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灾害、风险、预测、防治

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При создании логотипа конференции использован рисунок из книги С.М. Флейшмана «Селевые потоки» (Москва: Географгиз, 1951, с. 51).

Conference logo is based on a figure from S.M. Fleishman’s book on Debris Flows (Moscow: Geografgiz, 1951, p. 51).

AI landslide susceptibility mapping and statistical interpretation in the Mediterranean coastal zone between Oued Laou and El Jebha, Morocco

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Abstract. Effective management of areas prone to mass movement risks, particularly in landslide-prone regions like Morocco's coastal Rif, depends heavily on prior knowledge. Creating a landslide susceptibility map is crucial before risk assessment. This study utilized an artificial neural network (ANN) classifier to analyze relevant physical factors in the Mediterranean Rif coastal zone, producing a reliable susceptibility map.
Traditionally, landslide mapping involves identifying factors contributing to hillslope instability. Despite various Geographic Information System (GIS) approaches, achieving satisfactory outcomes remains challenging due to landslides' intricate nature. This investigation developed landslide susceptibility models using a multilayer perceptron (MLP) ANN. The methodology included creating a landslide inventory map, deriving hillslope factors from geology, geomorphometry, proximity, and thematic data from satellite imagery, and constructing ANN models.
Model validation employed receiver operating characteristic (ROC) curves, with area under the curve (AUC) values surpassing 0.90, indicating high accuracy. Visual comparisons between susceptibility maps and input factor maps highlighted roads and geology's significant influence on various mass movement types (complex, slide, flow, and rockfall). Statistical analysis revealed slope gradient and geology's impact on landslide types, with specific lithologic formations like gneiss-micaschists, peridotites, schists, and flysch playing crucial roles.
The appearance of new lithologic formations not in the training database underscores other influencing factors. This study's success suggests the method's potential applicability to the entire Rif mountains, offering valuable insights for future landslide susceptibility mapping. Utilizing advanced techniques, particularly ANN classifiers, shows promise in enhancing understanding and managing landslide risks in complex terrains.

Key words: *landslide, susceptibility, artificial intelligence, Rif, Morocco*

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Картографирование оползневой опасности прибрежной зоны Средиземного моря между Уэд-Лау и Эль-Джебхой (Марокко) с помощью ИИ и статистическая интерпретация результатов

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Аннотация. Эффективное управление территориями, подверженными рискам массовых смещений грунтов, особенно в регионах, подверженных оползням, таких как прибрежный горный район Эр-Риф в Марокко, во многом зависит от предварительного анализа. Создание карты оползневой опасности – первоочередной этап при оценке риска. В этом исследовании использовался классификатор искусственной нейронной сети (ИНС) для анализа соответствующих физических факторов в прибрежной зоне Эр-Рифа, что позволило создать карту оползневой опасности.

Традиционно картографирование оползней предполагает выявление факторов, способствующих нестабильности склонов. Несмотря на различные подходы к использованию географических информационных систем (ГИС), достижение удовлетворительных результатов остается сложной задачей из-за комплексной природы оползней. В ходе этого исследования были разработаны модели оценки подверженности территорий оползням с использованием ИНС многослойного перцептрона (МЛП). Методология включала создание карты оползней, определение коэффициентов уклона склонов на основе их геологического и геоморфологического строения, местоположения, данных спутниковых снимков, а также построение моделей ИНС.

При проверке модели использовались ROC-кривые, при этом значения площади под кривой (AUC) превышали 0,90, что указывает на высокую точность построений. Визуальное сравнение карт оползневой опасности и карт входных факторов выявило значительное влияние дорог и геологического строения на различные типы движения масс (комплекс процессов, оползень, селевой поток и камнепад). Статистический анализ выявил влияние крутизны склонов и их геологического строения на типы оползней, при этом решающую роль играют конкретные литологические образования, такие как гнейсо-слюдистые сланцы, перидотиты, сланцы и флиш.

