multi-Risk sciEnce for resilienT commUnities undeR a changiNgclimate

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Procedures to map the areal distribution of values of predisposing parameters

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1. Technical references

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2. Abstract

This Deliverable, part of **Milestone 2.3** of Spoke 2 in the Extended Partnership RETURN Project, deals with the theme "Identification of impact-oriented indicators" as outlined in the Executive Work Plan – Milestone 2.1. It summarizes the scientific research activities conducted from November 2023 to April 2024 by Task 2.2.3 ("Spatial analysis of proneness to ground instabilities: statistical and deterministic approaches") of Work Package 2.2 ("State of the art and knowledge base to define impact-oriented hazard indicators"). This task is a component of the vertical spoke VS2, "Ground Instabilities", and involves 57 researchers from various institutions.

The focus of **WP2** is on detecting and analysing predisposing factors to ground instabilities, while **WP3** and **WP4** concentrate on preparatory factors, and triggering and multiple geohazards cascading scenarios (MULTI-HAZARD), respectively. These work packages collectively aim to quantify the effects of ground instabilities on territories, buildings, and communities, and to develop an IT platform for the spatial and temporal analysis of these instabilities.

A significant phase within **Task 2.2.3** involved defining Ground Instability categories, which were categorized initially into landslides, subsidence, liquefaction, and sinkholes. A more detailed differentiation was later made, particularly distinguishing between slow and fast types of ground instability in subaerial phenomena. These categories have been detailed in **DV 2.2.3** and **DV 2.2.5** and are fundamental in guiding the project's direction.

This deliverable outlines the development process and objectives of **Task 2.2.3**, which involves spatial analysis of susceptibility to ground instabilities using both statistical and deterministic approaches. This task, along with Deliverable DV 2.2.4, is part of a broader project framework aimed at creating a Proof of Concept (PoC) for analysing ground instability. The process included compiling an inventory of Learning Examples (LEs), identifying and rationalizing preparatory processes, and using these insights to develop a prototype for susceptibility analysis.

The prototype is designed to accommodate various ground instabilities and incorporate diverse geo-spatial data without the need for specialized coding knowledge or commercial software. It features a user-friendly Graphical User Interface (GUI) developed in Matlab (with potential for conversion to R or Python for greater accessibility) that allows users to apply different susceptibility analysis methods. This GUI is detailed through statistical methods and development processes in subsequent chapters, with specific cases of ground instabilities discussed to illustrate adaptability beyond conventional basin-scale susceptibility analysis.

Ultimately, this deliverable aims to provide a functional prototype of the PoC that aligns with the project's initial phase and helps informatics experts refine the operational version of the PoC, demonstrating how input data, data structuring, and analysis techniques are expected to integrate and function.

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4. Introduction

This deliverable is prepared as part of Milestone 2.3 for Spoke 2, focusing on the topic "Statistical downscaling and bias correction indicators" as outlined in the Executive Work Plan. The objectives set for this milestone within Spoke 2 entail the identification of rationales, drawing from specific literature examples, to identify ground instabilities across macro-categories of factors (predisposing, preparatory, triggers). Additionally, it aims to construct analytical tools, organized in a logical-executive order (tool-chain), aimed at designing an IT platform. This platform aims to illustrate the spatial overlap (multiple-hazard) or temporal succession (multi-hazard, i.e., chain effects) of ground instability processes, enabling the quantification of their effects on the territory. Furthermore, it seeks to assess their impact on buildings and communities while evaluating their suitability and reliability.

4.1 Project framework

This report summarizes the scientific research activities carried out in the period November 2023 – May 2024 by the **Task 2.2.3** *"Spatial analysis of proneness to ground instabilities: statistical and deterministic approaches"* (hereinafter referred to as **TK3**) of the **Work Package 2.2** *"State of the art and knowledge base to define impact-oriented hazard indicators"* (hereinafter referred to as **WP2**) within the vertical spoke **VS2** "Ground Instabilities" of the Extended Partnership RETURN.

It should be noted that VS2 structured the work packages WP2, WP3 and WP4 by identifying the following areas of interest for each of them:

- WP2 focuses on the detection and analysis of **PREDISPOSING** factors to ground instabilities;
- WP3 targets **PREPARATORY** factors to ground instability;
- WP4 is centered on **TRIGGERING** and multiple geohazards cascading scenarios (**MULTI-HAZARD**).

In accordance with the definitions given within the VS2, the distinction between predisposing, preparatory and triggering factors/processes is made on a temporal basis: the predisposing factors are considered invariable on the observation scale, while the preparatory factors show changes or cyclical trends during the same period. As a consequence, a trigger is considered as a process that acts in a very short and well-defined time.

The partners involved in the **WP2** are ENEA, OGS, POLITO, UNIBA, UNIBO, UNIFI, UNIGE, UNINA, UNIPA, UNIPD and UNIROMA1. **WP2** leaders are Riccardo Fanti (UNIFI) and Mario Parise (UNIBA), **TK1** leader is Francesco Maria Chiocci (UNIROMA1), **TK2** leader is Mario Parise (UNIBA), **TK3** leader is Matteo Berti (UNIBO). 70 researchers participate in the activities of **WP2/TK2** (i.e., TK 2.2.3): 5 from ENEA, 4 from OGS, 5 from POLITO, 6 from UNIBA, 6 from UNIBO, 7 from UNIFI, 4 from UNIGE, 7 from UNINA, 12 from UNIPA, 6 from UNIPD and 8 from UNIROMA1.

The goal of **TK3** (*Spatial analysis of proneness to ground instabilities: statistical and deterministic approaches*) and the issue of **DV 2.2.6** (*Procedures to map the areal distribution of values of predisposing parameters*) have been interpreted within the framework of the entire Spoke work process.

In line with the core concept of the Project and **VS2**, the learning phase aimed to establish a framework for preparatory processes to serve as input for the Proof of Concept (PoC). This phase unfolded in three stages: firstly, compiling an inventory of Learning Examples (LEs); secondly, identifying the preparatory processes examined in each LE; and finally, formulating a rationale for each process based on the available LEs. **DV 2.2.3** (*Rationale for quantifying parameters measuring the susceptibility to ground instabilities in offshore and onshore areas*) and **DV 2.2.5** (*Rationale for selecting and scale-dependent weighting of predisposing factors*) represented the transitional descriptions from the aforementioned phases.

Following the submission of the two Rationales, our focus shifted towards developing and implementing a Proof of Concept (PoC) prototype aimed at conducting susceptibility analysis for ground instabilities. This prototype was informed by the outcomes of the internal validation of the Learning Examples (LEs) detailed in **DV 2.2.4** (*Data processing and analysis through the implementation of a geodatabase in advanced computing cloud systems*). Here, susceptibility maps for various types of ground instabilities were rigorously examined to identify the optimal approach and data structure for a unified analysis.

As anticipated in DV 2.2.4, the prototype has been devised with the following objectives in mind:

- Accommodating various types of Ground Instabilities.
- Utilizing methods with established reliability from international literature.
- Enabling the incorporation of diverse geo-spatial data (in terms of type, resolution, scale, etc.) deemed pertinent for the specific ground instability category, as identified in previous DVs.
- Allowing users to personalize the analysis effortlessly, without requiring specialized coding knowledge.
- Avoiding the use of commercial software.
- Facilitating straightforward implementation into the Proof of Concept (PoC).

To accomplish this objective, we have designed and crafted a Graphical User Interface (GUI) that enables the application of various susceptibility methods for ground instabilities in a user-friendly manner. The GUI was developed using Matlab but can be readily converted into R or Python for full open-accessibility. Within this deliverable, we delineate the statistical methods integrated into the GUI (Chapter 5) and detail the GUI's development process (Chapter 6). Chapter 7 encompasses descriptions of several distinct cases of ground instabilities, diverging from the conventional spatial susceptibility at the catchment scale. While these cases can be analyzed using the same mathematical methods implemented in the GUI, they necessitate specific procedures for data preparation and interpretation.

The primary objective of this deliverable is to furnish a functional prototype of the Proof of Concept (PoC), aligning with the initial phase of the tool chains outlined for Spoke V2. This prototype will aid informatics experts in refining the ultimate iteration of the operational PoC, offering a tangible demonstration of input data, data structuring, analysis techniques, and expected outcomes.

5.1 Selected methods for susceptibility assessment

The deliverable **DV2.2.5** (*Rationale for selecting and scale-dependent weighing of predisposing factors* - November 2023) provides a thorough review of the scientific literature to evaluate the common methods used in assessing susceptibility to ground instabilities. As detailed in the deliverable, the choice of method depends on several factors, such as the type of ground instability, the availability and quality of data, the objectives of the study, and the resources at hand. Due to the varying geological conditions, computational capabilities, and research aims, there is no universally applicable “best method” for any specific type of ground instability.

To support the Proof of Concept phase, various methods were explored and assessed based on a "popularity index," which reflects the frequency of method usage in the literature for specific processes. This index, derived from analyzing scholarly databases, suggests that commonly used methods are likely tailored and reliable for certain processes and can be suitable for susceptibility evaluations. The result of this evaluation is shown in Table 5.1.

				QUANTITATIVE														
				data-driven methods														
				Weights of evidence (WOE)	Logistic regression (LR)	Frequency ratio (FR)	Certainty factors (CF)	Evidential belief function (EBF)	Analytic Hierarchy Process (AHP)	Fuzzy logic (FL)	Random forest (RF)	Artificial neural networks (ANN)	K-Nearest Neighbor (KNN)	Support Vector Machine (SVM)	Decision trees (DT)	Naïve Bayes (NB)	Linear Discriminant Analysis (LDA)	Quadratic Discriminant Analysis (QDA)
Ground Instabilities	Subaerial Landslides	Subaerial Rapid Landslides Typologies	Rapid Flows (Debris flows, Mudflows)	1540	5270	2450	158	592	2510	2140	2450	3100	362	2550	1320	776	285	75
			Rapid Slides (Rock Slides, Rock Avalanches)	187	453	253	17	58	139	190	139	232	16	163	77	43	9	3
			Falls & Topples (Rock Falls, Rock Topples)	454	1270	693	43	176	514	644	435	679	79	497	292	175	64	8
		Subaerial Slow Landslides Typologies	Slow Flows (Earthflows)	272	543	133	41	115	191	242	212	338	38	241	152	108	44	12
			Slow Slides (Rotational and Planar Slides, Soil slips)	122	307	181	23	50	92	138	87	163	9	112	50	38	12	4
			Slow Spread/DsGSD	90	765	156	7	27	103	219	261	460	49	269	207	45	60	6
	Submarine Landslides	Submarine Landslides Typologies	Rapid Landslides Slow Landslides	41	150	69	3	23	58	95	85	114	11	79	42	23	7	0
	Sinkholes	Slow Sinkholes Typologies Rapid Sinkholes Typologies	Slow Sinkholes (All Types) Rapid Sinkholes (All Types)	246	1250	320	25	121	487	1440	1250	1020	480	1480	791	814	181	27
	Subsidence	Subsidence Typologies	Subsidence (All Types)	1480	6780	2310	127	825	4070	4210	4600	6090	739	4610	2480	928	561	89
	Liquefaction	Liquefaction Typologies	Liquefaction (All Types)	249	4400	861	51	101	1700	2870	2090	6070	459	3140	1390	507	377	61

Table 5.1: "Popularity index" of different data-drive methods (columns) for different type of ground instabilities (rows). The colors indicate the percentile classes for citations of each method: red= 75%-100%; orange=50%-75%; yellow=25%-50%; green=0%-25%.

As observed, Weight of Evidence, Logistic Regression, Frequency Ratio, Analytic Hierarchy Process, Fuzzy Logic, Random Forest, Artificial Neural Networks, and Support Vector Machine are among the most commonly utilized methods for assessing various types of ground instabilities. Among these, Artificial Neural Networks and Support Vector Machine methods can be quite intricate due to the specialized tuning of hyper-parameters. Conversely, Fuzzy Logic may pose computational challenges, particularly with large datasets or complex models, and the Analytic Hierarchy Process method may have limitations in handling uncertainty and imprecision compared to other methods.

Taking these factors into account, we have chosen to implement three well-known methods in our prototype application: Weight of Evidence, Logistic Regression, and Random Forest. These methods are selected for their versatility, reliability, and ease of use. Furthermore, we have examined a simplified technique suggested by Horton et al. (2013) for identifying areas susceptible to rockfalls, rock avalanches, and debris flows when landslide inventory data is not available for training data-driven methods. The key features of these four methods are outlined below.

5.1.1 Logistic Regression

Logistic Regression is a statistical method used for analyzing datasets in which there are one or more independent variables that determine an outcome. Unlike linear regression, which predicts continuous outcomes, logistic regression is specifically designed for binary outcomes, where the dependent variable is categorical and has only two possible values.

At its core, logistic regression models the relationship between a binary dependent variable and one or more independent variables. It estimates the probability that a given observation belongs to a particular category of the dependent variable. The logistic regression model applies a logistic function, also known as the sigmoid function, to transform the linear combination of predictor variables into a probability score between 0 and 1.

Logistic regression makes several key assumptions:

1. Linearity: the relationship between the independent variables and the log odds of the dependent variable is linear.
2. Independence of errors: the observations are independent of each other.
3. Absence of multi-collinearity: the independent variables are not highly correlated with each other.
4. Large sample size: logistic regression performs best with a large sample size to ensure reliable parameter estimates.

The logistic regression model is formulated as follows:

$$P(Y=1|X)=\frac{1}{1+\mathrm{e}^{-(\beta_0+\beta_1X_1+\beta_2X_2+\cdots+\beta_nX_n)}}$$

where:

- $P(Y=1|X)$ is the probability that the dependent variable Y equals 1 given the values of the independent variables X;
- β_0 is the intercept;
- $\beta_1, \beta_2 .. \beta_n$ are the coefficients of the independent variables;
- $X_1, X_2 .. X_n$ are the values of the independent variables.

The logistic function converts the linear combination of predictor variables into a probability score, which subsequently aids in categorizing observations into one of two classes, typically based on a pre-defined threshold (commonly set at 0.5). Logistic Regression finds extensive application in landslide susceptibility assessment, where it predicts the probability of slope failures or landslides in a specified area. susceptibilityThis estimation relies on establishing the relationship between predictor variables and landslide events.

5.1.2 Weight of Evidence

The Weight of Evidence (WoE) method is a statistical technique commonly employed in predictive modeling and risk assessment. It facilitates the analysis of the relationship between a binary outcome variable and one or more predictor variables. In the context of landslide susceptibility assessment, WoE offers valuable insights into the factors contributing to landslide occurrence and aids in the identification of high-risk areas.

At its core, the WoE method quantifies the strength of association between predictor variables and the occurrence of a binary outcome, such as landslide occurrence. It calculates the weight of evidence for each predictor variable, representing the degree of influence on the outcome variable. WoE assesses the odds of the event occurring in the presence of a particular predictor variable compared to its absence.

The WoE method operates under several key assumptions:

- Independence of observations: each observation in the dataset is assumed to be independent of others.
- Linearity of relationships: the relationship between predictor variables and the outcome variable is assumed to be linear on the log-odds scale.
- Absence of multi-collinearity: predictor variables are not highly correlated with each other, ensuring reliable estimation of model coefficients.

The WoE for a given predictor variable X is calculated using the following formula:

$$WoE(X) = \ln\left(\frac{\text{Odds of event occurring when variable } X \text{ is present}}{\text{Odds of event occurring when variable } X \text{ is absent}}\right) = ln\left(\frac{P1}{P2}\right)$$

The odds of the event occurring when the predictor variable is present are calculated as follows:

$$P1 = \frac{Number\ of\ events\ when\ variable\ X\ is\ present}{Number\ of\ non-events\ when\ variable\ X\ is\ present}$$

This represents the ratio of the probability of the event occurring to the probability of the event not occurring when the predictor variable is present.

Similarly, the odds of the event occurring when the predictor variable is absent are calculated as:

$$P2 = \frac{Number\ of\ events\ when\ variable\ X\ is\ absent}{Number\ of\ non-events\ when\ variable\ X\ is\ absent}$$

This represents the ratio of the probability of the event occurring to the probability of the event not occurring when the predictor variable is absent.

The WoE quantifies the strength of association between the predictor variable and the occurrence of the event, with positive values indicating a positive association and negative values indicating a negative association. This method is extensively applied not only in landslide susceptibility assessment but also in the mining industry, environmental risk analysis, and any scenario necessitating the analysis of the relationship between predictor variables and binary outcomes.

5.1.3 Random Forest

Random Forest is a versatile and powerful machine learning algorithm widely used for classification and regression tasks. It belongs to the ensemble learning family, where multiple models are combined to improve prediction accuracy and robustness. Random Forest is renowned for its ability to handle high-dimensional data, complex relationships, and noisy or missing features.

At its core, Random Forest builds a multitude of decision trees during the training phase. Each decision tree is constructed by selecting a random subset of features from the dataset and splitting the data into subsets based on the selected features. The process is repeated recursively until each subset contains data points belonging to a single class (for classification) or until a stopping criterion is met (for regression).

Random Forest operates under several key assumptions:

- Independence of trees: each decision tree in the forest is built independently, without any interaction or correlation with other trees.
- Random feature selection: at each node of the decision tree, a random subset of features is considered for splitting, reducing the risk of overfitting and enhancing model generalization.
- Bootstrap aggregation: Random Forest utilizes bootstrapping, where multiple subsets of the original dataset are sampled with replacement to train each decision tree. This helps in reducing variance and improving model stability.

The prediction process in Random Forest involves aggregating the predictions of individual decision trees. For classification tasks, the class with the most votes among all decision trees is assigned as the final prediction. For regression tasks, the average prediction of all decision trees is computed as the final prediction.

The randomness introduced during the construction of decision trees and the aggregation of predictions helps in reducing overfitting and improving model performance on unseen data. This methos finds typical applications in various domains including but not limited to finance, healthcare, environmental science, and remote sensing, where it is used for tasks such as classification, regression, feature importance analysis, and anomaly detection.

5.1.4 Flow-R

The three methods described above, like all data-driven approaches, rely on a map of ground instability features for model training and validation. This map can consist of points, such as debris flow initiation points or sinkhole locations, or polygons, such as inventories of slow-moving landslides. Regardless, this map is crucial to establish a statistical relationship between variables and predictors.

However, there are instances where a ground instability map may not be available. This could occur in areas where a landslide or instability inventory has not been conducted, or in cases where a particular type of instability has not yet been observed. This latter scenario is especially possible in the context of climate change, where shifts in rainfall patterns may alter geomorphic activity without historical data to reference.

