Modeling land susceptibility to wind erosion hazards using LASSO regression and graph convolutional networks

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Predicting land susceptibility to wind erosion is necessary to mitigate the negative impacts of erosion on soil fertility, ecosystems, and human health. This study is the first attempt to model wind erosion hazards through the application of a novel approach, the graph convolutional networks (GCNs), as deep learning models with Monte Carlo dropout. This approach is applied to Semnan Province in arid central Iran, an area vulnerable to dust storms and climate change. We mapped 15 potential factors controlling wind erosion, including climatic variables, soil characteristics, lithology, vegetation cover, land use, and a digital elevation model (DEM), and then applied the least absolute shrinkage and selection operator (LASSO) regression to discriminate the most important factors. We constructed a predictive model by randomly selecting 70% and 30% of the pixels, as training and validation datasets, respectively, focusing on locations with severe wind erosion on the inventory map. The current LASSO regression identified eight out of the 15 features (four soil property categories, vegetation cover, land use, wind speed, and evaporation) as the most important factors controlling wind erosion in Semnan Province. These factors were adopted into the GCN model, which estimated that 15.5%, 19.8%, 33.2%, and 31.4% of the total area is characterized by low, moderate, high, and very high susceptibility to wind erosion, respectively. The area under curve (AUC) and SHapley Additive exPlanations (SHAP) of game theory were applied to assess the performance and interpretability of GCN output, respectively. The AUC values for training and validation datasets were estimated at 97.2% and 97.25%, respectively, indicating excellent model prediction. SHAP values ranged between −0.3 and 0.4, while SHAP analyses revealed that the coarse clastic component, vegetation cover, and land use were the most effective features of the GCN output. Our results suggest that this novel suite of methods is highly recommended for future spatial prediction of wind erosion hazards in other arid environments around the globe.

KEYWORDS

deep learning, erodible susceptibility, feature selection, game theory, potential impact

1 Introduction

Soil erosion by water and wind are the two main processes leading to its degradation (Webb et al., 2016; Duniway et al., 2019; Soloki and Noori Nahad, 2019; Liu et al., 2021; Jia et al., 2022). Soil erosion by wind is an environmental hazard, which threatens land productivity and ecosystems, reduces atmospheric visibility during dust storms, and affects ecosystems, animal, and human health (Gregory et al., 2004). Wind erosion affects ~28% of degraded land worldwide (Oldeman, 1994; Borrelli et al., 2014). However, predicting susceptibility to wind erosion remains a difficult task to be accurately quantified (Webb and Strong, 2011; Forootan, 2022). On the other hand, predicting land susceptibility to wind erosion is highly beneficial for mitigating its negative consequences, such as depletion of soil organic carbon, decreased soil depth, reduced soil structure stability *in situ*, increased dust aerosol loading, degradation of air quality, and increased respiratory diseases off-site (Xu et al., 2018; Gholami et al., 2020a; Gholami et al., 2021a; Tian et al., 2021; Boroughani et al., 2022).

Wind erosion is a serious environmental problem in large areas of Iran, especially in the central, eastern, and southern parts of the country (Gholami et al., 2020a; Gholami et al., 2020b). It is estimated that an area of 23.8 million ha is affected by wind erosion, of which 51% is susceptible to aeolian entrainment, 31% experiences significant aeolian transport, and 18% represents the area dominated by sedimentation (Ahmadi, 1999). The frequency of dust storms has increased substantially across Iran over the last 20 years, exacerbated by prolonged dry conditions during 2000–2002 and 2008–2010 (Akoglu et al., 2015; Duniway et al., 2019; Hamzeh et al., 2021; Rashki et al., 2021). In order to mitigate the effects of wind erosion and associated dust storms on the atmosphere, geosphere, and biosphere, the prediction and mapping of land susceptibility to wind erosion are essential (Gholami et al., 2020c; Jafari et al., 2022; Pourhashemi et al., 2022).

Wind erosion depends on a range of variables such as vegetation cover, land surface characteristics, and climatic parameters (Gillette, 1979; Parajuli et al., 2014; Padarian et al., 2020). The contribution of each variable to erosion susceptibility remains poorly understood and is highly region-specific, while it is necessary to be defined in order to effectively model the spatial distribution of wind erosion hazards (Gholami et al., 2021c; Kannangara et al., 2022). Feature selection (FS) is a critical step in the application of data mining (DM) models (Kursa and Rudnicki, 2010). Various FS algorithms, such as Boruta, leave one feature out (LOFO), and DM models (e.g., random forest, tree-based genetic algorithms, multivariate adaptive regression spline (MARS), CForest, and Cubist), have been widely used to select key controlling factors for environmental hazards such as flood, land subsidence, landslides, and dust emissions (Hamza et al., 2019; Effrosynidis and Arampatzis, 2021).

Data mining (DM) is a component of data science (DS), which has frequently been widely used for spatial predictions in environmental and hydrological sciences (Gibert et al., 2018; Chowdhuri et al., 2021a; Chen et al., 2021; Saha et al., 2021; Arabameri et al., 2022; Chowdhuri et al., 2022; Saha et al., 2022). Over the past few years, different types of DM models (e.g., ANFIS, frequency ratio, weights of evidence, Cubist, CForest, and extreme gradient boosting) have been applied to map land susceptibility to wind erosion and dust emissions in various parts of Iran, vulnerable

to wind erosion, desertification, and climate change (Gholami et al., 2020a; Boroughani et al., 2020; Gholami et al., 2020c). Furthermore, recurrent neural network (RNN), restricted Boltzmann machine (RBM), gcForest, bidirectional long short-term memory (Bi-LSTM), and Gaussian copula-based multivariate model, as deep learning (DL) models, have been used for the spatial modeling of dust provenance over the globe (Gholami et al., 2021a; Gholami et al., 2021c). DL modeling is specifically interesting because this approach overcomes many of the restrictions placed on the modeling process by traditional machine learning (ML) or shallow models. In comparison with the traditional or shallow models, different architectures of DL transform the data presentation at one level into a representation at a higher level (LeCun et al., 2015). DL is increasingly being used as a tool to investigate a range of scientific problems, including spatial modeling of environmental issues (Chowdhuri et al., 2021b; Mohammadifar et al., 2021b; Gholami and Mohammadifar, 2022; Mohammadifar et al., 2022). Typical DL models can be divided into four classes, namely, stacked auto-encoder (SAE), deep belief network (DBF), recurrent neural network (RNN), and convolutional neural network (CNN) (Zhang et al., 2018), of which CNN is one of the most popular for prediction goals (Reiss and Bogenberger, 2016; Zhang et al., 2016). One branch of CNN, the convolutional graph neural networks (ConvGNNs), has been applied to a wide range of research topics including computer vision (Monti et al., 2017), natural language processing, traffic prediction (Li et al., 2018), social analysis (Backstrom and Leskovec, 2011), bioinformatics, and fraud detection (Akoglu et al., 2015; Zhang et al., 2017; Zhang et al., 2019), but has not yet been investigated for environmental issues. The ConvGNN approach shows promising results for environmental hazard prediction due to the advantage of graphs to capture structural relations between data over analysis of data in isolation. Overall, ConvGNNs (Zhang et al., 2019) can be classified into the spectral-based techniques (Defferrard et al., 2016; Kipf and Welling, 2016) and spatial-based techniques (Monti et al., 2017; Veličković et al., 2017). In addition, aspects of game theory may be used to assess the interpretability of predictive DM and DL models. Previous environmental studies have successfully made use of SHapley Additive exPlanations (SHAP) from game theory to interpret predictive DM models for digital soil mapping and soil erosion by water (Padarian et al., 2020; Mohammadifar et al., 2021a). These early results indicate that it may be beneficial to explore game theory through SHAP, in order to assess the interpretability of our GCN model outputs for wind erosion.

