Spatial prediction of shallow landslide: application of novel rotational forest-based reduced error pruning tree

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ABSTRACT
Landslides are a form of soil erosion threatening the sustainability of some areas of the world. There is, therefore, a need to investigate landslide rates and behaviour. In this research, we introduced a novel hybrid artificial intelligence approach of rotation forest (RF) as a meta classifier based on reduced error pruning tree (REPTree) as a base classifier called RF-REPTree, for landslide susceptibility mapping (LSM) in the Kalaleh watershed, Golestan Province, Iran. Some benchmark models, including the open-source Java decision tree (J48), naive Bayes tree (NBTree), and REPTree were used to compare the designed model. A total of 249 landslide locations were identified and mapped. The group was split into training (70%) and testing (30%) data for modelling and reliability analysis. Based on a literature review and multi-colinearity tests, 16 landslide conditioning factors (LCFs) were selected. Of the LCFs, the topographical position index (TPI) had the highest correlation with landslide occurrence. The LSM produced by RF-REPTree revealed that nearly 29% of the study areas have high to very high landslide susceptibility (LS). Statistical analysis of the model results included the receiver operating characteristic curve (ROC), the efficiency test, the true skill statistic (TSS), and the kappa index. ROC demonstrated that the AUC values of RF-REPTree, REPTree, J48, and NBTree models were 0.832, 0.700, 0.695, and 0.759 for succession rate curves and 0.794, 0.740, 0.788, and 0.728 for prediction rate curves, respectively. Therefore,

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all models were judged to be acceptably accurate for LSM. Among the LS models, the RF-REPTree model achieved the highest accuracy, followed by REPTree, J48, and NBTree. The results of LSM can be used to target the mitigation of landslide hazards and provide a foundation for sustainable environmental planning.

1. Introduction

Soil erosion is a global problem challenging sustainability (Bayat et al. 2019; Jiang et al. 2019; Lu et al. 2019b; Salesa et al. 2019; Guadie et al. 2020). Erosion caused by landslides affects watersheds at the landslide and sediment deposition (Chalise et al. 2019). Landslides, a form of soil erosion, affect sustainable development and land deterioration (Keesstra et al. 2018; Visser et al. 2019). Landslides can have high economic costs (Rangsiwanichpong et al. 2019) and are hazards to people (Gao and Sang 2017; Nachappa et al. 2020). They degrade land quality through erosion and sedimentation (Piacentini et al. 2018). They are found in most regions of the world (Gariano and Guzzetti 2016). Landslides influence the stream flows, which cause flooding and disturb the normal rhythms of stream (Keesstra et al. 2018a, 2019). Failing slopes can be activated by earthquakes (Roback et al. 2018), but precipitation tends to be the main factor triggering landslides (Sidle and Bogaard 2016). Their probability of occurrence is also tied to vegetation cover (Guo et al. 2020). Landslide research has been the foci of both basic (Whiteley et al. 2019) and applied sciences (Piciullo et al. 2018).

Iran’s mountains face significant landslide problems due to its distinctive geographical setting, climatic and geomorphological instabilities, rapid population growth, increasing demands for resources, and inadequate environmental management (Aghda et al. 2018). Gallicash watershed, in the Golestan Mountains of northern Iran, experiences landslide disasters every year (Arabameri et al. 2019c, 2020d). Landslides damage transportation infrastructure, communication lines, urban settlements, industries, and natural resources and stunt economic growth in this region (National Geosciences Database 2017). Every year in Iran, landslides destroy property worth 500 billion rials (approximately US$12 million in 2020) (National Committee on Natural Disaster Reduction of the Iranian Ministry of the Interior). Landslides are a significant concern in this country as they affect development throughout Iran.

Reports of landslides in this region have been recorded in the National Geosciences Database (2017). In terms of physiography, more than half of Iran’s land cover is either desert or semi-desert, one-third is covered by mountains terr, and the rest is alluvial plain (i.e. the Caspian and Khuzestan plains) (Haftlang and Lang 2003). Meteorologically, northern Iran receives an average of 2113 mm more precipitation than do the semi-arid and arid regions to the south. This dramatically increases the landslide problem in this region (Arabameri et al. 2019c). The management of landslides is essential for the safe and sustained economic and infrastructure development of this region. Landslide susceptibility mapping (LSM) is a rudimentary tool that can help design the framework for natural resource management and land use planning. The LSM tool has been deployed in many regions of the world for sustainable development (Hong et al. 2018). Delineation of landslide-susceptible areas
with a predictive model is critical for reducing losses of properties and lives (Gudiyangada Nachappa et al. 2019; Tavakkoli Pirililou et al. 2019). Different researchers have used LSM for sustainable planning and conservation strategies for specific purposes (Chen et al. 2018).

Landslide occurrence is influenced by topographical, climatological, lithological, and morphometric factors. Human activities like road construction, expansion of settlement, and land-use changes are aggravating the natural factors that generate landslides (Ahlmer et al. 2018). Researchers have used several topographical factors (i.e. altitude, slope, aspect, convergence index (CI), plan and profile curvature, stream power index (SPI), and topographic position index (TPI)), hydrological factors (i.e. drainage density (Dd), distance to stream, topographic wetness index (TWI)), and environmental factors (i.e. land use/land cover (LU/LC), normalized difference vegetation index (NDVI), distance to road, soil, and lithology) to create LSMs. Researchers reported that multi-collinearity tests were usually used to select the factors to include in modelling. Information gain ratio and relief-F tests have also been used to assess LS modelling (Chen et al. 2018; Hong et al. 2018; Roy et al. 2019). Nsengiyumva et al. (2018) stated that the most suitable LSCs produce accurate and meaningful predictive LS models that can provide information to decision makers and planners who can safely and sustainably use, develop, and manage natural resources, soils, roads, and urban infrastructure.

With increase in remote sensing and geography information system techniques (Zuo et al. 2015, 2017; Jiang et al. 2018; Zhou et al. 2020; Zhao et al., 2020; Yu et al., 2020), qualitative and quantitative methods can be used to evaluate LS (Ayalew and Yamagishi 2005). Qualitative methods require two data types (Xu et al. 2019; Wang et al. 2020; Zhang et al. 2020; Yu et al. 2021; Hu et al. 2021): a landslides inventory and heuristic datasets (Aleotti and Chowdhury 1999). The landslide inventory map (LIM) is the primary survey of landslides. Identifying landslide locations can be done through a field investigation, a perception survey of the local population, aerial photographs, high-resolution satellite images, or Google Earth images. Landslide inventory datasets are typically divided into two randomly selected sets at a 70:30 ratio for training and validation of LS modelling (Chen et al. 2018; Hong et al. 2018; Arabameri et al. 2019c, 2020d; Roy and Saha 2019a, 2019b). Therefore, the landslide inventory is used as the dependent variable in models. Some researchers used different approaches to model LS. Wu et al. (2016), Arabameri et al. (2019b), and Saha et al. (2019) used the analytical hierarchical process (AHP) as the expert knowledge-based and multi-criteria decision-making approach to analyze LS. Arabameri et al. (2019a, 2019b, 2019d), Roy and Saha (2019a), Regmi et al. (2014), Ciurleo et al. (2016), Abedini and Tulabi (2018), Chen et al. (2018), Hemasinghe et al. (2018), Ahmed and Dewan (2017), and Zhu et al. (2014) applied several multivariate statistical techniques: frequency ratio (FR), fuzzy logic (FL), weight-of-evidence (WoE), evidential belief function (EBF), statistical index (SI), landslide nominal risk factor (LNRF), certainty factor (CF), information value (IV), logistic regression (LR), and Dempster–Shafer (DS) models. More recently, machine-learning (ML) ensemble models have been used to map natural hazards. The ML models such as random forest (RAF), boosted regression tree (BRT), artificial neural network (ANN), multivariate
adaptive regression spline (MARS), J48 decision tree (JDT), least squares support vector machines (LSSVM), linear discriminant analysis (ADA), decision tree (DT), adaptive neuro-fuzz inference system (ANFIS), k-nearest neighbour (KNN), logistic model tree (LMT), alternate decision tree (ADTree), Bayesian logistic regression (BLR), support vector machine (SVM), convolutional neural network (CNN), and recurrent neural network (RNN) were used in LSM studies by Youssef et al. (2016), Zhou et al. (2018), Chen et al. (2018), Ghorbanzadeh et al. (2019, 2021) Ngo et al. (2021), and Arabameri et al. (2019a, 2019b, 2019c, 2019d, 2020a, 2020b, 2020c, 2020d). ML models are superior to statistical methods as they are more accurate, have no overfitting problems, and can analyze both continuous and categorical data simultaneously.

Without validation, ML models are meaningless (Xu and Chen 2013; Zhao et al. 2014; Li et al. 2018; Zhao et al. 2019; Chen et al. 2020; Tu et al. 2021; Shan et al. 2021). Several statistical techniques can be used to validate LSMs: the receiver operating characteristics (ROC) curve, seed cell area index (SCAI), quality sum index (Qs), root mean square error (RMSE), and mean absolute error (MAE) (Hong et al. 2018; Chen et al. 2019; Roy et al. 2019; Roy and Saha 2019b). ROC can measure any model’s accuracy (Hong et al. 2018; Arabameri et al. 2019c, 2020d; Chen et al. 2019).