Появление новых литологических образований, которых нет в обучающей выборке, говорит о наличии других влияющих факторов. Результаты данного исследования позволяют говорить о потенциальной применимости метода ко всем горам Эр-Риф, что дает ценную информацию для будущего картографирования оползневой опасности. Использование передовых методов, в частности классификаторов ИНС, позволяет надеяться на улучшение понимания природы оползневых рисков и управлении ими на сложно устроенных территориях.

Ключевые слова: *оползень, восприимчивость, искусственный интеллект, Эр-Риф, Марокко*

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Introduction

This work addresses the significant threat of landslides in Morocco, particularly in the Rif mountains, El Fellah et al. (1996) coast of the Bokoya between Torrès and Badis (Northern Rif), Faleh and Sadiki (2002) in the central Prerif, and Mansour (1998) in the southeast of Chaouen City, Western Rif, Morocco. Following El Kharim (2012) influenced by factors like rainfall, geology, elevation, and slope gradient. The region experiences various landslide behaviors causing damage to infrastructure and socio-economic activities. Previous studies focused on specific zones but lacked comprehensive landslide susceptibility mapping for future predictions [*Aleotti et al., 1996; Mayoraz et al., 1996*] and landslide susceptibility mapping, with conditioning factors [*Lee et al., 2001; Nefeslioglu et al., 2008*]. The current study introduces artificial neural networks, specifically multilayer perceptron (MLP), to model landslide susceptibility in the coastal area between Oued Laou and El Jebha cities. This region, prone to landslides, is also vulnerable to sea-level rise. The study emphasizes overlay analysis in urban planning, considering topography and predicting changes over time due to natural and human factors. Land use maps derived from satellite images reveal the impact of urban development on green areas [*Cetin, 2015; Cetin and Sevik, 2016; Cetin, 2016; Cetin et al., 2018; Kaya et al., 2018*]. The research aims to develop a sustainable landscape plan by evaluating various factors like potential visitors, vegetation cover, cultural values, and topography using Geographic Information System (GIS). The study involves four stages: evaluating the study area characteristics, producing data on landslide factors, constructing ANN models for different mass movement types, and evaluating and discussing the results.

Environmental context

The study area extends along the Mediterranean coast between Oued Laou and El Jebha towns, with a width of approximately 8 km parallel to the coast (Fig. 1). Various landslides occur in this zone due to geomorphological factors, especially in areas influenced by human activities such as roads. The region is part of the internal domain of the Rif chain, encompassing the Ghomarids, Septides, and a portion of the Dorsale Calcaire unit. Geological formations, including schists, sandstone, limestone, conglomerates, and phyllites, characterize the area (Fig. 2).

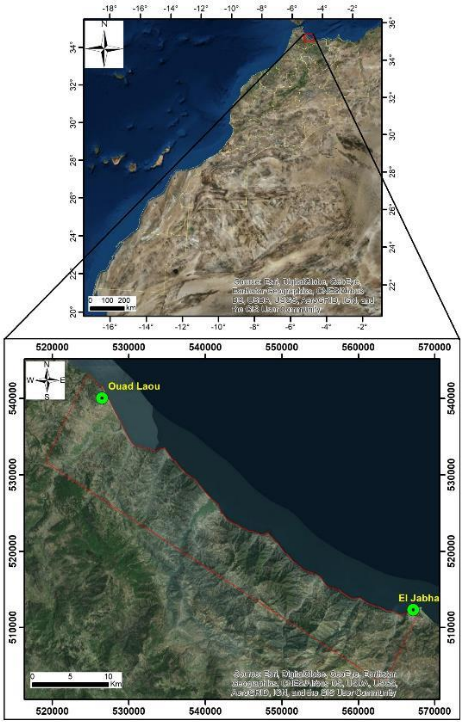

Fig. 1. Location map of the study

The Mediterranean climate in the study area is influenced by altitudes ranging from 0 to 1232 m. Rainfall is primarily caused by Atlantic perturbations (Azores) and occasionally by Mediterranean perturbations. Annual precipitation varies across locations, with Oued Laou receiving 634 mm, El Jebha 349 mm, and Al Hoceima 334.3mm. The rivers in the Rif domain exhibit a torrential regime, with low flows except in limestone regions where delayed flows may occur. Oued Laou River, the main stream, drains a catchment area of 930 km^2, with annual mean inputs directly linked to rainfall patterns.

