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GIS-based comparative landslide susceptibility mapping for Kelardasht county with ANN, SVM and RF models

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Abstract: This study presents a GIS-based comparative analysis for landslide susceptibility mapping in Kelardasht County, utilizing artificial neural networks (ANN), support vector machines (SVM), and random forest (RF) models. The study identifies key triggering factors, including slope angle, aspect, lithology, land-use, proximity to faults, proximity to rivers, proximity to cities, proximity to occurred landslides, rainfall, and elevation, and 42 historical landslide records. The methodology involves integrating spatial data into a GIS framework, applying data preprocessing and feature selection techniques, followed by training and validation of the ANN, SVM, and RF models. Model performance was assessed using mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and the receiver operating characteristic (ROC) curve. The RF model demonstrated superior accuracy with the highest area under the curve (AUC) value, followed by ANN and SVM, indicating its robustness in identifying high-susceptibility zones. Verification results confirm the reliability of the models, providing precise susceptibility maps that classify the region into five risk categories: very high, high, moderate, low, and very low. The findings offer essential insights for regional planners and policymakers, enabling informed decisions on mitigation strategies and land-use planning to minimize landslide impacts. This comparative approach underscores the value of machine learning models in advancing landslide susceptibility assessment.

Keywords: Landslide susceptibility, Machine learning, Geohazards, SVM, ANN.

I. INTRODUCTION

Landslides are a type of geohazard involving the downward movement of rock, soil, or debris along a slope, often caused by natural and human-induced factors (Azarafza et al., 2017). These events are frequent in areas with steep terrain, fragile geology, and high precipitation, and they can be triggered by events such as earthquakes, volcanic activity, deforestation, and unregulated construction (Huang & Zhao, 2018). The consequences of landslides are severe, ranging from loss of life and destruction of property to disruption of infrastructure and environmental degradation. The increasing frequency and magnitude of landslides, exacerbated by climate change and urban expansion, underscore the need for effective hazard assessment and management tools (Sarkar & Kanungo, 2004).

Landslide susceptibility mapping (LSM) is a critical process that predicts and classifies areas based on their likelihood of experiencing landslides (Broeckx et al., 2018). By identifying high-risk zones, LSM serves as a foundation for disaster prevention, emergency planning, and sustainable land-use management (Huang & Zhao, 2018). These maps are particularly important in regions with high population density or strategic infrastructure, as they enable stakeholders to implement measures that reduce landslide risks, such as reforestation, drainage improvement, and zoning regulations (Azarafza et al., 2021). Moreover, LSM informs the design of early warning systems and helps prioritize areas for monitoring and mitigation efforts (Kavzoglu et al., 2019). Various methods have been developed over the years for LSM. Traditional heuristic methods rely on expert judgment to assign weights to contributing factors, such as slope gradient, lithology, and rainfall (Ado et al., 2022). While simple and intuitive, these methods are subjective and may lack consistency. Statistical models, such as logistic regression and bivariate analysis, have improved the process by quantifying the relationships between landslide occurrences and contributing factors. These models provide reproducible results but are limited in their ability to handle complex datasets or capture non-linear relationships. In recent years, landslide sustainability assessment has garnered significant interest from geoscientists and geotechnical experts. This growing focus has led to the development and application of various approaches, including hybrid semi-quantitative and semi-qualitative decision-making techniques, statistical and geostatistical analyses, artificial intelligence (AI)-driven methodologies, and inventory-based probabilistic frameworks. Advances in geospatial technologies, including GIS and remote sensing, have further enhanced LSM by integrating diverse spatial data into a unified platform (Van Westen et al., 2003). However, even these advanced tools face limitations when dealing with dynamic and highly variable datasets (Ermini et al., 2005).

