Landslide Susceptibility Maps In Alpine Areas Subjected To Climate Change By Using A Machine Learning-Based Approach

LANDSLIDE SUSCEPTIBILITY MAPS IN ALPINE AREAS SUBJECTED TO CLIMATE CHANGE BY USING A MACHINE LEARNING-BASED APPROACH

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Abstract

The increasing frequency and intensity of landslides is a clear manifestation of climate change, particularly in mountainous regions such as the Northwestern Italian Alps. In these areas, heavy precipitation and temperature fluctuations, along with permafrost degradation, are major drivers of slope instability. This study aims to evaluate the future evolution of landslide susceptibility under climate change and its implications for critical infrastructure, focusing on high-voltage energy lines. An Extreme Gradient Boosting (XGBoost) model was applied to generate susceptibility maps using a combination of static and dynamic conditioning factors. A dataset of 728 spatially distributed points, comprising both landslide and non-landslide events, was used for model training and validation. To account for climate change impacts, downscaled projections from the Coupled Model Intercomparison Project Phase 6 (CMIP6) were used, incorporating data from global climate models under the high-emission scenario SSP5-8.5 for the period 2021–2040. Model performance was evaluated using the Area Under the ROC Curve (AUC), with values ranging from 0.92 to 0.99 across all months, indicating high predictive accuracy. A comparison of current (2003–2022) and future (2020–2040) susceptibility maps reveals a significant increase in areas classified as "Very High" susceptibility, rising from 9.96% to 12.85%, while "Very Low" susceptibility areas decrease from 17% to 13%. In addition, the exposure of high-voltage energy infrastructure was analyzed. The spatial overlap between energy lines and susceptibility classes shows that the proportion of energy lines located in "Very High" susceptibility zones is expected to increase from 13% to 17%, raising concerns for future infrastructure vulnerability and planning.

1. Introduction

Climate-change signals are increasingly evident in the mounting number and severity of landslides (Field et al., 2012). Altered rainfall regimes and temperature trends stand out as the main climatic triggers, with global-warming–driven intensification of precipitation widely recognised as a prime accelerator of slope failures (Gariano and Guzzetti, 2016). In alpine terrain, the thaw of permafrost commonly initiates rockslides and other mass-movement processes (Barla et al., 2000; Gruber and Haeberli, 2007; Huggel, 2009).

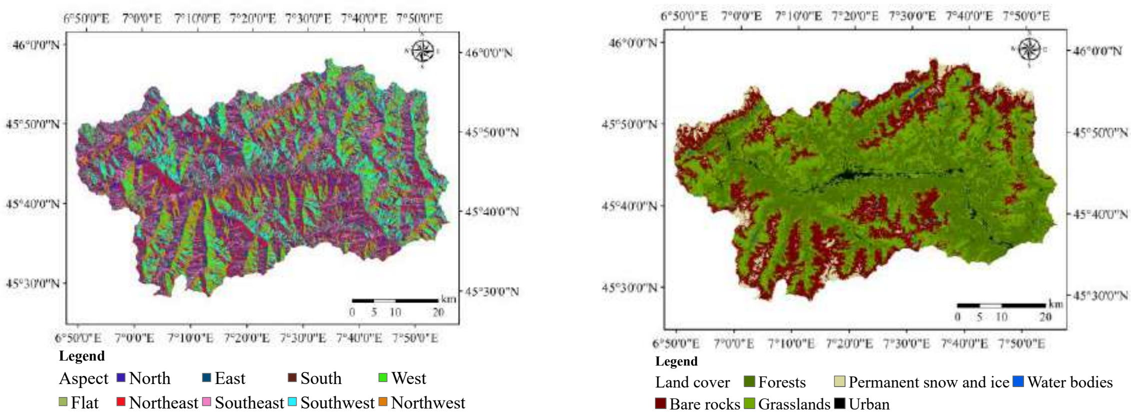
For any study area, therefore, it is vital to delineate zones susceptible to landslides and to explore how evolving climate signals may reshape that hazard pattern (Insana et al., 2021). A few investigations have already combined climate-change scenarios with the landslide susceptibility map (LSM), but their geographic and methodological coverage remains limited. Janizadeh et al. (2023), for example, produced LSMs for Iran under multiple Shared Socio-economic Pathways (SSPs) and future time slices, whereas Saha et al. (2021) tested how varying Representative Concentration Pathways (RCPs) alter rockfall and debris-flow likelihood. Even so, most existing work either omits temperature as an explicit predictor or ignores the short-term precipitation and temperature conditions that immediately precede individual failures.

