LANDSLIDE SUSCEPTIBILITY MODELLING AND INFRASTRUCTURE EXPOSURE IN THE ZILLERTAL, AUSTRIAN ALPS

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ABSTRACT

Landslides are a major threat in alpine regions, as steep terrain, complex geology and locally concentrated infrastructure increase societal exposure to landslide hazards. This study develops a landslide susceptibility model for the Zillertal (Tyrol, Austria), utilizing a Random Forest modelling approach. A high-resolution landslide susceptibility map was created using seven geomorphometric, geological and structural conditioning factors. Despite varying positional accuracy of the landslide inventory, the model achieved a respectable performance and predictive capacity (AUC = 0.874). To improve practical usability, susceptibility classes were overlaid with transport infrastructure and built-up areas. The results indicate significant exposure of roads, railways and settlements within high-susceptibility zones. Additionally, a 500 m buffer was applied to assess potential exposure in the surrounding areas and provisionally account for runout. Overall, the study demonstrates that machine-learning-based susceptibility modelling can produce robust and planning-relevant results even where landslide inventories have varying positional accuracy, highlighting its potential for hazard assessment in data-constrained alpine environments.

Keywords – *Random Forest, alpine hazards, landslide susceptibility, geomorphometry, machine learning, spatial planning.*

1. INTRODUCTION

Landslides can be considered one of the most relevant natural hazards in mountainous regions, where steep terrain, complex geology and intense precipitation regimes interact to produce highly dynamic slope processes (Ado et al., 2022; Schlögl et al., 2025). Growing population and infrastructure in the European Alps increase exposure to landslide hazards and especially mass movements pose a substantial threat to settlements, critical infrastructure and the population (Lima et al., 2021; Wood et al., 2016). Effective spatial prediction of landslide-prone areas is therefore a central component in modern hazard management and spatial planning (Reichenbach et al., 2018; Schlögl et al., 2025).

During the past two decades, landslide susceptibility mapping has progressed from heuristic and purely statistical approaches towards machine-learning-based methods capable of modelling even complex, non-linear relationships between environmental factors and slope instability. Some quite comprehensive reviews demonstrate that ensemble algorithms, particularly Random Forest (RF), can reliably achieve high predictive performances and robustness in a wide range of geomorphic scenarios if applied correctly (Ado et al., 2022; Reichenbach et al., 2018).

In this context, recent studies emphasize not only classification accuracy, but also the importance of feature selection, geomorphic plausibility and model interpretability; especially in alpine regions where terrain derivatives are usually highly correlated (Li et al., 2024; Schlögl et al., 2025). Due to a growing need for more mapping directly relevant for decision makers, research increasingly tries to link susceptibility outputs with elements at risk, such as infrastructure and residential areas.

Despite clear advancements, gaps persist, two of which are discussed in this paper. First, many regional studies require high-quality, event-based inventories that are rarely available for less populated regions like alpine valleys. This circumstance can limit transferability to data-scarce regions. Second, susceptibility models are often evaluated in isolation, without systematically integrating exposure of critical assets. This limits their practical applicability for local authorities.

In this context, the present study seeks to develop a landslide susceptibility model for the Zillertal (Tyrol, Austria) by using a RF approach working with limited data. The objectives comprise the following:

1) to generate a high-resolution susceptibility map based on geomorphometric, geological and structural conditioning factors;
2) to evaluate the model performance and predictor relevance while ensuring statistical and geomorphic plausibility; and
3) to analyze the resulting susceptibility classes with transport infrastructure and built-up areas to quantify spatial exposure.

Through combining machine learning based susceptibility modelling with an applied overlay analysis, this study aims to bridge the gap between methodological performance and practical usability, as well as to provide a transferable workflow for alpine hazard assessment in contexts with limited high-quality data availability.

2. MATERIAL AND METHODS

2.1 Study Area and Data Restriction

The research focuses on the Zillertal, a major alpine valley in Tyrol, Austria, possessing a complex geological, high relief landscape and susceptibility to mass movements. Its location within Austria can be seen in figure 1 on the next page.