This study aimed to investigate novel tools for the prediction of susceptibility to wind erosion on the central Iranian Plateau (Semnan Province). To the best of our knowledge, this work is the first attempt at mapping wind erosion hazards by combining LASSO regression, graph convolutional networks (GCNs), and game theory. Game theory (SHAP) was applied to assess the interpretability of the DL results. The main objectives and goals of this study were as follows: 1) the identification of the most important factors controlling wind erosion for the study area using LASSO regression, 2) the spatial prediction of land susceptibility to wind erosion by applying a GCN deep learning model with Monte Carlo dropout, 3) the evaluation of the GCN model using the receiver-operating characteristic area under curve (ROC-AUC) approach, and 4) the examination of the
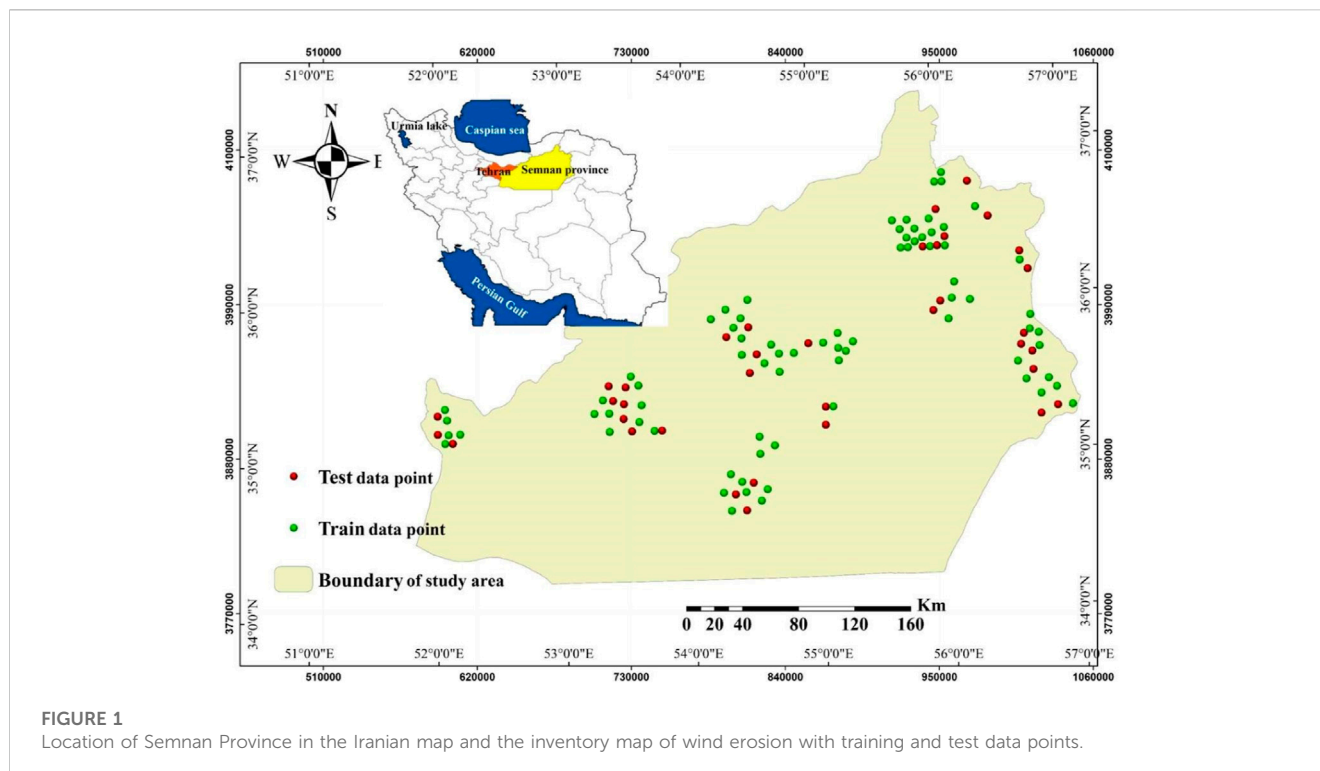
FIGURE 1
Location of Semnan Province in the Iranian map and the inventory map of wind erosion with training and test data points.

interpretability of our predictive GCN model using game theory. We assess, on the basis of our case study, whether this approach could be applied for spatial mapping of dryland hazards such as wind erosion and dust plume transport worldwide.

2 Materials and methods

2.1 Study area

Semnan Province is a region covering 97,322 km^2 in the northern part of the central Iranian Plateau, lying on the southern margins of the Alborz mountain range (Figure 1). The region is hyper-arid to semi-arid, with rough terrain and low population density, covering the northern part of the Kavir Desert. The altitude of the study area ranges substantially from 658 m in the south and central parts to 3,885 m in the north. Mean annual precipitation follows a steep gradient from 75 mm in the hyper-arid south to 699 mm in the more mountainous and vegetated northern part. The topography and climatic conditions contribute to significant variability in soil organic carbon stock (OCS) contents across the province, with values ranging from near zero in the central and southern parts to 78% in the north.