The objective of this study is to generate landslide susceptibility maps for both the present (2003–2022) and a near-future period (2020–2040), with a particular focus on evaluating their potential impacts on energy infrastructure. Susceptibility maps were produced on a monthly basis, resulting in 12 individual maps for each time frame. To enhance usability and facilitate analysis, an envelope map was created for each period, representing the maximum susceptibility across all months.

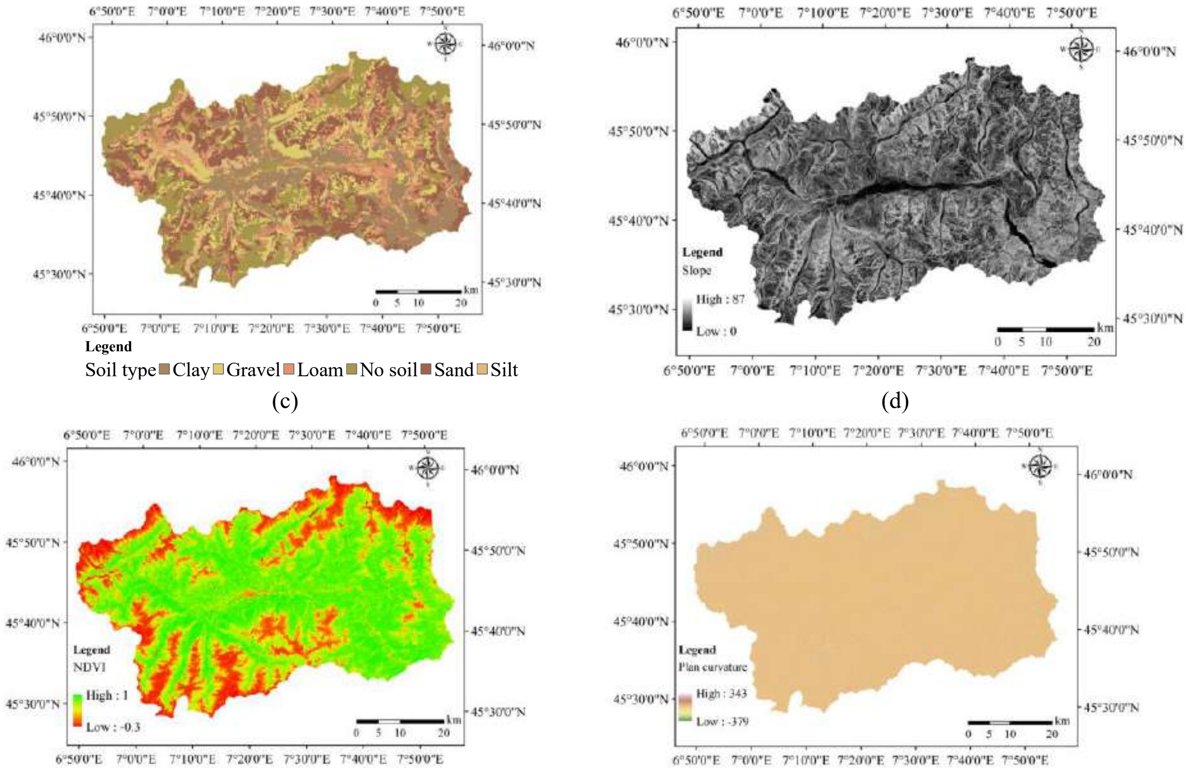
2. Methodology

The study focuses on the Aosta Valley, a mountainous region in northwestern Italy that encompasses some of the highest peaks in Europe. The area's complex topography contributes significantly to its vulnerability to slope instability. To develop an LSM for this region, the initial step was the identification of appropriate Landslide Conditioning Factors (LCFs). Based on a comprehensive literature review, a set of LCFs was compiled and evaluated for relevance to the current study. Certain factors were intentionally excluded: for instance, "Distance to roads" was omitted to prevent bias towards infrastructure, while "Distance to faults" was excluded due to the relatively low seismicity of the region. To address multicollinearity among the predictor variables, the Variance Inflation Factor (VIF) was computed. Multicollinearity, where independent variables are highly correlated, can distort model outputs by inflating the standard errors of coefficient estimates, leading to unreliable interpretations (Dormann et al., 2013). Variables with a VIF above 5, such as "Elevation" and "Topographic Wetness Index," were excluded to maintain model robustness.

Ultimately, ten static LCFs were retained: "Aspect" (i.e., slope dip direction), "Land cover", "Lithology", "Normalized Difference Vegetation Index (NDVI)", "Plan curvature", "Profile curvature," "Slope," "Soil type," "Stream Power Index," and "Sediment Transport Index." Additionally, three dynamic LCFs were included: "Monthly average cumulative precipitation," "Seven-day precipitation," and "Monthly average temperature." Figure 1 presents six of the thirteen LCFs used in this study.