While these provide a higher level of precision than conventional and individual machine learning models, hybrid models and ensemble methods are interested in mapping susceptibility to landslide (Hong et al. 2019; Moayedi et al. 2019; Chen et al. 2020; Mehrabi et al. 2020). Combining two or more methods will correct flaws in a single approach, improve results, and increase the model’s predictive capability (Yang et al. 2014; Moosavi and Niazi 2016). To resolve the previous statement, and in light of the findings of machine learning models for landslide modelling published in the literature, the reduced error pruning tree (REPTree) and rotational forest (RF) and their ensembles were used to model landslide susceptibility in our study field. Until now, the REPTree and RF ensemble have not been used to determine landslide susceptibility. The method aims to increase the efficiency of any given learning algorithm by fitting a collection of low-error models and then combining them into an ensemble that can yield superior results (Shin et al. 2012).

In this study, tree-based ML techniques – the open-source Java DT (J48), naive Bayes tree (NBTree), and reduced error pruning tree (REPTree), and a novel ensemble rotational forest-based REPTree (RF-REPTree) – were used to model LS. Pham et al. (2019) used REPTree and its ensemble techniques such as bagging-based REPTree, multiboost-based REPTree, rotation forest-based REPTree, random subspace-based REPTree for LS assessment and prediction. Hong et al. (2019) used J48 and its ensemble with adaboost, bagging, and rotational forest models. All studies provided insightful results. Following Hong et al. (2019), this study introduced a novel hybrid artificial intelligence approach of rotation forest (RF) as a meta classifier based on reduced error pruning tree (REPTree). This study’s goals were to predict LS and determine the ML model that is best able to achieve this goal in the Kalaleh catchment, Iran.

2. Study area

The Kalaleh River watershed, a part of the Gorganroud watershed, occupies an area of approximately 5368 km² located between 37°07’ and 37°43’ N and 54°58’ and
The watershed is in northern Iran and drains into the Caspian Sea (Figure 1). The highest elevations in the basin are 2870 m above sea level (a.s.l.), and the lowest is 13 m a.s.l. Though Iran is generally known to be arid and semi-arid, the Kalaleh basin climate is semi-arid in the east and humid in the west. Temperatures range annually from 11 to 18.1°C and the average annual precipitation varies from 195 to 946 mm (IRIMO 2012). About 36% of precipitation falls from January through to March. The basin’s topography is a complex array of mountains, hills, plateaus and upper terraces, Piedmont plains, alluvial plains, and lowlands. Sedimentary rocks – including calcareous, sandstone, shale, dolomite, and marl – are found throughout the region, and the surface is also covered with conglomerates, loess sediments, and alluvium (GSI 1997).

The soils of the watershed are Entisols (25.6%), Alfisols (25.1%), Inceptisols (19.7%), and Mollisols (29.3%). Forests (25.88%), irrigated lands (10.44%), orchards (0.01%), dry-farming (47.1%), water bodies (0.69%), mixed agriculture and orchards (14.7%), surface rock (0.08%), and urban (0.98%) are the land use/land covers. The Kalaleh watershed contains the population centre of Golestan Province. It housing nearly 1.2 million residents. The basin maintains an agriculture-based economy (46% of the population works in agriculture), with manufacturing and mining accounting for a smaller part of the economy (20% of the population). The region also contains many wildlife habitats. Rivers flow from west to east in the watershed. They include
the Qazanabad, Taghi Abad, Mohammad Abad, Kaboodvall, Ramayan, Gharehay, Narmab, Goli Tape, Gallicash, Tangrah, and Ghary Navi rivers. They originate from the highlands in the south and northeast, passing through Gonbad and Gorgan’s plains, and converge in the Mazandaran Sea. The most prominent formations in the region are the Caspian Sea and faults in the northern part of Alborz. These faults are northeast/southwest to northeast/southeast (Shahpasandzadeh 2004). In recent years, population growth on erodible soils has led to accelerated soil erosion and depletion (Lar Consulting Engineering 2007). Subsequently, the Kalaleh River basin suffers high soil erosion, flash flooding, landslides, and high sediment yields (Saadat et al. 2008).

3. Materials and methods

Various types of data were acquired from several sources (Yang et al. 2015). The data were primary and secondary (Yang and Sowmya 2015). The primary data included a field survey of landslides with handheld GPS and a perception survey of local communities to determine the frequency of landslides and the landslide locations. Secondary data included historical/archival reports, newspaper reports, topographical maps, lithological maps, soil maps, a DEM, and Landsat data. The historical data were collected from the Civil Defense and Engineering Department of Iran. An ALOS PALSAR DEM of high resolution (12.5 m × 12.5m) was downloaded from the Alaska Satellite Facility. The Landsat 8OLI/TIRS was downloaded from United States Geological Survey. The lithological map (scale 1: 50,000) was acquired from the Geological Department of Iran. The soil map (scale 1:50,000) was attained from the Land Use Department of Iran. The topographical map (scale1:500,000) was collected from the Topographical Department of Iran. Historical rainfall records from rain gauges in the catchment were acquired from the Meteorological Department of Iran’s Islamic Republic (IRIMD). The ALOS PALSAR DEM was selected as the base map, and the other factors, at lower resolutions, were compiled within it to prepare LSMs of the study area (Figure 2). The essential components of the methodology are:

1. Data were collected from numerous sources, the LIM was prepared, and LCFs were compiled.
2. Multi-collinearity analysis using the tolerance (TOL) and variance inflation factor (VIF) was conducted to select the factors suitable for LS analysis.
3. LSMs were prepared using J48, NBTree, REPTree, and RF-REFTree models.
4. The LS models were validated with AUROC, TSS, efficiency, and the kappa index.

3.1. Preparation of LIM

The landslides and LCFs are the essential elements of LS mapping (Ercanoglu and Gokceoglu 2004). The primary and secondary data, historical landslide records (ILWP 2007; FRWO 2013) and aerial photos (scale 1:20,000 and 1:40,000), were used to generate a LIM. An extensive field investigation with handheld GPS was conducted to verify the LIM. A total of 249 landslides were found and verified. Based on the
previous literature, 70% of the landslide inventory data were randomly assigned to a group for training purposes, and the remaining 30% were used for testing (Figure 1).

Same number of non-landslide points was randomly selected for running the models. The landslides in the study area are predominantly translational slides, rotational slides, and debris flows (Figure 3): 87 (34.93%) translational slides, 75 (30.12%) soil creeps, 47 (19.87%) rotational slides, 27 (10.84%) earth flows, and 13 (5.22%) debris flows. An estimated total area of 16,213,651 m² was covered by landslides. The smallest landslide was 191.76 m² and the largest was 1,254,925 m². The average size was 562,782 m².
3.2. Multi-collinearity analysis of influential factors

A multi-collinearity check is vital for choosing LSM parameters, as a linear association between the parameters will reduce a model's predictive accuracy (Chen et al. 2017). The TOI and VIF are essential methods in multi-collinearity analysis. The threshold limits of TOI and VIF are $\geq 0.10$ and $\leq 10$ (Chen et al. 2017; Arabameri et al. 2019c; Roy et al. 2019). If the landslide conditioning factors maintain the threshold limits of TOI and VIF, they are appropriate for use in LSM (Chen et al. 2017). These techniques, TOI, and VIF, were used (in SPSS software) to analyze the multi-collinearity among the landslide conditioning factors in Kalaleh watershed following Chen et al. (2017), Arabameri et al. (2019a, 2019b), Roy and Saha (2019b), and Roy et al. (2019). The LCFs selected include elevation, slope, plan curvature.

Figure 3. Some photographs of landslides in the study area.
(PC), CI, topographic positioning index (TPI), topographic ruggedness index (TRI), topographic wetness index (TWI), distances to stream, road, and faults, lithology, soil types, LU/LC, and NDVI.

