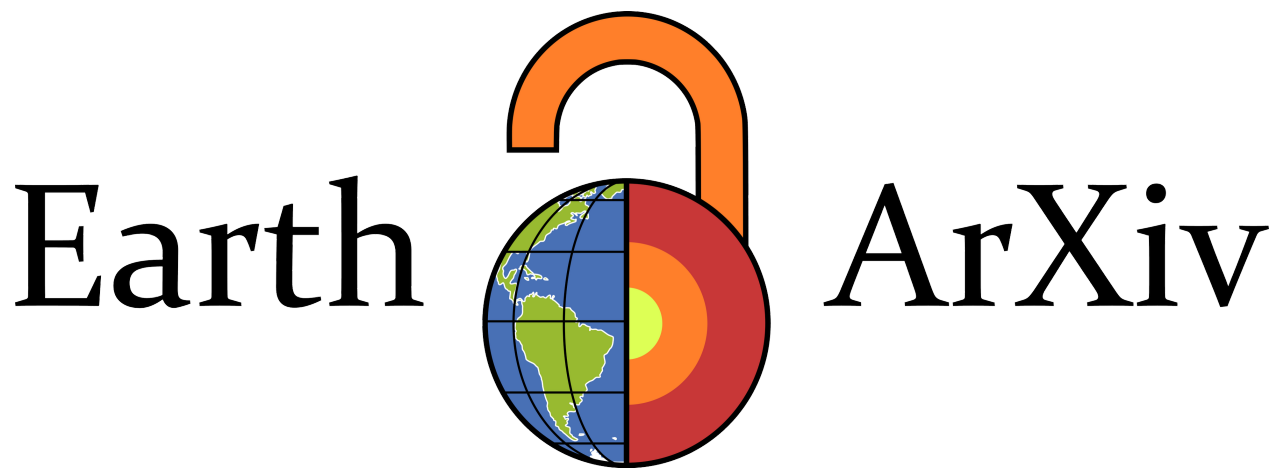




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1 **Role of Topo-Climatic Factors in Landslide Susceptibility**

2 **Mapping: A Machine Learning Perspective**

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7

8 **Abstract**

9 With the rapid growth of machine learning (ML) applications in landslide susceptibility
10 mapping (LSM), many studies have relied on large and diverse datasets to improve predictive
11 performance. However, in data-scarce regions, model transferability becomes challenging, and
12 not all input variables contribute meaningful information to landslide prediction, leading to the
13 well-known problem of “garbage in, garbage out”. Therefore, careful selection of physically
14 meaningful predictors is essential. In this study, we develop a Random Forest–based framework
15 for landslide mapping using topographic and climatic factors only as inputs. Notably, the model
16 incorporates effective rainfall (ER), derived from a process-based hydrological model, and a
17 recently proposed topographic metric, topographic source density (D_{ts}), that were not used in
18 previous LSM studies. Results demonstrate that incorporating these predictors substantially
19 improves model performance, achieving a receiver operating characteristic area under the
20 curve (ROC-AUC) of 0.972. Overall, the findings suggest that a physically meaningful
21 machine learning approach can reliably predict regional landslide susceptibility.

22

23 **Keywords:** Landslide susceptibility mapping; Machine learning; Random Forest; Effective
24 rainfall; Topographic source density; Topographic controls; Climatic controls; Model
25 interpretability; California.

1. Introduction

Landslides are among the most serious natural hazards worldwide. According to the World Bank data, nearly 3.7 million square kilometres of inland area on Earth are prone to landslides, affecting the lives of more than 300 million people (Dilley et al., 2005). Slope instability is governed by the complex interaction of topographic, climatic, hydrological, geological, and land-use factors, making the modelling of landslide occurrence particularly challenging at regional scales (Crozier, 1986; Guzzetti et al., 1999; Aleotti & Chowdhury, 1999; Sidle & Ochiai, 2006). In recent years, data-driven and machine-learning models have gained prominence in landslide susceptibility mapping (LSM) due to their ability to capture nonlinear and multivariate relationships among conditioning factors (Catani et al., 2013; Tien et al., 2020). Ensemble approaches, particularly Random Forest, have proven effective in handling complex datasets and improving predictive performance. However, the strong emphasis on prediction accuracy often comes at the expense of physical interpretability (Reichenbach et al., 2018). When a large number of correlated variables are supplied to a model, the algorithm may reproduce statistical associations without necessarily representing the underlying processes that govern slope instability.

Machine-learning models learn only from the information provided to them, and predictors that are weakly related or physically irrelevant may still appear important if they improve statistical performance (Domingos, 2012; Reichenbach et al., 2018). Such practices risk prioritizing accuracy over understanding, leading to the well-known limitation of “garbage in, garbage out” (GIGO), where unreliable inputs undermine the robustness and interpretability of model outputs (Bishop, 2006; Korup & Stolle, 2014). This disconnect between predictive skill and process understanding underscores the need for parsimonious, process-informed, and physically meaningful predictor selection to ensure model reliability, transferability, and scientific insight, particularly in regions where training data are limited.

Among the numerous factors influencing landslide occurrence, topographic and climatic variables represent the primary controls governing slope instability (Montgomery & Dietrich, 1994; Sidle & Ochiai, 2006). Topographic factors define the long-term preconditioning of slopes through their influence on gravitational stress, runoff concentration, and erosion dynamics, whereas climatic factors regulate transient triggering mechanisms such as rainfall-induced pore-water pressure and soil saturation (Bogaard & Greco, 2018; Iverson, 2000).

Recognizing that topographic preconditioning and climatic triggering together control landslide occurrence, and that high-quality terrain and precipitation data are widely available at regional scales, this study evaluates the role of selected topo-climatic factors in landslide susceptibility mapping. Focusing on California, a region characterized by diverse terrain, pronounced climatic gradients, and frequent rainfall-induced landslides, the study developed a Random Forest based model to map the landslide susceptibility. By emphasizing both predictive performance and physical interpretability, this study aims to bridge the gap between data-driven modelling and process-based understanding of landslide susceptibility.

2. Topo-Climatic Controls on Landslide Susceptibility

Beyond their impact on human lives and infrastructure, landslides also reshape Earth's surface, altering topography in remarkably short periods of time (Keefer, 1994; Korup et al., 2010). Yet, the same ever-evolving topography is itself a fundamental driver of slope instability (Montgomery & Dietrich, 1994). Although a landslide may appear to be a sudden event, its occurrence is rarely the result of a single day's conditions. Rather, slope failure is typically the outcome of cumulative processes shaped over millions to billions of years (Larsen & Montgomery, 2012). Numerous studies have demonstrated a strong connection between topography and landslide occurrence (Fausto Guzzetti et al., 1999; Montgomery & Dietrich, 1994; Reichenbach et al., 2018). Consequently, a wide range of topographic factors have been investigated to characterize landslide susceptibility (Reichenbach et al., 2018; Van Westen et al., 2006).

As landscapes evolve through the interaction of several physical processes, they preserve signatures within their topography that reflect the processes shaping them (Howard, 1994; Raina et al., 2025; Tucker & Slingerland, 1997; Whipple & Tucker, 1999). One such signature that we previously proposed is topographic source density (D_{ts}), defined as the density of topographic source pixels within a landscape (Raina & Biswal, 2025). Topographic source pixels are the pixels from which flow is initiated in a DEM-based flow-routing framework. They differ from channel sources, which represent the initiation of a hydraulic channel and depend on various physical factors and, in practice, on the threshold used to define channel initiation. D_{ts} was shown to capture the balance between key landscape evolution processes and exhibits a strong climatic dependence. Because the same processes controlling its development also influence hillslope gradients, drainage organization, hydrologic flow paths,

soil saturation, and pore water pressure, D_{ts} may additionally contain important information related to slope instability and landslide susceptibility.

In addition to topography, climate and its variability exert strong controls on slope stability and landslide triggering, with precipitation and temperature serving as the dominant climatic drivers (Iverson, 2000; Sidle & Ochiai, 2006). In mountainous regions, many landslides are rainfall induced, reflecting the close coupling between hydrologic forcing and slope failure processes (Caine, 1980; F Guzzetti et al., 2007). On natural hillslopes, pore water pressures evolve dynamically in response to climatic variability and subsurface hydrologic processes (Bogaard & Greco, 2016; Iverson, 2000). Consequently, landslide initiation is often governed not only by instantaneous rainfall intensity, but also by the cumulative hydrologic response of the soil mantle to antecedent precipitation (Glade et al., 2000). This understanding has motivated the development of antecedent rainfall concepts, which incorporate rainfall history and hydrologic memory to better represent the transient buildup of pore water pressure preceding slope failure (Guzzetti et al., 2008).