Other significant streams include Tihissasse, with a catchment area of 622 km^2 and 825 mm mean annual precipitation; Amter, draining 295 km^2 with 805 mm mean annual rainfall; and Oûrînga, covering 510 km^2 with a mean rainfall of 790 mm. These streams exhibit varying specific flows, influenced by geological factors, catchment area characteristics, and precipitation patterns, with their hydrological regimes explained by the dominance of specific facies and steep slopes in their watersheds.

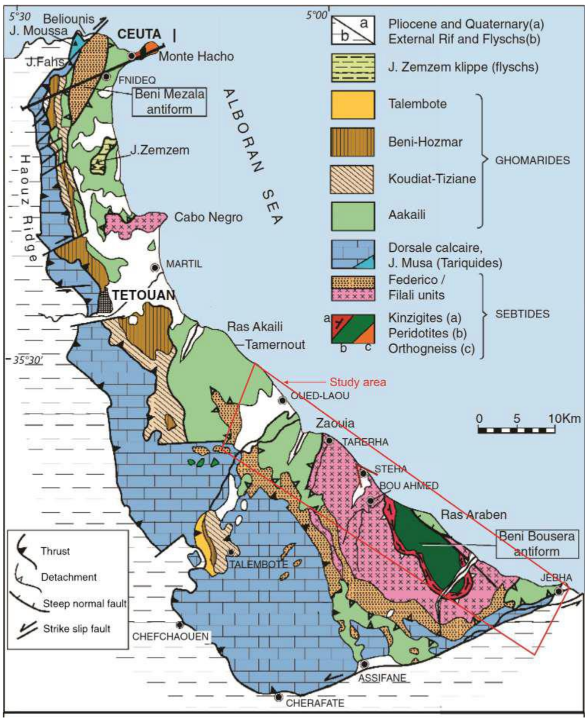

Fig. 2. Geological and structural settings of the study area in the Rif internal zones, modified after Chalouan and Michard (1990)

Method

Various methods have been explored to assess landslides, categorized into three groups: statistical approaches [*Nefeslioglu et al., 2008; Nefeslioglu and Gokceoglu, 2011*], machine learning techniques [*Bedarnik et al., 2010; Pradhan, 2010; Sezer et al., 2011; Nefeslioglu et al., 2012; San, 2014; Ada and San, 2018*], and a combination of index maps [*Turrini and Visintainer, 1998; Ayenew and Barbieri, 2005*]. Despite their differences, these methods share uncertainties stemming from limited knowledge and high variability [*Akgun et al., 2012*].

The Artificial Neural Network (ANN) approach stands out due to its several advantages. Unlike expert systems, ANN doesn't rely on predefined rules but internally identifies patterns within input data to derive output conclusions. The structure of ANN neurons, as depicted in (Fig. 3) [*Hagan et al., 1996*], involves scalar inputs multiplied by weights and offsets, forming the network output. Excitatory and inhibitory connections are determined by the sign of weights, while offsets prevent the network from outputting zero when inputs are zero. The output enters an activation function, determining the transfer rate to the next neuron.