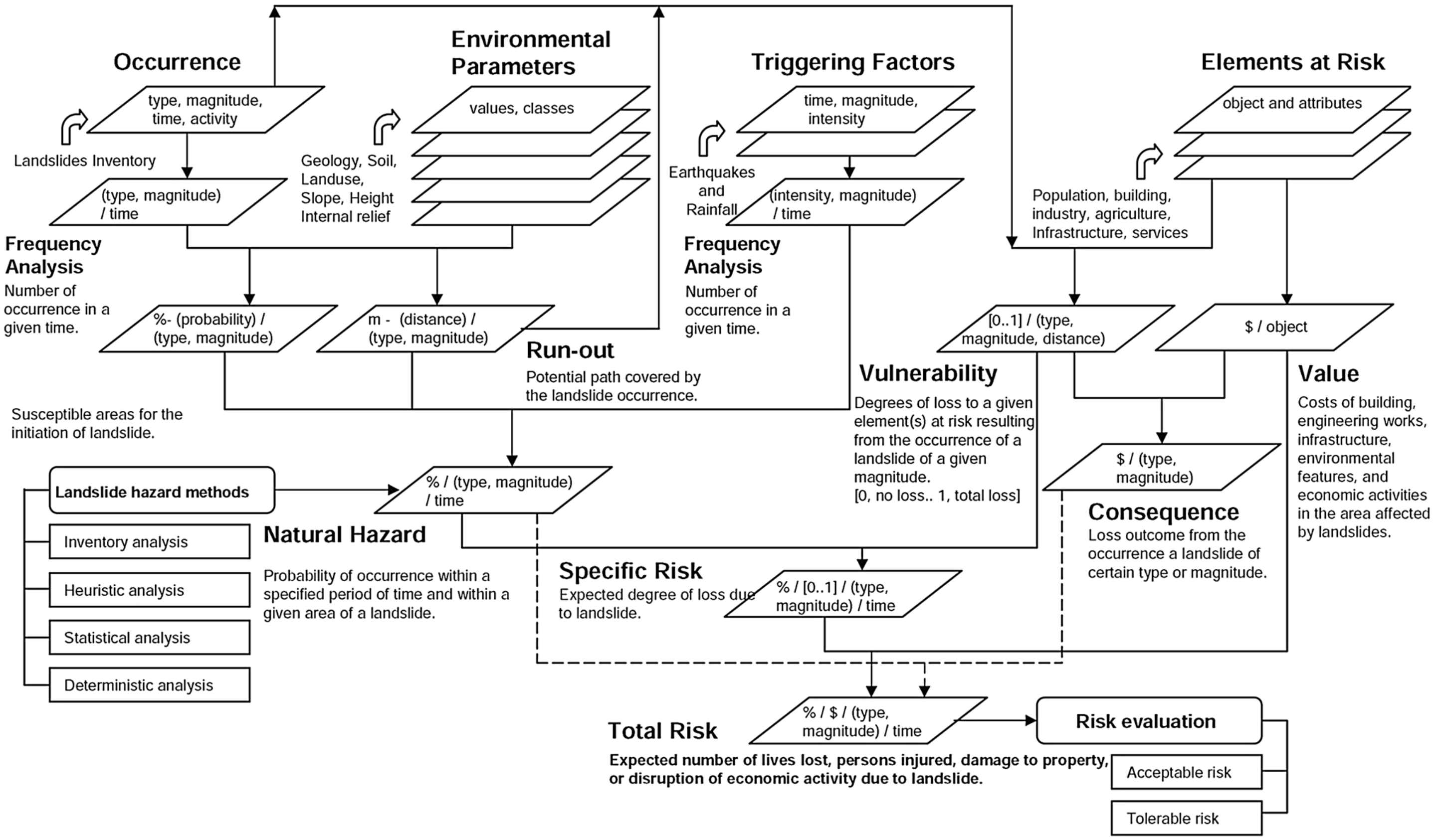

Fig. 1 A recommended framework for LSM (Abella & Van Westen, 2007)

The increasing complexity of geoenvironmental systems and the dynamic nature of landslide triggers necessitate advanced tools capable of handling multidimensional datasets with precision (Wang et al., 2021). Traditional methods for LSM, often fall short in addressing non-linear interactions among variables like slope, rainfall, lithology, and land use. AI-driven methodologies, particularly machine learning, offer a transformative solution by enabling data-driven analyses that uncover intricate patterns and relationships in diverse datasets (Lei et al., 2020). These capabilities make AI indispensable for regions where conventional methods struggle to provide accurate predictions, especially in terrains with highly variable conditions (Ado et al., 2022).

Machine learning has revolutionized the field of LSM, offering capabilities that surpass traditional methods. Machine learning algorithms, such as artificial neural networks (ANN), support vector machines (SVM), and random forest (RF), are designed to process large datasets and uncover complex, non-linear relationships between landslide triggers and occurrences (Zhao et al., 2022). Unlike traditional methods, machine learning models are data-driven, reducing reliance on subjective assumptions. These algorithms adaptively learn patterns from data, enabling more accurate predictions and accommodating the dynamic nature of environmental systems (Qi et al., 2021). Furthermore, machine learning models excel at handling interactions between multiple factors, such as the combined effect of slope, rainfall, and land use, which are challenging to address with traditional statistical methods (Lei et al., 2020). Also, the use of machine learning in LSM significantly enhances the efficiency and scalability of the mapping process (Hong et al., 2019). AI methodologies automate the analysis of vast datasets, reducing the time and labor required compared to manual or semi-quantitative approaches. This is particularly important in disaster-prone regions where timely assessments can save lives and mitigate economic losses (Arabameri et al., 2019). The ability of AI-driven models to handle complex, non-linear data relationships, combined with their capacity for rapid processing and continuous learning, positions them as an essential tool for advancing landslide risk management (Wang et al., 2021). By adopting these methodologies, geoscientists and policymakers can develop more accurate and reliable landslide susceptibility maps, ultimately fostering safer and more resilient communities (Zhao et al., 2022). The integration of machine learning with GIS platforms further enhances the practical utility of LSM. GIS provides a robust framework for spatial data management and visualization, allowing machine learning algorithms to generate spatially explicit susceptibility maps. These maps offer high-resolution insights into landslide risks, empowering planners, engineers, and policymakers to make informed decisions. Additionally, machine learning models can be continuously updated with new data, ensuring their relevance in dynamic environments.

In this study, we apply three widely used machine learning models (ANN, SVM, and RF) for landslide susceptibility mapping in Kelardasht County, a region known for its susceptibility to landslides due to its rugged terrain, fragile geology, and intense rainfall patterns. By leveraging the capabilities of these advanced models, we aim to provide accurate susceptibility maps that can guide risk mitigation strategies. This comparative approach not only evaluates the performance of different models but also highlights the strengths of machine learning in addressing the challenges of landslide susceptibility assessment. The results of this research contribute to advancing the scientific understanding of landslide risks and support the development of proactive measures to reduce the impacts of these hazards.

II. STUDIED LOCATION

Kelardasht County is located in northern Iran, nestled within the Alborz Mountain range. This region is known for its rugged terrain, lush forests, and significant climatic variability, making it a unique yet challenging environment (Kavoosi & Ezoji, 2021). Location of the studied County is illustrated in Figure 2. Geographically, Kelardasht is bordered by steep slopes and valleys, with elevations ranging from lowland plains to towering peaks. Its proximity to the Caspian Sea significantly influences the area's climate, contributing to heavy rainfall and periodic storms (Kardavani et al., 2014). These climatic conditions, combined with the region's topographical complexity, make Kelardasht particularly vulnerable to natural hazards, especially landslides (Ehteshami-Moinabadi & Nasiri, 2019). The geology of Kelardasht is characterized by a mix of sedimentary, metamorphic, and igneous rock formations. The region's bedrock is primarily composed of limestone, marl, and shale, materials that are often prone to weathering and erosion (Ahmadlou et al., 2022). Additionally, the area's geomorphological features, including steep slopes, deep valleys, and fault lines, amplify its susceptibility to landslides (Ehteshami-Moinabadi & Nasiri, 2019). Active tectonic processes in the Alborz Mountains further destabilize the slopes, creating conditions conducive to mass movements (Kavoosi & Ezoji, 2021). Land use practices such as deforestation, unplanned urban expansion, and road construction exacerbate the natural vulnerabilities, increasing the likelihood of slope failures (Ahmadlou et al., 2022). Figure 3 is provided geological map of studied area.

