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ASSESSING THE IMPACTS OF CLIMATE CHANGE ON LANDSLIDE SUSCEPTIBILITY IN NORTHWESTERN ALPS

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The impacts of climate change are increasingly visible through the rising frequency and intensity of landslides. Heavy rainfall and temperature changes in mountainous areas are major contributors to landslide events, with permafrost thawing linked to the latter. This study assesses how climate change may influence landslide proneness in the Italian Northwestern Alps by using Extreme Gradient Boosting (XGBoost) to model and map susceptibility under both current and projected climate conditions. Key static and dynamic variables were gathered across the study area to forecast landslide susceptibility. For model training and validation, a dataset of 728 points, including both landslide and non-landslide occurrences, was used. Monthly susceptibility maps were generated for 2003-2022; however, only two months (May and February) are presented in this paper. May represents the month with the most landslides, while February represents the month with the fewest. To account for climate change effects, downscaled data from the Coupled Model Intercomparison Project Phase 6 (CMIP6) was applied, incorporating projections from global climate models based on shared socio-economic pathways (SSPs). The high-emission scenario (SSP585) was employed to estimate precipitation and temperature impacts on landslide susceptibility for the period 2021–2040. Model performance for each month was assessed using the area under the curve (AUC) metric, showing high predictive accuracy with values surpassing 0.96. The comparison of current and future landslide susceptibility reveals a marked increase in landslide risk due to climate change, with February experiencing the greatest impact. This study paves the way for future research on how landslides may impact regional infrastructure.

Keywords: Landslides, Susceptibility mapping, Climate change, Machine learning, CMIP6, GIS.

1. Introduction

The effects of climate change are becoming increasingly evident, with a notable rise in the frequency and intensity of landslides (Field et al., 2012). Climatic factors, including changes in rainfall patterns and temperature, are among the critical triggers for these events. Remarkably, increased rainfall due to global warming is identified as a key factor exacerbating the frequency of landslides (Gariano and Guzzetti, 2016). Additionally, in mountainous regions, rock slides and landslides are often a consequence of permafrost thawing (Barla et al., 2000; Gruber and Haeberli, 2007; Huggel, 2009).

For each region, it is essential to identify areas prone to landslides and to examine how changes in climatic signals may affect landslide occurrence (Insana et al., 2021). This approach enables more accurate projections of landslide events in the future. While some studies have assessed the impacts of climate change on landslide susceptibility maps (LSMs), they remain limited in scope. For instance, Janizadeh et al. (2023) examined the effect of climate change on landslide susceptibility in Iran, employing various Shared Socioeconomic Pathways (SSPs) over different time periods to obtain LSMs. Similarly, Saha et al. (2021) analyzed the effects of different Representative Concentration Pathways (RCPs) on rockfall and debris flow occurrences. However, few studies have integrated temperature as a significant factor in landslide occurrence, and to our knowledge, none have explicitly considered the precipitation and temperature immediately preceding the landslide events. To assess the accuracy of the models, these studies used the Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC) plot, quantifying the ability of classification models to distinguish between classes (Jiménez-Valverde, 2012).

This study aims to assess the impacts of climate change on landslide susceptibility under both current and projected conditions, focusing on SSP585, a high-emission scenario characterized by rapid economic growth and limited climate mitigation efforts, leading to significant global warming by the end of the century. To evaluate climate change effects, monthly temperature and precipitation values were incorporated, enabling the creation of monthly LSMs. For the sake of conciseness, LSMs for only two months (February and May) are presented in this paper.

