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Landslide Susceptibility Analysis using Artificial Neural Networks for Chalus County, Iran

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Abstract: Landslides are among the most critical natural hazards, causing significant environmental and economic damage. This study focuses on landslide susceptibility analysis in Chalus County, Iran, using Artificial Neural Networks (ANNs) to predict high-risk areas. A dataset of 77 recorded historical landslides was compiled through field surveys, remote sensing, and satellite imagery analysis. Various conditioning factors, including elevation, geology, slope angle, rainfall, temperature, aspect, NDVI (normalized difference vegetation index), weathering, distance to cities, distance to landslides, distance to rivers, distance to roads, and distance to faults, were integrated into a GIS-based modeling framework. The ANN model was trained using a dataset divided into training and validation subsets, ensuring robust predictive performance. The results demonstrated that ANNs effectively identify landslide-prone regions, with high accuracy in distinguishing between stable and unstable areas. The susceptibility map produced highlights that northern and mountainous regions of Chalus County are highly vulnerable to landslides, primarily due to steep slopes, heavy precipitation, and geological instability. Model validation using statistical accuracy measures, including the Area Under the Curve (AUC), precision, and recall, confirmed the reliability of the predictions. The findings of this study provide valuable insights for urban planners, geologists, and policymakers in risk assessment and land-use planning. Implementing these results can support early warning systems and mitigation strategies to minimize landslide-related hazards in the region. Future research should explore hybrid AI models and additional geospatial datasets to enhance predictive capabilities further.

Keywords: Landslide susceptibility, Artificial intelligence, Neural networks, Machine learning, ArcGIS.

I. INTRODUCTION

Landslides are among the most destructive geological hazards on Earth, causing severe damage to infrastructure and posing significant threats to human life, particularly in regions prone to frequent landslides (Nanehkaran et al., 2023). A landslide can be defined as the mass movement of rock, debris, or soil downslope due to gravitational forces. This phenomenon occurs in areas where the shear stress of the material exceeds its shear strength, leading to slope instability. Landslides vary in size and intensity and can result from both natural and human-induced factors (Cemiloglu et al., 2023). They are one of the most critical natural hazards and active geomorphological processes, contributing to erosion and significant surface changes (Ermini et al., 2005). Landslide movements can take various forms, including falls, topples, slides (rotational and translational), lateral spreads, flows, and complex movements as a combination of two or more types (Yong et al., 2022).

As known, landslides pose serious geological hazards with severe consequences, including property damage, infrastructure destruction, injuries, and fatalities (Reichenbach et al., 2018). Additionally, landslides can play a critical role in volcanic degassing, lakebed destabilization, and submarine sediment displacement, impacting the environment on a larger scale (Zêzere, 2002). Landslides can be classified into several types based on the nature of movement and the material involved. Generally, landslides are categorized into five main types: falls, topples, slides, spreads, and flows (Erener & Düzgün, 2012). Each type has distinct characteristics and occurs under different geological and environmental conditions (Nikoobakht et al., 2022). Falls involve the free-fall or rapid descent of rock or soil from a steep slope or cliff. They are often triggered by weathering, erosion, or seismic activity and commonly occur in mountainous regions with unstable rock formations. Topples, on the other hand, occur when a block of rock or soil tilts forward and collapses due to gravitational forces and external disturbances, such as earthquakes or heavy rainfall (Nanehkaran et al., 2022).

Slides are further divided into rotational slides and translational slides. Rotational slides, also known as slumps, occur when a mass of soil or rock moves along a curved surface, creating a concave scarp at the top (Abramson et al., 2001). Translational slides, in contrast, involve the movement of material along a relatively flat or planar surface, often influenced by weak soil layers, bedding planes, or fault zones (Duncan et al., 2014). Spreads are characterized by the lateral extension of rock or soil over a weaker underlying layer, such as soft clay or liquefiable sand. These movements are often gradual and are commonly associated with earthquake-induced liquefaction or subsurface material failure (Salunkhe et al., 2017). Flows represent the most fluid type of landslide, where water-saturated soil or debris moves in a chaotic manner (Duncan et al., 2014). Flows can be categorized into debris flows, mudflows, earthflows, and lahars (Abramson et al., 2001). Debris flows contain a mix of rock, soil, and organic material, moving rapidly down slopes, especially in areas with intense rainfall. Mudflows consist of fine-grained sediments mixed with water, forming fast-moving slurry. Earthflows typically occur on gentle slopes and move slower than other types of flows (Rogers & Chung, 2016). Lahars, which are volcanic mudflows, form when volcanic ash mixes with water from rainfall or melting ice (Baumann et al., 2018). Each type of landslide poses unique risks and challenges for hazard assessment and mitigation. Understanding these classifications helps in predicting occurrences, designing preventive measures, and reducing landslide-related damages in vulnerable regions (Dai et al., 2002).

It is widely recognized that two main categories of factors contribute to landslides as dynamic and static factors. Dynamic factors, primarily including rainfall and seismic events, have the potential to cause widespread changes in the Earth's crust. Static factors, on the other hand, are related to the geological, geomorphological, environmental, and soil properties that influence a slope’s susceptibility to landslides (Jia et al., 2008). Identifying landslide-prone areas is essential for minimizing their impact by assessing and addressing high-risk regions (Zhou et al., 2015). This process not only highlights potential landslide-prone zones but also establishes an active early warning mechanism (Cemiloglu et al., 2023). Landslides are triggered by a combination of internal and external factors. Internal factors include the geomechanical, geomorphological, and hydraulic properties of slope materials, whereas external factors encompass triggers such as rainfall and earthquakes (Nanehkaran et al., 2023). In many cases, human activities such as unregulated excavation on slopes; can significantly influence landslide occurrences (Nikoobakht et al., 2022). Landslides are defined as the mass movement of rock, soil, and debris under the direct influence of gravity, triggered by rainfall, earthquakes, volcanic eruptions, slope erosion by rivers, and human activities such as slope cutting and excavation (Duncan et al., 2014). Intense rainfall is a major contributor to landslides, often acting as a primary trigger alongside earthquakes or being exacerbated by human activities (Huang & Zhao, 2018). With climate change, extreme rainfall events have become more frequent, leading to an increasing recurrence of rainfall-induced landslides (RILs). During extreme rainfall events, increased water saturation in the soil weakens slope stability (Huang et al., 2022). Water infiltration raises the slope’s weight, reduces pore-water suction, decreases effective stress, and affects shear strength, ultimately leading to a loss of cohesion as saturation progresses (Dahal et al., 2008). This reduction in soil strength presents a significant risk for slope failure (Yalçinkaya & Bayrak, 2005).

Nowadays, the need for quantitative risk assessment and zonation of landslides is increasingly recognized (Roccati et al., 2021) were presented in Figure 1. Iran, characterized by mountainous topography, high tectonic and seismic activity, diverse climatic and geological conditions, provides a natural setting for a wide range of landslides (Pourghasemi et al., 2013). Due to unfavorable geographical conditions, inadequate comprehensive management, and failure to adhere to environmental thresholds, Iran is considered a high-risk country (Ngo et al., 2021). Therefore, in areas with a high landslide hazard, mapping techniques are crucial for accurately assessing slope failures, determining landslide magnitudes, and estimating displacement characteristics (Cemiloglu et al., 2023). Predicting hazardous events like landslides remains highly challenging since no laboratory can comprehensively measure the required variables, refine techniques, and directly apply results (Pourghasemi et al., 2012).