A fundamental concept in hydrology may relevant to these processes is effective rainfall (ER), defined as the portion of precipitation that contributes to runoff or streamflow generation (Beven, 2012; Biswal, 2016; Chow et al., 1988; Singh, 1988). However, not all rainfall reaching the ground follows the same hydrologic pathway. Part of the water is lost through evaporation, transpiration, or deep groundwater percolation, while another portion infiltrates into the soil and moves through subsurface flow paths of varying lengths and travel times (Beven, 2012; Dunne & Leopold, 1978). These differences in subsurface flow pathways are critical for landslide physics because infiltrated water controls the spatial and temporal evolution of pore water pressure within hillslopes (Bogaard & Greco, 2018; Iverson, 2000). Water retained within the soil mantle may increases soil saturation, reduces effective stress, and weakens slope materials, thereby promoting slope failure (Sidle & Ochiai, 2006). Therefore, incorporating ER into landslide susceptibility assessment may provide a more physically meaningful representation of hydrologic triggering mechanisms.

3. Study Area

3.1. California: A Region of Climatic and Topographic Diversity

In the present study, California, United States of America, was selected as the study area. Covering approximately 423,970 km², California encompasses some of the most diverse physical landscapes in North America. Elevation ranges from −86 m in Death Valley to over 4,400 m at Mount Whitney, resulting in pronounced contrasts in climate, vegetation, and geomorphic processes (Persad et al., 2020; USGS, 2020). California is subdivided into eleven geomorphic provinces with distinct physiographic characteristics, as shown in Figure 1 (Harden, 2004). The state's climate is equally heterogeneous and is broadly characterized by a Mediterranean regime, although precipitation exhibits strong spatial gradients from north to south and from coastal to interior regions (Dettinger et al., 2011). The combination of complex topography, strong climatic gradients, and frequent high-intensity rainfall events makes California one of the most landslide-prone regions in the United States (Keefer & Larsen, 2007). This diversity of controlling factors provides an ideal natural setting for examining the role of topographic and climatic variables in LSM.

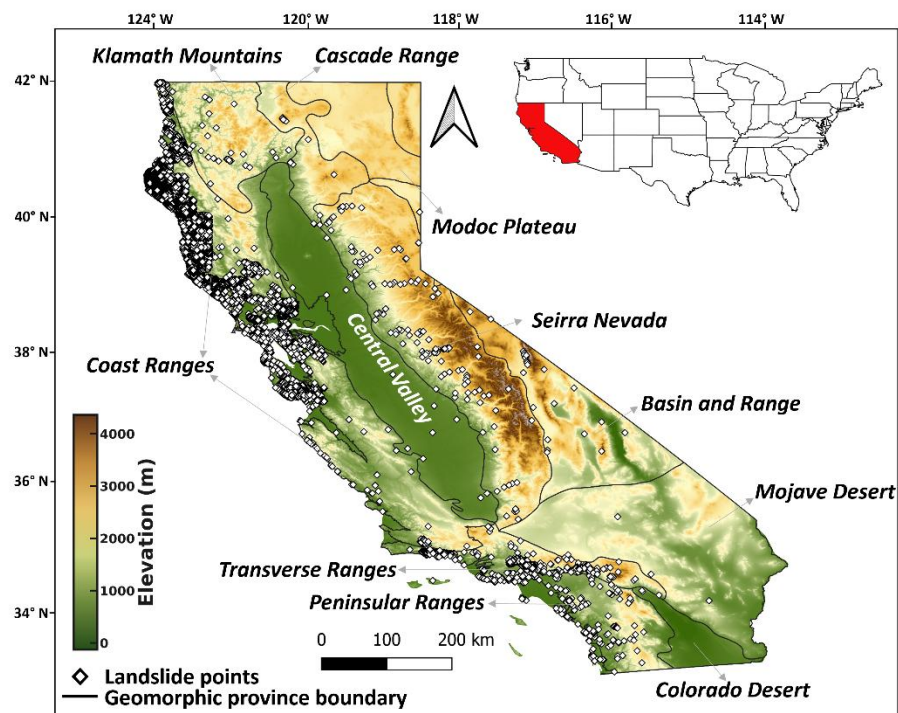


Figure 1. Landslide Distribution Map Across the Geomorphic Provinces of California, highlights spatial clustering of landslides in the Coast Ranges, Sierra Nevada foothills, Transverse Ranges, and Peninsular Ranges, with minimal activity in the Central Valley and desert regions.

4. Data and Methodology

4.1. Landslide Inventory

A landslide inventory forms the foundation of any ML-based LSM (Fausto Guzzetti et al., 1999; Van Westen et al., 2006). In this study, the landslide inventory was obtained from the United States Geological Survey (USGS) Landslide Inventory, Version 3 (point dataset), compiled under the National Landslide Hazards Program (NLHP) (USGS, 2025). The dataset provides spatial locations of documented landslides across the United States, together with information on landslide type, occurrence dates, source inventory, and confidence in the mapped landslide location and extent.

4.1. Predictor Selection and Data Processing

4.1.1. Topographical factors

The conventional topographic factors considered in this study include elevation, slope, aspect, and profile curvature, which are among the most commonly used predictors in LSM (Guzzetti et al., 1999; Lee et al., 2025; Pourghasemi et al., 2012; Sharma et al., 2024). These four variables were used to develop the Conventional Topographic Model (CTM). To evaluate the contribution of topographic source density (D_{ts}), it was subsequently added as an additional predictor, and a separate Enhanced Topographic Model (ETM) was developed. All topographic factors were derived from the 30m SRTM DEM obtained from the USGS Earth Explorer. Slope, aspect, and profile curvature were derived from standard terrain analysis using ArcGIS hydrology toolbox, D_{ts} required an additional processing step. The DEM was subdivided into 10×10 -pixel sub-grids to create a consistent analysis unit. A flow-accumulation grid was then computed from this resampled DEM, and source pixels were identified as locations where the flow-accumulation value equals 0 (no upstream pixel is contributing flow). D_{ts} for each sub-grid was calculated as the ratio of source pixels to the total number of pixels in the sub-grid, as shown in figure 2.

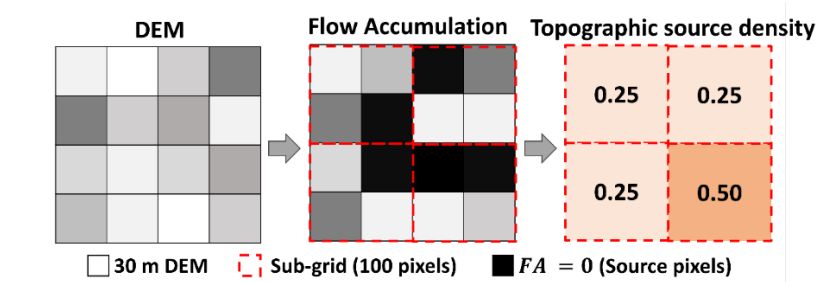


Figure 2. Workflow for calculating topographic source density.

4.1.2. Effective Rainfall Descriptors Based on the Dynamic Budyko Model

To derive daily ER , we used precipitation and temperature data from the Climate Prediction Centre (CPC) 0.25° global unified gauge-based daily gridded datasets, for the period 1979–2018. Potential evapotranspiration (PET) was estimated using the Hargreaves & Samani (1985) method. Daily ER was estimated using the Dynamic Budyko framework (Biswal, 2016; Istalkar & Biswal, 2024). Unlike the classical Budyko curve, which links long-term mean precipitation and potential evapotranspiration, the Dynamic Budyko formulation operates at the daily scale by using the instantaneous dryness index to partition precipitation into ER and rainfall losses. This approach incorporates day-to-day variability in atmospheric demand and moisture conditions, enabling a physically consistent and computationally simple estimation of daily ER .