(a) (b)



(e) (f)

Figure 1 Example of six LCFs used for the assessment of LSMs in the analyzed region: a) aspect, b) land cover, c) soil type, d) slope, e) NDVI, and f) plan curvature

A dataset comprising 3,628 events was acquired from regional agencies and classified into five categories: "Hydrological Alerts," "Rock Falls," "Landslides," "Potential Instabilities," and "Floods." For the purposes of this study, only records categorized as "Landslides" were retained. To align with the availability of climate data, only events occurring between 2003 and 2022 were considered, resulting in a total of 369 landslide points. To construct a balanced training dataset, an equal number of non-landslide points were randomly selected from locations situated at least 500 meters away from any recorded landslide event.

Daily precipitation and temperature records for the 2003–2022 period were obtained and spatially interpolated across the study area, generating approximately 7200 raster maps for each parameter. For each landslide event, dynamic variables were extracted, including monthly average temperature, and cumulative precipitation over the 7-day and 30-day periods preceding the event. These dynamic Landslide Conditioning Factors (LCFs), combined with static LCFs, formed the basis of the dataset used to train and evaluate the Extreme Gradient Boosting (XGBoost) model. The XGBoost algorithm then was applied to each 12 dataset, resulting in 12 different LSMs. XGBoost operates by sequentially training decision trees, where each new tree is fitted to the residual errors of the preceding ones. The predictions from all trees are then aggregated using a weighted sum, and the final output is obtained by applying a logistic function to this combined result (Chang et al. 2018).