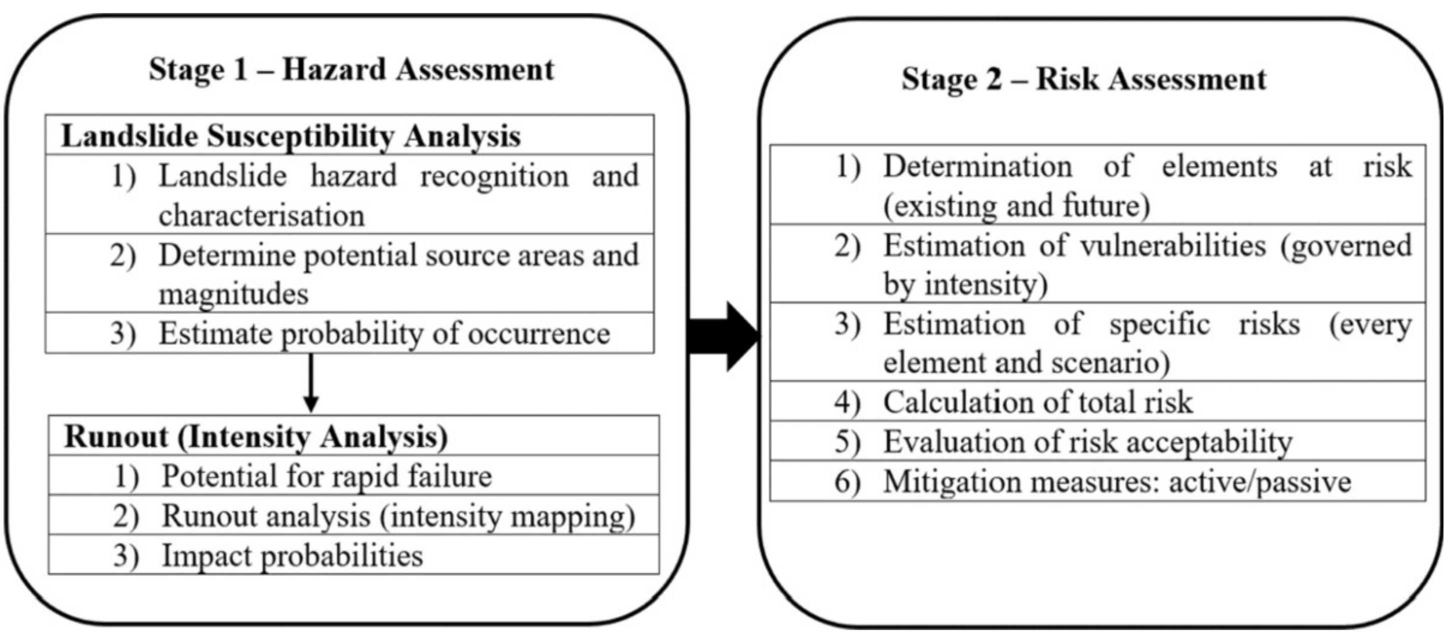

Fig. 1 Landslides hazard/risk assessment (Sim et al., 2022)

Landslide hazard assessment methods are generally categorized into three main approaches: qualitative, quantitative, and semi-quantitative. Qualitative approaches often rely on aerial imagery, field interpretation, and expert judgment. Despite the promising results and high performance of various models, geologists continuously seek more accurate methods to identify landslide-prone areas and generate reliable maps for environmental planning (Pourghasemi et al., 2014).

In recent decades, the rapid advancement of GIS technology and increasing computational power in AI-based algorithms has significantly improved the accuracy and reliability of landslide prediction (Cemiloglu et al., 2023). Additionally, GIS enables the extraction of critical geospatial data such as land cover, geology, geomorphology, and drainage patterns, while existing thematic information can be updated to quantify human-induced impacts on land stability (Nanehkaran et al., 2023). As a computer-based system for collecting, processing, transforming, visualizing, querying, analyzing, modeling, and outputting spatial data, GIS has gained substantial attention in natural disaster management due to its exceptional spatial data processing capabilities (Zhou et al., 2015). GIS-based analysis plays a key role in deriving macroscopic variables such as elevation, slope angle, slope aspect, and drainage density from Digital Elevation Models, DEM (Arabameri et al., 2020). Furthermore, integrating remote sensing data into GIS can contribute to the development of a decision-support system for enhanced monitoring and prediction of future landslide activity in high-risk areas (Cemiloglu et al., 2023).

II. Landslide Susceptibility Analysis

Landslide susceptibility analysis refers to the process of identifying and predicting areas that are prone to landslides based on various environmental, geological, and climatic factors (Yalçinkaya & Bayrak, 2005). It aims to determine the probability of landslide occurrence in a given region without considering the exact timing of events (Baumann et al., 2018). By analyzing historical landslide data and related conditioning factors such as slope, geology, rainfall, vegetation, and human activities, susceptibility models can classify areas into different risk levels, helping in hazard mitigation and land-use planning (Roccati et al., 2021). One of the main advantages of landslide susceptibility analysis is its ability to provide proactive hazard assessment, reducing potential damage to infrastructure and human life (Erener & Düzgün, 2012). It allows for efficient risk zoning, enabling planners and policymakers to implement preventive measures such as slope stabilization, drainage improvement, and controlled land development. Additionally, it aids in prioritizing resources, ensuring that high-risk areas receive necessary interventions before disasters occur (Ado et al., 2022).

Despite its benefits, landslide susceptibility analysis has some limitations. One major challenge is data availability and quality, as landslide occurrence is influenced by complex and dynamic interactions between multiple factors (Merghadi et al., 2020). In some cases, subjective bias in data selection and model assumptions can affect accuracy (Ngo et al., 2021). Additionally, uncertainties in climate change projections and human activities make it difficult to develop fully reliable models (Dai et al., 2002). Qualitative approaches rely on expert judgment, field observations, and aerial photo interpretation to identify susceptible zones (Nanehkaran et al., 2023). These methods are cost-effective and rapid, but they are subjective and lack reproducibility (Pourghasemi et al., 2014). Heuristic models, such as geomorphological mapping and inventory-based classifications, fall under this category and are often used as an initial assessment in areas with limited data (Huang & Zhao, 2018). Quantitative approaches utilize statistical and computational models to establish relationships between past landslides and conditioning factors (Azarafza et al., 2018). These include logistic regression, artificial neural networks (ANNs), decision trees, and support vector machines (SVMs). These methods offer high accuracy and automation, but they require large, high-quality datasets and significant computational resources (Nikoobakht et al., 2022). Semi-quantitative approaches combine both qualitative and quantitative techniques. Methods such as the Analytic Hierarchy Process (AHP) and fuzzy logic integrate expert judgment with statistical weighting to improve predictive capability (Nanehkaran et al., 2021). These models are particularly useful in data-scarce regions, where fully quantitative methods may not be feasible.

Geographic Information Systems (GIS) and remote sensing technologies play a crucial role in landslide susceptibility analysis. GIS enables the integration, manipulation, and visualization of spatial datasets, while remote sensing provides up-to-date land cover, topographic, and climatic data (Ngo et al., 2021). The combination of these technologies enhances the efficiency and accuracy of susceptibility mapping, especially in large and inaccessible areas (Nanehkaran et al., 2023). Also, landslide susceptibility analysis is essential for disaster risk reduction and urban planning. It helps authorities develop land-use policies that restrict construction in high-risk areas and implement engineering solutions to stabilize slopes (Baumann et al., 2018). Additionally, integrating susceptibility maps into early warning systems enables better preparedness, reducing casualties and economic losses during extreme events (Sim et al., 2022).

With advancements in artificial intelligence (AI), deep learning models and hybrid AI techniques are being increasingly applied to landslide susceptibility analysis. These methods improve prediction accuracy by capturing complex nonlinear relationships between multiple variables (Kavzoglu et al., 2019). Moreover, the integration of big data analytics, satellite imagery, and real-time monitoring will further enhance hazard assessment capabilities (Merghadi et al., 2020). Machine learning (ML) has as part of AI revolutionized landslide susceptibility analysis by enhancing prediction accuracy and automating complex data processing tasks (Kavzoglu et al., 2019). One of the main advantages is its ability to handle large and high-dimensional datasets efficiently, allowing for the integration of multiple conditioning factors such as slope, geology, climate, and vegetation. ML models can identify nonlinear relationships between these variables, making them more reliable than traditional statistical methods (Ado et al., 2022). Additionally, ML eliminates subjective biases by learning patterns from historical landslide data rather than relying solely on expert judgment (Cemiloglu et al., 2023). Another key benefit of ML models is their adaptability to different geographical conditions (Marjanović et al., 2011). Once trained, an ML algorithm can be applied to various regions with minimal modifications, making it a versatile tool for global landslide hazard assessments (Pham et al., 2016). An example of machine learning application has been provided in Figure 2. Furthermore, these models continuously improve over time, learning from new data and refining their predictions. The automation of susceptibility mapping reduces manual workload and speeds up the decision-making process, which is crucial for real-time hazard assessment and early warning systems (Chen & Chen, 2021). Despite their advantages, ML models have some limitations. One major challenge is data dependency—they require a large volume of high-quality, well-labeled training data for accurate predictions (Ado et al., 2022). In regions with limited landslide records, training an effective model becomes difficult. Additionally, ML algorithms often act as "black boxes", meaning that their decision-making processes lack transparency, making it challenging to interpret results for non-technical stakeholders such as policymakers and urban planners (Kavzoglu et al., 2019). ML models can be computationally intensive, requiring high-performance hardware for training and validation. This may limit their accessibility in resource-constrained settings (Merghadi et al., 2020).

