Detection of land subsidence using hybrid and ensemble deep learning models

Applied Geomatics

Kariminejad, Narges; Mohammadifar, Aliakbar; Sepehr, Adel; Garajeh, Mohammad K.; Rezaei, Mahrooz et al

https://doi.org/10.1007/s12518-024-00572-9

Applied Geomatics
https://doi.org/10.1007/s12518-024-00572-9

ORIGINAL PAPER

Detection of land subsidence using hybrid and ensemble deep learning models

Narges Kariminejad[1] · Aliakbar Mohammadifar[2] · Adel Sepehr[3] · Mohammad Kazemi Garajeh[4] · Mahrooz Rezaei[5] · Gloria Desir[6] · Adolfo Quesada-Román[7] · Hamid Gholami[2]

Received: 19 August 2023 / Accepted: 26 June 2024

Abstract
Land subsidence (LS) is among the most prominent forms of subsurface erosion and geomorphological hazards. This study used two deep learning (DL) models consisting of the hybrid CNN-RNN and ensemble DL (EDL) merged with two dense models. The main variables controlling LS (consisting of environmental, hydrological, hydrogeological, digital elevation model, and soil characteristics), were used as the input for the predictive DL models. Likewise, to establish the degree of performance of each parameter, different control points have been established. We then trained and tested our DL models using the receiver-operating characteristic-area under curve (ROC-AUC) and precision-recall plots. The measures based on the game theory consisting of permutation feature importance measure (PFIM) and SHapley Additive exPlanations (SHAP) were employed to assess the features relative importance and interpretability of the predictive model output. Our findings show that the ensemble CNN-RNN model performed well with the ROC-AUC curve (0.95) of class 1 (land subsidence) for training data for detecting and mapping land subsidence compared to EDL with the ROC curve (0.93) of class 1 (land subsidence) for training datasets. The CNN-RNN also performed well with the precision-recall curve (0.954) of class 1 for testing data for detecting and mapping land subsidence compared to the EDL model with the precision-recall curve (0.95) of class 1. The results of this research revealed that much of the study area is susceptible to land subsidence. The results of the model sensitivity analysis suggested that the groundwater drop rate is the most sensitive for the model. Based on the SHAP values, the groundwater drop rate was identified as the most contributed feature to the model output. The importance of this study is at a broader level, especially in arid and semiarid environments with similar geomorphological, and climatic conditions.

Keywords Land subsidence · Hybrid and ensemble deep learning · Feature selection

Introduction

Currently, among the 43 known geological hazards in the world, 32 of them have occurred in Iran, and it can be said that among them, five geological hazards such as earthquakes, floods, landslides, droughts, and land subsidence seriously threaten the country of Iran (Soltani et al. 2015). In general, Iran includes six large watersheds and 609 plains. About 267 out of 609 plains are deficient in water. Due to the importance of water in people's lives and

✉ Narges Kariminejad
narges.karimi991@gmail.com

✉ Aliakbar Mohammadifar
aliakbar.mohamadifar@yahoo.com

✉ Hamid Gholami
hgholami@hormozgan.ac.ir

1 Department of Natural Resources and Environmental Engineering, College of Agriculture, Shiraz University, Shiraz, Iran

2 Department of Natural Resources Engineering, University of Hormozgan, Bandar-Abbas, Hormozgan, Iran

3 Lands Division, Department of Resources, Queensland Government, Brisbane, QLD, Australia

4 Sapienza University of Rome, Rome, Italy

5 Meteorology and Air Quality Group, Wageningen University & Research, PO. Box 47, Wageningen 6700 AA, The Netherlands

6 Department of Earth Sciences, University of Zaragoza, Zaragoza, Spain

7 Department of Geography, Universidad de Costa Rica, San Pedro de Montes de Oca, Costa Rica

Published online: 08 July 2024

agriculture, most of these areas may not have any remaining water shortly (Doosti Sabzi et al. 2023). Land subsidence may have occurred due to over-harvesting and drying of underground aquifers (Najafi et al. 2020). The importance of this study is at a broader level, especially in arid and semiarid environments with similar geological, geomorphological, and climatic conditions. Land subsidence is a global problem and morphological phenomenon (García-Soriano et al. 2020). This phenomenon occurs under the influence of human activities and natural factors and may be a threat to human life (Liu et al. 2023). Although excessive extraction of groundwater is the most common cause of land subsidence, this phenomenon can also be caused by other natural or human events such as mining and dissolution of minerals, groundwater extraction (Teatini et al. 2006; Minderhoud et al. 2017). According to the definition of the United States Geological Survey, the phenomenon of land subsidence includes the collapse or downward settlement of the earth's surface, which has a small horizontal displacement vector. Besides, this is another definition of land subsidence that may suit better. It stated that land subsidence is defined as the downward, vertical movement of the Earth's surface, which can be brought on by both natural and human forces. Land subsidence differs from slope movement in that it requires little to no horizontal movement (Marker 2013).

In general, different methods are used all over the world to evaluate and zone the susceptibility of land subsidence (Galloway and Burbey 2011. From a general point of view, they can be separated into ground-based and remote-sensed geodetic surveys and techniques (Galloway and Burbey 2011). In the first ones, precise differential leveling (Karila et al. 2013), extensometry (Burbey 2020), and GPS (Baldi et al. 2009; Tangdamrongsub et al. 2019) employed for land subsidence detection and mapping. These approaches, for instance, extensometry have an advantage over satellite-based data for detecting and mapping land subsidence in which extensometer data provide continuous measurements at very high precision over a known depth interval (Burbey 2020). However, the use of ground-based methods to detect land subsidence is expensive, time-consuming, and labor-intensive, particularly, over a large area (Karanam et al. 2021). In this regard, employing remote sensing-based approaches can be more effective (Zhu et al. 2022). Terrestrial LIDAR and interferometry (Chen et al. 2016; Amighpey and Arabi 2016; Yang et al. 2022; Pu et al. 2022; Luqmanul Hakim et al. 2023; Bokhari et al. 2023; Xu et al. 2023) are remotely sensed techniques, which have applied for land subsidence detection and mapping. Previous studies have applied machine learning approaches as well as InSAR data (Arabameri et al. 2020; Azarakhsh et al. 2022; Luqmanul Hakim et al. 2023; Bokhari et al. 2023; Xu et al. 2023) for detecting and mapping land subsidence. More recently, the successful application of DL models as a new generation of data mining methods has been reported for the spatial modeling of different environmental and natural hazards (e.g., soil salinity, wind erosion, landslide, etc.) (Rezaei et al. 2023; Gholami et al. 2023a; Gholami and Mohamadifar 2022) especially LS (Mohamadifar et al. 2023). Machine learning algorithms are one of the best methods of prioritizing and determining the importance of factors affecting the target performance (i.e., land subsidence) (Kariminejad et al. 2022). The main advantage of machine learning algorithms over traditional statistics-based methods, especially in the field of earth sciences and ecology, is their possibility to model high-dimensional and non-linear datasets, including complex interactions and missing values. Countless researchers have used GIS-based machine-learning algorithms in various fields of geosciences and hydrology, including groundwater mapping. According to the literature, however, rare studies have applied deep learning data-driven approaches for detecting and mapping land subsidence.

The agricultural sector is the main consumer of water resources in Iran. Various reports have been presented regarding groundwater reservoirs in large parts of central, eastern, and southern Iran are considered as the only source of water supply for agricultural, drinking, and industrial purposes (Ghordoyee Milan et al. 2023). Since 1986, the phenomenon of tunnel formation of agricultural water wells has been observed in Iran, especially in the plains of Kerman, Sirjan, Rafsanjan, and Zarand. The first report of land subsidence in Rafsanjan Plain was presented in 1967 along with the phenomenon of tunnel formation in agricultural wells (Hosseini Milani, 1373). Recently, the occurrence of land subsidence has been reported in more than 150 important cities of the world and many places such as Mexico, Australia, Colombia, China, America, Thailand, India, Japan, Iran, Italy, Holland, Venezuela, Egypt, Saudi Arabia, England, France, Palestine, Poland, and Sweden subsidence has occurred (Lashkaripour et al. 2014; García-Soriano et al. 2020). As a result of land subsidence in the Abarkoh (Abarqo) plain, transitional pits with a diameter between 3 and 9 m have been created (Hashmi, 1381). In the central plain of Hamedan, Faminin and the northern part of Qahavand, a subsidence depression of 2 m in depth and 33 m in diameter has been reported. Also, between 1371 and 1383 another 34 residences were created in this province (Lashkaripour et al. 2009).

In summary, it is emphasized on the importance of these results in arid/semiarid contexts for future assessments. Ecosystems in arid/semiarid areas around the globe appeared to be under different processes of land degradation. These regions should be considered susceptible to land degradation. Such areas constitute some 40% of the global terrestrial region (UNEP). They include Asia, southwestern central Asia, northern Africa, Pakistan, northwestern India, and much of Australia. These regions are home to an estimated one-sixth of the world's population (Hillel and Hatfield 2005). These are the reasons why the assessment of land subsidence-related issues in Iran, the Middle East, arid/semiarid regions worldwide are important to be discussed. Furthermore, the main aim of the present study is the detection of land susceptibility to the subsidence hazard using hybrid CNN-RNN and EDL merged with two dense models in Razavi Khorasan province as an area with arid and semi-arid climate in Iran. The game theory-based indices such as SHAP and PFIM were applied to the interpretability of the predictive model output.

Study area

Razavi Khorasan province, with an area of about 117,769 square kilometers, is located in the northeast of Iran, within the coordinates of 56° 19′ to 61° 16′ E Longitude and 33° 52′ to 37° 42′ N Latitude (Fig. 1). Razavi Khorasan province is very diverse in terms of climatic and natural characteristics due to its large land area (Shiravi et al. 2016). This province has a border with the country of Turkmenistan in the North and Northeast with a length of approximately 531.6 km and a border with the country of Afghanistan in the East with a length of about 302 km.

Materials and methods

Data and information

The method used in this research, according to its type and nature, was based on the use of field and laboratory methods. To this end, previous studies and reports related to factors affecting the formation of subsidence and pipe collapse were used (Schumann and Poland 1970; Chen et al. 2003; Chai et al. 2004; Teatini et al. 2006; Galloway and Burbey 2011; Minderhoud et al. 2017). Moreover, all the detailed studies and implementation projects of watershed management that have been carried out in Razavi Khorasan province in the last decade were reviewed. To conduct this study, appropriate mapping methods were identified to determine the spatial distribution of land subsidence. In the domain of learning-based approaches, the use of ground control points (GCPs) is critical. To this end, GCPs collected from the study area using Global Positioning System (GPS), inventory maps, and Google Earth (Fig. 1). Of these GCPs, 70% were applied to train models, and the rest of them were employed for testing the results of networks. Preparing various predisposing variables as introduced in Fig. 2 (elevation, slope, aspect, curvature, land use, distance from roads, distance from waterways, lithology, and soil types) were the next steps of the current study (Fig. 3). These variables are selected based on available data, field surveys, and literature review (Ingebritsen and Ikehara, 1999; Faunt et al. 2016; Rahmati et al. 2019a, b; Dinar et al. 2021; Zhang et al. 2023). To gather the input data, the best sources were selected according to the objectives of this research.