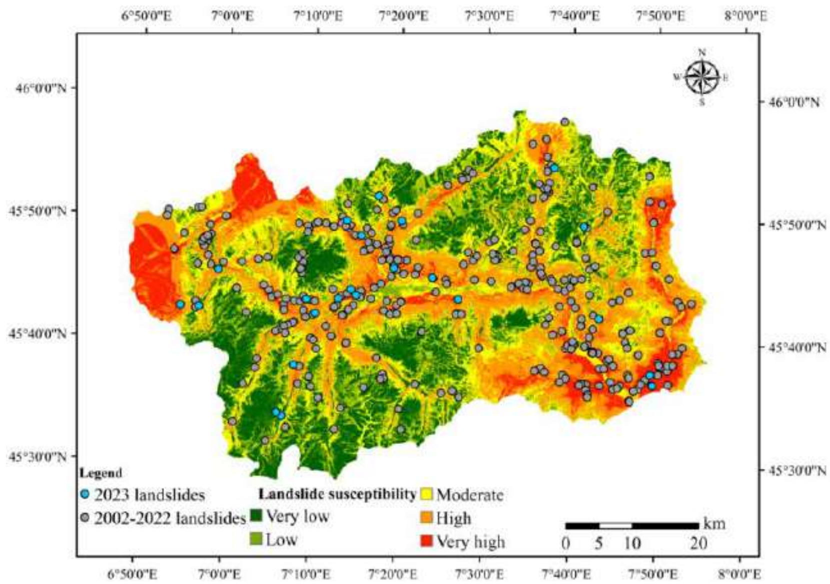
To investigate the potential impacts of climate change on future landslide susceptibility, climate projections from the sixth phase of the Coupled Model Intercomparison Project (CMIP6) were used. This dataset incorporates outputs from 14 global climate models (GCMs) under various Shared Socioeconomic Pathways (SSPs). For this study, the CMCC-ESM2 model under the high-emission SSP585 scenario was selected to simulate changes in temperature and precipitation for the 2021–2040 period.

Finally, high-voltage energy lines were mapped and overlaid with the landslide susceptibility results to evaluate potential interactions and identify segments of infrastructure at elevated risk.

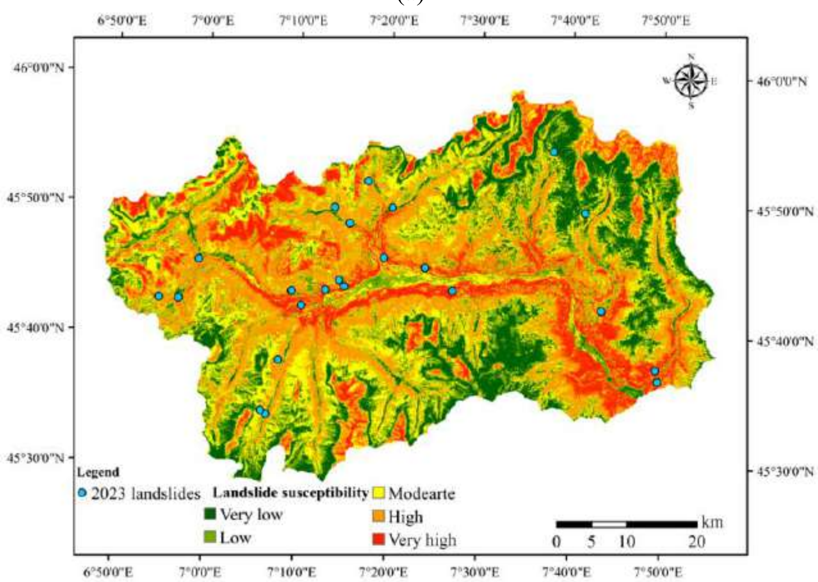
3. Results

Figure 2 illustrates the envelope maps for two time periods: (a) 2003–2022 and (b) 2020–2040. For each period, monthly LSMs were first generated. Subsequently, the maximum values across all 12 months were extracted to produce the envelope maps, representing the highest susceptibility values observed throughout the year. Between 2003 and 2022, approximately 9.96% of the study area was classified as having "Very high" landslide susceptibility. Projections for the following two decades (2020–2040) indicate an increase in this category to 12.85%. The "High" susceptibility class remains relatively stable across both periods, covering roughly 29% of the area. Conversely, the "Very Low" susceptibility class is expected to decrease from 17% in 2003–2022 to 13% in 2020–2040, indicating a general trend toward increasing hazard levels.