In a Multilayer Perceptron (MLPC), a type of supervised feedforward multilayer network, signals propagate directly between layers and are modified by connection weights. MLPC, often utilizing a sigmoid function in hidden layers, can identify non-linear relationships. The backpropagation learning algorithm adjusts weights by propagating errors from output to inner layers, aiming to minimize errors. The chosen MLPC in this study had specific characteristics: an input database consisting of 20-linear-vector, and 220264 columns and a target of a linear-vector ($1 \times 2{,}202{,}684$), Levenberg-Marquardt backpropagation for learning, gradient descent weight with time and Bayesian learning function for learning adaptation, normalized mean square as a performance function, one hidden layer with 30 neurons. The GIS environment in ArcGIS for Desktop (v 10.6.1) and MATLAB (R2015b) facilitated data preparation and supervised classification execution.

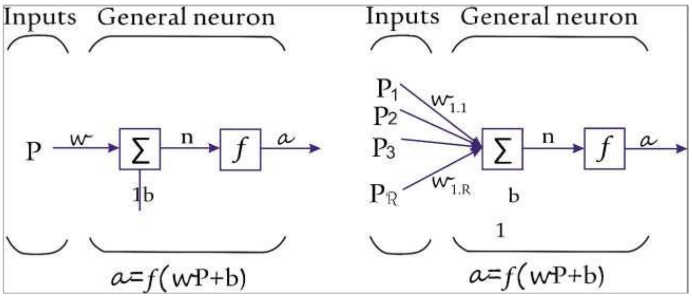

Fig. 3. Schematic model of an individual neuron with an input signal (left) and with multiple signals (right inputs) [*Hagan et al., 1996*]

Analysis and results

The multilayer neural network algorithm processed input and output data, allocating 70% for learning, 15% for testing, and 15% for validation. To assess the reliability of landslide susceptibility models (Figs. 4*a*, 5*a*, 6*a*, 7*a*), performance curves indicating error gradients, regression lines for cross-checking, and ROC curves for spatial model performance were examined. The ROC curve's area under the curve (AUC) served as an indicator of spatial model performance (Figs. 4*d*, 5*d*, 6*d*, 7*d*), with values above 0.90 for all landslide types, confirming acceptable accuracies. Different types of landslide susceptibility models were constructed, each exhibiting normal performance curves (Figs. 4*c*, 5*c*, 6*c*, 7*c*), except for the flow class, suggesting potential overfitting. Regression curves indicated close alignment between outputs and targets, with R values exceeding 0.90 during learning, validation, and testing phases, indicating well-fitted models (Figs. 4*b*, 5*b*, 6*b*, 7*b*). AUC values above 0.90 for all landslide types further validated the models' accuracy.

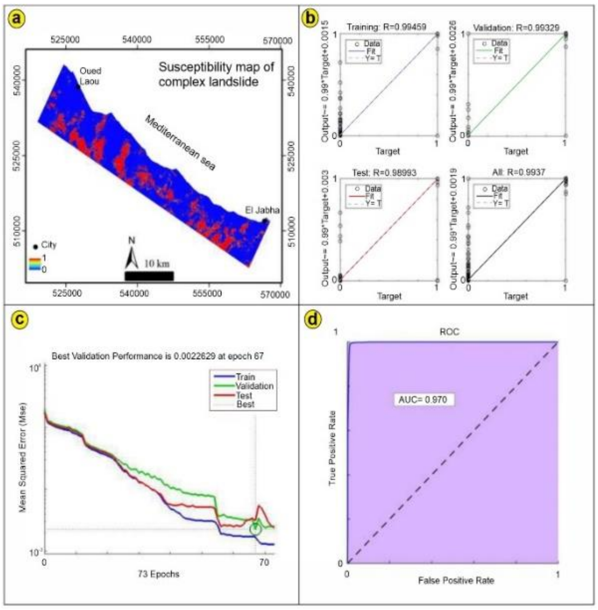

Fig. 4. Susceptibility map of complex landslide (a). Regression error curves (b). Performance curves (c). ROC curve (d)

