

LANDSLIDE SUSCEPTIBILITY MAP BASED ON MACHINE LEARNING: A VALIDATION BASED ON THE HEAVY RAINFALL EVENT OF MAY 2023 IN EMILIA ROMAGNA, ITALY

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This study develops and validates landslide susceptibility models using machine learning techniques, specifically the Random Forest (RF) algorithm implemented on the Google Earth Engine (GEE) platform. The models are applied at both national and regional scales in Italy, targeting two landslide categories: "All" (All types) and "Rainfall-induced" (Rapid). A national-level susceptibility map is generated using input data from the all country, while the regional-level map is obtained using only a subset of the data. The case of the extreme rainfall event in May 2023 in the Emilia Romagna region of Italy is examined to test the performance of the models. In this event, more than 65,000 landslides occurred across 72 km². The results are critically analysed to understand how scale and data volume affect accuracy. The national models provide a broad overview but may miss localized variations captured by the provincial models. The provincial "All" model excels, with 83.45% of landslides in the highest susceptibility categories, benefiting from larger training data. However, the provincial "Rapid" model underperforms due to limited training data. The study highlights the importance of scalability and data quality. National models offer a useful starting point, while provincial refinement with localized data can significantly enhance predictions. A multi-scale approach combining national coverage with provincial specificity is recommended for future analyses to improve landslide risk assessment and management strategies.

Keywords: Landslide susceptibility mapping, Machine Learning, Disaster risk reduction

1. Introduction

Landslides are a significant geohazard that pose substantial risks to infrastructure, human lives, and the environment (Simetal., 2022), and posing challenges for the communities in the mountainous region. Accurate mapping of landslide susceptibility is crucial for disaster risk reduction and informed land-use planning is the need of time to cater the need of informed planning and preparedness for the disaster. This study focuses on developing and refining landslide susceptibility models using a Random Forest (RF) algorithm implemented on the Google Earth Engine (GEE) platform (Gorelick et al., 2017). The present study explores the effectiveness of predictive models at both national and regional scales, targeting two sets of landslides, named "All" (All landslide types considered without distinction) and "Rainfall-induced" (Rapid).

In May 2023, the region Emilia Romagna (Italy) has been hit by two extremely intense precipitation events that reached a cumulative precipitation of more than 210mm and 240mm respectively (Arpae-SIMC, 2023; Fornasiero et al., 2023). More than 65 thousand landslides were recorded for a total area of more than 72km² (Brath et al., 2023). Majority of these landslides were new activations, and more than half were located in areas currently not classified as susceptible to landslides. This provide the motivations for improving landslide susceptibility mapping and the event is used in the following for validation purposes.

Selecting the appropriate variables for landslide studies is always challenging and a frequent subject of debate among researcher (Shahabi et al., 2015; Meena et al., 2022). Each study area presents unique characteristics, meaning that factors influencing landslides in one region may not necessarily be relevant in another. This variability is due to differences in thematic features, geographical conditions, available data, and study objectives. This pose the question if a model trained at (large) national scale can be accurate at a (small) regional scale. This study addresses this question by preparing landslide susceptibility maps both using data at the national scale and at the regional scale and validating the model with the landslides observed in May 2023 event. By presenting national and provincial model outputs, the study provides insights into the scalability and localization of landslide prediction models. The findings are intended to support more effective landslide risk management strategies in diverse geographic contexts.

2. Methodology

The variables influencing landslide susceptibility can be broadly categorized into terrain features and environmental factors. Terrain variables include such as Aspect, Eastness, and Northness, which determine the slope direction and influence sun exposure and water runoff. Curvature metrics such as Mean Curvature,

Maximal Curvature, Minimal Curvature, Gaussian Curvature, Horizontal Curvature, and Vertical Curvature describe the terrain's shape, impacting water flow and slope stability. Elevation and HAND (Height Above Nearest Drainage) are crucial for assessing slope height and proximity to water bodies, thereby influencing landslide risk through gravitational forces and soil saturation. Environmental factors, on the other hand, include variables like Hillshade, Mean Precipitation (Rain), and NDVI (Normalized Difference Vegetation Index), which affect soil moisture levels and erosion potential. Soil characteristics, such as Soil Density and Slope Steepness, are critical in determining soil strength and the gravitational pull on slopes. Additional topographic indices like TPI (Topographic Position Index) and the Shape Index provide insights into landscape positioning and relief, which are essential for understanding water flow patterns and landslide susceptibility. For this analysis, 18 variables were selected, and variables like Aspect, Eastness, Elevation, Gaussian Curvature, HAND, Hill shade, Horizontal Curvature, Maximal Curvature, Mean Curvature, Minimal Curvature, Northness, Shape Index, Slope, TPI, and Vertical Curvature were extracted from a 30-meter spatial resolution SRTM Digital Elevation Model (DEM) using Google Earth Engine (GEE). Additionally, Rainfall, NDVI, and Soil Density data were also obtained from the GEE repository.