Kelardasht has a long history of landslide occurrences, with records indicating numerous events that have caused significant damage to infrastructure, agricultural lands, and local communities. These landslides are often triggered by intense rainfall, seismic activity, or human interventions, underscoring the need for proactive hazard assessment. Given the region's economic reliance on agriculture, tourism, and transportation, the impact of landslides extends beyond immediate destruction to long-term socio-economic challenges. LSM is therefore of paramount importance for Kelardasht, offering a scientific basis for mitigating risks and guiding sustainable development. Accurate LSM can inform land-use planning, infrastructure design, and disaster preparedness, ensuring the safety and resilience of the region's communities and resources.

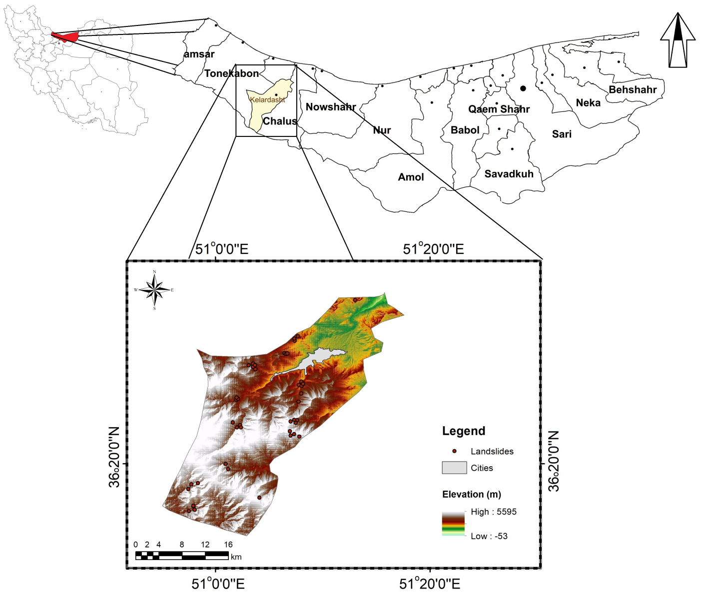

Fig. 2 Location of studied area

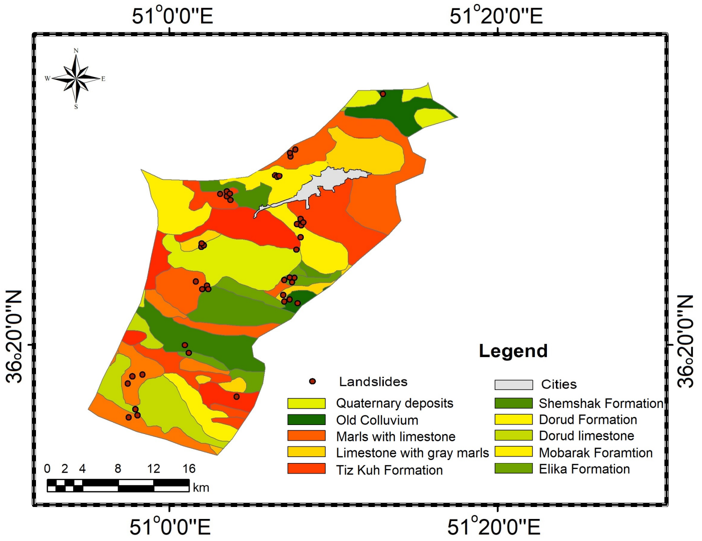

Fig. 3 Geological map of studied area

III. KEY TRIGGERING FACTORS

Selecting key triggering factors is fundamental in LSM as these factors directly influence the accuracy and reliability of the resulting susceptibility models (Yong et al., 2022). Triggering factors, such as slope angle, lithologies, and rainfall, determine the likelihood of slope failure by shaping the conditions that lead to landslides. Accurate identification of these factors allows for a more precise representation of the geophysical and environmental dynamics at play, enabling the development of maps that reflect real-world susceptibility patterns (Günther et al., 2013). Omitting critical factors or including irrelevant ones can skew results, leading to misinformed decisions and increased risks for affected communities (Pham et al., 2016). Each triggering factor provides unique insights into the conditions that contribute to landslides, and their combined analysis allows for a comprehensive understanding of the hazard (Dou et al., 2015).

For instance, while slope angle is a direct indicator of gravitational forces acting on a slope, lithology explains the material strength and resistance to weathering. Factors such as rainfall and proximity to faults introduce temporal and spatial variability, making the inclusion of these triggers essential for dynamic and adaptable models (Thiery et al., 2007). In Kelardasht County, the diversity of geological formations and climatic conditions necessitates the careful selection of factors to account for the region's complex susceptibility patterns.

Moreover, selecting appropriate triggering factors facilitates effective risk management and mitigation strategies based on LSM. By identifying the dominant causes of landslides in a given area, stakeholders can implement targeted interventions, such as reforestation on steep slopes, drainage systems to manage rainfall, or construction restrictions near fault lines. In Kelardasht, incorporating factors like land use and proximity to rivers can inform sustainable urban planning and infrastructure development. Thus, the thoughtful selection and analysis of key triggering factors not only improve the scientific rigor of LSM but also contribute to the creation of safer, more resilient communities. The following key triggering factors are selected for LSM in studied area. These factors have been selected based on literature reviews, remote sensing analysis and field survey.