Besides, by field survey and using a global positioning system device (GPS), the statistics of subsidence occurrences in Razavi Khorasan province were examined and their location was identified. After preparation of the location of subsidence and gathering soil samples with their input feature layout in ArcGIS 10.8, the following 5 steps were taken: (1) feature selection with mutual information classification (MIC), (2) modeling process, (3) model assessment, (4) features interaction, their importance and contributions on the model output by PFIM and SHAP, and (5) sensitivity analysis. Based on these steps, the flowchart of the present study is prepared and shown in Fig. 3.

Feature selection

A successful modelling process depends on several key factors such as input variables, and the application of efficient and valid models. Therefore, identifying the important variables from the non-important variables by feature selection is a key step for the accurate modelling phase especially spatial modelling of LS hazard. Therefore, here we applied Mutual Information Classification (MIC) to select the most appropriate variables for running land subsidence models. MIC is calculated by comparing the entropy of the dataset before and after a transformation. Mutual information is a quantity that measures the relationship between two random variables that are sampled simultaneously. It, in particular, measures how much information is communicated, on average, in one random variable about another (Huang et al. 2022). All appropriate features and their weights including sand contents, groundwater loss, silt contents, groundwater table, river distance, bulk density, organic carbon, and land use were prepared and used for the further steps based on MIC, which is shown in Fig. 4.

DL models to map LS

In this research, two deep learning models were used to prepare susceptibility maps of the study area to the occurrence of land subsidence. Deep learning (DL) models are employed e.g., for correlation analysis, classification, clustering, predictions, and time series analysis. We used prediction method algorithms, aiming to find the relationship between dependent and independent variables and predict values for points without input information. Here, we applied two-hybrid and ensemble DL models to map LS.

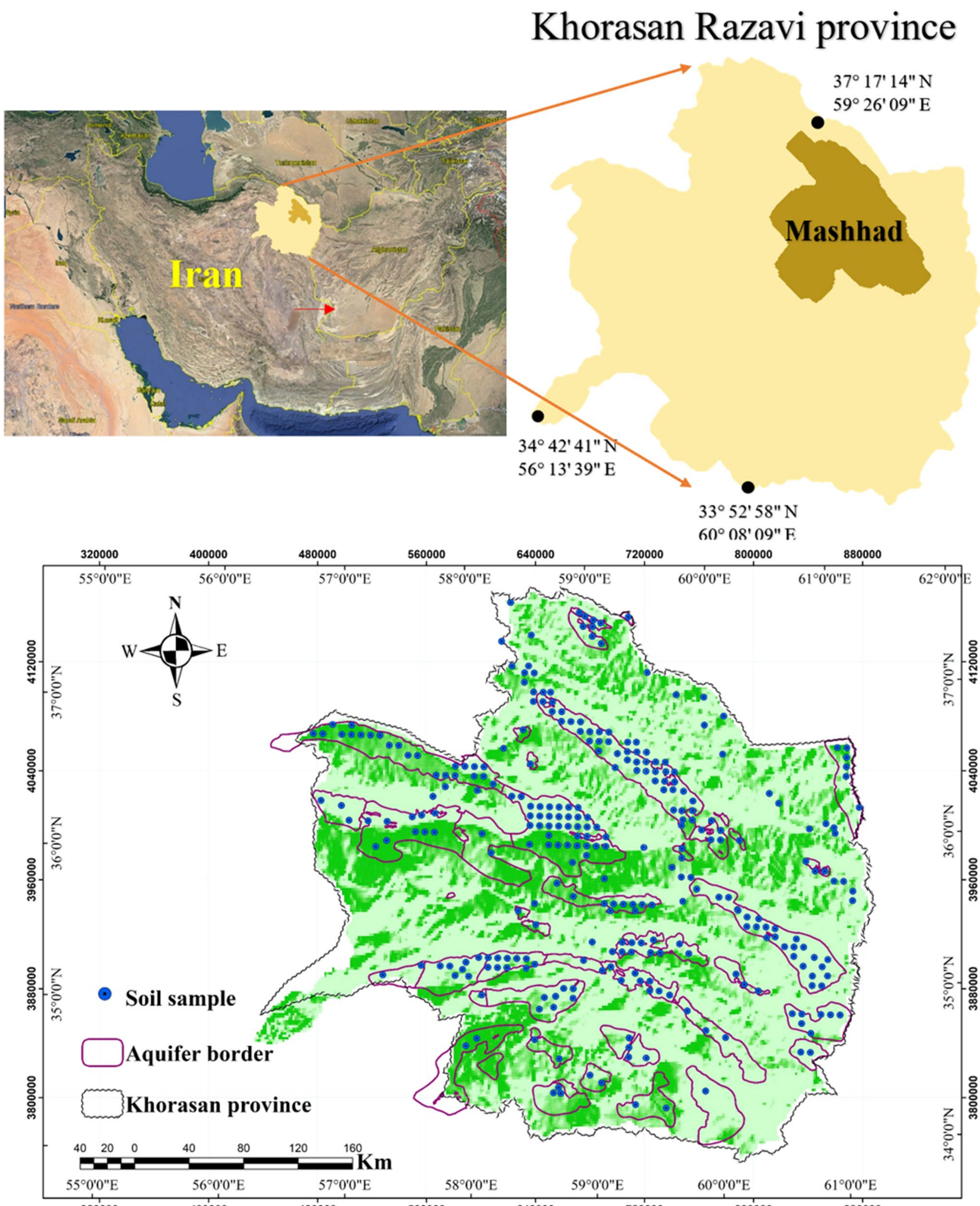


Fig. 1 Location of Khorasan Razavi Province in the Iranian map and the inventory map of land subsidence with training and test data points

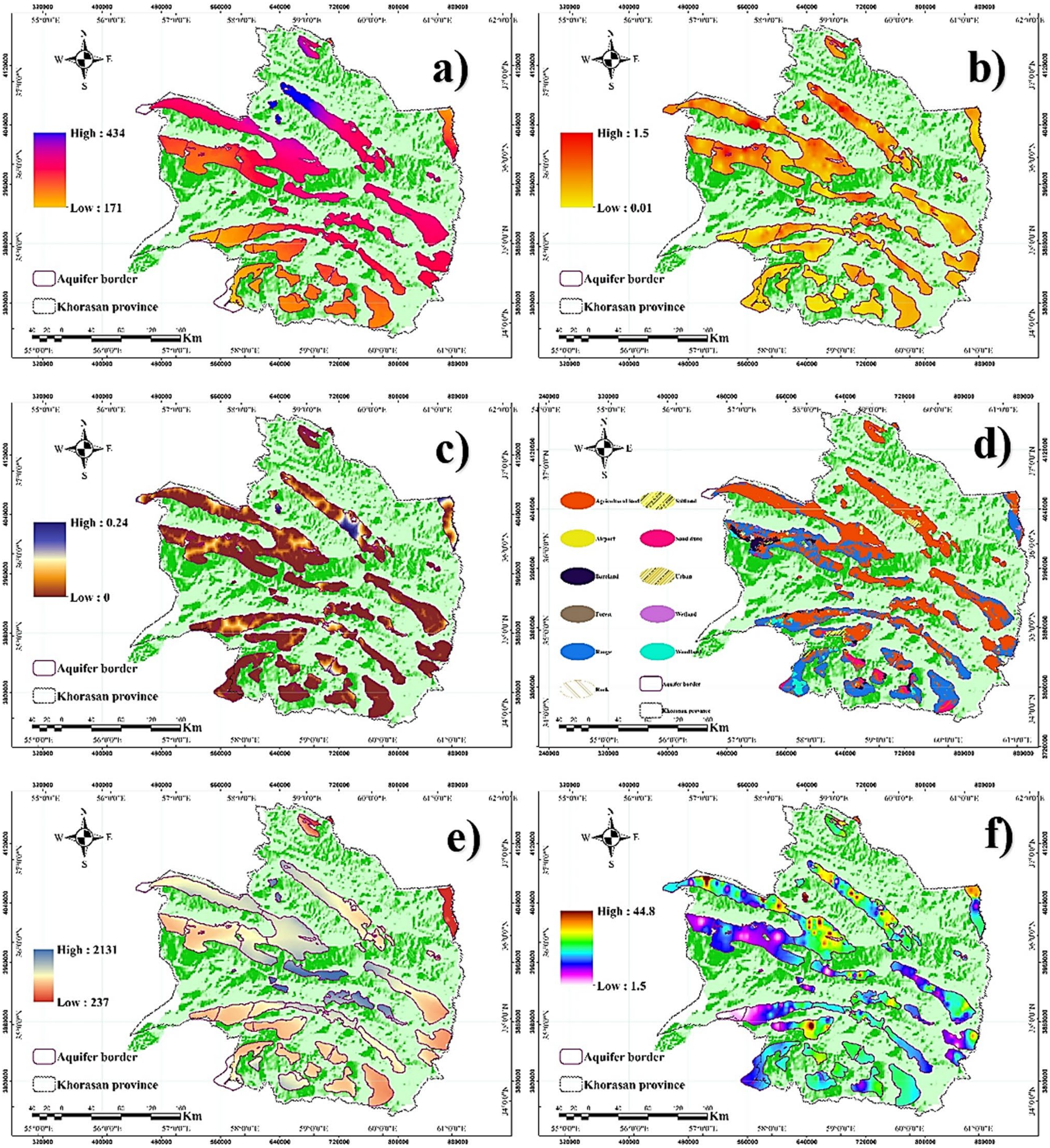


Fig. 2 Various predisposing variables for detecting and mapping land subsidence, including (**a**) precipitation, **b** soil organic carbon, **c** river distance, **d** land use, **e** DEM, **f** soil clay content, **g** soil bulk density, **h** an average of water table in the last 10 years, **i** water loss, **j** village distance, **k** sand content, **l** soil EC, **m** slope, **n** silt content, and **o** observed well

Hybrid CNN-RNN model

A hybrid CNN-RNN as a deep network that has shown significant success in image and video processing is one of the models used in this study. Due to data availability and advances in computational resources (e.g., GPUs), CNN-RNN proved to be a suitable option, especially for image analysis tasks (Kazemi Garajeh et al. 2022a). Generally, there are several well-known CNN-RNN architectures to output the recognition results (Kazemi Garajeh et al. 2021).