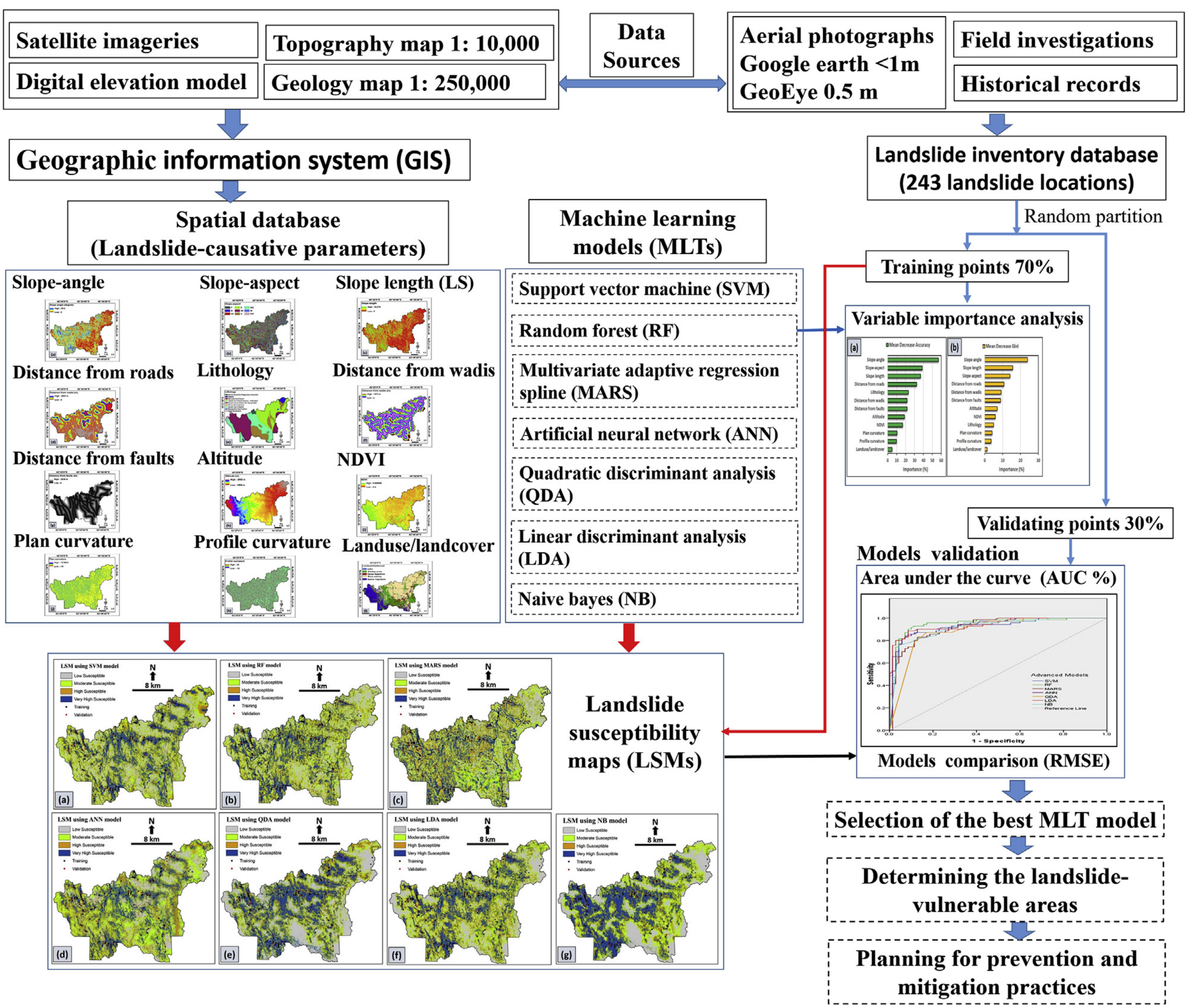

Fig. 2 A example of ML process that used in landslide susceptibility analysis (Adapted from Youssef & Pourghasemi, 2021)

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Overfitting is another issue, where a model performs well on training data but fails to generalize to new, unseen data. To overcome this, careful model tuning and cross-validation techniques must be applied, adding to the complexity of implementation (Nanehkaran et al., 2023). Machine learning can be seamlessly integrated with GIS and remote sensing data, enhancing the accuracy of susceptibility maps. This integration allows for better spatial analysis, helping urban planners, geologists, and policymakers make informed decisions regarding land-use planning, infrastructure development, and emergency response strategies (Marjanović et al., 2011).

Landslides are caused by a combination of geological, hydrological, and climatic factors, many of which are highly nonlinear and dynamic. Traditional statistical models often struggle to capture these complex interactions, leading to lower prediction accuracy. ML, on the other hand, excels at recognizing hidden patterns in large datasets, making it an essential tool for improving susceptibility analysis (Yang et al., 2023). With the advancement of remote sensing technologies and IoT-based monitoring systems, vast amounts of real-time environmental data are being collected. Machine learning algorithms can process this data in real time, providing early warnings for potential landslides. This capability is crucial for disaster preparedness and mitigation, reducing casualties and infrastructure damage in high-risk areas (Thirugnanam et al., 2022). As results, despite some challenges, machine learning offers unparalleled advantages in landslide susceptibility analysis. Its ability to handle large datasets, detect complex patterns, and provide real-time predictions makes it an indispensable tool for geoscientists, disaster management experts, and urban planners. As technology continues to evolve, further integration of AI-driven approaches will enhance landslide risk assessment and mitigation strategies worldwide.

III. Studied Location

Chalus County, located in Mazandaran province, northern Iran, is renowned for its picturesque landscapes and strategic significance. The county's administrative center is the city of Chalus, situated along the southern coast of the Caspian Sea. Covering an area of approximately 1,597.30 km^2, Chalus County shares borders with Nowshahr County to the east and Kelardasht County to the west. Its geographical coordinates place it at the heart of the Alborz mountain range, providing a unique blend of coastal and mountainous terrains (Soleimani et al., 2020). Figure 3 shows the location map of studied County. The climate of Chalus County is predominantly warm and humid, influenced by its proximity to the Caspian Sea and the surrounding Alborz mountains. This combination results in significant precipitation throughout the year, contributing to the region's lush greenery and dense forests. The average annual temperature is approximately 11.6°C (52.9°F), with precipitation levels reaching about 1,075 mm annually. The consistent rainfall supports diverse flora and fauna, making it a vital ecological zone in Iran (Rajabi et al., 2018). Geologically, Chalus County is characterized by its complex mountainous structures, primarily composed of sedimentary rocks such as limestone and shale (Sorbi & Farrokhnia, 2018). The Alborz mountain range, which dominates the county's landscape, was formed during the Alpine orogeny, resulting in rugged terrains and steep slopes (Davidson et al., 2004). This geological setting has made the region susceptible to natural phenomena like landslides, especially during periods of heavy rainfall. The diverse topography also includes river valleys and coastal plains, offering a variety of natural habitats (Wei et al., 2012). In recent years, Chalus County has experienced development in infrastructure and public services, aiming to improve the quality of life for its residents (Soleimani et al., 2020). Efforts have been made to balance economic growth with environmental conservation, recognizing the importance of preserving the region's natural heritage (Rajabi et al., 2018). Sustainable practices in agriculture, forestry, and tourism are being promoted to ensure that development does not compromise the ecological balance of this unique region (Sorbi and Farrokhnia, 2018).