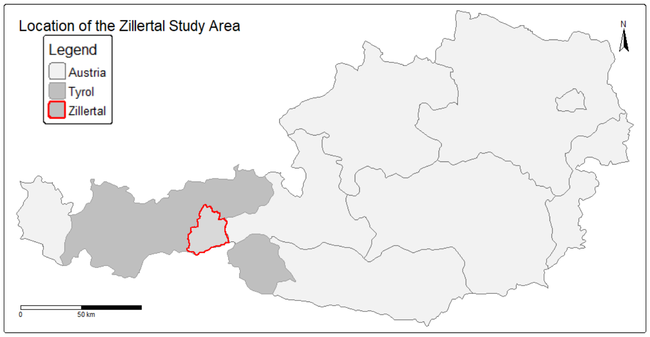

Figure 1. Location of the Zillertal study area within Austria and the federal state of Tyrol. Municipal boundaries based on BEV (2019).

To define the study area for the model, due to a lack of an available Zillertal boundaries shapefile, administrative boundaries from the VGD-Tirol dataset were processed in R to isolate the 25 specific municipalities that are officially part of the Zillertal, including Mayrhofen, Tux, and Zell am Ziller.

These units were aggregated and the borders, excluding the Zillertal outline dissolved, to form a contiguous 1072 km^2 Zillertal polygon, which served as the spatial mask for all subsequent terrain and landslide data. Topographic analysis relied on a 10 m resolution Digital Elevation Model (DEM). Although a high resolution is essential for capturing the subtle terrain variations that drive landslide processes in rugged alpine environments, available computers were unable to process higher than 10 m resolution even though 1 m resolution data would have been available (Noël et al., 2023).

2.2 Landslide Inventory and Sampling Strategy

The analysis utilized the Austria landslide inventory, which was deliberately not filtered for positional accuracy to include the highest possible number of records, as the Zillertal would have too little landslide data to work with otherwise. With location inaccuracies of up to 1000 meters (QUAL_LAGE < 6), this meant that some landslide locations would be unreliable, but this trade-off was deemed necessary to achieve a meaningful confusion matrix.

Landslide susceptibility was modelled using RF regression based on a balanced dataset of landslide (positive) and non-landslide (negative) samples. A total of 199 landslide points were cropped to the Zillertal shapefile. To ensure clear environmental differentiation, an equal number of 199 non-landslide points were randomly sampled from a "landslide-free" zone, defined as the Zillertal territory excluding a 1000 m buffer around and including the 199 known landslide locations. This large buffer was chosen due to the maximum inaccuracies in landslide location of up to 1000 m. Figure 2 shows the landslide locations and non-landslide samples and their distribution in the Zillertal DEM. The final combined dataset of 398 points was partitioned using a 70/30 split, dedicating 278 points for model training and 120 points for independent testing.

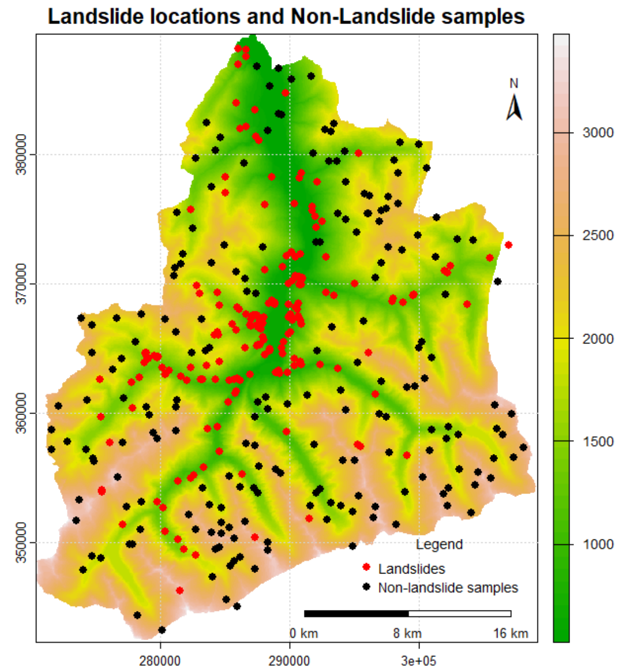

Figure 2. Spatial distribution of mapped landslide locations (red points) and non-landslide samples (black points) within the Zillertal study area. The background DEM provides topographic context. Landslide inventory data: GeoSphere Austria (n.d.).

2.3 Selection of Conditioning Factors and Feature Screening

Based on established literature regarding geomorphometric parameters and landslide triggers, as well as previous modelling experiences, seven initial Landslide Conditioning Factors (LCFs) were prepared: Altitude, Slope, Aspect, Topographic Position Index (TPI), Terrain Ruggedness Index (TRI), Bedrock Geology, and Euclidean Distance to Faults. Geology was converted into numeric IDs based on lithological descriptions to allow for statistical processing.

