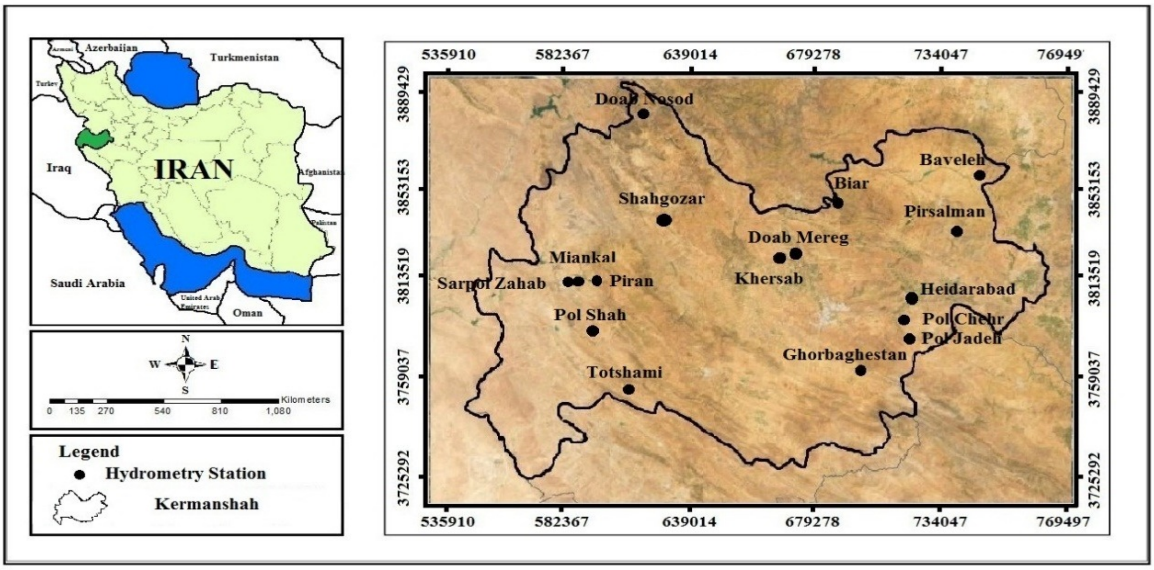


Figure 1. Map of study area.

mospheric effects. The brightness temperature difference (BTD) was calculated using the formula:

$$BTD = BT11 - BT12 \tag{1}$$

This calculation assists in identifying temperature anomalies associated with dust storms, as dust particles absorb and scatter thermal radiation differently from the surrounding atmosphere, making BTD a reliable indicator of dust presence. We applied atmospheric and radiometric corrections utilizing the MODIS Reprojection Tool to enhance the precision of our analysis (Jalal and Mahdi, 2024; O'Neill et al., 2025). These corrections were critical for minimizing reflections and atmospheric interference, which could skew the results.

Numerous factors influence dust emissions, including climatic variables, soil characteristics, and physiographic and

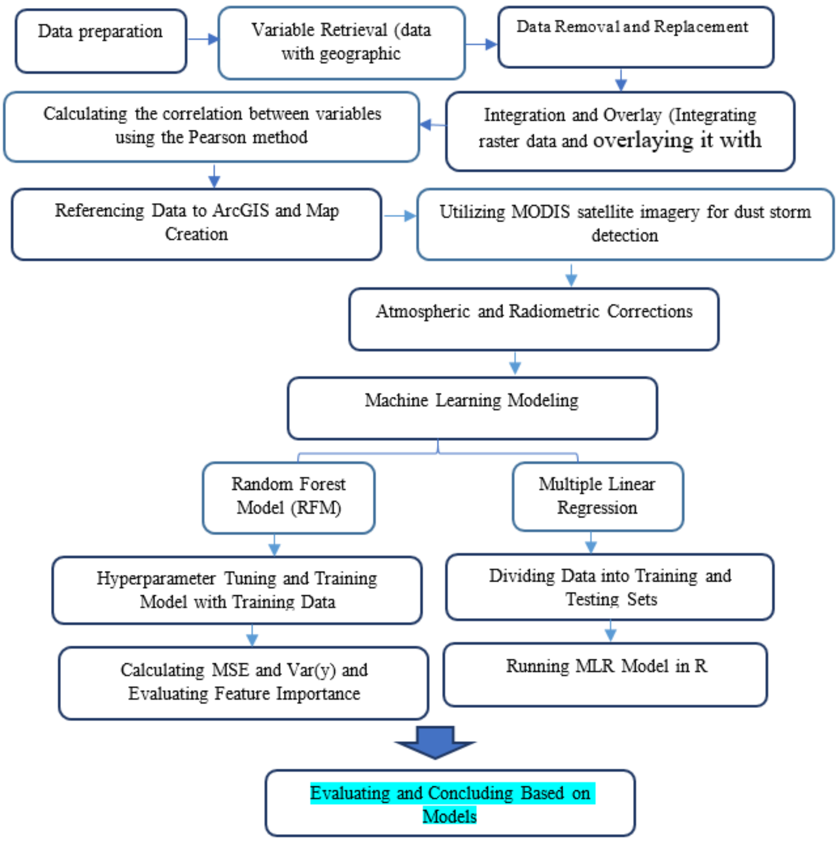


Figure 2. Flowchart comparing random forest and regression models for dust storm assessment in Kermanshah Province..

Table 1. Specifications of the MODIS imager used.

Factor	Value
Satellite Name	Terra MODIS (Sensor: MODIS)
Image Temporal Resolution	Daily
Image Resolution	1 Kilometer
Product Name	MOD11A1 (for temperature) and MCD12Q1.061 (for land cover)
Data Type	Thermal images and land cover data
Data Source	NASA, MODIS
Data Acquisition Years	2000 to 2020

topographic features (Gholami et al., 2021; Ebrahimi Khusfi and Soleimani Sardo, 2021; Wang et al., 2024). Our analysis focused on 11 significant factors impacting dust emissions, which we categorized as follows:

Meteorological variables: Day and night temperatures, relative humidity, and precipitation.

Soil and landscape characteristics: Soil moisture and lithology.