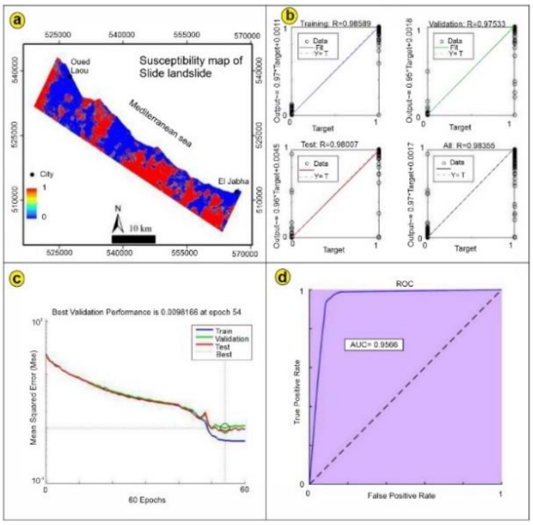

Fig. 5. Susceptibility map of slide (a). Regression error curves (b). Performance curve (c). ROC curve (d)

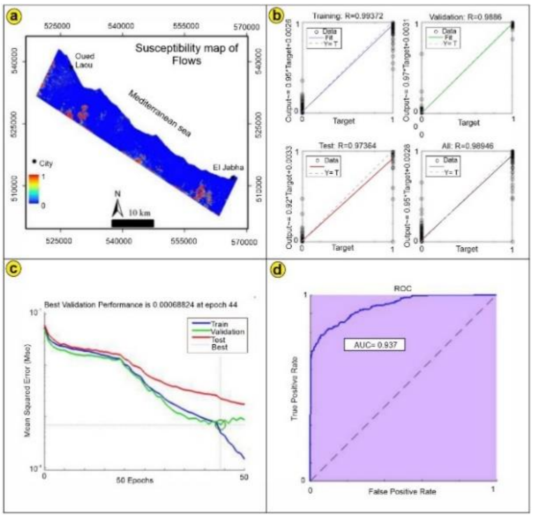

Fig. 1. Susceptibility map of flow (a). Regression error curves (b). Performance curves (c). ROC curve of flows (d)

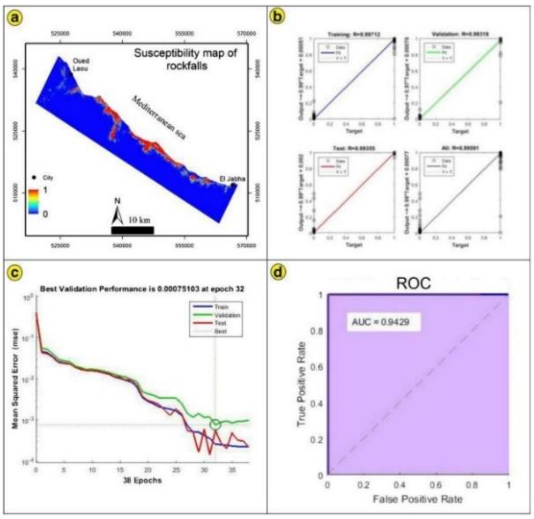

Fig. 2. Susceptibility map of rockfall source area (a). Regression error curves (b). Performance curves (c). ROC curve (d)

Rockfall events in the western part of the Oued Tihissasse valley are linked to the main road's location and steeper slope gradients (Fig. 8*a*). The mean slope gradient is 22° with a standard deviation of 10.4°, and rockfalls generally occur in slopes ranging from 11.6 to 32.4°. The prediction of rockfall source areas indicates a prevalence in gneiss-micaschists (2.9% of the total study area) and peridotites (1.3% of the study area) The landslide susceptibility model focused on rockfall events highlighted areas along the road network, logically linked to increased slope gradients caused by road construction. Landslide susceptibility mapping shows a different distribution, with predicted slides mainly in the middle, southeast, and northwest parts of the study area (Fig. 8*b*), occurring in slopes between 13 and 31°. Complex landslides are predicted at medium and high altitudes, primarily on gneiss-micaschists (6% of the study area) and schists (4.6% of the total area). These findings align with field observations, highlighting gneiss-micaschists as the formations where complex slides predominantly occur. Flows (Fig. 8*d*) are limited and occur in zones with weathered schist, gneiss-micaschists, and flysch with slope gradients between 12.3 and 29.7°.