### 3.3. Generation of effective factors

Eight topographical (elevation, slope, PC, TRI, TPI, TWI, slope length, and CI), two hydrological (rainfall, distance to stream), two lithological (geology, distance to fault), and four environmental (LU/LC, NDVI, soil type, distance to road) factors were used in the LS analysis (Chen et al. 2017; Arabameri et al. 2019a, 2019b, 2019c, 2019d, 2020a, 2020b, 2020c, 2020d; Rahamati et al. 2019). To assess LS by the soft computing techniques as direct methods, inclusion of suitable LCFs is necessary to run the process. The incorporation of several effective variables can increase the models’ prediction capabilities and performances. Lithology, slope, and aspect are vital LCFs, and they are extensively used for the analysis of LSM. Chen et al. (2017, 2019) and Hong et al. (2018) produced LSMs using several factors that included topographical, hydrological, lithological, and environmental factors. The ALOS PALSAR DEM was used as the elevation map of the study area (Figure 4(a)). The high-resolution PALSAR DEM provided more accurate results than the ASTER and SRTM DEMs (Arabameri et al. 2019c). Elevation effect on rainfall and vegetation (Feng et al. 2020). The higher elevations and hills are more susceptible to landslides than lower elevations (Roy et al. 2019; Roy and Saha 2019b). Landslides are controlled by the slope (Nefeslioglu et al. 2008). The slope map (Figure 4(b)) was produced using ALOS PALSAR DEM and the spatial analyst tool in ArcGIS. The slope of the study area ranges from 0 to 73 degrees (Figure 4(b)). The PC, CI, TWI, TRI, SPI, and slope-length (Figure 4(c–g)) maps were derived from ALOS PALSAR DEM using SAGA GIS. Maps showing distances to stream, roads, and faults (Figure 4(i–k)) were prepared in GIS using the Euclidian distance buffering tool. Climate change accelerates hydrological cycles, alters the magnitude and timing of streamflow, and threatens the water resources and environmental sustainability of basins (Lu et al. 2019a; Tian et al. 2020). The precipitation map (Figure 4(l)) was created from the station data using the kriging interpolation method. The lithological map (Figure 4(m)) was digitized and described briefly (Table 1). Human activities can affect the natural environment (Feng et al. 2020). The LU/LC (Figure 4(n)) map was derived from Landsat 8 OLI/TIRS imagery using the maximum likelihood classification method. The land-use types found in the region were forest (A), agriculture (B), orchard (C), fry-farming (D), water (E), agri-orchard (F), rock (G), and urban (H) land uses. The soil map (Figure 4(o)) was digitized, and four soil orders were found: Alfisols, Inceptisols, Mollisols, and Entisols. The NDVI was derived from Landsat 8 OLI/TIRS imagery using the NDVI method (Figure 4(p)).

### 3.4. Methods

Three ML models and one ensemble framework model (J48, REPTree, NBTree, and RF-REPTree) were used to model LS.
J48 is a decision-tree algorithm capable of detecting changes of vector attributes for any number of instances (Kaur and Chhabra 2014). Using tree classification, the algorithm produces rules for target-variable prediction; data distribution can also be

Figure 4. Landslide conditioning factors: (a) elevation, (b) slope, (c) plan curvature (PC), (d) convergence index (CI), (e) topographical wetness index (TWI), (f) topographical positioning index (TPI), (g) stream power index (SPI), (h) slope length (LS), (i) distance to stream, (j) distance to road, (k) distance to fault, (l) rainfall, (m) lithology, (n) land use/land cover, (o) soil, and (p) normalized differential vegetation index (NDVI).

3.4.1. J48

J48 is a decision-tree algorithm capable of detecting changes of vector attributes for any number of instances (Kaur and Chhabra 2014). Using tree classification, the algorithm produces rules for target-variable prediction; data distribution can also be
conceptualized clearly (Kaur and Chhabra 2014). J48 has more capacity to count missing values, setting rules, and tree pruning. It can provide more accurate results from data mining. The J48 model uses the C4.5 algorithm to create a very well-organized DT by statistical classification (Witten 2011). Using information gain and entropy equations from any data with class levels can select any attribute (Bashir and Chachoo 2017).

### 3.4.2. REPTree

The REPTree, generated by combining reduced-error pruning (REP) with a DT, is a fast decision-tree learning process that employs splits and prunes (Quinlan 1987). In this approach, the DT uses the training dataset to model; when the DT’s performance is high, the REP minimizes tree structure complexity (Mohamed et al. 2012). The pruning method accounts for backward overfitting problems (Quinlan 1987; Yu et al. 2020). The REPT algorithm finds the optimal form of the most precise sub-tree,

| Group | Unit | Description | Formation |
|-------|------|-------------|-----------|
| A     | Cm   | Dark grey to black fossiliferous limestone with subordinate black shale | MOBARAK |
|       | Dp   | light red to white, thick bedded quartzarenite with dolomite intercalations and gypsum | PADEHA |
|       | DCkh | Yellowish, thin to thick – bedded, fossiliferous argillaceous limestone, dark grey limestone, greenish marl and shale, locally including gypsum | – |
| C     | E1c  | Pale-red, polygenic conglomerate and sandstone | – |
|       | E1m  | Marl, gypsiferous marl and limestone | – |
| D     | Jsc  | Conglomerate | – |
|       | Jd   | Well – bedded to thin – bedded, greenish – grey argillaceous limestone with intercalations of calcareous shale | DALICHAI |
| E     | Jl   | Light grey, thin – bedded to massive limestone | LAR |
|       | Jmz  | Grey thick – bedded limestone and dolomite | MOZDURAN |
|       | Jch  | Dark grey argillaceous limestone and marl | CHAMAN BID |
|       | Kat  | Olive green glauconitic sandstone and shale |AITAMIR |
|       | Ksn  | Grey to block shal and thin layers of siltstone and sandstone | SANGANEH |
|       | Ksr  | Ammonite bearing shale with intercation of orbitolin limestone | SARCHESHEM |
|       | Ku   | Upper cretaceous, undifferentiated rocks | – |
|       | Kad-ab | Undifferentiated unit including argillaceous limestone, marl and shale | – |
| F     | Pz   | Undifferentiated lower Paleozoic rocks | – |
|       | Pz1av| Andesitic volcanic | – |
|       | pC-C | Late proterozoic – early Cambrian undifferentiated rocks | – |
|       | Pr   | Dark grey medium – bedded to massive limestone | – |
|       | Pz1a.bv | Andesitic basaltic volcanic | – |
|       | Pd   | Red sandstone and shale with subordinate sandy limestone | DORUD |
|       | Plc  | Polymeric conglomerate and sandstone | – |
|       | P    | Undifferentiated Permian rocks | – |
| G     | Qsw  | Swamp | – |
|       | Qft2 | Low level piedmont fan and valley terrace deposits | – |
|       | Qm   | Swamp and marsh | – |
|       | Qft1 | High level piedmont fan and valley terrace deposits | – |
|       | Qs,d | Unconsolidated wind blown sand deposit including sand dunes | – |
|       | Qal  | Stream channel, braided channel and flood plain deposits | – |
| H     | TRe  | Thick bedded grey o’olitic limestone ; thin – platy, yellow to pinkish shaly limestone with worm tracks and well to thick bedded dolomite and dolomitic limestone | ELIKAH |
|       | TRJs | Dark grey shale and sandstone | SHEMSHAK |
depending on the post-pruning approach (Esposito et al. 1999). This model’s efficiency is based on information gain from entropy or reduction of variance and reduced errors of techniques for pruning (Srinivasan and Mekala 2014).

3.4.3. NBTree

The naïve Bayes tree (NBTree) classifier is a novel ML technique and a DT (Kohavi 1996). The naïve Bayes emerge from pattern detection, commonly used in data mining and ML searches for classification problems due to its simplicity and linear run time (Farid et al. 2014). The NBTree algorithm, a basic probabilistic method, can estimate class membership probability (Farid et al. 2014). Naïve Bayes classifier trees can be used to evaluate and pick the class that maximizes the subsequent class’s likelihood. The NBTree classification procedure is as follows:

\[
\begin{align*}
    c^* &= \text{arg max}_{c_j \in C} p(c_j) \prod_{i=1}^{m} p(a_i | c_j) \\
    &= \mu \text{arg max}_{c_j \in C} \prod_{i=1}^{m} p(a_i | c_j)
\end{align*}
\]

where \( c \) is a class, and \( k \) is the number of classes. NB’s biggest drawback is a strong assumption that an attribute is unique; this is what makes it so simple. However, an NBTree was proposed to strengthen naïve Bayes’ presumption of attribute independence (Wang et al. 2015). This model uses a DT for its basic structure and sets a naïve Bayes classifier on each leaf node of the developed DT; the NBTree shows impressive classification precision (Wang et al. 2015). While, during the development of an NBTree, a metric of recognition precision is used, rather than measuring the information gained. An NBTree filters the information from the root node to a given leaf node down the tree and then uses the training cases that fall into that leaf node to build a naïve Bayes classifier that identifies a landslide occurrence (Wang et al. 2015). An NBTree also exceeds DT or naïve Bayes models individually regarding classification accuracy and AUC (Kohavi 1996).

3.4.4. Rotational forest

Rotational forest (RF) is a hybrid ensemble method consists of individual decision trees and categories (Rodriguez et al. 2006; Rodriguez 2007). A tree with a specific dataset in association with a rotated feature space must be arranged in RF. RF utilizes principal component analysis (Wold et al. 1987) to derive the learning sets’ characteristics and produce training sets for running the base classifiers.

For this analysis, \( S = (s_1, s_2, \ldots, s_n) \) are the LCFs. \( Y = (y_1, y_2) \) are the variable dependency categories, i.e. landslide and non-landslide. Training data are represented by \( D \). \( T \) represents LCFs data set. \( T \) is grouped into different \( k \) sub-classes. \( E_{ij} \) shows LCFs in \( T_{ij} \) from \( E \). \( E'_{ij} \) is chosen randomly by the bootstrap method from \( E_{ij} \). To have the constants of \( r_{1j}^{(1)}, r_{1j}^{(2)}, \ldots, r_{1j}^{(T_1)} \), where the \( r'_{ij} \) size is \( T \times 1 \), \( E'_{ij} \) have to be calculated over. Ensemble RF is then produced concerning the rotation matrix via the primary categorization and conversion method (Xia et al. 2014). \( R_i \) is the rotation matrix acquired through the Ri matrix’s reorganization that can be described in Equation (8).
In fact, the obtained coefficients, which are built for each individual class by the average combination technique, order a sparse rotation matrix as in Equation (3), called $R_i$.

$$\xi_k(\varepsilon) = \frac{1}{n} \sum_{i=1}^{n} \alpha_{i,k}(x_{R_i}), \ k = 1, 2, \ldots, C,$$

(3)

where $\alpha_{i,k}(x_{R_i})$ demonstrates the produced probability of $C_i$ classifier in which the $k$ class is enabled by $\varepsilon$. Finally, $\varepsilon$ is because of the greatest confidence group.