2. Methodology

The study area of interest is the Aosta Valley, a mountainous area in the Northwest of Italy, where Europe's tallest summits are located. The complex topography of the Aosta Valley makes the region particularly susceptible to slope instability. To create a LSM for this region, the first step involved identifying effective Landslide Conditioning Factors (LCFs). Based on a literature review, a number of LCFs were collected and their relevance for the current study was assessed. Some of them were excluded for specific reasons. For example, "Distance to roads" was omitted to avoid model dependence on road proximity, while "Distance to faults" was excluded due to the region's low seismic activity. Additionally, to address multicollinearity, the Variance Inflation Factor (VIF) was calculated for all parameters. Multicollinearity refers to the situation where predictor variables in a statistical model are highly linearly related. This condition inflates the variance of parameter estimates, making them unstable and potentially leading to incorrect conclusions about variable importance (Dormann et al., 2013). Variables with a VIF exceeding 10, such as “Elevation” and “Topographic wetness index”, were removed to ensure the robustness of the model.

Eventually, ten static LCFs were considered, including “Aspect” (i.e., the dip direction of the slope), “Land cover”, “Lithology”, “Normalized Difference Vegetation Index” (NDVI), “Plan curvature”, “Profile curvature”, “Slope”, “Soil type”, “Stream power index”, “Sediment transportation index”. Also, three dynamic LCFs were “Monthly average cumulative precipitation”, “Seven days precipitation” and “Monthly average temperature”. Figure 1 illustrates six of the twelve LCFs ultimately selected for this study.