Before training the model, a Multicollinearity Analysis was performed using the Variance Inflation Factor (VIF) to prevent model overfitting. Factors exceeding a VIF threshold of 5 were flagged for redundancy and removed, as high correlation between variables can lead to biased importance rankings (Dai et al., 2023).

2.4 Statistical Modelling and Evaluation Metrics

A RF regression model was implemented due to its ability to capture complex, non-linear relationships between environmental predictors and landslide occurrence (Dai et al., 2023). Model parameters were optimized by tuning the mtry (number of variables at each split) using a starting value of 2, while the number of trees (ntree) was set to 1000. To assess the model's robustness, performance was evaluated using a Confusion Matrix to derive Accuracy, Precision, Recall, and the F1-score. Additionally, a Receiver Operating

Characteristic (ROC) curve was generated to calculate the Area Under the Curve (AUC), providing a definitive measure of the model's ability to discriminate between stable and unstable slopes (Maia et al., 2025).

2.5 Susceptibility Classification

Landslide susceptibility classes were defined by transforming the continuous output of the RF model into a discrete categorical scale. Initially, the model generated a probability raster where each cell contained a value between 0 and 1, representing the statistical likelihood of landslide occurrence. To make these results interpretable for hazard exposure assessment, a reclassification matrix was implemented using the raster library in R to group these probabilities into five distinct classes: Very low, Low, Moderate, High, and Very high. A thresholding logic was used, where probabilities from 0.00 to 0.25 were assigned to Class 1 (Very low), above 0.25 to 0.50 to Class 2 (Low), above 0.50 to 0.70 to Class 3 (Moderate), above 0.70 to 0.90 to Class 4 (High), and values above 0.90 to 1.00 to Class 5 (Very high). This systematic binning allows for a clear spatial visualization of regional susceptibility, which was subsequently used to calculate the total area (km^2) and pixel frequency for each susceptibility level within the Zillertal study area. Final mapping was enhanced by assigning a specific color palette to these classes, ranging from dark green for "Very low" to dark red for "Very high", to highlight critical landslide susceptibility zones for infrastructure and residential areas.

2.6 Infrastructure and Residential Areas Overlay

To comprehensively evaluate the impact of potential mass movements on human activity and regional infrastructure, a spatial overlay analysis was integrated into the modelling workflow.

This process began with the identification of critical assets, specifically focusing on residential built-up areas and transit networks within the defined Zillertal boundaries. Built-up areas were isolated from the CORINE Land Cover (CLC) 2018 dataset by filtering for urban fabric and infrastructure codes, including continuous (111) and discontinuous (112) residential zones (Antofie et al., 2025). Simultaneously, the regional rail network, primarily the Zillertalbahn, was extracted from the "Verkehrswege" dataset using a multi-step selection process that combined specific object codes (e.g., "B-L", "B-LB") with keyword-based string matching for terms such as "Bahnlinie" or "Gleis".

To account for the surrounding zone of influence and potential impact reach (runout), a 500 m buffer was applied to these filtered vector geometries, including the high-ranking road network (Landesstraßen B and Landesstraßen L).

The exposure of these assets was then quantified by calculating the percentage of each buffered infrastructure zone that intersects with the different susceptibility classes. This calculation was performed by rasterizing the vector buffers to match the 10 m resolution of the susceptibility map and applying a mask to extract class frequencies.

By comparing the total area of each buffered asset against the area falling into "High" and "Very High" susceptibility zones, the study provides a statistically robust assessment of infrastructure exposure to landslide susceptibility (Antofie et al., 2025).

3. RESULTS

3.1 Multicollinearity and Variable Refinement

Initial screening of the seven conditioning factors revealed significant redundancy between specific topographic variables. The VIF results for Slope (8.02) and TRI (8.07) both exceeded the critical threshold of 5, indicating that these variables provided nearly identical information to the model. To resolve this, TRI was removed from the final analysis, which successfully reduced all remaining VIF values to under 1.25, thereby ensuring that the remaining predictors were statistically independent.

