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MACHINE LEARNING-DRIVEN INSIGHTS INTO SOIL–VEGETATION–ATMOSPHERE INTERACTIONS ON CLIMATE-IMPACTED SLOPES

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1 Introduction

The selection of ecological indicators for assessing landslide susceptibility is highly context-dependent, varying significantly based on regional characteristics, data availability, and the specific objectives of the study. Despite this variability, certain indicators such as the Normalized Difference Vegetation Index (NDVI) and Land Use Land Cover (LULC) are consistently employed due to their relevance in reflecting vegetation health, land surface changes, and human-induced disturbances. NDVI helps capture variations in vegetation cover, which can influence slope stability, while LULC provides critical insights into land modification and land management practices that may exacerbate or mitigate landslide risks. Factors like Net Primary Productivity (NPP), Remote Sensing Ecological Index (RSEI) are less common (Broquet, M. et.al. 2024). These indicators are often used in conjunction with other environmental, topographic, and climatic factors to develop a comprehensive understanding of landslide susceptibility across different landscapes. In May 2023, Emilia-Romagna region in Italy experienced an exceptionally intense rainfall event which triggered more than 65 thousand landslides (Geoportale: https://regione.emilia-romagna.it). This offers a unique opportunity with its precisely located failure points (landslide) which gives fine temporal resolution for "pre- vs. post-failure" ecological indices, statistical robustness from a large, heterogeneous sample, and rich spatial variability (from dense forests to agricultural terraces), immediate validation opportunities, and all these factors make it especially beneficial for evaluating how NPP, RSEI, and NDVI relate to both the initiation of landslides and the subsequent ecological recovery, further help to check which ecological feature is most suited for landslide susceptibility analysis under climate change scenarios (Duan, Y. et.al. 2025).

This study employs a data-driven framework on the Google Earth Engine (GEE) platform, integrating 20 geospatial and climatic parameters to model landslide susceptibility using Random Forest (RF) and LightGBM (LGBM) on GoogleColab used to introduce Explainable AI (XAI). Explainable AI (XAI) techniques, such as SHapley Additive exPlanations (SHAP), Local Interpretable Model-agnostic Explanations (LIME), and Diverse Counterfactual Explanations (DiCE), enable quantifying and visualizing how each ecological feature contributes to a model's predictions. This ensures that the selected variables are scientifically meaningful and operationally robust, while also revealing complex associations between features and landslide predictability by understanding the influence of each feature on the model's outputs. This XAI-driven insight not only helps in selecting the best-performing ecological factors but also supports detailed local interpretation of decisions and predictability. RF and LGBM are trained and tested on a subset of this specific event. In this study, RSEI, NPP and NDVI are integrated as variables along with other variables for generating a landslide susceptibility map of Region Emilia Romagna using RF.

RF and LGBM offer different possibilities to understand the results of classification at the global level and local (pixel) level along with XAI, if only global explanation (feature importance's averaged over the entire dataset) is required, RF's built-in feature importance can be adequate (Li, M. et. al. 2024); however, LGBM's smoother continuous probabilities make local-linear surrogates (LIME) more faithful and counterfactual searches (DiCE) more plausible. Faster predictions allow LIME and DiCE to sample more points, yielding richer, more robust explanations. LGBM offers finer control over calibration and local decision-surface complexity, directly benefiting explainability tools. For these reasons, when primary goal is high-quality, stable local explanations and counterfactuals, LightGBM is the preferred choice (Levent, I. et.al.2025; David, R. et.al. 2006; and Zhang, D., & Gong, Y. 2020).

2 Adopted tools and techniques

To enhance the interpretability of machine learning (ML) models, several techniques are employed to better understand how input features influence predictions, in this study we employed (Table 1):

- Feature Importance: This refers to techniques that assign scores to input features based on their impact on the model's predictions. Common methods include permutation importance and model-specific measures (e.g., Gini importance in random forests).
- SHAP (SHapley Additive exPlanations): SHAP values provide a unified measure of feature contribution based on cooperative game theory. They quantify how much each feature contributes to the difference between a model's prediction and the average prediction, offering consistent and locally accurate explanations (Yan, Y.et al. 2021).
- LIME (Local Interpretable Model-agnostic Explanations): LIME approximates the model locally around a prediction by fitting a simpler, interpretable model (e.g., linear regression). This approach helps explain individual predictions by highlighting which features were most influential in a specific instance.
- DiCE (Diverse Counterfactual Explanations): DiCE generates diverse counterfactual instances that would have led to different outcomes. These counterfactuals help identify minimal and actionable changes to the input features needed to alter the model's decision, supporting transparency and decision-making.