2.2 Mapping factors controlling wind erosion

Initially, maps for 15 potential factors controlling wind erosion in Semnan Province were generated (S1 and S2). The potential factors were selected based on previous studies investigating land susceptibility to wind erosion in Iran (Gholami et al., 2020b; Gholami et al., 2020c; Gholami et al., 2021b). These factors include topography, which is expressed through a digital elevation model (DEM), and spatial distribution of precipitation, evaporation, surface wind speed, normalized difference vegetation index (NDVI), soil bulk density, nitrogen and organic carbon stock (OCS), surface cation exchange capacity (CEC), proportion of surface sediment of clay, silt, sand, and percentage of the coarse fragment, lithology, and land use. The topographical data for the DEM were downloaded from https://earthexplorer.usgs.gov with a spatial resolution of 30 m × 30 m. Climatic/meteorological data (precipitation, evaporation, and wind speed) were derived and interpolated from measurements at 27 synoptic meteorological stations in Semnan Province and surrounding areas averaged over the period 2012–2019, and mapped in ArcGIS. The NDVI data were retrieved for June 2020 using the MODIS (Moderate Resolution Imaging Spectroradiometer) satellite sensor on the assumption that June is representative for average annual vegetation cover in Semnan Province. We assume that since vegetation in the province is sparse and comprises bushes, shrubs, and minimal tree cover, variability in NDVI values is minimal over the spring and summer months in Semnan Province. Soil characteristics were obtained from publicly available data (https://soilgrids.org) and mapped with a spatial resolution of 50 m × 50 m. The geology of Semnan Province is characterized by a number of lithological units ranging in age from Paleozoic through to Quaternary. In this study, we used existing geological maps generated by the Iranian Geological Survey and Mineral

| Data type	Source/spatial resolution/scale
DEM	USGS/30 m × 30 m
Climatic data	27 synoptic meteorological stations/annual
Soil data	https://soilgrids.org//250 m × 250 m
NDVI	MODIS satellite product (MOD13Q1)/250 m × 250 m
Lithology map	Geological Survey and Mineral Exploration of Iran/1:200,000
Land use map	Iran Forest, Rangeland, and Watershed Management Organization/1:200,000
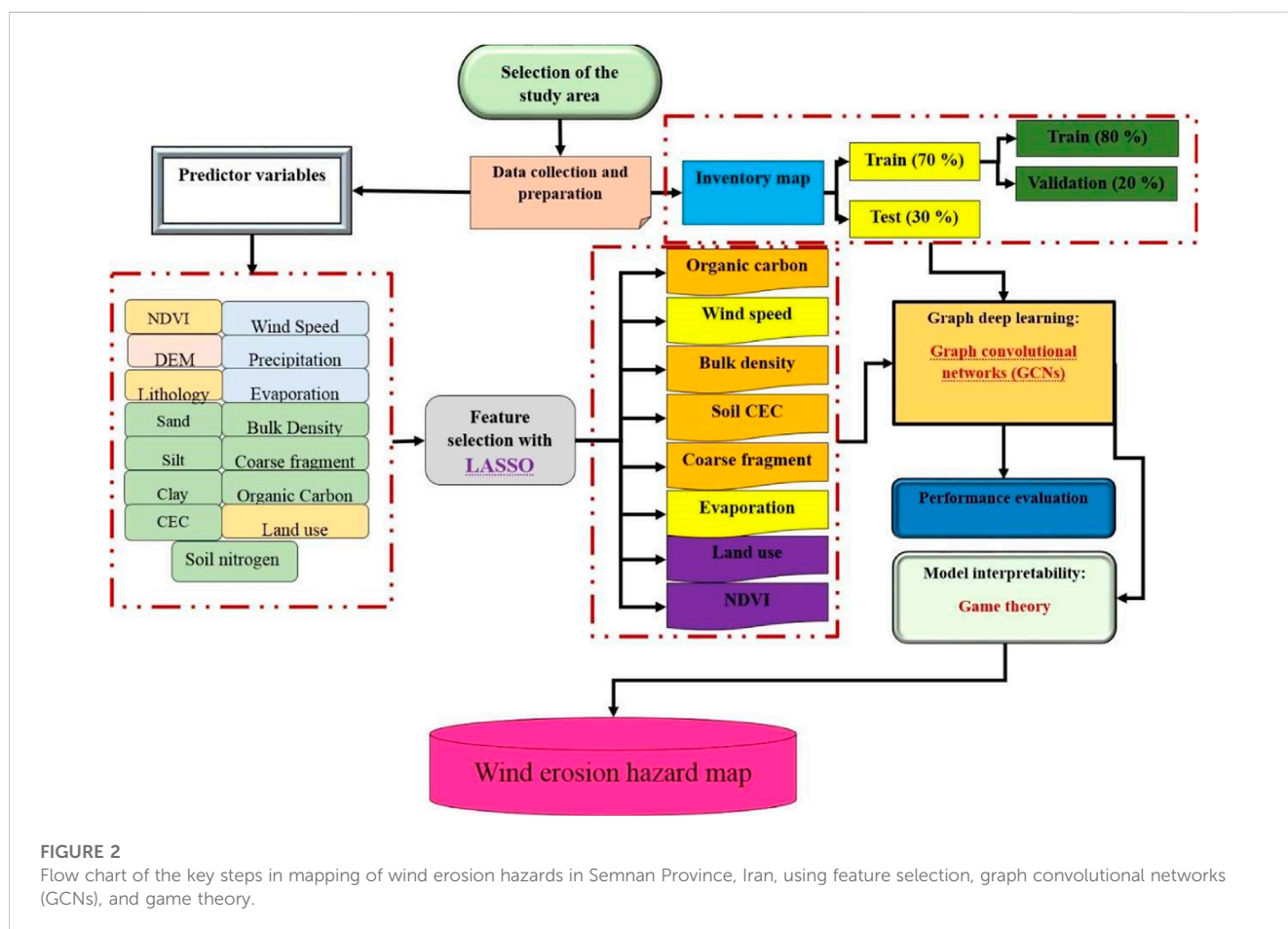
FIGURE 2
Flow chart of the key steps in mapping of wind erosion hazards in Semnan Province, Iran, using feature selection, graph convolutional networks (GCNs), and game theory.

Exploration department. Furthermore, we incorporated land use maps for the year 2020 from the Iran Forest, Rangeland, and Watershed Management Organization (IFRWMO). Since the spatial resolution of potential factors in various constructed maps is not uniform, all input layers used for modeling were converted to a consistent spatial resolution of 50 × 50 m. The details of input data used in the modeling process are presented in Table 1. It should be noted that most of the variables here are used as controls for the topographical, land use, and soil characteristics of the examined area that are fixed and not changed along season.

2.3 Inventory map of wind erosion

We then developed an inventory map for predicting land susceptibility to wind erosion (Gholami et al., 2020a) over the study region, using a previously generated map of the regions for which active wind erosion has been monitored from the IFRWMO. Furthermore, 70% and 30% of the pixels (80 pixels and 33 pixels, respectively) in these regions (Figure 1) were randomly selected for training and test (validation) datasets, to build a new predictive model. We additionally selected 80% (training) and 20% (validation) of the training dataset for our predictive models.

3 Mapping wind erosion hazards using LASSO regression, deep learning, and game theory

In Figure 2, we summarize our workflow for mapping of land susceptibility and wind erosion hazards in Semnan Province, including feature selection by LASSO regression, the GCN deep learning model, and game theory-based interpretation. This workflow may be applied in other dryland environments and for spatial mapping of various environmental hazards around the globe. Each step is detailed in the following subsections.

3.1 Feature selection by LASSO regression

Feature selection (FS) describes the process of narrowing down the potential factors (explanatory features or variables), which can be used to describe a response feature (Fonti and Belitser, 2017). In this case, the response feature is the susceptibility to wind erosion and the explanatory features are the 15 parameters (potential factors) mapped in Supplementary Figures S1, S2.