As known, Chalus County, located in the Alborz mountain range, has a complex geological structure that significantly influences its susceptibility to natural hazards, particularly landslides (Ehteshami-Moinabadi, 2022). The region's geological formations mainly consist of sedimentary rocks, including limestone, sandstone, and shale, which have been subjected to extensive tectonic activity. The presence of fault lines and folds, resulting from the collision between the Arabian and Eurasian tectonic plates, has created an unstable geological environment. These factors contribute to the county's vulnerability to mass movements, particularly along steep slopes and river valleys (Ehteshami-Moinabadi & Nasiri, 2019). The region's tectonic activity plays a crucial role in shaping its geological hazards. The Alborz Mountains are part of an active orogenic belt, with numerous faults traversing the landscape. The North Alborz Fault and other minor fault systems contribute to frequent seismic activity, which can trigger landslides, ground subsidence, and soil liquefaction. Earthquakes in the region, even at moderate magnitudes, can lead to significant slope instability, particularly in areas with loose or weathered materials (Aghanabati, 2012). Figure 4 presents an adapted geological map form the geological data for studied area form 1:100,000 and 1:250,000 maps provided by Geological Survey of Iran (GSI) in 2009 (GSI, 2009).

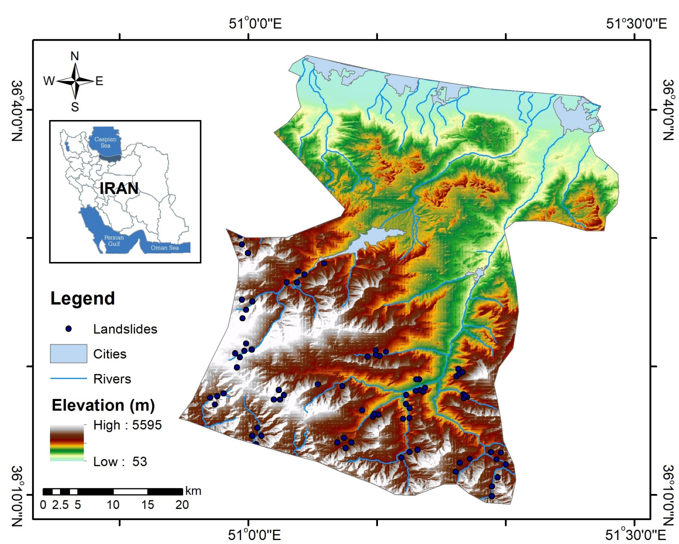

Fig. 3 Location of studied area

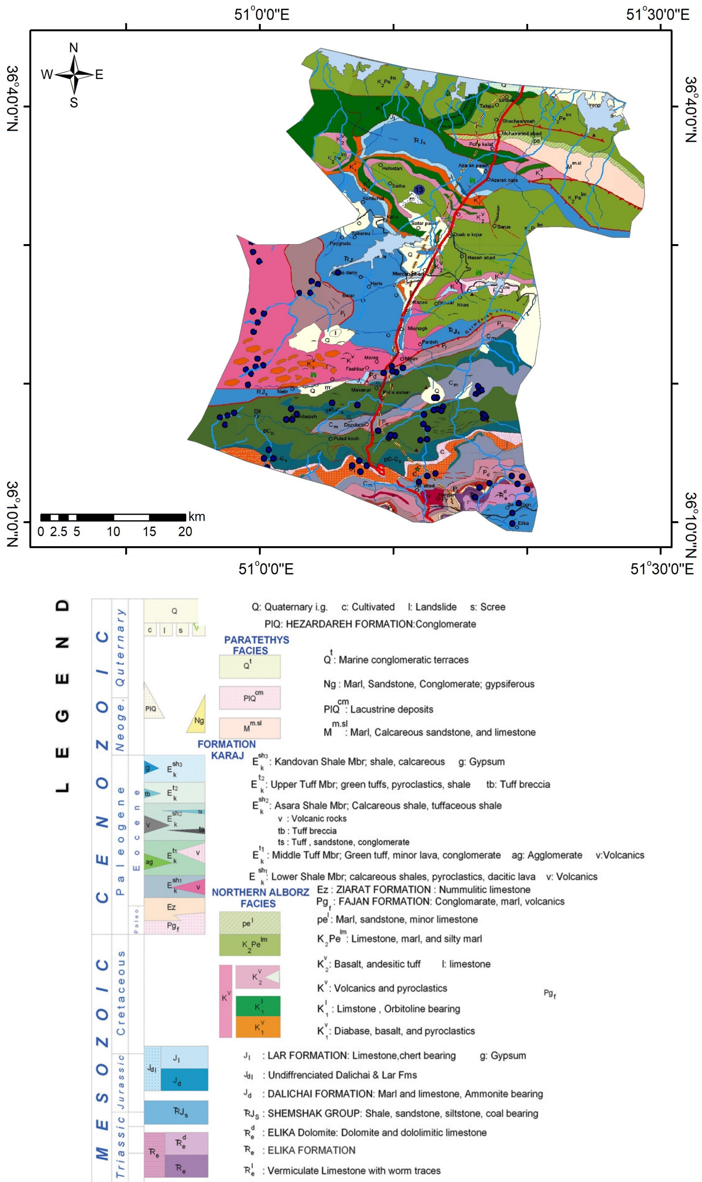

Fig. 4 Geological map of Chalus County (GSI, 2009)

Landslides are one of the most significant geological hazards in Chalus County due to its mountainous terrain, high precipitation levels, and seismic activity (Ehteshami-Moinabadi & Nasiri, 2019). The combination of weak rock formations, weathering processes, and intense rainfall creates favorable conditions for slope failures. Additionally, human activities such as deforestation, road construction, and urban expansion further destabilize slopes, increasing the likelihood of landslides (Rajabi et al., 2018). The Chalus Road, a vital transportation route connecting northern Iran to Tehran, is particularly prone to landslides and rockfalls, often leading to road closures and disruptions (Aghanabati, 2012). Heavy rainfall is another major factor influencing landslide occurrences in Chalus County. The humid climate, driven by moisture from the Caspian Sea, results in frequent and intense precipitation events. Rainwater infiltrates the soil, reducing its shear strength and increasing pore water pressure, which can lead to slope failures. Prolonged wet periods, especially during autumn and winter, significantly heighten landslide risks (Ehteshami-Moinabadi & Nasiri, 2019).

The region's river systems also contribute to slope instability. The Chalus River, along with its tributaries, actively erodes valley walls, undercutting slopes and creating conditions conducive to mass movements. Riverbank collapses and sediment accumulation in water channels further amplify the risks of landslides and debris flows, particularly during heavy rainfall or rapid snowmelt (Kardavani et al., 2014). Geological formations in Chalus County also exhibit varying degrees of resistance to erosion and slope failure (Aghanabati, 2012). Harder limestone and sandstone units generally form more stable slopes, while softer shale and marl formations are more susceptible to weathering and landslides. The interbedding of these rock types, combined with their fractured and faulted nature, leads to complex failure mechanisms, including rockfalls, debris flows, and rotational slides (GSI, 2009). In addition to landslides, other geological hazards such as soil erosion, rockfalls, and flash floods pose significant threats to infrastructure and settlements in the region (Ehteshami-Moinabadi & Nasiri, 2019). Steep slopes with sparse vegetation are particularly prone to surface erosion, which can lead to sediment deposition in rivers and increased flood risks. Moreover, the combination of seismic activity and weak geological formations heightens the potential for catastrophic ground failures in certain areas (Zabihi et al., 2019). To mitigate these hazards, it is essential to implement proper land-use planning, slope stabilization measures, and early warning systems (Aghanabati, 2012). Reinforcing road embankments, constructing retaining walls, and employing bioengineering techniques can help reduce landslide risks (Ehteshami-Moinabadi & Nasiri, 2019). Additionally, continuous monitoring of geological conditions using remote sensing and GIS-based analysis can provide valuable insights for hazard assessment and risk management (Amini Hosseini & Ghayamghamian, 2012).