The relevance of ecological parameters for landslide susceptibility assessment is discussed in the following sections both at the global and local level. The results show that according to the features importance at the global level, in RF method, NDVI and NPP appears to be equally important, but analyzing the results of SHAP, LIME and DiCE at the pixel level, it becomes clear that NPP is a better choice, if used without distinction in type of vegetation.

Table 1. Summary of explainability tools used

Type	Purpose	Inference	Output Type
Feature Importance	Assess overall contribution of each feature	Identify which features are most influential in the model's decisions	Numerical importance scores
SHAP	Global and local feature impact	How much did each feature contribute?	SHAP values per feature
LIME	Local explanation of prediction	Why did the model make this decision?	Top contributing features
DiCE	Counterfactual suggestions	What minimal changes change/turn the result?	New input suggestions

3 Landslide susceptibility map (LSM)

LSM shown in Figure1. Its preparation begins by loading the landslide feature collection, assigning each feature a random value, and limiting to 40,000 samples. The "presence" attribute is converted to integers to split into landslide (467) and non-landslide (738) subsets (total 1205 points), which are then randomly partitioned into 70 % training and 30 % testing sets. A 20-band predictor image is sampled at each location to extract feature values (30m resolution). A Random Forest classifier (100 trees, minimum leaf pop. = 5) is trained using "landslide" as the target and all bands as inputs. The model is applied across the predictor image to generate a landslide probability map, which is rescaled and exported. Variable importance and out-of-bag error are reported, and testing results (AUC-ROC=0.90) are also exported. Finally, probabilities (0–100 %) are classified into six susceptibility categories: Very Low (0–15 %), Low (15–30 %), Low–Moderate (30–45 %), Moderate–High (45–60 %), High (60–80 %), and Very High (≥ 80 %).

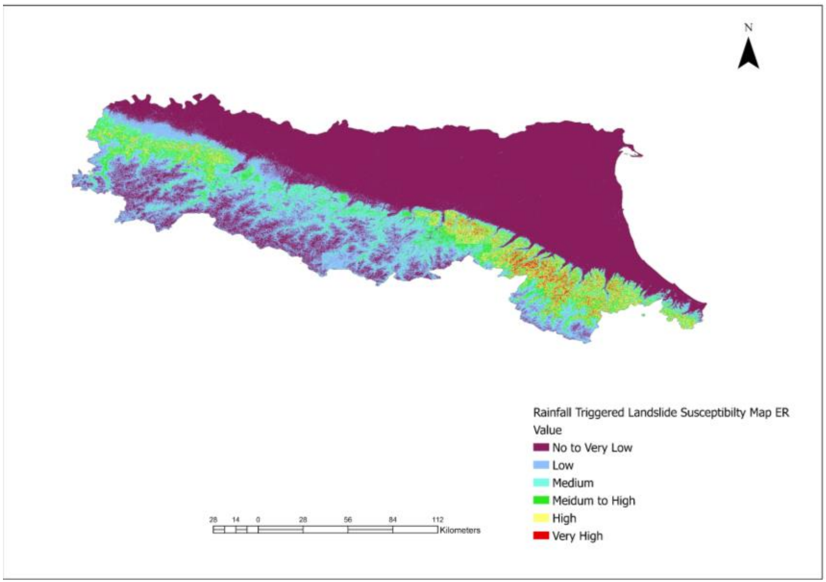


Figure 1. Landslide Susceptibility Map (LSM)

4 Impact of parameters at global level: feature importance and SHAP analysis

Figure 2 shows that, based on feature importance derived from the Random Forest (RF) model in Google Earth Engine (GEE) at the global scale, NDVI and NPP appear to be equally important predictors. However, further analysis using SHAP (Figure 3) values reveals that NPP has a more significant impact on model predictions compared to NDVI (Nohara, Y. et.al. 2021) and RSEI contribution appears less significant in comparison to NDVI and NPP.