The most influential factors controlling wind erosion in our study area were selected using the LASSO regression, a type of FS algorithm proposed by Tibshirani (1996). LASSO is considered to be the optimal approach for FS in our study since it combines the qualities of ridge regression and subset selection, thus improving the model's accuracy and interpretability. LASSO is a regression analysis that performs both variable selection and regularization in order to enhance the prediction accuracy and interpretability of the resulting model, which is a major reason for its selection against other regression approaches. Furthermore, LASSO is a forward-looking variable selection method for regression, which is a type of penalized least-squares approach incorporating L1-penalty function (Muthukrishnan and Rohini, 2016). The LASSO approach transforms each coefficient by a constant component λ, truncating at 0, with the objective of minimizing prediction errors (Fonti and Belitser, 2017). Therefore, LASSO decreases the residual sum of squares, subject to the sum of the absolute value of the coefficient being less than a constant. During the application of FS, the features (variables) that still had a non-zero coefficient after the shrinking process were selected to be part of our model. The LASSO can be written as follows:

$$\hat{\beta}^{lasso} = \underset{\beta}{\arg\min} \sum_{i=1}^{N}\left(y_i - \beta_0 - \sum_{j=1}^{P} x_{ij}\beta_j \right)^2 subject\ to \sum_{j=1}^{P}|\beta_j| \leq t, \tag{1}$$

where β_0 and β_j are the constant coefficient and the coefficient vector, respectively, y_i indicates the outcome, and $x_i = (x_1, x_2, \ldots, x_p)_i^t$ is the covariate vector for the ith case.

3.2 Graph convolutional networks

Here, we undertake the first known study using convolutional graph neural networks (ConvGNNs) to investigate wind erosion susceptibility. The first adoption of neural network approaches to

directed acyclic graphs was reported by Sperduti and Starita (1997). Neural networks have since been more widely applied in the form of graph neural networks (GNNs) of various kinds for a wide range of applications (Gori et al., 2005; Scarselli et al., 2009; Gallicchio and Micheli, 2010). Among these, graph convolutional networks (GCNs; Figure 3), first proposed by Kipf and Welling (2016), are a type of spectral-based convolutional GNN (Wu et al., 2020), which introduce a first-order approximation of Chebyshev spectral CNNs (hereafter ChebNet) (Defferrard et al., 2016).

In this study, we train GCNs using a Monte Carlo dropout (Gal and Ghahramani, 2016). Assuming K = 1 and $\lambda_{max} = 2$, the equation of $\mathbf{X} *_G \mathbf{g}\theta = \sum_{i=0}^{K} \theta_i T_i (\tilde{\mathbf{L}})\mathbf{X}$, is simplified as follows:

$$\mathbf{X} *_G \mathbf{g}\theta = \theta_0 \mathbf{X} - \theta_1 \mathbf{D}^{-\frac{1}{2}} \mathbf{A}\mathbf{D}^{-\frac{1}{2}} \mathbf{X}, \tag{2}$$

where, K, G, $\boldsymbol{\Theta}$, and $\mathbf{X}$ indicate the layer index, a graph, the learnable model variable, and the feature vector, respectively.

To restrain the number of variables and avoid over-fitting, we assumed $\theta = \theta_0 = -\theta_1$ for our GCNs, leading to the following definition of graph convolution:

$$\mathbf{X} *_G \mathbf{g}\theta = \theta\left(\mathbf{I_n} + \mathbf{D}^{-\frac{1}{2}} \mathbf{A}\mathbf{D}^{-\frac{1}{2}}\right)\mathbf{X}. \tag{3}$$

To allow multiple channels of inputs and outputs, our GCN modifies Eq. 3 into a compositional layer as follows:

$$\mathbf{H} = \mathbf{X} *_G \mathbf{g}\Theta = f\left(\bar{\mathbf{A}}\mathbf{X}\Theta\right), \tag{4}$$

where $\bar{\mathbf{A}} = \mathbf{I_n} + \mathbf{D}^{-\frac{1}{2}} \mathbf{A}\mathbf{D}^{-\frac{1}{2}}$ and $f(.)$ indicates an activation function. Applying $\mathbf{I_n} + \mathbf{D}^{-\frac{1}{2}} \mathbf{A}\mathbf{D}^{-\frac{1}{2}}$ empirically causes numerical instability to GCNs (Wu et al., 2020). To solve this problem, GCNs use a normalization trick to replace $\bar{\mathbf{A}} = \mathbf{I_n} + \mathbf{D}^{-\frac{1}{2}} \mathbf{A}\mathbf{D}^{-\frac{1}{2}}$ by $\bar{\mathbf{A}} = \tilde{\mathbf{D}}^{-\frac{1}{2}} \tilde{\mathbf{A}}\tilde{\mathbf{D}}^{-\frac{1}{2}}$ with $\tilde{\mathbf{A}} = \mathbf{A} + \mathbf{I_n}$ and $\tilde{\mathbf{D}}_{\mathbf{ii}} = \sum \tilde{\mathbf{A}}_{\mathbf{ij}}$. Here, $\boldsymbol{\theta}$ is the learnable model variable, while $\mathbf{A}$ and $\mathbf{D^j}$ indicate the graph adjacency matrix and the degree matrix of A. $D_{ii} = \sum_{j=1}^{n} A_{ij}$.

The predicted susceptibility values for all the pixels ranged between 0 and 1, with higher values indicating higher susceptibility to wind erosion. We divided susceptibility predictions into four classes: low (0–0.25), moderate (0.25–0.50), high (0.50–0.75), and very high (0.75–1).