Slope angle: The slope angle is one of the most critical factors influencing landslide susceptibility. Steeper slopes tend to be more unstable due to gravitational forces that exceed the shear strength of soil or rock, especially when combined with external triggers such as rainfall or seismic activity. In Kelardasht County, the rugged terrain with numerous steep slopes makes certain areas highly prone to landslides. Figure 4 provide slope angle variation map of studied area. Steep slopes in conjunction with weak geological formations further amplify the risk, especially during intense rainfall events, which can saturate the soil and reduce cohesion, leading to slope failure.

Slope aspect: Aspect refers to the orientation of a slope relative to the cardinal directions, which influences solar radiation, temperature, and moisture levels. In Kelardasht, slopes facing north receive less sunlight, retaining higher moisture levels, which can weaken soil strength and increase landslide susceptibility. Conversely, south-facing slopes may experience vegetation loss due to drier conditions, reducing root cohesion and making them equally prone to instability. The slope aspect variations have been provided in Figure 5.

Lithology: Lithology, or the type of rock and soil composition in an area (see Figure 3), directly affects the susceptibility of slopes to landslides. In Kelardasht, the dominant lithologies include limestone, shale, and marl, which are particularly prone to weathering and erosion. Weak and fractured rock types, combined with tectonic activity, make the area highly vulnerable to landslides. The geological composition determines the shear strength, permeability, and stability of slopes, all of which are critical in assessing landslide risk.

Land-use: Land-use patterns, including deforestation, agriculture, and urban development, significantly influence slope stability. In Kelardasht, unplanned urbanization and agricultural expansion on steep slopes have reduced vegetation cover, which plays a crucial role in anchoring soil and mitigating erosion. These activities disturb the natural equilibrium of the slopes, making them more susceptible to landslides, particularly during periods of heavy rainfall. The land-use map has been provided in Figure 6.

Proximity to faults: Fault lines are zones of weakness in the Earth's crust, and their proximity is a critical factor in landslide susceptibility. Kelardasht is situated in a tectonically active region, with several faults traversing the area. The distance to the faults in studied area has been provided in Figure 7. Seismic activity along these faults can destabilize slopes, either directly causing landslides or weakening the structural integrity of rocks and soils, making them more prone to failure under other triggering conditions.

Proximity to rivers: Rivers and streams contribute to slope instability through erosion at their banks and bases. In Kelardasht, the proximity to rivers is a significant factor, as the region's waterways often undercut slopes, reducing their stability and increasing the likelihood of landslides. Heavy rainfall exacerbates this process, as increased water flow intensifies erosion and saturation of the surrounding soils. The distance to the rivers in studied area has been provided in Figure 8.

Proximity to cities: Urban areas in close proximity to unstable slopes face heightened risks due to anthropogenic activities such as construction, road building, and land alteration. In Kelardasht, expanding urbanization has led to increased pressure on marginal lands, often located near high-risk zones. The proximity to cities is an important factor as it not only increases the vulnerability of populations but also amplifies the impact of landslides on infrastructure and economic activities. The distance to the cities in studied area has been provided in Figure 9.

Proximity to occurred landslides: Past landslides serve as an indicator of areas with high susceptibility. In Kelardasht, the presence of historical landslide records highlights zones of inherent instability due to specific geological, hydrological, or human-induced conditions. Proximity to previously occurred landslides is crucial in identifying high-risk areas and understanding the recurrence potential under similar triggering factors. The distance to the historical occurred landslides map in studied area has been provided in Figure 10. The 42 historical landslide records in Kelardasht provide a valuable dataset for analyzing the spatial and temporal patterns of landslide occurrences. These records help identify high-risk zones and validate the factors contributing to landslide susceptibility. They also serve as a foundation for calibrating and validating predictive models.

Rainfall: Rainfall is a primary triggering factor for landslides, as it leads to increased pore water pressure and reduced shear strength in soils. In Kelardasht, the region's high precipitation, especially during intense storms, often results in soil saturation and slope failures. Rainfall patterns are critical for understanding temporal variations in landslide risk, particularly in areas with pre-existing vulnerabilities. The rainfall variations have been provided in Figure 11.

Elevation: Elevation plays a significant role in influencing climatic conditions, vegetation cover, and the overall geomorphology of an area. In Kelardasht, the varying elevations create diverse microenvironments that affect slope stability differently. Higher elevations are often associated with steeper slopes and thinner soils, increasing landslide susceptibility, while lower elevations may experience more erosion due to river activity. The elevation map has been provided in Figure 12.