Land use and vegetation: Vegetation cover, assessed through NDVI.

These factors were selected based on previous studies highlighting their substantial influence on dust emission dynamics.

We ground-referenced the datasets and applied necessary corrections using ArcGIS 10.8.2 (ESRI, USA) to calculate the indices of dust harvesting sources. The Digital Elevation Model (DEM) for Kermanshah Province was generated from a topographic map at a 1:50,000 scale with an accuracy of 50 m. The slope layer was derived from this DEM. NDVI maps were created from MODIS imagery processed through ENVI software (Harris Geospatial, USA). For soil erosion mapping, we utilized the national soil erosion map provided by the Natural Resources and Watershed Management Organization. Land cover classification in Kermanshah Province was based on the MCD12Q1.061 product from MODIS satellite imagery, spanning 2000 to 2020 (García-Álvarez et al., 2022; Li et al., 2023). Precipitation data for the two decades in Kermanshah Province were obtained through the CHIRPS Pentad product, processed using Java programming (Python Software Foundation, USA) within Google Earth Engine (Google, USA) (Helmi and Abdelhamed, 2023; El Khalki et al., 2023). Soil moisture data were acquired by integrating surface soil moisture observations from the SMAP satellite (NASA, USA) with a modified Palmer two-layer model via the EnKF 1-D data assimilation approach (Batchu et al., 2023). Additionally, moisture data specific to Kermanshah Province were extracted from the GLDAS-2.1 dataset (NASA/GSFC, USA) within Google Earth Engine (Hu et al., 2021; Li et al., 2022; Amini et al., 2023).

For validation, we incorporated data from 16 hydrometric stations in Kermanshah Province (figure 1). These stations include: Doab Nosud, Totshami, Shahgozar, Piran, Mian Kal, Sarpol Zahab, Pol Shah, Pol Chehr, Kherasabad, Doab Mereg, Biar, Ghorbaghestan, Pole Jadeh, Pir Salman, Baveleh, and Hyderabad. Among them, Baveleh station proved most effective for providing valuable information, while Totshami station was deemed unsuitable and others like Pol Chehr, Biar, Sarpol Zahab, and Pol Jadeh exhibited limited potential.

To analyze dust sampling points, we employed the "Extract Multi Values to Points" function in ArcGIS, transferring raster values into a point shapefile. Statistical modeling was conducted using Python, involving correlation and regression analyses (R^2) on pixel values associated with dust sampling points. In *R*, we performed data preparation by loading libraries such as raster and dplyr, defining variables, creating a spatial dataset, and executing Random Forest and Multiple Linear Regression models. This process included data splitting, model training, and performance evaluation based on metrics such as Mean Squared Error (MSE) and R^2.

For predicting dust sources, we utilized two modeling approaches: Random Forest (RFM) and Multiple Linear Regression (MLR). The RFM algorithm constructs an ensemble of decision trees to enhance predictive accuracy (Tsai et al., 2020; Chen et al., 2021; Azlim Khan and Ahamed Hassain Malim, 2023). MLR, as a generalized form of linear regression, was also employed (Zou et al., 2023; Lipatov et al., 2024). Prior to model execution, we identified independent and dependent variables, coding them as spatial data with geographic coordinates in *R* through resampling. In the Random Forest model, we selected 1,000 trees to balance computational efficiency and predictive accuracy, setting the minimum samples required for node splitting at 600 and for leaves at 300, in order to mitigate overfitting. We optimized hyperparameters iteratively using a test dataset and various loss functions through grid search and cross-validation, monitoring performance metrics such as MSE. During this process, invalid or missing data (NAs) were replaced with valid entries. Raster data were integrated with shapefile data, and Pearson correlation analysis assessed relationships between independent and dependent variables to identify influential variables. The final Random Forest (RF) model was executed with fine-tuned hyperparameters to ensure stable and accurate performance. During RF model training, MSE and the variance explained (Var(y)) were calculated every 25 trees. Feature importance was eval-

uated using established methods to quantify each feature's contribution to impurity reduction.
Subsequently, we developed a Multiple Linear Regression (MLR) model, preparing a correlation matrix to understand variable interdependencies. The dependent variable was divided into training (70%) and testing (30%) datasets. This split ensured robust model training while preventing overfitting by evaluating performance on unseen data. The dependent variable, "grid_code," represented sampling points for dust modeling, reflecting PM10 concentration. Independent variables included DEM, erosion rate, humidity, land cover, lithology, daytime land surface temperature (LST), nighttime LST, NDVI, precipitation, slope, and soil moisture. The MLR was coded and executed in *R* (*R* Foundation for Statistical Computing, Austria), and model accuracy assessed using the correlation coefficient and Root Mean Square Error (RMSE).
We implemented a rigorous validation process to ensure the reliability of our methods, controlling data quality through atmospheric correction and radiometric calibration. Model-predicted dust emission indices were compared against data from hydrometric stations, and statistical analyses, including multiple regression and correlation analyses, assessed variable relationships. Machine learning models underwent evaluation through cross-validation and sensitivity analysis to examine the impact of input variations on model outputs, while acknowledging any methodological limitations.