3.3 Assessing GCN performance to spatial modeling of wind erosion

Previous studies have used several statistical indicators to assess the reliability and feasibility of predictive DM and DL models in environmental challenges (Gholami et al., 2021a; Gholami et al., 2021c), including root-mean-square error (RMSE), mean absolute error (MAE), mean bias error (MBE), the Nash–Sutcliffe efficiency coefficient (NSC), Taylor diagram, and the receiver-operating characteristic–area under curve (ROC-AUC). In this study, we applied the ROC-AUC (Hong et al., 2017) to evaluate the developed GCN model for spatial prediction of wind erosion susceptibility in Semnan Province. Using the area under curve (AUC) value, we classified the accuracy of the model prediction into five categories: poor (50%–60%), moderate (60%–70%), good (70%–80%), very good (80%–90%), and excellent (90%–100%) (Tibshirani, 1996).
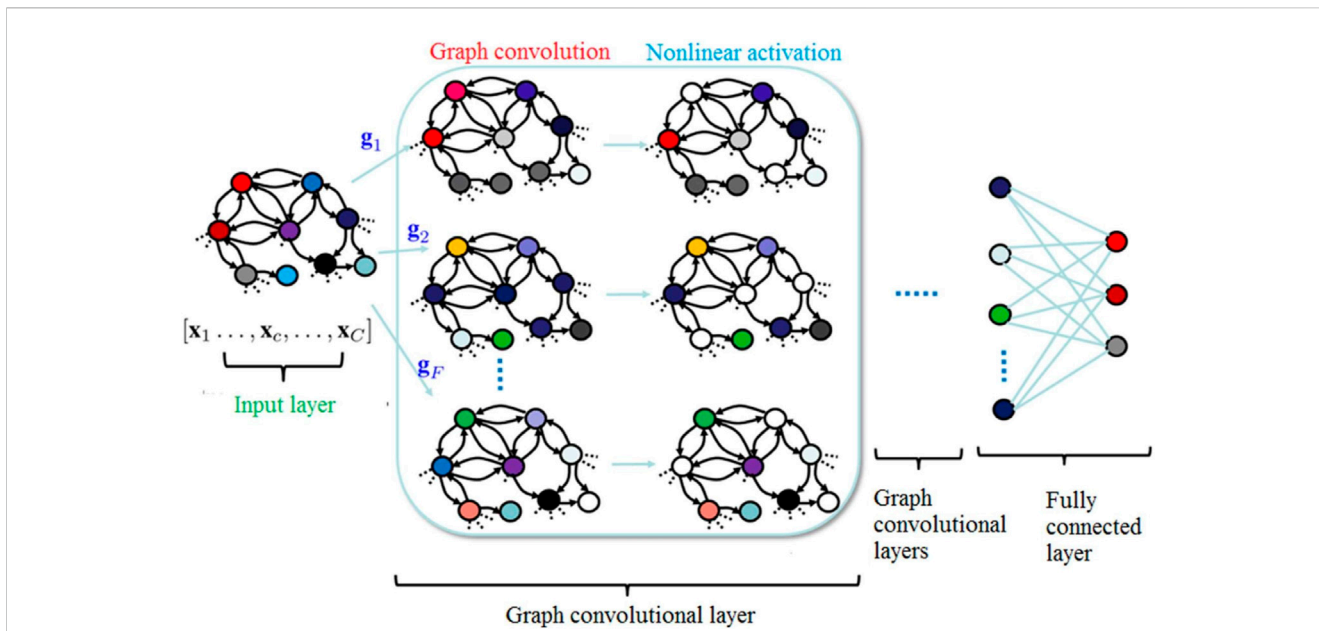
FIGURE 3
Conceptual diagram of our graph convolutional network (GCN) model for predicting land susceptibility to wind erosion.
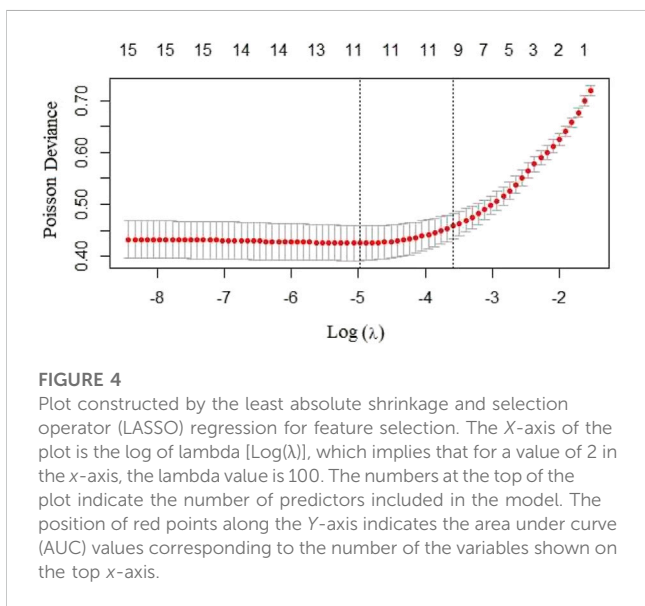
FIGURE 4
Plot constructed by the least absolute shrinkage and selection operator (LASSO) regression for feature selection. The X-axis of the plot is the log of lambda [Log(λ)], which implies that for a value of 2 in the x-axis, the lambda value is 100. The numbers at the top of the plot indicate the number of predictors included in the model. The position of red points along the Y-axis indicates the area under curve (AUC) values corresponding to the number of the variables shown on the top x-axis.

3.4 Interpretability of GCNs using game theory

In addition, we interpreted our GCN model for predicting wind erosion hazards using the game theory approach of SHapley Additive exPlanations (SHAP) (Lundberg and Lee, 2017; Kannangara et al., 2022). SHAP values indicate the contribution of a given factor to the final predictions of a model. SHAP specifies the explanation as follows:

$$g(z') = \emptyset_0 + \sum_{j=1}^{M} \emptyset_j z_j', \qquad (5)$$

TABLE 2 Values of the potential factors controlling wind erosion, as estimated by the least absolute shrinkage and selection operator (LASSO) regression.

Potential factor	Value	Decision
Soil nitrogen	0	Reject
OCS	−0.04	Accept
Precipitation	0	Reject
Sand content	0	Reject
Silt content	0	Reject
Wind speed	−0.17	Accept
Bulk density	0.01	Accept
CEC	0.01	Accept
Clay content	0	Reject
Coarse fragment	−0.01	Accept
DEM	0	Reject
Evaporation	0.04	Accept
Lithology	0	Reject
Land use	0.01	Accept
NDVI	−5.03	Accept

where g, z' ∈ (Akoglu et al., 2015), and M are the explanation model, the coalition vector, and the maximum coalition size, respectively.

For calculating SHapley values, we fit a model $f_{SU(i)}$, involving factor i, and another additional model, fs. All possible subsets $S \subseteq F$ comprise the empty set and the set F of all factors. The final factor

contribution, $\emptyset_i \in R$, is the weighted average of all marginal contributions (Padarian et al., 2020), which is given as

$$\emptyset_i = \sum_{S \subseteq F \ (i)} \frac{|S|! \, (|F| - |S| - 1)!}{|F|!} \left[f_{SU(i)} \left(x_{SU(i)} \right) - f_{S(x_S)} \right]. \quad (6)$$

4 Results and discussion

4.1 Discriminating important from non-important features influencing wind erosion

The results of the LASSO regression, which was used to select the important factors responsible for wind erosion, are presented in Figure 4; Table 2. Figure 4 shows that AUC values decrease with the increasing number of the potential factors controlling wind erosion, which indicates that the model's accuracy increases when more potential factors are considered within the LASSO regression.

Out of the 15 features examined as potential factors controlling wind erosion, seven were identified as non-important in our study area and were excluded from further analysis. These non-important factors comprise soil nitrogen, precipitation, sand, silt, and clay content; topography (DEM); and lithology.

The LASSO regression identifies precipitation as a non-important factor for land susceptibility to wind erosion hazards in Semnan Province. Precipitation is generally considered an important factor controlling aeolian erosion and dust storms since low precipitation has a positive feedback effect for reducing soil moisture and vegetation growth, thereby enhancing erosion by wind (Sissakian et al., 2013; Parajuli et al., 2014). In the case of Semnan, the mountainous areas within the province receive relatively high rainfall and have a correspondingly lower vulnerability to aeolian erosion. This context reduces the relative importance of precipitation for dust emission in the study region, highlighting the sensitivity of local factors in the LASSO regression process. This suggests that in other arid regions, the current non-important factors may be highly sensitive to land susceptibility to wind erosion (Gholami et al., 2020a; Gholami et al., 2021a; Gholami et al., 2021c).