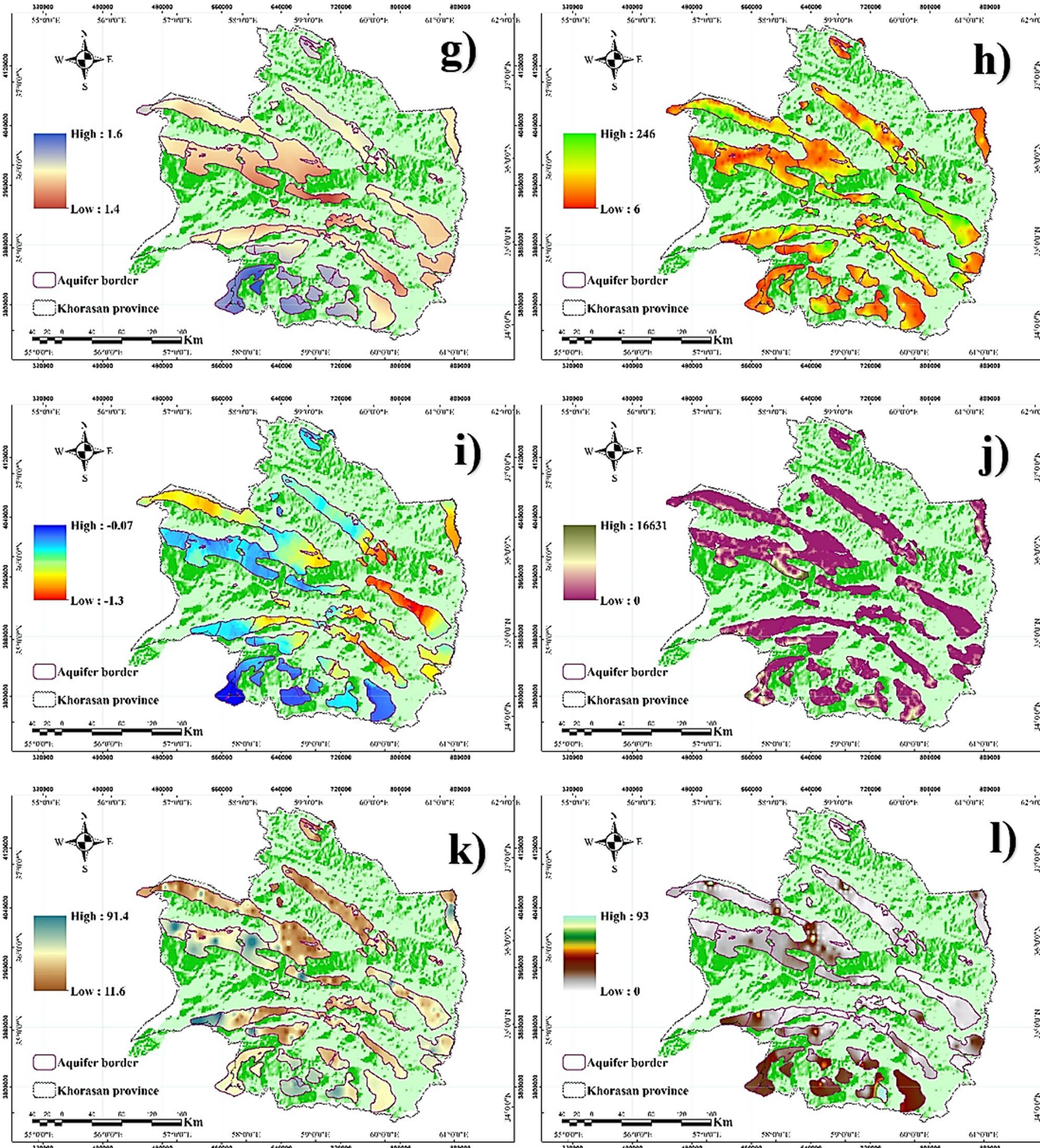


Fig. 2 (continued)

The combination of CNN-RNN as a successful model in some regression and classification tasks can take both sequential and local, and specifications of input maps (Nasir et al. 2021). For instance, this model can be applied for emotion detection (Kollias and Zafeiriou 2020), as it can know scene variables applying the CNN and sequential processing of data applying the RNN. The RNN can also learn context and temporal data from text files, and capture conjunctions between essential features and text entities, which are calculated using the capability of CNN (Zhang et al. 2018). Besides advantages, the model has several disadvantages, such as the adversity in discovering the

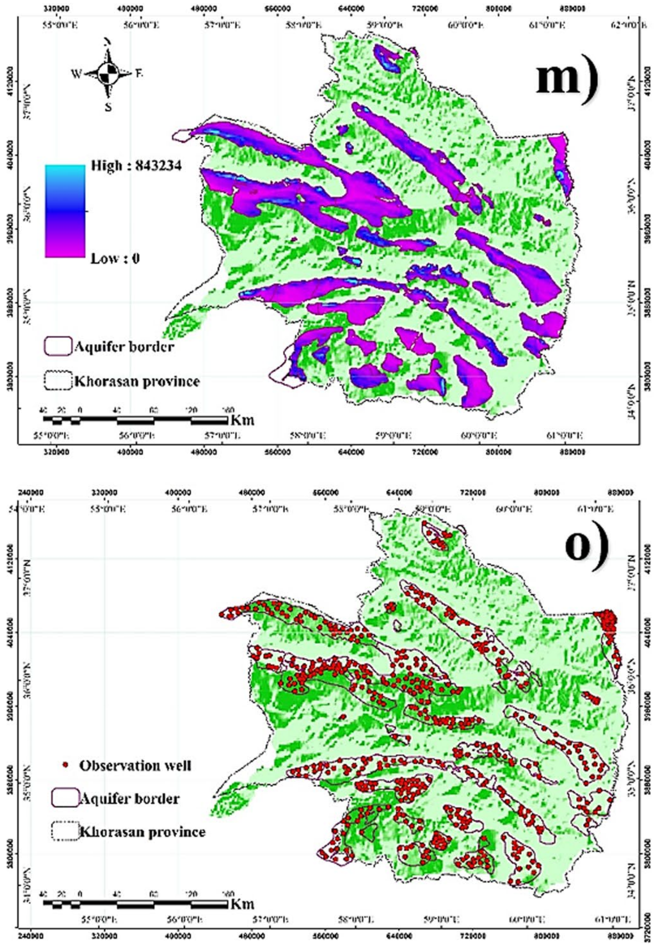


Fig. 2 (continued)

optimal hyper-features for each dataset, the difficulty in interpretability, and the need for big data-train (Drumond et al. 2019). Therefore, in the present research, it is applied to know if it is appropriate for the preparation of the sensitivity map of land subsidence.

Ensemble deep learning (EDL) model

The first step to building new DL models is to create a "ground truth" dataset (Rezaee et al. 2018). For this purpose, the input layer receives the information of predictor variables of a sample to determine the sensitivity of the case study to land subsidence. Neurons are the main parts of all layers in the neural network, which present processed land subsidence as convolutional layers in the hidden layers. Several factors are included in each convolutional layer, including pooling operation, multiple weights, and an activation function. Through pooling, the results of the previous convolutional layer are combined into a single value at the next convolutional layer, thereby reducing property vector size (Kazemi Garajeh et al. 2022b). The max-pooling operator was employed in this study to downsample the feature maps in the encoder. All convolutional layers were then weighted and formed the weighted sum, which passed through an activation function to produce the result. This study applied ReLu (Rectified Linear Unit) to generate out of the models, which its efficiency for deep learning algorithms have proven by previous researchers (Wang et al. 2018; Scardapane et al. 2019; Kazemi Garajeh et al. 2022c). The ReLu and its derivative can write as follows:

$$g(z) = \max(0, z) \tag{1}$$

$$g(z) = \begin{cases} 0, z < 0 \\ 1, z > 1 \end{cases} \tag{2}$$

In the next step, the loss/cost function is employed to increase predicted accuracy and decrease errors in the network (Han et al. 2018). This study applied cross-entropy

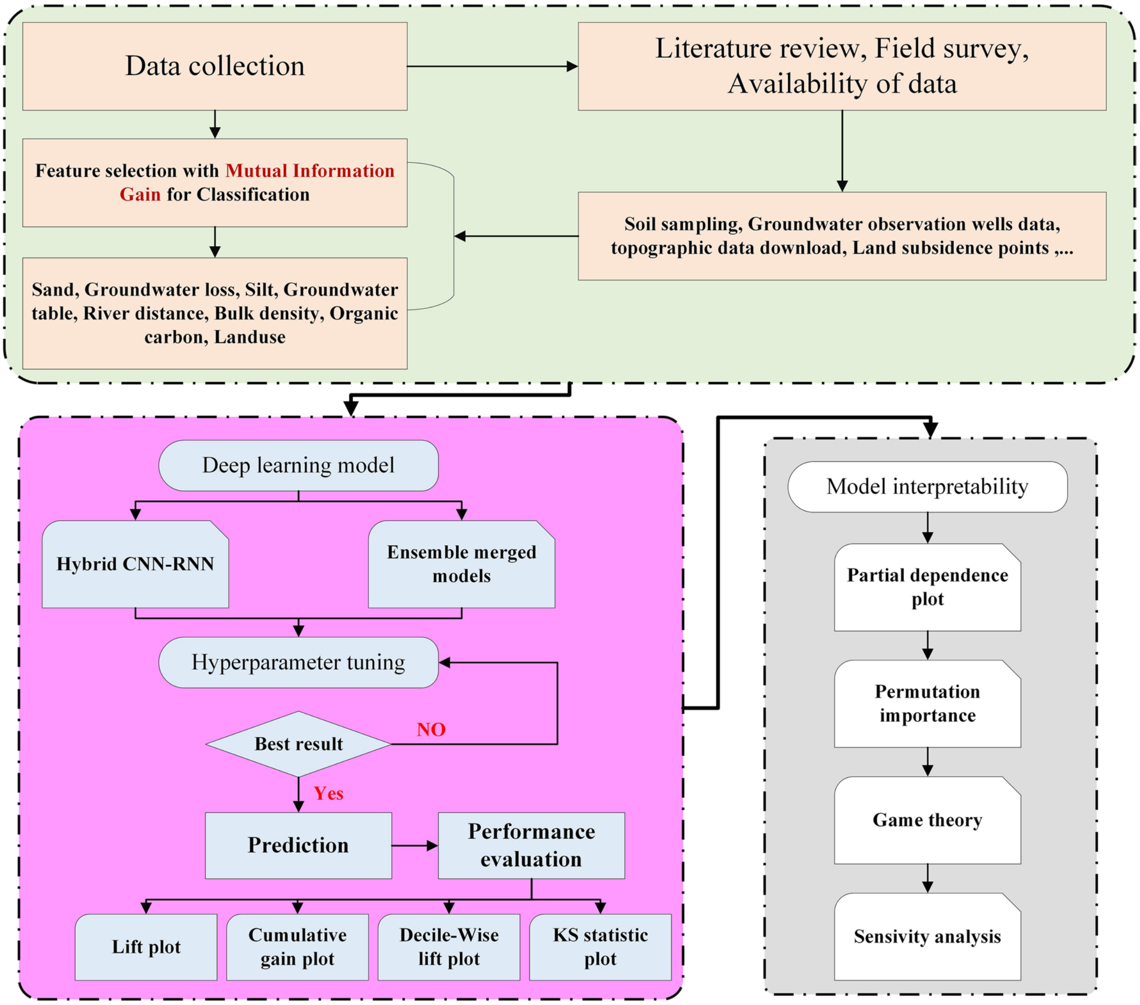
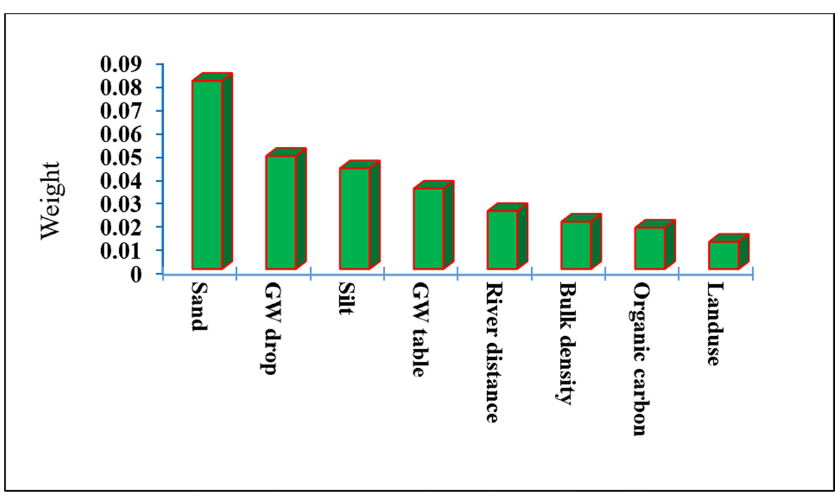


Fig. 3 An overview of the present study for detecting and mapping land subsidence

Fig. 4 The weights calculated by MIC for the important variables



as a well-known function in the domain of binary classification. The output of this function is likely to be between 0 and 1, which is defined by the Eq. (4):

$$L(y,\hat{y}) = -\frac{1}{N}\sum_{i=1}^{N}(y_i \log\log(\hat{y}_i) + (1-y_i)\log\log(1-\hat{y}_i)) \quad (3)$$

where, N represents all employed samples, y_i denotes the real output of sample i (0 or 1), $\hat{y}_i$ presents a forecasted likelihood of sample i having the output 1, and y and y_i illustrate real outputs' vectors and forecasted probabilities.