3. Results and discussion

Fig. 3 the Trend and Regression Chart of Maximum Dust in Kermanshah Province (20-Year Period) provides a historical context for dust levels, showcasing long-term trends that are critical for understanding seasonal and annual variations.
During the study period, dust levels exhibited notable variations. The regression line chart indicates a general decline in maximum dust levels over the years. With a correlation coefficient of 0.015 between the year and maximum dust levels, the relationship is deemed weak. This suggests a need to investigate other factors that may influence dust occurrences.
The peak frequency of dust storms occurred on average from 2007 to 2010, while the lowest levels were recorded in 2001. Regression analysis of annual averages indicates a moderately positive correlation between the years studied and incoming dust quantities.
Figures 4a and 4b illustrate the maximum annual dust levels and the average annual dust levels in Kermanshah Province, respectively. These maps reveal the spatial distribution of dust levels across the region, which is critical for identifying hotspots and areas at greater risk of dust storm impacts. In conclusion, while a general decline in maximum dust levels has been observed, further exploration of additional contributing factors is essential to fully understand dust dynamics in Kermanshah Province. The spatial maps presented aid in pinpointing vulnerable areas that may require targeted intervention and management strategies.
Dust levels are highest in the extreme western part of Kermanshah Province, particularly in the counties of Qasr-e Shirin, Gilan-e Gharb, Sarpol-e Zahab, and Thalath Babajan. Several factors contribute to this increase: Proximity to the borders of Iraq, Syria, and Saudi Arabia; high daily temperatures; sparse vegetation or barren land; specific agricultural practices; loose alluvial deposits; low elevation; low relative humidity; and limited soil moisture. Additionally, external dust sources significantly elevate pollution levels in these areas. As we move from west to east across the province, maximum observed dust levels generally decrease. Data on 20-year average annual dust levels indicate that the peak frequency of dust storms occurred between 2007 and 2010, followed by a decline. During this period, the western and southwestern regions of Kermanshah Province experienced substantial dust storm activity, while central areas faced dust-related challengesThese findings underscore the urgent need for strategic planning in dust management to mitigate its adverse effects on public health.
Table 2 summarizes the correlation and regression analysis between influential variables and dust levels in Kermanshah Province, providing numerical evidence to support the relationships depicted in the figures and emphasizing their statistical significance.
Pearson correlation analysis between independent variables and dust levels reveals that certain factors positively impact dust emissions, while others exert a negative influence. Specific variables, such as the "daytime temperature map"

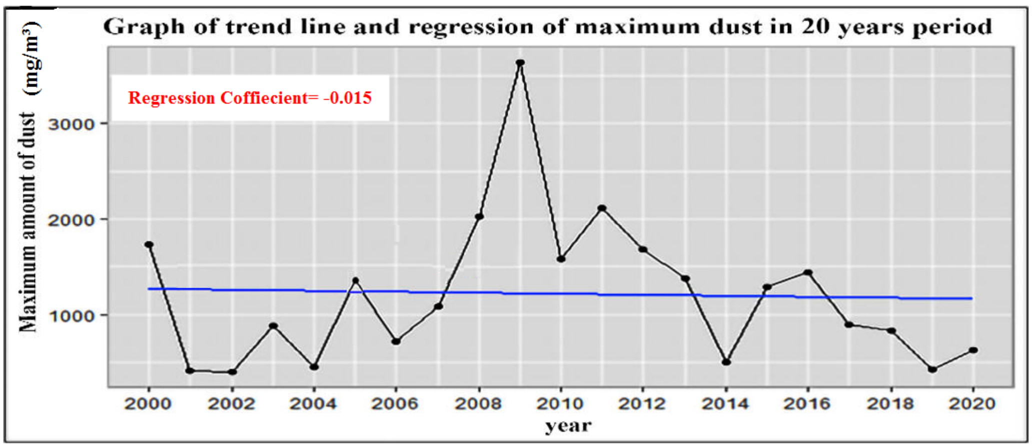
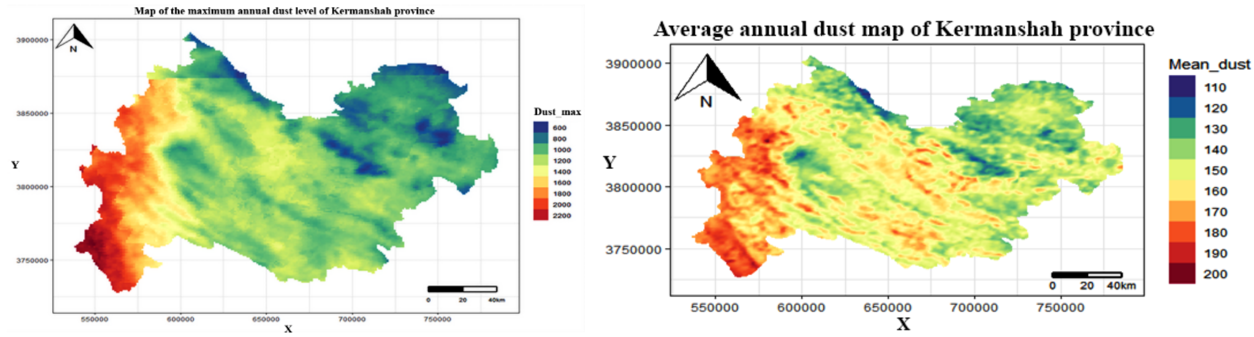


Figure 3. Trend and regression chart of maximum dust in Kermanshah Province.



(a) (b)

Figure 4. (a) Map of maximum annual dust levels in Kermanshah Province, (b) Map of average annual dust levels in Kermanshah Province.

and "nighttime temperature map," exhibit higher R^2 values, indicating a strong positive effect on dust emissions. Conversely, the "Digital Elevation Model" and "Soil Moisture Map" have a negative impact, suggesting that increased elevation and soil moisture can help diminish dust emissions. Other factors, such as the "Lithology Layer," show moderate effects, while the "Vegetation Cover Map," "Land Use Map," and "Land Erosion Map" may be statistically significant. However, their influence on dust emissions is limited, overshadowed by more impactful factors and data constraints.

Figure 5 visually represents the interactions among these variables, enhancing the understanding of their influence on dust levels. In conclusion, addressing high dust levels in Kermanshah Province requires strategic planning and targeted interventions based on empirical findings. Understanding the complex relationships among environmental factors is essential for developing effective dust management strategies to protect public health and mitigate environmental impacts.

Figure 5 serves as a visual aid to better understand how these various variables interact and influence dust level.

An analysis of dust sources in Kermanshah Province, utilizing MODIS satellite imagery, reveals that mountainous areas exhibit the lowest dust concentrations. Statistical analyses indicate that the Digital Elevation Model (DEM) accounts for approximately 65.8% of the variance in dust levels, underscoring altitude's significant role in reducing dust particle concentrations. This finding aligns with Munroe et al. (2023), who noted that most dust in the region originates from arid, low-altitude areas.