Although percentage fractions of unconsolidated silt, clay, and sand often influence dust emission and transport (Bagheri-Bodaghabadi and Jafari, 2022), our LASSO regression classified these factors as non-important for Semnan Province. Clearly, then, the fact that our LASSO regression finds typically influential factors to be non-important for our study region indicates that the classification of the importance of potential factors is highly region-specific and depends on local geographical, land cover, and meteorological conditions. Important factors are likely to depend on the type of soil, the dimension of desert areas, and topography.

LASSO criteria identified eight features as important variables for wind erosion in Semnan Province: wind speed, evaporation, OCS, bulk density, cation exchange capacity (CEC), coarse fragment, land use, and NDVI. Only these eight features entered into the spatial modeling process using GCNs to predict land susceptibility to wind erosion hazards in Semnan Province.

4.2 Map of wind erosion hazards

Figure 5 shows the map of susceptibility to wind erosion in Semnan Province, as produced by the GCN deep learning model using the eight important factors (Figure 4; Table 2).

According to the results, a substantial proportion of the region (c. 65%) exhibits high or very high susceptibility to wind erosion, which is 33.2% (= 32,300 km^2) and 31.4% (= 30,581 km^2), respectively. Areas classified as having low and moderate susceptibility to wind erosion represent 15.5% (= 15,136 km^2) and 19.8% (= 19,305 km^2) of the total area in Semnan Province, respectively.

The southern and central parts of the study area are classified as having very high susceptibility to wind erosion (Figure 5) and, therefore, suffer from extreme soil erosion hazards. These areas lie within the Kavir Desert, which is known as a generation point (dust source) for dust storms impacting the whole central Iranian Plateau (Bagheri-Bodaghabadi and Jafari, 2022; Marjovvi et al., 2022). The Kavir Desert experiences high evaporation rates, low surface soil moisture, and high wind speeds; it contains only sparse vegetation cover and has low soil OCS and low CEC. Furthermore, these regions contain substantial unconsolidated fine-grained sand at the surface, sourced by alluvial input from inland streams. Dry river beds and ephemeral lakes have long been recognized as areas with high potential for wind erosion and dust emissions across the Middle East (Rashki et al., 2017). Such areas, with high sediment availability and frequent high wind speeds, often become the major sources of erodible sand for dust/sand storms in Semnan Province.

The part of Semnan Province with the lowest susceptibility to wind erosion is located in the north within the Alborz mountain range. This area (c. 35.5% of the province) is characterized by steep slopes, relatively high vegetation cover, and low evaporation rates, as well as by high proportions of silt-sized sediment and coarse fragments on the surface (Supplementary Figures S1, S2). Each of these factors represents negative feedback for wind erosion (Parajuli et al., 2019) and is likely to contribute to the GNS assessment of low susceptibility in our study. Although this part of Semnan Province was found to have the lowest susceptibility to wind erosion, it is nevertheless the part of the Iranian Plateau that is more susceptible to wind erosion than other areas (Gholami et al., 2020c; Gholami et al., 2021b).

Figure 6 summarizes the results of sensitivity analysis for our GCN deep learning model. We found that the most sensitive features for the model are surface coarse fragment cover, evaporation, and land use; these factors exhibit the highest slopes on the graph and the largest variation in the normalized predictor change. The high importance of these features for soil susceptibility to wind erosion indicates strong regional dependence specific for Semnan Province. Using the same deep learning methods, we would likely find the deciding factors to be different in other arid environments (Gholami et al., 2021b; Gholami et al., 2021c; Gholami and Mohammadifar, 2022).

Overall, wind erosion and its contribution to desertification and land degradation is controlled by the arid climate, high evaporation rates, low precipitation, sparse vegetation cover, and intense winds (Keramat et al., 2011) in Semnan Province and in central Iran, more broadly. However, the balance and drivers of the determining factors—demonstrated here to be regionally specific—may be
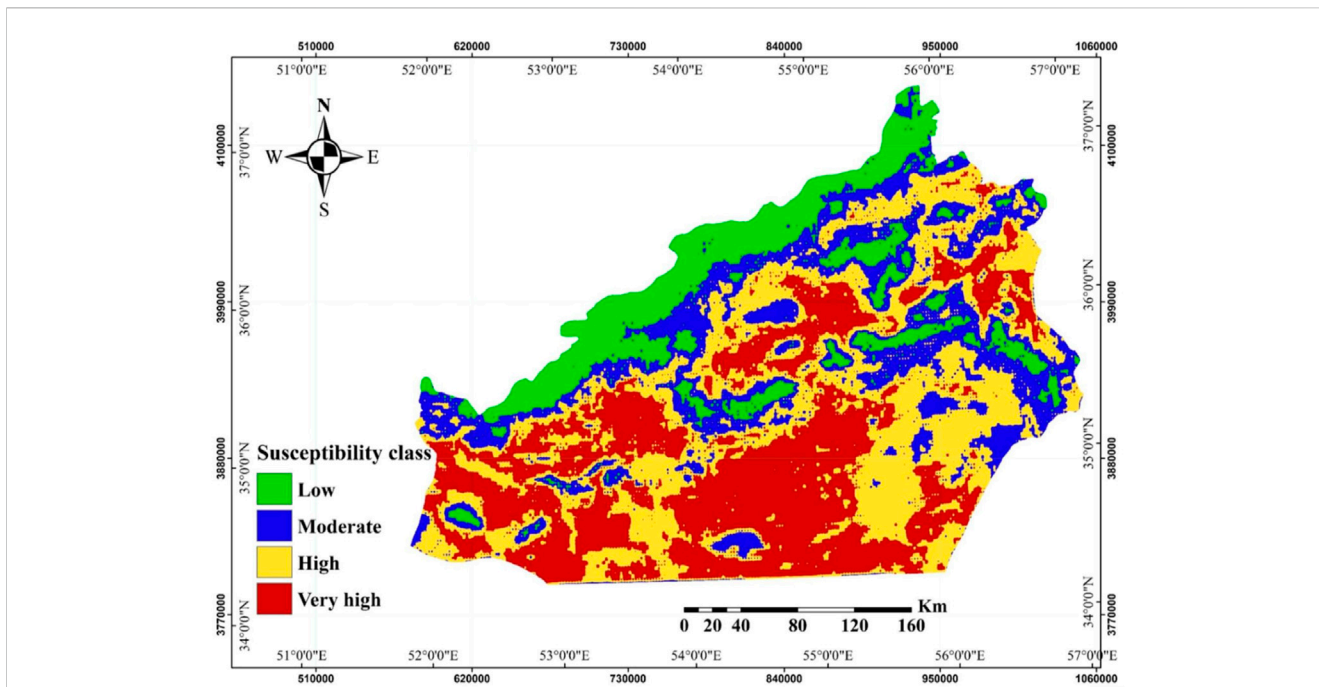
FIGURE 5
Map of wind erosion hazards generated by the graph convolutional network (GCN) model in Semnan Province, Iran.
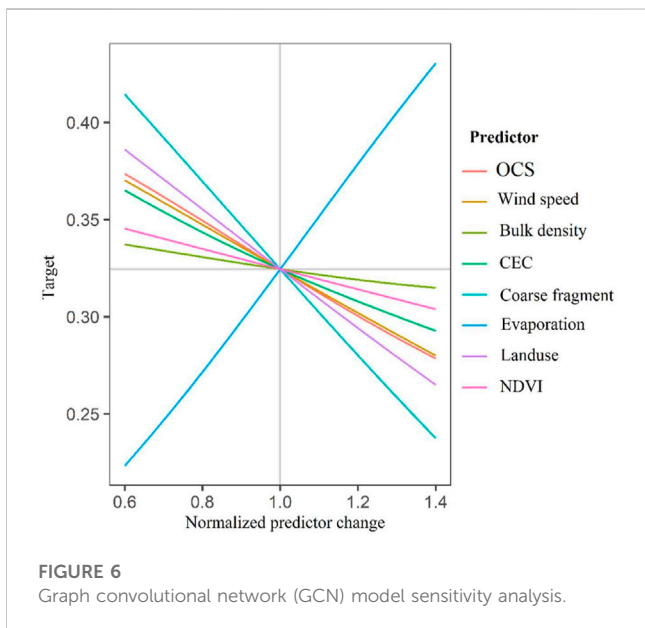
FIGURE 6
Graph convolutional network (GCN) model sensitivity analysis.