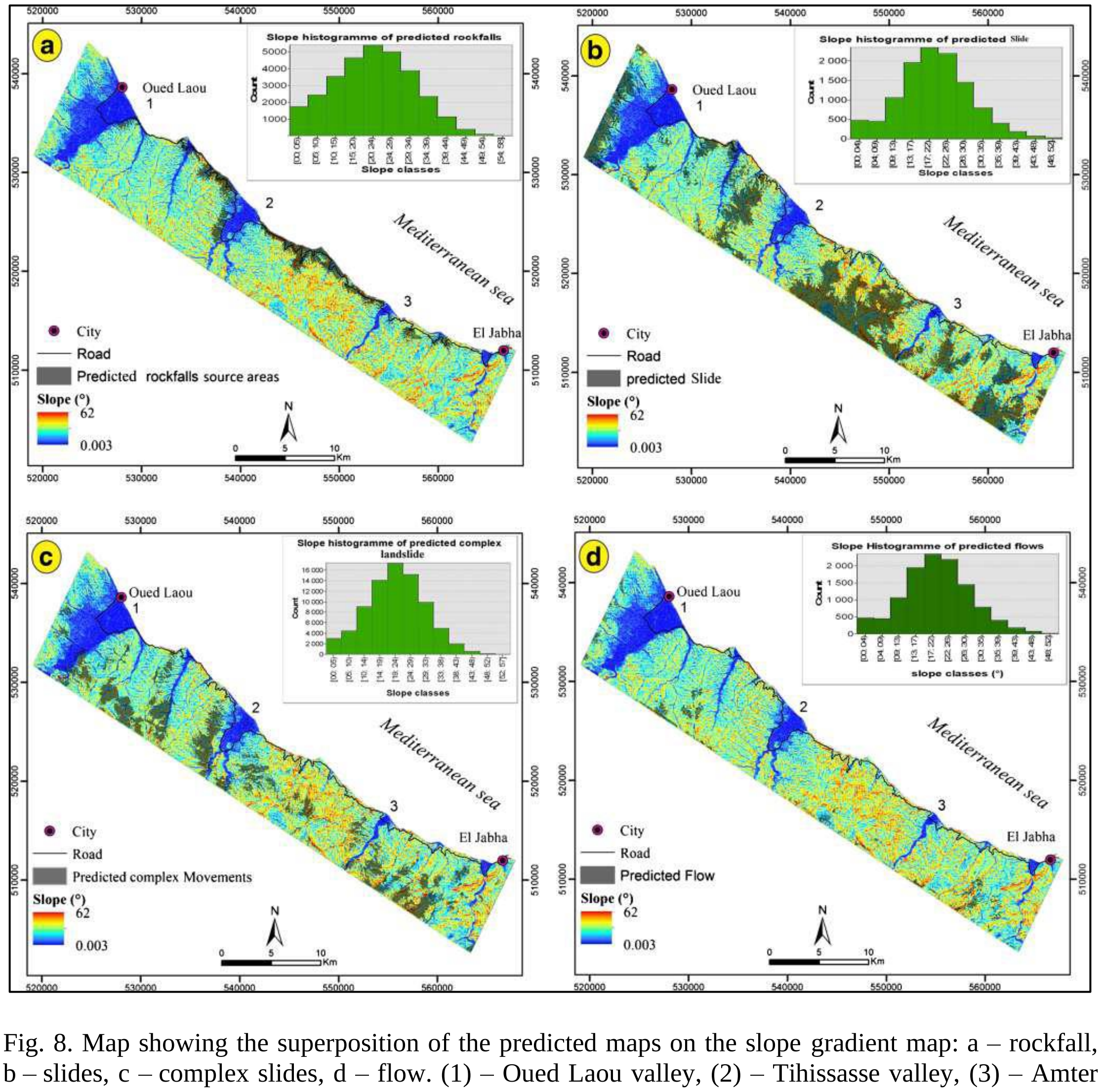

Fig. 8. Map showing the superposition of the predicted maps on the slope gradient map: a – rockfall, b – slides, c – complex slides, d – flow. (1) – Oued Laou valley, (2) – Tihissasse valley, (3) – Amter valley