When a ground instability map is unavailable, applying data-driven methods becomes impractical, posing challenges to susceptibility analysis. To address this issue, several researchers have explored the use of geomorphological approaches to predict areas prone to instability. One such method is employed in the Flow-R software (Horton et al., 2013). The method builds upon the concepts introduced by Rickenmann and Zimmermann (1993) and Heinimann (1998), who identified the "lower threshold" for debris flow initiation based on datasets of real events. The authors defined two curves representing the lower limit for debris flow initiation sources, one for rare events and the other for extreme events (Horton et al., 2008). The threshold for rare events is:

$$\begin{cases} \tan \alpha_{thres} = 0.32 S_{acc}^{-0.2} & if \;\; S_{acc} < 2.5\ km^2 \\ \tan \alpha_{thres} = 0.26 & if \;\; S_{acc} \geq 2.5\ km^2 \end{cases}$$

where:

- α_{thres} is the slope threshold, and
- S_{acc} is the surface of the upslope contributing area.

Using these formulas, it becomes possible to identify areas prone to debris flows. However, it is essential to acknowledge that these formulas were developed specifically for the central Alps region and may vary for other geographical locations. Hence, it is advisable to employ this approach solely for an initial assessment of debris flow susceptibility. It is also important to remark that this method is not applicable to other types of ground instability phenomena.

5.2 Data structure

All methodologies for assessing ground instability that depend on data analysis use geospatial information. This includes various terrain attributes like slope angle, aspect, and curvature, along with soil properties, land use/land cover patterns, lithology, precipitation levels, and historical records of ground instability specific to the area being studied. These datasets require pre-processing to ensure they are consistent, accurate, and compatible for analysis. This pre-processing may include tasks such as data cleaning, interpolation, re-sampling, and standardization.

It is important to note that the data utilized in the analysis cannot be generalized. As explained in DV 2.2.3 (*Rationale for the quantification of parameters measuring the proneness to ground instabilities in offshore and onshore areas* – November 2023), each category of ground instability is affected by a distinct set of factors that are specific to the geographic and geological context of the area. DV 2.2.3 provides an overview of the main factors that predispose different types of ground instability, offering a foundational framework for preparing datasets.

More specifically, the data structure needed for effectively assessing ground instability should possess several key characteristics:

- No Data values. In geospatial data analysis, cells within a data raster that fall outside the study area's boundary are generally marked as NoData. NoData serves as a universal indicator that certain cells should be excluded from analysis. However, the specific value assigned to NoData can vary based on the type of variable and the GIS software used to process the data. For instance, if the raster variable is an 8-bit positive integer, NoData might be set to 0 or 255. Conversely, if the variable is a 32-bit floating number, NoData is typically set to -9999 or -3.4E+38. It is crucial to ensure that layers with varying NoData values can be correctly stored and analyzed.

- Class subdivisions. Certain susceptibility methods, such as Weight of Evidence or Random Forest, require that continuous variables are divided into classes. The criteria for these class subdivisions are not standardized and can vary depending on the specific needs of the analysis. For example, the subdivision of slope angles might be finer in regions with steep slopes to better address the risk of shallow landslides, whereas broader subdivisions might be used in areas with slow-moving landslides in clay soils. Therefore, it is essential to create a data structure that is both simple and flexible, capable of supporting a subdivision in classes tailored for a specific ground instability across different geological conditions.

- Target layer. In data-driven approaches, the target layer represents the specific ground instability phenomena that are used to train and validate the model. This layer could include points that mark the initiation areas of shallow landslides or sinkhole locations, as well as polygons that delineate regions of deep-seated landslides or subsidence zones. Consequently, it is crucial to design a data structure that can effectively handle various forms of geographic targets, each corresponding to different types of ground instability phenomena.

- Data layers. As mentioned earlier, different types of ground instability—or even the same type in varying regions—may necessitate different data layers for analysis. Furthermore, it is often beneficial to conduct multiple analyses using various combinations of data layers to assess the impact of different predisposing factors. Therefore, the data should be organized to facilitate quick and straightforward sensitivity analysis on these predisposing factors.

To simplify meeting these requirements, we have established the data structure illustrated in Figure 5.1. All necessary data for the susceptibility analysis are stored in a single designated folder. This folder houses the raster files for various data layers, such as slope, lithology, and soil use, alongside raster files representing different types of ground instability (e.g., rockfall, debris flow, subsidence, sinkhole). It is important that all raster files are collinear, sharing identical cell sizes and spatial extents. Such an arrangement ensures a streamlined and orderly data structure, vital for managing large datasets or concurrent projects efficiently.

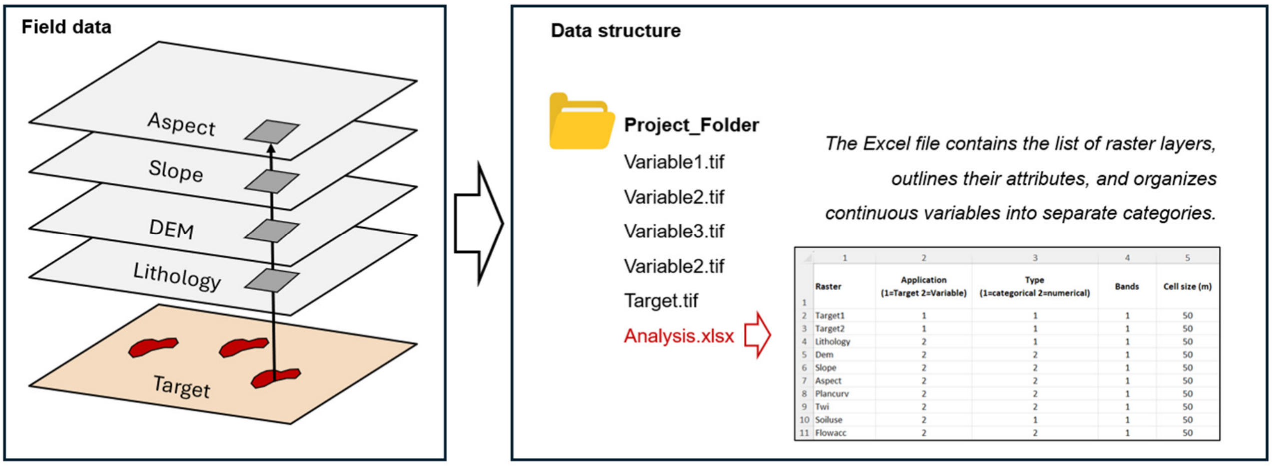


Figure 5.1. Data structure used for the susceptibility analysis. All raster layers are kept in a specific project folder, accompanied by an Excel spreadsheet that details the characteristics of each raster and the parameters used in the analysis.

Configuration details for the raster files are compiled in an Excel spreadsheet named 'Analysis.xlsx'. This spreadsheet functions as an external configuration tool, allowing users to input or modify key parameters that influence the processing of raster files. 'Analysis.xlsx' includes fields for critical parameters like the NoData value, which defines how the system addresses missing or irrelevant data within raster files.

Additional parameters covered include variable types and subdivision in classes, essential for several data-driven methods. Users can easily alter analysis parameters by simply updating the spreadsheet. This flexibility is especially advantageous for iterative testing or adapting the model to various data types, facilitating rapid adjustments to new applications without necessitating changes to the programming code.

6. Prototype application

a. 6.1 Aim of the prototype

In line with the Executive Working Plan of WP2, we have developed a specialized graphical user interface (GUI) for ground instability susceptibility analysis. This GUI is the initial component in the suite of tools anticipated by the project and is crafted to function as an operational tool for the researchers involved. It also serves as a prototype for the Proof of Concept, which will be the final deliverable of Spoke VS2.

The GUI includes a range of methods specifically designed for evaluating susceptibility to ground instabilities. The application simplifies the analysis process, making it accessible to all users regardless of their expertise in programming or data analysis. While the GUI broadens accessibility to a wide range of users, it is crucial to note that a thorough understanding of geological processes related to instabilities is essential to conduct effective analyses and achieve meaningful results.

These are the core goals of the prototype application:

- Operational Efficiency: The GUI is engineered to maximize user efficiency, reducing the technical barriers commonly associated with geospatial data analysis. Users can perform susceptibility analyses through a simple interface that guides them through the necessary steps from data input to result interpretation.
- Versatility in Analysis: the GUI offers a flexible analysis environment suitable for various types of ground instabilities. Users can select from different modeling approaches embedded within the tool, and test different combinations of input data to perform sensitivity analysis.
- Adaptability and Customization: Through an external configuration via an Excel spreadsheet, users can easily customize analysis parameters to fit their specific project needs and data conditions. This feature is critical for adapting the tool to various regional contexts and data availability, enhancing its applicability across different geographic areas.

As a prototype, the GUI was developed with a focus primarily on functionality rather than aesthetic details or the use of advanced graphical tools. Moreover, the data are not yet organized into a database. The refinement of these elements, including enhancing the interface's visual design and integrating the data into a structured geodatabase, will be the objectives for the final version of the Proof of Concept, which will be crafted by specialized software engineers.

b. 6.2 Overview of the Graphical User Interface

The Graphical User Interface was developed in MATLAB R2024a. MATLAB provides a versatile platform to create user-friendly interfaces for data analysis and visualization using interactive controls such as sliders, buttons, and text boxes. Additionally, MATLAB's architecture is specifically designed to handle large datasets effectively, utilizing efficient memory management and mathematical functionalities that are ideal for operations on arrays. A key aspect of this is the encouragement of memory pre-allocation for arrays. This strategy helps to significantly reduce computational overhead by eliminating the need to dynamically allocate memory as arrays expand. Such capabilities are particularly valuable when managing large raster arrays, which are common in spatial susceptibility assessments.

Graphical user interfaces comparable to those created in MATLAB can also be developed using programming languages such as R or Python. Both languages provide powerful tools for data analysis and visualization and, unlike MATLAB, are open-source and freely available. This makes R and Python cost-effective alternatives for developing advanced applications without the financial implications of licensed software. Our decision to use MATLAB is driven by our more extensive expertise with this platform compared to the others, making it a preference based on familiarity and proficiency, rather than a necessity.

Figure 6.1 illustrates the GUI and its key panels.

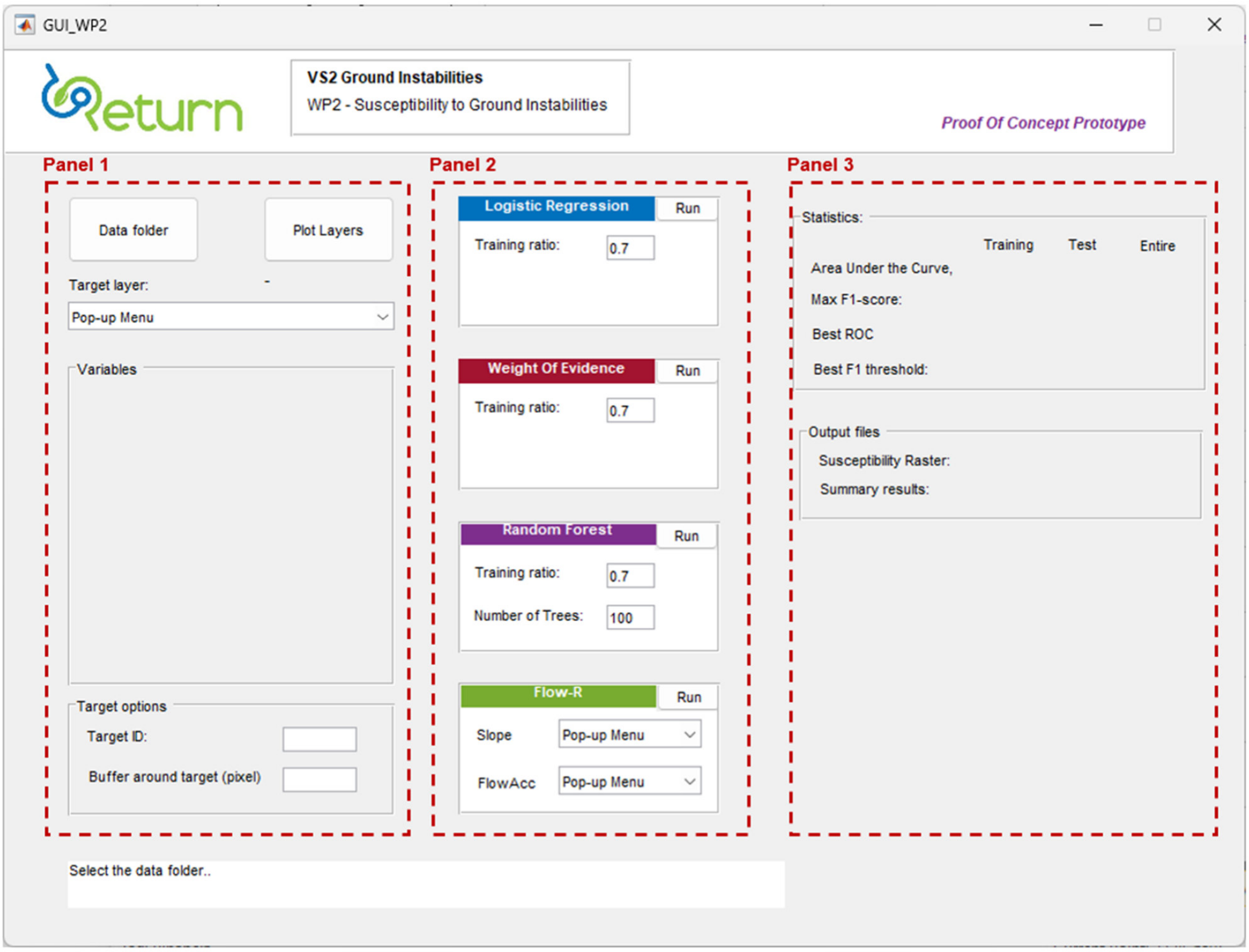


Figure 6.1. Overview of the Graphical User Interface (GUI) highlighting key panels. Each panel is designed for specific tasks as described in the text

Panel 1 focuses on input data layers, which are imported from the data folder. Once imported, these layers appear either in the Target combo box or in the Variables checkbox, depending on their function. The lower tab, "Target options," enables users to specify the ID of the target if the target layer includes various types of ground instability. It also allows for the creation of a buffer around point targets to expand the analysis area.

Panel 2 encompasses the four susceptibility methods that were previously outlined. Each method provides a variety of settings, including the percentage of the dataset allocated for training (Training Ratio) and the number of trees in the Random Forest model. Users can test different models by clicking the respective "Run" button. The analysis utilizes the data and target layers specified in Section 1, which can be selected by checking the appropriate checkbox or altering the selection in the Target combo box.

Panel 3 presents a summary of the analysis results. The "Statistics" tab shows the Area Under the Curve (AUC) scores derived from comparing observed and predicted stability conditions across pixels. It lists separate AUC values for the Training and Test datasets, as well as for the combined area (Training+Test). This tab also displays the Optimal Threshold for binary classification and the peak F1-score. In addition to these performance metrics, the GUI also features the susceptibility map (Target Susceptibility Index), charts showing the relative importance of variables, and ROC curves for the Training, Test, and entire area datasets.

A detailed explanation of the three sections is provided in the following chapter, which serves as the User Guide for the application.

c. 6.3 User Guide

The analysis of ground instability susceptibility can be divided into the four steps outlined below.

1. Create the raster layers

The first step is to create the raster layers needed for the analysis. Raster layers are divided into Variables and Target.

Variables represent the factors that predispose an area to instability, such as slope angle, lithology, aspect, and land use. As previously discussed in section 5.2, the choice of predisposing factors varies with the type of ground instability and the region's geological conditions. The table in **DV 2.2.3** (*Rationale for the quantification of parameters measuring the proneness to ground instabilities in offshore and onshore areas* – November 2023), which is reproduced in Table 6.1, details the primary predisposing factors for different types of ground instabilities. This table provides guidance for selecting variables, although the informed judgment of the user is essential for making appropriate choices.

The Target is a raster map representing the ground instability process, which is used to train and validate the data-driven model. It could, for example, be a rasterized map of polygons depicting areas impacted by landslides, subsidence, or sinkholes, or a rasterized map of points that indicate the origin points of shallow landslides. In this latter case, target areas might be depicted as single pixels. The representation of target areas can vary according to the focus of the analysis; it might highlight a specific part of the unstable zone, such as the detachment zone of an earthflow, or encompass the entire affected area. Data-driven methods prove particularly effective in these settings, as they can identify pixels where the combination of variables aligns with those of the target, thus facilitating the detection of specific characteristics of the instability phenomena.

Variables and Target rasters need to be collinear, meaning they must align in terms of spatial geometry and resolution across various layers. Data-driven analysis is not constrained by spatial resolution, as these methods can handle pixels of any size. Nonetheless, it is important that the pixel size is sufficiently small to effectively represent both the instability process and the environmental variables. For example, for analyzing small shallow landslides on a local scale, a pixel size of 1-2 meters may be necessary, while a pixel size of several tens of meters might be suitable for studying large landslides on a regional scale. Once the raster layers are prepared, store them as GeoTIFF files in a designated project folder.