From the daily ER series, six statistical descriptors were derived to capture different hydrological aspects relevant to landslide triggering. ER_{p90} , ER_{p95} , and ER_{p99} represent the 90th, 95th, and 99th percentiles of daily ER , reflecting the impact of moderate to extreme rainfall events. ER_m represents the long-term average ER , indicating the general wetness regime, while ER_{std} measures variability, capturing fluctuations that can contribute to stress–strain cycles in hillslopes. ER_0 , the fraction of days with nonzero ER , serves as a proxy for the persistence of soil wetness and frequency of hydrologic loading. These six ER descriptors were subsequently combined with the topographic predictors to develop a Topo-Climatic Model (TCM). ER_{100} was intentionally excluded because it represents a single maximum event and is therefore more sensitive to measurement errors, outliers, and exceptionally rare storms. Instead, ER_{99} was used to capture extreme rainfall conditions more robustly while avoiding excessive influence of a single anomalous observation on the Random Forest model.

4.2.Preparation of Landslide Binary Data

The landslide inventory available for this study is point based, whereas LSM requires raster formatted data. To enable raster-based analysis, all predictor variables and the landslide inventory were first resampled and aligned to a common spatial resolution to ensure spatial consistency across datasets. A spatial resolution of 100 m was selected because it is representative of typical hillslope dimensions and is widely adopted in regional scale landslide susceptibility studies (Pourghasemi et al., 2012; Reichenbach et al., 2018; Van Westen et al., 2006). Following spatial alignment, the point-based landslide inventory was converted into a binary raster. Each pixel of the inventory grid was assigned a value of 1 if it contained at least

one mapped landslide point and a value of 0 otherwise, thereby distinguishing landslide from non-landslide areas.

4.3. Implementation of the Random Forest Model

Random Forest (RF) is an ensemble learning method introduced by Breiman (2001) that improves predictive performance by combining the outputs of multiple decision trees. Here, Landslide susceptibility was modelled using a RF classification approach. The RF algorithm constructs a large number of decision trees using bootstrapped subsets of the training data, while a random subset of predictor variables is considered at each node split (Breiman, 2001). Final class predictions are obtained by aggregating the outputs of all trees, which reduces overfitting and enhances model robustness. The workflow adopted for RF-based LSM is illustrated in Figure 3.

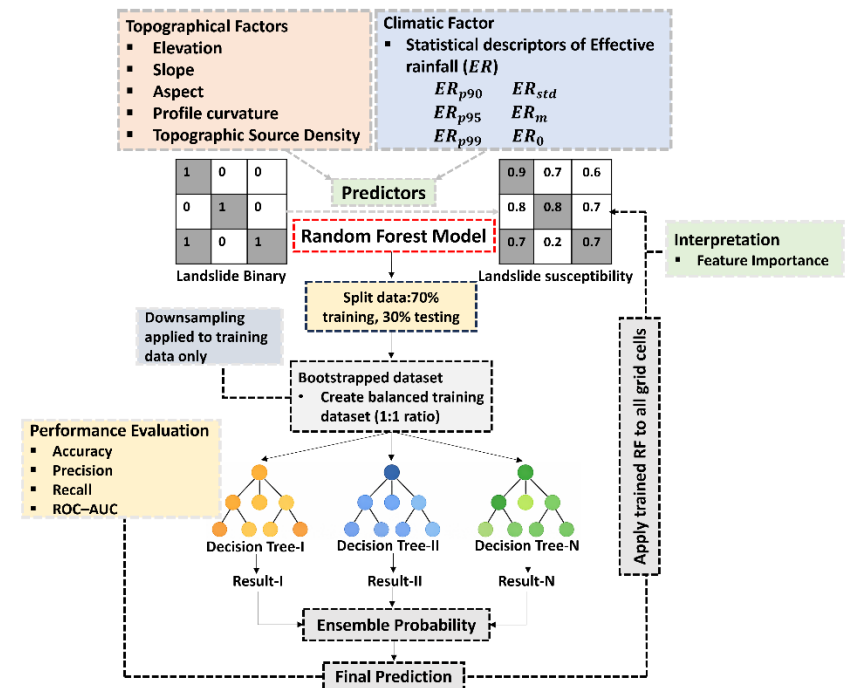


Figure 3. Workflow of the Random Forest-based LSM

To optimize model performance and minimize overfitting, stratified 5-fold cross-validation was implemented within the training dataset, ensuring that the proportion of landslide and non-landslide samples was preserved in each fold (James et al., 2021; Kohavi, 1995). Hyperparameter tuning was conducted using a grid-search approach by systematically evaluating combinations of the number of trees ($n_estimators$), the number of predictor variables considered at each split ($max_features$), and the maximum tree depth (max_depth). For each hyperparameter combination, the model was trained on four folds and validated on

the remaining fold, repeating the process across all five folds. Model performance was assessed using the mean receiver operating characteristic area under the curve (ROC–AUC) obtained from the cross-validation runs (Fawcett, 2006). The hyperparameter combination yielding the highest mean ROC–AUC was selected as the optimal model configuration. Subsequently, the final RF model was trained using the complete training dataset and the selected hyperparameters, and its predictive performance was evaluated on the independent test dataset using standard classification metrics. The detailed workflow of the hyperparameter optimization is illustrated in Figure 4.

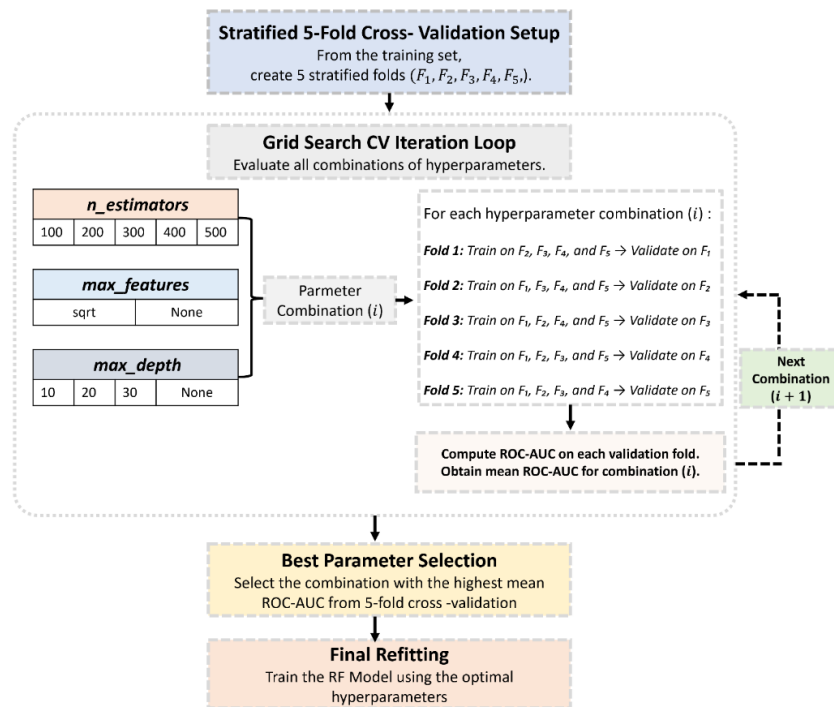


Figure 4. Workflow for Random Forest hyperparameter optimization using grid search and stratified 5-fold cross-validation.

A critical challenge in LSM is the issue of class imbalance, where the number of non-landslide pixels (majority class) greatly exceeds the number of landslide pixels (minority class) (Reichenbach et al., 2018). Such imbalance can bias machine-learning models toward the majority class, resulting in high overall accuracy but poor predictive performance for the minority class, which is the primary focus of susceptibility mapping (He & Garcia, 2009; Pourghasemi & Rahmati, 2018). To address this issue, a controlled down sampling strategy was applied during model training. All landslide pixels were retained, and an equal number of non-landslide pixels were randomly selected without replacement, resulting in a balanced dataset with a one-to-one ratio of landslide and non-landslide samples. The balanced dataset

was used exclusively for model training, while the trained Random Forest model was subsequently applied to the complete set of grid cells across the study area.

4.5. Model Performance Evaluation and Interpretation

The performance of the Random Forest models was evaluated using standard classification metrics to assess their ability to distinguish between landslide and non-landslide pixels. The evaluation metrics used in this study are summarized in Table 1. In this context, true positives (TP) and true negatives (TN) represent correctly classified landslide and non-landslide pixels, respectively. False positives (FP) represent non-landslide pixels incorrectly classified as landslide pixels, while false negatives (FN) represent landslide pixels incorrectly classified as non-landslide pixels. The true positive rate (TPR), also referred to as recall or sensitivity, is calculated as: $TPR = \frac{TP}{TP+FN}$, and The false positive rate (FPR) is calculated as: $FPR = \frac{FP}{FP+TN}$. These two quantities are used to construct the receiver operating characteristic (ROC) curve, which provides the basis for calculating the area under the curve (ROC-AUC).

