multi-Risk sciEnce for resilienT commUnities undeR a changiNg climate

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AUTHORS

Filippo Catani (UNIPD), Ascanio Rosi (UNIPD), Sansar Raj Meena (UNIPD), Lorenzo Nava (UNIPD), Kushanav Bhuyan (UNIPD), Pierluigi Confuorto (UNIFI), Rita Tufano (UNINA)

1. Technical references

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Project Coordinator	Domenico Calcaterra UNIVERSITA DEGLI STUDI DI NAPOLI FEDERICO II domcalca@unina.it
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PP = Restricted to other programme participants (including the Commission Services)

RE = Restricted to a group specified by the consortium (including the Commission Services)

CO = Confidential, only for members of the consortium (including the Commission Services)

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2. ABSTRACT

This document describes the activities undertaken in the framework of Task 2.3.3: Deep Learning (DL) and machine learning (ML) for mass wasting characterization in subaerial and submarines areas.

The main goal of the work is to establish a rationale for selecting the most influential factors (predisposing-WP2, preparatory-WP3 and triggering-WP4) and the most suitable learning models to characterize ground instability phenomena, both in subaerial and submerged environments.

After an initial assessment of ML and DL methodologies and their use in ground instability assessment, a meticulous review of all available Learning Examples (LEs) was undertaken. The aim was to identify LEs incorporating ML (in its broader sense) or DL methodologies. This scrutiny led to the discernment of 22 LEs featuring learning models.

A subsequential statistical analysis of the LEs revealed comprehensive coverage of processes and control parameters of WP2 and WP3 are covered.

Landslides represent the most frequently examined form of ground instability (39.3% slow landslides and 32.1% rapid landslides), followed by subsidence (10.7%) sinkholes (10.7%) and liquefaction (7.1%).

The activity proceeded with a more in-depth description of the learning approached available for each ground instability process as the final step toward the creation of the rationales.

The rationalization phase was carried out trough the creation of LE-level toolchains related specifically to the application of ML and/or DL methods to the selected processes and environments.

The toolchains have been represented following standard block-diagram recommendations and stems derived from LEs. To adequately address the recommended conceptual and logical scheme of application of machine learning methods, blocks related to pre-processing, processing, and post-processing have been included.

A final generalization phase of the LE-based toolchain was made for each instability process, in attempt to define a framework for the implementation of ML and DL methods in ground displacement risk mitigation and assessment.

The work revealed that, from one hand, ML and DL can represents useful tools for decision makers, facilitating more informed choices in field as land-use planning, infrastructure development, and emergency response, treated by other Return Spokes with special reference to TS1, TS2, TS3.

To the other and, the analyses conducted on the LEs revealed that DL applications in the domain of ground instability still suffer some gaps in current research and tool development, even due to the complex interactions between factors that characterize ground instabilities and the paucity of data with required accuracy.

The absence of comprehensive ML/DL tools for multi-hazard assessment and runout estimation in the available dataset of LEs, as well as the building of risk scenarios, represents a critical gap in our ability to address natural hazards related to mass movements effectively and should be addressed in the next project phase.

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4. Introduction

This Deliverable is drawn up as part of Milestone 2.2 of Spoke 2 having as its topic (from the Executive Work Pan – Milestone 2.1) "Identification of impact-oriented indicators". The Deliverables of Spoke 2 for this Milestone have therefore set themselves as an overall objective the identification of rationales, starting from specific learning examples of literature, for identifying both the ground instabilities through macrocategories of factors (predisposing, preparatory, triggers) and the construction of analytical tools which, arranged in a specific logical-executive order (tool-chain), should lead to the design of an IT platform for the restitution in the PoC of the spatial overlap (multiple-hazard) or the temporal succession (multi-hazard, i.e. chain effects) of ground instability processes. This will allow quantifying the ground instabilities effects on the territory with a view to their impact on buildings and communities also evaluating their suitability and reliability.

This specific deliverable report describes the activities undertaken in the framework of Task 2.3.3: Deep Learning (DL) and machine learning (ML) for mass wasting characterization in subaerial and submarines areas (hereafter named TK3) included in the Work Package WP2.3: Monitoring & Modelling: toward a digital twin of ground instabilities effects (hereafter WP3), which is, in turn, part of the Vertical Spoke 2 – VS2: Ground Instabilities, that is one of the components of the Extended Partnership RETURN.