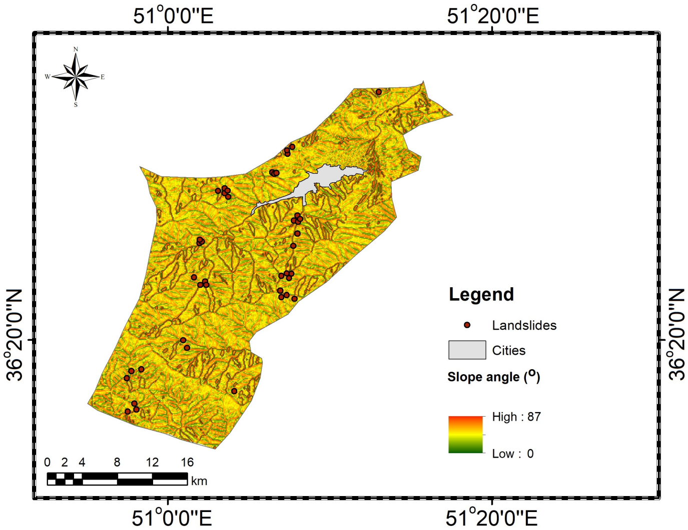

Fig. 4 Slope angle variation in studied area

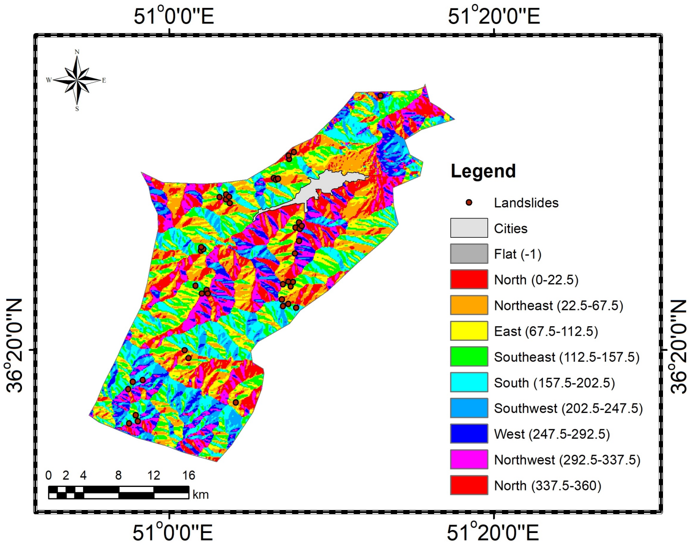

Fig. 5 Slope aspect variation in studied area

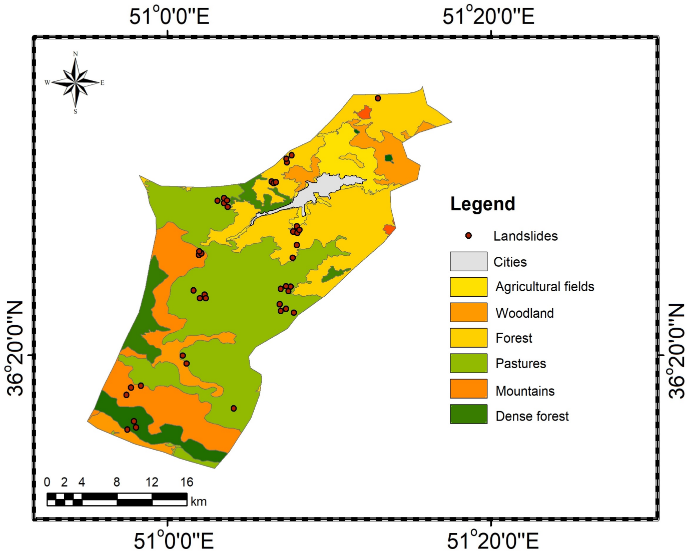

Fig. 6 The land-use map for studied area

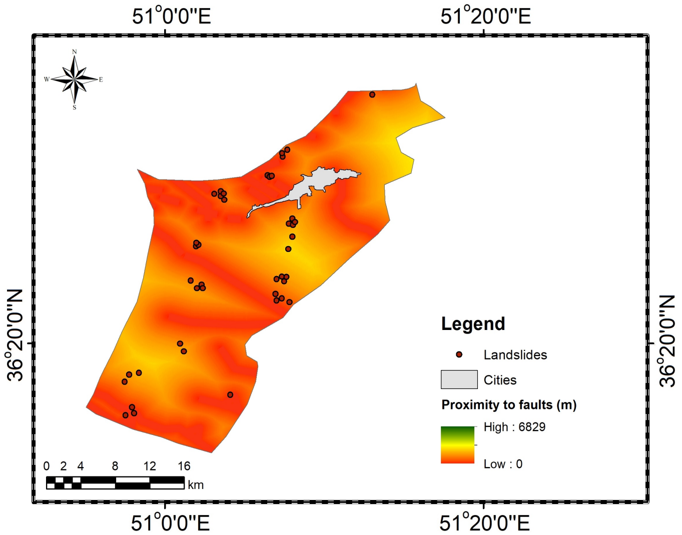

Fig. 7 Distance to the faults in studied area

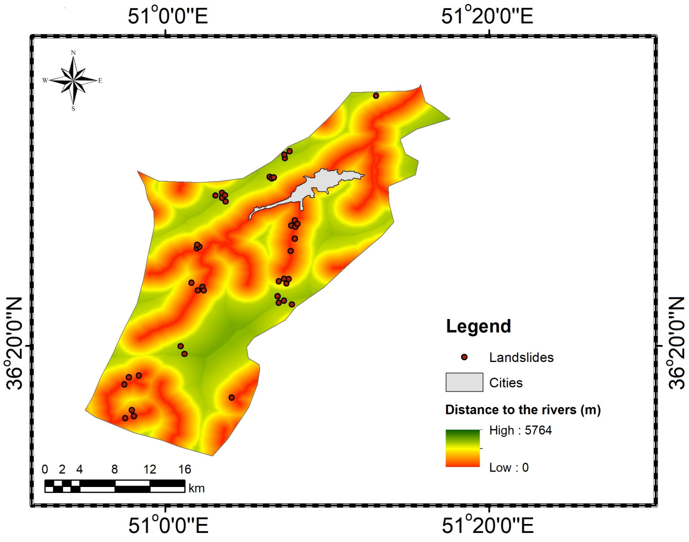

Fig. 8 Distance to the rivers in studied area

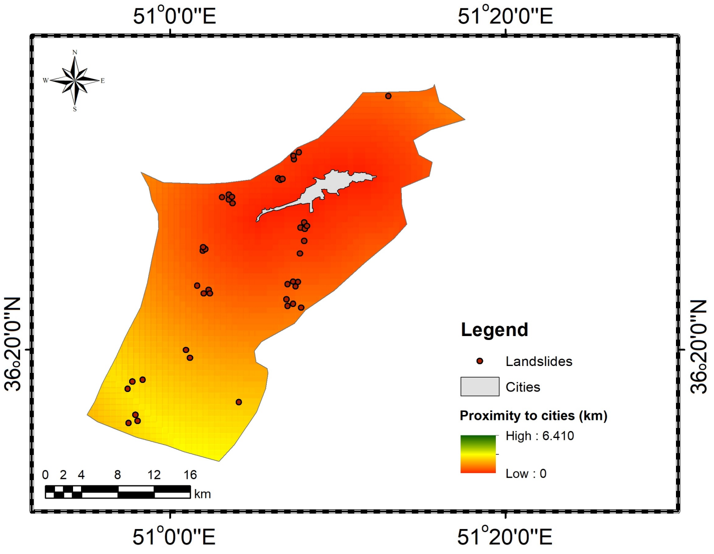

Fig. 9 Distance to the cities in studied area

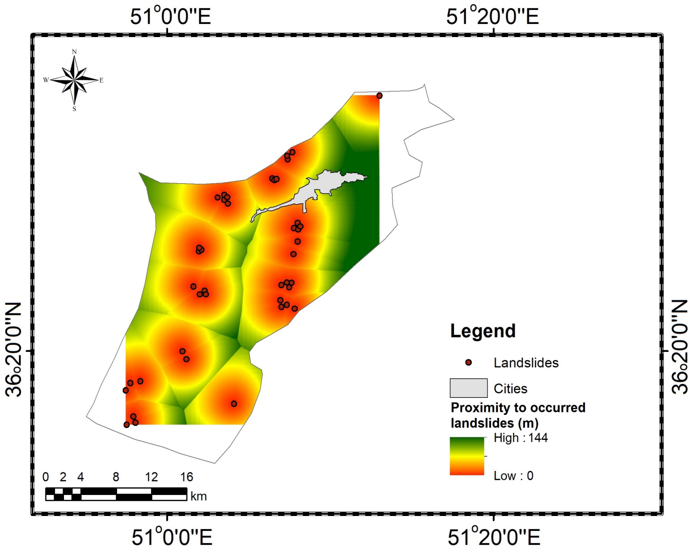

Fig. 10 Distance to the occurred landslides in studied area

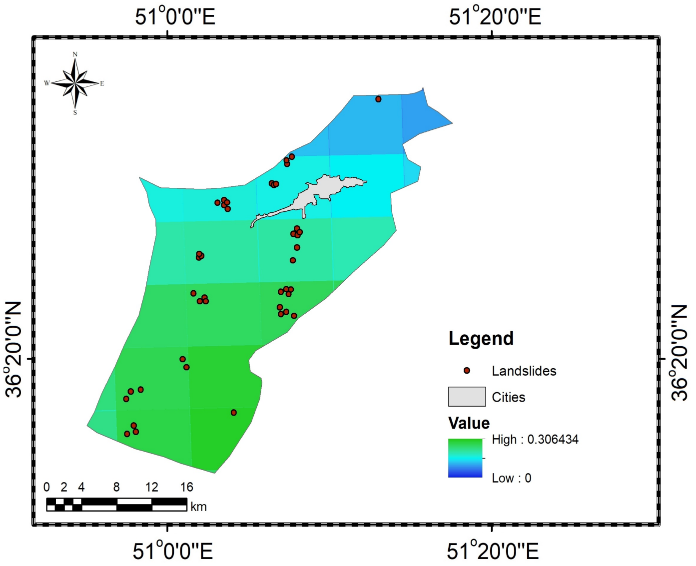

Fig. 11 Rainfall variation in studied area

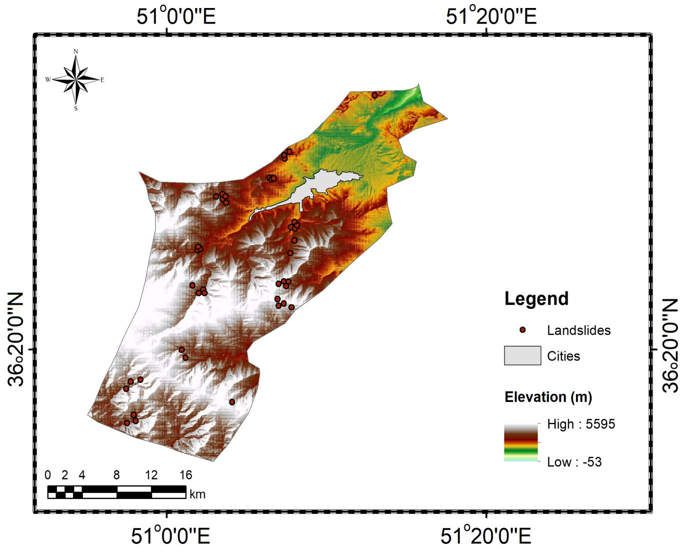

Fig. 12 Elevation variations in studied area

IV. MATERIALS AND METHODS

The methodology for this study is designed to develop accurate and reliable LSM for Kelardasht County by leveraging machine learning techniques integrated with a Geographic Information System (GIS) framework. A systematic approach was adopted, beginning with the collection and preparation of geospatial data, followed by the identification of key triggering factors. The study utilized 42 historical landslide records to train and validate machine learning models, including ANN, SVM, and RF. Each model's performance was evaluated based on its ability to predict landslide-prone areas, ensuring robust and actionable outputs. The research workflow included multiple stages: data acquisition, preprocessing, feature selection, model training, prediction, and validation. Initially, spatial and environmental data, including DEM, geological maps, and land use data, were integrated into the GIS framework. Triggering factors such as slope angle, aspect, lithology, rainfall, and proximity to rivers and faults were derived and spatially analyzed. Each factor was categorized and normalized to ensure consistency in the input data, facilitating effective model training.

Three advanced machine learning algorithms were employed to analyze the dataset and predict landslide susceptibility. The ANN model was configured with multiple hidden layers and neurons to capture complex non-linear relationships between input factors. The SVM model utilized a radial basis function (RBF) kernel to optimize the classification of landslide-prone and non-landslide-prone areas, while the RF model employed an ensemble approach by constructing multiple decision trees to enhance prediction accuracy and reduce overfitting. The models were implemented in Python using libraries such as TensorFlow, and Pandas. Each model was trained using 70% of the dataset, while the remaining 30% was reserved for validation. The spatial data was divided into grid cells, and historical landslide records were used to label the cells as landslide-prone or non-prone. The models were iteratively fine-tuned by adjusting hyperparameters to maximize their predictive performance.