The last phase is to optimize the results of the model. In optimization, the loss/cost function is minimized or maximized in order to improve training results (Scardapane et al. 2019). This study applied ADAM (Adaptive Moment Optimization) algorithm, which has several advantages over other optimizers such as SGD (Stochastic Gradient Descent), AdaGrad (Adaptive Gradient), and RMSprop (Root Mean Square Propagation) (Kingma and Ba 2014). Several problems with other optimization algorithms can be corrected with ADAM, including slow convergence, large fluctuations in the loss/cost function due to parameter updates with high variance, and vanishing of the learning rate (Kazemi Garajeh et al. 2023). Equations (4) and (5) are given ADAM:

$$m_t^{(j)} = \beta_1 m_{t-1}^{(j)} + (1-\beta_1)g_t^{(j)} \quad (4)$$

$$v_t^{(j)} = \beta_2 v_{t-1}^{(j)} + (1-\beta_2)(g_t^{(j)})^2 \quad (5)$$

where, β_1 and β_2 are usually chosen to be 0.9 and 0.999, respectively. The first and second moments are then bias-corrected:

$$\hat{m}_t^{(j)} = \frac{m_t^{(j)}}{1-\beta_1^t}, \hat{v}_t^{(j)} = \frac{v_t^{(j)}}{1-\beta_2^t} \quad (6)$$

And used to weight the update:

$$w_{t+1}^{(j)} = w_t^{(j)} - \frac{\alpha}{\sqrt{\hat{v}_t^{(j)}} + \epsilon}\hat{m}_t^{(j)} \quad (7)$$

where, α represents the primary learning rate that is 0.001.

Accuracy assessment

The classification results were evaluated using the receiver operating characteristic (ROC) curve and precision-recall plot. The ROC curve applies true and false positives to validate the results of the classification. Pixels that are correctly labeled as susceptible to land subsidence are displayed as true positives, while pixels incorrectly labeled as susceptible to land subsidence are displayed as false positives. Figures 7 and 8 show the results of the applied ROC curve. Equation (8) also represents the ROC curve.

$$ROC = \sum_{i-1}^{x}[X_{i+1} - X_i] \times [X_i + [X_i + \frac{Y_{i+1} - Y_i}{2}] \quad (8)$$

where X_i is sensitivity and Y_i is specificity on the graph.

Feature interaction, permutation feature importance measure (PFIM) and SHAP

We can express the H-statistic for the interaction between features j and k as follows (Mohammadifar et al. 2021):

$$H_{jk}^2 = \sum_{i=1}^{n}[PD_{jk}(x_j^{(i)}, x_k^{(i)}) - PD_j(x_j^{(i)}) - PD_k(x_k^{(i)})]^2 / \sum_{i=1}^{n} PD_{jk}^2(x_j^{(i)}, x_k^{(i)}) \quad (9)$$

where, PD_{jk} (x_j, x_k) is the 2-way partial dependence function of both features, and PD_j (x_j) and PD_k (x_k) indicate the partial dependence functions of the single features.

The sample applies to measuring whether a feature j interacts with any other feature:

$$H_j^2 = \sum_{i=1}^{n}\left[f(x^i) - PD_j(x_j^{(i)}) - PD_{-k}(x_{-j}^{(i)})\right]^2 / \sum_{i=1}^{n} f^2(x^{(i)}) \quad (10)$$

The importance of controlling variables and their contribution to the used model outputs can be statistically assessed by applying PFIM and SHAP respectively (Mohammadifar et al. 2021; Gholami et al. 2023b). We used the permutation importance analysis to calculate the importance of the independent features controlling LS. Relative importance was appointed from the contribution of the features to the predictor in decreasing the prediction errors.

The SHAP values of the game theory were applied to assess the contribution of each variable to the output of the predictive model for the susceptibility of the area to land subsidence. The value, and then the relative importance of each feature, are shown by the color scheme. Also, overlapping locations are defined in the y-axis to show a sense of the pattern of the SHAP values per variable, as per the observed approach.

Sensitivity analysis

It has been described as a spatial process that calculates the response of one model to changes in input variables. It partitions the outputs under various conditions of the parameters and model components, for defining the main revealing features. It can both decrease uncertainty in various deep learning models and enhance the stability of different outputs. This is obtained by showing the effect of defining small changes to exact input datasets on assessment outcomes (Ravalico et al. 2010). Although, the combination of sensitivity and uncertainty analyses makes better realization of the relative influences of the hypotheses and input variables of deep learning models (Feizizadeh and Blaschke 2014). Here, we applied a Shuffled feature sensitivity to assess the predictive model's sensitivity.

Results

Identifying important and non-important variables controlling LS by MIC

The results of MIC algorithm for identifying important variables controlling LS and their weights is presented in Fig. 4. Among 16 variables explained as potential variables for LS control, eight variables consisting of

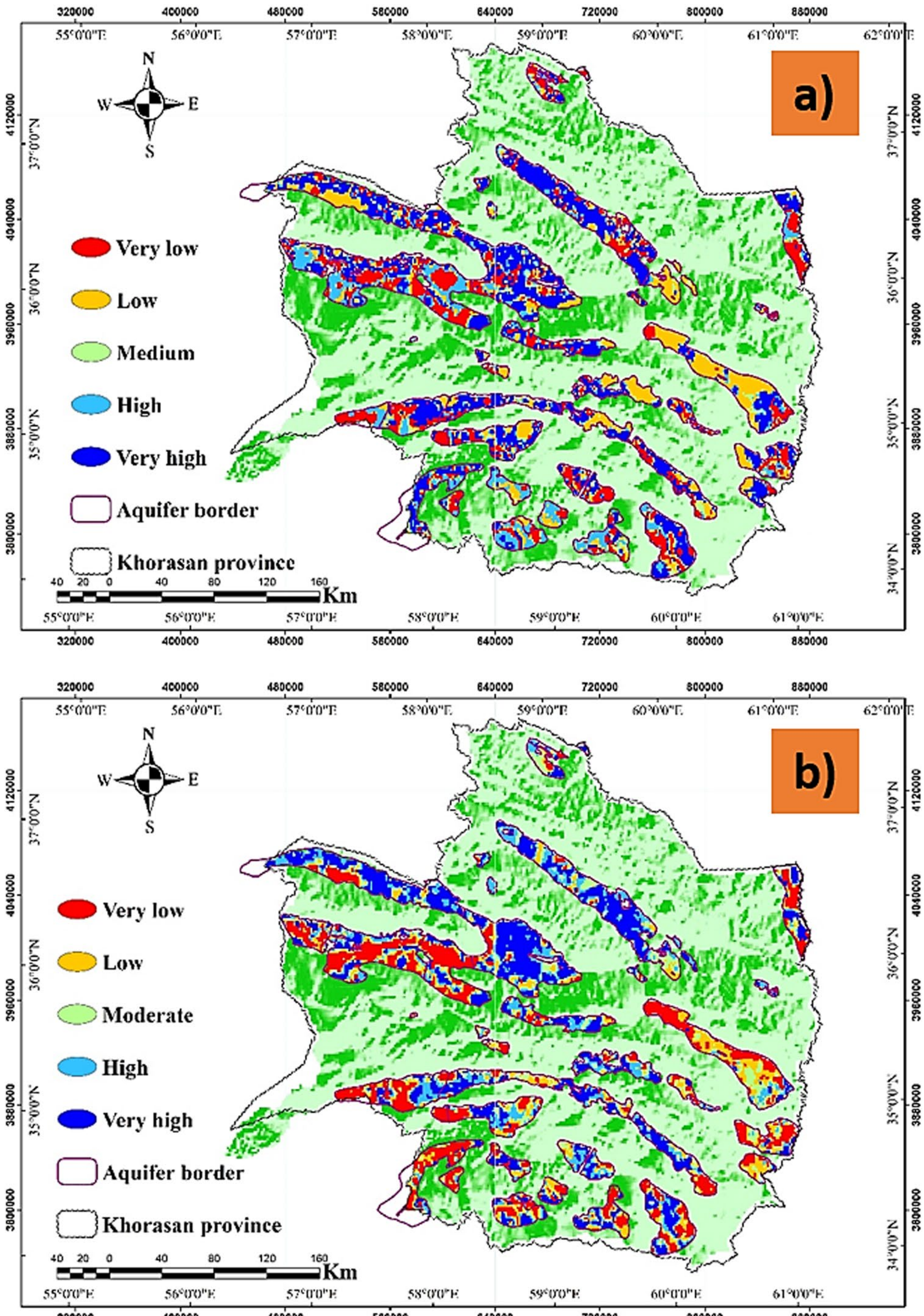


Fig. 5 LS hazard maps produced by (**a**) hybrid CNN-RNN model, and (**b**) EDL model

soil sand percent, groundwater (GW) drop rate, soil silt percent, GW table level, distance to river, soil bulk density, soil organic carbon, and landuse were identified as important variables controlling LS by MIC respectively, and their weights were as follows: soil sand content with weight = 0.08 > 0.048 > 0.043 > 0.034 > 0.024 > 0.02 > 0.017 > landuse with weight = 0.011. Overall, LS impacted by many variables and their importance are variable from place to other place, and it is depending on the area conditions. Soil organic carbon can impact on the LS occurrence indirectly, because high organic carbon is indicating development agricultural activities in the study area by pumping the groundwater from the aquifers and its consequence is dropping the ground water level.