At higher elevations, lower dust concentrations occur for several reasons. Steep slopes, prevalent in these areas, typically experience less dust compared to gentler inclines and lower terrains. Additionally, steep slopes affect rainfall and snow distribution, receiving more precipitation than flat, low-altitude regions. This leads to enhanced vegetation cover, which further mitigates dust production. Figure 5 supports this observation, demonstrating that mountainous regions with steep inclines have the lowest dust levels.

Vegetation cover is crucial in preventing dust formation. Research by Yang et al. (2024) in China highlights a correlation between increased vegetation density and decreased dust sources. Similarly, Alsubhi et al. (2022) found that

Table 2. Correlation and regression between influential variable data and dust in Kermanshah Province.

Variable	Correlation	Y	R^2	Impact	Significance (95% CI)
DEM	-0.810	183.32+x0.02-	0.660	Negative impact	Meaningful
Night mode temperature map	0.720	128.47+x2.55	—	Positive impact	No meaningful
Day mode temperature map	0.770	84.03+x2.39	—	The most positive impact	Meaningful
Lithology layer	0.390	136.62+x4.18	—	Medium impact	Meaningful
Atmospheric humidity map	0.730	13.09+x33409.77	0.520	Positive impact	Meaningful
Soil moisture map	-0.450	169.36+x3.21-	-0.449	Negative impact	Meaningful
Rainfall map	-0.140	161.13+x1.14-	—	No significant impact	No meaningful
Slope map	-0.300	157.27 +0.41-	0.090	No significant impact	No meaningful
Vegetation map	-0.190	162.38 +x46.54-	0.040	No significant impact	Meaningful
Land cover map	-0.410	179.96+x2.31-	0.160	No significant impact	Meaningful
Land erosion map	0.280	139.63+x2.50	0.080	No significant impact	Meaningful

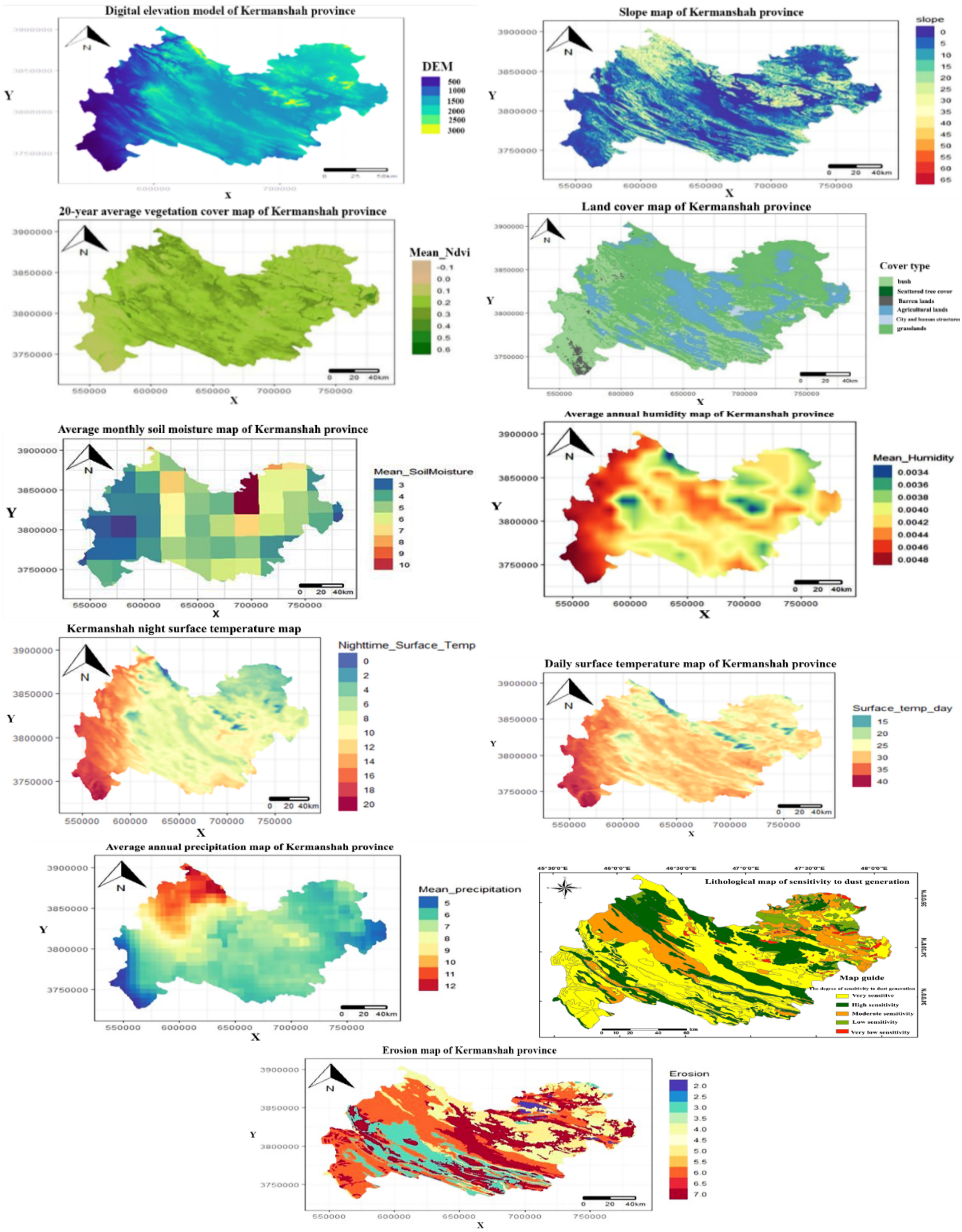


Figure 5. Influential variables on dust dispersion from the ground levels of Kermanshah Province.

the intensity of vegetation cover near dust sources is significantly lower than in more vegetated areas. Continuous natural vegetation effectively reduces wind erosion and prevents dust generation.