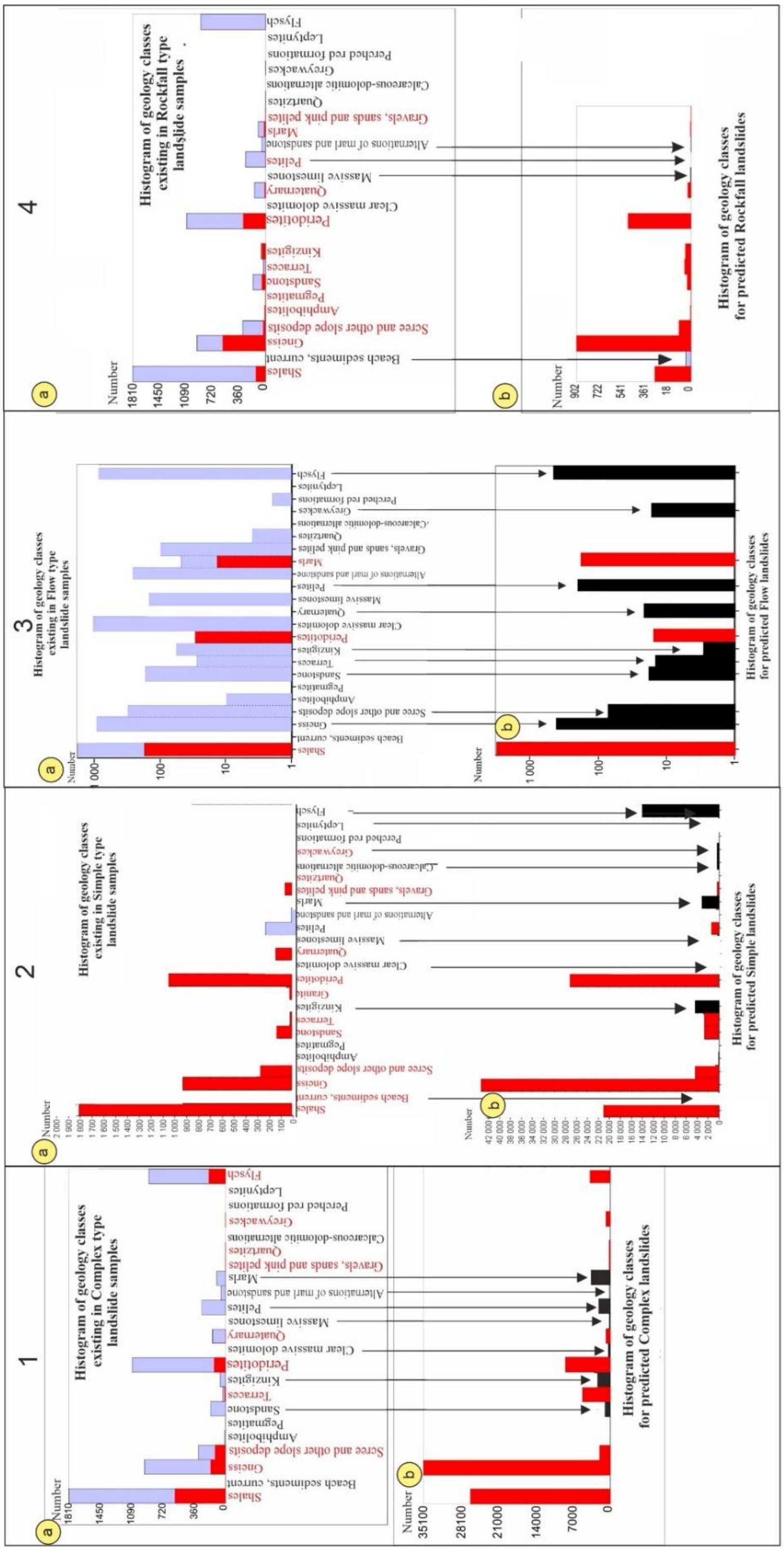

Fig. 3. Map showing the superposition of geological map: 1) complex slides, 2) slide, 3) flow slide, 4) rockfall

Geologically, rockfall source areas mainly occurred in gneiss-micaschists and peridotites (Figs. 9, 4*a*, *b*), emphasizing the impact of hard formations on rockfall occurrences. In contrast, the landslide susceptibility map for slides showed a different spatial distribution, predominantly located outside valleys in the central, southeast, and northwest parts of the study area. Slides were associated with gneiss-micaschists, peridotites, schists, and flysch (Figs. 9, 2*a*, *b*), and complex slides concentrated in medium- and high-altitude zones, occurring on gneiss-micaschists, schists, and peridotites (Figs. 9, 1*a*, *b*). Flows exhibited a negligible area, limited to weathered schist, gneiss-micaschists, and flysch, associated with specific slope gradients (Figs. 9, 3*a*, *b*). Overall, the study highlighted the influence of slope gradient and geology on landslide types, with gneiss-micaschists, peridotites, schists, and flysch playing crucial roles. The appearance of several lithologic formations which were not in the training database, as new formations of occurrence of predicted landslides especially flow type is a fact there is other factors influencing the occurrence.

The study concluded that the Artificial Neural Network (ANN) method demonstrated high prediction capacity, particularly for data-scarce regions. However, limitations such as the need for extensive databases and model retraining in different regions were acknowledged. Expert systems were considered an alternative, but their prediction capacities were deemed lower than ANN models. The study emphasized the ongoing need to investigate landslide susceptibility models, especially in data-scarce regions, using both data-driven methods and expert systems to enhance prediction capabilities at regional scales.