The general frame is the RETURN project (multi-Risk sciencE for resilienT commUnities undeR a chaNging climate), devoted to the study of natural risks and their impacts on the anthropic and the natural context with particular attention to the effects related to climatic drivers. A detailed description of the project is beyond the scope of this report and can be found at the link https://www.fondazionereturn.it/. Here it is worth recalling that, among the several natural phenomena addressed, the attention of VS2 focuses on ground instabilities, specifically landslides, sinkholes, subsidence, and liquefaction.

Such phenomena are approached in terms of three different factors controlling the destabilization process:

- **PREDISPOSITION** (accounted for in WP2)
- **PREPARATION** (WP3)
- **TRIGGERING** and **CASCADING** HAZARD (WP4)

In short, the main aspect characterizing each factor is the temporal scale: "predisposition" refers to all phenomena that can be considered invariant at the scale of observation (morphology, geological features); "preparation" accounts for cyclical changes or trend that can be monitored and measured in the same timeframe (rainfall, groundwater level, sedimentation rate); "trigger" describes the impulsive, almost instantaneous event, causing the detachment (seismic shaking, intense rainfall). In this regard, the preparatory factors represent a contribution to a time-dependent quantification of expected effects in view of scenario modelling and restitution.

Such aspects are mainly studied in two distinct stages: in the first one, which is called "**learning phase**", the focus is on what is already available in previous studies and on what we can "learn" from them; the second one is the "**generation phase**", where all the information gathered from the first are applied to new contexts, to validate the assumptions and the results produced.

Following the Executive Working Plan of RETURN, which was delivered as Milestone 2.1 on 31 Dec 2022, the institutions cooperating with the WP3 objectives are: ENEA, OGS, POLITO, UNIBA, UNIBO, UNIFI, UNIGE, UNINA, UNIPA, UNIPD and UNIROMA1. WP3 leader and coordinator is Salvatore Martino (UNIROMA1), TK1 leader is Chiara Colombero (POLITO), TK2 leader is Filippo Zaniboni (UNIBO), TK3 is led by Filippo Catani (UNIPD).

The output of this Task, as well as its main derivation in the form of specific method-related toolchains for the correct implementation of ML and DL techniques into the VS2 process analysis, must fit into the larger design of the conceptual data flow exemplified in Figure 1.

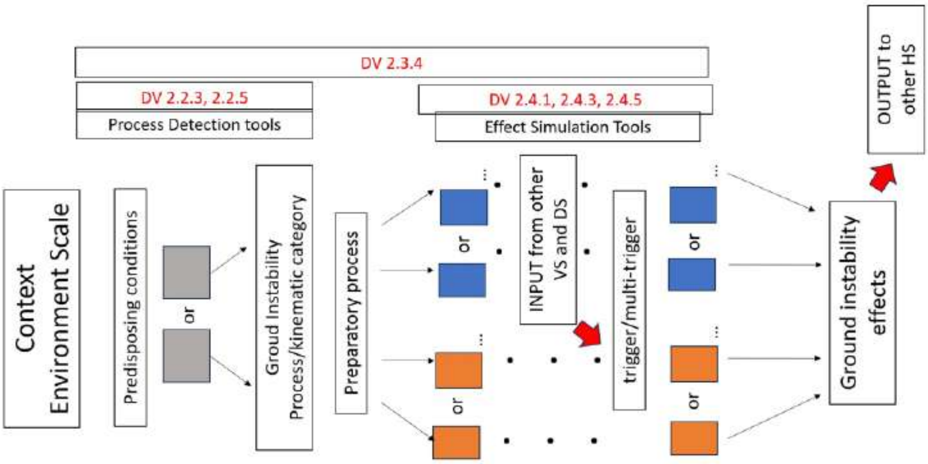

Figure 1 – General Spoke conceptual data flow, linking WP2, WP3, and WP4 tools and procedures.

4.1 Aim of the document

This report refers to the activities carried out in the period 01/12/2022 – 30/11/2023, that are dedicated to the learning phase, which has as the main goal the development and realization of a Rationale for all ground instability processes that will be used as input to the Proof of Concept (PoC). This stage has been carried out simultaneously by all WPs (then for different factors causing the instability) and has been structured in different ways within each WP.