↓ Predisposing Factors ↓		Log			Slow Landslides Typologies				Rapid Landslides Typologies			Sinkholes Typologies		Subsidence Typologies	Liquefaction Typologies
Macro-category	Main Factors	qualitative	semi-quantitative	quantitative	Slow Flows *(Earthflows)*	Slow Slides *(Rotational and Planar Slides, Soil slips)*	Spreads *(except Liquefaction)*	Slow Slope Deformations *(Rock/Soil SD, Creep, DsGSD)*	Rapid Flows *(Debris flows, Mudflows)*	Rapid Slides *(Rock Slides, Rock Avalanches)*	Falls & Topples *(Rock Falls, Rock Topples)*	Slow Sinkholes	Rapid Sinkholes	Subsidence (All Types)	Liquefaction (All Types)
Geology	Lithology	x					X		X	X	X			X	X
	Structural features (large scale)	x	x				X	X		X		X	X	X	
	Stratigraphic features	x				X		X		X				X	X
	Karstification degree		x									X	X		
	Talus/Weathering		x		X	X		X	X		X	X	X		
Geomorphology	Slope morphology/Topography			x	X	X	X	X	X	X	X	X	X	X	X
	Upslope area			x	X				X						
	Undercutting	x				X					X				
	Erosion by running water	x			X	X			X				X		
	Glaciers and snowfields	x					X	X	X						
	Distance from coastline			x								X	X		
	Overburden thickness			x								X	X		
	Cave geometry and size			x								X	X		
	Presence of previous events	x	x			X			X	X	X	X	X		
Physical and mechanical properties	Rock mass structure		x	x			X	X		X	X	X	X		
	Grainsize distribution/Particle shape		x	x	X				X						X
	Porosity/Density			x	X				X			X	X	X	X
	Shear strength			x	X	X	X		X	X	X				
	Mineralogy and plasticity			x											X
	Hydraulic Properties		x	x	X	X		X	X			X	X	X	
Seismotectonics	Seismic activity		x	x						X	X				X
	Faulting System/Distance to faults	x		x						X	X	X	X	X	
	Site effects (amplification/resonance)			x						X	X				
Land Cover & Vegetation	Land Use/Land Cover		x		X	X			X		X	X	X	X	
	Soil Type/Soil Thickness		x	x	X	X			X			X	X	X	
	Vegetation	x	x		X	X		X	X		X	X	X		
Hydrogeology	Groundwater/Saturation		x	x		X	X	X				X	X	X	X
	Rising acid fluids	x													
	Water inflow/outflow during flood/seastorm	x	x									X	X		
Climate	Rainfall Regime			x	X	X	X	X				X	X	X	
	Temperature Regime			x			X	X							
Anthropogenic Factors	Structures/Infrastructures/Buildings			x		X							X	X	
	Groundwater/Gas/Oil exploitation			x										X	
	River banks/levees typology		x												X
	Slope/Drainage changes		x	x	X	X			X		X				

Table 6.1. Key Predisposing Factors for Various Types of Ground Instability. The table cells show the significance of each factor in relation to different instability types (see DV 2.2.3 for details).

Next, create an empty Excel spreadsheet called Analysis.xlsx. This spreadsheet will catalog all details of the raster layers and their classification into different classes. The file should include a main sheet named 'Layers' and additional sheets for each individual raster layer. An example of this spreadsheet is illustrated in Figure. 6.2.

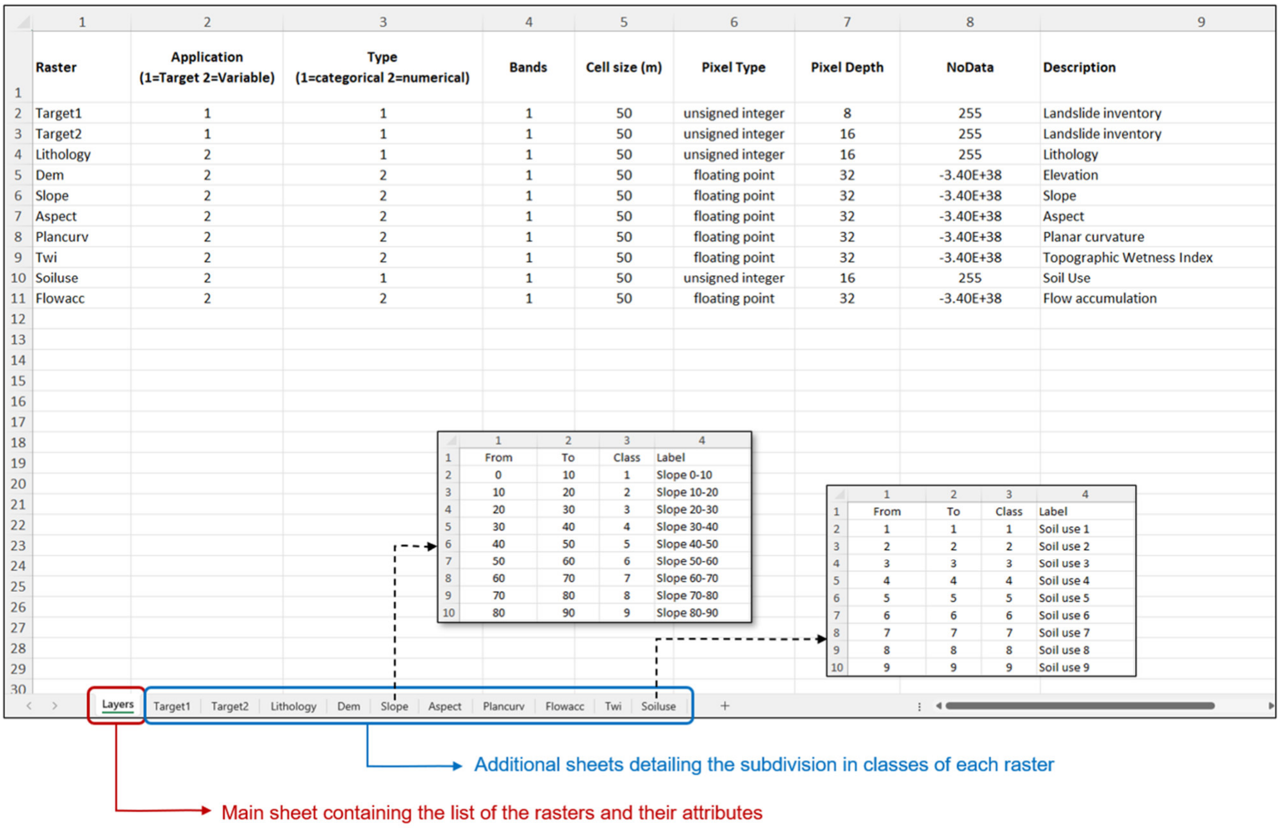


Figure 6.2. General structure of the Excel spreadsheet Analysis.xlsx. The small insets show the subdivision in classes for a continuous (slope) and categorical (soil use) raster variable.

Below is a table that describes the fields on the 'Layers' sheet:

Field	Explanation
Raster	Name of the raster layer (omit the .tiff extension)
Application	Purpose of the raster in the analysis: 1=Target, 2=Variable
Type	Data classification: 1=categorical, 2=continuous
Bands	Number of data bands of the raster (typically 1)
Pixel size (m)	Dimension of the pixel in meters
Pixel type	Data type of the pixel (e.g., unsigned integer, floating point)
Pixel depth (bits)	Number of bits used to represent pixel's data
NoData	Value assigned to pixels that are outside the study area or where data are invalid, missing, or not applicable
Description	Brief explanation of the raster, used as a label in plots

Only the Raster, Application, NoData, and Description fields (highlighted in orange) are mandatory for the analysis. However, providing complete information for each layer is advisable to ensure comprehensive documentation.

The NoData issue demands special attention. NoData values are typically used to differentiate between areas with valid data and areas where data should be ignored during processing and analysis. Different software and data formats may represent NoData values differently. Commonly, a specific number or flag is used to denote NoData. For example, in floating-point datasets, a specific unusual number such as -9999 or -3.4E+38 might be used. In most GIS software, users have the flexibility to define which value should be recognized as NoData during data import or processing. This designated NoData value must be reported in the Analysis.xlsx spreadsheet to ensure that Matlab accurately accounts for it during analysis.

The additional sheets in the Excel file detail the subdivision in classes of the raster layers. This subdivision is achieved by defining a range of values in the "From - To" fields, assigning a corresponding class index, and specifying the labels used for plotting (see the inset for slope in Figure 6.2.). A pixel is categorized into a specific class if its value is equal to or greater than the "From" value and less than the "To" value. For instance, in the table of Fig. 6.4 a value of 9.5° would be categorized into class 1, whereas a value of 10° would fall into class 2. For categorical variables, which are already predefined as classes, the same value should be entered in both the "From" and "To" fields (see the inset for soil use in Figure 6.2.).

The content of the Excel file is read every time the GUI is launched. Therefore, the application must be restarted to ensure any changes to the raster's classes or characteristics take effect.

2. Load the data

To load the data, launch the application, click the 'Data folder' button, and select the project folder. Raster layers marked as 1 in Analysis.xlsx ('Layers' sheet – 'Application' field) will be loaded into the Target combobox, while those marked as 2 will appear as individual checkboxes in the Variables pane.

To verify the accuracy of the raster layers, click the 'Plot Layers' button. The application will generate separate figures for each raster contained in the project folder. Each figure consists of two plots: the upper plot displays the map with the original raster values, and the lower plot shows the values re-classified according to the class indexes specified in Analysis.xlsx for that particular raster. An example of such a figure for the slope raster is shown in Figure 6.3.

Before initiating the analysis, configure the settings in the 'Target Option' pane. Enter the ID for unstable pixels in the 'Target ID' textbox; typically, '1' is used for unstable and '0' for stable pixels. If the Target raster differentiates types of instability, such as rockfalls and debris flows, identified by numbers like '1' and '2', specify the ID corresponding to the instability type you want to analyze for susceptibility. In the 'Buffer around target' textbox, define the buffer size if the target is represented by single pixels. This is the number of pixels to include around each unstable pixel to expand the area analyzed. Utilizing a buffer can incorporate more data into the analysis, potentially leading to more accurate susceptibility results.

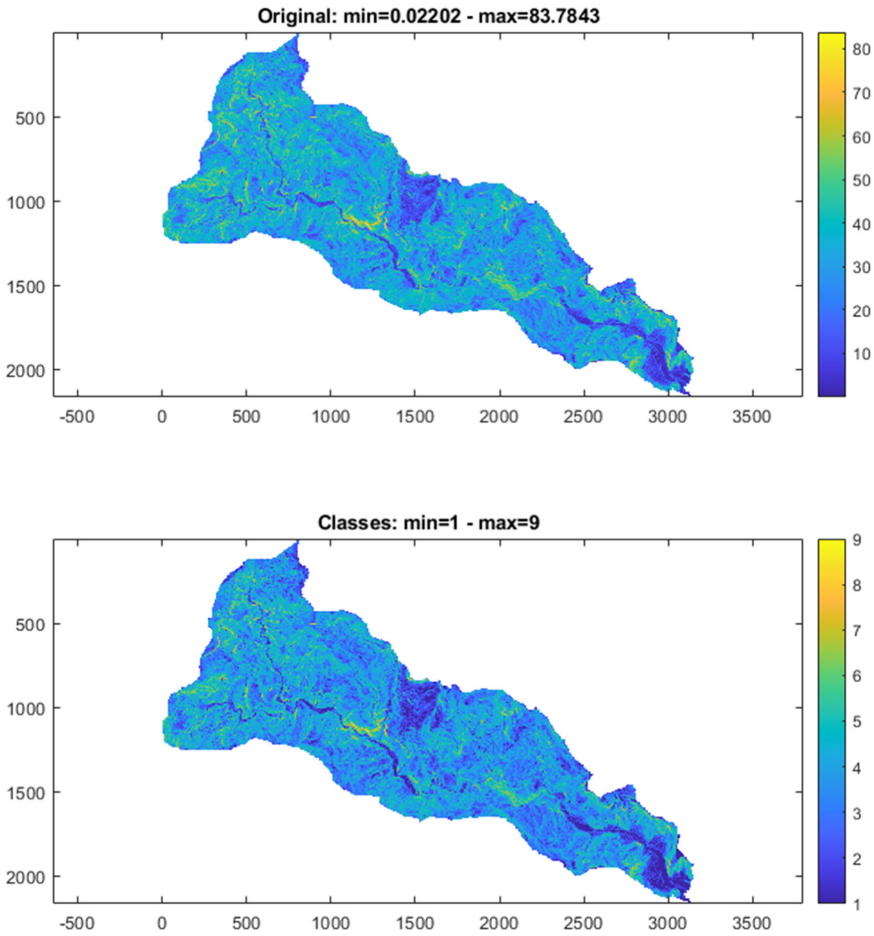


Figure 6.3. Illustration of a Slope Raster Plot Generated via the 'Plot Layer' Button. The upper plot displays the slope map in a range of colors that correspond to the actual slope values in degrees, ranging from 0° to 84°. The lower plot represents the same map with slope values categorized into 9 classes, as defined in the Analysis.xlsx file.

3. Run the analysis

The application supports four different susceptibility models, detailed in section 5.1. Three of these, Logistic Regression, Weight of Evidence, and Random Forest, are data-driven methods. The fourth, Flow-R, employs a simple geomorphic approach and does not require training data.

Each model requires specific parameters to be set before running the analysis.

For Logistic Regression and Weight of Evidence, the 'Training ratio' must be specified. This ratio determines the proportion of the Target dataset used to train the models. The default value is 0.7, indicating that 70% of the Target dataset is used for training, with the remaining 30% reserved for validation. The training dataset is generated through random sampling using the MATLAB function *cvpartition* with the 'Stratify' option set to 'True'. This ensures that the data is split in such a way that each partition accurately reflects the overall class distribution, which is especially valuable for managing unbalanced datasets.

The Random Forest needs to define both the 'Training ratio' and the 'Number of Trees'. The 'Number of Trees' refers to the total count of decision trees that make up the ensemble. Random Forest is an ensemble learning method used primarily for classification and regression tasks, and it operates by building multiple decision trees during the training phase. Increasing the number of trees can lead to better model performance up to a point, as it makes the predictions more stable and less susceptible to the noise in any single tree. However, more trees also mean higher computational cost in terms of both training time and memory usage.

Common starting points for the number of trees might be around 100 to 500, but this can vary significantly depending on the specific characteristics and complexity of the data. Proper tuning of this parameter is essential for developing an effective predictive model, and can be easily done by changing the value in the textbox.

The Flow-R model requires setting two parameters: the slope and flow accumulation rasters. These are the only variables utilized in the prediction algorithm, as detailed in section 5.1.4.

After setting the model parameters, the analysis can be initiated by clicking the corresponding 'Run' button.

4. View the results

The primary outcome of the analysis is the Target Susceptibility Map, which identifies areas susceptible to ground instability. This map appears in a popup window and is also saved in the project folder as a GeoTIFF file. The map displays values that vary based on the method used:

- Logistic Regression and Weight Of Evidence assign each pixel a value between 0 and 1, indicating the probability of instability in that pixel.
- Random Forest and Flow-R, on the other hand, use a binary classification system, marking pixels as stable (0) or unstable (1).

Figure 6.4 compares the results obtained using Weight Of Evidence and Random Forest methods for the Learning Example of the Briga basin in the Messina area (refer to DV2.2.4, section 5.3). Note that the Weight Of Evidence method yields a continuous probability scale from 0 to 1, whereas Random Forest outputs a binary result.

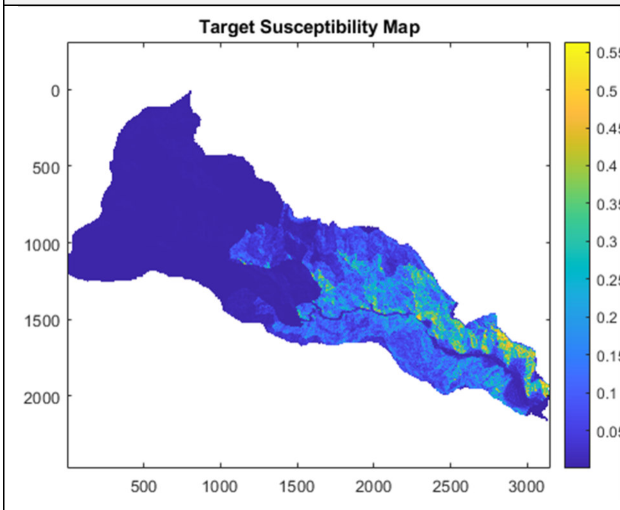
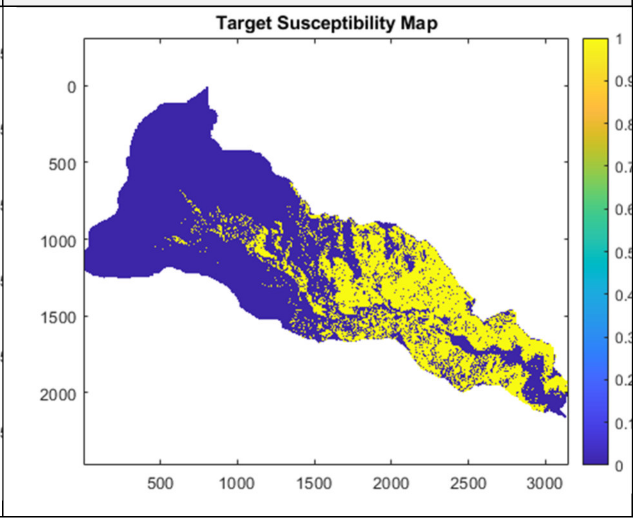
Weight of Evidence	Random Forest
	

Figure 6.4. Susceptibility map obtained for the Briga basin (Messina) by the Weight Of Evidence (left) and the Random Forest (right) methods.

In addition to the Target Susceptibility Map, the application provides a range of plots and performance metrics that assist the user in interpreting the results. The following describes these additional outputs:

- **Area Under the Curve**. The 'Statistics' pane within the GUI (Figure 6.5) offers a summary of various statistical indicators that reflect the model's effectiveness. The most important of these is the Area Under the Curve (AUC). The AUC is a measure of the area beneath the entire Receiver Operating Characteristic (ROC) curve, which plots the true positive rate against the false positive rate at different thresholds. This metric indicates how effectively the model can differentiate between classes, in this case, stable versus unstable pixels.

The AUC is calculated for three scenarios: the training dataset, the test dataset, and the combined area of both. The AUC for the training dataset assesses the model's ability to explain unstable pixels using the predictors, while the AUC for the test dataset provides a reliable indication of the model's predictive power. The combined area's AUC offers a comprehensive evaluation of the model's overall performance. Users are advised to experiment with varying 'Training Ratios' to observe how the model performs; AUC values above 0.7-0.8 for both training and test datasets, with a small proportion of training data, suggest that the model has identified a strong correlation between the variables and the target.

- **Max F1-score**. The F1-score is a statistical measure used to evaluate the accuracy of a binary classification model. It is the harmonic mean of precision and recall, providing a single metric that balances both the model's ability to correctly label positives (precision) and its ability to find all the positive samples (recall). The F1-score reaches its best value at 1 (perfect precision and recall) and its worst at 0. It is particularly useful when the classes are unevenly distributed, as it is affected by the abundance of true negatives.

  Unlike the AUC, which assesses a model's overall ability to distinguish between positive and negative classes across all possible thresholds, the F1-score offers a point estimate at a specific threshold for classifying observations. The values displayed in the 'Statistics' pane represent the highest F1-scores achieved for the training, test, and overall dataset across a broad spectrum of potential thresholds.

- **Susceptibility thresholds**. For methods such as Weight of Evidence and Logistic Regression, which yield a continuous scale of susceptibility values, it is beneficial to establish a probability threshold for categorizing pixels into binary states of stable or unstable. The values shown in the 'Statistics' pane represent the optimal thresholds determined using the ROC curve and the F1-score. In the case of the ROC curve, the optimal threshold is the point nearest to the (0,1) corner, which indicates perfect prediction. For the F1-score, the optimal threshold corresponds to the point where the F1-score is maximized.