Landslide events from 2003 to 2022 were used for training and testing the model. The model's performance during this phase was evaluated using the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) on a monthly basis, with AUC values ranging from 0.95 to 0.99, indicating a high level of predictive accuracy across different temporal conditions. For independent verification, landslide occurrences from 2023, excluded from the modeling process, were employed in a “geotechnical validation”. Approximately 75% of the 2023 landslide events were located in areas categorized as either "High" or "Very high" susceptibility, further supporting the model’s reliability in identifying hazardous zones.



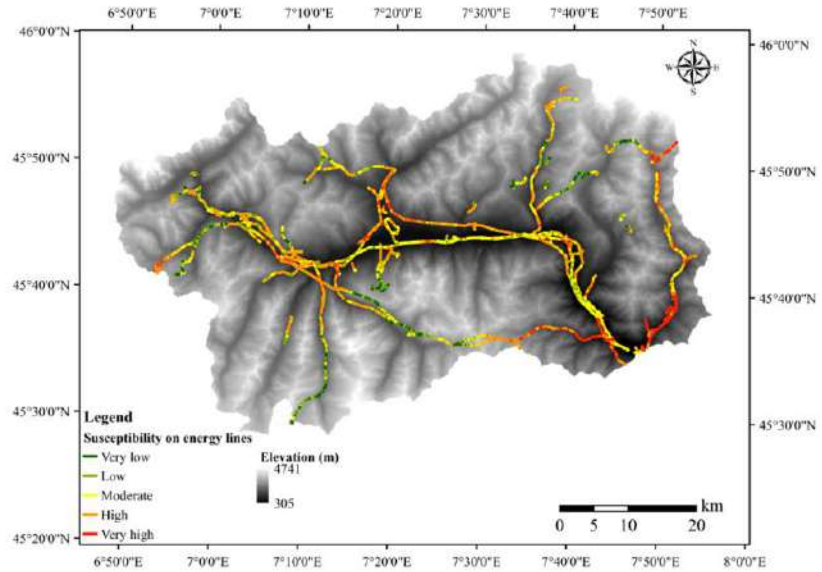
(a)



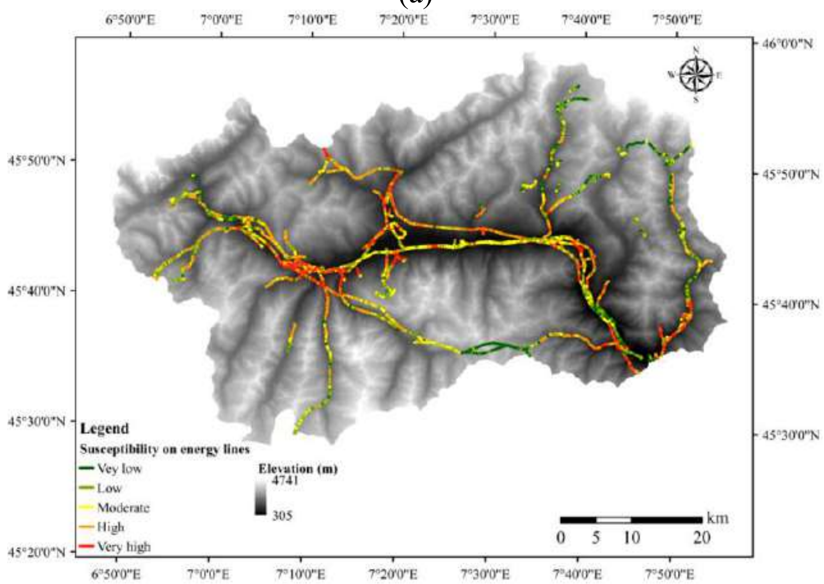
(b)

Figure 2 Landslide susceptibility maps for (a) 2003-2022, and (b) 2020-2040.

Furthermore, to assess the interaction between high-voltage energy infrastructure and landslide susceptibility, the locations of high-voltage power lines were identified using aerial imagery. Following digitization, a shapefile was created, and susceptibility values were extracted from the corresponding raster layers.
Results indicate that the proportion of energy lines located in areas classified as "Very High" landslide susceptibility is projected to increase from 13% in the historical period to 17% in the future scenario. In contrast, the percentage of energy lines situated in areas with "High" susceptibility is expected to decline from 35% to 25%.