Data preparation was a critical step in ensuring the accuracy and reliability of the models. High-resolution spatial data were sourced from geological surveys, satellite imagery, and meteorological records. The 42 historical landslide records were digitized and georeferenced to align with the GIS database. DEM were processed to derive slope, aspect, and elevation layers, while proximity maps for rivers, faults, cities, and previous landslides were generated using spatial analysis tools. All input factors were standardized to a uniform scale to prevent bias in the model training process. Correlation analysis was performed to identify and remove redundant factors, ensuring that only relevant and independent variables were used. Data augmentation techniques were applied to balance the dataset, addressing the issue of class imbalance between landslide-prone and non-prone areas.

The verification of the models was carried out using multiple statistical metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). The Receiver Operating Characteristic (ROC) curve and the Area Under the Curve (AUC) were also calculated to assess the classification performance. The ANN model exhibited the highest accuracy, followed by SVM and RF, with AUC values exceeding 0.80 for all models, indicating strong predictive capabilities.

Validation was conducted by comparing the predicted susceptibility maps with actual landslide occurrences in the test dataset. A confusion matrix was generated to evaluate precision, recall, and overall accuracy. The models demonstrated high agreement with historical landslide patterns, confirming their reliability. Additionally, a spatial overlay analysis was performed to visualize and compare susceptibility zones across the three models, providing further confidence in the results. This comprehensive methodology ensures that the generated landslide susceptibility maps are both scientifically rigorous and practically useful for disaster management and planning in Kelardasht County.

V. Result and Discussion

The findings of this study provide a comprehensive understanding of landslide susceptibility in Kelardasht County using machine learning models. The results demonstrate that the susceptibility is significantly higher in the southern and southwestern regions of the county compared to the northern areas. This is attributed to the geomorphological features of the Alborz mountain range, which dominate the southern landscape and exhibit steep slopes, fractured lithology, and extensive fault networks. These factors collectively create favorable conditions for landslide occurrences, as identified in the susceptibility maps generated through machine learning analysis. The predictive performance of the machine learning models was assessed using the ROC curve, as shown in Figure 13. Figure 14 illustrates the spatial distribution of landslide susceptibility, with the ANN model providing the most detailed and accurate mapping of high-risk zones. The southern and southwestern regions exhibit the highest susceptibility scores, corroborating with historical landslide records and the influence of triggering factors such as proximity to faults and rivers. Conversely, the northern part of the county shows relatively low susceptibility, likely due to gentler slopes and more stable geological formations. This spatial differentiation highlights the critical role of geomorphological and environmental factors in landslide risk assessment.

The ANN model achieved an impressive accuracy of 91%, outperforming the SVM and RF models, which recorded accuracies of 88% and 80%, respectively. The high AUC value for the ANN model underscores its superior capability to capture complex, non-linear relationships between input factors and landslide occurrences. The SVM model also performed well, demonstrating its reliability in classifying landslide-prone areas, while the RF model, despite its relatively lower accuracy, still provided valuable insights into susceptibility patterns. The ANN model's superior performance can be attributed to its capacity to process and integrate large, multi-dimensional datasets effectively. This model excelled in identifying intricate correlations among key triggering factors such as slope angle, lithology, rainfall, and land use. The ANN-derived susceptibility maps not only align closely with historical landslide data but also offer a granular depiction of risk zones, making them highly practical for local authorities and planners. The SVM model, while slightly less accurate, proved to be efficient in separating high-risk and low-risk zones, offering a computationally less intensive alternative to ANN.

In contrast, the RF model, which employs an ensemble of decision trees, demonstrated moderate predictive performance. While its accuracy was lower compared to the other models, it provided robust classifications in areas with clear triggering factors, such as steep slopes or proximity to faults. However, its limitations in handling the complex interdependencies between factors were evident in regions with overlapping influences, such as urbanized areas near rivers or fault zones. The results emphasize the importance of utilizing advanced machine learning techniques for landslide susceptibility mapping. The ANN model, in particular, proved to be the most effective tool for capturing the multi-dimensional nature of landslide triggers in Kelardasht. Its ability to process diverse data inputs and deliver accurate predictions underscores its value for disaster risk management and urban planning. The SVM and RF models, while slightly less effective, still contribute valuable perspectives and can be used in scenarios where computational efficiency is a priority. In conclusion, the study highlights the spatial variability of landslide susceptibility in Kelardasht County and demonstrates the critical importance of selecting appropriate machine learning models for hazard mapping. The ANN model, with its superior predictive performance, emerges as the most reliable choice for detailed and actionable LSM outputs. These findings provide a robust foundation for developing targeted risk mitigation strategies and fostering resilience in high-risk areas of the county.

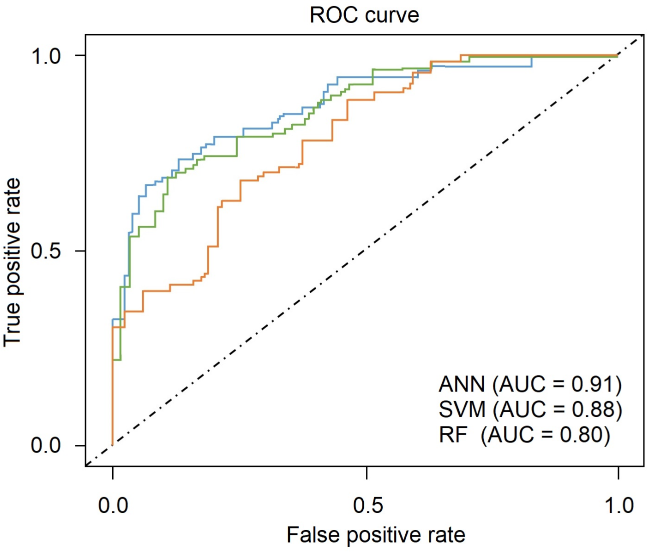

Fig. 13 ROC analysis results for applied models

Table 1 The evaluation metrics for applied models (error table)