LS hazard maps generated by hybrid and ensemble DL models

In this study, hybrid CNN-RNN and EDL models were used for detecting and mapping land subsidence. Figure 5 show the results of CNN-RNN and EDL for detecting and mapping land subsidence. Table 1 represent further details regarding the area of land subsidence for each class. According to Table 1, the area of land subsidence is estimated at about 22.52%, 20.78%, 16.77%, 12.41%, and 27.50% for very low, low, moderate, high, and very high classes, respectively for CNN-RNN. Area of land subsidence for very low, low, moderate, high, and very high classes also calculated about 23.12%, 13.87%, 13.56%, 19.08%, and 30.33%, respectively using ensemble merged models, as shown in Table 1.

Table 1 The area of LS hazard classes estimated by hybrid CNN-RNN model and EDL model

Hybrid CNN-RNN model		
LS hazard class	Area (ha)	Present (%)
Very low	636369.45	23.13
Low	381680.71	13.87
Moderate	373330.88	13.57
High	525218.66	19.09
Very high	834732.09	30.34
EDL model		
LS hazard class	Area (ha)	Percent (%)
Very low	619879.09	22.52
Low	571962.75	20.78
Moderate	461804.92	16.78
High	341623.73	12.41
Very high	756993.99	27.50

Assessment of LS hazard predictive models performance

The results of accuracy assessment using precision-recall and ROC curves for both datasets (training and test) used in CNN-RNN and EDL models are presented in Figs. 6 and 7. According to the training dataset, EDL with precision-recall = 0.952, and ROC = 0.95 performed slightly better than CNN-RNN with precision-recall = 0.936, and ROC = 0.93, but based on the test dataset, CNN-RNN with precision-recall = 0.952, and ROC = 0.95 performed slightly better than EDL with precision-recall = 0.903, and ROC = 0.90. Overall, based on the precision-recall and ROC curves with values > 0.90 for both datasets, both models performed very well.

Feature interaction

The overall interaction strength among eight features was selected as important features identified by MIC (Fig. 8). The results showed that sand content (higher than 0.3), bulk density, and groundwater table had the highest interaction with land occurred subsidence in Khorasan Razavi Province. According to this graph, the lowest interaction strength is specified to river distance (less than 0.2).

Determining feature importance by permutation feature importance measure (PFIM)

When features interact with each other in a predictive model, the prediction cannot be expressed as the sum of feature effects, because the effect of one feature depends on the value of the other feature (Mohammadifar et al. 2021). The plot constructed based on the PFIM shows overall interaction strength vs. features. The importance of controlling factors of land subsidence was calculated using PFIM. Based on the results, the overall interaction strength for eight features was as follows: soil sand content > soil bulk density > groundwater table level > soil organic carbon > groundwater drop rate > soil silt content > landuse > distance to river. Overall, soil sand content and distance to river have the highest and lowest interaction with another feature (Fig. 9).

The interpretability of predictive model output by SHapley Additive exPlanations (SHAP)

The contribution of eight features controlling LS in the study area on the predictive model output was interpreted by SHAP. SHAP has an advantage of combining factor

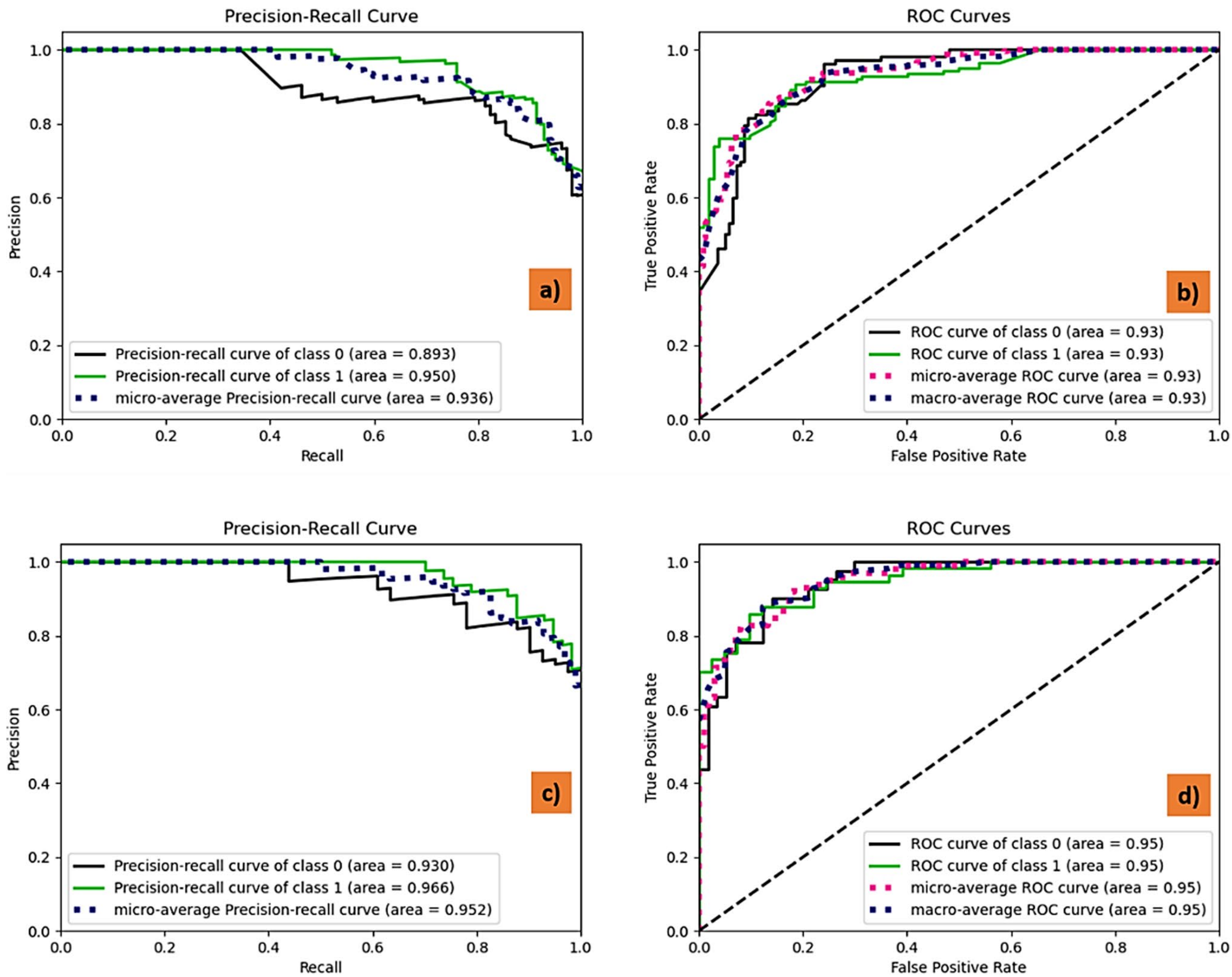


Fig. 6 The precision-recall (**a** and **c**) and ROC (**b** and **d**) curves for assessing predictive CNN-RNN model performance for training dataset (**a** and **b**), and test dataset (**c** and **d**)

importance with factor effects. The color in the SHAP figure shows the factor from low to high. The overlapping points represent the distribution of SHAP values per factor. The order of importance based on shape was as follows: (put orders based on SHAP). The SHAP values indicate the impact of the features on model output. Based on the SHAP plot (Fig. 10), the groundwater drop rate and distance to river have the highest and lowest contributions to the predictive model output respectively.

Sensitivity analysis of predictive model

The results of the sensitivity analysis for the predictive model are presented in Fig. 11. In the model sensitivity analysis, different values were generated for each variable. The results suggested that the groundwater drop rate is the most sensitive for the model, and the feature's sensitivity was in the following order: groundwater drop rate > soil organic carbon > soil bulk density > soil sand content > groundwater table level > distance to river > soil silt content > landuse.

Discussion

Comparison of our predictive hybrid and ensemble DL models performance with other models applied in similar geomorphic conditions of arid/semi-arid areas

This study applied a deep learning CNN and a hybrid approach of CNN and RNN for detecting and mapping land subsidence in Khorasan Razavi Province, Iran. Our findings show that the hybrid approach of CNN-RNN performed well for detecting land subsidence compared to a single CNN, as

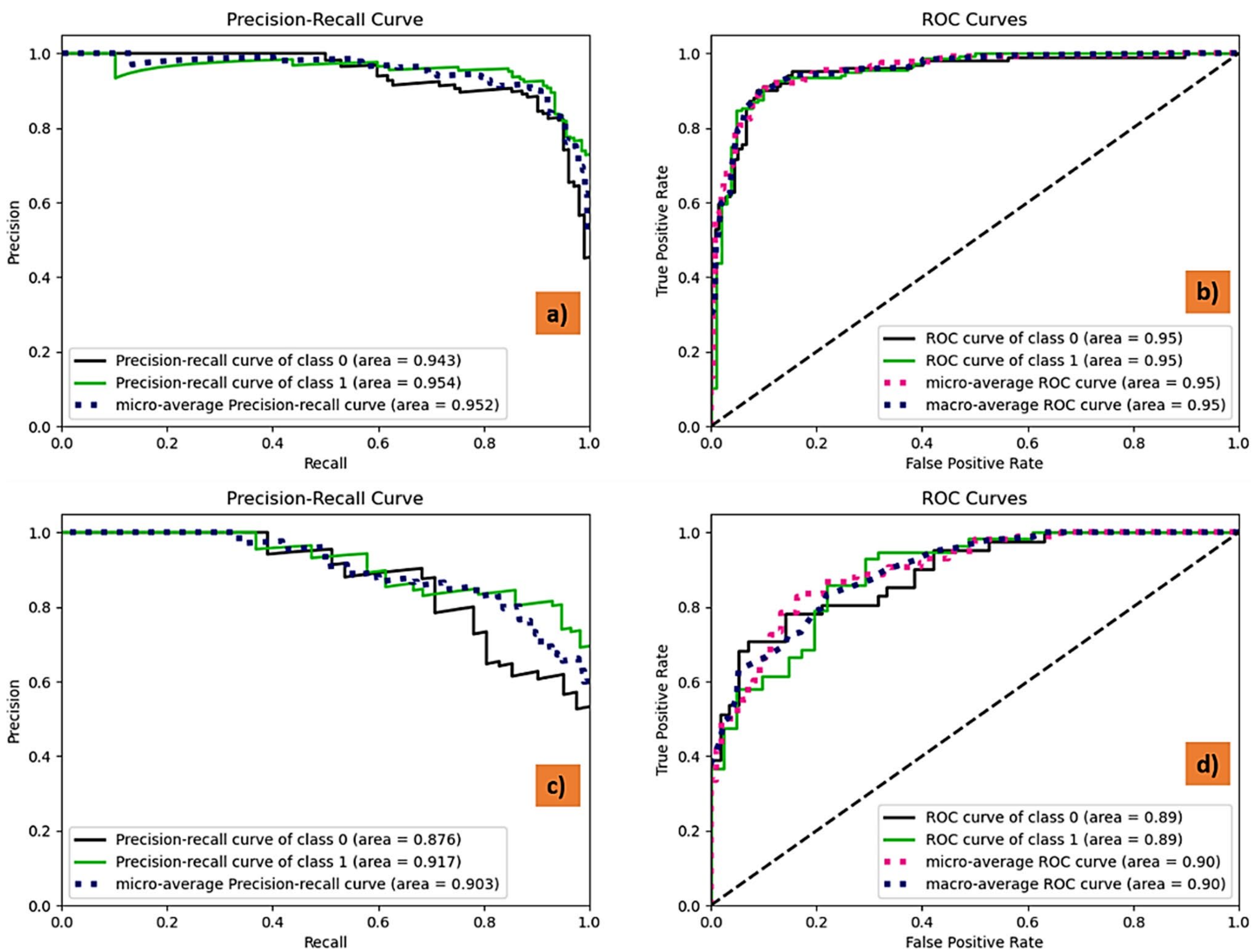


Fig. 7 The precision-recall (**a** and **c**) and ROC (**b** and **d**) curves for assessing predictive EDL model performance for training dataset (**a** and **b**), and test dataset (**c** and **d**)