altered by future climatic change, including extensive droughts and increasing average temperatures, and by anthropogenic degradation of ecosystems and mismanagement of water, soil, and plant resources over the whole Middle East region (Amiraslani and Dragovich, 2011; Middleton, 2017; Middleton, 2019; Emamian et al., 2021; Papi et al., 2022). On this basis, continued monitoring of the relative contributions of various controlling factors to dynamic phenomena such as desertification and dust storms in arid environments is recommended.

4.3 Assessment of GCN model performance

The performance of our GCN modeling results was assessed using the area under curve (AUC) approach on the training and test datasets (Figure 7). The calculated AUC values for the training and validation datasets were found to be the same (97.2% and 97.25%, respectively), thus indicating an excellent prediction accuracy (Yesilnacar, 2005). The results show that GCNs significantly improve the performance of the predictions for land susceptibility to wind erosion and support the findings of previous studies, which suggested that GCNs are an efficient graph model for semi-supervised learning (Chen et al., 2018) and constitute a useful tool for completing missing data (Belghaddar et al., 2021). The DL hybrid models (e.g., convolutional neural network-gated recurrent unit (CNN-GRU) and dense layer deep learning–random forest (DLDL-RF)) were also recently shown to be efficient methods for classifying dust sources in the Middle East (Gholami and Mohammadifar, 2022).

4.4 Relative contributions of the most important factors for wind erosion hazards

The SHAP values of the game theory were used to determine the contribution of each feature to our GCN model output for land susceptibility to wind erosion. We found that the contributions of the variables followed the order: coarse fragments > NDVI > land use > SOM > wind speed > CEC > bulk density > evaporation. Figure 8 illustrates the relative contributions of these parameters based on SHAP values and combines the feature importance with feature effects. The value, and therefore the relative importance of each parameter, is given
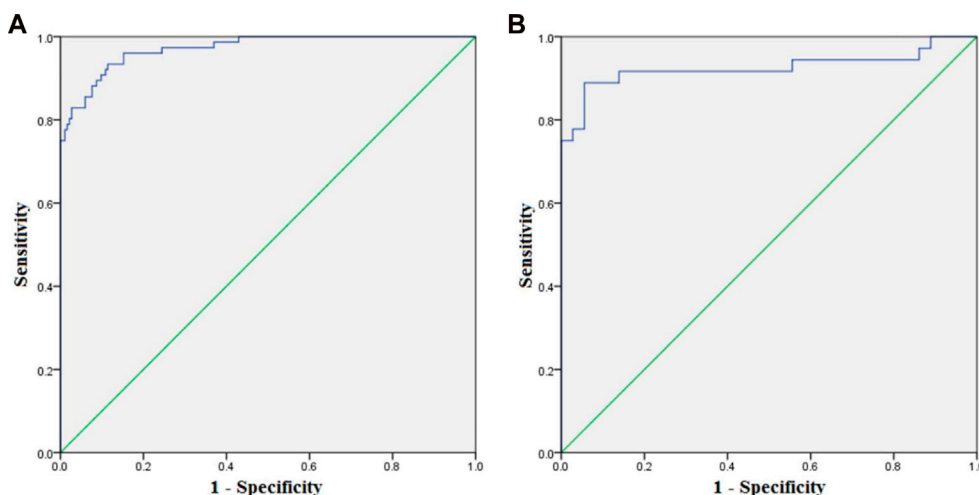
FIGURE 7
Validation of the wind erosion hazard map generated by the graph convolutional network (GCN) model for **(A)** training and **(B)** test datasets using the area under curve (AUC).
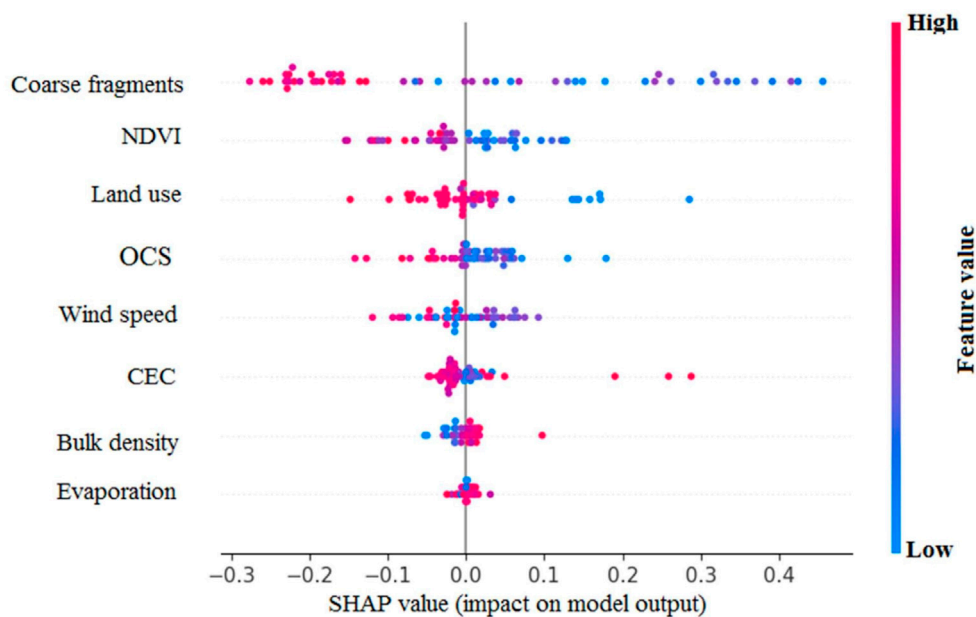
FIGURE 8
SHapley Additive exPlanation (SHAP) values for the eight most important features identified by the least absolute shrinkage and selection operator (LASSO) regression.

by the color scheme. Overlapping points are projected in the *y*-axis to give a sense of the distribution of the SHAP values per feature, as per the published approach (Gholami et al., 2021c).