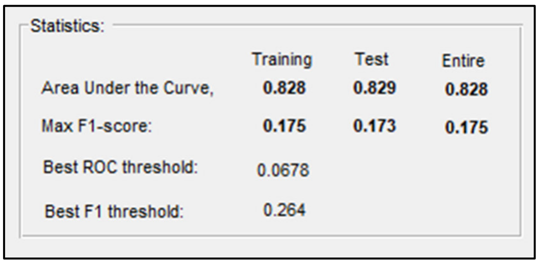


Figure 6.5. The 'Statistics' pane of the GUI provides a summary of the key performance metrics for the susceptibility model, including the Area Under the ROC Curve and the maximum F1-score, as well as the optimal thresholds for transforming continuous probability values into binary classifications of stable or unstable pixels. Numbers refer to the Briga basin (Messina).

- **ROC plots**. The application generates individual plots for the ROC curve along with the principal statistical parameters of the model for the training, test, and entire area dataset (refer to Figure 6.6 for an example). Each plot displays the ROC curve to the right, highlighting the points that correspond to the optimal threshold close to the (0,1) corner (Optimal Threshold Point) and to the highest F1-score (Optimal F1-score). Adjacent to the plot, a table presents the confusion matrix and the performance metrics, calculated from a binary classification of the outputs (0=stable, 1=unstable) based on the Optimal Threshold Point.

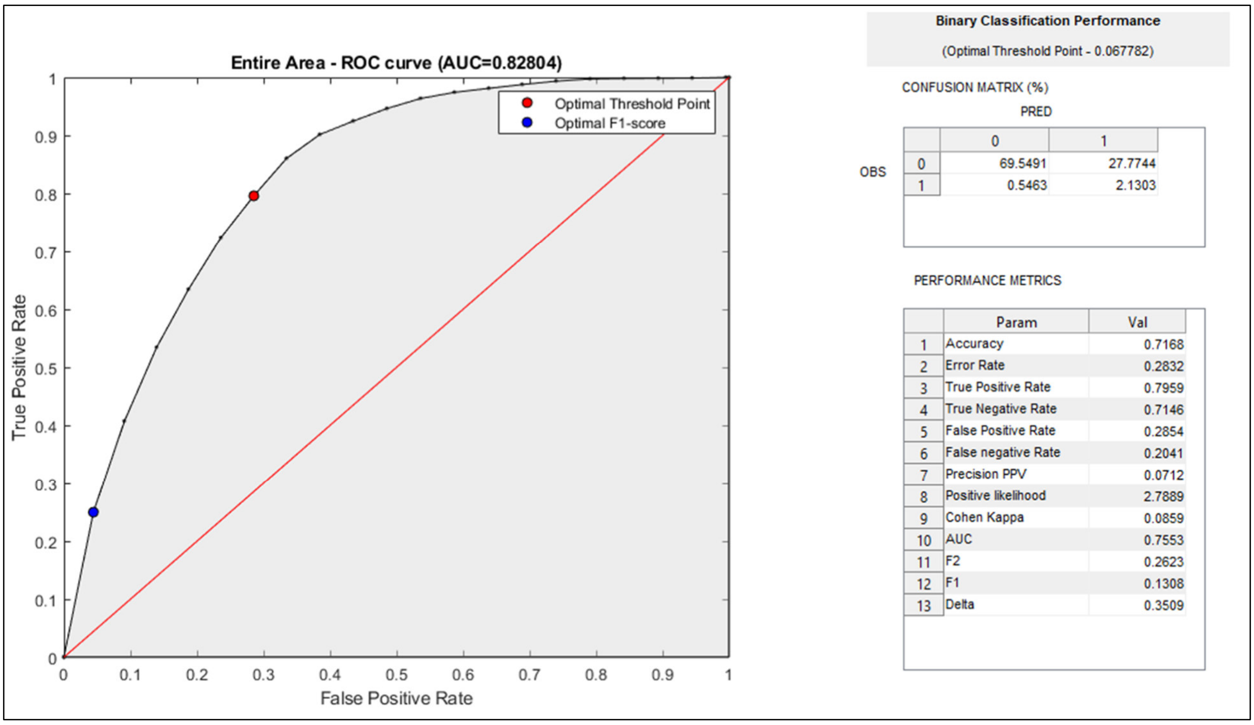


Figure 6.6. ROC plot, confusion matrix, and performance metrics generated by the application applying the Weight Of Evidence to the Briga basin (Messina).

- **Importance of variables**. The application utilizes various graphical outputs to assess the statistical relevance of each predisposing factor to the susceptibility index, aiding in identifying the factors that significantly influence the likelihood of instability.

  For Logistic Regression, the application employs Partial Dependence Plots (PDPs) and Coefficient Plot (CP). PDPs demonstrate the effect of a single predictor variable on the model's predicted outcome while holding other variables constant. For instance, in a landslide susceptibility model, PDPs can show how changes in factors like slope or aspect influence the likelihood of a landslide independently from other variables. CP displays the size and direction of each coefficient in Logistic Regression, where positive coefficients, which increase the log-odds of the event, signify factors that heighten susceptibility, and negative coefficients, which decrease the log-odds, indicate factors that reduce susceptibility. The magnitude of these coefficients indicates their impact strength.

  For the Weight of Evidence method, the importance of factors is depicted through the Contrast Index, calculated as the difference between the positive and negative weights of evidence (refer to Figure 6.7 for an example). These weights represent the logarithmic ratios of probabilities showing the presence or absence of a predictor in areas where the event occurs compared to the entire study area. A positive Contrast Index indicates a predictor that increases the likelihood of an event, while a negative index suggests a decrease. The magnitude of this index reflects the strength of the predictor's impact, offering insights into how significantly each factor contributes to the event's occurrence.

  For Random Forest models, the application uses the *OOBPermutedVarDeltaError* function to determine the importance of each predictor variable. This metric measures the increase in prediction error when the values of a specific predictor variable are shuffled among the out-of-bag (OOB) observations, with other variables remaining unchanged. It effectively quantifies the impact of disordering the data for each predictor on the model's accuracy.

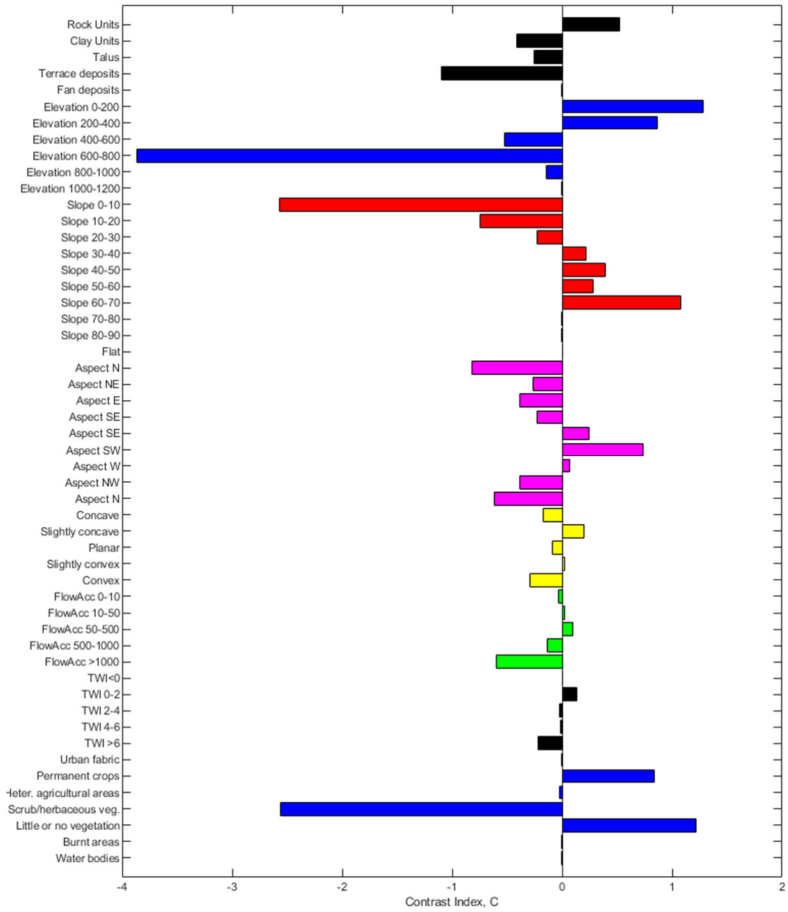


Figure 6.7. Bar Plot Displaying the Contrast Index from the Weight of Evidence Analysis for the Briga Basin (Messina).

The performance metrics and statistical parameters that highlight the relevance of the predisposing factors are also stored in an Excel spreadsheet named after the method used (e.g., WOE_res.xlsx). This file includes the weights or coefficients for each factor, as derived from the training dataset.

While the application offers a variety of plots and statistical parameters that facilitate the interpretation of results, it is crucial to emphasize the importance of the expert judgment in the process. The application's tools and outputs are designed to assist in the analysis, but the application of any susceptibility methods for ground instability ultimately depends on the discernment and expertise of professionals in the field. These methods should be viewed as aids, not replacements, for the nuanced evaluations that experienced geologists or scientists provide. Their insights are essential in accurately interpreting the data, understanding the local context, and making informed decisions regarding ground instability.

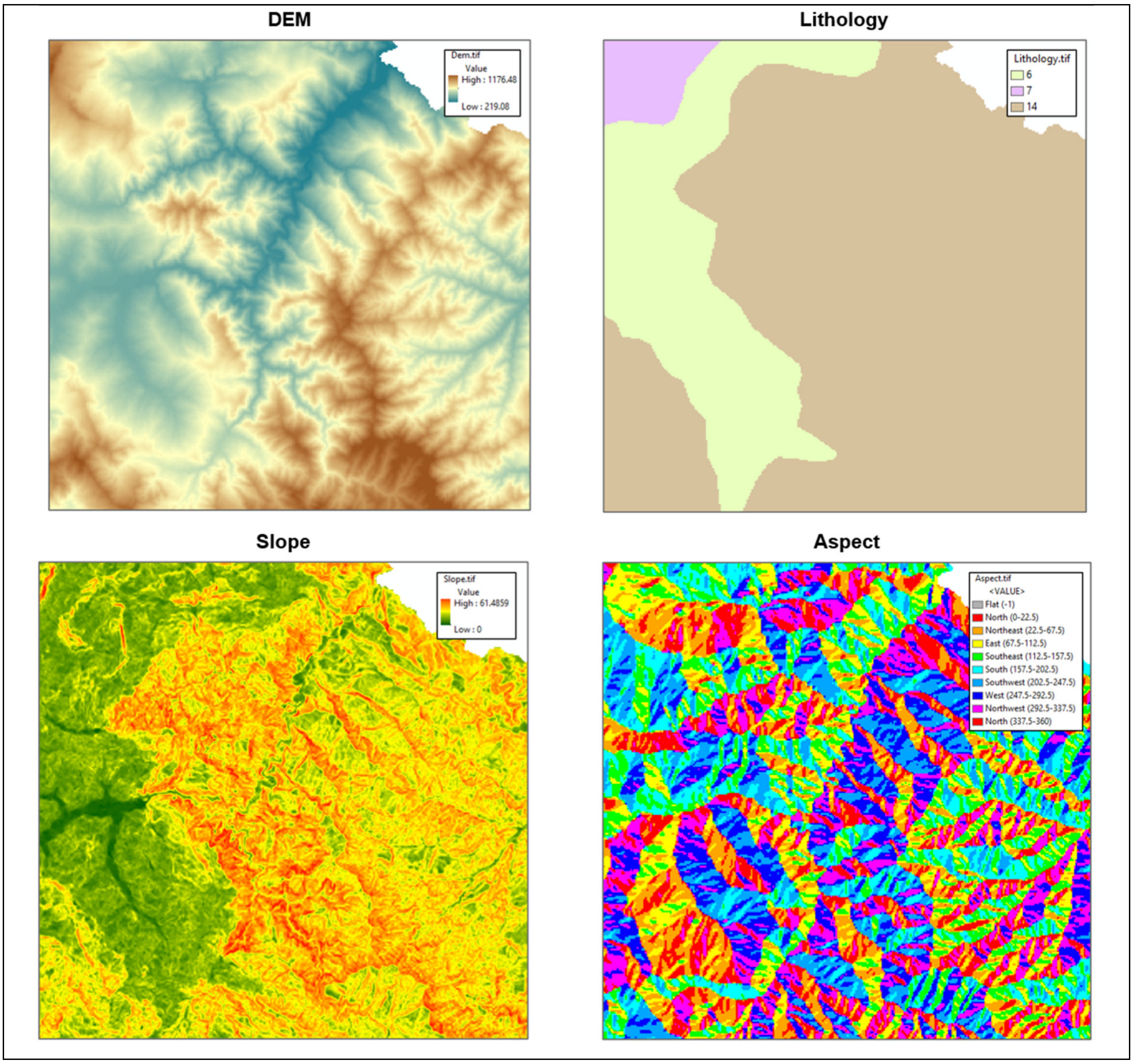
d. 6.4 Sample application

In this section we conduct a susceptibility analysis of ground instability within a sample area, providing a practical example to illustrate the operational steps previously outlined. The sample area is derived from a small section of the Arno river basin in Tuscany, covering approximately 15x15 kilometers.

1. Create the raster layers

Raster layers necessary for the analysis are generated using GIS software. The Digital Elevation Model (DEM) serves as the foundational layer, setting the standard for pixel size, cell centroids, and coordinate system for all subsequent rasters. In this example, the DEM has a pixel size of 50 meters and uses a WGS84 projected coordinate system.

Derived from the DEM are four raster layers: slope, aspect, planar curvature, and Topographic Wetness Index. Additionally, a lithology layer representing the bedrock is created by rasterizing the geological map, using the DEM as the reference raster. Ultimately, six rasters are produced, each depicting different predisposing factors relevant to the study area (Figure 6.8).



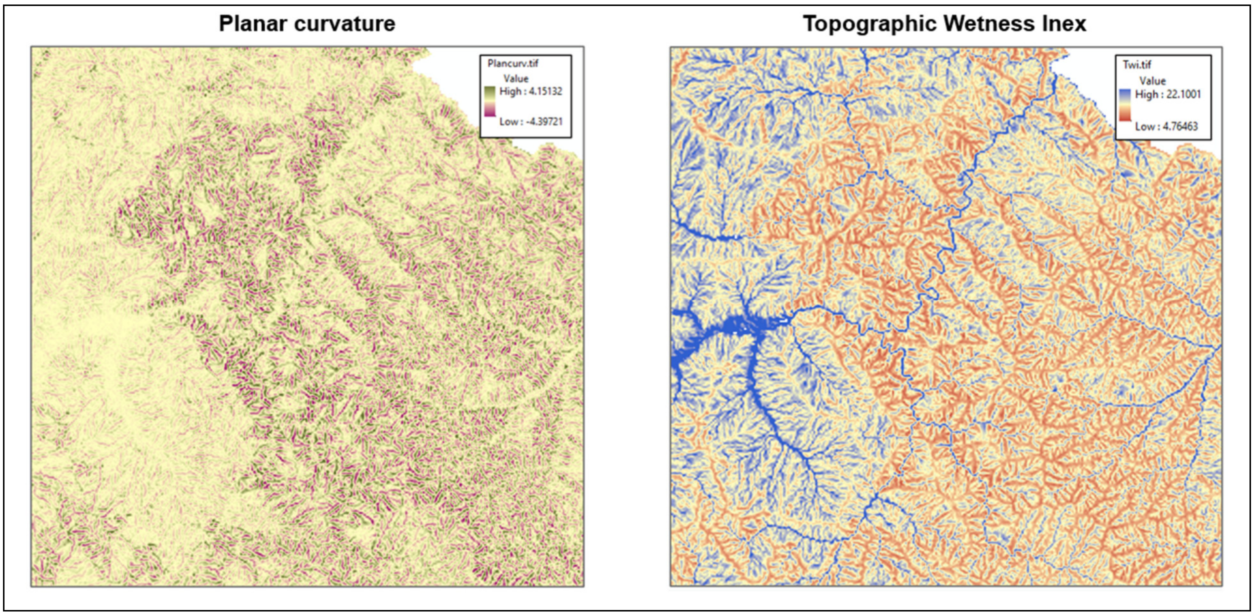


Figure 6.8. Raster layers of the predisposing factors for ground instability.

The Target layer should indicate the ground instability process considered in the analysis. For testing purposes, in this sample application the unstable pixels are artificially generated rather than obtained by a landslide inventory. Specifically, 1300 landslide locations were randomly selected among the 6656 pixels that satisfy the following conditions:

- slope angle between 30° and 40°;
- lithological unit 14;
- aspect SE, S, or SW.

Figure 6.9 shows the Target raster synthetically obtained using these criteria. This method allows us to predict the outcomes of the analysis, checking whether the susceptibility models accurately produce maps, identify key variables, and achieve expected performance metrics.

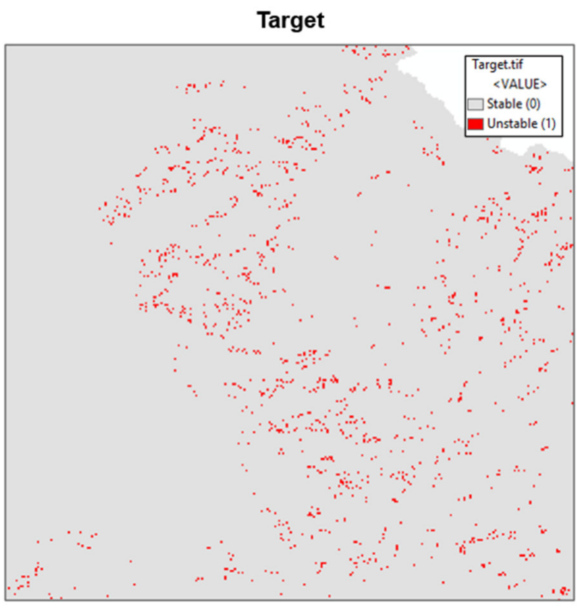


Figure 6.9. Synthetic raster of unstable pixels (Target layer).

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All raster files are stored as GeoTIFFs in the project folder named "Test_Area." This folder also includes the Excel file, "Analysis.xlsx." Within this file, the 'Layers' sheet catalogs the rasters along with their respective parameters. The additional sheets provide a classification breakdown for each raster (Figure 6.10).