### 3.4.5. Random forest

Breiman (2001) introduced random forest, an important method of ML. It was used to calculate regression, grouping, clustering, and interaction. A single DT may provide high variance and bias for classification. The RAF can solve the bias and minimize the error using an ensemble tree (Taalab et al. 2018; Chen et al. 2021). To form a forest, RAF creates thousands of binary trees. Based on a bootstrap model, each tree is grown using the classification and regression trees (CART) technique with a random subset of variables chosen at each node. The out-of-bag (OOB) error rate is calculated using results left out of the bootstrap sample. Finally, the majority vote among all trees will have been produced, the model is constructed, and class memberships are decided (Micheletti 2014). Therefore, two forms of error occurred: the mean decreases in accuracy and the mean decreases in Gini coefficients. Such tests are commonly used to rate and choose variables. To reduce the OOB error and improve model performance (Taalab et al. 2018), the user should optimize two a priori parameters to run the RAF model: the number of trees in the forest (ntree), and the number of variables tested at each node (mtry).

### 3.5. Model evaluation and assessment techniques

#### 3.5.1. ROC curve

ROC curves have been used for many purposes. Saha (2017), Hembram and Saha (2020), Hembram et al. (2019a, 2019b), Roy and Saha (2019a, 2019b), Dao et al. (2020), Bui et al. (2019), Paul et al. (2019), Xi et al. (2019), Arabameri et al. (2019c), Roy et al. (2019), Chen et al. (2021), Chen and Chen (2021) used ROC curves for mapping gully erosion, landslides, land subsidence, and groundwater potential. Using training and validation datasets, the LSMs were evaluated with different methods, including true skill statistic (TSS), efficiency (Equation (6)), and AUROC, and also these techniques (Arabameri et al. 2019c; Rahamati et al. 2019). These techniques were commonly used to compare and assess data miming models (Allouche et al.
2006; Xia et al. 2017; Chen et al. 2016; Wang et al. 2017; Hu et al. 2015). True-positive (TP) and true-negative (TN) are the numbers of pixels classified correctly, while false-positive (FP) and false-negative (FN) are the numbers of pixels classified incorrectly (Zhang et al. 2021). The probability value of 0.5 is the threshold (Ahmadlou et al. 2018). If a model has a probability of >0.5, then it is considered helpful for landslide assessments. If the value is <0.5, then it is deemed useless for assessments. This threshold has been used in land-subsidence modelling (Frattini et al. 2010). TSS (Equation (7)) was determined by varying sensitivity (TP, Equation (4)) and specificity (Equation (5)). Data-specific prevalence or data set sizes do not affect TSS (Allouche et al. 2006). The AUROC measures a predictor’s efficiency by measuring the area under the sensitivity curve against the specificity (1 – specificity) at various false positive (FB) cut-off thresholds ranging from 0 to 1. The AUROC values were categorized into five groups: poor accuracy (AUROC ≤ 0.6), average accuracy (AUROC = 0.6–0.7), good accuracy (AUROC = 0.7–0.8), excellent accuracy (AUROC = 0.8–0.9), and excellent accuracy (AUROC = 0.9–1) (Fressard et al. 2014).

\[
TPR = \frac{TP}{TP + FN} \quad (4)
\]

\[
FPR = \frac{TN}{FP + TN} \quad (5)
\]

\[
Efficiency = \frac{TP + TN}{TP + TN + FP + FN} \quad (6)
\]

where TPR means the true-positive rate and FPR means false-positive rate, and

\[
TSS = TPR + FPR - 1 \quad (7)
\]

3.5.2. Cohen’s kappa index

Cohen’s kappa index was used to validate the LSMs developed by the J48, REPTree, NBTree, and RF-REPTree approaches. Cohen’s kappa coefficient is a statistical measure of qualitative items. It measures inter-rater agreement. The kappa index is believed to be a more effective measurement than simple calculations of agreement. The kappa index relies on measurements of the agreement found (P_{obs}) in the maps and also that the prediction was by chance (P_{exp}) (Cohen 1960; Guzzetti 2006):

\[
k = \frac{P_{obs} - P_{exp}}{1 - P_{exp}} \quad (8)
\]

where \(P_{obs}\) and \(P_{exp}\) can be calculated with:

\[
P_{obs} = \frac{TP + TN}{N} \quad (9)
\]

\[
P_{exp} = \frac{(TP + FN)(TP + FP) + (FP + TN)(FN + TN)}{N^2} \quad (10)
\]
where \( N \) refers to the number of pixels in a map. Variable \( k \) ranges from \(-1\) to \(+1\); values when near 1 indicate perfect agreement. The kappa index can be used to assess the precision, efficacy, and reliability of landslide models (Hoehler 2000). The kappa index’s accuracy value was graded into six (mostly) proportionately stratified categories: excellent (0.81–1.0), very good (0.61–0.80), good (0.41–0.60), moderate (0.21–0.40), poor (>0–0.2), and very weak (0) (Landis and Koch 1977).

4. Results

### 4.1. Multi-collinearity assessment

Based on TOI and VIF statistics analysis, the 16 landslide conditioning factors had no multi-collinearity problems (Table 2). Therefore, all factors were used as potential predictive factors to discern LS.

### 4.2. Effective factor assessment by RAF

Analysis of the contributions of LEFs using suitable techniques is essential in any kind of spatial modelling of natural processes for management (Chen et al. 2017; Rahamati et al. 2019; Roy and Saha 2019b; Roy et al. 2019; Arabameri et al. 2020d). LEF weights were calculated by the RAF model (Table 3). The results revealed that

| Factors                          | Collinearity statistics | Factors                          | Collinearity statistics |
|----------------------------------|-------------------------|----------------------------------|-------------------------|
|                                  | Tolerance | VIF       |                                  | Tolerance | VIF       |
| Elevation                        | 0.628     | 1.592     | Plan curvature                   | 0.800     | 1.249     |
| Soil type                        | 0.711     | 1.407     | Convergence index                | 0.593     | 1.687     |
| Topographical position index     | 0.955     | 1.048     | Slope                            | 0.324     | 3.085     |
| Distance to stream               | 0.785     | 1.274     | Rainfall                         | 0.392     | 2.552     |
| Stream power index               | 0.257     | 4.368     | Lithology                        | 0.883     | 1.132     |
| Distance to road                 | 0.824     | 1.214     | Land use                         | 0.766     | 1.306     |
| Topography wetness index         | 0.232     | 4.566     | NDVI                             | 0.410     | 2.437     |
| Distance to fault                | 0.667     | 1.498     | Stream length                    | 0.332     | 2.756     |

| Landslide conditioning factors   | Mean decrease Gini |
|----------------------------------|---------------------|
| TRI                              | 3.23                |
| LULC                             | 1.28                |
| Slope                            | 3.35                |
| Distance to fault                | 3.88                |
| Soil                             | 1.12                |
| NDVI                             | 3.31                |
| Distance to road                 | 4.62                |
| TWI                              | 3.01                |
| CI                               | 2.93                |
| SPI                              | 4.42                |
| Lithology                        | 2.78                |
| Plan curvature                   | 2.99                |
| Rainfall                         | 8.17                |
| Elevation                        | 5.80                |
| Distance to stream               | 7.72                |
| TPI                              | 21.09               |
TPI, with a relative importance of 21.09, is the most critical factor. It was followed by: precipitation (8.17), distance to stream (7.72), elevation (5.8), distance to the road (4.62), SPI (4.42), distance to fault (3.88), slope (3.35), NDVI (3.31), TRI (3.23), TWI (3.01), PC (2.99), CI (2.93), lithology (2.78), soil type (1.42), and LU/LC (1.28) was of the most minor importance (Figure 5).

4.3. Modelling landslide-susceptible areas

The LSMs were produced using training datasets and tree-based models (Figure 6). The performance of the LS models varied. The LS index value was determined for each pixel. Susceptibility was reclassified into classes using the natural break classification method in GIS (Irigaray et al. 2007) into five classes: very low, low, moderate, high, and very high. Approximately 23.62% of the study area in the J48 LSM (Figure 6(a)) was classified as having very high LS. The high LS area was 14.84%, the moderate was 32.55%, the low was 17.73%, and the very low was 11.27% (Figure 7 and Table 4). The NBTree LSM (Figure 6(b)) classification proportions were 18.46% very high, 35.56% high, 25.27% moderate, 10.09% low, and 10.63% very low. The very high LS class covers 18.30% of the REPTree LSM (Figure 6(a)). High LS covered 8.56%, moderate covered 10.81%, low covered 29.31%, and very low covered 33.02%. The RF-REPTree ensemble LSM classified 12.81% as very high LS, 17.36% high, 20.74% moderate, 24.72% low, and 24.34% very low.