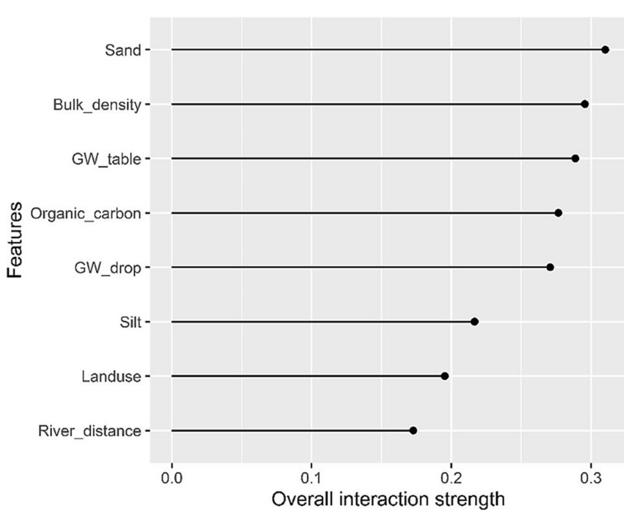


Fig. 8 The overall interaction strength among eight features selected as important features identified by MIC

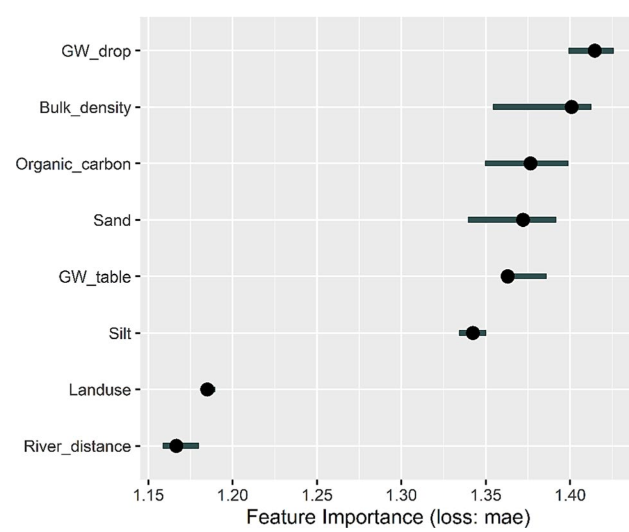


Fig. 9 The feature importance determined by PFIM

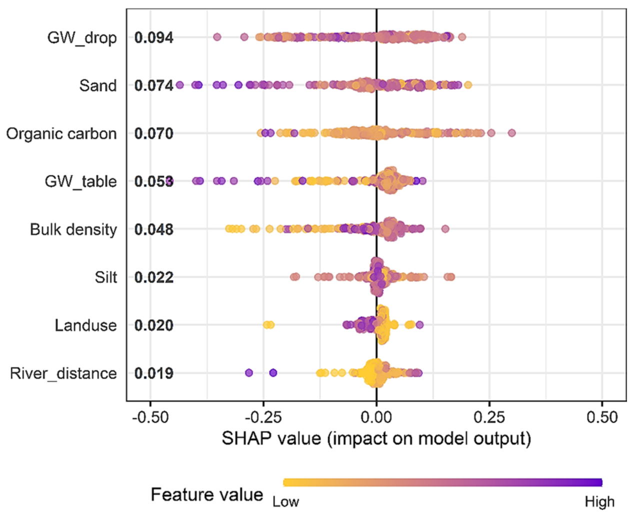


Fig. 10 The SHAP values for each feature

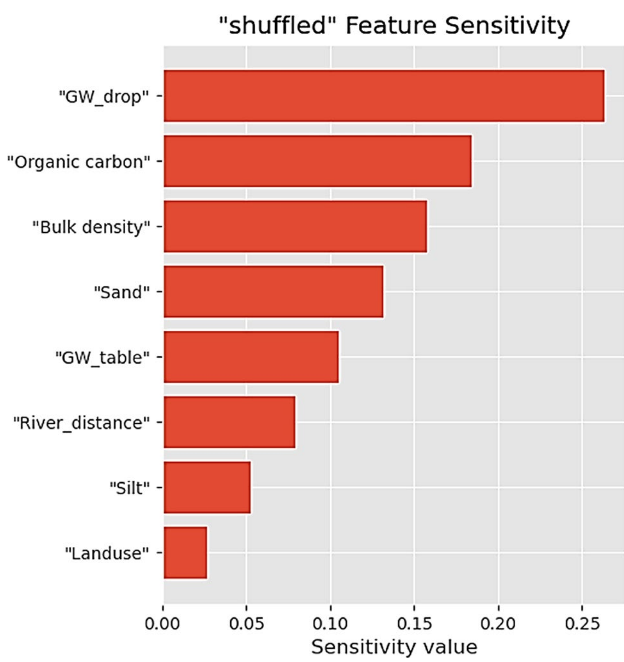


Fig. 11 The sensitivity analysis of the predictive model

shown in Figs. 7 and 8. This study evaluated a single CNN and hybrid approach of CNN-RNN for detecting and mapping land subsidence. The results of this study show that an integrated approach of CNN-RNN can be an appropriate alternative for detecting and mapping land subsidence. Deep learning techniques can essentially apply the same convolution procedure, which makes easier training networks. CNN can learn the filter weights through back-propagation (training). Also, there are usually many filters for each layer, each with a different weight matrix, applied to the same data (Scardapane et al. 2019).

Land subsidence-related issues in Iran, the Middle East, and arid/semiarid regions worldwide

The location of ancient Iran in the arid and semi-arid belt of the Earth, along with active tectonics, has brought a different degree of resilience and face to the biomes of this land (Labbaf Khaneiki and Al-Ghafri 2022). In the recent decades, especially the last half century, the inhabitants of this land who are the heirs of the aqueduct and the native knowledge of their ancestors, in exploiting these dry lands beyond their capacity, have brought the scar of the destruction of the ancient aquifers of the Middle East with a scratch on the face of the fertile plains (Michel 2017). It is a wound that has left large cracks on the face of the ecosystem and apart from the fact that it is associated with the collapse of the ecological environment, it affects civilization with social, economic, and cultural damage, which today is a large part of the eastern region of Iran (Madani and Mahoozi 2021). Moreover, as the origin of civilization, culture, and art in Tus and Neyshabur has faced a danger from this context (Ashraf et al. 2019). According to the country's official statistics, Razavi Khorasan is considered one of the critical provinces in terms of subsidence rate, so in plains such as Kashmir and Neyshabur, the annual subsidence rate has exceeded 15 cm. The trend of aquifer decline in plains like Neyshabur during the last two decades is very worrying so that the average deficit of the Neyshabur plain reservoir is about 80 million cubic meters per year (Doosti Sabzi et al. 2023). Therefore, the basic issue in these plains is the creation of facies such as subsidence and sinkholes caused by different size letters and their control and management methods.

The results of this research show that lithology can be an important factor in Razavi Khorasan province in the formation and expansion of facies such as subsidence. According to the results of this research, it can be said that if the geomorphological issues of Mashhad are not paid attention to, environmental hazards such as sinkholes and subsidence will threaten Hashemiyeh, Haft Tir, Namaz Boulevard, water, and electricity, and Kohsar mountains in Mashhad in the future. Land subsidence may happen suddenly, but the phenomenon related to cracks resulting from subsidence is a gradual process (Liu et al. 2023). The movement of tectonic plates causes morphogenesis, for example, in some orogenic areas, and in some places, subsidence occurs. Earthquake phenomena and slope movements, mass movements, instability of slopes, and events related to mountain slopes due to earth-building activities and morphogenic and erosion processes are natural. Such phenomena have various advantages and disadvantages, but what is important today is the role of humans and the way of behavior and it is their performance in nature that changes the shape and structure of ecosystems (Goudie 2022).

Based on a natural process, a part of the tectonic plate gradually descends. For example, based on a study conducted in America (Ingebritsen and Ikehara 1999; Faunt et al. 2016), an electricity tower was marked for several years. After several years, it was found that the power tower naturally fell a little lower than its previous height, which was the result of a tectonic phenomenon. Sometimes these meetings cause a huge depression, which is scientifically called a graben. For example, Mashhad is a plain between two mountains and is considered a geological graben. These cracks and fissures are generally formed in the plains with fine-grained soil and moisture-absorbing minerals, which is better called the fissure resulting from subsidence, and in central Iran, it is known as the phenomenon of plain fissure or cracking. This phenomenon happens in many places of the world, from the United States of America to European countries, China, Iran, and India. Furthermore, our results are relevant for arid environments, considering that the country of Iran is located in the dry and semi-arid belt of the world and more than 85% of its area of one billion and 600 million hectares is in a dry and semi-arid climate and it has a third of the world's average precipitation level (Michel 2017). We should know that living in an arid environment requires a special way of adaptation and behavior on the part of humans and the inhabitants of these ecosystems. Unfortunately, in recent decades, unwise behaviors and decisions, in addition to greed for exploiting natural resources with an emphasis on hydric ones in this arid ecosystem of the Middle East, it has made Iran more prone to land subsidence and cracks in the increasingly populated plains (Haji-Aghajany and Amerian 2020; Zhao et al. 2023). Iran's ancestors have adapted to this dry and semi-arid climate and have created the most professional way of water management, the aqueduct. Unfortunately, today most of these aqueducts have been destroyed and now deep wells are used for water supply.

The noteworthy point in Razavi Khorasan province is that the plains of Mashhad and Neyshabur are in a critical state due to the phenomenon of subsidence and cracks in the plain. Overexploiting the water resources causes excessive moisture in the ground and creates some cracks. This process has continued until now we see the formation of huge cracks with a width of more than 10 m, a depth of more than 50 m, and a length of more than one kilometer, and for this reason, it is called the death of the plain. The death of a plain occurs if a plain cannot be revived, now this phenomenon can be seen in Neyshabur Plain and Kashmir. The phenomenon of the death of the plain leads to problems such as the destruction of railway tracks and the protrusion of water pipes, which is called pipe formation (Mahmoudpour et al. 2016). Furthermore, due to varying resilience levels in different regions, it is unfortunate that there is no suitable water development model for different areas within Iran. Currently, the development approach in regions like Gilan, which receives 2000 mm of rainfall annually, does not differ from that in Khorasan, which only receives 150 mm of rainfall per year. This uniformity in development is causing issues, as excessive exploitation of water resources in a dry, semi-arid climate leads to land subsidence. In 1975, recognizing these challenges, the parliament approved a law prohibiting the exploitation of water wells to prevent such conditions. However, there have been instances where thousands of wells were licensed for exploitation within a single year. Additionally, Iran is one of the few countries where deep waters are being extracted, leading to significant drops in some plains, such as a decline of 250 to 300 m in central Iran, Kerman, and Isfahan. Additionally, in certain plains where water used to be accessible at a depth of 50 m, it now requires excavation at depths exceeding 250 m and beyond. Moreover, the southeastern and southern provinces have been granted permission to extract deep groundwater. Over the past three decades in Iran, human activities have played a significant role in contributing to land subsidence through the excessive exploitation of both surface and underground water resources.