Layers

Raster	Application	Type (1=categorical 2=numerical)	Bands	Cell size (m)	Pixel Type	Pixel Depth	NoData	Description
Target	1	1	1	50	floating point	16	255	Landslide inventory
Lithology	2	1	1	50	unsigned integer	16	255	Lithology
Dem	2	2	1	50	floating point	32	-3.40E+38	Elevation
Slope	2	2	1	50	floating point	32	-3.40E+38	Slope
Aspect	2	2	1	50	floating point	32	-3.40E+38	Aspect
Plancurv	2	2	1	50	floating point	32	-3.40E+38	Planar curvature
Twi	2	2	1	50	floating point	32	-3.40E+38	Topographic Wetness Index

Layers | Target | Lithology | Dem | Slope | Aspect | Plancurv | Twi

Target

From	To	Class	Label
0	0	0	Stable
1	1	1	Unstable

Lithology

From	To	Class	Label
6	6	1	Unit 6
7	7	2	Unit 7
14	14	3	Unit 14

DEM

From	To	Class	Label
-100	250	1	Elevation 0-250
250	500	2	Elevation 250-500
500	750	3	Elevation 500-750
750	1000	4	Elevation 750-1000
1000	1250	5	Elevation 1000-1250
1250	1500	6	Elevation 1250-1500
1500	1750	7	Elevation 1500-1750
1750	2000	8	Elevation 1750-2000
2000	2250	9	Elevation 2000-2250

Slope

From	To	Class	Label
0	10	1	Slope 0-10
10	20	2	Slope 10-20
20	30	3	Slope 20-30
30	40	4	Slope 30-40
40	50	5	Slope 40-50
50	60	6	Slope 50-60
60	70	7	Slope 60-70
70	80	8	Slope 70-80
80	90	9	Slope 80-90

Aspect

From	To	Class	Label
-1	0	1	Flat
0	22.5	2	Aspect N
22.5	67.5	3	Aspect NE
67.5	112.5	4	Aspect E
112.5	157.5	5	Aspect SE
157.5	202.5	6	Aspect S
202.5	247.5	7	Aspect SW
247.5	292.5	8	Aspect W
292.5	337.5	9	Aspect NW
337.5	360	10	Aspect N

Planar curvature

From	To	Class	Label
-200	-0.4	1	Concave
-0.4	0.4	2	Planar
0.4	200	3	Convex

Topographic Wetness Index

From	To	Class	Label
0	6	1	TWI<6
6	7	2	TWI 6-7
7	8	3	TWI 7-8
8	10	4	TWI 8-10
10	30	5	TWI >10

Figure 6.10. Contents of Analysis.xlsx for the sample application.

2. Load the data

To load the data into the GUI, click the 'Data folder' button. The application will automatically categorize the Target and Variable layers based on the values (1 or 2) specified in Analysis.xlsx. Figure 6.11 displays the GUI after the data loading is complete.

By default, all variable raster layers are selected and included in the analysis. If the project folder contains more than one Target layer, the specific Target layer for analysis must be chosen from the 'Target layer' dropdown menu.

In this sample application, the unstable pixels in the Target layer are designated as 1, making the default value in the 'Target ID' textbox suitable. This value may need adjustment if the Target layer includes various types of ground instability encoded with different values. Setting the 'Buffer around target' textbox to zero indicates that the analysis will strictly use the individual unstable pixels to train and validate the model, without incorporating a surrounding buffer.

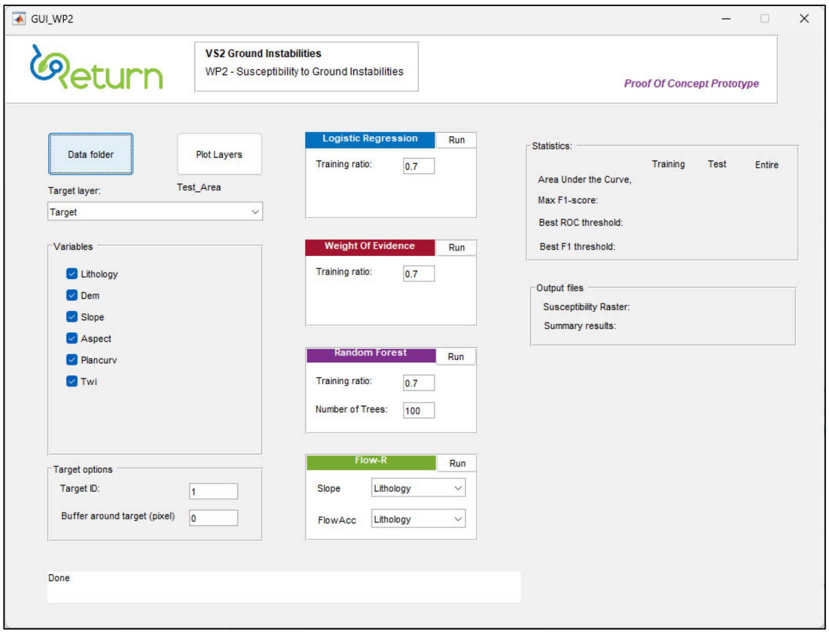
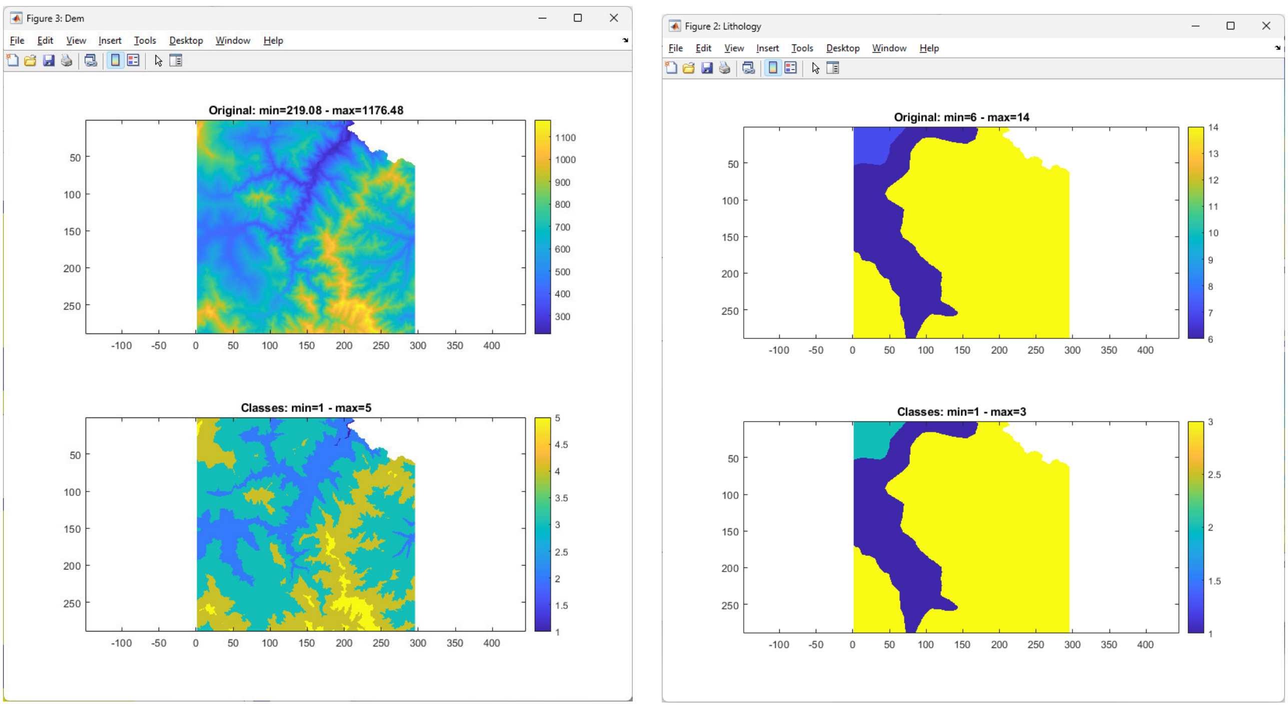


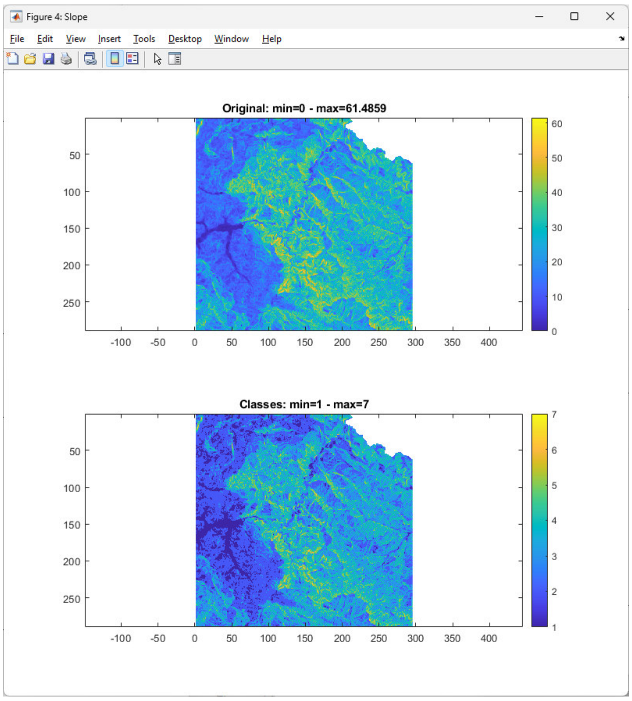
Figure 6.11. Application GUI after data layers are loaded.

Before initiating the analysis, it is advisable to visualize the data layers by clicking the 'Plot Layers' button. The resulting popup figures will display the rasters showing both original and classified values. These visuals are helpful for detecting any errors and ensuring that the data has been loaded correctly (Figure 6.12).

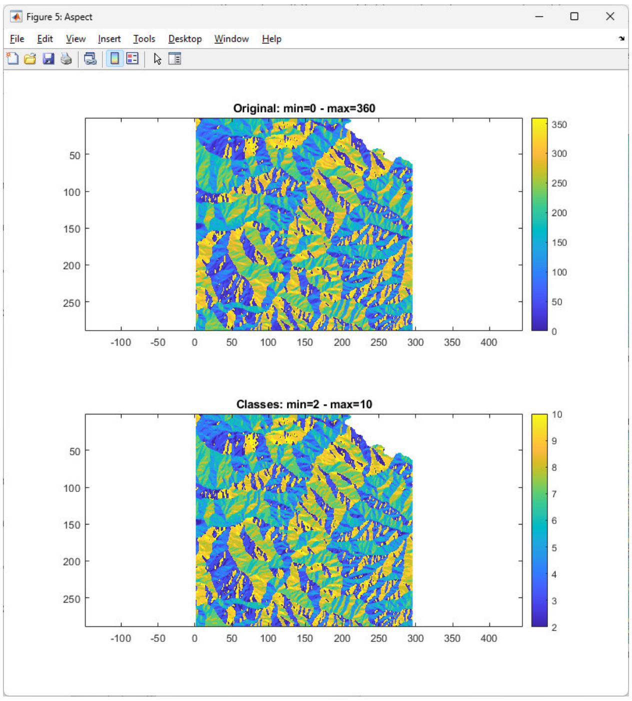
DEM Lithology



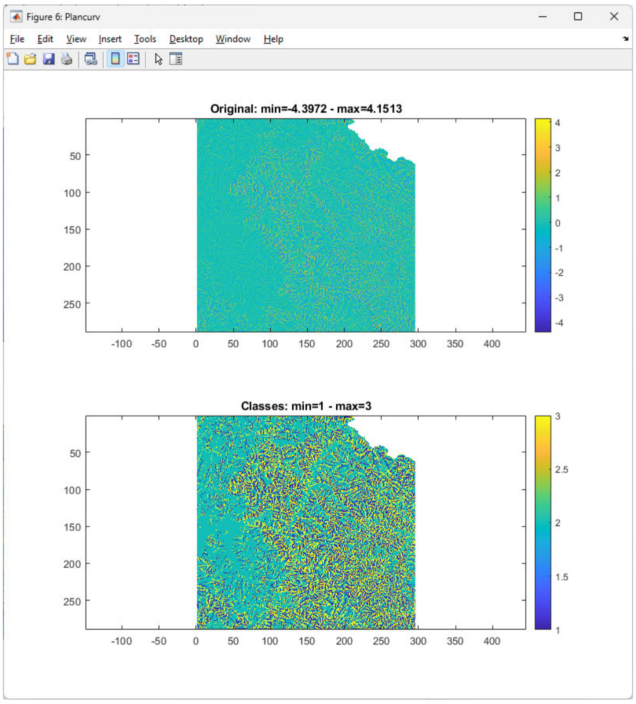
Slope



Aspect



Planar curvature



Topographic Wetness Index

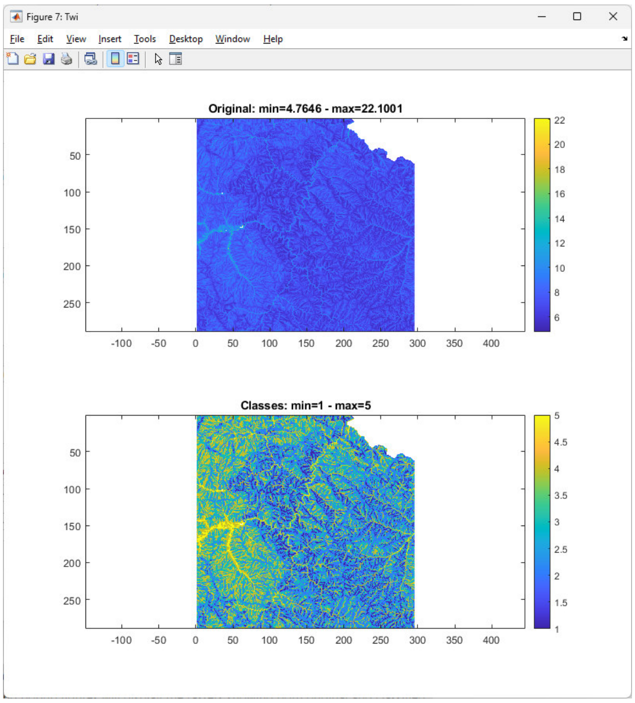


Figure 6.12. Plots of data layers generated by the GUI. Original raster values are displayed at the top and classified values at the bottom.

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3. Run the analysis

To begin the analysis, click the 'Run' button corresponding to the selected method. The application supports three data-driven methods: Logistic Regression, Weight Of Evidence, and Random Forest, all of which can be applied without restrictions. These methods are suitable for any ground instability type or predisposing factors as long as a Target layer is present. If a Target layer is absent, the Flow-R method is available; however, it should be reserved for debris flows and is not appropriate for other types of ground instability.

In our example, we will proceed with the Weight Of Evidence (WOE) and Random Forest (RF) models. For the WOE model, the only required setting is the 'Training ratio', which is the proportion of target pixels used for training the model. For the RF model, we must also specify the number of trees. We will use the default settings provided by the GUI, which are a Training ratio of 0.7 and 100 trees.

All methods will utilize the raster layer chosen via the checkboxes in the 'Variables' pane. To exclude layers from the analysis, simply uncheck them.

4. View the results

Figure 6.13 shows a comparison of the susceptibility maps generated using the Weight Of Evidence and Random Forest methods. As previously mentioned, the Weight Of Evidence method yields probability values ranging from 0 to 1, which represent the likelihood of a landslide based on the aggregated evidence from all variables. In contrast, the Random Forest method operates as a binary classification system, assigning a value of 0 for stable areas and 1 for regions prone to landslides.

The two methods are in good agreement, with the most susceptible areas occurring where the three key predisposing factors used to generate the target points (slope, lithology, and aspect) have values deemed as critical (compare Figure 6.13 with 6.8). To create a binary susceptibility map using the Weight of Evidence (WOE) method, the Optimal Threshold indicated in the 'Statistics' pane for the entire area (0.28 in this case) can be applied. Values below this threshold are classified as 0 (stable), and values above it are classified as 1 (unstable)

Statistics:

	Training	Test	Entire
Area Under the Curve,	0.931	0.926	0.929
Max F1-score:	0.285	0.267	0.28
Best ROC threshold:	0.326		
Best F1 threshold:	0.539		

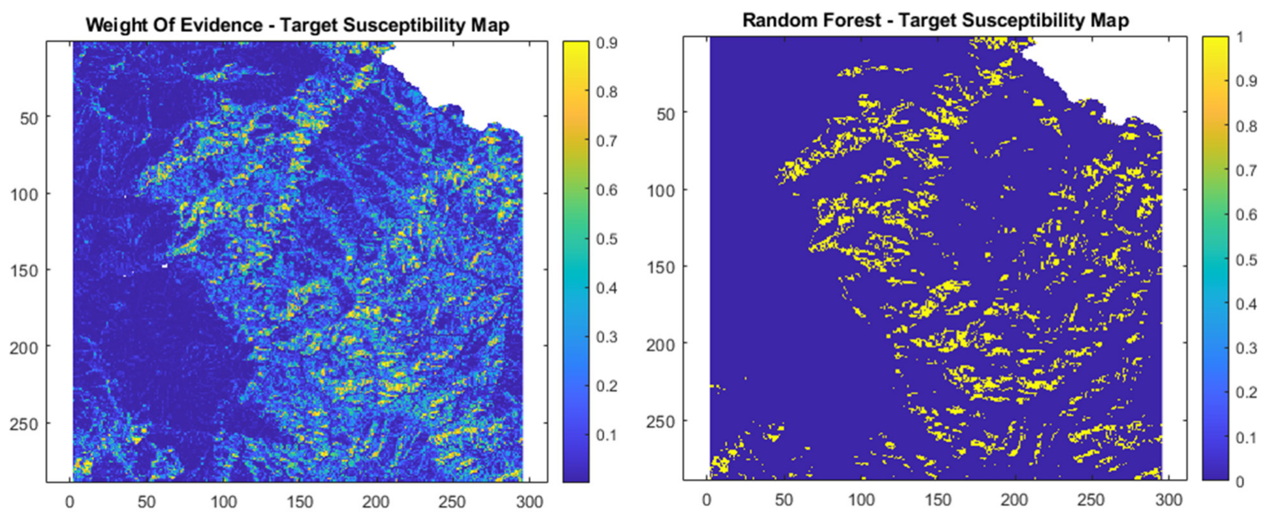
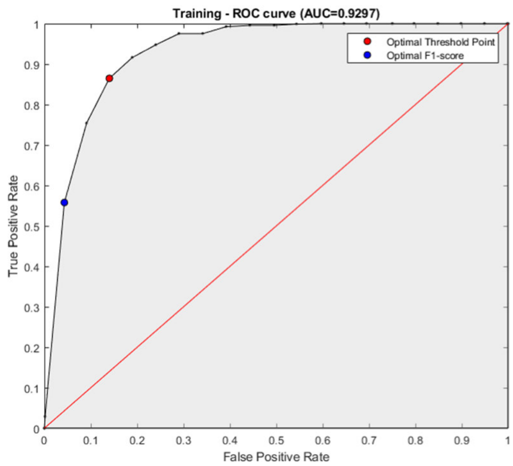


Figure 6.13. Comparison of susceptibility maps using Weight Of Evidence (left) and Random Forest (right) methods, based on the six Predisposing Factors (Figure 6.8) and artificially generated target points (Figure 6.9).