IV. Landslide Triggering Factors

The selection of landslide-triggering factors plays a critical role in accurately assessing landslide susceptibility in Chalus County. Our study incorporated a combination of remote sensing techniques, field surveys, and historical landslide records to ensure a comprehensive and data-driven approach. The dataset includes 77 recorded historical landslides, which serve as a reference for validating the model's effectiveness in predicting susceptible areas. To analyze the topographic conditions, we used Digital Elevation Model (DEM) data to extract key parameters such as elevation, slope angle, and aspect. Elevation influences precipitation distribution and erosion potential, while slope angle directly affects gravitational forces acting on a slope. The aspect determines exposure to climatic conditions such as sun radiation and wind, impacting soil moisture and vegetation cover. These factors were derived from ASF data (vertex.daac.asf.alaska.edu), ensuring accuracy in terrain representation. The DEM data used in this study had a ±30m resolution and was freely available for research purposes. This dataset provided high-quality topographic information, enabling the extraction of key parameters such as elevation, slope angle, and aspect with sufficient accuracy for landslide susceptibility analysis. The ±30m resolution was chosen as it offers a good balance between computational efficiency and spatial detail, making it suitable for regional-scale studies like this one.

Geological characteristics, including lithology and weathering, were considered essential in assessing slope stability. The type of bedrock and the degree of weathering influence shear strength and material cohesion, making these critical parameters in landslide studies. Geological data were obtained from the GSI database (https://www.gsi.ir), providing detailed information on rock formations and soil properties across Chalus County. Climatic factors such as rainfall and temperature were also integrated into the analysis. Rainfall is a primary landslide trigger as it increases pore water pressure, reducing shear strength and causing slope failures. Temperature variations impact freeze-thaw cycles, further destabilize slopes in colder months. These meteorological datasets were sourced from the Iran Meteorological Organization, IMO (https://www.irimo.ir) to ensure reliability in assessing precipitation patterns and temperature fluctuations.

Vegetation cover, represented by the Normalized Difference Vegetation Index (NDVI), was analyzed to understand its role in slope stabilization. Dense vegetation helps bind soil particles and reduces erosion, whereas sparse vegetation can indicate areas prone to instability. NDVI values were extracted using free version satellite imagery from Landsat TM8 and ETM^{+} imagery (USGS, 2023), providing insight into land cover variations across the study area. Proximity factors, including distance to cities, distance to landslides, distance to rivers, distance to roads, and distance to faults, were incorporated to assess human and geological influences on landslide susceptibility. Proximity to cities and roads reflects the impact of urbanization and infrastructure development, while distance to rivers and faults highlights the role of hydrological and tectonic forces in triggering landslides. By integrating these diverse datasets, our study provides a robust framework for assessing landslide susceptibility in Chalus County. The combination of topographic, geological, climatic, vegetation and proximity factors ensures a holistic approach to understanding and mitigating landslide hazards in the region. Figure 5 presents the selected landslide triggering factors considered in this study, including elevation, geology, slope angle, rainfall, temperature, aspect, NDVI, weathering, distance to cities, distance to landslides, distance to rivers, distance to roads, and distance to faults. These factors were integrated into a GIS-based modeling framework.

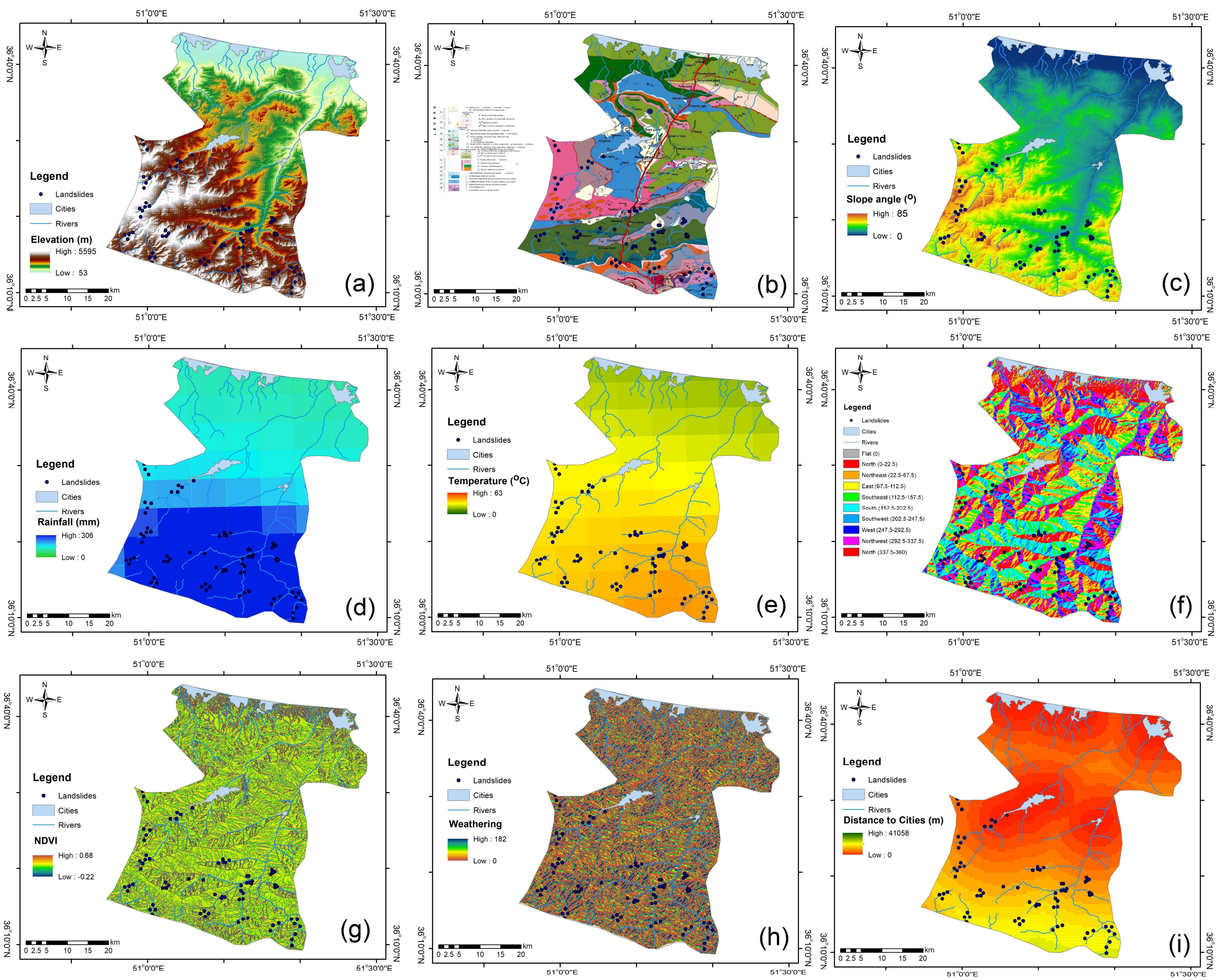

Fig. 5 Selected landslide triggering factors considered in this study: (a) elevation, (b) geology, (c) slope angle, (d) rainfall, (e) temperature, (f) aspect, (g) NDVI, (h) weathering, (i) distance to cities, (j) distance to landslides, (k) distance to rivers, (l) distance to roads, and (m) distance to faults,