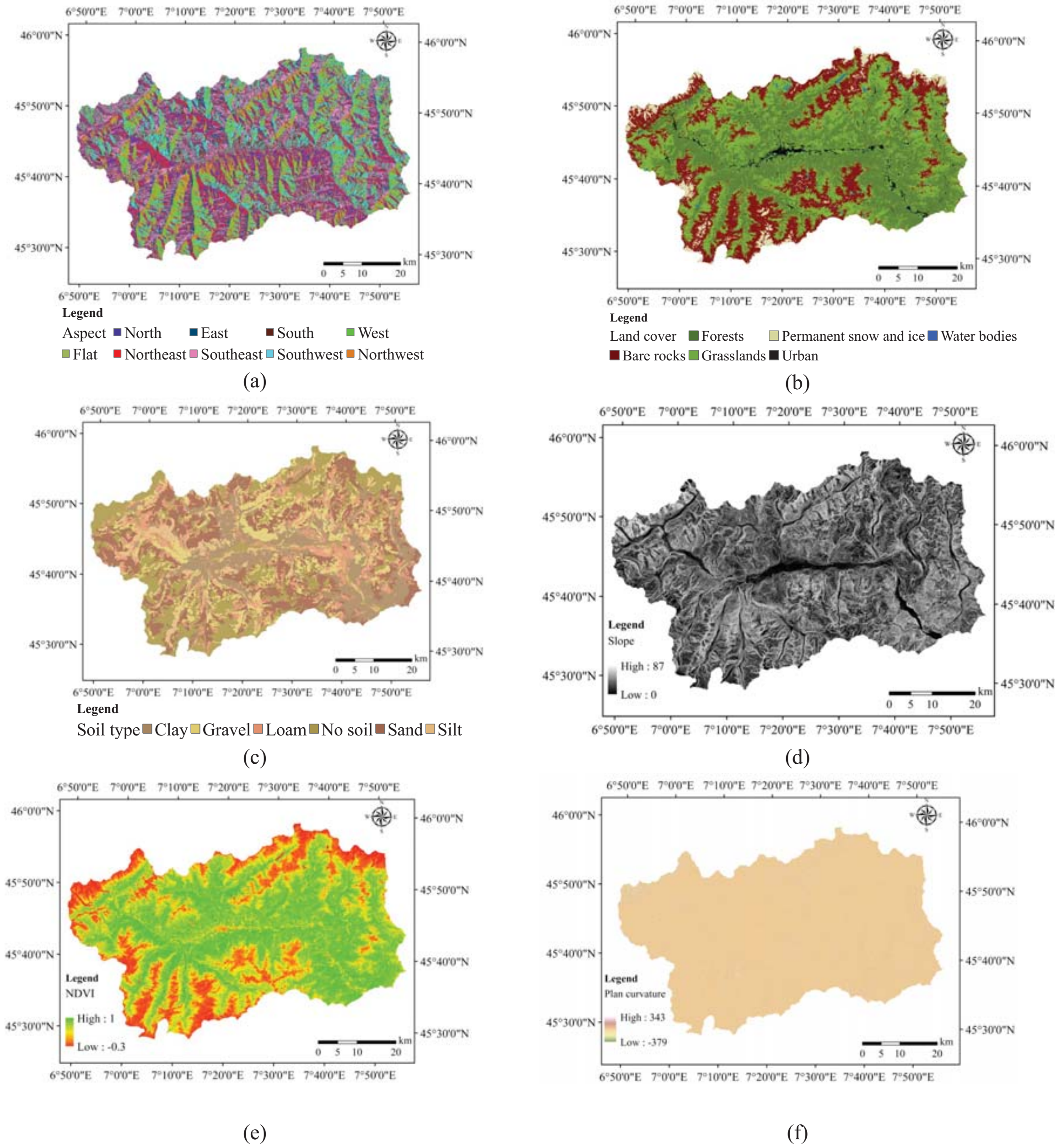

Fig. 1. Example of six LCFs used for the assessment of LSMs in the analyzed region: a) aspect, b) land cover, c) soil type, d) slope, e) NDVI, and f) plan curvature.

A dataset containing 3628 events was obtained from regional agencies, categorized into five groups: “Hydrological Alerts”, “Rock Falls”, “Landslides”, “Potential Instabilities” and “Floods”. From these, only “Landslides” events were selected for the analysis. Given that temperature and precipitation data were available only for 2003–2022, landslides within this period were included, resulting in 369 points of landslide events. An equal number of non-landslide points was randomly selected from areas at least 500 meters away from landslide locations to balance the training dataset. Daily temperature and precipitation data from 2003 to 2022 were collected, resulting in 7,200 maps for each parameter, sourced from meteorological stations and interpolated across the study area. For each landslide event, the monthly average temperature, along with cumulative precipitation for the seven and thirty days preceding the event, were extracted. These dynamic LSFs, combined with static factors, were used to construct the dataset, which was then employed to test and train the Extreme Gradient Boosting (XGBoost) algorithm. To assess the impacts of climate change on landslide susceptibility, downscaled data from Phase 6 of the Coupled Model Intercomparison Project (CMIP6) was used. This data integrates projections from fourteen global climate models (GCMs) under Shared Socioeconomic Pathways (SSPs). In this study, the CMCC-ESM2 model, under the SSP585 scenario for the period 2021–2040, was employed to assess potential changes in precipitation and temperature and their impacts on landslide susceptibility.

3. Results

After training the model using landslide data from 2003 to 2022 and generating monthly LSMs for this period, the trained model was then applied to produce monthly LSMs for the 2021–2040 period. This approach allows to examine the monthly effects of precipitation and temperature, acknowledging that landslide probability varies throughout the year. The results show that February, a month with the fewest number of landslides in the region, will experience a higher increase in very susceptible areas from 5.51% to 7.15%. The reason lies in the fact that precipitation levels in February are already high, and with rising temperatures, as predicted in the SSP585 scenario, the likelihood of landslides could increase significantly (Figure 2(b)).