External factors must also be considered. Dust from the deserts of Iraq, as mentioned by Beyranvand et al. (2023), significantly impacts western provinces like Kermanshah. This is evident in the weak correlation observed between vegetation cover and dust levels within the province. Figure 5 illustrates that areas with lower vegetation density, particularly in the western and southwestern regions, experience higher dust intensity. Even in central areas, regions with less robust vegetation cover show elevated dust levels. Despite some increase in vegetation from agricultural expansion and the cultivation of previously abandoned lands, this growth may not sufficiently address the areas identified as dust sources. Statistical and spatial analyses confirm that dust levels are rising in regions with sparse or insufficient vegetation. Therefore, enhancing vegetation is vital for protecting soil against erosive winds and mitigating dust storm risks. The loss of vegetation due to human activities exacerbates wind erosion, consequently increasing the likelihood of dust storms.

Analysis of land cover reveals a relatively weak negative correlation (-0.41) between land cover and dust levels, indicating that greater land cover typically corresponds with lower dust levels. This finding is consistent with studies by Li et al. (2023). Moreover, vegetation promotes increased soil moisture (Alsubhi et al., 2022), which further inhibits dust production. Elevated soil moisture enhances the cohesion among soil particles, raising the threshold for wind erosion and thereby reducing dust generation. Soil moisture also significantly influences dust dispersion potential (Liu et al., 2023), with the highest moisture levels observed in spring and the lowest in summer. Unfortunately, Kermanshah Province, particularly its western and southwestern regions most prone to dust storms, suffers from very low surface soil moisture.

In summary, the western half of Kermanshah Province exhibits a strong interplay among climatic factors, vegetation, and dust production. Research emphasizes the significance of moisture levels. Shao (2024) illustrated that air moisture impacts soil moisture and dust dispersion, noting that low moisture levels facilitate the spread of fine dust particles. Studies by Boloorani et al. (2022) and Yang et al. (2024) confirm that higher temperatures increase evaporation rates and decrease soil moisture, leading to more frequent dust storms.

Precipitation plays a critical role in reducing the likelihood of dust storms (Alsubhi et al., 2022). The annual average precipitation map (Figure 5) indicates significant variations across Kermanshah Province, with the highest amounts concentrated in the northwest and the lowest in dust-prone areas in the west, southwest, and parts of the east. Precipitation levels directly correlate with the frequency of dust events, reaffirming that lower precipitation results in higher dust occurrences. Alsubhi et al. (2022) identified wind speed and precipitation as key determinants of dust sources, a conclusion supported by findings from Boloorani et al. (2022). Numerous studies, including those by Albugami et al. (2019), (Ghanem, 2020), and Okin (2022), have concluded that increased precipitation and soil moisture can effectively reduce dust phenomena, corroborating the results of this study. Hamzeh et al. (2021) observed that dust activity in the deserts of Iraq and southwestern Iran is most pronounced under conditions of low precipitation and sparse vegetation cover, a finding echoed by Li et al. (2023). Additionally, Yang et al. (2024) identified precipitation, evaporation, and soil moisture as critical factors influencing dust aerosol variations, with the interaction between precipitation and temperature providing considerable explanatory power.

Erosion and soil lithology are also important factors influencing dust occurrence in Kermanshah Province. The findings suggest that the southern and southwestern regions experience high rates of soil erosion, with notable erosion detected in eastern areas, likely exacerbated by agricultural expansion. This results in poor vegetation cover and low soil moisture, both contributing to dust development in the province. Furthermore, the lithology map indicates that the southern and southwestern areas are significantly impacted by dust emissions, highlighting the critical role of soil characteristics in exacerbating dust phenomen.

3.0.1 Multiple linear regression model

Figure 6 demonstrates the effectiveness of our regression model in predicting dust levels, showcasing the correlation between actual and predicted data.

The Multiple Linear Regression (MLR) model accounts for approximately 72.1% of the variation in dust levels (R-squared $= 0.721$), with a statistically significant overall P-value of less than 0.050. Key variables impacting dust levels include the Digital Elevation Model (DEM), erosion, relative humidity, land cover, geology, daytime temperature, vegetation density ratio, and soil moisture. On the other hand, nighttime temperature, precipitation, and slope do not significantly influence dust levels. These findings underscore the vital roles of vegetation density and topography

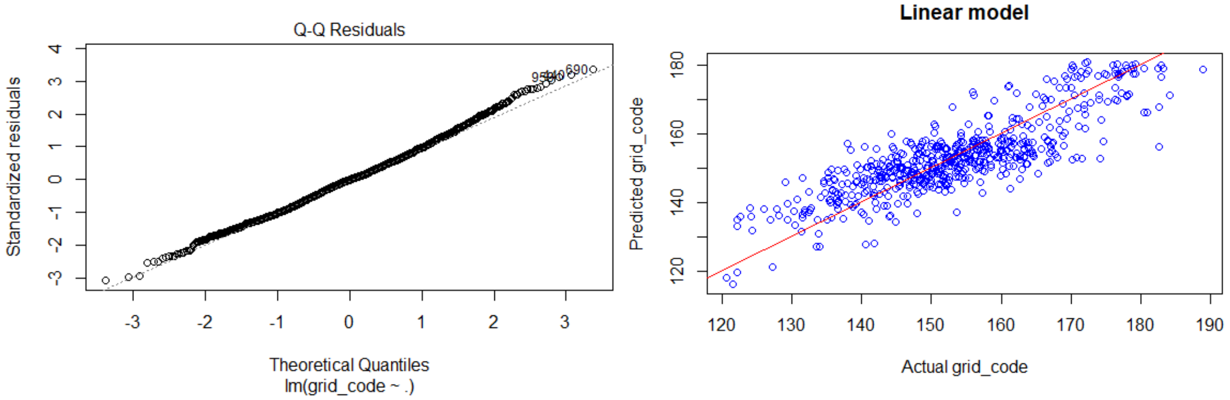


Figure 6. Normal distribution between actual values and predicted values of the multiple linear regression model. Correlation between actual data and predicted data of the multiple linear regression model.

in reducing dust concentrations, consistent with existing literature. The model demonstrates a strong correlation of 0.840 between observed and predicted dust levels, with a Root Mean Square Error (RMSE) of 7.05. This level of error suggests that there are additional influencing factors, such as wind speed and specific soil types, that were not accounted for in the model. The results have significant implications for managing dust storms in Kermanshah Province, emphasizing the necessity for interventions, such as increasing vegetation cover and implementing erosion control measures. Future research should aim to incorporate a wider range of variables and utilize more sophisticated modeling techniques to enhance dust prediction accuracy and management strategies.