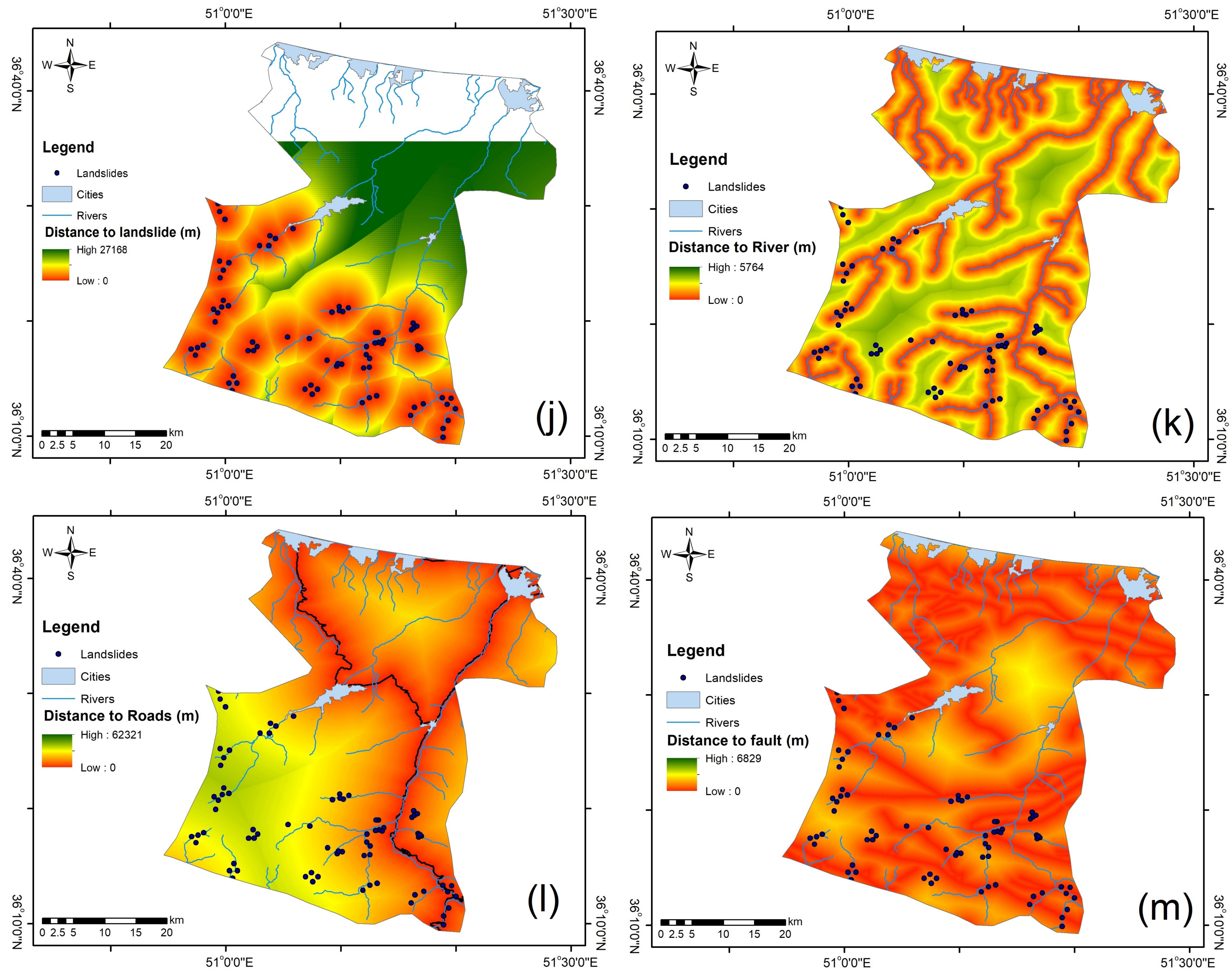

Fig. 5 Continued

V. Materials and Methods

This study employs Artificial Neural Networks (ANNs) to analyze landslide susceptibility in Chalus County, integrating historical landslide records, remote sensing data, and GIS-based spatial analysis. A dataset of 77 recorded historical landslides was utilized, along with multiple landslide triggering factors such as elevation, geology, slope angle, rainfall, temperature, aspect, NDVI, weathering, and various proximity measures (distance to cities, landslides, rivers, roads, and faults). These factors were processed and structured into an ANN framework to predict susceptible regions. In this regard, the study used diverse datasets sourced from multiple organizations. DEM data with a ±30m resolution, enabling the extraction of elevation, slope angle, and aspect. Geological maps and geo-data, while rainfall and temperature data were collected from the IMO. Landsat TM8 and ETM$^+$ satellite images were used to derive NDVI and weathering conditions. Proximity measures were calculated using GIS-based spatial analysis.

After preparation of data and selecting triggering factors for landslides, to ensure compatibility with the ANN model, all input variables were normalized using the Min-Max normalization technique. This method scales the values between 0 and 1, preserving the relationships among data points while preventing biases in the training process (Huqqani et al., 2022). The Min-Max normalization is defined as (Lee et al., 2020):

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

where X represents the original value, X_{min} and X_{max} denote the minimum and maximum values of the dataset, and X′ is the normalized output. This transformation ensures that all input variables contribute equally to model training (Lee et al., 2020). Min-Max normalization was chosen for this study to standardize the range of input variables between 0 and 1, ensuring that all landslide-triggering factors contribute equally to the analysis. Given that the dataset includes diverse parameters such as elevation, rainfall, temperature, and distance to faults, each with different units and scales, normalization is essential to prevent features with larger numerical ranges from dominating the model. By scaling values proportionally, Min-Max normalization preserves the original distribution and relationships within the data while improving model convergence during training. This approach enhances computational efficiency, prevents gradient-related issues, and ensures stable learning in ANNs. One of the key advantages of Min-Max normalization in landslide susceptibility analysis is its ability to maintain interpretability and consistency in spatial data representation (Ba et al., 2017). Since landslide susceptibility models rely on GIS-based spatial analysis, having input features within a uniform range improves pattern recognition and ensures smoother integration into predictive frameworks (Gigović et al., 2019). Additionally, normalization helps in faster and more stable optimization, reducing the risk of numerical instability or biases in weight adjustments (Huqqani et al., 2022). Compared to other normalization techniques, Min-Max is particularly effective when datasets do not have significant outliers, making it a suitable choice for this study's structured and well-preprocessed data.

In this study, the dataset was divided into two subsets: 70% for training and 30% for testing. This split was chosen to ensure that the model receives a sufficient amount of data for learning patterns while reserving an adequate portion for evaluating its performance. Training the ANN on 70% of the dataset allows the model to generalize the relationships between landslide-triggering factors and historical landslide occurrences. With a balanced split, the model can learn effectively without overfitting to specific data points, ensuring better predictive capability when applied to new or unseen data. The decision to allocate 30% of the dataset for testing ensures a reliable assessment of the model's accuracy and generalization ability. A smaller testing set might not provide enough variability to evaluate the ANN's performance effectively, while a larger test set could reduce the amount of training data, leading to insufficient learning. By maintaining a 70-30 split, the model achieves an optimal balance between learning and validation, allowing for an accurate and unbiased evaluation of its predictive strength in landslide susceptibility analysis.

The ANN model architecture used in this study consists of multiple layers designed to capture complex relationships between landslide-triggering factors and historical landslide occurrences. Figure 6 illustrates an example of ANN model architecture. The model comprises an input layer, one or more hidden layers, and an output layer. The input layer receives normalized data representing 13 selected factors, including elevation, geology, slope angle, rainfall, temperature, aspect, NDVI, weathering, distance to cities, distance to landslides, distance to rivers, distance to roads, and distance to faults. These features are processed through weighted connections and activation functions within the hidden layers. The hidden layers play a crucial role in extracting patterns from the input data by applying non-linear transformations, allowing the model to learn the complex dependencies between different variables. The number of neurons in each hidden layer is optimized to balance computational efficiency and predictive accuracy. The output layer of the ANN model provides a probability score indicating the susceptibility of different areas to landslides. The activation function in the output layer is selected based on the classification approach, with softmax or sigmoid functions commonly used for probability estimation. To improve model performance, backpropagation with an Adam optimization algorithm is used to minimize prediction errors by adjusting the network's weights iteratively. The loss function used was binary cross-entropy, which is suitable for binary classification tasks like landslide susceptibility analysis. The training process iteratively adjusted weights to minimize the loss function until the model reached optimal performance. Additionally, techniques such as dropout regularization are employed to prevent overfitting and enhance generalization. The designed ANN model effectively integrates spatial data within a GIS-based framework, allowing for reliable and data-driven landslide susceptibility mapping.