As expected, the two susceptibility models demonstrate a strong ability to identify unstable areas. For instance, the ROC curves for the Weight of Evidence method are close to the upper-left corner for the training, test, and entire area datasets (see Figure 6.14). The Area Under the Curve (AUC) values are consistently high at 0.93 for all these cases.



Binary Classification Performance

(Optimal Threshold Point - 0.31283)

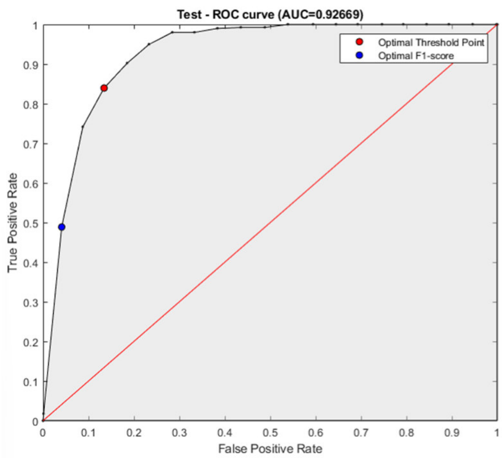
CONFUSION MATRIX (%)

PRED

OBS	0	1
0	84.5864	13.7744
1	0.2216	1.4175

PERFORMANCE METRICS

	Param	Val
1	Accuracy	0.8600
2	Error Rate	0.1400
3	True Positive Rate	0.8648
4	True Negative Rate	0.8600
5	False Positive Rate	0.1400
6	False negative Rate	0.1352
7	Precision PPV	0.0933
8	Positive likelihood	6.1754
9	Cohen Kappa	0.1431
10	AUC	0.8624
11	F2	0.3259
12	F1	0.1684
13	Delta	0.1946



Binary Classification Performance

(Optimal Threshold Point - 0.31283)

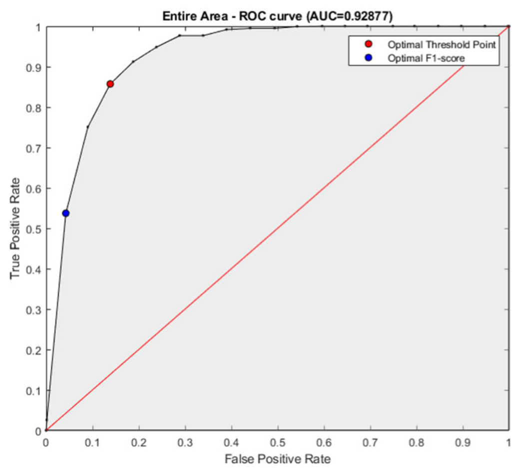
CONFUSION MATRIX (%)

PRED

OBS	0	1
0	85.1520	13.2105
1	0.2627	1.3748

PERFORMANCE METRICS

	Param	Val
1	Accuracy	0.8653
2	Error Rate	0.1347
3	True Positive Rate	0.8396
4	True Negative Rate	0.8657
5	False Positive Rate	0.1343
6	False negative Rate	0.1604
7	Precision PPV	0.0943
8	Positive likelihood	6.2515
9	Cohen Kappa	0.1443
10	AUC	0.8526
11	F2	0.3252
12	F1	0.1695
13	Delta	0.2092



Binary Classification Performance

(Optimal Threshold Point - 0.31283)

CONFUSION MATRIX (%)

PRED

OBS	0	1
0	84.7561	13.6052
1	0.2339	1.4047

PERFORMANCE METRICS

	Param	Val
1	Accuracy	0.8616
2	Error Rate	0.1384
3	True Positive Rate	0.8573
4	True Negative Rate	0.8617
5	False Positive Rate	0.1383
6	False negative Rate	0.1427
7	Precision PPV	0.0936
8	Positive likelihood	6.1976
9	Cohen Kappa	0.1434
10	AUC	0.8595
11	F2	0.3257
12	F1	0.1687
13	Delta	0.1988

Figure 6.14. ROC curves and performance metrics obtained by the WOE methods for the training (top), test (middle), and entire are (bottom) dataset.

The plot of the Contrast Index, which highlights the relative importance of variables in determining susceptibility, aligns with expectations (see Figure 6.15). The three predisposing factors most strongly correlated with ground instability are lithology Unit 14, slope class 30°-40°, and aspect SE-S-SW. These are the same factors used to randomly generate the target points.

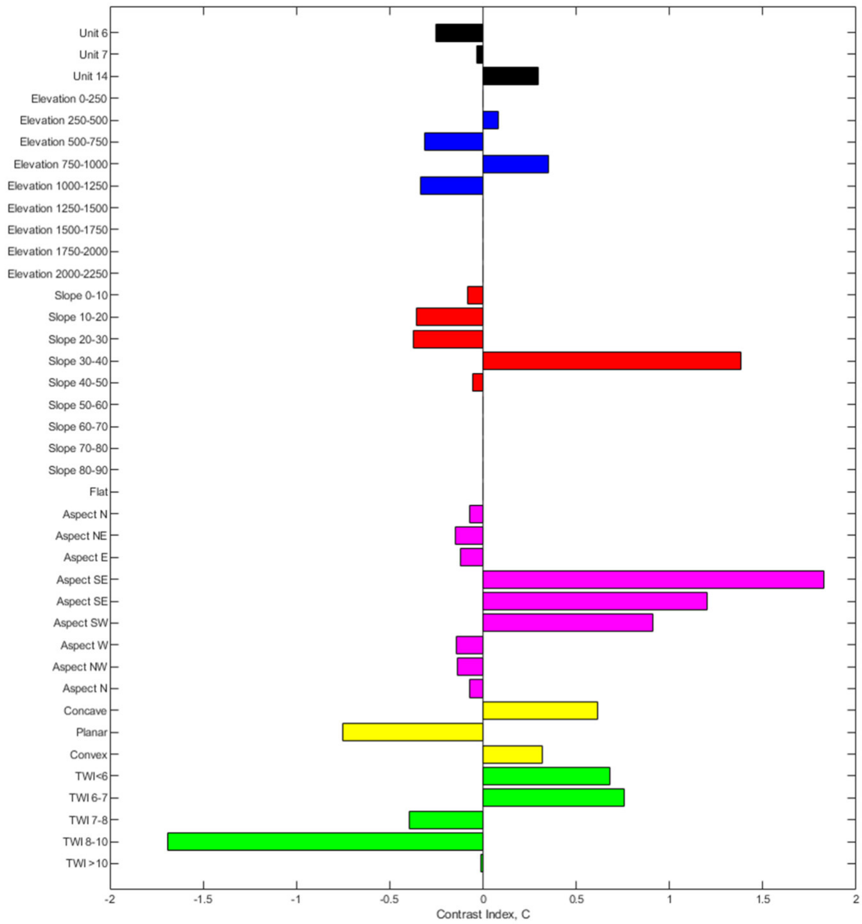


Figure 6.15. Plot displaying the relative importance of predisposing factors based on the Contrast Index calculated using the WOE method.

Based on these results, one could decide to run a susceptibility analysis using only these three more relevant predisposing factors. To do this, simply uncheck the unwanted layers in the 'Variables' pane of the GUI and run the analysis again. The results of this analysis are summarized in Figure 6.17. It can be seen that the WOE is even better, reaching an AUC score of 0.96 and a ROC curve close to the perfect prediction.

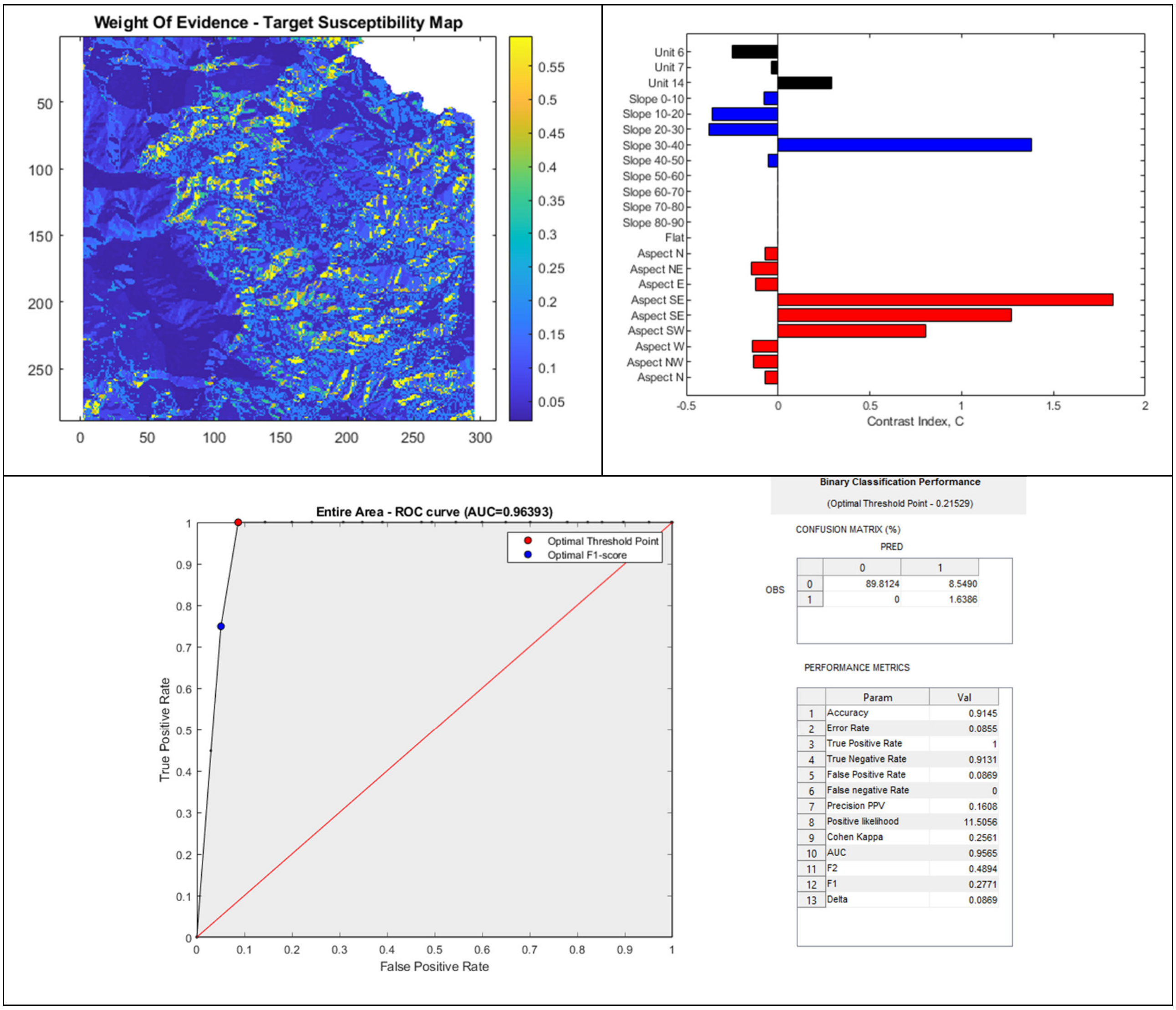


Figure 6.17. Results of the susceptibility analysis performed using only the three predisposing factors used to generate the target points.

The GUI is designed to facilitate the analysis under various conditions easily, allowing for the examination of how predisposing factors, analysis parameters, and different methods impact the results. This sensitivity analysis offers an initial understanding of the uncertainties involved in the predictions and serves as a foundation for more sophisticated methods to be developed in subsequent tasks.

7. Special cases

The GUI detailed in this document is tailored to evaluate susceptibility to ground instability at a basin scale, which is the predominant focus of analysis in the field, especially concerning slope stability issues. It operates by analyzing collinear raster layers to generate a susceptibility map as its primary output.

However, there are scenarios where susceptibility analysis targets potential instabilities along linear features such as roads, railway lines, or other linear infrastructures. There are also situations where the instability process is influenced by factors not easily represented by raster layers. An example of this is soil liquefaction, which depends on soil parameters (notably grain size distribution and void ratio), that vary with depth and are only known at specific vertical points. In these instances, the current GUI setup is not directly applicable, although the methods it uses remain relevant.

This chapter outlines the approaches to susceptibility analysis for two specific cases: instability along linear infrastructures and soil liquefaction. These scenarios require specialized analysis and are not yet incorporated into the GUI but could be integrated in future updates.

7.1 Susceptibility along linear infrastructures

7.1.1. Case study: Elva Valley

The case study focuses on the Elva Valley road, a 9 km long provincial road characterized by steep rock walls and tunnels. It is situated in the Maira Valley, Piedmont, and serves as a connector between the village of Elva and the main Maira Valley road.

The particular section under study extends about 4.5 km and has experienced notable instability since the 1970s. This instability includes frequent occurrences of individual rock blocks falling, with volumes ranging from a few cubic centimeters to approximately 1 cubic meter, affecting the entire road. Additionally, more intense localized instability events have also been documented, involving larger volumes of rock (from a few cubic meters up to 2500 cubic meters), which have disrupted traffic. The types of instability observed in the rock mass include planar and three-dimensional sliding, rockfalls, and toppling, as documented by Migliazza et al. (2021).

1.1.1. Data and methods

When assessing susceptibility along a linear feature like a road, the approach differs from areal analysis using raster data, as described in section 6.3. For linear features, susceptibility is calculated along different segments of the infrastructure, with all relevant factors tailored to these specific segments.

In this case study on the Elva Valley road, the evaluation of rockfall susceptibility involved dividing the road into "homogeneous" sectors. We identified a total of 88 sectors, each ranging in length from 0.02 to 0.17 km (refer to Figure 7.1). These sectors were established based on consistent morphological, geological, and geo-structural conditions.

km	Sector Legth (km)	km	Sector Legth (km)
km 0 + 100	0,1	km 2 + 240	0,05
km 0 + 160	0,05	km 2 + 290	0,05
km 0 + 180	0,04	km 2 + 340	0,05
km 0 + 260	0,08	km 2 +400	0,05
km 0 + 310	0,05	km 2 + 470	0,05
km 0 + 360	0,04	km 2 + 520	0,05
km 0 + 400	0,05	km 2 + 650	0,06
km 0 + 450	0,03	km 2 + 680	0,05
km 0 + 510	0,05	km 2 + 720	0,02
km 0 + 550	0,02	km 2 + 760	0,05
km 0 + 570	0,02	km 2 + 810	0,04
km 0 + 600	0,03	km 2 + 860	0,05
km 0 + 650	0,05	km 2 + 910	0,05
km 0 + 700	0,04	km 2 + 930	0,04
km 0 + 870	0,05	km 3 + 010	0,05
km 0 + 950	0,04	km 3 + 070	0,04
km 1	0,09	km 3 + 120	0,05
km 1 + 80	0,06	km 3 + 170	0,05
km 1 + 130	0,03	km 3 + 250	0,06
km 1 + 180	0,08	km 3 + 280	0,05
km 1 + 200	0,02	km 3 + 330	0,04
km 1 + 250	0,05	km 3 + 360	0,03
km 1 + 280	0,08	km 3 + 460	0,07
km 1 + 300	0,05	km 3 + 490	0,05
km 1 + 350	0,04	km 3 + 520	0,05
km 1 + 400	0,04	km 3 + 550	0,04
km 1 + 450	0,05	km 3 + 600	0,05
km 1 + 490	0,04	km 3 + 640	0,04
km 1 + 520	0,05	km 3 + 690	0,05
km 1 + 560	0,07	km 3 + 770	0,07
km 1 + 600	0,16	km 3 + 820	0,16
km 1 + 650	0,04	km 3 + 870	0,04
km 1 + 700	0,05	km 4 + 030	0,05
km 1 + 750	0,05	km 4 + 070	0,05
km 1 + 800	0,03	km 4 + 120	0,03
km 1 + 850	0,06	km 4 + 160	0,06
km 1 + 900	0,02	km 4 + 250	0,02
km 1 +930	0,03	km 4 + 290	0,03
km 1+960	0,05	km 4 + 330	0,05
km 2	0,08	km 4 + 370	0,08
km 2 + 030	0,05	km 4 + 410	0,05
km 2 + 070	0,05	km 4 + 450	0,05
km 2 + 120	0,08	km 4 + 500	0,08
km 2 + 170	0,03	km 4 + 550	0,03

Figure 7.1. Illustration of the Elva Valley road divided into homogeneous sectors. The table shows the sectors with their distance from the starting point of the road and the length of each sector.

The method chosen for conducting the susceptibility analysis is the Weight of Evidence (section 5.1.2). For the susceptibility analysis along a linear infrastructure, the use of this statistical method also requires defining variables to be used as predisposing factors and a dataset to be used for training.