3.0.2 Random forest model

Fig. 7 The Importance of Each Predictor Variable in the Random Forest Model emphasizes the relative significance of different predictors, providing insights into which factors are most influential in dust dispersion.

The Random Forest Model (RFM) effectively demonstrates reasonable accuracy in predicting dust levels in Kermanshah Province. The Mean Squared Error (MSE) of the model was 29.5, and it explained 18.4% of the variance in dust levels. The Digital Elevation Model (DEM) emerged as the most influential factor, while erosion and land cover were identified as having the least impact. A strong correlation of 0.900 between the actual and predicted data indicates that the RFM successfully captures the underlying data patterns. DEM maps, surface temperature maps (both day and night), and atmospheric moisture significantly influence the model's predictions. Elevation plays a critical role, accounting for over 80% of the variation in dust levels. In mountainous areas, suitable vegetation cover and strong air currents aid in dust dispersal and inhibit the formation of dust nuclei. Surface soil moisture, influenced by atmospheric moisture, surface temperature, and precipitation, is also a crucial predictor in this analysis. Overall, the RFM proves to be particularly effective due to its capability to analyze the nonlinear relationships among the spatial and geographical factors influencing dust dynamics.

Figure 8 visually depicts the predicted dust levels across the region, generated by our analysis. Meanwhile, figure 9 illustrates various dust risk zones in Kermanshah Province using the Multiple Linear Regression (MLR) method.

Very high dust levels in Kermanshah Province are primarily concentrated in the extreme western and southwestern regions, covering approximately 3,000 km^2 of barren land with sparse vegetation, making it highly susceptible to dust emissions. This area also experiences significant dust influx from neighboring countries, including Iraq, Syria, and Saudi Arabia. Surrounding this zone is a severe dust zone that spans 6,127 km^2, influenced by both local disturbances and external dust sources. A moderate dust zone encompasses approximately 8,500 km^2, raising concerns about its potential to escalate into higher-risk categories and pose ecological hazards. Conversely, low and very low dust zones are located in mountainous regions, which benefit from better vegetation cover and higher moisture levels. These zones cover about 6,400 km^2 and experience significantly less dust accumulation due to consistent air currents.

Overall, the findings highlight the urgent need for effective management strategies to address dust storms throughout Kermanshah Province. Since 2016, Iran has implemented broader measures, including the restoration of water rights for internal wetlands and the establishment of an air pollution monitoring network. Collaborative efforts with the Ministry of Foreign Affairs also led to the development of information processing systems and the documentation of dust storm events, culminating in the adoption of three UN resolutions. However, the effectiveness of these initiatives has been hampered by management challenges, low prioriti-

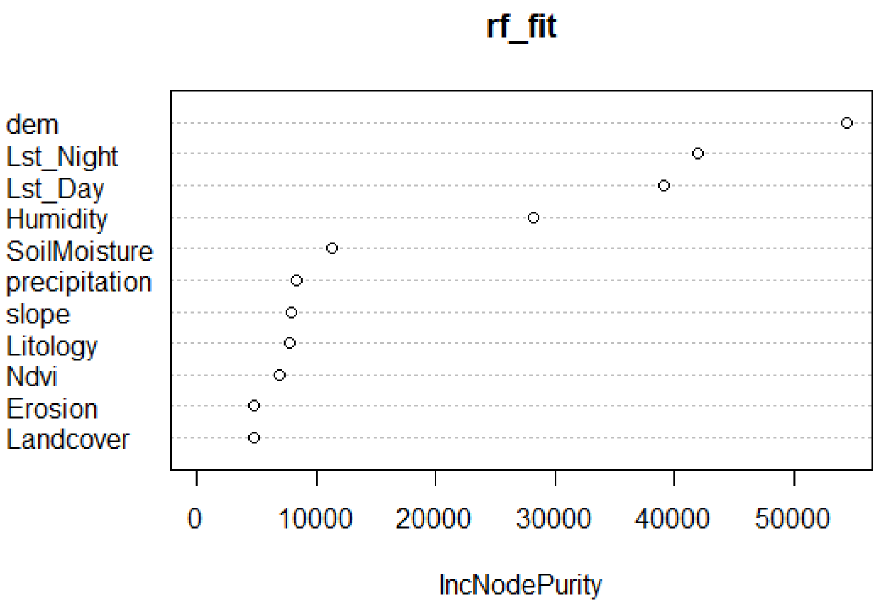


Figure 7. Importance chart of each predictor variable in the random forest model Using the Random Forest Model (RFM), this research achieved significant success in predicting dust levels in Kermanshah Province.