4.4. Model evaluation and comparison

The LSMs were evaluated with the ROC curve, TSS, efficiency, and kappa index methods on the training and validation datasets (Figure 8). According to ROC, the highest reliability was achieved by the RF-REPTree (AUC values of 0.832 and 0.794 for the testing and validation datasets, respectively). The AUCs for testing and
validation of the REPTree were 0.700 and 0.740. For the J48 model, they were 0.695
and 0.788 and for the NBTree they were 0.759 and 0.728. The true positive rates for
RF-REPTree, REPTree, J48, and NBTree were 0.707, 0.667, 0.680, and 0.760 for the
training dataset, and 0.822, 0.753, 0.695, and 0.667 for the validation dataset, respect-
ively. The false-positive rates for the RF-REPTree, REPTree, NBTree, and J48 were
0.227, 0.213, 0.213, and 0.320 for the training data, and 0.259, 0.420, 0.293, and 0.270
for the validation data, respectively (Table 5). Efficiency values were calculated for all
four models. For the training data: J48 = 0.720, NBTree = 0.733, REPTree = 0.727,
and RF-REPTree = 0.740. And for the validation data: J48 = 0.698, NBTree = 0.701,
REPTree = 0.667, and RF-REPTree = 0.782. TSS values for the training data were J48 = 0.480, NBTree = 0.467, REPTree = 0.453, and RF-REPTree = 0.440. And they were J48 = 0.397, NBTree = 0.402, REPTree = 0.333, and RF-REPTree = 0.563 for the testing data. Finally, the kappa index showed that the accuracy was highest for the ensemble model (RF-REPTree) at 0.402. NBTree, REPTree, and J48 followed this.
All models had good to very good accuracy, but the ensemble model was the most accurate LS model.

**5. Discussion**

To reduce the detrimental impacts of landslides, delineating the areas of highest LS with accurate tools is essential. Research has been conducted comparing different LS modelling methods, but the advances in ML techniques for mapping extreme natural processes have increased their usefulness for hazard assessments. In our research, three tree functions and one novel ensemble (J48, REPtree, NBTree, and RF-REPTree) were used to identify the most landslide-prone areas. The models have indicated that the Kalaleh catchment is a very a landslide-prone watershed. The proportions of the basin that were classified as having very high LS were: 23.62% (J48), 18.46% (NBTree), 18.30% (REPTree), and 12.81% (RF-REPTree). The centre of the catchment was always classified as very high LS. Steep slopes, weak lithology, fragile soils, high precipitation, and poorly engineered and poorly constructed roads and infrastructure may contribute to the high LS in this area. The RAF model indicated that TPI, rainfall, distance to stream, elevation, SPI, distances to roads and faults, and TRI contributed substantially to LS.

All models were validated with ROC, efficiency, TSS, and the kappa index, and they demonstrated that all models are suitable for mapping LS, but the novel ensemble (RF-REPTree) was the best performer. The REPTree algorithm prevents backward overfitting and seeks the most reliable subtree with the least variation based on the post-pruning approach (Quinlan 1987; Esposito et al. 1999). Moreover, the RF classifier prevents noise and dramatically reduces classification errors (Breiman 2001). Sampling by bootstrap may reduce the sensitivity of a single classifier to noise in a data set, however, resulting in a corresponding reduction in classification variance. When two or more methods are combined, they may overcome individual approaches’ limitations, enhance efficiency, and increase the model’s prediction accuracy (Yang et al. 2014; Moosavi and Niazi 2016). In this study, new ensemble architectures were used, and the results were higher than in earlier studies (Dahal and Hasegawa 2008; Poudyal et al. 2010; Pandey et al. 2020). We also noticed that the two models’ ensemble (RF and REPTree) achieved better outputs than other machine learning approaches. In this study, RF-REPTree was found to have better predictive capability than the standalone models, similar to the results in Hong et al. (2018), and Chen

| Models | Validation dataset | Training dataset |
|--------|-------------------|-----------------|
|        | J48   | NBTree | REPTree | RF-REPTree | J48   | NBTree | REPTree | RF-REPTree |
| TN     | 51    | 59     | 59      | 58         | 127   | 123    | 101     | 129        |
| FP     | 24    | 16     | 16      | 17         | 47    | 51     | 73      | 45         |
| FN     | 18    | 24     | 25      | 22         | 58    | 53     | 43      | 31         |
| TP     | 57    | 51     | 50      | 53         | 116   | 121    | 131     | 143        |
| TPR    | 0.760 | 0.680  | 0.667   | 0.707      | 0.667 | 0.695  | 0.753    | 0.822      |
| TPR    | 0.320 | 0.213  | 0.213   | 0.227      | 0.270 | 0.293  | 0.420    | 0.259      |
| efficiency | 0.720 | 0.733  | 0.727   | 0.740      | 0.698 | 0.701  | 0.667    | 0.782      |
| TSS    | 0.440 | 0.467  | 0.453   | 0.480      | 0.397 | 0.402  | 0.333    | 0.563      |
| Kappa  | 0.379 | 0.395  | 0.387   | 0.402      | 0.384 | 0.584  | 0.592    | 0.670      |
et al. (2019). The RF-REPTree ensemble models’ performance is better than that of previous landslide ensemble models (Wu et al. 2020). Ensemble ML methods have been used to model other processes like gully erosion, groundwater, land subsidence, and others (Arabameri et al. 2019c; Rahamati et al. 2019; Roy and Saha 2019b; Roy et al. 2019). Their results also showed that ensemble models performed better than standalone models.

To tackle landslides, it is essential to delineate the area’s susceptibility to landslides and determine the main factors. A significant benefit of the ML algorithms used here is that they simplify finding the relevant data by investigating multiple databases. These algorithms can tackle specific purposes and can be used in conjunction with automated analysis of large datasets to aid decision-makers. The results could help reduce the risk of landslide in the Kalaleh River watershed and its surroundings having similar terrain and geology.

6. Conclusion

The ML models J48, NBTree, REPTree, and RF-REPTree successfully created LSMs for Kalaleh watershed, Iran. ROC curves and statistical techniques were used to evaluate and compare the LSMs carefully. The results indicate that the accuracies of all the models were either excellent or very good. The ensemble RF-REPTree model is the best predictive model, and it was followed in rank order by the J48, REPTree, and NBTree models. The ML ensemble is an efficient and accurate tool, overcoming errors and providing output results quite quickly. The outcome of the analysis of variable significance showed that the TPI is the most significant LCF. Rainfall and distance to stream were the second and third most important factors. Soil types and LU/LC were the least important factors. These results could help land resource managers cope with currently high levels of uncertainty surrounding landslides and help them understand the relationships between factors and landslides more profoundly. This study highlights the very high LS of the central portion of this catchment. Therefore, it is suggested that immediate, targeted management and planning for landslides is needed to prevent severe consequences in the Kalaleh River watershed. This modelling method could be used to guide future landslide vulnerability research, particularly for vulnerability tied to land-use change. ML ensemble simulation can improve model accuracy and decrease model uncertainty, reducing classification problems like overfitting. These models can be applied to other regions with similar geo-environmental characteristics as the Kalaleh River watershed.

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Data availability statement

The data that support the findings of this study are available on request from the authors.

Disclosure statement

No potential conflict of interest was reported by the author(s).

References

Abedini M, Tulabi S. 2018. Assessing LNRF, FR, and AHP models in landslide susceptibility mapping index: a comparative study of Nojian watershed in Lorestan province, Iran. Environ Earth Sci. 77:405.

Aghda SF, Bagheri V, Razifard M. 2018. Landslide susceptibility mapping using fuzzy logic system and its influences on mainlines in lashgarak region, Tehran, Iran. Geotech Geol Eng. 36(2):915–937.

Ahlmer AK, Cavalli M, Hansson K, Koutsouris AJ, Crema S, Kalantari Z. 2018. Soil moisture remote-sensing applications for identification of flood-prone areas along transport infrastructure. Environ Earth Sci. 77(14):533.

Ahmadlou M, Karimi M, Alizadeh S, Shizradi A, Parvinnejhad D, Shahabi H, Panahi M. 2019. Flood susceptibility assessment using integration of adaptive network- based fuzzy inference system (ANFIS) and biogeography-based optimization (BBO) and BAT algorithms (BA). Geocarto Int. 34(11):1252–1272.

Ahmed B, Dewan A. 2017. Application of bivariate and multivariate statistical techniques in landslide susceptibility modeling in Chittagong City Corporation, Bangladesh. Remote Sens. 9(4):304.

Aleotti P, Chowdhury R. 1999. Landslide hazard assessment: summary review and new perspectives. Bull Eng Geol Environ. 58(1):21–44.

Allouche O, Tsoar A, Kadmon R. 2006. Assessing the accuracy of species distribution models: prevalence, kappa, and the true skill statistic (TSS). J Appl Ecol. 43(6):1223–1232.