In our case, 12 variables were identified to be used as predisposing factors: Slope height, Slope angle, Degree of overhang, Vegetation, Structural condition, Rock character, Geology, Abundance of many blocks, Abundance of free blocks, Abundance of plane failure, Number of sets, and Faults. For each of the 88 sectors of Elva Valley road, the 10 variables were defined as summarized in Figure 7.2.

km		Sector Legth	Slope height [m]	Slope angle [°]	Degree of overhang [m]	Vegetation	Structural condition	Rock character	Geology [sedimentary]	Abundance [%] (many blocks)	Abundance [%] (free blocks)	Abundance [%] (plane. F.)	Number of sets	Faults
km 0 + 100	0,1	0,1	25	80	1,2	Shrubs, small trees	iscontinuous joints, favorable orientatio	Homogenous/massive	Raveling, occasional small blocks	35	0	10	4	No
km 0 + 160	0,16	0,05	25	80	1,2	Sparse trees, shrubs	Discontinuous joints, adverse orientation	Small x 1	Raveling, occasional small blocks	35	0	5	4	Small x 1
km 0 + 180	0,18	0,04	25	60	0,3	Dense forest	iscontinuous joints, favorable orientatio	Homogenous/massive	Raveling, occasional small blocks	5	0	0	3	No
km 0 + 260	0,26	0,08	30	90	1,2	Shrubs, small trees	Discontinuous joints, adverse orientation	Homogenous/massive	Overhangs, some large unstable blocks	40	0	60	3	No
km 0 + 310	0,31	0,05	30	90	1,2	Shrubs, small trees	Discontinuous joints, adverse orientation	Homogenous/massive	Overhangs, some large unstable blocks	50	0	30	3	No
km 0 + 360	0,36	0,04	15	80	1,2	Sparse trees, shrubs	iscontinuous joints, favorable orientatio	Homogenous/massive	Raveling, occasional small blocks	0	0	0	3	No
km 0 + 400	0,4	0,05	30	80	1,2	Shrubs, small trees	iscontinuous joints, favorable orientatio	Homogenous/massive	Overhangs, some large unstable blocks	60	0	0	4	No
km 0 + 450	0,45	0,03	32	90	1,2	Sparse trees, shrubs	Discontinuous joints, adverse orientation	Homogenous/massive	Overhangs, some large unstable blocks	40	20	0	3	No
km 0 + 510	0,51	0,05	25	90	1,2	Sparse trees, shrubs	Discontinuous joints, adverse orientation	Small x 1	Overhangs, some large unstable blocks	0	50	50	4	Small x 1
km 0 + 550	0,55	0,02	32	90	1,2	Grass, bare land	Discontinuous joints, adverse orientation	2	Overhangs, some large unstable blocks	50	30	0	3	2
km 0 + 570	0,57	0,02	20	90	1,2	Sparse trees, shrubs	Discontinuous joints, adverse orientation	Homogenous/massive	Overhangs, some large unstable blocks	60	0	0	3	No
km 0 + 600	0,6	0,03	20	85	1,2	Shrubs, small trees	iscontinuous joints, favorable orientatio	Homogenous/massive	Raveling, occasional small blocks	0	0	60	3	No
km 0 + 650	0,65	0,05	32	90	1,2	Sparse trees, shrubs	Discontinuous joints, adverse orientation	Homogenous/massive	Overhangs, some large unstable blocks	70	0	0	3	No
km 0 + 700	0,7	0,04	20	80	1,2	Sparse trees, shrubs	iscontinuous joints, favorable orientatio	Homogenous/massive	Raveling, occasional small blocks	0	0	20	3	No
km 0 + 870	0,87	0,05	30	90	1,2	Grass, bare land	Discontinuous joints, adverse orientation	Homogenous/massive	Overhangs, some large unstable blocks	80	20	0	3	No
km 0 + 950	0,95	0,04	15	70	1,2	Dense forest	iscontinuous joints, favorable orientatio	Homogenous/massive	Raveling, occasional small blocks	0	20	0	3	No
km 1	1	0,09	15	70	1,2	Sparse trees, shrubs	iscontinuous joints, favorable orientatio	Homogenous/massive	Raveling, occasional small blocks	80	0	0	3	No
km 1 + 80	1,08	0,06	20	80	1,2	Sparse trees, shrubs	iscontinuous joints, favorable orientatio	Homogenous/massive	Raveling, occasional small blocks	60	0	10	3	No
km 1 + 130	1,13	0,03	20	80	1,2	Shrubs, small trees	iscontinuous joints, favorable orientatio	Homogenous/massive	Raveling, occasional small blocks	60	0	20	3	No
km 1 + 180	1,18	0,08	25	85	1,2	Shrubs, small trees	iscontinuous joints, favorable orientatio	Small x 1	Raveling, occasional small blocks	60	0	20	3	Small x 1
km 1 + 200	1,2	0,02	30	90	1,2	Shrubs, small trees	iscontinuous joints, favorable orientatio	Homogenous/massive	Raveling, occasional small blocks	40	0	70	3	No
km 1 + 250	1,25	0,05	20	90	1,2	Shrubs, small trees	iscontinuous joints, favorable orientatio	Homogenous/massive	Raveling, occasional small blocks	60	0	20	3	No
km 1 + 280	1,28	0,08	20	90	1	Shrubs, small trees	iscontinuous joints, favorable orientatio	Homogenous/massive	Raveling, occasional small blocks	40	0	70	3	No
km 1 + 300	1,3	0,05	15	85	1	Shrubs, small trees	iscontinuous joints, favorable orientatio	Homogenous/massive	Raveling, occasional small blocks	40	0	80	3	No
km 1 + 350	1,35	0,04	20	85	1,2	Shrubs, small trees	Discontinuous joints, adverse orientation	Homogenous/massive	mall overhangs, numerous small blocks	30	0	80	3	No
km 1 + 400	1,4	0,04	25	85	1,2	Shrubs, small trees	Discontinuous joints, adverse orientation	Homogenous/massive	Overhangs, some large unstable blocks	30	0	80	3	No
km 1 + 450	1,45	0,05	25	90	1,2	Shrubs, small trees	Discontinuous joints, adverse orientation	Homogenous/massive	Overhangs, some large unstable blocks	40	0	60	3	No
km 1 + 490	1,49	0,04	15	70	1	Sparse trees, shrubs	Discontinuous joints, adverse orientation	Homogenous/massive	Raveling, occasional small blocks	15	0	45	3	No
km 1 + 520	1,52	0,05	15	70	1	Sparse trees, shrubs	Discontinuous joints, adverse orientation	Homogenous/massive	Raveling, occasional small blocks	15	0	60	3	No
km 1 + 560	1,56	0,07	15	70	1	Sparse trees, shrubs	Discontinuous joints, adverse orientation	Homogenous/massive	Raveling, occasional small blocks	40	0	40	3	No
km 1 + 600	1,6	0,16	15	70	1,2	Sparse trees, shrubs	Discontinuous joints, adverse orientation	Small x 1	Raveling, occasional small blocks	30	0	40	3	Small x 1

Figure 7.2. Extract from the dataset used for the susceptibility analysis. For each sector of the Vallone dell'Elva road, 12 predisposing factors were defined.

The 12 variables were then divided into classes as reported in Table. 7.1.

Predisposing factors	Classes	Predisposing factors	Classes
Slope height [m]	6-10	Geology [sedimentary]	Raveling, occasional small blocks
	10-15		Small overhangs, numerous small blocks
	15-20		Overhangs, some large unstable blocks
	20-30	Abundance [%] (many blocks)	0-5
	>30		6-15
Slope angle [°]	50-60		30
	60-70		31-60
	70-80		61-90
	80-90	Abundance [%] (free blocks)	0-20
Degree of overhang [m]	0,3-1		20-30
	1-1,2		30-40
	>1,2		> 40
Vegetation	Dense forest	Abundance [%] (plane. failure)	0-5
	Grass, bare land		5-15
	Shrubs, small trees		15-30
	Sparse trees, shrubs		30-60
Structural condition	Discontinuous joints, adverse orientation		>60
	Discontinuous joints, favorable orientation	Number of sets	3
Rock character	Homogenous/massive		4
	2		5
	3	Faults	NO
	Small x 1		2-3

Table 7.1. Classification of Predisposing Factors

The Weight of Evidence method was applied using a script developed in the R programming environment, following the mathematical procedure outlined in section 5.1.2. The primary distinction is that calculations are performed for road sectors instead of pixels. Similarly, a training dataset is required to train the model.

For this purpose, sectors of the road where rockfalls have been documented were used, and these were designated with a flag of 1.

7.1.3. Results

The results obtained by the WOE method show a probability value of collapse occurrence for each road sector, with a minimum value of 0.013 and a maximum value of 0.971. The resulting ROC curve shows an Area Under the Curve (AUC) value of 0.797, indicating that the model has good predictive capability (Figure 7.3).

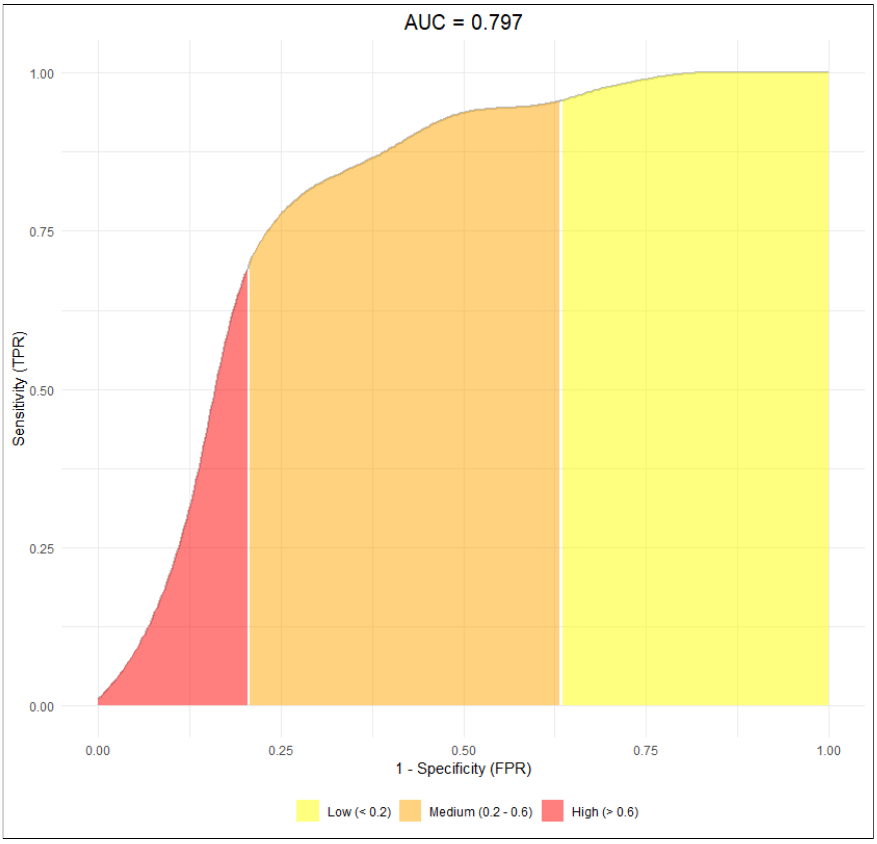


Figure 7.3. ROC curve obtained by the WOE method applied along linear road sectors.

Like spatial analysis, the probability values can be converted into binary classifications of stable (0) or unstable (1) sectors using the Optimal Threshold from the ROC curve. Alternatively, two threshold values can be set to define three levels of susceptibility, such as:

- "low" susceptibility (probability < 0.2),
- "medium" susceptibility (probability between 0.2 and 0.6),
- "high" susceptibility (probability > 0.6).

The results can then be displayed as seen in Figure 7.4, where each road sector is categorized according to its susceptibility class.

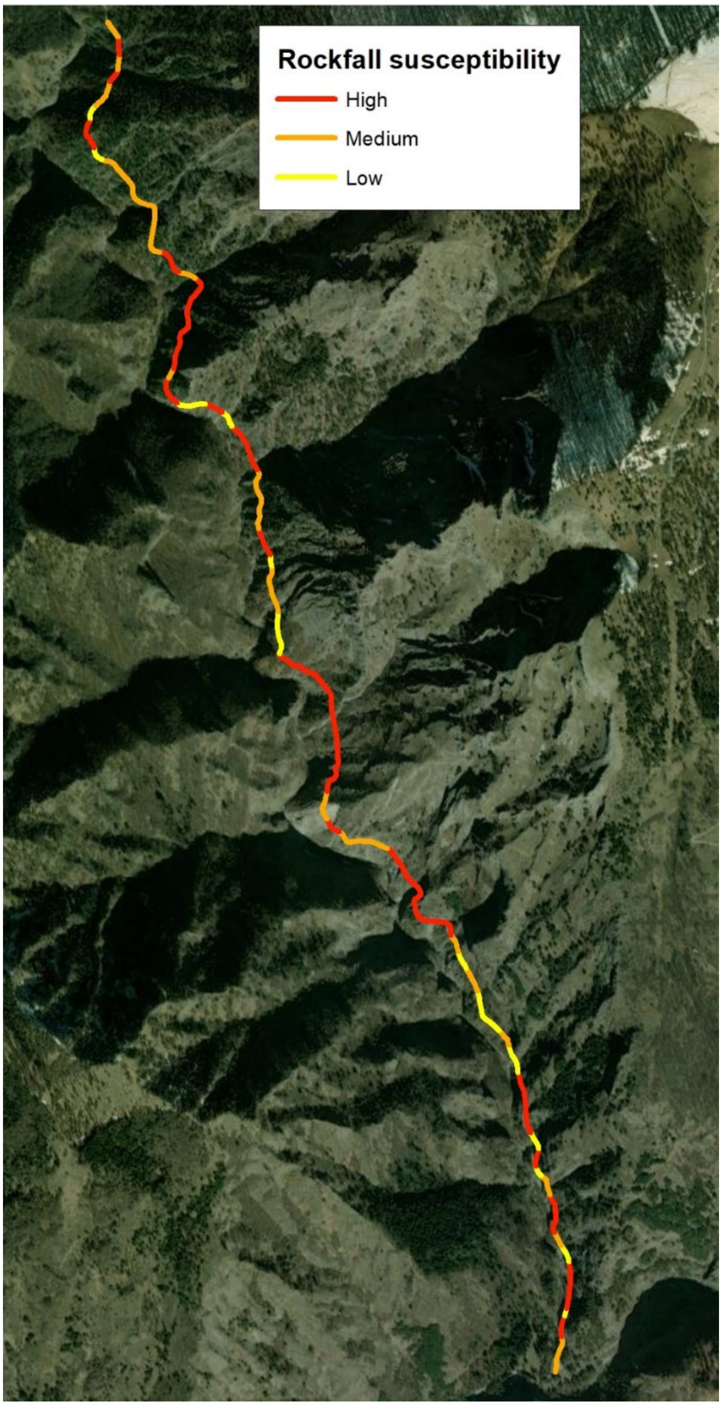


Figure7.4. Rockfall Susceptibility map of Elva Valley road

7.2 Susceptibility to soil liquefaction

This section summarizes the soil liquefaction analysis carried out in the Emilia-Romagna Region by UNINA for WP4. It specifically focuses on evaluating susceptibility as it is commonly conducted for soil liquefaction assessments (referred to as level 1 analysis, see below).

This approach differs from the spatial assessment discussed in the previous chapter as it relies on boolean logic rather than a data-driven methodology. Boolean logic involves checking a sequence of conditions laid out in a flow-chart format that determines a specific susceptibility class. This method does not require a training dataset because the conditions are generally considered valid, having been developed from a comprehensive dataset of liquefaction events.

7.2.1. Case study: Emilia-Romagna Region

The Emilia Romagna Region was affected by a significant seismic sequence in May 2012. The major seismic event on May 20, 2012 (Mw=6.1) led to extensive liquefaction phenomena. The area impacted by these intense shakes was the Po Valley, situated in the foreland basin between the Alps and the Northern Apennines, within the Emilia-Romagna Region of Northern Italy.

Beginning on May 19, 2012, the Emilia Romagna region, along with neighboring Veneto and Lombardy, experienced a prolonged seismic sequence with approximately two thousand shakes. This resulted in the collapse of many buildings and 27 fatalities. The epicenter of the May 20 earthquake was located between the provinces of Modena and Ferrara, with the hypocenter at a depth of 6.3 km, classifying it as a shallow earthquake.

This event was notable as it highlighted that soil liquefaction can also occur in Italy. The most noticeable effects of liquefaction following the 2012 earthquake were seen in San Carlo (Municipality of Sant'Agostino) and Mirabello, where the subsoil comprised alluvial sediments from river and levee depositional environments, consisting of alternating layers of silty-clayey deposits and sandy soils. Typical effects of liquefaction have been documented, such as sand boils, vents, sinkholes, craters, surface ruptures, and extensional fissures.

7.2.2. Data and methods

Liquefaction susceptibility can be assessed at four levels. Specifically, by understanding the geological and geomorphological characteristics of the area and the depth of the water table, a basic susceptibility map (level 1), also known as a "screening map," can be developed to identify which macro sectors are more prone to liquefaction.

As reported by Youd and Perkins (1978), the susceptibility at level 1 can be determined using the "if/then (else)" logic Boolean scheme (Figure 7.5). According to this scheme, low susceptibility is assigned if the deposits belong to river channels, flood/alluvial plains, beach plains, and lacustrine environments of pre-Pleistocene age with a water table depth of less than 15 meters. Medium susceptibility is assigned if the deposits belong to Holocene floodplains, beaches, or delta/fan-delta environments, or Pleistocene lacustrine deposits with a water table depth of less than 15 meters. High susceptibility occurs if the deposits belong to Holocene river channels, pyroclastic soils, or Pleistocene/Holocene loess.

Moreover, it must be considered that liquefaction events do not occur in mountain, foothill, and hill environments, nor in plain areas where the PGA is very low (< 0.01g) or the water table is deeper than 15 meters, resulting in null susceptibility.

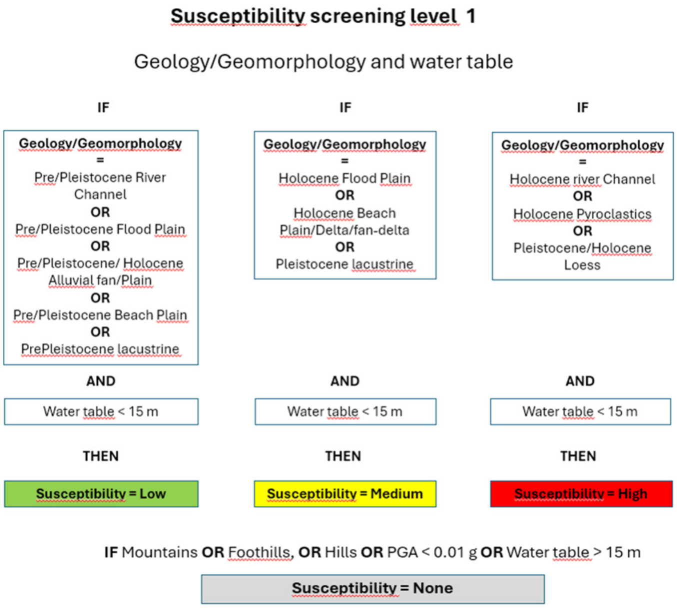


Figure 1.5. Scheme to evaluate the susceptibility liquefaction of level 1, considering geology/geomorphology and water table.

Given that liquefaction is never observed in areas with low seismicity, the distribution of PGA values can be considered both a predisposing and a triggering factor. Therefore, the scheme for assessing liquefaction susceptibility can be updated to include this parameter.

According to NTC (2018), the PGA value must exceed 0.1g to induce liquefaction. PGA values can be obtained by simulating earthquake scenarios using an appropriate GMPE or by importing results from the National Seismic Hazard Map for a specified return period. The latter approach tends to be more conservative.