The model is trained and tested with the comprehensive landslide inventory dataset of IFFI– Inventory of landslides in Italy (<https://www.progettoiffi.isprambiente.it/en/italian-landslide-inventory-iffi/>); and ITALICA <https://doi.org/10.5281/zenodo.8009366>. Recently occurred landslide data taken from Geoportale (regione.emilia-romagna.it) relative to the event of 2023 in Emilia Romagna is used for validation.

To assess landslide susceptibility on a large scale, we employed Random Forest (RF) classifiers at the pixel scale using GEE (Huang et al., 2020). The RF classifier is known for its robustness in handling high-dimensional datasets (Prakash, et al. 2020), and model evaluated using the set of input features, with the dataset split into 70% for training and 30% for testing, and model performance was optimized for out-of-bag error. The accuracy of the models was assessed using the Area Under the Curve - Receiver Operating Characteristic (AUC-ROC) metric to ensure reliable predictions and feature importance also obtained. The model gives landslide susceptibility scores (as the metric of susceptibility is in between 0-100) divides areas into six classes based on their likelihood of experiencing landslides: Very Low (0-15%), Low (15-30%), Low to Moderate (30-45%), Moderate to High (45-60%), High (60-80%), and Very High susceptibility (80% and above) and final map prepared using ARCGIS Pro

3. Result and Discussion

Four landslide susceptibility maps are prepared for the region Emilia-Romagna, namely:

- AN: Landslide Type All, modelled at the national scale;
- AP: Landslide Type All, modelled at the regional scale;
- RN: Landslide Type Rainfall-induced, modelled at the national scale;
- RP: Landslide Type Rainfall-induced, modelled at the provincial scale.

The national-level models (AN and RN) are trained with the data of the whole country, considering a large area (301,340 km²) and a significant number of landslide points (22400 and 6321 respectively), while the provincial models (AP and RP) focused on a smaller subset, i.e. only the landslides registered in the region Emilia Romagna (22,451 km²), that represent the area of interest (AOI), and a reduced number of landslide points (2456 and 281). Fig.1 shows the landslide susceptibility maps obtained with the 4 models.

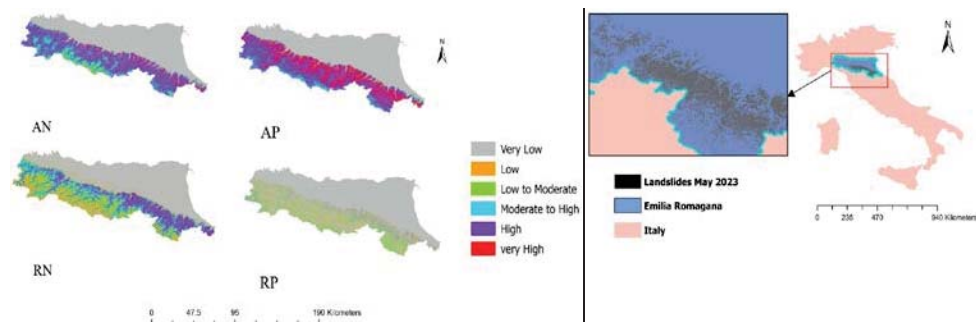


Fig.1. Landslide Susceptibility Map for different Landslide Type in Emilia Romagna

Fig. 2. and Fig. 3. represent bar plot illustrating variable (feature) importance and Receiver Operating Characteristic (ROC) curve for the AN, AP, RN and RP. The AUC-ROC curve graph compares the prediction accuracy of the RF model across different landslide types, showing that all models perform well (AUC > 83%). The results indicate that variable importance varies significantly depending on the landslide

type, with Rainfall, Elevation, and NDVI being crucial in general. It should be noted that the variable importance is different for the national and provincial models even for the same landslide type, could be due to the differences in scale, data heterogeneity, training size, and local environmental conditions lead to varying importance rankings for the same landslide type at two different scale; for example, AP shows Elevation and Hillshade as most important factors, while AN has rain and NDVI.

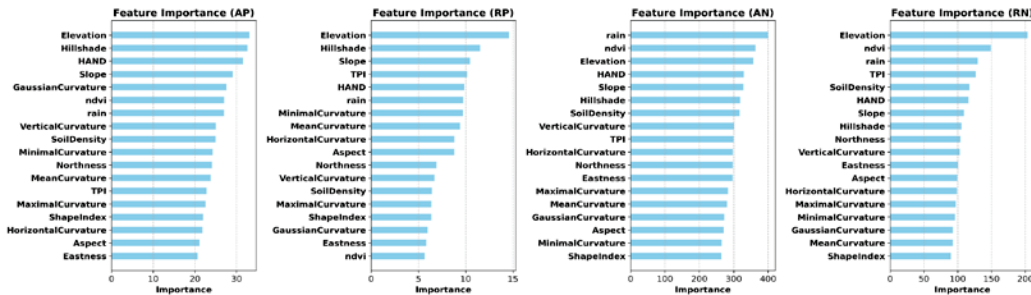


Fig.2.Bar plot illustrating variable importance in predicting the AN, AP, RN and RP using Landslides Random Forest model