Conclusion

In conclusion, this study employed morphological analysis, GIS analyses, and fieldwork to create a comprehensive database for implementing an ANN algorithm of the MLPC type. The primary objective was to predict landslide occurrences for various landslide types. Although landslides impact only about 1.22% of the total region, their substantial influence on anthropogenic activities, particularly roads, underscores the necessity for producing landslide susceptibility maps to guide appropriate land use planning. The implementation of the algorithm involved 20 data vectors, and the models demonstrated high predictive accuracy, as indicated by AUC values exceeding 0.90 on the ROC curve. Validation, achieved through a comparison of inventory and susceptibility maps, highlighted a strong correlation between landslides and high susceptibility values. The study identifies the region's heightened susceptibility to slides, complex movements, rockfalls, and a slight vulnerability to flows. The statistical study shows the influence of slope gradient and geology on landslide types, with gneiss-micaschists, peridotites, schists, and flysch playing crucial roles. The appearance of several lithologic formations which were not in the training database, as new formations of occurrence of predicted landslides especially flow type is a fact there is other factors influencing the occurrence.

The landslide susceptibility maps generated through the ANN algorithm offer reliable insights applicable in landscape management, regional risk assessment, and remediation strategies. Effective planning and mitigation measures can be implemented by considering these maps, particularly in relation to main roads and villages. For future endeavors, it is recommended to extend the production of landslide susceptibility maps to cover all Rif mountains, employing the back-propagation ANN algorithm.

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