3.2 Model Performance and Accuracy

High predictive robustness was demonstrated by the optimized RF model when applied to the 30% independent test set. The Confusion Matrix reported an Accuracy of 87.39%, with the model correctly identifying equally 52 out of 60 landslide points and 52 out of 60 non-landslide points. This resulted in a Recall of 0.881 and a Precision of 0.867. The discriminatory power of the model was further confirmed by the ROC-AUC value of 0.874, which can be observed in figure 3, indicating an "excellent" classification performance according to standard geostatistical scales (Hosmer & Lemeshow, as cited in Maia et al., 2025).

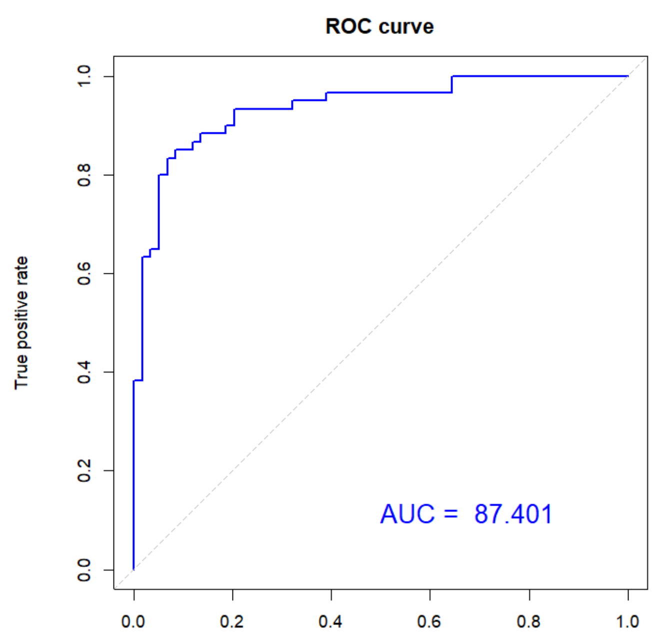

Figure 3. ROC curve of the RF landslide susceptibility model for the Zillertal study area. The AUC value shown in the figure

(87.401) represents a percentage value, corresponding to an AUC of 0.874 on the conventional 0-1 scale.

3.3 Feature Importance Ranking

Altitude was identified as the overwhelmingly dominant predictor of landslide susceptibility in the Zillertal, achieving an importance score of 100.55 %IncMSE (Percent Increase in Mean Squared Error). This confirms that elevation acts as a primary control on the spatial distribution of mass movements in this region, landslides seemingly happening at lower altitudes rather than higher ones. Following Altitude, Geology (16.51 %IncMSE), Distance to Faults (12.76 %IncMSE), and TPI (10.05 %IncMSE) were identified as the next most significant drivers. In contrast, Slope and Aspect contributed less to the model's overall predictive accuracy in this specific dataset.

3.4 Landslide Susceptibility Mapping and Spatial Distribution

The susceptibility modelling output, a five-category susceptibility map (fig. 4), reveals that Very Low and Low susceptibility areas are extensive, covering 560.0 km² (52.2%) and 221.6 km² (20.7%) of the Zillertal, consisting mostly of high elevation zones above 2000 m, while Moderate susceptibility areas account for 143.9 km² (13.4%). The most critical zones, classified as High and Very High susceptibility, cover approximately 123.8 km² (11.6%) and 22.4 km² (2.1%), respectively. These high-susceptibility zones are predominantly located along the steep flanks of the main valley at lower altitudes, well below 2000 m of elevation, reaching the valley floor below 1500 m.

3.5 Infrastructure and Residential Area Exposure Analysis

The overlay analysis, illustrated in figure 5, identified significant potential impacts on regional infrastructure. Using a 500 m buffer, the model indicates that 13.8% of the Zillertal high level road network and 5.2% of the local rail segments intersect zones of High or Very High susceptibility in a 500 m radius. Without any buffer, 8.5% of roads remain in high susceptibility zones, while 0% of rails are exposed. Figure 6 on the following page enables a detailed overview of the exact percentages for each category.

Furthermore, the analysis of built-up areas (figure 6) showed that while most residential areas are located in low to moderate susceptibility valley bottoms, a significant portion of urban infrastructure (14.1%) is highly susceptible when using a 500 m safety buffer. Even without any buffer a critical 5.3% of built-up areas are directly located in highly susceptible zones.

These findings provide an objective statistical foundation for local authorities to prioritize structural mitigation measures, such as deflection dams or slope stabilization, or even relocation of susceptible infrastructure and buildings along the most vulnerable transit corridors (Antofie et al., 2025).