By combining the geological and geomorphological characteristics of the deposits, the depth of the water table, and the PGA values, susceptibility classes obtained from the previous approach can be refined from low to very high. Specifically, as shown in Figure 7.6, susceptibility is low if pre-Pleistocene/Pleistocene deposits with a water table depth of less than 15 meters and low PGA values are present. The susceptibility level is very high when Holocene river channels, pyroclastic soils, or loess deposits are found along with a water table depth of less than 15 meters and PGA values greater than 0.1g.

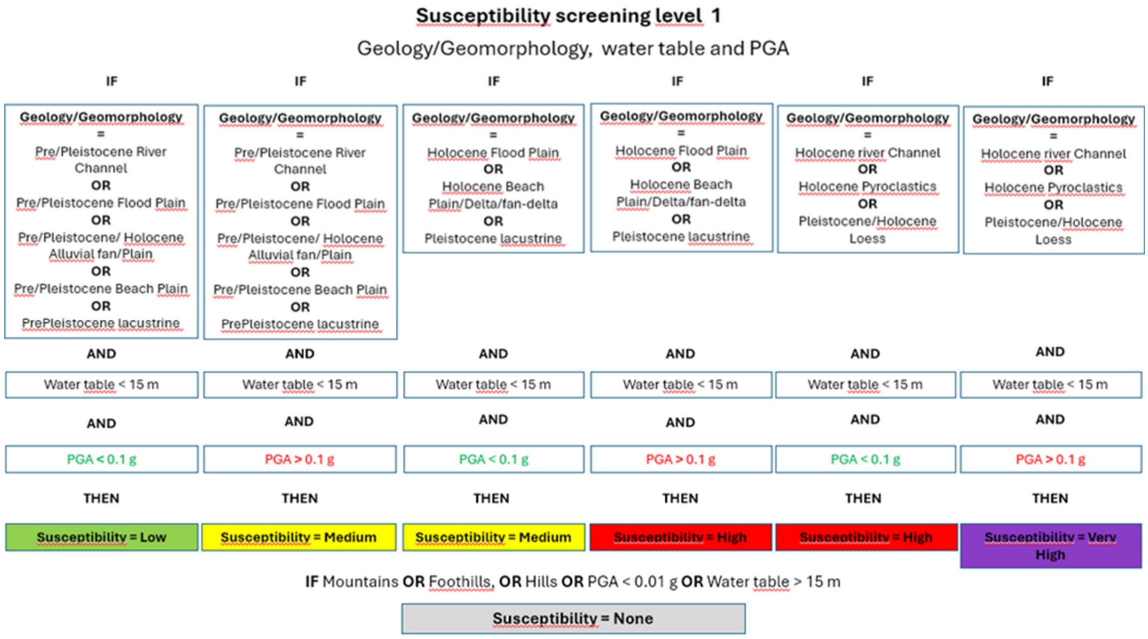


Figure 7.6. Scheme to evaluate the susceptibility liquefaction of level 1, considering geology/geomorphology, water table and PGA

The test area for applying the liquefaction tool chain was selected based on the sector with the highest density of events. Additionally, data necessary for developing the tool chain, such as geological and geotechnical investigations, water table depth, and PGA values, were collected.

Geological and geotechnical investigations were sourced from the database created by the Geology, Soil, and Seismic Area of the Emilia-Romagna Region. Water table depth values were obtained by interpolating average groundwater levels from point data downloaded from the ARPAE database (Regional Agency for Prevention, Environment, and Energy of Emilia-Romagna). This data pertains to monitoring conducted from 2009 to 2022 at groundwater stations within the regional network for environmental quality. Finally, the PGA (Peak Ground Acceleration) values associated with the 2012 Emilia earthquake, which had a magnitude of 5.8, were obtained from the INGV archive. Using this data, two levels of the tool chain were developed.

7.2.3. Results

An initial susceptibility map can be generated by intersecting geological/geomorphological data with water table maps in a GIS environment. The depth of the water table was determined by interpolating point data from the monitoring database at ARPAE (Regional Agency for Prevention, Environment, and Energy of Emilia-Romagna) stations (refer to Figure 7.7).

Subsequently, the susceptibility map can be refined by incorporating the Peak Ground Acceleration (PGA) map. The PGA data, associated with the magnitude 5.8 Emilia earthquake of 2012, shows that instances of liquefaction occurred within a PGA range of 0.18 - 0.30 g, with few points recording PGAs under 0.18 g (see Figure 7.8).

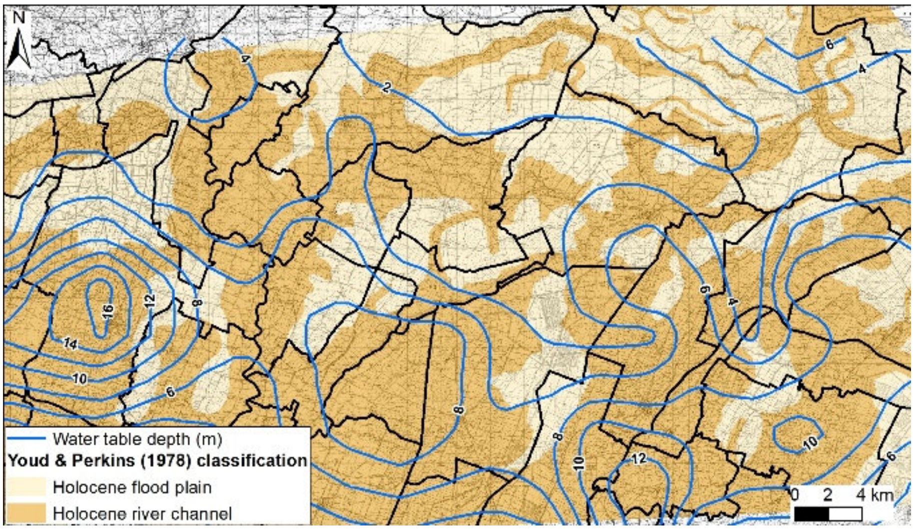


Figure 7.7. Geological/geomorphological setting and mean water table depth in the study area.

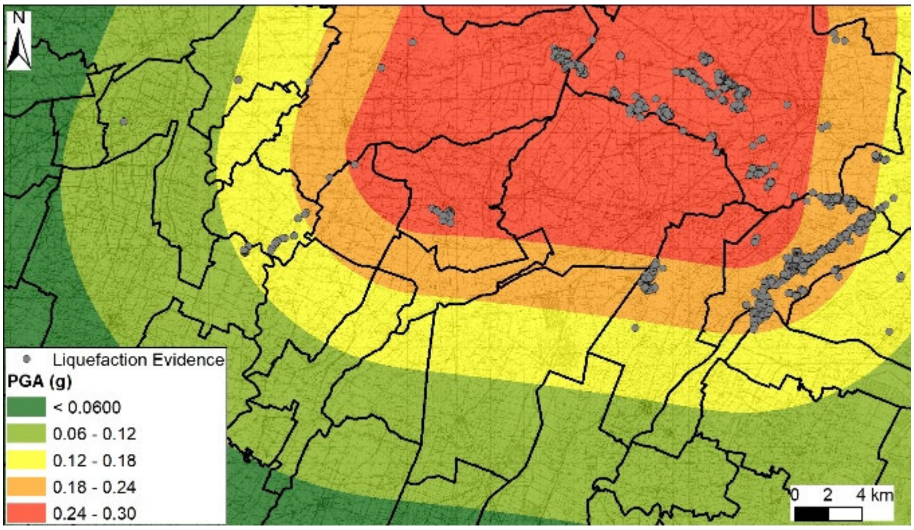


Figure 7.8. PGA map referred to 2012 Emilia earthquake with magnitude of 5.8.

The final susceptibility maps for liquefaction is Figure 7.9. Since the water table depth in the area is always less than 15 meters, the susceptibility directly depends on the distribution of Holocene floodplain and river channel deposits. The contribution of PGA is also evident: most liquefaction events fall within the high and very high susceptibility classes.

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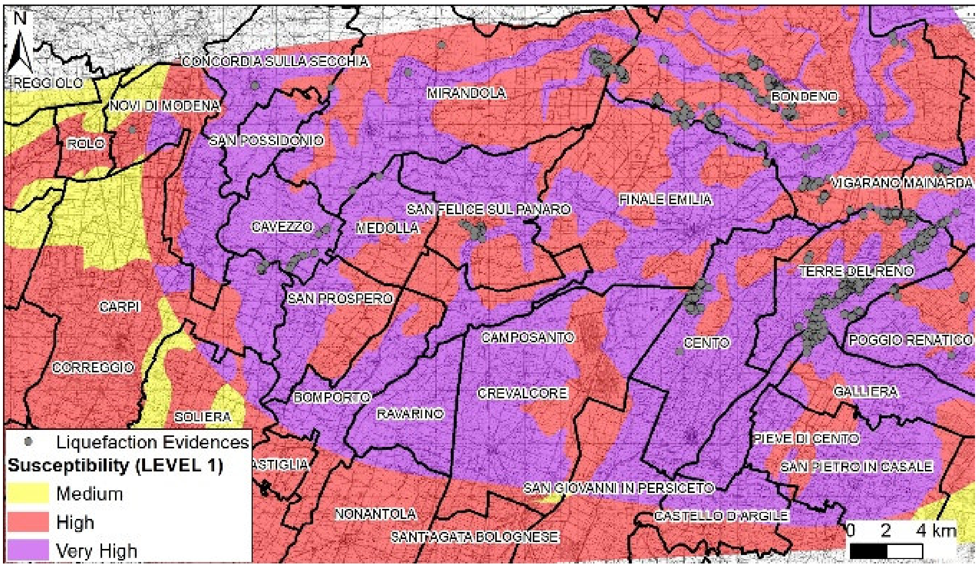

Figure 7.9. Susceptibility map of level 1 and liquefaction evidence

8. Conclusions

The work described in this **DV 2.2.6** must be considered as a synergistic and complementary contribution with what is described in **DV 2.2.4**: as reported in the conclusions of **DV 2.2.4**, in fact, the entire work must be framed as such a systematic approach aimed at improving our understanding of the complexity of slope dynamics and their impact on urban resilience and safety.

As part of these activities, the working group assigned to Work Package 2 (WP2), in collaboration with the Spoke Coordination and other working groups in different Work Packages (WPs), has sought to interpret the objectives set out in the Executive Working Plan as an integrated and synergistic process. This approach is particularly evident in the context of **Task 2.2** and **DV 2.2.4**, where the focus was on proposing operational solutions to assessing ground instability hazards entailing a detailed identification of the predominant types of instability processes affecting the area.

In this framework, the joint process carried out within **TK 2.2** and **TK 2.3** and described both by this **DV** and by **DV 2.2.4**, can be considered as summarized in three phases (Figure 8.1).

Stage 1. Expert-based identification of ground instability processes

Stage 2. Susceptibility analysis

Stage 3. Connection to **WP3** and **WP4**

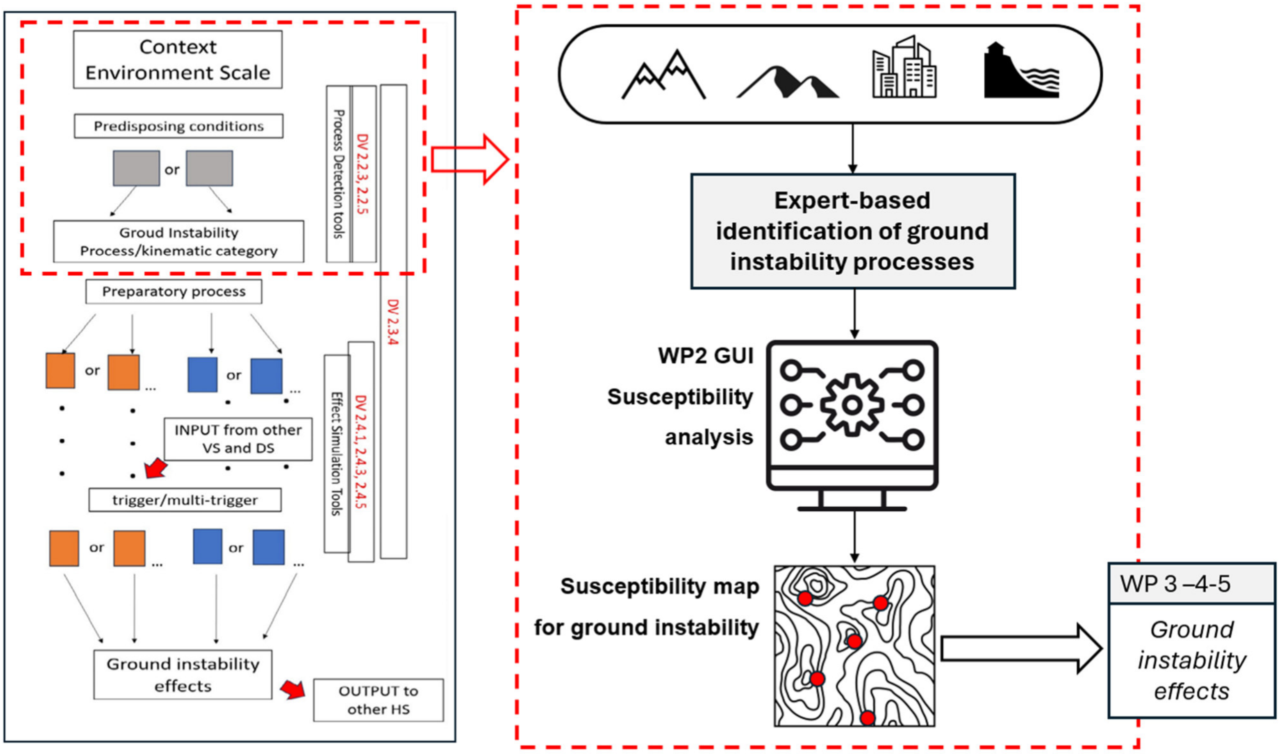

Figure 8.1: Overview of the synergistic approach of **TK 2.2** and **TK 2.3** (see also **DV 2.2.4**)

The prototype presented in this DV are to be understood as the realization of the whole process, summarized as follows.

Stage 1. Expert-based identification of ground instability processes

The first stage in assessing ground instability hazards entails a detailed identification of the predominant types of instability processes affecting the area. This critical initial step is foundational for guiding subsequent analysis and mitigation strategies, including the choice of proper tools for analyzing preparation, triggering and propagation (WP3 and WP4).

The initial assessment of ground instability hazards extensively relies on expert judgment to interpret data from various sources. Professional geologists conduct thorough evaluations of the geological and geomorphological settings, including rock types, soil properties, landforms, and structural landscape features, all vital for determining susceptibility to different instability processes. Historical data is also crucial; by examining past instability events, experts can discern patterns, frequencies, and triggers, which are essential for predicting future occurrences and assessing potential risks. Additionally, maps and remote sensing data, including land use data and satellite imagery, are crucial for identifying signs of potential instability.

These analyses enable experts to determine the types of ground instabilities prevalent in the area and identify the primary predisposing factors to be considered in the susceptibility assessment.

Stage 2. Susceptibility analysis

The second stage in assessing ground instability involves the application of susceptibility models. This can be done using the graphical user interface (GUI) that has been developed for this purpose as described above. This interface incorporates both data-driven methods—Logistic Regression, Weight of Evidence, and Random Forest models—and a geomorphic method, Flow-R. The GUI streamlines the assessment process, enabling users to easily select and apply these models based on their specific requirements.

Users can input their data, choose their preferred modeling approach, and rapidly generate susceptibility maps. The GUI is designed to be intuitive, facilitating the analysis of various types of ground instabilities affected by different predisposition factors. It also provides detailed statistical parameters that help assess the prediction's accuracy and evaluate the associated uncertainties.

Stage 3. Connection to **WP3** and **WP4**

The third stage in assessing ground instability builds directly on the outputs from the susceptibility assessment, focusing on the analysis of preparatory (**WP3**) and triggering (**WP4**) factors that contribute to ground instability. This stage utilizes the identified potentially unstable locations and selects specific analytical tools based on the type of ground instability recognized in the first stage, whether it involves landslides, subsidence, liquefaction, or other processes.

Different ground instabilities demand distinct analytical approaches. For instance, landslides may require the integration of hydrological models to examine the impact of water on slope stability, while subsidence issues might call for assessments of soil compressibility or the effects of extractive activities. Similarly, in areas prone to liquefaction, seismic analysis tools are essential to evaluate how earthquake-induced forces will interact with saturated soils.

This stage involves a meticulous examination of both long-term conditions that predispose areas to instability—such as vegetation cover and hydrological conditions—and more immediate triggering events like climatic extremes, human activities, or seismic disturbances. The analysis will use tailored tools identified in the **WP3** and **WP4** deliverables based on the learning cases proposed by the project's participants.

The GUI realized as a product of **WP2** represents the instrument for a semi-automatic realization of this part of the ground instability analysis and can be regarded as a prototype of the PoC.

This can constitute the starting point to hinge the subsequent tool chains (WP3 and WP4) and the conceptual basis for the realization of spatial and temporal studies on severity in terms of ground effect susceptibility.

The construction process of this product, which represents one of the objectives of the Spoke and the entire project, will be carried out in several subsequent development phases. The work performed in the **WP2** will constitute the basis for comparison with the IT specialists who will be responsible for its creation. In this sense, we can consider what has been done and described so far as a first and fundamental element of the analysis chain, whose translation into the Proof of Concept (PoC) will be the challenge of the next objectives.

The **WP2** team emphasizes the importance of the step defined as Phase 1 (Expert-based identification of ground instability processes): in fact, the PoC cannot in any way ignore a phase in which expert geologists determine the prevailing ground instabilities and identify the main predisposing factors. The construction of a PoC that takes into account this expert judgment, not always reducible to the result of a deterministic or statistical analysis and which still requires a holistic assessment of the situation, represents the central theme to be addressed in the next steps of the project.

It is crucial to understand that expert judgment provides an integrated and in-depth view of ground instability, going beyond mere numerical data to include environmental, historical, and contextual factors. This initial phase of identifying ground instabilities, therefore, not only prepares the discussion for subsequent PoC development phases but also provides a solid methodological foundation to ensure that the final product is accurate, reliable, and aligned with real ground conditions. Collaboration with IT specialists will be essential to translate these complex assessments into an effective technological product, capable of meeting the project's needs and providing useful and applicable results in the field. In summary, the work carried out in this phase represents a fundamental milestone for the project's success, laying the groundwork for future achievements and the practical implementation of the identified solutions.

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