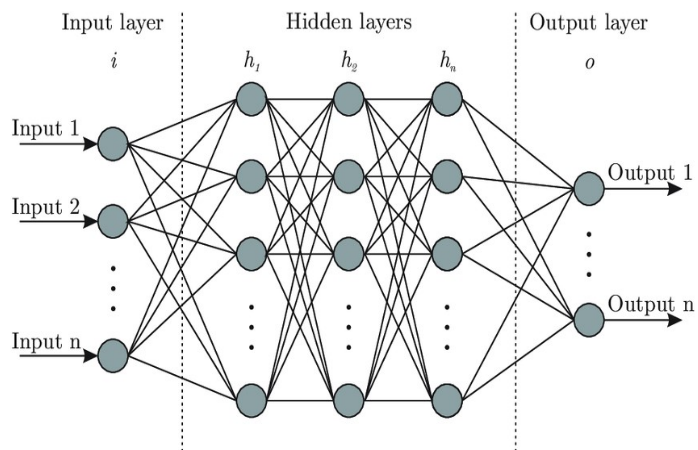

Fig. 6 An example of ANN model architecture (Bre et al., 2018)

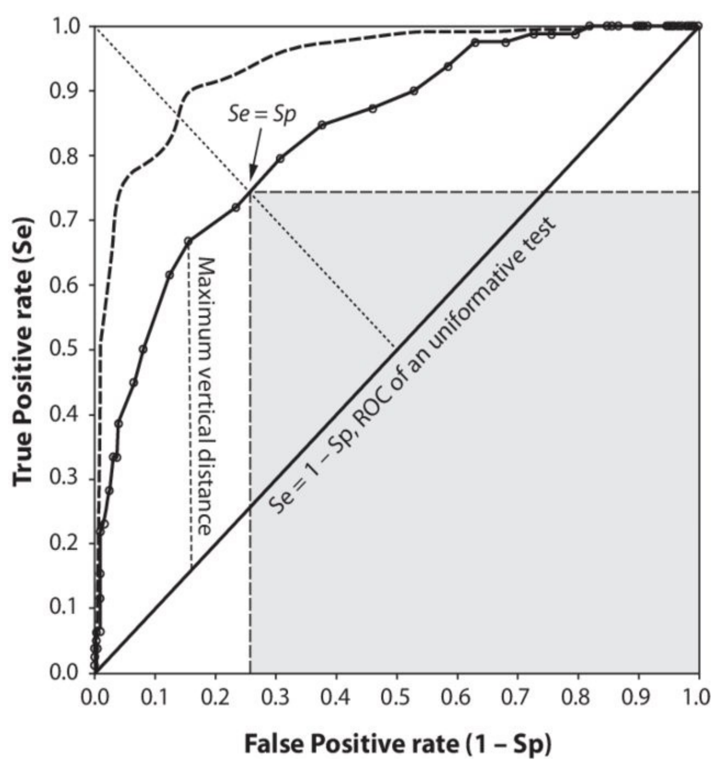

Fig. 7 A common form of ROC curve analysis (Habibzadeh et al., 2016)

https://doi.org/10.22034/CGEL.2.2.e100039

The Receiver Operating Characteristic (ROC) curve is a crucial performance evaluation metric used in this study to assess the predictive capability of the ANN model for landslide susceptibility analysis. The ROC curve plots the True Positive Rate (sensitivity) against the False Positive Rate (1-specificity) at various threshold levels. This graphical representation helps determine how well the model differentiates between landslide-prone and non-landslide-prone areas. The Area Under the Curve (AUC) value, ranging from 0 to 1, is used to quantify model performance, with values closer to 1 indicating a higher predictive accuracy. Figure 7 is providing a ideal form of ROC curve analysis. One of the main advantages of using the ROC curve is its ability to provide a threshold-independent assessment, meaning it evaluates model performance across different classification thresholds rather than relying on a single cut-off value. This makes it particularly useful for landslide susceptibility analysis, where the optimal threshold may vary based on risk tolerance and planning needs. Additionally, the ROC curve allows for a direct comparison between training and testing datasets, ensuring that the model generalizes well to unseen data. By plotting the ROC curve for both training and testing datasets, we can assess the model's reliability and avoid issues like overfitting or underfitting. This approach ensures that our ANN model provides a robust and accurate susceptibility map for Chalus County.

Once the ANN model was trained and validated, the results were integrated into a GIS framework to generate a landslide susceptibility map. The model's output was classified into five susceptibility levels: Very Low, Low, Moderate, High, and Very High. This spatial representation aids in visualizing high-risk areas, enabling efficient decision-making for disaster management. To ensure model robustness, sensitivity analysis was performed by varying input parameters and observing their impact on predictions. Additionally, validation against historical landslide records confirmed the reliability of the ANN-based approach in identifying susceptible zones.

VI. Results and Discussion

The results of the ANN-based landslide susceptibility analysis in Chalus County are shown in Figure 8 that reveals significant spatial variations in landslide-prone areas. The susceptibility map, generated using 13 triggering factors, demonstrates that the highest landslide susceptibility is concentrated in the southwestern and southern parts of the study area. These regions correspond to the steep and rugged terrains of the Alborz mountain range, where geological formations, high precipitation levels, and slope instability collectively increase the likelihood of landslides. In contrast, the northern and northeastern areas, which extend toward the Caspian Sea basin, exhibit lower landslide susceptibility due to their relatively gentle topography and more stable geological conditions.

The ANN model effectively captured the complex relationships between landslide occurrences and their associated triggering factors. The use of historical landslide data, including 77 recorded events, provided a reliable reference for training and testing the model. By employing a 70-30 data split, the model was able to generalize well, ensuring robust prediction capabilities. Additionally, the Min-Max normalization technique enhanced the stability of the model by bringing all input variables within a uniform scale, thereby preventing any single factor from disproportionately influencing the results. A detailed examination of individual triggering factors further validates the susceptibility mapping. Elevation, slope angle, and geological characteristics play a crucial role in determining landslide-prone zones. The areas with the highest elevations and steepest slopes, particularly in the Alborz mountain range, correspond to zones with high landslide susceptibility. Additionally, lithological units composed of weathered rock formations and loose sediments further contribute to instability. These findings align with previous studies in similar mountainous terrains, reinforcing the reliability of the model's outputs.

Rainfall and temperature variations were also found to significantly influence landslide susceptibility. The southern parts of Chalus County experience higher precipitation levels, which contribute to slope saturation, soil weakening, and increased chances of slope failure. This observation is particularly important in areas with pre-existing geological weaknesses, where prolonged rainfall acts as a primary triggering mechanism. The ANN model effectively identified these patterns, demonstrating its capability to integrate multiple environmental factors in a cohesive landslide prediction framework. Another critical factor affecting landslide distribution is vegetation cover, represented by the NDVI index. Areas with dense vegetation generally exhibited lower landslide susceptibility due to the stabilizing effects of plant roots on soil and slope structures. However, deforested and sparsely vegetated regions, particularly in steep mountainous slopes, showed a higher probability of landslides. This finding underscores the importance of land cover management and afforestation programs in mitigating landslide risks. The proximity to roads, rivers, and human settlements also emerged as significant factors in landslide susceptibility. Areas closer to roads and human developments exhibited a higher frequency of landslides, likely due to slope modifications, excavation activities, and improper drainage systems. Similarly, proximity to rivers played a role in increasing slope instability, particularly in areas where riverbank erosion was evident. These findings highlight the need for sustainable infrastructure planning and construction practices to reduce human-induced landslide risks.

The results further confirm a strong correlation between landslide occurrences and fault proximity. The presence of geological faults contributes to structural weaknesses, increasing the likelihood of slope failures. Many historical landslides in Chalus County were recorded near active fault lines, emphasizing the significance of tectonic activity in regional landslide susceptibility. This aspect should be considered in future geotechnical assessments and land-use planning to minimize risks in fault-affected zones. To assess the reliability of the ANN model, we utilized the ROC curve for performance evaluation. The ROC curve has been shown in Figure 9. The results demonstrated high accuracy, confirming that the model successfully distinguished landslide-prone areas from stable regions. The high AUC values for both training and testing datasets indicate strong predictive capabilities, reinforcing the ANN's effectiveness in landslide susceptibility mapping. A comparison of the landslide susceptibility map with geological and topographical characteristics validates the findings of this study. The alignment between high-susceptibility zones and regions with steep slopes, weak lithology, and high precipitation further supports the robustness of the model. These results provide essential insights for hazard mitigation strategies, land-use planning, and infrastructure development in Chalus County. As results, this study highlights the effectiveness of ANN-based modeling in landslide susceptibility assessment. The generated susceptibility map serves as a valuable tool for planners, engineers, and decision-makers, aiding in disaster risk management and sustainable development. Future research could further refine this model by integrating higher-resolution datasets, additional environmental variables, and hybrid machine learning approaches to enhance landslide prediction accuracy.