Table 1. Summary of model evaluation metrics

Metric	Definition	Formula	Interpretation
Accuracy	Proportion of correctly classified samples	$\frac{TP + TN}{TP + FP + TN + FN}$	Measures overall classification performance
Precision	Proportion of predicted landslide pixels that are actual landslides	$\frac{TP}{TP + FP}$	Higher values indicate a lower false alarm rate
Recall	Proportion of actual landslide pixels correctly identified	$\frac{TP}{TP + FN}$	Higher values indicate better detection of true landslides
ROC-AUC	Area under the Receiver Operating Characteristic curve	$AUC = \sum_{i=1}^{n-1} \frac{(TPR_i + TPR_{i+1})}{2} (FPR_{i+1} - FPR_i)$	Discriminates landslide and non-landslide pixels across thresholds; values closer to 1 indicate better performance.

Machine-learning models are often criticized for their “black-box” nature and limited interpretability, which can hinder their application in hazard assessment (K. Youssef et al.,

2023). To address this issue, model interpretability was examined using variable importance, a commonly applied machine-learning interpretation tool (Goldstein et al., 2015). Variable importance was quantified using the mean decrease in impurity metric, which measures the contribution of each predictor to reducing classification uncertainty across the ensemble of decision trees.

5. Results

5.1. Role of Topographic Source Density and Effective Rainfall in Model Performance

The results demonstrate a progressive improvement in landslide susceptibility prediction with the addition of physically meaningful predictors. The Conventional Topographic Model (CTM) achieved an accuracy of 0.776, precision of 0.794, recall of 0.812, and a ROC-AUC of 0.837 (Table 2). These results indicate that conventional topographic variables provide a reasonable baseline for capturing terrain controls on landslide occurrence. The addition of topographic source density (D_{ts}) in the Enhanced Topographic Model (ETM) improved all evaluated performance metrics. Accuracy increased from 0.776 to 0.824, while precision and recall increased from 0.794 to 0.813 and from 0.812 to 0.854, respectively. The ROC-AUC also increased from 0.837 to 0.885. This improvement indicates that D_s provides additional information beyond conventional topographic variables. A much larger improvement was observed when the effective rainfall (ER) descriptors were incorporated into the ETM to develop the Topo-Climatic Model (TCM) (Fig. 5). The TCM achieved an accuracy of 0.941, precision of 0.918, recall of 0.928, and a ROC-AUC of 0.972 (Table 2).

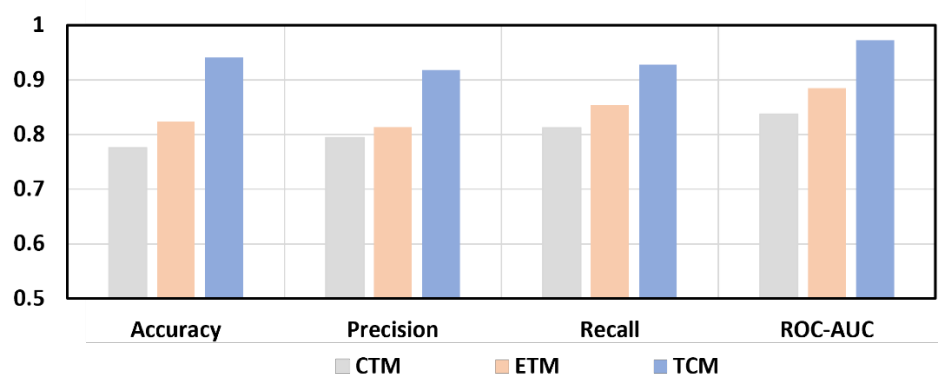


Figure 5. Comparison of the predictive performance of the Conventional Topographic Model (CTM), Enhanced Topographic Model (ETM), and Topo-Climatic Model (TCM).

Table 2. Performance comparison of landslide susceptibility models.

Model	Description	Accuracy	Precision	Recall	ROC-AUC
Conventional Topographic Model (CTM)	Four conventional topographic predictors: elevation, slope, aspect, and profile curvature	0.776	0.794	0.812	0.837
Enhanced Topographic Model (ETM)	Adds Topographic Source Density (D_{ts}) to the four conventional topographic predictors	0.824	0.813	0.854	0.885
Topo-Climatic Model (TCM)	Adds statistical descriptors of effective rainfall (ER) to the enhanced topographic predictors	0.941	0.918	0.928	0.972

5.2.Feature Importance of Topo-Climatic Predictors

Figure 6 summarizes the relative importance of the predictors used in the Random Forest models for ETM and TCM. Among all topographic predictors, elevation emerged as the most important predictors (Figure 6b). The ER descriptors collectively formed the most influential group of predictors, emphasizing the dominant role of hydrologic forcing in landslide initiation. Among all ER descriptors, ER_m exhibited the highest importance, followed by ER_{p99} and ER_0 . These variables contributed substantially more to the model than the remaining ER descriptors. Among the traditional topographic predictors, D_{ts} exhibited higher importance than slope, profile curvature and aspect (Figure 6a), indicating it also contributes significantly to model performance and landslide susceptibility prediction.

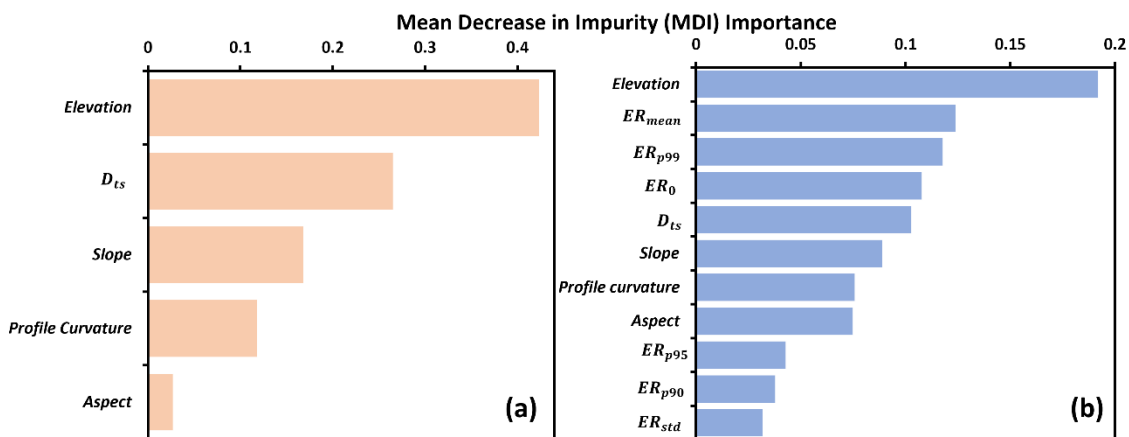


Figure 6. Mean Decrease in Impurity (MDI) feature importance for the (a) Enhanced Topographic Model (ETM) and (b) Topo-Climatic Model (TCM).

5.3. Spatial Distribution of Landslide Susceptibility Across Geomorphic Provinces

Moderately high susceptibility was also observed within the Klamath Mountains and Sierra Nevada, where approximately 16% and 15% of the terrain, respectively, fell within the high to very high susceptibility classes. In contrast, the Cascade Range displayed comparatively limited high susceptibility coverage, with only about 5% of the area classified as high to very high. Arid regions such as the Mojave Desert and Colorado Desert exhibited minimal susceptibility, with less than 1% of the terrain categorized as high to very high susceptibility. These areas were dominated by very low to low susceptibility classes throughout most of their extent. Overall, the spatial distribution of susceptibility closely follows California's major mountain belts and regions of pronounced terrain dissection, whereas low susceptibility dominates the relatively flat and arid desert regions.