If structures such as houses, settlements, railway tracks, and villages are exposed to the cracks caused by the subsidence of the earth, they will be destroyed. Currently, the worst conditions are related to central Iran, which was observed in Isfahan. The damages caused by these gaps have also reached the ancient works. This problem can threaten many urban areas in the Mashhad metropolis, such as the 9th, 11th, and 12th districts of Mashhad, and in this sense, the Mashhad plain is in a critical situation. Moreover, 50% of Iran's geological formations are limestone. Regarding the difference between sinkholes and subsidence, a sinkhole is a kind of karst phenomenon that occurs as a result of the dissolution of soil and dissolvable formation. Although indiscriminate construction and mining aggravate the creation of sinkholes, which is considered a type of subsidence, its system is different from subsidence, which sometimes reaches a depth of more than 50 m. For example, there are large sinkholes in Hamadan's Kobudar Ahang, which were created due to mining. This phenomenon is evident in Fars province as well. The most important problem in geomorphological issues is that there is no map of land capability and suitability in Iran. If there was a map, we would have found out that the southern heights should not have been destroyed and the construction should not have taken place on the slopes of the mountains.

Neyshabur and Kashmir are the most critical plains of Razavi Khorasan. According to the farmers of these areas, they dig more than 200 m to reach the water. Moreover, there is a deficit of 80 million cubic meters of the water reservoir in Neyshabur, and 15 cm of land subsidence occurs in Neyshabur every year (Salmani Sabzevar et al. 2021). Unfortunately, the country's officials do not have an ecological view of land exploitation and management, and the prevailing view is non-ecological thinking. Currently, the accepted view about water in our country is inter-basin water transfer. Besides this, there is no specific cultivation pattern for agriculture. For example, the same summer plants of West Azerbaijan are also cultivated in Khorasan. Currently, more than 85% of the country's water resources consumption is related to the agricultural sector. In the last 50 years, both in the academic sector and in the governance sector, management has not been based on ecological thinking (Abrishamchi et al. 2020). In addition, there is no coherence in the bodies of organizations and the Geological Organization, Environmental Organization, Forestry Organization, Ministry of Energy, municipalities, and other related institutions are not coordinated with each other and a coherent law has not been formulated in the area of land management and risks such as land subsidence. Non-ecological thinking causes problems such as social disorder, immigration, economic problems, and depression. As long as the rulers have non-ecological thinking, the country cannot move toward development.

Finally, due to the multivariate nature of many geomorphic systems and their intricate relationships with feedback mechanisms, relying solely on the experience and expertise of researchers, as well as subjective approaches, will likely result in varied conclusions during the final interpretation. To address this challenge and enhance objectivity, it is crucial to adopt statistical methods that involve formulating and testing hypotheses. These statistical approaches help simplify complex relationships and identify the key factors influencing geomorphic processes. One suitable method to reduce errors in decision-making and enhance objectivity is the prioritization of factors using random forest algorithms. Additionally, employing deep learning algorithms for modeling can assist in generating sensitivity maps related to the occurrence of the two erosion facies under consideration. These statistical methods aid in simplifying complex relationships and identifying the factors that govern geomorphic processes. By utilizing these techniques, a more comprehensive and objective understanding can be achieved.

Conclusion

Razavi Khorasan province is a region with a unique and complex topography with miscellaneous land uses. This province is one of the most susceptible regions of Iran to erosion. Therefore, due to the high potential of this province regarding domain instabilities, it has been selected as the case study of this research, and the topographical, hydrological, petrological, soil, and biological factors affecting the occurrence of domain instabilities have been investigated. To achieve the goals of this research, five main steps were used collecting statistics of subsidence positions and sampling the soil of these points, accessing a satellite image of the spot, prioritizing factors affecting the occurrence of land subsidence erosions, and spatial modeling of land subsidence erosions and evaluation of sensitivity maps to their occurrence.

The zoning of land subsidence sensitivity using the DL model and its accuracy assessment based on 30% of erosion points and the ROC curve, shows good accuracy of the model for Razavi Khorasan province. The analyses derived from the results of this research showed that land subsidence affects the environment in two aspects. First, by destroying the soil horizons, it destroys the soil bed. It also causes intensification in the discharge of surface runoff and reduces the volume of underground water flow by shortening the connection between the upstream and downstream areas. Therefore, it is necessary to carry out more research on the expansion and progress of subsidence through accurate data and appropriate spatial statistics methods.

Due to the existence of much subsidence in Razavi Khorasan Province, this erosive landform on the one hand led to severe water discharge from Razavi Khorasan Province, and on the other hand, they are considered a suitable substrate for the growth of plants and biodiversity. Therefore, land subsidence accelerates the intensity of desertification both as a threat and as an opportunity, they provide a suitable platform for the growth of plants, animals, and birds. Therefore, the way to turn threats into opportunities or vice versa depends on the management practice and strategy of the region, which is considered as the management of arid and semi-arid regions and can provide a new horizon for policy making, planning, and decision-making. Finally, the principle of the complexity of land subsidence mechanisms and the factors affecting them are emphasized. This is especially useful because the nature of erodible facies of land subsidence is complex and does not easily yield to surface calculations of scientists.

Acknowledgements We are grateful to Professor Francisco Gutiérrez for his constructive remarks that significantly improved the quality of this manuscript. We wholeheartedly thanked the International Association of Geomorphology (IAG) for bringing us as young geomorphologists together to do valuable scientific research.

Authors' contributions The manuscript is written by the activities of all authors together.

Funding Funding was not received for this work.

Data Availability Data will be made available on request.

Declarations

Ethics approval and consent to participate We further confirm that any aspect of the work covered in this manuscript that has involved human patients has been conducted with the ethical approval of all relevant bodies and that such approvals are acknowledged within the manuscript. We confirm that the manuscript has been read and approved by all named authors. We also confirm that the order of authors listed in the manuscript has been approved by all named authors.

Consent for publication We understand that this Corresponding Author is the sole contact for the Editorial process. She is responsible for communicating with the other authors about progress, submissions of revisions, and final approval of proofs.

Competing interests The authors declare that they have no competing interests. Authors' contributions All authors read and approved the final manuscript.

References

Abrishamchi A, Khakbazan Fard F, Taghavi A (2020) Planning for groundwater sustainable use: a case study in Nishapur Plain, Iran. Agric Water Manage 229:105835

Amighpey M, Arabi S (2016) Studying land subsidence in Yazd Province, Iran, by integration of InSAR and leveling measurements. Remote Sens Appl: Soc Environ 4:1–8

Arabameri A, Saha S, Roy J, Tiefenbacher JP, Cerda A, Biggs T, Pradhan B, Thao Thi Ngo P, Collins AL (2020) A novel ensemble computational intelligence approach for the spatial prediction of land subsidence susceptibility. Sci Total Environ 726:138595

Ashraf S, Agha Kouchak A, Nazemi A, Mirchi A, Sadegh M, Moftakhari HR, Hassanzadeh E, Miao C-Y, Madani K, Baygi MM et al (2019) Compounding effects of human activities and climatic changes on surface water availability in Iran. Clim Change 152:379–391. https://doi.org/10.1007/s10584-018-2336-6

Azarakhsh Z, Azadbakht M, Matkan A (2022) Estimation, modeling, and prediction of land subsidence using Sentinel-1 time series in Tehran-Shahriar plain: A machine learning-based investigation. Remote Sens Appl: Soc Environ 25:100691

Baldi P, Casula G, Cenni N, Loddo F, Pesci A (2009) GPS-based monitoring of land subsidence in the Po Plain (Northern Italy). Earth Planet Sci Lett 288(1–2):204–212

Bokhari R, Shu H, Tariq A, Al-Ansari N, Guluzade R, Chen T, Jamil A, Aslam M (2023) Land subsidence analysis using synthetic aperture radar data. Heliyon 9(3):e14690

Burbey TJ (2020) Extensometer forensics: what can the data really tell us? Hydrogeol J 28:637–655. https://doi.org/10.1007/s10040-019-02060-6

Chai JC, Shen SL, Zhu HH, Zhang XL (2004) Land subsidence due to groundwater drawdown in Shanghai. Geotechnique 54(2):143–147

Chen C, Pei S, Jiao J (2003) Land subsidence caused by groundwater exploitation in Suzhou City. China Hydrogeol J 11:275–287

Chen M, Tomás R, Li Z, Motagh M, Li T, Hu L, Gong H, Li X, Yu J, Gong X (2016) Imaging Land Subsidence Induced by Groundwater extraction in Beijing (China) using Satellite Radar Interferometry. Remote Sens 8:468

Dinar A, Esteban E, Calvo E, Herrera G, Teatini P, Tomás R, Li Y, Ezquerro P, Albiac J (2021) We lose ground: global assessment of land subsidence impact extent. Sci Total Environ 786:147415

Doosti Sabzi B, Yazdi N, Maleki A (2023) Chap. 15 - Technological solutions for adaptation with Iran's water resources crisis. In: Ayyoob S, Khavarian-Garmsir AR (eds) Urban Climate Adaptation and Mitigation. Elsevier, pp 327–343

Drumond TF, Viéville T, Alexandre F (2019) Bio-inspired analysis of deep learning on not-so-big data using data-prototypes. Front Comput Neurosci 12:100

Faunt C.C., Sneed M, Traum J, Brandt J.T. (2016) Water availability and land subsidence in the Central Valley, California, USA. Hydrogeol J 24(3):675

Feizizadeh B, Blaschke T (2014) An uncertainty and sensitivity analysis approach for GIS-based multicriteria landslide susceptibility mapping. Int J Geogr Inf Sci 28(3):610–638

Galloway DL, Burbey TJ (2011) Review: regional land subsidence accompanying groundwater extraction. Hydrogeology 19:1459–1486

García-Soriano D, Quesada-Román A, Zamorano-Orozco JJ (2020) Geomorphological hazards susceptibility in high-density urban areas: a case study of Mexico City. J S Am Earth Sci 102:102667

Gholami H, Mohammadifar A (2022) Novel deep learning hybrid models (CNN-GRU and DLDL-RF) for the susceptibility classification of dust sources in the Middle East: a global source. Sci Rep 12(1):19342

Gholami H, Mohammadifar A, Fitzsimmons KE, Li Y, Kaskaoutis DG (2023a) Modeling land susceptibility to wind erosion hazards using LASSO regression and graph convolutional networks. Front Environ Sci 11:520

Gholami H, Mohammadifar A, Golzari S, Song Y, Pradhan B (2023b) Interpretability of simple RNN and GRU deep learning models used to map land susceptibility to gully erosion. Sci Total Environ 904:166960