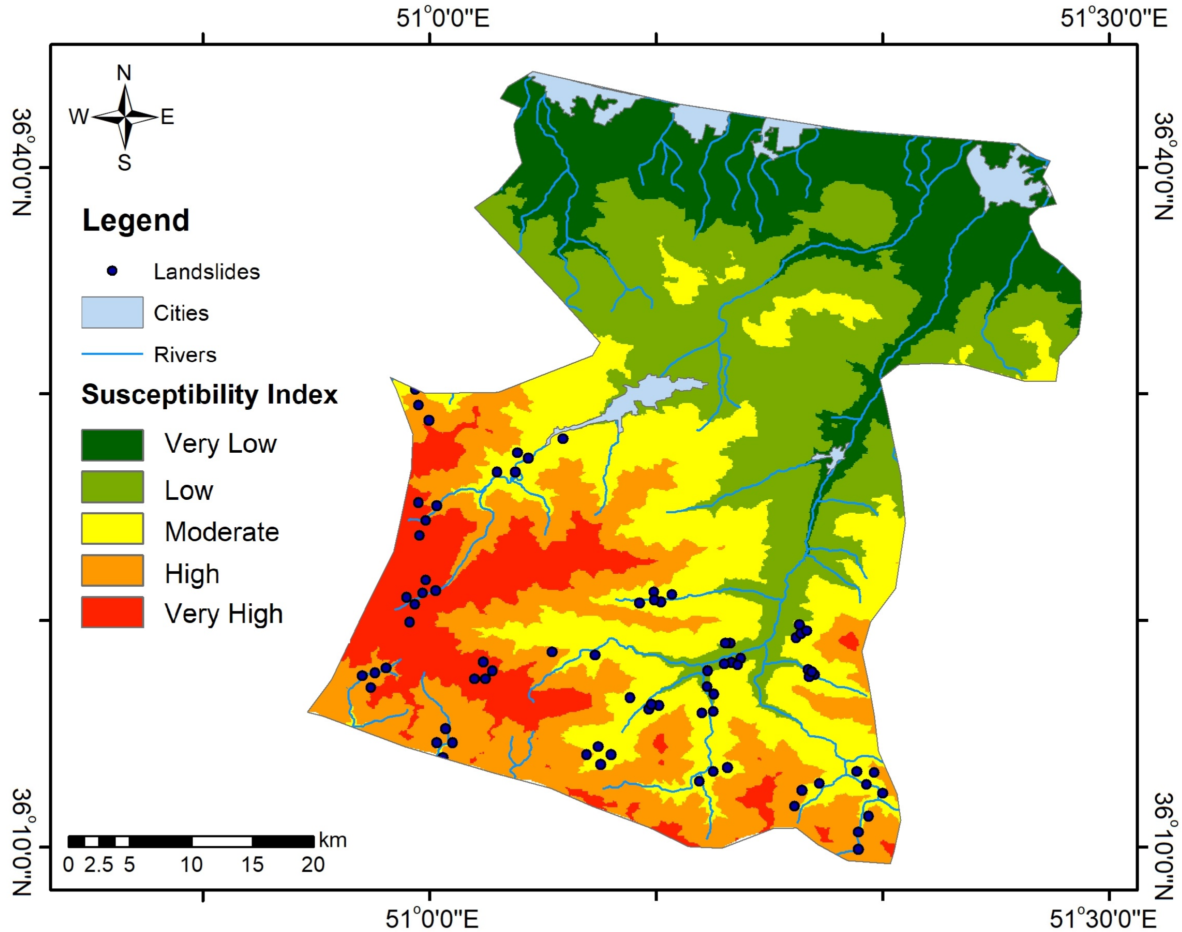

Fig. 8 Landslide susceptibility map for studied area

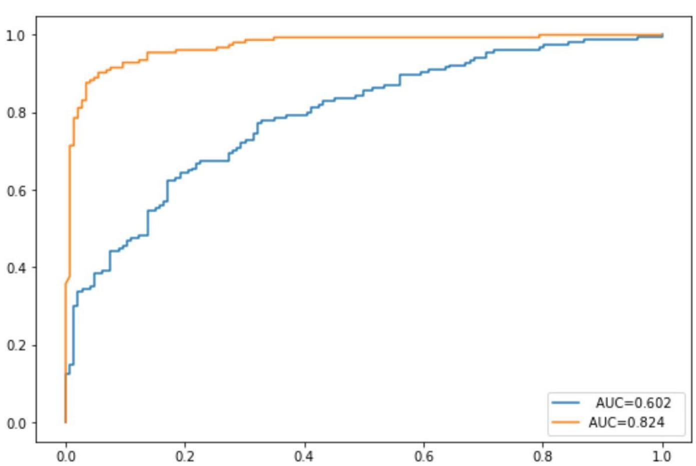

Fig. 9 ROC curve results for ANN-based model

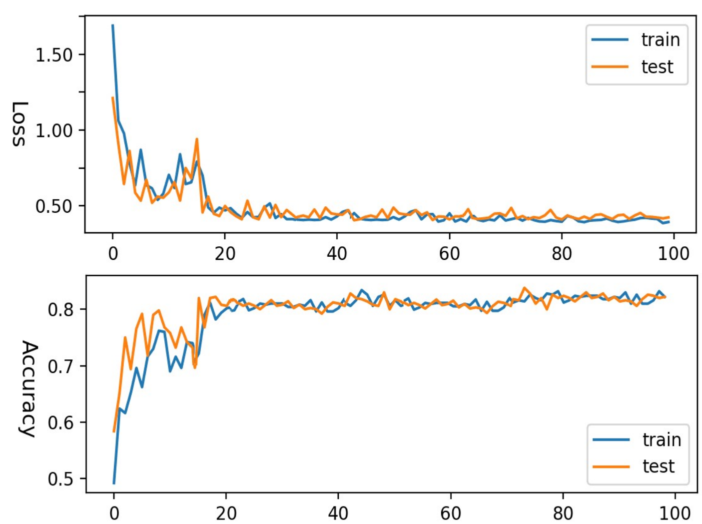

Fig. 10 Loss function and Accuracy of ANN model

VII. Conclusion

This study employed an ANN model to assess landslide susceptibility in Chalus County, utilizing a comprehensive dataset of 77 historical landslides and 13 triggering factors. The analysis integrated remote sensing data, and field surveys to develop a reliable susceptibility map. The findings indicate that the southern and southwestern regions, primarily within the Alborz mountain range, exhibit high to very high landslide susceptibility, whereas the northern and northeastern areas near the Caspian Sea demonstrate lower susceptibility. The ANN model effectively captured the complex relationships between landslide occurrences and their influencing factors. Elevation, slope angle, geology, rainfall, and proximity to faults emerged as key contributors to landslide susceptibility. The Min-Max normalization technique ensured data consistency, while the 70-30 train-test split improved model generalization. The ROC curve confirmed the model's high accuracy in distinguishing landslide-prone areas. The susceptibility map provides critical insights for disaster risk management, infrastructure planning, and environmental conservation in Chalus County. Areas with high susceptibility require immediate attention for slope stabilization, proper drainage systems, and controlled land use to mitigate landslide risks. The study also highlights the impact of human activities, such as road construction and deforestation, in increasing landslide occurrences, emphasizing the need for sustainable development practices.

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Authors' contributions

Morteza Ebadati and Meysam Jabbari Moghadam conducted the main data analysis, contributed to the data collection, preprocessing, and interpretation, and were responsible for drafting the initial manuscript. Feng-Hu Sun and Yu Lee performed supervision, conceptual guidance, and critical revision of the manuscript. Meysam Jabbari Moghadam provided overall project administration and final approval of the version to be published. All authors read and approved the final manuscript.

Conflict of interest

The authors have not disclosed any competing interests.

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