Concerning TK3, which deals with Deep Learning (DL) and machine learning (ML) for mass wasting characterization in subaerial and submarines areas, the reported work phase setting up the first milestone deals with the analysis and synopsis of the Learning Example corpus as derived by Spoke VS2 procedures to describe and rationalize the methods using Deep Learning (DL) and Machine Learning (ML) for mass wasting characterization in subaerial and submarines areas. The report has been articulated more in detail in the following sections:

I) Overview on machine learning (ML) and deep learning (DL) basics (Section 5.1)

II) Overview on machine and deep learning for ground instabilities studies (Section 5.2)

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III) Summary statistics and assessments on usage of ML and DL inside the LEs (Section 6.1)

IV) Inventory of ML and DL methods inside the Learning Examples (LE, Section 6.2)

V) Definition of a series of toolchains for the implementation of ML and DL models in the relevant Learning Examples (Section 7.1).

VI) Tentative preliminary definition of some examples of general-purpose portable toolchains using state-of-the-art ML and DL techniques, as learned from LEs (Section 7.2).

VII) Conclusions (Section 8).

The main goal of task 2.3.3 is the definition of a series of rationales for the implementation of ML and DL methods into the general toolchains to characterize ground instabilities. Due to the very nature of this Task, the report encompasses processes and parameters beyond those considered in the sole WP3. Therefore, the description spans across predisposing, preparatory and triggering factors and the developed rationales will guide the user toward an optimal selection of ML and DL to be used in several LEs and more in general to analyze and represent ground instability processes based on the type of ground instability and the expected output.

As a consequence, the analysis of the available learning examples for this Task has been forcefully done on the entire original corpus of LEs, based on all the collected papers used in the first phase of work for VS2. This, in turn, implies that in the remaining part of the document we will refer to specific LEs and not to the derivations of them in terms of predisposing parameters or preparatory processes. In fact, the ML and DL methods cited in the corpus are very often not included in the tool sets derived from WP2 and WP3 parameter-specific tasks and we had to revise all the available papers again. Those papers, therefore, constitute the main reference ID for our summary table and synopsis. For completeness and easiness of comparison, however, we have also added, to each single ML/DL toolchain, references to the connected structured forms and tools as provided by other WP2, WP3, and WP4 Tasks.

5. ML and DL definitions and basics

5.1 Machine learning and Deep Learning basics

Artificial Intelligence (AI) is a vibrant field with various practical applications, ranging from automating routine tasks to understanding speech, images, aiding medical diagnoses, and supporting scientific research. In its early phase, AI focused on problems describable by formal rules, which were intellectually challenging for humans but computationally straightforward.

However, the real hurdle lay in solving tasks that were intuitive for humans yet difficult to articulate formally, like recognizing spoken words or images. This challenge gave rise to the paradigm of allowing computers to learn from experience and comprehend the world through a hierarchy of concepts, introducing the field of deep learning (Lecun et al., 2015).

It emphasized the accumulation of knowledge from experiences, avoiding the necessity for humans to explicitly specify all the required information. By constructing complex concepts from simpler ones in a hierarchical manner, computers using this approach could learn deeply, thereby earning the moniker "deep learning".

Efforts to hard-code vast knowledge into formal languages (knowledge base approach) faced limitations, such as the Cyc project's struggles with understanding contextual nuances, highlighting the difficulty in capturing informal knowledge within a computer (Lenat and Guha, 1990). This necessity led to the emergence of machine learning (ML), enabling systems to acquire their knowledge from raw data and make subjective decisions (Mor-Yosef et al., 1990). Simple algorithms, like logistic regression and naive Bayes, empowered machines to make decisions based on representations of the data provided.

The efficacy of machine learning algorithms heavily relies on the representation of the data. For instance, logistic regression's performance in recommending medical procedures is contingent on the features provided by the doctor, indicating the significance of appropriate data representations. Selecting the right features for a task significantly impacts the effectiveness of machine learning algorithms.

While certain tasks, like speaker identification, benefit from clearly defined features, others, like detecting objects in images, face challenges due to the complexity of defining relevant features.

In summary, the evolution of AI and the emergence of machine learning represent a transition from manually programming knowledge to enabling computers to learn from data (Russell and Norvig, 2010; Goodfellow et al., 2016). The quality and relevance of the features extracted significantly influence the performance and capabilities of AI systems in comprehending and interacting with the world.

5.2 Machine learning methods applied to ground displacements

The integration of machine learning (ML) in ground displacement analysis has significantly advanced the hazard assessment, mapping, and monitoring of these processes. In the realm of mapping, the traditional approach involves pixel-wise classification and object-based algorithms, each with its limitations.