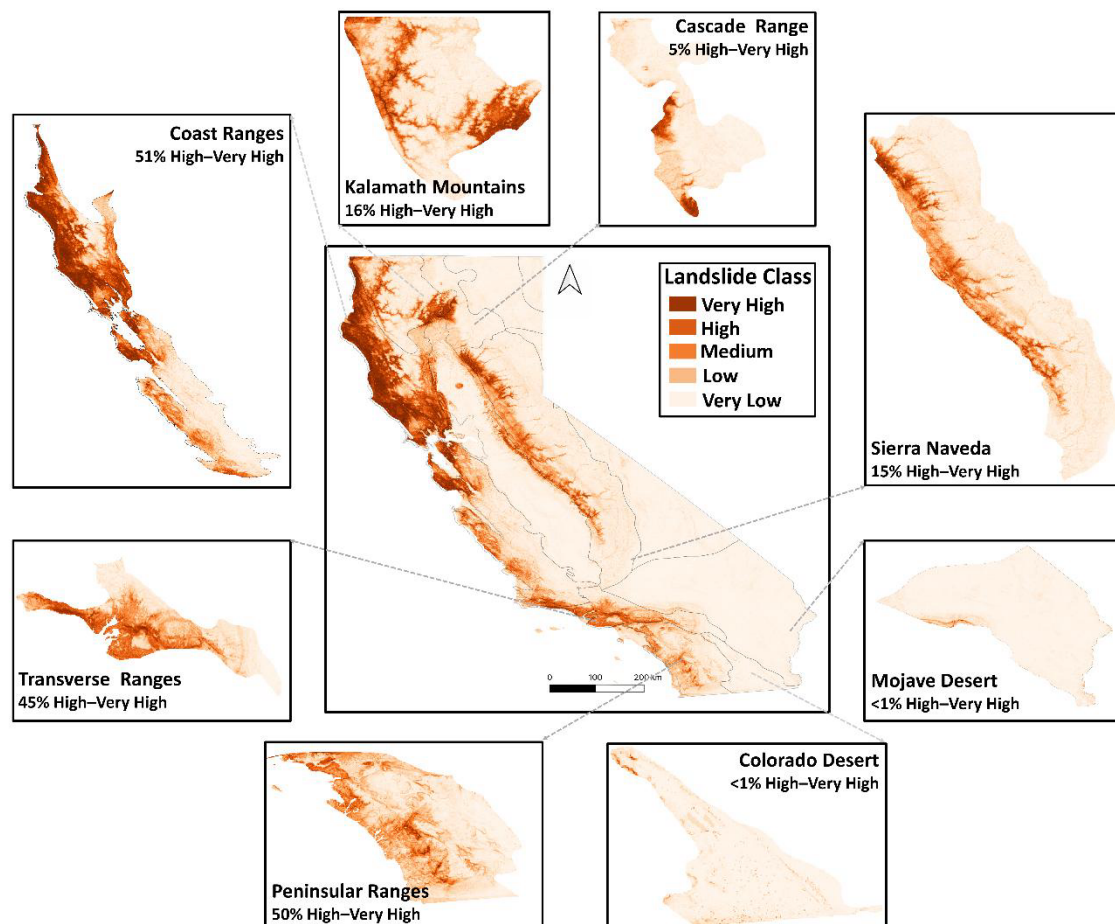


Figure 7. Spatial distribution of landslide susceptibility across California and major geomorphic provinces derived from the Random Forest model.

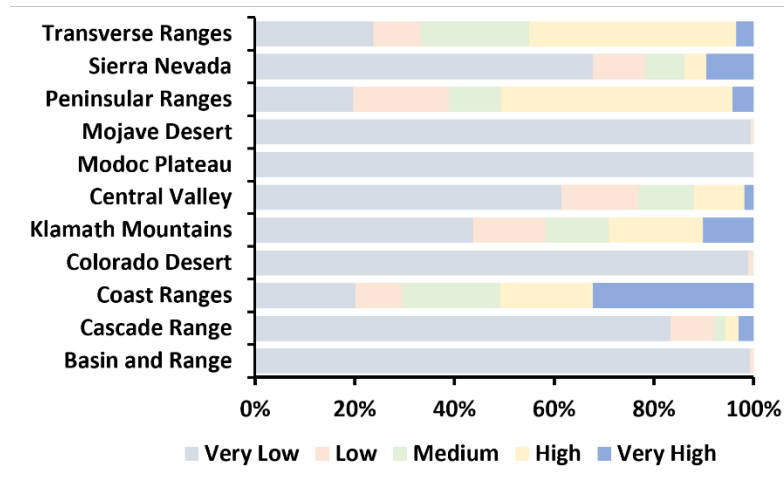


Figure 8. Proportional distribution of landslide susceptibility classes across major geomorphic provinces of California. Each stacked bar represents the percentage area within a province classified as very low, low, medium, high, and very high susceptibility.

6. Discussion

6.1. Performance of a Parsimonious Topo-Climatic Predictor Set

In landslide susceptibility mapping (LSM), the ROC-AUC is widely regarded as one of the most informative performance metrics because it provides a threshold independent measure of model discrimination ability (Fawcett, 2006; Fausto Guzzetti et al., 2006). Reported ROC-AUC values in susceptibility studies typically range from approximately 0.80 to 0.95, depending on the predictor set, modelling framework, spatial scale, and validation strategy employed (Merghadi et al., 2020; Reichenbach et al., 2018). Classical statistical approaches and early machine learning models generally occupy the lower to middle portion of this range, whereas more recent ensemble-based methods frequently achieve values exceeding 0.90 (Pourghasemi & Rahmati, 2018; Youssef et al., 2015; Reichenbach et al., 2018). Although a small number of studies have reported ROC AUC values above 0.97, such exceptionally high performance is often associated with validation schemes susceptible to spatial autocorrelation effects, which can lead to optimistic estimates of predictive skill (Lee et al., 2025; Reichenbach et al., 2018; Sharma et al., 2024).

Within this context, the presented topo-climatic model achieved a ROC AUC of 0.972, placing it near the upper range of reported regional scale landslide susceptibility models. More importantly, this performance was obtained using a relatively small set of physically meaningful predictors rather than a large collection of environmental variables. This finding

suggests that effective representation of the dominant controls on landslide occurrence may be more important than simply increasing the number of predictors. The strong performance of the model indicates that the selected variables successfully capture both the long-term topographic preconditioning and the short-term hydrologic triggering mechanisms that govern slope failure. The ability of a parsimonious predictor set to achieve such high predictive performance further supports the value of process-informed variable selection and suggests that physically interpretable predictors can offer both scientific insight and predictive capability in landslide susceptibility modelling.

6.2 Physical Interpretation of Highly Important Predictors

Elevation emerged as a highly important predictor in our study, consistent with several previous landslide susceptibility studies (e.g., Halder et al., 2025; Kunwar et al., 2025; Yin et al., 2021; Rabby et al., 2023). However, elevation may not represent a direct causal control on landslide initiation; rather, it can act as an indirect proxy for multiple environmental and geomorphic controls, which vary systematically with altitude. Thus, its high importance may reflect its ability to integrate information from several landslide-controlling factors.

As shown in Figure 6, the *ER* descriptors collectively exhibit the highest feature importance among all predictor groups, highlighting their substantial contribution to model performance. Beyond their predictive value, these variables also provide important insights into the hydrologic controls governing landslide occurrence. Slope failure is fundamentally driven by the evolution of pore water pressure within hillslopes, which is regulated by infiltration, subsurface flow, and soil moisture storage. *ER* directly influences these processes by controlling the amount of water available for soil saturation and pore pressure development. Among all *ER* descriptors, ER_{mean} exhibited the highest importance, followed by ER_{p99} and ER_0 . This ranking suggests that long-term average hydrologic conditions exert the strongest control on regional landslide susceptibility, while hydrologic extremes and the frequency of hydrologically active conditions provide additional information regarding landslide triggering potential. The importance of ER_0 further emphasizes the role of rainfall persistence, showing that areas experiencing frequent wet days are more susceptible even when individual events are not extreme (Berti et al., 2012). Lower-ranked descriptors such as ER_{p95} , ER_{p90} , and ER_{std} contribute less but still capture variability in rainfall intensity and dispersion that modulate slope response. Together, these findings indicate that landslide occurrence is influenced not

only by short-duration extreme events but also by the cumulative effects of persistent moisture availability, emphasizing the critical role of hydrologic memory in controlling slope instability.