(a)



(b)

Figure 3: Landslide susceptibility on energy lines for (a) 2002-2022, and (b) 2020-2040.

4. Conclusion

This study demonstrates the growing impact of climate change on landslide susceptibility in the Northwestern Italian Alps and its potential consequences for critical infrastructure. Using the XGBoost model, high-resolution susceptibility maps were produced, showing strong predictive performance with AUC values exceeding 0.95. The integration of CMIP6 climate projections under the high-emission

scenario SSP5-8.5 revealed a notable increase in areas classified as “Very high” susceptibility, from 9.96% in 2003–2022 to 12.85% in 2020-2040, and a decrease in “Very low” susceptibility areas.
The exposure assessment of high-voltage energy lines further emphasizes the importance of this work. Results indicate that energy lines located in “Very High” susceptibility zones are projected to increase from 13% to 17%, signaling an elevated risk to infrastructure due to climate-induced geohazards. These findings underline the urgent need for climate-adaptive planning and risk mitigation strategies to ensure the resilience of essential infrastructure in vulnerable mountainous regions.

Bibliografia

Barla, G., F. Dutto, and G. Mortara, (2000). “Brenva glacier rock avalanche of 18 January 1997 on the Mount Blanc range, northwest Italy”. Landslide news*,* 13, pp.2-5.

Chang, Y.-C., Chang, K.-H. and Wu, G.-J. (2018) ‘Application of extreme gradient boosting trees in the construction of credit risk assessment models for financial institutions’, Applied Soft Computing, 73, pp. 914–920.

Dormann, C.F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., Marquéz, J.R.G., Gruber, B., Lafourcade, B., Leitão, P.J. and Münkemüller, T., (2013). “Collinearity: a review of methods to deal with it and a simulation study evaluating their performance”. *Ecography*, 36(1), pp.27-46.

Field, C.B., Barros, V., Stocker, T.F. and Dahe, Q. eds., (2012). Managing the risks of extreme events and disasters to advance climate change adaptation: special report of the intergovernmental panel on climate change. Cambridge University Press.

Gariano, S.L. and Guzzetti, F., 2016. “Landslides in a changing climate”. *Earth-science reviews*, 162, pp.227-252.

Gruber, S. and Haeberli, W., (2007). “Permafrost in steep bedrock slopes and its temperature-related destabilization following climate change”. *Journal of Geophysical Research: Earth Surface*, 112(F2).

Huggel, C., (2009). “Recent extreme slope failures in glacial environments: effects of thermal perturbation”. *Quaternary Science Reviews*, 28(11-12), pp.1119-1130.

Insana, A., Beroya-Eitner, M. A., Barla, M., Zachert, H., Žlender, B., van Marle, M., Kalsnes, B., Bračko,T., Pereira,C., Prodan,I., Szymkiewicz,F., Löfroth, H. (2021). “Climate Change Adaptation of Geo-Structures in Europe: Emerging Issues and Future Steps”. *Geosciences*, 11(12), 488.

Janizadeh, S., Bateni, S.M., Jun, C., Pal, S.C., Band, S.S., Chowdhuri, I., Saha, A., Tiefenbacher, J.P. and Mosavi, A., (2023). “Potential impacts of future climate on the spatio-temporal variability of landslide susceptibility in Iran using machine learning algorithms and CMIP6 climate-change scenarios”. *Gondwana Research*, 124, pp.1-17.

Saha, A., Pal, S.C., Santosh, M., Janizadeh, S., Chowdhuri, I., Norouzi, A., Roy, P. and Chakrabortty, R., (2021). “Modelling multi-hazard threats to cultural heritage sites and environmental sustainability: The present and future scenarios”. *Journal of Cleaner Production*, 320, p.128713.