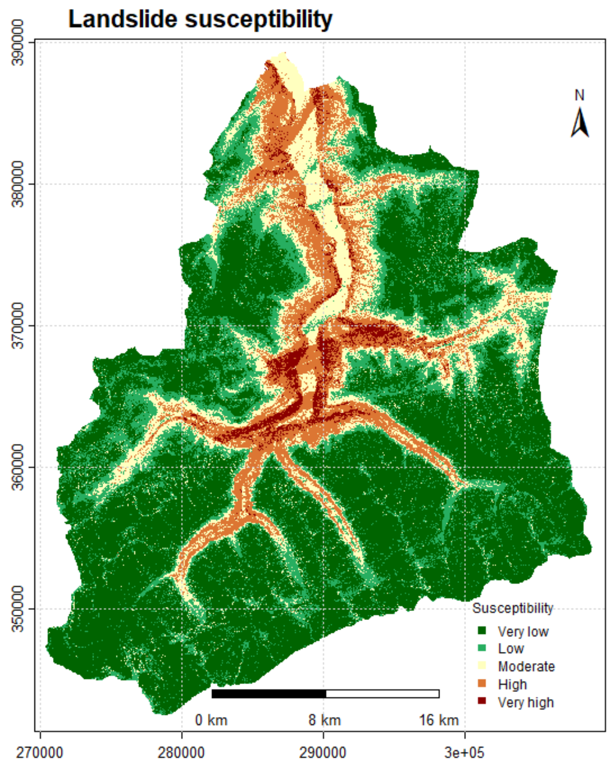

Figure 4. Landslide susceptibility map of the Zillertal study area, classified into five susceptibility classes.

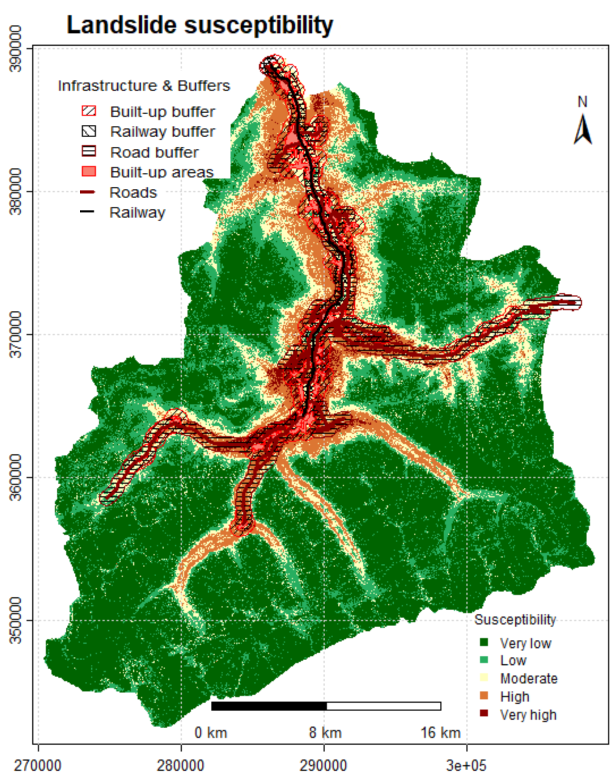

Figure 5. Landslide susceptibility map of the Zillertal study area overlaid with critical infrastructure and buffer zones.