6.3 Landslides Through the Lens of Geomorphology: The Role of Topographic Source Density

Although in the model interpretation D_{ts} exhibits lower feature importance than elevation and the dominant ER descriptors (Figure 5), however, its contribution remains comparable to or greater than several commonly used topographic predictors. It is important to note that lower-ranked predictors are not necessarily unimportant. Feature importance values indicate the relative contribution of each variable to landslide discrimination within the Random Forest model rather than their physical relevance (Breiman, 2001; Molnar, 2022). Variables with lower importance may still exert significant controls on landslide occurrence, but their explanatory power can be partially shared with stronger predictors. Because Random Forest prioritizes variables that most effectively separate landslide and non-landslide pixels across the entire study area, physically meaningful predictors may receive lower rankings when their effects overlap with dominant controls (Goldstein et al., 2015).

To examine the relationship between landscape organization and slope instability, D_{ts} values were grouped into uniform intervals between 0 and 1, and the total number of landslides within each interval was computed (Figure 9a). Landslide occurrence concentrated within intermediate D_{ts} ranges. These D_{ts} ranges likely correspond to landscapes with sufficiently steep and dissected slopes that are more prone to failure. This may suggest that D_{ts} may capture fundamental aspects of landscape organization relevant to landslide susceptibility. To better understand the role of D_{ts} in the model, partial dependence plots (PDPs) were examined. PDPs provide insight into the marginal influence of an individual predictor while accounting for the average effects of all other variables in the model (Molnar, 2022). The PDP for D_{ts} (Figure 9b) reveals a distinctly non-linear relationship with landslide susceptibility. Predicted susceptibility initially increases with D_{ts} , reaches a maximum at intermediate values, and subsequently declines as D_{ts} increases further.

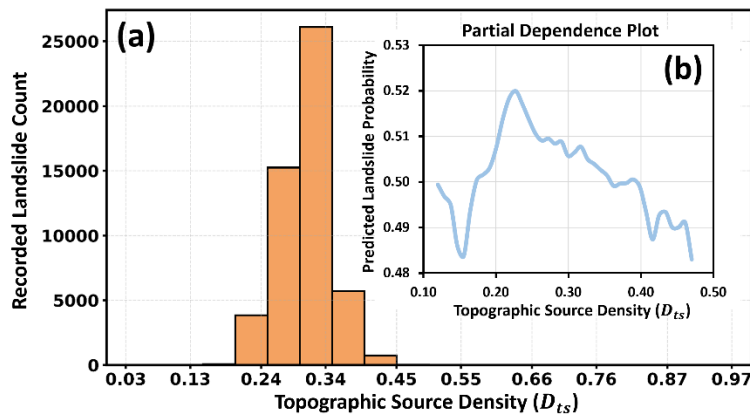


Figure 9. (a) Frequency of recorded landslides within topographic source density (D_{ts}) intervals. (b) Partial dependence plot showing the effect of D_{ts} on the predicted probability of landslide occurrence estimated by the Random Forest model.

This pattern is particularly noteworthy because it mirrors the empirical distribution of landslides shown in Figure 9a, where landslide occurrence is concentrated within intermediate D_{ts} landscapes. Geomorphologically, this behaviour may reflect the balance between competing landscape evolution processes. Low D_{ts} landscapes are typically characterized by subdued relief and limited hillslope dissection, resulting in lower susceptibility to slope failure (Raina & Biswal, 2025). In contrast, intermediate D_{ts} landscapes represent terrains where hillslope gradients, drainage organization, and hydrologic connectivity are sufficiently developed to promote instability. At very high D_{ts} , however, landscapes may become increasingly dissected and efficiently drained, reducing water accumulation and limiting the persistence of elevated pore water pressures that promote slope failure. This suggests that D_{ts} captures meaningful geomorphic controls on landslide occurrence.

6.4 Spatial Patterns of Landslide Susceptibility and Their Controls

The susceptibility map (Figure 6) reveals a clear concentration of high and very high susceptibility zones within California's mountainous regions, particularly the Coast Ranges, Transverse Ranges, Peninsular Ranges, and parts of the Sierra Nevada. In contrast, extensive portions of the Central Valley and arid southeastern regions exhibit consistently low susceptibility. These spatial patterns indicate that landslide occurrence in California is strongly controlled by the interaction of topographic, climatic, and geologic factors. Topography exerts a primary control by regulating slope gradients, local relief, and landscape organization.

Mountainous regions characterized by steep slopes and highly dissected terrain provide favourable conditions for slope instability, whereas the low-relief landscapes of the Central Valley exhibit limited susceptibility. These patterns are further reinforced by regional lithologic contrasts. California encompasses a wide range of geological materials, including weak sedimentary and *mélange* units within the Coast Ranges and more resistant granitic lithologies in the Sierra Nevada, which influence both weathering processes and slope stability (Jibson et al., 2000; Keefer, 1994).

Climatic forcing further modulates these geomorphic controls. Annual precipitation exceeds 2,000 mm in northern coastal and orographic regions, while desert provinces receive less than 150 mm annually. In particular, atmospheric river events frequently deliver prolonged and intense precipitation that can generate widespread increases in soil moisture and pore water pressure, triggering both shallow and deep-seated landslides (Guzzetti et al., 2008; Ralph et al., 2019). The high importance of *ER* descriptors in the Random Forest model reinforces the importance of antecedent wetness and cumulative hydrologic forcing in shaping regional susceptibility patterns.

It is important to note that the present study extends beyond susceptibility map generation by explicitly quantifying the relative contributions of topo-climatic controls. The model's ability to assign low susceptibility to geomorphologically stable regions further demonstrates its specificity and reduces the risk of overprediction, a common limitation of regional-scale susceptibility assessments. While the current framework provides a static representation of landslide susceptibility, future studies should integrate dynamic precipitation forecasts and hydrologic predictions to develop time-varying hazard assessments. Such efforts are particularly relevant to mountainous regions such as the Sierra Nevada, where snowmelt-driven hydrological processes have been identified as important contributors to slope instability (Peterson et al., 2005). Future research should also investigate landslides within a landscape evolution framework to better understand how different stages of landscape development influence the frequency, magnitude, and spatial distribution of landslide events.

6. Summary and Conclusions

This study focuses on the role of topographic and climatic predictors in LSM, recognizing that terrain characteristics and hydroclimatic forcing represent the primary controls on slope

instability. The Conventional Topographic Model (CTM), based on elevation, slope, aspect, and profile curvature, provided a reasonable baseline with a ROC-AUC of 0.837. Incorporating Topographic Source Density (D_{ts}) in the Enhanced Topographic Model (ETM) improved the ROC-AUC to 0.885, demonstrating that D_{ts} provides complementary geomorphic information beyond conventional topographic variables. The addition of effective-rainfall (ER) descriptors produced a substantial further improvement, with the Topo-Climatic Model (TCM) achieving a ROC-AUC of 0.972. This improvement highlights the importance of incorporating process-informed predictors into machine-learning frameworks.

Feature-importance analysis further showed that ER descriptors provided the strongest predictive contribution, highlighting the importance of cumulative and persistent hydrologic conditions in explaining landslide susceptibility. Elevation also emerged as a highly important predictor, potentially reflecting its role as an indirect proxy for multiple environmental and geomorphic gradients. In addition, the nonlinear relationship between D_{ts} and landslide susceptibility, identified through partial dependence analysis and landslide-frequency distributions, suggests that landslide susceptibility varies with the degree of landscape organization. The concentration of landslides within intermediate D_{ts} ranges indicate that specific states of topographic organization may provide favourable conditions for slope instability.

The spatial distribution of susceptibility classes reveals pronounced regional contrasts across California. High and very high susceptibility zones are concentrated in steep, tectonically active, and rainfall-exposed regions such as the Coast Ranges, Klamath Mountains, Sierra Nevada, and the Transverse and Peninsular Ranges. In contrast, low-relief and arid regions, including the Great Valley, Mojave Desert, Colorado Desert, Modoc Plateau, and Basin and Range provinces, are dominated by very low susceptibility, reflecting limited slope gradients and reduced moisture availability. These spatial patterns are physically consistent with established geomorphic and climatic controls on landslide processes. Overall, the present study demonstrates that integrating ER with topographic measures of landscape organization can substantially improve regional-scale landslide susceptibility assessment. Beyond improving predictive performance, the results highlight the importance of considering both hydrologic forcing and landscape structure in understanding landslide occurrence. The resulting model may provide a valuable basis for regional risk screening, disaster preparedness, and offers a

transferable methodological framework for landslide hazard assessment.