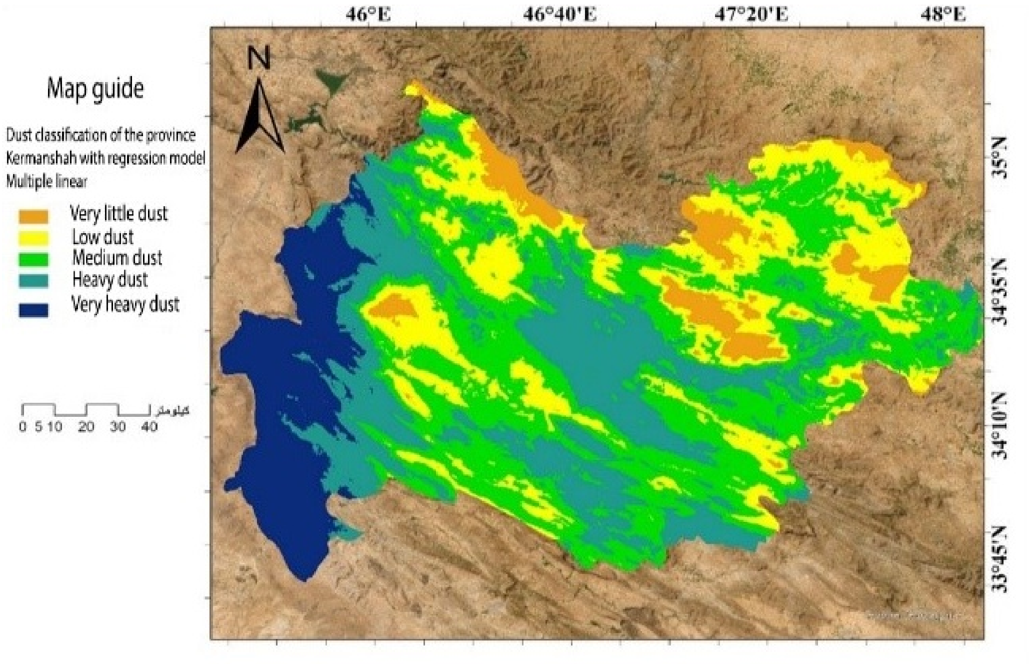


Figure 8. Dust modeling map of Kermanshah Province using the multiple linear regression method.

zation of environmental issues, and regional conflicts, which have affected their full implementation. In addition, the Natural Resources and Watershed Management Department afforested approximately 6,080 hectares in Kermanshah and Ilam provinces in early 2014, marking initial efforts to combat desertification.

Figure 10 visually represents the results of our regression analysis, allowing readers to see the predicted dust levels across the region.

The analysis reveals subtle differences in the geographical distribution of dust risk zones compared to the MLR model, but significant discrepancies exist in the specific areas classified as risk zones. As illustrated in figure 10, the dust zone patterns generally resemble those of the linear regression model and correlate with the time series data of dust levels in Kermanshah Province. Notably, the largest areas fall within the moderate and severe dust zones. The overall dust situation in Kermanshah Province is a concern, as the RFM indicates that the extreme west and southwest regions experience the highest levels of particulate pollution. Furthermore, areas in the central and southern parts of the province also fall within the severe dust zone, while higher-altitude and mountainous regions exhibit the least dust accumulation. Cumulatively, approximately 16,367 km^2 out of the province's total area of 24,640 km^2 (around 67%) are classified as moderate to critical risk zones.

Our analysis demonstrates that the Random Forest Model (RFM) significantly outperforms the Multiple Linear Regression (MLR) model in terms of accuracy in dust image classification and lower error rates. This outcome showcases the RFM's ability to effectively learn and predict overall data patterns. A correlation of 0.90 was observed between the actual data and the data predicted by the Random Forest Model, indicating a strong positive relationship between these two datasets. Furthermore, the Root Mean Squared Error (RMSE) for the Random Forest Model was 5.59, which

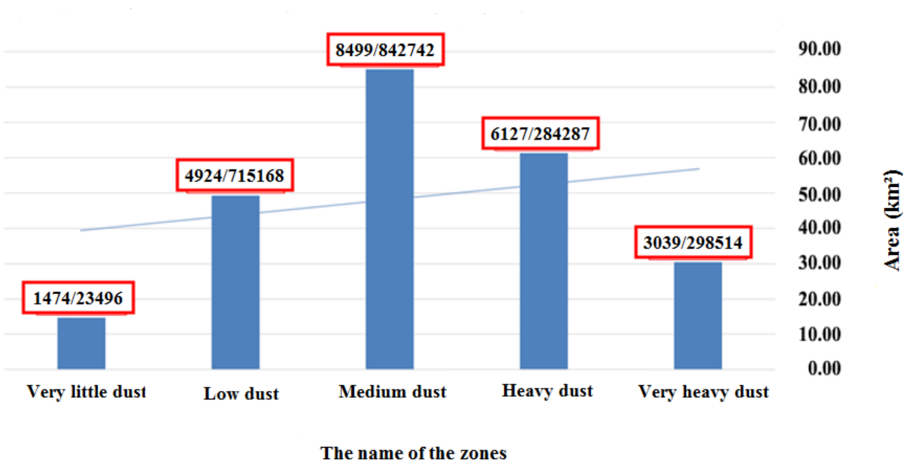


Figure 9. Area of various dust risk zones in Kermanshah Province using the multiple linear regression method.

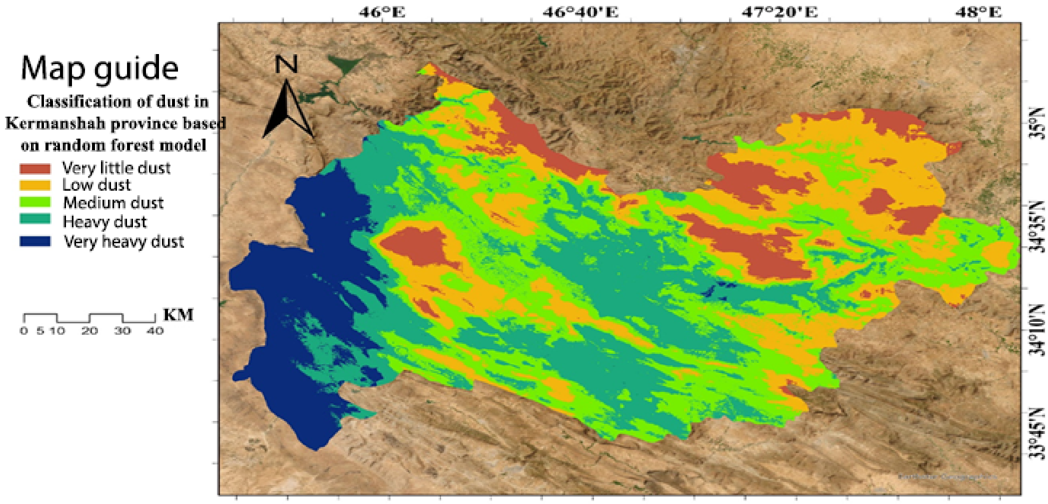


Figure 10. Dust modeling map of Kermanshah Province using the random forest method.

indicates that, on average, the model's predictions deviate from the actual data by approximately 5.59 units. Table 3 summarizes the comparative performance of the RFM and MLR models, detailing their strengths and weaknesses.