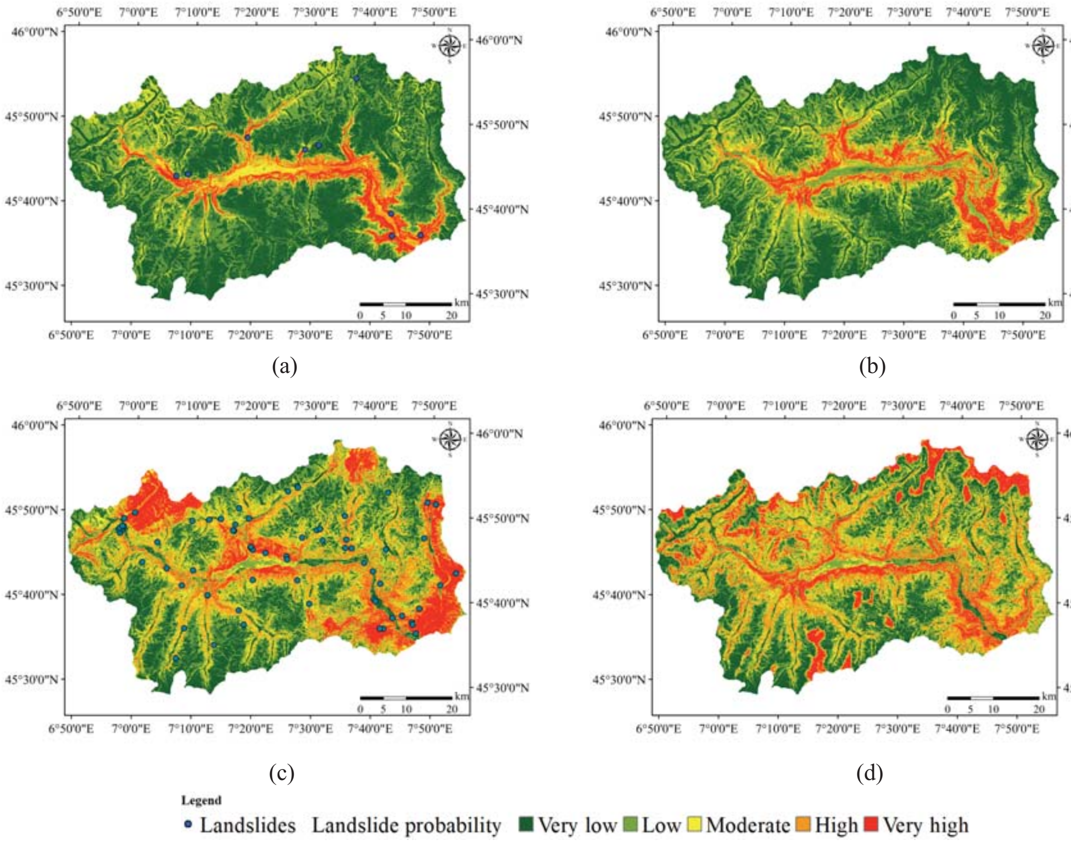

Fig. 2. LSM for a) February 2003-2022, b) February 2021-2040, c) May 2003-2022, d) May 2021-2040.

For May, the month with the highest number of landslides in the region, it can be seen that the "Very high" probability of landslides is already high and, still, it will witness a rise from 13.50% to 14.54% (Figure 2(d)). Results also indicate that in the near future, the northeastern part of the region will face a higher likelihood of landslides. A possible reason is that much of this area is covered by ice (Figure 1(b)), and a rise in temperature, as projected in SSP585, could shift precipitation from snowfall to rainfall and accelerate the melting of existing snow cover, thereby increasing landslide probability. The feature importance analysis revealed that temperature was the most significant factor contributing to landslide susceptibility during the cold months (October to February), while precipitation was the primary factor in the hot months (June to August).

4. Discussion and conclusion

This study examined the impacts of climate change on landslide susceptibility in the Northwestern Alps region. Several landslide conditioning factors were taken into account. The final model was trained and tested with 12 conditioning factors and 369 landslide occurrences recorded from 2003 to 2022. Monthly landslide susceptibility maps were generated using the XGBoost algorithm, and future LSMs were projected under the high-emission SSP585 scenario for the period 2021–2040. The results indicate considerable changes in high-susceptibility areas across the region, with a particularly notable increase in February. Model accuracy was also robust, with AUC values of 0.99 and 0.96 for February and May, respectively, reflecting high predictive performance. Such changes in susceptibility are highly relevant to promptly steer local authorities' actions addressed to mitigate the landslide risk, especially with regard to the potential consequences for people, property, and infrastructure.

While the model demonstrated strong accuracy, future improvements could involve accounting for potential changes in the seven-day precipitation parameter, as extreme values leading up to landslide events are also expected to shift. Additionally, combining all the monthly LSMs into a single map would make it more practical for authorities to assess and take necessary actions to address potential impacts on infrastructure.

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