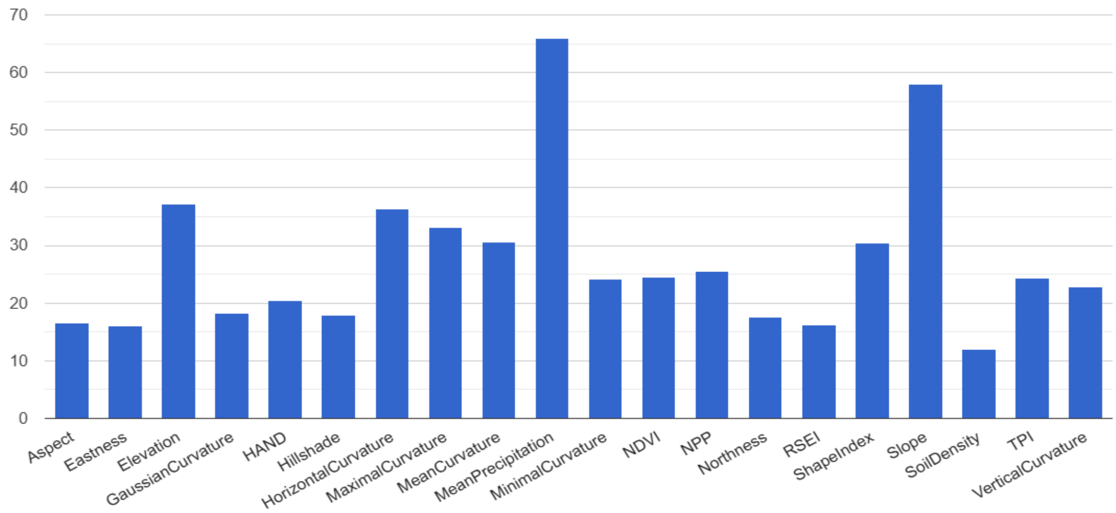


Figure 2. Feature Importance for Rainfall Triggered Landslides using Random Forest (RF)

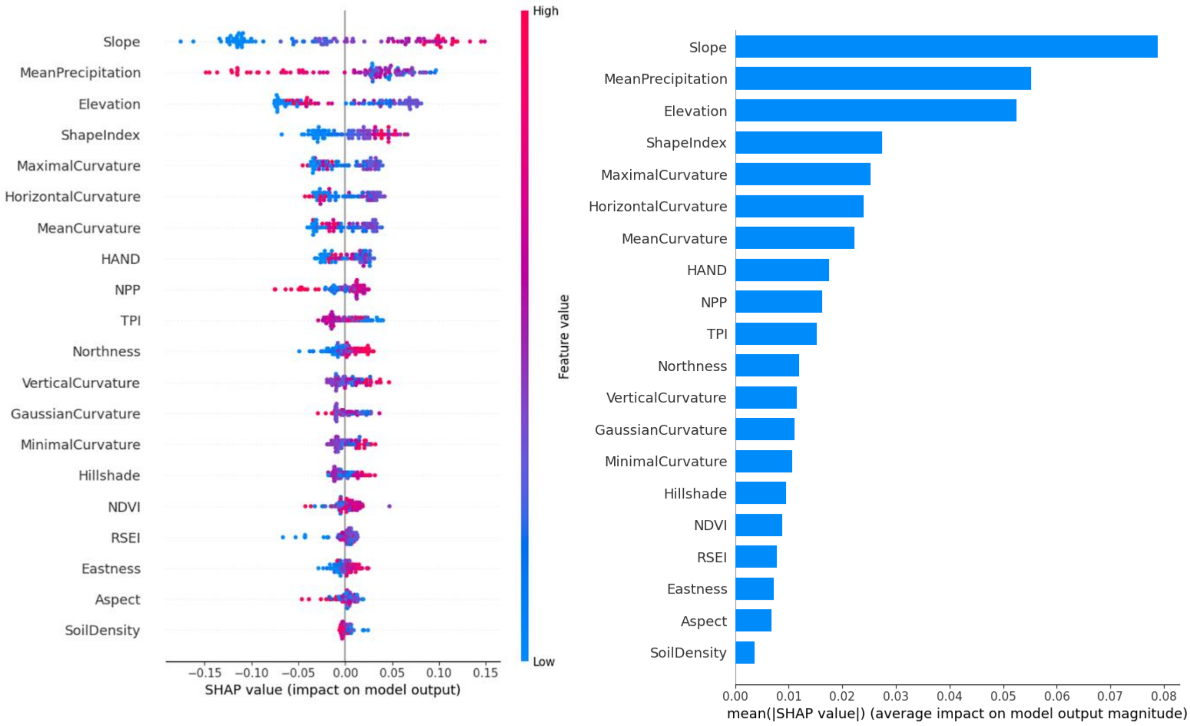


Figure 3. Impact of features (Variables) in prediction of Model Using SHAP

5 Impact of parameters at pixel level: LIME and DiCE

LIME and DiCE are better suited to investigate the results of the model at the local (pixel) level (Bujar, R. et.al. 2024). To this purpose, two points are considered: point 1 is classified as a pixel having Landslide and point 2 is classified as pixel having Non-Landslide respectively as original outcome.