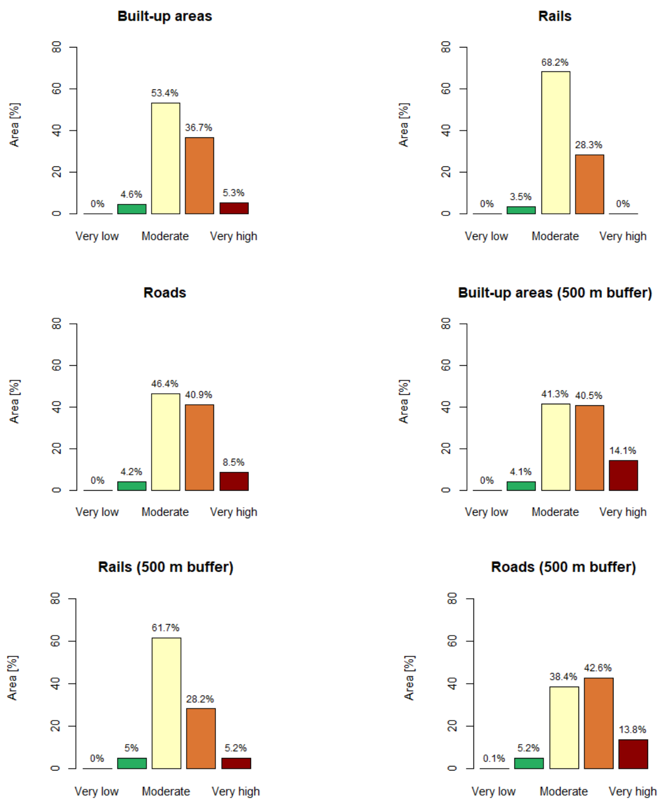

Figure 6. Proportional distribution of built-up areas, roads and railways across landslide susceptibility classes, shown for the original infrastructure footprints and for 500 m buffer zones.

4. DISCUSSION

The RF model developed for the Zillertal reached an AUC of 0.874, which is well within the acceptable range reported by recent machine-learning-based (ML-based) landslide susceptibility studies. A comprehensive review by Ado et al. (2022) shows that a considerable number of ML models achieve AUC values above 0.80. Among these, particularly ensemble approaches such as RF frequently exceed 0.85 and, in some cases, even approach or surpass AUC values of 0.90 (Ado et al., 2022), although exceedingly high values always need critical evaluation. The present model therefore perfectly fits within the performance spectrum that is considered reliable for regional susceptibility mapping and confirms this by a high, but still realistic AUC value.

It also must be considered that positional uncertainties of up to 1000m in landslide sample location might have had a lowering impact on AUC value, but this has not been investigated further. The fact that the model still achieves excellent discrimination confirms the robustness of RF in contexts of noisy and heterogeneous training data. This is also a key advantage emphasized in the consulted literature (Ado et al., 2022; Li et al., 2024).

Another important result of this study is the particular dominance of altitude as a conditioning factor. Li et al. (2024) similarly describe elevation and distance to faults as the most impactful predictors in their RF-based susceptibility model. This reflects that altitude often functions as a proxy for a set of geomorphic and environmental gradients. In alpine regions, elevation is closely connected with lithology, weathering regimes, vegetation cover and hydrological conditions. However, the extreme importance of altitude in the Zillertal possibly also indicates a structural bias in the landslide inventory, as recorded events are concentrated at lower elevations where settlements, transport corridors as well as human observation density are highest (Schlögl et al., 2025). Such “valley bottom clustering” has also been observed in other mountainous regions and can cause models to learn exposure patterns in addition to purely geomorphic controls. Schlögl et al. (2025), in their Austrian Alps case study, explicitly emphasize that feature importance needs to be interpreted from a geomorphic perspective and that researchers must distinguish between physically meaningful predictors and artefacts introduced by data availability or reporting bias. Accordingly, altitude in the Zillertal model should not be understood as a causal driver per se, but as an integrative proxy for both terrain configuration and anthropogenic presence.

Further, the multicollinearity analysis as well as the subsequent removal of TRI aligns with recommendations from recent ML-based susceptibility studies. Ado et al. (2022) and Li et al. (2024) point out that many geomorphometric indices contain overlapping information and that redundant predictors can distort variable importance and thereby reduce interpretability. Additionally, Schlögl et al. (2025) argue that feature selection is not only a statistical step, but a requirement for geomorphic plausibility. The low remaining VIF values in this study indicate that the final predictor set contains complementary terrain information and thus improves both model stability and reliability.

Spatially, the susceptibility pattern in the Zillertal is consistent with observations from comparable alpine regions reported by Schlögl et al. (2025), where areas of high and very high susceptibility are predominantly concentrated along steep valley flanks and structurally controlled corridors. In the Zillertal, zones of high susceptibility form linear bands along the main valley and its tributaries, which reflects the interaction between tectonic structures, fluvial incision and progressive slope over-steepening. Those are process regimes typical for the Eastern Alps, where the Zillertal is located. Low and very low classes dominate across more than 70 % of the study area; confirming that large parts of the high alpine terrain are comparatively stable regarding shallow landslides and hazard is spatially concentrated in morphodynamically active “belts”.