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DATA AVAILABILITY

The landslide inventory data used in this study are publicly available from the U.S. Geological Survey (USGS) Landslide Inventories across the United States, Version 3.0 (February 2025). Available at: <https://www.usgs.gov/data/landslide-inventories-across-united-states-ver-30-february-2025>. All other processed and derived datasets generated during this study are available from the corresponding author upon reasonable request.

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

- Aleotti, P., & Chowdhury, R. (1999). Landslide hazard assessment : summary review and new perspectives. *Bulletin of Engineering Geology and the Environment*, 58(1), 21–44.
<https://doi.org/10.1007/s100640050066>
- Berti, M., Martina, M. L. V, Franceschini, S., Pignone, S., Simoni, A., & Pizziolo, M. (2012). Probabilistic rainfall thresholds for landslide occurrence using a Bayesian approach. *Journal of Geophysical Research: Earth Surface*, 117(October), F04006.
<https://doi.org/10.1029/2012JF002367>
- Beven, K. (2012). *Rainfall-Runoff Modelling: The Primer*. Chichester, UK: Wiley-Blackwell.
<https://doi.org/10.1002/9781119951001>
- Biswal, B. (2016). Dynamic hydrologic modeling using the zero-parameter Budyko model with instantaneous dryness index. *Geophysical Research Letters*, 43(18), 9696–9703.
<https://doi.org/10.1002/2016GL070173.1>

- Bogaard, T., & Greco, R. (2018). Invited perspectives : Hydrological perspectives on precipitation intensity-duration thresholds for landslide initiation : proposing hydro-meteorological thresholds. *Natural Hazards and Earth System Sciences*, 18(1), 31–39. <https://doi.org/10.5194/nhess-18-31-2018>
- Bogaard, T. A., & Greco, R. (2016). Landslide hydrology : from hydrology to pore pressure. *WIREs Water*, 3(June), 439–459. <https://doi.org/10.1002/wat2.1126>
- Breiman, L. (2001). Random Forests. *Machine Learning*, 45(1), 5–32. <https://doi.org/10.1023/A:1010933404324>
- Caine, N. (1980). The rainfall intensity-duration control of shallow landslides and debris flows. *Geografiska Annaler: Series A, Physical Geography*, 62(1), 23–27. <https://doi.org/10.2307/520449>
- Catani, F., Lagomarsino, D., Segoni, S., & Tofani, V. (2013). Landslide susceptibility estimation by random forests technique : sensitivity and scaling issues. *Natural Hazards and Earth System Sciences*, 13(11), 2815–2831. <https://doi.org/10.5194/nhess-13-2815-2013>
- Chow, V. Te, Maidment, D. R., & Mays, L. W. (1988). *Applied Hydrology*. New York: McGraw-Hill.
- Christopher M. Bishop. (2006). *Pattern Recognition and Machine Learning*. New York: Springer.
- Crozier, M. J. (1986). *Landslides: Causes, Consequences and Environment*. London: Croom Helm. <https://doi.org/10.4324/9780203477674>
- Dettinger, M. D., Ralph, F. M., Das, T., Neiman, P. J., & Cayan, D. R. (2011). Atmospheric Rivers, Floods and the Water Resources of California. *Water*, 3(1), 445–478. <https://doi.org/10.3390/w3020445>
- Dilley, M., Chen, R. S., Deichmann, U., Lerner-Lam, A. L., Arnold, M., Agwe, J., et al. (2005). *Natural Disaster Hotspots A Global Risk*.
- Domingos, P. (2012). A few useful things to know about machine learning. *Communications of the ACM*, 55(10), 78–87. <https://doi.org/https://doi.org/10.1145/2347736.2347755>
- Dunne, T., & Leopold, L. B. (1978). *Water in Environmental Planning*. San Francisco: W. H. Freeman and Company.
- Fawcett, T. (2006). An introduction to ROC analysis. *Pattern Recognition Letters*, 27(8), 861–874. <https://doi.org/10.1016/j.patrec.2005.10.010>
- George H. Hargreaves, & Zohrab A. Samani. (1985). Reference Crop Evapotranspiration from Temperature. *Applied Engineering in Agriculture*, 1(2), 96–99.

<https://doi.org/10.13031/2013.26773>

Glade, T., Crozier, M. J., & Smith, P. (2000). Applying Probability Determination to Refine Landslide-triggering Rainfall Thresholds Using an Empirical “Antecedent Daily Rainfall Model.” *Pure and Applied Geophysics*, 157(6–8), 1059–1079.

<https://doi.org/10.1007/s000240050017>

Goldstein, A., Kapelner, A., Bleich, J., Pitkin, E., Oldstein, A. G., Apelnor, A. K., et al. (2015). Peeking Inside the Black Box : Visualizing Statistical Learning With Plots of Individual Conditional Expectation. *Journal of Computational and Graphical Statistics*, 24(1), 44–65. <https://doi.org/10.1080/10618600.2014.907095>

Guzzetti, F., Peruccacci, S., Rossi, M., & Stark, C. P. (2007). Rainfall thresholds for the initiation of landslides in central and southern Europe. *Meteorology and Atmospheric Physics*, 267, 239–267. <https://doi.org/10.1007/s00703-007-0262-7>

Guzzetti, Fausto, Carrara, A., Cardinali, M., & Reichenbach, P. (1999). Landslide hazard evaluation : a review of current techniques and their application in a multi-scale study , Central Italy. *Geomorphology*, 31(1–4), 181–216. [https://doi.org/10.1016/S0169-555X\(99\)00078-1](https://doi.org/10.1016/S0169-555X(99)00078-1)

Guzzetti, Fausto, Reichenbach, P., Ardizzone, F., Cardinali, M., & Galli, M. (2006). Estimating the quality of landslide susceptibility models, 81, 166–184. <https://doi.org/10.1016/j.geomorph.2006.04.007>

Guzzetti, Fausto, Peruccacci, S., Rossi, M., & Stark, C. P. (2008). The rainfall intensity-duration control of shallow landslides and debris flows: An update. *Landslides*, 5(1), 3–17. <https://doi.org/10.1007/s10346-007-0112-1>

Halder, Krishnagopal; Srivastava, Amit Kumar; Ghosh, Anitabha; Das, Subhabrata; Banerjee, Santanu; Pal, Subodh Chandra; Chatterjee, Uday; Bisai, Dipak; Ewert, Frank; Gaiser, T. (2025). Improving landslide susceptibility prediction through ensemble recursive feature elimination and meta-learning framework. *Scientific Reports*, 15(5170). <https://doi.org/10.1038/s41598-025-87587-3>

Harden, D. R. (2004). *California Geology* (2nd ed.). Upper Saddle River, New Jersey: Prentice Hall.

He, H., & Garcia, E. A. (2009). Learning from Imbalanced Data. *IEEE Transactions on Knowledge and Data Engineering*, 21(9), 1263–1284. <https://doi.org/10.1109/TKDE.2008.239>

Howard, A. D. (1994). A detachment-limited model of drainage basin evolution. *Water Resources Research*, 30(7), 2261–2285. <https://doi.org/10.1029/94WR00757>