Ghordoyee Milan S, Kayhomayoon Z, Arya Azar N, Berndtsson R, Ramezani MR, Moghaddam K, H (2023) Using machine learning to determine acceptable levels of groundwater consumption in Iran. Sustainable Prod Consum 35:388–400

Goudie AS (2022) The impacts of humans on geomorphology. Geol Soc Lond Mem 581:121–134

Haji-Aghajany S, Amerian Y (2020) Atmospheric phase screen estimation for land subsidence evaluation by InSAR time series analysis in Kurdistan, Iran, J Atmos Solar-Terr Phys 205:105314

Han W, Feng R, Wang L, Cheng Y (2018) A semi-supervised generative framework with deep learning features for high-resolution remote sensing image scene classification. ISPRS J Photogramm Remote Sens 145:23–43

Hillel D, Hatfield JL (eds) (2005) Encyclopedia of soils in the environment, vol 3. Elsevier, Amsterdam

Huang B, Tan G, Dou H, Cui Z, Song Y, Zhou T (2022) Mutual gain adaptive network for segmenting brain stroke lesions. Appl Soft Comput 129:109568

Ingebritsen SE, Ikehara ME (1999) Sacramento-San Joaquin Delta: the sinking heart of the state. Land subsidence in the United States, vol 1182. Circular, pp 83–94

Karanam V, Motagh M, Garg S, Jain K (2021) Multi-sensor remote sensing analysis of coal fire induced land subsidence in Jharia Coalfields, Jharkhand, India. Int J Appl Earth Obs Geoinf 102:102439

Karila K, Karjalainen M, Hyyppä J, Koskinen J, Saaranen V, Rouhiainen PA (2013) Comparison of precise leveling and persistent scatterer SAR Interferometry for building subsidence rate measurement. ISPRS Int J Geo-Inf 2:797–816

Kariminejad N, Pourghasemi HR, Hosseinalizadeh M (2022) Analytical techniques for mapping multi-hazard with geo-environmental modeling approaches and UAV images. Sci Rep 12(1):14946

Kazemi Garajeh M, Malaky F, Weng Q, Feizizadeha B, Blaschke T, Lakes T (2021) An automated deep learning convolutional neural network algorithm applied for soil salinity distribution mapping in Lake Urmia. Iran. Sci Total Environ 778:146253

Kazemi Garajeh M, Blaschke T, Haghi H, Weng V, Valizadeh Kamran Q, Li K, Z (2022a) A comparison between Sentinel-2 and Landsat 8 OLI Satellite images for soil salinity distribution mapping using a deep learning convolutional neural network. Can J Remote Sens 48(3):452–468

Kazemi Garajeh M, Weng Q, Hossein Haghi V, Li Z, Kazemi Garajeh A, Salmani B (2022b) Learning-based methods for detection and monitoring of shallow Flood-affected areas: impact of shallow-Flood spreading on Vegetation Density. Can J Remote Sens 48(4):481–503

Kazemi Garajeh M, Li Z, Hasanlu S et al (2022c) Developing an integrated approach based on geographic object-based image analysis and convolutional neural network for volcanic and glacial landforms mapping. Sci Rep 12:21396. https://doi.org/10.1038/s41598-022-26026-z

Kazemi Garajeh M, Salmani B, Naghadehi Z (2023) An integrated approach of remote sensing and geospatial analysis for modeling and predicting the impacts of climate change on food security. Sci Rep 13:1057. https://doi.org/10.1038/s41598-023-28244-5
Kingma D, Ba J (2014) Adam: amethod for stochastic optimization. International Conference on Learning Representations
Kollias D, Zafeiriou S (2020) Exploiting multi-cnn features in cnn-rnn based dimensional emotion recognition on the omg in-the-wild dataset. IEEE Trans Affect Comput 12(3):595–606
Labbaf Khaneiki M, Al-Ghafri S, A (2022) The circle of water justice in the history of Iran. Water Secur. 16:100122
Lashkaripour GR, Ghafoori M, Barani R, H.R (2009) An investigation on the mechanism of earth-fissure and land subsidence in the western part of Kashmar plain. Geol Stud 1(1):95–111
Lashkaripour GR, Ghafoori M, Maddah MM (2014) An investigation on the mechanism of land subsidence in the Northwest of Mashhad city, NE Iran. J Biodivers Environ Sci (JBES) 5:321–327
Liu Z, Hay-Man Ng A, Wang H, Chen J, Du Z, Ge L (2023) Land subsidence modeling and assessment in the West Pearl River Delta from combined InSAR time series, land use and geological data. Int J Appl Earth Obs Geoinf 118:103228
Luqmanul Hakim W, Fulki Fadhillah M, Park S, Pradhan B, Won JS, Lee CW (2023) InSAR time-series analysis and susceptibility mapping for land subsidence in Semarang, Indonesia using convolutional neural network and support vector regression. Remote Sens Environ 287:113453
Madani K, Mahoozi S (2021) Iran's 'Water Bankruptcy' is a Warning for the Entire Middle East. https://dawnmena.org/irans-water-bankruptcy-is-a-warning-for-the-entire-middle-east
Mahmoudpour M, Khamehchiyan M, Nikudel MR, Ghassemi MR (2016) Numerical simulation and prediction of regional land subsidence caused by groundwater exploitation in the southwest plain of Tehran, Iran. Eng Geol 201:6–28
Marker BR (2013) Land subsidence. Encyclopedia of Earth Sciences Series
Michel D (2017) Iran's impending water crisis. Water, Security and US Foreign Policy, Routledge, pp 168–188
Minderhoud PSJ, Erkens G, Pham VH, Bui VT, Erban L, Kooi H, Stouthamer E (2017) Impacts of 25 years of groundwater extraction on subsidence in the Mekong delta, Vietnam. Environ Res Lett 12(6):064006
Mohammadifar A, Gholami H, Comino JR, Collins AL (2021) Assessment of the interpretability of data mining for the spatial modelling of water erosion using game theory. CATENA 200:105178
Mohammadifar A, Gholami H, Golzari S (2023) Stacking-and voting-based ensemble deep learning models (SEDL and VEDL) and active learning (AL) for mapping land subsidence. Environ Sci Pollut Res 30(10):26580–26595
Naghibi SA, Khodaei B, Hashemi H (2022) An integrated InSAR-machine learning approach for ground deformation rate modeling in arid areas. J Hydrol 608:127627
Najafi M, Jamali V, Schober R, Poor HV (2020) Physics-based modeling and scalable optimization of large intelligent reflecting surfaces. IEEE Trans Commun 69(4):2673–2691
Nasir JA, Khan OS, Varlamis I (2021) Fake news detection: a hybrid CNN-RNN based deep learning approach. Int J Inform Manage Data Insights 1(1):100007
Pu C, Xu Q, Zhao K, Chen W, Wang X, Li H, Liu J, Kou P (2022) Spatiotemporal evolution and surface response of land subsidence over a large-scale land creation area on the Chinese Loess Plateau. Int J Appl Earth Obs Geoinf 111:102835
Rahmati O, Falah F, Naghibi SA, Biggs T, Soltani M, Deo RC, Cerdà A, Mohammadi F, Bui DT (2019a) Land subsidence modelling using tree-based machine learning algorithms. Sci Total Environ 672:239–252
Rahmati O, Golkarian A, Biggs T, Keesstra S, Mohammadi F, Daliakopoulos IN (2019b) Land subsidence hazard modeling: machine learning to identify predictors and the role of human activities. J Environ Manage 236:466–480
Ravalico JK, Dandy GC, Maier HR (2010) Management option Rank Equivalence (MORE)–A new method of sensitivity analysis for decision-making. Environ Model Softw 25(2):171–181
Rezaee M, Mahdianpari M, Zhang Y, Salehi B (2018) Deep convolutional neural network for complex wetland classification using optical remote sensing imagery. IEEE J Sel Top App Earth Observ Rem Sens 11:3030–3039
Rezaei M, Mohammadifar A, Gholami H, Mina M, Riksen MJ, Ritsema C (2023) Mapping of the wind erodible fraction of soil by bidirectional gated recurrent unit (BiGRU) and bidirectional recurrent neural network (BiRNN) deep learning models. CATENA 223:106953
Sabzevar MS, Rezaei A, Khaleghi B (2021) Incremental adaptation strategies for agricultural water management under water scarcity condition in Northeast Iran. Reg Sustain 2(3):224–238
Scardapane S, Van Vaerenbergh S, Totaro S, Uncini A (2019) Kafnets: kernel-based non-parametric activation functions for neural networks. Neural Netw 110:19–32
Schumann HH, Poland JF (1970) Land subsidence, earth fissures and groundwater withdrawal in South-Central Arizona, U. S. A
Shiravi M, Sepehr A, Mosaedi A, Parvian N (2016) Desertification susceptibility in ecoregions of Khorasan-Razavi based on Life Cycle Assessment (LCA). Phys Geogr Res Q 48(2):305–320
Soltani N, Keshavarzi B, Moore F, Tavakol T, Lahijanzadeh AR, Jaafarzadeh N, Kermani M (2015) Ecological and human health hazards of heavy metals and polycyclic aromatic hydrocarbons (PAHs) in road dust of Isfahan metropolis. Iran. Sci Total Environ 505:712–723
Tangdamrongsub N, Han S, Jasinski MF, Šprlák M (2019) Quantifying water storage change and land subsidence induced by reservoir impoundment using GRACE, Landsat, and GPS data. Remote Sens Environ 233:111385
Teatini P, Ferronato M, Gambolati G, Gonella M (2006) Groundwater pumping and land subsidence in the Emilia-Romagna coastland, Italy: modeling the past occurrence and the future trend. Water Resour Res, 42(1)
Wang S, Quan D, Liang X, Ning M, Guo Y, Jiao L (2018) A deep learning framework for remote sensing image registration. ISPRS J Photogramm Remote Sens 145:148–164
Xu Y, Lu Z, Bürgmann R, Hensley S, Fielding E, Kim J (2023) P-band SAR for ground deformation surveying: Advantages and challenges. Remote Sens Environ 287:113474
Yang C, Lv S, Hou Z, Zhang Q, Li T, Zhao C (2022) Monitoring of land subsidence and ground fissure activity within the Su-Xi-Chang area based on time-series InSAR. Remote Sens 14:903. https://doi.org/10.3390/rs14040903
Zhang X, Chen F, Huang R (2018) A combination of RNN and CNN for attention-based relation classification. Procedia Comput Sci 131:911–917
Zhang J, Ke C, Shen X, Lin J, Wang R (2023) Monitoring land subsidence along the subways in Shanghai on the basis of time-series InSAR. Remote Sens 15(4):908
Zhao F, Gong W, Tang H, Pudasaini P, Ren S, Cheng T, Z (2023) An integrated approach for risk assessment of land subsidence in Xi'an, China using optical and radar satellite images. Eng Geol 314:106983
Zhu X, Ning Z, Cheng H, Zhang P, Sun R, Yang X, Liu H (2022) A novel calculation method of subsidence waterlogging spatial information based on remote sensing techniques and surface subsidence prediction. J Clean Prod 335:130366