Land susceptibility to wind erosion has previously been shown to be driven by a wide range of topographic and bio-climatic variables including surface roughness (which equates to our coarse fragment parameter), mineralogy, vegetation cover (comparable with NDVI), soil characteristics (e.g., soil texture, bulk density, and organic matter),

wind speed, precipitation, and evaporation (Goudie and Middleton, 2006; Shao, 2008). Depending on the meteorological, topographical, and soil conditions in the study area, factors controlling the wind erosion may be highly variable from place to place. For example, Gholami et al. (2020c) reported that DEM-extracted variables are the most important factors that control wind erosion in the Jazmurian Basin, while in Central Asia, other parameters like precipitation, bulk density, slope, and lithology (among others) mostly controlled land

susceptibility to wind erosion using the LOFO algorithm (Gholami et al., 2021c). Precipitation can act as a roughness factor for controlling wind erosion in arid and semi-arid regions, while lithology can be another effective variable. Geological formations such as Qsd (sand dune unit) or Qal (Quaternary alluvial deposits) are the most susceptible units against wind erosion because they have single-grain structures with loose particles (Li et al., 2022; Li et al., 2023). The current results largely support these arguments while additionally identifying the main contributing factors and their relative contributions using novel techniques. Our novel approach also predicts the spatial variability of wind erosion hazards and enables the assessment of model performance.

Another important finding here is that factor contributions are strongly regionally controlled but are scale-dependent. A previous study focusing on Isfahan Province, immediately southwest of our study area (Gholami et al., 2020c), based on the monotone multi-layer perception neural network (MMLPNN), found that topography (DEM), precipitation, and NDVI were the three most important factors controlling wind erosion and, therefore, contrasts with current results. Therefore, the characteristics and relative importance of potential controlling factors are highly region-specific, even for neighboring provinces on the central Iranian Plateau. Over larger scales, however, we start to see similarities in the major factors controlling wind erosion. Analyses using SHAP values for Central Asia—a similar approach to the methods used in this study—revealed that surface coarse fragment concentration, soil bulk density, and precipitation were the most important factors controlling land susceptibility to wind erosion over a much larger area than that investigated here (Gholami et al., 2021c). Overall, the comparison with previous works that examined land susceptibility to wind erosion over arid areas in Iran and Central Asia revealed significant similarities in the factors that control wind erosion, despite some regional differences, and indicated the importance of defining scale in these sorts of studies.

We found that neural network techniques are a useful and accurate tool for investigating the spatial variability and intensity of land susceptibility to wind erosion (Luo et al., 2020). Our approach may be applied not only to mapping wind erosion hazards but also to a range of other environmental problems requiring spatial characterization, such as soil characteristics and the interaction between atmospheric circulation and the land surface. Our results provide an efficient means to measure soil erosion hazards, which can then be used for assessments of weather systems, ecosystem restoration, human health (Xiao et al., 2017; Wu et al., 2020; Emamian et al., 2021; Tian et al., 2021), land management, and hazard mitigation in arid areas (Sharifikia, 2013; Xu et al., 2019). Policymakers, as end users of results regarding mapping of land susceptibility and wind erosion, can use maps that are produced in this study, to alert residents in high-risk areas for devastating phenomena like severe dust storms and apply appropriate mitigating strategies against natural hazards.

4.5 Advantages and limitations to our DL approach

Data science (DS) is an emerging research field that helps us better understand the complex mechanisms behind environmental phenomena (Gibert et al., 2018). DS has several advantages and can support a) systematic and objective exploration and visualization of data, b) improving data quality, c) discovery of patterns contained in large time series, and d) producing new validated and transferable knowledge (Gibert et al., 2018). DL models—a fully data-driven approach—are especially interesting in environmental issues because they overcome many of the restrictions placed on the modeling process by traditional machine learning models (LeCun et al., 2015; Van Dao et al., 2020).

The accuracy of the input data to the modeling process is specifically important for generating more accurate and reliable predictive maps for environmental applications. Additional accuracy may be achieved with higher spatial resolution of the imagery such as in NDVI, digital elevation, and soil mapping that would lead to improvements in spatial mapping. Due to the desert and remote characteristics of Semnan Province, meteorological stations are rather scarce with unsuitable spatial coverage. Therefore, interpolation of the meteorological data was associated with higher uncertainty. Meteorological variables (wind speed and rainfall) are also sensitive to the length of instrumental data records (Li et al., 2018). Detailed analysis of various natural and anthropogenic factors affecting land susceptibility to wind erosion and dust storms is crucial for efficient management and mitigation strategies of these phenomena in central Iran.

5 Conclusion

This study is the first attempt to apply GCNs to aeolian geomorphology with the aim of predicting land susceptibility to wind erosion. Our novel methodology comprises feature selection using LASSO regression, the prediction of wind erosion hazards by GCNs, and the assessment of the accuracy and elucidation of major contributing parameters identified in our GCN model output using game theory.

The case study region is Semnan Province in the central Iranian plateau. The applied methodology showed that ~65% of the total area in Semnan Province is prone to high and very high wind erosion hazards, rendering the area as one of the most susceptible to wind erosion parts of the arid central Iranian Plateau. We also found that the main factors contributing to erosion susceptibility are not necessarily the most typical since wind erosion is largely controlled by the proportion of surface coarse fragments, vegetation cover, and land use, as well as by evaporation, wind speed, bulk density, and cation exchange capacity.

The game theory was used for the first time to test the performance and interpretability of the GCN model, using the area under curve (AUC) and SHapley Additive exPlanations (SHAP). The assessment showed that our GCN approach reliably characterized land susceptibility to wind erosion. The SHAP values showed that proportions of coarse fragments, NDVI, land use, and wind speed contributed mostly to land degradation and wind erosion in Semnan Province.

Our methodology can be used to predict the hazards of wind erosion in other arid environments around the globe and may be extended to address several environmental issues from small to large scales.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material; further inquiries can be directed to the corresponding author.

Author contributions

HG: formal analysis, investigation, visualization, writing—original draft, supervision, project administration, and writing—review and editing. AM: software and formal analysis. KF: visualization, writing—original draft, and review and editing. YL: formal analysis and investigation. DK: visualization, writing—original draft, and review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2023.1187658/full#supplementary-material

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