- Istalkar, P., & Biswal, B. (2024). Streamflow prediction in ungauged basins: How dissimilar are drainage basins? *Journal of Hydrology*, 637, 131357.
<https://doi.org/10.1016/j.jhydrol.2024.131357>
- Iverson, M. R. (2000). Landslide triggering by rain infiltration. *Water Resources Research*, 36(7), 1897–1910. <https://doi.org/10.1029/2000WR900090>
- James, Gareth; Witten, Daniela; Hastie, Trevor; Tibshirani, R. (2021). *An Introduction to Statistical Learning: With Applications in R*. Springer. Retrieved from
<https://doi.org/10.1007/978-1-0716-1418-1>
- Jibson, R. W., Harp, E. L., & Michael, J. A. (2000). A method for producing digital probabilistic seismic landslide hazard maps. *Engineering Geology*, 58(3–4), 271–289.
[https://doi.org/10.1016/S0013-7952\(00\)00039-9](https://doi.org/10.1016/S0013-7952(00)00039-9)
- Keefer, D. K. (1994). Statistical analysis of an earthquake-induced landslide distribution—The 1989 Loma Prieta, California event. *Engineering Geology*, 37(3–4), 231–249.
[https://doi.org/10.1016/S0013-7952\(00\)00037-5](https://doi.org/10.1016/S0013-7952(00)00037-5)
- Keefer, D. K., & Larsen, M. C. (2007). Assessing Landslide Hazards. *Science*, 316(May), 1136–1139. <https://doi.org/10.1126/science.1143308>
- Kohavi, R. (1995). A study of cross-validation and bootstrap for accuracy estimation and model selection. In *Proceedings of the 14th International Joint Conference on Artificial Intelligence (IJCAI-95)* (pp. 1137–1143). Morgan Kaufmann.
- Korup, Oliver; Densmore, Alexander L.; Schlunegger, F. (2010). The role of landslides in mountain range evolution. *Geomorphology*, 122(1–2), 77–93.
<https://doi.org/https://doi.org/10.1016/j.geomorph.2009.09.017>
- Korup, O., & Stolle, A. (2014). Landslide prediction from machine learning. *Geology Today*, 30(1), 26–33. <https://doi.org/10.1111/gto.12034>
- Kunwar, S., Khali, H., Tr, P., Meer, M. S., & Das, J. (2025). Integrating GIS and ensemble learning models to predict landslide-prone zones in Chamoli. *Discover Applied Sciences*, 7(1320). <https://doi.org/10.1007/s42452-025-07694-8>
- Larsen, I. J., & Montgomery, D. R. (2012). Landslide erosion coupled to tectonics and river incision. *Nature Geoscience*, 5(7), 468–473.
<https://doi.org/https://doi.org/10.1038/ngeo1479>
- Lee, S., Roh, M., Jo, H., Joon, K., & Lee, W. (2025). Machine learning-based rainfall-induced landslide susceptibility model and short-term early warning assessment in South Korea. *Landslides*, 22(8), 2809–2827. <https://doi.org/10.1007/s10346-025-02513-y>
- Merghadi, A., Yunus, A. P., Dou, J., Whiteley, J., Thaipham, B., Tien, D., et al. (2020).

- Earth-Science Reviews Machine learning methods for landslide susceptibility studies : A comparative overview of algorithm performance. *Earth-Science Reviews*, 207(May), 103225. <https://doi.org/10.1016/j.earscirev.2020.103225>
- Molnar, C. (2022). *Interpretable Machine Learning: A Guide for Making Black Box Models Explainable* (2nd ed.). Independently published. Retrieved from <https://christophm.github.io/interpretable-ml-book/>
- Montgomery, D. R., & Dietrich, W. E. (1994). A physically based model for the topographic control on shallow landsliding. *Water Resources Research*, 30(4), 1153–1171. <https://doi.org/10.1029/93WR02979>
- Persad, G. G., Swain, D. L., Kouba, C., & Ortiz-Partida, J. P. (2020). Inter-model agreement on projected shifts in California hydroclimate characteristics critical to water management. *Climatic Change*, 162(3), 1493–1513. <https://doi.org/10.1007/s10584-020-02882-4>
- Peterson, B. D., Smith, R., Stewart, I., Knowles, N., Soulard, C., Hager, S., & Norton, G. A. (2005). *Snowmelt Discharge Characteristics Sierra Nevada , California*. <https://doi.org/https://doi.org/10.3133/sir20055056>
- Pourghasemi, H. R., & Rahmati, O. (2018). Prediction of the landslide susceptibility : Which algorithm , which precision ? *Catena*, 162(December 2017), 177–192. <https://doi.org/10.1016/j.catena.2017.11.022>
- Pourghasemi, H. R., Pradhan, B., & Gokceoglu, C. (2012). Application of fuzzy logic and analytical hierarchy process (AHP) to landslide susceptibility mapping at Haraz watershed, Iran. *Natural Hazards*, 63(2), 965–996. <https://doi.org/10.1007/s11069-012-0217-2>
- Rabby, Yasin Wahid; Li, Yingkui; Hilafu, H. (2023). An objective absence data sampling method for landslide susceptibility mapping. *Scientific Reports*, 13(1740), 1–15. <https://doi.org/10.1038/s41598-023-28991-5>
- Raina, S. S., & Biswal, B. (2025). *Ridge Density as a Topographic Fingerprint of Landscapes*. <https://doi.org/https://doi.org/10.22541/essoar.176555586.68724090/v1>
- Raina, S. S., Borse, D., & Biswal, B. (2025). On Hack ’ s law and efficiency of landscapes. *Earth Surface Processes and Landforms*, 50(15), 1–11. <https://doi.org/https://doi.org/10.1002/esp.70207>
- Ralph, F. Martin; Rutz, Jonathan J.; Cordeira, Jason; Dettinger, Michael; Anderson, Mark; Reynolds, David; Schick, Lori J.; Smallcomb, C. (2019). A scale to characterize the strength and impacts of atmospheric rivers. *Bulletin of the American Meteorological*

- Society*, 100(2), 269–289. <https://doi.org/10.1175/BAMS-D-18-0023.1>
- Reichenbach, P., Rossi, M., Malamud, B. D., Mihir, M., & Guzzetti, F. (2018). A review of statistically-based landslide susceptibility models. *Earth-Science Reviews*, 180(March), 60–91. <https://doi.org/10.1016/j.earscirev.2018.03.001>
- Roy C. Sidle; Hirotaka Ochiai. (2006). *Landslides: Processes, Prediction, and Land Use*. Washington, DC: American Geophysical Union. <https://doi.org/10.1029/WM018>
- Sharma, N., Saharia, M., & Ramana, G. V. (2024). High resolution landslide susceptibility mapping using ensemble machine learning and geospatial big data. *Catena*, 235(October 2023), 107653. <https://doi.org/10.1016/j.catena.2023.107653>
- Singh, V. P. (1988). *Hydrologic Systems: Rainfall-Runoff Modeling*. Englewood Cliffs, New Jersey: Prentice-Hall.
- Tien, D., Tsangaratos, P., Nguyen, V., & Liem, N. Van. (2020). Comparing the prediction performance of a Deep Learning Neural Network model with conventional machine learning models in landslide susceptibility assessment. *Catena*, 188(July 2019), 104426. <https://doi.org/10.1016/j.catena.2019.104426>
- Tucker, G. E., & Slingerland, R. (1997). Drainage basin responses to climate change. *Water Resources Research*, 33(8), 2031–2047. <https://doi.org/10.1029/97WR00409>
- USGS. (2020). Highest and Lowest Elevations. Retrieved from <https://www.usgs.gov/educational-resources/highest-and-lowest-elevations>
- USGS. (2025). Landslide Inventories across the United States, Ver. 3.0 (February 2025). Retrieved from <https://www.usgs.gov/data/landslide-inventories-across-united-states-ver-30-february-2025>
- Van Westen, C. J., Van Asch, T. W. J., & Soeters, R. (2006). Landslide hazard and risk zonation — why is it still so difficult? *Bulletin of Engineering Geology and the Environment*, 65(2), 167–184. <https://doi.org/10.1007/s10064-005-0023-0>
- Whipple, K. X., & Tucker, G. E. (1999). Dynamics of the stream-power river incision model: Implications for height limits of mountain ranges, landscape response timescales, and research needs. *Journal of Geophysical Research: Solid Earth*, 104(B8), 17661–17674. <https://doi.org/10.1029/1999JB900120>
- Yin, X., Yue, J., Guo, Z., Chen, Y., Hu, J., & Travé, A. (2021). Large-Scale Landslide Susceptibility Mapping Using an Integrated Machine Learning Model: A Case Study in the Lvliang Mountains of China. *Frontiers in Earth Science*, 9(722491). <https://doi.org/10.3389/feart.2021.722491>
- Youssef, A. M., Pourghasemi, H. R., El-Haddad, B. A., & Dhahri, S. F. (2015). Landslide

susceptibility maps using different probabilistic and bivariate statistical models and comparison of their performance at Wadi Itwad Basin , Asir Region , Saudi Arabia. *Bulletin of Engineering Geology and the Environment*, 75, 525.

<https://doi.org/10.1007/s10064-015-0734-9>

Youssef, K., Shao, K., Moon, S., & Bouchard, L. (2023). Landslide susceptibility modeling by interpretable neural network. *Communications Earth & Environment*, 4(1).

<https://doi.org/10.1038/s43247-023-00806-5>