Arabameri A, Chen W, Blaschke T, Tiefenbacher JP, Pradhan B, Tien Bui D. 2020a. Gully head-cut distribution modeling using machine learning methods – a case study of NW Iran. Water. 12(1):16.

Arabameri A, Chen W, Lombardo L, Blaschke T, Tien Bui D. 2020b. Hybrid computational intelligence models for improvement gully erosion assessment. Remote Sens. 12(1):140.

Arabameri A, Lee S, Tiefenbacher JP, Ngo PTT. 2020c. Novel ensemble of MCDM-artificial intelligence techniques for groundwater-potential mapping in arid and semi-arid regions (Iran). Remote Sens. 12(3):490.

Arabameri A, Pradhan B, Lombardo L. 2019a. Comparative assessment using boosted regression trees, binary logistic regression, frequency ratio and numerical risk factor for gully erosion susceptibility modelling. CATENA. 183:104223.

Arabameri A, Pradhan B, Rezaei K, Conoscenti C. 2019b. Gully erosion susceptibility mapping using GIS-based multi-criteria decision analysis techniques. CATENA. 180:282–297.

Arabameri A, Pradhan B, Rezaei K, Sohrabi M, Kalantari Z. 2019c. GIS-based landslide susceptibility mapping using numerical risk factor bivariate model and its ensemble with linear multivariate regression and boosted regression tree algorithms. J Mt Sci. 16(3):595–618.

Arabameri A, Roy J, Saha S, Blaschke T, Ghorbanzadeh O, Tien Bui D. 2019d. application of probabilistic and machine learning models for groundwater potentiality mapping in Damghan Sedimentary Plain, Iran. Remote Sens. 11(24):3015.

Arabameri A, Saha S, Roy J, Chen W, Blaschke T, Tien Bui D. 2020d. Landslide susceptibility evaluation and management using different machine learning methods in the Gallicash River Watershed, Iran. Remote Sens. 12(3):475.
Ayalew L, Yamagishi H. 2005. The application of GIS-based logistic regression for landslide susceptibility mapping in the Kakuda–Yahiko Mountains, central Japan. Geomorphology. 65(1–2):15–31.

Bashir U, Chachoo M. 2017. Performance evaluation of j48 and bayes algorithms for intrusion detection system. Int J Netw Secur Appl. 9(4):01–11.

Bayat F, Monfared AB, Jahansooz MR, Esparza ET, Keshavarzi A, Morera AG, Fernández MP, Cerdà A. 2019. Analyzing long-term soil erosion in a ridge-shaped persimmon plantation in eastern Spain by means of ISUM measurements. CATENA. 183:104176.

Breiman L. 2001. Random forests. Mach Learn. 45(1):5–32.

Bui DT, Moayedi H, Kalantar B, Osouli A, Pradhan B, Nguyen H, Rashid ASA. 2019. A novel swarm intelligence – Harris hawks optimization for spatial assessment of landslide susceptibility. Sensors. 19:3590.

Chen X, Chen W. 2021. GIS-based landslide susceptibility assessment using optimized hybrid machine learning methods. CATENA. 196:104833.

Chalise D, Kumar L, Kristiansen P. 2019. Land degradation by soil erosion in Nepal: a review. Soil Syst. 3(1):12.

Chen Hao, Heidari A.A., Chen Huiling, Wang M., Pan Z., Gandomi A.H., 2020. Multi population differential evolution-assisted Harris hawks optimization: Framework and case studies. Future Gener Comput Syst 111, 175–198.

Chen H.-L, Wang G., Ma C., Cai Z.-N., Liu W.-B., & Wang S.-J. (2016). An efficient hybrid kernel extreme learning machine approach for early diagnosis of Parkinson’s disease. Neurocomputing, 184, 131–144.

Chen W, Chen X, Peng J, Panahi M, Lee S. 2021. Landslide susceptibility modeling based on ANFIS with teaching-learning-based optimization and Satin bowerbird optimizer. Geosci Front. 12(1):93–107.

Chen W, Chen Y, Tsangaratos P, Ilia I, Wang X. 2020. Combining evolutionary algorithms and machine learning models in landslide susceptibility assessments. Remote Sens. 12(23):3854.

Chen W, Hong H, Li S, Shahabi H, Wang Y, Wang X, Ahmad BB. 2019. Flood susceptibility modelling using novel hybrid approach of reduced-error pruning trees with bagging and random subspace ensembles. J Hydrol. 575:864–873.

Chen W, Panahi M, Pourghasemi HR. 2017. Performance evaluation of GIS-based new ensemble data mining techniques of adaptive neuro-fuzzy inference system (ANFIS) with genetic algorithm (GA), differential evolution (DE), and particle swarm optimization (PSO) for landslide spatial modelling. CATENA. 157:310–324.

Chen W, Xie X, Peng J, Shahabi H, Hong H, Bui DT, Duan Z, Li S, Zhu AX. 2018. GIS-based landslide susceptibility evaluation using a novel hybrid integration approach of bivariate statistical based random forest method. CATENA. 164:135–149.

Chen Y, Zheng W, Li W, Huang Y. 2021. Large group activity security risk assessment and risk early warning based on random forest algorithm. Pattern Recogn Lett. 144:1–5.

Ciurleo M, Calvello M, Cascini L. 2016. Susceptibility zoning of shallow landslides in fine grained soils by statistical methods. CATENA. 139:250–264.

Cohen J. 1960. A coefficient of agreement for nominal scales. Educ Psychol Meas. 20(1):37–46.

Dahal RK, Hasegawa S. 2008. Representative rainfall thresholds for landslides in the Nepal Himalaya. Geomorphology. 100(3–4):429–443.

Dao DV, Jaafari A, Bayat M, Mafi-Gholami D, Qi C, Moayedi H, Phong TV, Ly H-B, Le T-T, Trinh PT, et al. 2020. A spatially explicit deep learning neural network model for the prediction of landslide susceptibility. CATENA. 188:104451.

Ercanoglu M, Gokceoglu C. 2004. Use of fuzzy relations to produce landslide susceptibility map of a landslide prone area (West Black Sea Region, Turkey). Eng Geol. 75(3–4):229–250.

Esposito F, Malerba D, Semeraro G, Tamma V. 1999. The effects of pruning methods on the predictive accuracy of induced decision trees. Appl Stoch Models Bus Ind. 15(4):277–299.
Farid DM, Zhang L, Rahman CM, Hossain MA, Strachan R. 2014. Hybrid decision tree and naïve Bayes classifiers for multi-class classification tasks. Expert Syst Appl Int J. 41(4):1937–1946.

Feng S, Lu H, Tian P, Xue Y, Lu J, Tang M, Feng W. 2020. Analysis of microplastics in a remote region of the Tibetan Plateau: implications for natural environmental response to human activities. Sci Total Environ. 739:140087.

Feng W, Lu H, Yao T, Yu Q. 2020. Drought characteristics and its elevation dependence in the Qinghai–Tibet plateau during the last half-century. Sci Rep. 10(1):1–11.

Forestry, Rangel and and Watershed Organization (FRWO). 2013. List of landslides in the Iran. Study Group on Landslides, Office of Engineering and Design Evaluation, Elsevier, Engineering Geology.

Frattini P, Crosta G, Carrara A. 2010. Techniques for evaluating the performance of landslide susceptibility models. Eng Geol. 111(1–4):62–72.

Fressard M, Thiery Y, Maquaire O. 2014. Which data for quantitative landslide susceptibility mapping at operational scale? Case study of the Pays d’Auge plateau hillslopes (Normandy, France). Nat Hazards Earth Syst Sci. 14(3):569–588.

Gao J, Sang Y. 2017. Identification and estimation of landslide-debris flow disaster risk in primary and middle school campuses in a mountainous area of Southwest China. Int J Disaster Risk Reduct. 25:60–71.

Gariano SL, Guzzetti F. 2016. Landslides in a changing climate. Earth Sci Rev. 162:227–252.

Geology Survey of Iran (GSI). 1997. http://www.gsi.ir/Main/Lang_en/index.html.

Ghorbanzadeh O, Blaschke T, Gholamnia K, Meena SR, Tiede D, Aryal J. 2019. Evaluation of different machine learning methods and deep-learning convolutional neural networks for landslide detection. Remote Sens. 11(2):196.

Ghorbanzadeh O, Meena SR, Abadi HSS, Piralilou ST, Zhiyong L, Blaschke T. 2021. Landslide mapping using two main deep-learning convolution neural network (CNN) Streams combined by the Dempster–Shafer (DS) model. IEEE J Sel Top Appl Earth Obs Remote Sens. 14:452–463.

Guadie M, Molla E, Mekonnen M, Cerdà A. 2020. Effects of soil bund and stone-faced soil bund on soil physicochemical properties and crop yield under rain-fed conditions of Northwest Ethiopia. Land. 9(1):13.

Gudiya Nagappa T, Tavakkoli Piralilou S, Ghorbanzadeh O, Shahabi H, Blaschke T. 2019. Landslide susceptibility mapping for Austria using geons and optimization with the Dempster-Shafer theory. Appl Sci. 9(24):5393.