The infrastructure overlay adds a dimension that is increasingly emphasized in the literature: for example, Schlögl et al. (2025) stress that susceptibility models should be evaluated not only regarding their statistical performance, but also by their utility for decision-making. In narrow alpine valleys, transport infrastructure is structurally situated in geomorphologically active zones. The finding that 13.8 % of the 5 high-level roads in the area and 5.2 % of rail segments intersect with high- or very-high-susceptibility zones within a 500 m buffer is therefore consistent with regional patterns in comparable alpine regions.

Moreover, similar studies report a strong increase in exposure when runout extent and secondary effects are considered. The significant increase in exposed assets after applying buffers indicates that underestimating real-world hazard impacts might carry significant risk, highlighting why it is important to include generous impact zones into planning-oriented analysis. Overestimating runout distance might be more expensive in planning but a larger buffer accounts for conservative models that often underestimate hazard zones due to pixel sizing or overlooked conditioning factors.

5. LIMITING FACTORS

Despite the discussed strengths, there are several limitations that constrain the reliability and accuracy of the performed susceptibility modelling. Specifically, the use of a landslide inventory unfiltered for positional accuracy creates spatial uncertainty that can artificially broaden high-susceptibility belts and thus inflate the perceived role of altitude as a conditioning factor. Additionally, the 10 m DEM resolution used for the modelling likely impacted the accuracy of the results due to the loss of fine-scale geomorphometric details. Moreover, the balanced sampling strategy, although useful for addressing class imbalance in binary classification, does not reflect the actual distribution, frequency or non-occurrence of landslides, therefore potentially overstating predictive confidence on a regional scale. Schlögl et al. (2025) warn that model plausibility and inventory quality are as essential as AUC values for practical use. Future research should therefore integrate higher-quality event-based inventories, temporal triggering variables (e.g. extreme precipitation) and combine susceptibility with runout modelling to better represent process dynamics.

Nevertheless, the RF Zillertal model shows that even under data limitations, RF-based susceptibility mapping can produce spatially coherent and practically relevant results, confirming, in line with current research trends (Ado et al., 2022; Li et al., 2024; Schlögl et al., 2025), the effectiveness of machine-learning approaches for alpine hazard assessment and demonstrating why it is necessary to geomorphologically interpret and critically reflect on data-driven patterns.

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6. CONCLUSIONS AND OUTLOOK

Overall, this study demonstrates that machine-learning-based landslide susceptibility modelling can produce reliable and spatially coherent results even under restrictive data conditions. By using a RF approach, a high predictive performance (AUC = 0.874) is achieved for the Zillertal, even though including imprecise landslide records. This means the model can successfully capture the spatial concentration of instability along valley flanks and structurally controlled corridors, which are characteristic in alpine geomorphic systems.

Moreover, the dominant role of altitude as the primary conditioning factor points toward both the Zillertal's high relief geomorphic structure as well as the inherent bias of landslide inventories regarding inhabited and accessible areas. This result confirms that it is necessary to interpret model outputs from a geomorphic and data-critical point of view instead of only relying on statistical performance. Additionally, feature selection based on multicollinearity analysis was essential for maintaining the model's plausibility and interpretability.

Apart from susceptibility mapping, integrating infrastructure and settlement overlays allows a planning-relevant analysis. The significant exposure of roads, railways and built-up areas within high-susceptibility zones confirms that alpine transport and settlement corridors are structurally forced into geomorphologically hazardous terrain. The buffer-based analysis further indicates that if intersections on pixel-level, missing conditioning factors or conservative models cause underestimation of real-world hazard susceptibility, this can lead to restricted hazard zoning, thus emphasizing the importance of considering unaccounted runout extent and secondary impacts in hazard assessments.

Although the use of unfiltered inventories and moderate sample numbers influence the reliability of derived probabilities, the resulting susceptibility map nonetheless provides a credible first-order assessment of spatial patterns of landslide susceptibility in the Zillertal, which was confirmed by a high AUC value.

While RF proved robust even under conditions of limited high-quality data availability, it does not explicitly model spatial dependence. Future work could therefore explore "spatially aware" approaches such as geographically weighted models or hybrid combinations of machine learning and process-based frameworks. Moreover, future research should focus on incorporating higher-quality event-based inventories, high-resolution DEMs, dynamic triggering factors such as extreme precipitation and runout modelling to better reflect process dynamics.

The present study confirms that Random Forest models are suitable for alpine landslide susceptibility mapping and illustrates how data-based methods can support and improve hazard management when carried out with sound geomorphic reasoning.

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