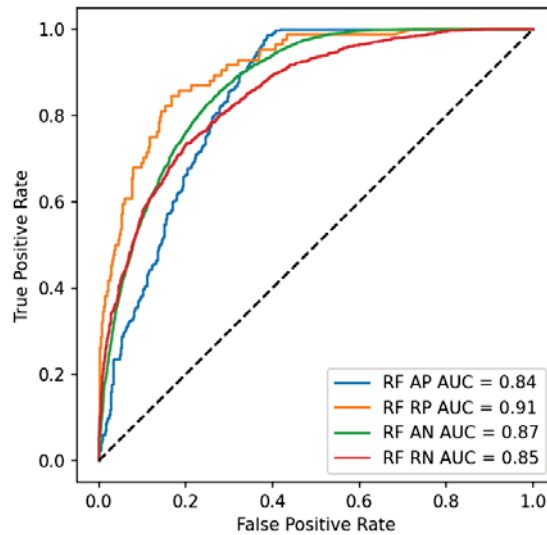


Fig.3.Receiver Operating Characteristic (ROC) curve for the AN, AP, RN and RP using Landslides Random Forest model

Table 1 represents the results of validation conducted using independent data of landslides occurred after the precipitation events (not included in the training or testing phases) to assess the influence of scale on model performance. From Table 1 and Fig 1 National Models AN and RN (301,340 km²) capture a broader range of variability in predisposing factors, which might result in a generalized susceptibility prediction. This is evident in the AN model, where 66.3% of the newly observed landslide points fall into the "High and Very High" susceptibility category, and small fraction into lower categories (e.g., 7% in "Very Low"). For the RN model, 76.8% of points fall in the highest risk category, with a proportion (~23.2%) scattered across the lower to moderate categories.

By starting with a national-scale susceptibility map and then clipping it for provincial analysis, we're essentially testing how well a generalized model (trained on broad national data) adapts to a smaller scale. Since the AOI remains consistent, differences in model performance between national and provincial cases can be attributed to model granularity, training data volume, and the inherent variability captured at different scales rather than differences in geographic coverage. The national models (AN and RN) provide a broader, more generalized susceptibility overview, which may be useful for national-level risk assessments and planning. However, they may miss finer, localized variations in landslide susceptibility that are captured in the provincial models.

The provincial models (AP and RP) allow for finer-scale analysis. The significant difference between the performance of AP and RP underscores the importance of model specificity. AP benefits from a larger training dataset (2,456 landslides points) compared to RP (only 281 landslides points), leading to better detection of high-risk zones. This highlights that while a reduced area of interest (AOI) can improve model specificity, it also requires sufficient training data to perform well. The success of AP suggests that high density of available landslide data in the region can significantly enhance prediction accuracy for specific

regions. This aligns with the finding that AP captures the highest proportion (83.45%) of landslides in the "High and Very High" category, likely because it incorporates localized patterns that the broader national model might average out which covers around 66.3%. The underperformance of RP proves that scaling down in area requires a proportional increase in data quality to maintain or improve prediction accuracy but this was not possible in the present study due to scarcity of data.

Table 1 Showing percent of landslides falls in different susceptibility range

Landslide Type	Model case	No. of Landslide points (LSP)	Area (KM ²)	Susceptibility Range Validation Percent (%)				
				Very Low	Very Low to Low	Low to Moderate	Moderate to High	High and Very High
AN	National	22400	301340	7	0.9	5.98	19.7	66.3
AP	Provincial	2456	22451	10.9	0.85	0.79	3.95	83.45
RN	National	6321	301340	5.3	0.4	2.4	15.8	76.8
RP	Provincial	281	22451	21.1	23.5	22.4	20.3	12.8

4. Conclusions:

The approach of using an Italian region, with clipped Emilia Romagna for focused analysis, effectively shows how susceptibility classification can vary with scale. Models trained on a national scale provide a broad assessment but may lack the sensitivity required for localized predictions, which can be addressed by refining the model with regional data. Training data volume is crucial, especially for provincial models, to ensure accurate classification into high-risk categories. Thus, investing in collecting more regional-specific data would significantly enhance the reliability of the susceptibility maps at smaller scales. This nuanced analysis of both area-based impact and the effect of using a national map for provincial analysis provides a clear roadmap for refining landslide susceptibility models to better inform risk management strategies and suggests that using a national model can be taken as a baseline which can be refined with localized training data to further improve prediction accuracy for specific regions which lacks in data and to gain homogeneity in methodology throughout the country. This analysis provides insights into the model's strengths and areas for improvement based on susceptibility range validation, guiding future modeling efforts for more accurate landslide risk prediction.

Future analysis should consider a multi-scale modeling approach where a national-level model is used for initial risk identification, followed by provincial-scale models refined with additional local data. This could improve overall model performance, combining the strengths of broad coverage with localized specificity. This idea consists in the implementation of transfer learning techniques, that could offer more reliable solution especially when data and scaling is an issue for the future studies.

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