Guo W-Z, Chen Z-X, Wang W-L, Gao W-W, Guo M-M, Kang H-L, Li P-F, Wang W-X, Zhao M. 2020. Telling a different story: the promote role of vegetation in the initiation of shallow landslides during rainfall on the Chinese Loess Plateau. Geomorphology. 350:106879.

Guzzetti F. 2006. Landslide hazard and risk assessment [dissertation]. Bonn: Universitäts- und Landesbibliothek Bonn.

Haftlang KK, Lang KKH. 2003. The book of Iran: a survey of the geography of Iran. UK: Alhoda.

Hemasinghe H, Rangali RSS, Deshapriya NL, Samarakoon L. 2018. Landslide susceptibility mapping using logistic regression model (a case study in Badulla District, Sri Lanka). Procedia Eng. 212:1046–1053.

Hembram TK, Paul GC, Saha S. 2019a. Comparative analysis between morphometry and geoenvironmental factor based soil erosion risk assessment using weight of evidence model: a study on Jainti River basin, Eastern India. Environ Process. 6(4):883–913.

Hembram TK, Paul GC, Saha S. 2019b. Spatial prediction of susceptibility to gully erosion in Jainti River basin, Eastern India: a comparison of information value and logistic regression models. Model Earth Syst Environ. 5(2):689–708.

Hembram TK, Saha S. 2020. Prioritization of sub-watersheds for soil erosion based on morphometric attributes using fuzzy AHP and compound factor in Jainti River basin, Jharkhand, Eastern India. Environ Dev Sustain. 22(2):1241–1268.
Hoehler FK. 2000. Bias and prevalence effects on kappa viewed in terms of sensitivity and specificity. J Clin Epidemiol. 53(5):499–503.

Hong H, Liu J, Bui DT, Pradhan B, Acharya TD, Pham BT, Zhu AX, Chen W, Ahmad BB. 2018. Landslide susceptibility mapping using J48 Decision Tree with AdaBoost, Bagging and Rotation Forest ensembles in the Guanzhong area (China). CATENA. 163:399–413.

Hong H, Shahabi H, Shirzadi A, Chen W, Chapí K, Ahmad BB, Roodposhti MS, Yari Hesar A, Tian Y, Tien Bui D. 2019. Land slide susceptibility assessment at the Wuning area, China: a comparison between multi-criteria decision making, bivariate statistical and machine learning methods. Nat Hazards. 96(1):173–212.

Hu J., Chen H., Heidari A.A., Wang M., Zhang X., Chen Y., Pan Z., 2021. Orthogonal learning covariance matrix for defects of grey wolf optimizer: insights, balance, diversity, and feature selection. Knowl Based Syst 213, 106684.

Hu L., Hong G., Ma J., Wang X., Chen H., 2015. An efficient machine learning approach for diagnosis of paraquat-poisoned patients. Comput. Biol. Med. 59, 116–124.

Iranian Landslide Working Party (ILWP). 2007. Iranian landslides list. Iran: Forest, Rangeland and Watershed Association; p. 60.

Irigaray C, Fernández T, El Hamdouni R, Chacón J. 2007. Evaluation and validation of landslide-susceptibility maps obtained by a GIS matrix method: examples from the Betic Cordillera (southern Spain). Nat Hazards. 41(1):61–79.

IRIMO. 2012. Summary reports of Iran’s extreme climatic events. Ministry of Roads and Urban Development, Iran Meteorological Organization. Elsevier, Engineering geology, www.cri.ac.ir.

Jiang Q, Shao F, Lin W, Gu K, Jiang G, Sun H. 2018. Optimizing multistage discriminative dictionaries for blind image quality assessment. IEEE Trans Multimed. 20(8):2035–2048.

Jiang C, Zhang H, Wang X, Feng Y, Labovskii L. 2019. Challenging the land degradation in China’s Loess Plateau: benefits, limitations, sustainability, and adaptive strategies of soil and water conservation. Ecol Eng. 127:135–150.

Kaur G, Chhabra A. 2014. Improved J48 classification algorithm for the prediction of diabetes. Int J Comput Appl. 98(22):13–17.

Keesstra S, Mol G, de Leeuw J, Okx J, Molenaar C, de Cleen M, Visser S. 2018. Soil-related sustainable development goals: four concepts to make land degradation neutrality and restoration work. Land. 7(4):133.

Keesstra S, Nunes JP,Sacop, Parsons T, Poeppl R, Masselink R, Cerdà A. 2018a. The way forward: can connectivity be useful to design better measuring and modelling schemes for water and sediment dynamics? Sci Total Environ. 644:1557–1572.

Keesstra SD, Rodrigo-Comino J, Novara A, Giménez-Morera A, Pulido M, Di Prima S, Cerdà A. 2019. Straw mulch as a sustainable solution to decrease runoff and erosion in glyphosate-treated clementine plantations in Eastern Spain. An assessment using rainfall simulation experiments. CATENA. 174:95–103.

Kohavi R. 1996. Scaling up the accuracy of Naive-Bayes classifiers: a decision-tree hybrid. Proceedings of the Second International Conference on Knowledge Discovery and Data Mining. Portland, OR: AAAI Press.

Landis JR, Koch GG. 1977. The measurement of observer agreement for categorical data. Biometrics. 33(1):159–174.

Lar Consulting Engineering. 2007. The study on flood and debris flow in the Golestan Province, Regional Water Board in Golestan. Tehran: Ministry of Energy.

Li C., Hou L., Sharma B.Y., Li H., Chen C., Li Y., Zhao X., Huang H., Cai Z., Chen H., 2018. Developing a new intelligent system for the diagnosis of tuberculous pleural effusion. Comput Methods Programs Biomed 153, 211–225.

Lu H, Guan Y, He L, Adhikari H, Pellikka P, Heiskanen J, Maeda E. 2019a. Patch aggregation trends of the global climate landscape under future global warming scenario. Int J Climatol. 40(5):2674–2685.
Lu H, Tian P, He L. 2019b. Evaluating the global potential of aquifer thermal energy storage and determining the potential worldwide hotspots driven by socio-economic, geo-hydrologic and climatic conditions. Renew Sustain Energy Rev. 112:788–796.

Mehrabi M, Pradhan B, Moayed H, Alamri A. 2020. Optimizing an adaptive neuro-fuzzy inference system for spatial prediction of landslide susceptibility using four state-of-the-art metaheuristic techniques. Sensor. 20(6):1723.

Micheletti N, Foresti L, Robert S, Leuenberger M, Pedrazzini A, Jaboyedoff M, Kanevski M. 2014. Machine learning feature selection methods for landslide susceptibility mapping. Math Geosci. 46(1):33–57.

Moayedi H, Mehrabi M, Kalantar B, Abdullahi MM, Rashid AS, Foong LK, Nguyen H. 2019. Novel hybrids of adaptive neuro-fuzzy inference system (ANFIS) with several metaheuristic algorithms for spatial susceptibility assessment of seismic-induced landslide. Geomat Nat Hazards Risk. 10(1):1879–1911.

Mohamed WNHW, Salleh MNM, Omar AH. 2012. A comparative study of reduced error pruning method in decision tree algorithms. 2012 IEEE International Conference on Control System, Computing and Engineering (ICCSCE). IEEE; p. 392–397.

Moosavi V, Niazi Y. 2016. Development of hybrid wavelet packet-statistical models (WP-SM) for landslide susceptibility mapping. Landslides. 13(1):97–114.

Nachappa TG, Ghorbanzadeh O, Gholamnia K, Blaschke T. 2020. Multi-hazard exposure mapping using machine learning for the State of Salzburg, Austria. Remote Sens. 12(17):2757.

National Geosciences Database. 2017. www.ngdir.ir.

Nefeslioglu HA, Duman TY, Durmaz S. 2008. Landslide susceptibility mapping for a part of tectonic Kelkit Valley (Eastern Black Sea region of Turkey). Geomorphology. 94(3–4):401–418.

Ngo PTT, Panahi M, Khosravi K, Ghorbanzadeh O, Karimnejad N, Cerda A, Lee S. 2021. Evaluation of deep learning algorithms for national scale landslide susceptibility mapping of Iran. Geosci Front. 12(2):505–519.

Nsengiyumva JB, Luo G, Nahayo L, Huang X, Cai P. 2018. Landslide susceptibility assessment using spatial multi-criteria evaluation model in Rwanda. Int J Environ Res Public Health. 15(2):243.

Pandey VK, Pourghasemi HR, Sharma MC. 2020. Landslide susceptibility mapping using maximum entropy and support vector machine models along the Highway Corridor, Garhwal Himalaya. Geocarto Int. 35(2):168–187.

Paul GC, Saha S, Hembram TK. 2019. Application of the GIS-based probabilistic models for mapping the flood susceptibility in Bansloi Sub-basin of Ganga-Bhagirathi River and their comparison. Remote Sens Earth Syst Sci. 2(2–3):120–146.

Pham BT, Prakash I, Singh SK, Shirzadi A, Shahabi H, Tran TTT, Bui DT. 2019. Landslide susceptibility modeling using reduced error pruning trees and different ensemble techniques: hybrid machine learning approaches. CATENA. 175:203–218.

Piacentini T, Galli A, Marsala V, Miccadei E. 2018. Analysis of soil erosion induced by heavy rainfall: a case study from the NE Abruzzo Hills Area in Central Italy. Water. 10(10):1314.