5.1 Point 1

Figure 4 presents the LIME local explanation for point 1, where the model predicts a 66% probability of a landslide (see Table 2). The blue bars (left) represent features that contribute to a prediction of *No Landslide*, while the orange bars (right) indicate features that push the prediction toward *Landslide*. In this instance (see Table 3), high mean precipitation (1.72 compared to a threshold of 0.85) emerges as the strongest factor opposing a landslide (+0.20), acting as a protective feature. Conversely, a steep slope (1.33 vs. 0.71) is the most influential feature promoting a landslide (+0.18). Additional, though weaker, contributions from elevation, low soil density, and Topographic Position Index (TPI) also support the landslide prediction.

Table 4 illustrates a counterfactual explanation generated using DiCE, showing the minimal feature changes required to shift a model prediction from *No Landslide* to *Landslide*. For example*, a reduction in NDVI (vegetation index) moves the prediction toward landslide, suggesting that vegetation stress is a key risk factor*. Similarly, a significant increase in slope can locally drive the model's decision toward a landslide outcome. These results demonstrate how small but critical changes in specific features can alter model predictions, providing actionable insights for interpreting and mitigating landslide susceptibility.

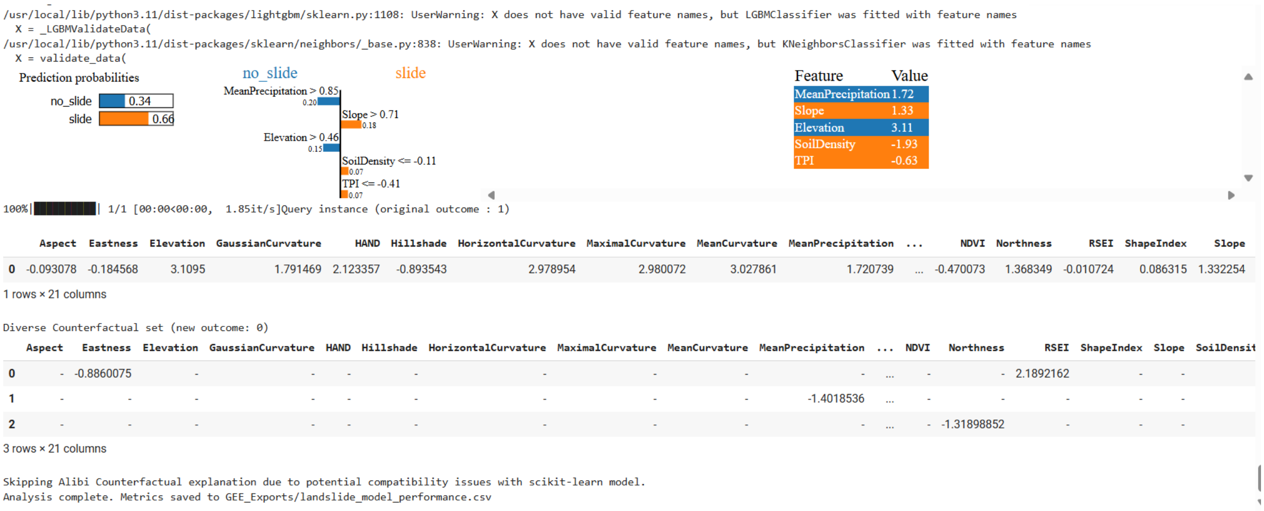


Figure 4. Snapshot of the analysis tool LIME and DiCE using LGBM point 1

Table 2. Model prediction summary point 1

Predicted Class	Probability
Landslide	0.66
No Landslide	0.34

Table 3. Point 1 LIME Local Explanation: **Top** features that LIME found most influential for *this* prediction

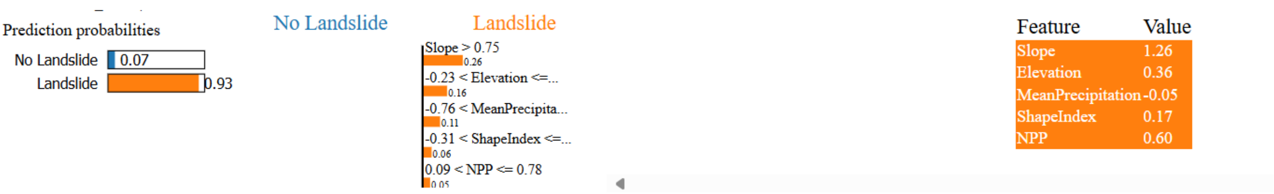
Feature	Condition	Contribution Toward Landslide	Standardized Value
Mean Precipitation	Precipitation > 0.85	-0.26	1.72
Slope	Slope > 0.71	0.18	1.33
Elevation >	Elevation > 0.46	0.15	3.11
Soil Density	Soil Density ≤ –0.11	0.07	–1.93
TPI	TPI ≤ –0.41	0.07	–0.63