This outcome is consistent with the inherent strengths of the Random Forest Model (RFM). While linear models excel at capturing linear relationships, such as that between temperature and precipitation, dust events arise from complex and often nonlinear interactions among multiple variables. The superior performance of the RFM is attributed to its robust algorithms, which effectively analyze nonlinear, multivariate relationships between dependent and independent variables. This capability leads to more accurate outputs and a reduction in prediction errors. This finding aligns with existing scholarly work. Prior research, including studies by Pourhashemi et al. (2023) and Ebrahimi Khusfi et al. (2021), has highlighted the advantages of the RFM over alternative modeling techniques. A comparative assessment of the area coverage provided by the two models, as illustrated in figure 11, further substantiates this conclusion.

Figure 11 shows that both models generate nearly identical high and very high dust zones. However, the linear regression model's moderate dust zone is larger, while the random forest model (RFM) encompasses a substantially greater area in the low and very low dust zones. These results indicate the RFM's transferability to regions with similar environmental conditions. This transferability arises from the model's reliance on key factors influencing dust emissions, which tend to be consistent across comparable climates. The RFM effectively identifies these factors, making reasonably accurate predictions and demonstrating strong generalizability across diverse conditions. Calibration with local data enables the model to accurately predict dust patterns in new areas, enhancing our understanding of dust phenomena and providing insights for future initiatives.

Table 3. Comparison of features of Multiple Linear Regression (MLR) and RFM models in prediction and data analysis.

Feature	MLR	RFM
Prediction Accuracy	72.1% (R-squared = 0.721)	18.4% (MSE = 29.5)
Correlation between Actual and Predicted Data	0.840	0.900
RMSE	7.05	-
Key variables	DEM, erosion, relative humidity, land cover	DEM, erosion, land cover
Limitations	Assumes linearity, sensitive to outliers	Complexity and lack of interpretability
Interpretability	Higher (linear model)	Lower (black box model)
Computational resource requirement	Lower	Higher
Ability to identify non-linear relationships	Limited	Strong
Practical application	Dust management considering linear factors	Analysis of complex and non-linear relationships

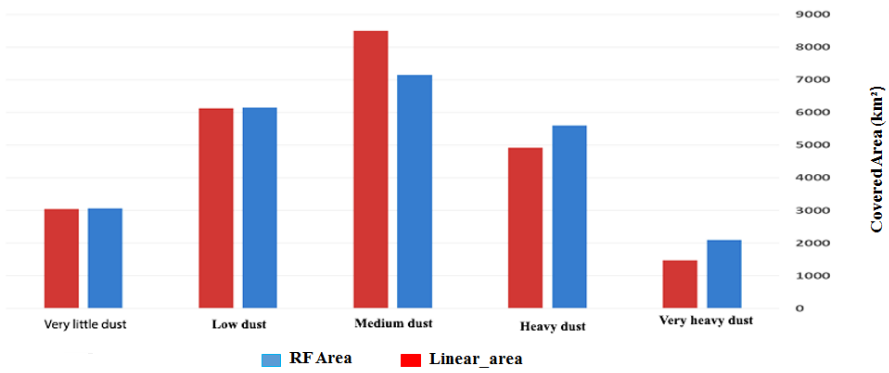


Figure 11. Comparison of area coverage of multiple linear regression and random forest models for dust in Kermanshah Province.

4. Conclusion

This research successfully identifies dust sources in Kermanshah Province using remote Sensing and machine learning techniques, providing practical recommendations for the control and mitigation of dust storms in the region. Key findings indicate that severe dust events are concentrated in the western and southwestern parts of the province. These areas are characterized by barren lands, low soil moisture, and sparse vegetation. Furthermore, these regions are significantly impacted by transboundary dust from neighboring countries, including Iraq, Syria, and Saudi Arabia. The Random Forest Model (RFM) demonstrates superior performance compared to the Multiple Linear Regression (MLR) model in classifying dust images and predicting vulnerable areas, showing a lower error rate and indicating greater effectiveness for this purpose.

The dust hazard zoning maps generated by the RFM serve as valuable tools for optimizing resource allocation to vulnerable areas. These maps help local authorities identify regions requiring immediate intervention. Identified interventions include implementing windbreaks, applying mulch, and initiating vegetation restoration projects. Additionally, soil moisture reduction has been recognized as a critical factor in dust emission. Therefore, targeted irrigation in vulnerable areas, particularly in agricultural zones experiencing salinity issues due to excessive irrigation, is of utmost importance. Furthermore, the restoration of water resources and vegetation in affected areas, the promotion of conservation agriculture, and sustainable grazing management practices are essential to prevent pasture degradation and overgrazing.

The results of this study can effectively contribute to the development of a national plan to combat dust storms. The dust hazard zoning maps and data on factors affecting dust emissions can be utilized to establish quantitative and qualitative targets for this plan. Moreover, these results can assist in developing environmental standards for agricultural and industrial activities to ensure that these practices help reduce dust emissions. International cooperation with neighboring countries is crucial for managing transboundary dust. Based on the study's findings, joint programs for water resource management, vegetation restoration, and soil erosion control in border areas should be developed and implemented.

This study acknowledges several limitations. Firstly, the availability and quality of satellite data may introduce biases, as variations in data resolution and accuracy can affect the reliability of the findings. Secondly, assumptions inherent in the modeling process, such as the selection of parameters and algorithms, can also influence the results. Additionally, the scale-specific nature of the model may limit its generalizability to other contexts or regions.

Future research should expand the geographical scope of dust source identification to other regions of Iran and explore advanced machine learning techniques to enhance predictive accuracy. Furthermore, a comprehensive examination of the social and economic impacts of dust storms on local communities is essential to provide a clearer understanding of this phenomenon. Finally, long-term studies to assess the effectiveness of the proposed management strategies are necessary for refining and improving approaches to reduce the occurrence of dust storms.

Authors contributions
Authors have contributed equally in preparing and writing the manuscript.

Availability of data and materials
The authors declare that they don't need research data support with this submission. Also, the authors are sure that all data and materials as well as software application or custom code support their published claims and comply with field standards.

Conflict of interests
The author declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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