Picillo L, Calvello M, Cepeda JM. 2018. Territorial early warning systems for rainfall-induced landslides. Earth Sci Rev. 179:228–247.

Poudyal CP, Chang C, Oh HJ, Lee S. 2010. Landslide susceptibility maps comparing frequency ratio and artificial neural networks: a case study from the Nepal Himalaya. Environ Earth Sci. 61(5):1049–1064.

Quinlan JR. 1987. Simplifying decision trees. Int J Man Mach Stud. 27(3):221–234.

Rangswiwanichpong P, Kazama S, Ekkawatpanit C, Gunawardhana L. 2019. Evaluation of cost and benefit of sediment based on landslide and erosion models. CATENA. 173:194–206.

Regmi AD, Devkota KC, Yoshida K, Pradhan B, Pourghasemi HR, Kumamoto T, Akgun A. 2014. Application of frequency ratio, statistical index, and weights-of-evidence models and their comparison in landslide susceptibility mapping in Central Nepal Himalaya. Arab J Geosci. 7(2):725–742.
Roback K, Clark MK, West AJ, Zekkos D, Li G, Gallen SF, Chamlagain D, Godt JW. 2018. The size, distribution, and mobility of landslides caused by the 2015 Mw7.8 Gorkha earthquake, Nepal. Geomorphology. 301:121–138.

Rodriguez JJ. 2007. Rotation forest and random oracles: two classifier ensemble methods. Paper presented at the Computer-Based Medical Systems; Maribor.

Rodriguez JJ, Kuncheva LI, Alonso CJ. 2006. Rotation forest: a new classifier ensemble method pattern analysis and machine intelligence. IEEE Trans Pattern Anal Mach Intell. 28(10): 1619–1630.

Roy J, Saha S. 2019a. GIS-based gully erosion susceptibility evaluation using frequency ratio, cosine amplitude and logistic regression ensembled with fuzzy logic in Hinglo River Basin, India. Remote Sens Appl Soc Environ. 15:100247.

Roy J, Saha S. 2019b. Landslide susceptibility mapping using knowledge driven statistical models in Darjeeling District, West Bengal, India. Geoenviron Disasters. 6(1):11.

Roy J, Saha S, Arabameri A, Blaschke T, Bui DT. 2019. A novel ensemble approach for landslide susceptibility mapping (LSM) in Darjeeling and Kalimpong districts, West Bengal, India. Remote Sens. 11(23):2866.

Saadat H, Bonnell R, Sharifi F, Mehuys G, Namdar M, Ale-Ebrahim S. 2008. Landform classification from a digital elevation model and satellite imagery. Geomorphology. 100(3-4): 453–464.

Saha S. 2017. Groundwater potential mapping using analytical hierarchical process: a study on Md. Bazar Block of Birbhum District, West Bengal. Spat Inf Res. 25(4):615–626.

Shahpasandzadeh M. 2004. Seismology and seism tectonics of Golestan Province, northeast Iran. International Institute Seismology and Earthquake Engineering, Seismology Research Institute of the Seismic Group; Elsevier, Automation in Construction; p. 8. Persian.

Shan W., Qiao Z., Heidari A.A., Chen H., Turabieh H., Teng Y., 2021. Double adaptive weights for stabilization of moth flame optimizer: Balance analysis, engineering cases, and medical diagnosis. Knowl Based Syst 214, 106728.

Siddle RC, Bogaard TA. 2016. Dynamic earth system and ecological controls of rainfall-initiated landslides. Earth Sci Rev. 159:275–291.

Shin Y, Kim T, Cho H, Kang KI. 2012. A formwork method selection model based on boosted decision trees in tall building construction. Autom Constr. 23:47–54.

Taalab K, Cheng T, Zhang Y. 2018. Mapping landslide susceptibility and types using random forest. Big Earth Data. 2(2):159–120.

Tavakkoli Piralilou S, Shahabi H, Jarihani B, Ghorbanzadeh O, Blaschke T, Gholamnia K, Meena SR, Aryal J. 2019. Landslide detection using multi-scale image segmentation and different machine learning models in the higher Himalayas. Remote Sens. 11(21):2575.

Tian P, Lu H, Feng W, Guan Y, Xue Y. 2020. Large decrease in streamflow and sediment load of Qinghai–Tibetan Plateau driven by future climate change: a case study in Lhasa River Basin. CATENA. 187:104340.

Tu J, Chen H., Liu J., Heidari A.A., Zhang X., Wang M., Ruby R., Pham Q.-V., 2021. Evolutionary biogeography-based whale optimization methods with communication structure: towards measuring the balance. Knowl Based Syst 212, 106642.

Visser S, Keesstra S, Maas G, De CM. 2019. Soil as a basis to create enabling conditions for transitions towards sustainable land management as a key to achieve the SDGs by 2030. Sustainability. 11(23):6792.

Wang M., Chen H., 2020. Chaotic multi-swarm whale optimizer boosted support vector machine for medical diagnosis. Appl. Soft Comput. 88, 105946.
Wang M., Chen H., Yang B., Zhao X., Hu L., Cai Z., Huang H., Tong C., 2017. Toward an optimal kernel extreme learning machine using a chaotic moth-flame optimization strategy with applications in medical diagnoses. Neurocomputing 267, 69–84. https://doi.org/10.1016/j.neucom.2017.04.06

Wang S, Jiang L, Li C. 2015. Adapting naive Bayes tree for text classification. Knowl Inf Syst. 44(1):77–89.

Whiteley JS, Chambers JE, Uhlemann S, Wilkinson PB, Kendall JM. 2019. Geophysical monitoring of moisture-induced landslides: a review. Rev Geophys. 57(1):106–145.

Witten IH, Frank E, Hall MA. 2011. Data mining: practical machine learning tools and techniques. Chemometrics and intelligent laboratory systems, Elsevier Science Publishers B.V., Amsterdam - Printed in The Netherlands.

Wold S, Esbensen K, Geladi P. 1987. Principal component analysis. Chemom Intell Lab Syst. 2(1–3):37–52.

Wu Y, Ke Y, Chen Z, Liang S, Zhao H, Hong H. 2020. Application of alternating decision tree with AdaBoost and bagging ensembles for landslide susceptibility mapping. CATENA. 187: 104369.

Xi W, Li G, Moayed H, Nguyen H. 2019. A particle-based optimization of artificial neural network for earthquake-induced landslide assessment in Ludian county, China. Geomat Nat Hazards Risk. 10(1):1750–1771.

Xia J, Du P, He X, Chanussot J. 2014. Hyperspectral remote sensing image classification based on rotation forest. IEEE Geosci Remote Sens Lett. 11(1):239–243.

Yu H, Li W, Chen C, Liang J, Gui W, Wang M, Chen H, 2020. Dynamic Gaussian bare bones fruit fly optimizers with abandonment mechanism: method and analysis. Eng Comput. 1–29.

Yu C., Chen M., Cheng K., Zhao X., Ma C., Kuang F., Chen H., 2021. SGOA: annealing behaved grasshopper optimizer for global tasks. Eng Comput 1–28.

Zhao X. Li, D., Yang B., Ma C., Zhu Y., Chen H., 2014. Feature selection based on improved ant colony optimization for online detection of foreign fiber in cotton, Applied Soft Computing 24, 585–596.
Zhao X., Zhang X., Cai Z., Tian X., Wang X., Huang Y., Chen H., Hu L., 2019. Chaos enhanced grey wolf optimization wrapped ELM for diagnosis of paraquat-poisoned patients. Comput Biol Chem 78, 481–490.

Zhang Y., Liu R., Wang X., Chen H., Li C., 2020. Boosted binary Harris hawks optimizer and feature selection. Eng Comput 1–30.

Zhang Y., Liu R., Heidari A.A., Wang X., Chen Y., Wang M., Chen H., 2021. Towards augmented kernel extreme learning models for bankruptcy prediction: algorithmic behavior and comprehensive analysis. Neurocomputing 430, 185–212.

Zhou Y, Tian L, Zhu C, Jin X, Sun Y. 2020. Video coding optimization for virtual reality 360-degree source. IEEE J Sel Top Signal Process. 14(1):118–129.

Zhou C, Yin K, Cao Y, Ahmed B, Li Y, Catani F, Pourghasemi HR. 2018. Landslide susceptibility modeling applying machine learning methods: a case study from Longju in the Three Gorges Reservoir area, China. Comput Geosci. 112:23–37.

Zhu AX, Wang R, Qiao J, Qin CZ, Chen Y, Liu J, Du F, Lin Y, Zhu T. 2014. An expert knowledge-based approach to landslide susceptibility mapping using GIS and fuzzy logic. Geomorphology. 214:128–138.

Zuo C, Chen Q, Tian L, Waller L, Asundi A. 2015. Transport of intensity phase retrieval and computational imaging for partially coherent fields: the phase space perspective. Opt Lasers Eng. 71:20–32.

Zuo C, Sun J, Li J, Zhang J, Asundi A, Chen Q. 2017. High-resolution transport-of-intensity quantitative phase microscopy with annular illumination. Sci Rep. 7(1):1–22.