Table 4. Counterfactual via DiCE examples that would flip the model's decision for Point 1

Counterfactual (CF)	Changed Feature	Standardized Value	Outcome
CF1	Aspect	–0.886	No Landslide
CF2	Mean Precipitation	–1.402	Landslide
CF3	NDVI	–1.319	Landslide

5.2 Point 2

For Point 2 (Figure 5), the model strongly predicts a landslide, as summarized in Table 5. LIME local explanations (Table 6) identify terrain steepness (slope), elevation, and precipitation trends as the primary contributors driving the prediction. Counterfactual analysis using DiCE (Table 7) demonstrates that relatively small changes particularly in Net Primary Productivity (NPP) or slope are sufficient to reverse the model's prediction, indicating sensitivity to these features.

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100%|██████████| 1/1 [00:00<00:00,  2.82it/s]Query instance (original outcome : 0)
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	Aspect	Eastness	Elevation	GaussianCurvature	HAND	Hillshade	HorizontalCurvature	MaximalCurvature	MeanCurvature	MeanPrecipitation	...	NDVI	NPP	Northness	RSEI	ShapeIndex
0	-1.330603	-0.26473	3.89874	0.567508	1.348051	-0.63469	4.040055	4.043398	3.983351	0.032198	...	0.302495	1.724224	-1.419539	0.71772	-0.437412

1 rows × 21 columns

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Diverse Counterfactual set (new outcome: 1)
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	Aspect	Eastness	Elevation	GaussianCurvature	HAND	Hillshade	HorizontalCurvature	MaximalCurvature	MeanCurvature	MeanPrecipitation	...	NDVI	NPP	Northness	RSEI	ShapeIndex	Slope
0	-	-	-	-	-	-	-	-	-	-	...	-	0.6976215	-	-	-	-
1	-	-	3.5140207	-	-	-	-	-	-	-	...	-	-0.9622975	-	-	-	-
2	-	-	-	-	-	-	-	-	-	-	...	-	0.3602648	-	-	-	1.8851273

Figure 5. Snapshot of the analysis tool LIME and DiCE using LGBM point 2

Table 5. Model prediction summary point 2

Predicted Class	Probability
Landslide	0.93
No Landslide	0.07

Table 6. Point 2 LIME Local Explanation: **Top** features that LIME found most influential for *this* prediction

Feature	Condition	Contribution Toward Landslide	Standardized Value
Slope	Slope > 0.75	0.26	1.26
Elevation	-0.23 < Elevation <=	0.16	0.36
Mean Precipitation	-0.76 < MeanPrecip <=	0.11	-0.05
Shape Index	-0.31 < Shape Index <=	0.08	0.17
NPP	0.06 < NPP <= 0.78	0.05	0.60

Table 7. Counterfactual via DiCE examples that would flip the model's decision for Point 2

Counterfactual (CF)	Changed Features	Standardized Value	Outcome
CF1	NPP	0.698	Landslide
CF2	Elevation	3.514	Landslide
CF3	NPP, Slope	NPP: 0.360, Slope: 1.885	Landslide

6 Conclusions

The integration of explainable machine learning methods emphasizes the importance of interpretable and robust predictive models for climate adaptation and slope stabilization, especially as extreme environmental events are expected to increase in frequency and intensity. By quantifying each feature's contribution, XAI helps to prioritize ecological factors that genuinely improve model performance. Furthermore, local-level explanations enable detailed decision-making, showing how small changes in ecological variables might alter predicted susceptibility in specific pixels or zones. LGBM compatibility with explainability tools such as LIME and DiCE makes it particularly well-suited for complex, high-dimensional geospatial analyses.

SHAP values provide global consistency and quantify each feature's overall impact on the model's output, while LIME offers localized, instance-level explanations that can be used to audit or justify specific risk assessments. DiCE adds a complementary perspective by generating counterfactual scenarios, allowing exploration of model robustness and identification of actionable feature thresholds. Together, these tools deliver both "why" and "what-if" perspectives, enabling more transparent and trustworthy decision-making in landslide susceptibility modeling.

The findings demonstrate that, at a global level, feature importance analysis using the Random Forest algorithm suggests comparable significance for NDVI (Normalized Difference Vegetation Index) and NPP (Net Primary Productivity). However, more granular, pixel-level analyses using SHAP, LIME, and DiCE reveal that NPP is a more effective predictor of landslide risk particularly when vegetation type is not explicitly differentiated. This highlights the value of localized explainability techniques in refining ecological variable selection beyond what global importance rankings can capture.

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