Analysis method		MAE	MSE	RMSE	R^2
ANN	Train	0.127	0.158	0.133	0.93
	Test	0.159	0.177	0.135	0.89
SVM	Train	0.215	0.250	0.236	0.87
	Test	0.232	0.270	0.266	0.85
RF	Train	0.252	0.254	0.240	0.83
	Test	0.289	0.254	0.283	0.80

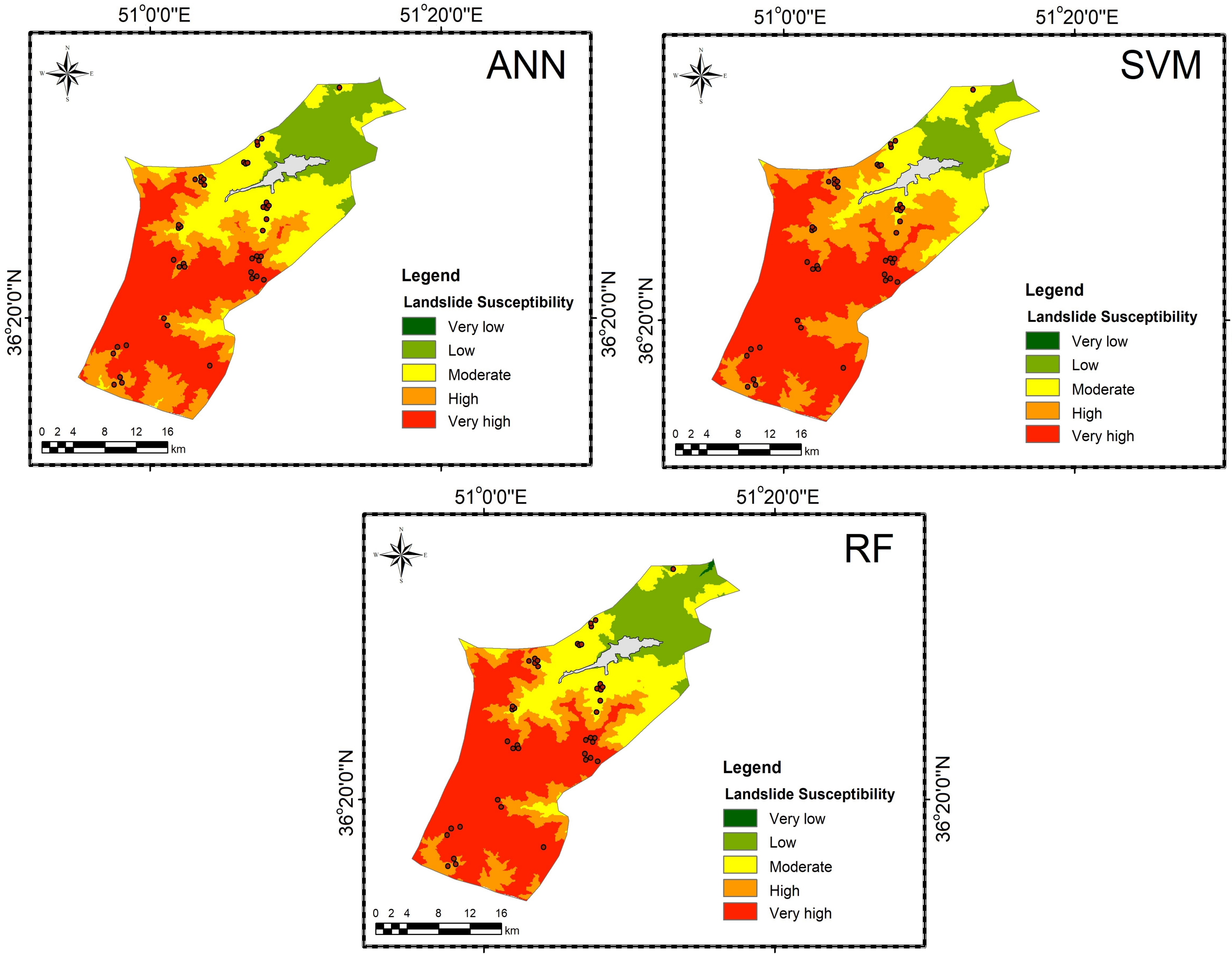

Fig. 14 The estimated LSM map of the County

VI. CONCLUSION

This study successfully developed and validated LSM for Kelardasht County using advanced machine learning models, including ANN, SVM, and RF. The analysis demonstrated that the ANN model outperformed the other two algorithms, showcasing superior predictive accuracy and reliability. With its ability to capture complex, non-linear relationships between input factors and landslide occurrences, the ANN model achieved the highest AUC score and exhibited robust classification performance. The ANN model's strength lies in its adaptability to large, multi-dimensional datasets and its capability to integrate diverse triggering factors, such as slope angle, lithology, rainfall, and proximity to faults and rivers. Its performance was further validated through statistical metrics, including MAE, MSE, and RMSE, as well as a detailed spatial comparison of predicted susceptibility zones with historical landslide records. The ANN-derived LSM provided a highly accurate representation of landslide-prone areas, making it a valuable tool for risk assessment and land-use planning. Given the complexity and variability of the terrain and environmental conditions in Kelardasht County, the superior performance of the ANN model highlights its potential as a leading methodology for landslide susceptibility mapping. This approach not only enhances the precision of hazard prediction but also provides a reliable foundation for informed decision-making in disaster management, infrastructure development, and environmental conservation. Future studies may build on these findings by incorporating additional datasets and exploring hybrid models to further improve landslide risk assessment.

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AUTHORS' CONTRIBUTIONS

Abbas Abgrami and Wu-Feng Zhang conducted the main data analysis, contributed to the data collection, preprocessing, and interpretation, and were responsible for drafting the initial manuscript. Hu Mao performed supervision, conceptual guidance, and critical revision of the manuscript. Li Wang 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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