However, the evolution of deep learning models, particularly convolutional neural networks (CNNs) and transformer-based systems, has substantially enhanced accuracy in mapping, allowing adaptability to diverse geographic conditions.

These models show promise in automatic landslide detection from various data sources, including optical and SAR imagery. In contrast to Object-Based Image Analysis (OBIA) methods, deep learning networks exhibit the capability to operate effectively with minimal human intervention once adequately trained on reliable data (Amatya et al., 2021; Blaschke, 2010).

Additionally, these models can transfer learned knowledge from one region to another through transfer learning, facilitating the detection of landslides in diverse areas.

Transfer learning allows the utilization of complex Convolutional Neural Network (CNN) models designed for general image recognition, such as ResNet, VGGNet, GoogLeNet, and Inception, for specific landform classification and mapping purposes, as demonstrated on non-nadir and drone optical imagery by (Catani, 2021).

This approach becomes crucial when large training datasets are unavailable. AlexNet (Krizhevsky et al., 2017)and VGGNet (Simonyan & Zisserman, 2014) have been employed for image classification tasks, providing outcomes in the form of eigenvector values. However, these models only classify scenes as containing a landslide or not, lacking the ability to delineate landslide boundaries.

For generating landslide inventories, reliance on pixel-based segmentation models is essential. Fully Convolutional Networks (FCNs), based on semantic segmentation, replace fully connected layers in traditional CNNs with transposed convolutional layers to classify each pixel into "landslide" or "non-landslide" classes.

Unlike conventional pixel-based methods, CNNs learn both spatial and spectral information during training, and transfer learning enables adaptation to new study areas. Recent research by Ghorbanzadeh et al. (2019), Meena et al. (2021), Nava et al., (2022a, 2022b), Bhuyan et al., (2023a, 2023b), and Prakash et al., (2020, 2021) highlights the effectiveness of FCNs in automatic landslide detection globally using Earth Observation (EO) data, even during adverse conditions such as large storms and cloud cover.

The use of Synthetic Aperture Radar (SAR) amplitude data, in combination with topographic information, further enhances the model's performance. Advancements in computer vision have introduced transformer-based models like Vision Transformers (ViT), Swin Transformer, and SegFormer, increasingly applied in landslide detection applications (Li et al., 2023; Tang et al., 2022).

These transformer models offer advantages over traditional architectures by capturing long-range dependencies in spatial context, improving accuracy in landslide detection, and overcoming challenges in multi-temporal mapping Regarding landslide monitoring and early warning systems, ML has substantially improved forecasting accuracy.

Rainfall thresholds, critical for predicting landslides, have been traditionally based on historical data, yet ML-based models, using machine learning and deep learning techniques, have enhanced these thresholds by incorporating various influencing variables.

These ML-powered systems enable more precise calibration, thus improving the predictability of landslide occurrences. Accurate landslide early warning systems are crucial risk-reduction tools, minimizing economic losses and fatalities (Hong et al., 2017). These systems predict landslide behavior based on historical data, often using critical rainfall thresholds. While widely applied, AI, particularly Machine Learning (ML) and Deep Learning (DL), enhances reliability and objectivity in calibration. AI models excel in landslide displacement forecasting, considering various conditioning variables. Rainfall, a common landslide trigger, prompts the establishment of critical rainfall thresholds.

Traditional methods use binary classification to distinguish landslide-triggering and non-triggering rainfall. AI algorithms, such as Support Vector Machines (SVM) and Random Forests, automate and improve threshold determination. Deep Learning approaches, like unsupervised Deep Belief Networks (DBN), effectively extract patterns from rainfall time series data for landslide prediction (Nocentini et al., 2023). Deep-seated landslides, driven by factors like groundwater level changes, pose distinct challenges. SVM models, using historical rainfall data, predict fluctuations in groundwater levels to establish critical thresholds.

Velocity criteria approaches, utilizing SVM models, discriminate between acceleration crises and stable periods, aiding in landslide detection. Moreover, AI models have demonstrated success in forecasting landslide displacement, outperforming conventional approaches and providing a higher degree of precision and stability across different cases.

Various models, including Artificial Neural Networks (ANN) (Khashei & Hajirahimi, 2019), SVM (Zhang et al., 2021; Zhu & Hu, 2012), Gaussian Process, and Extreme Learning Machines (ELM), have been employed for landslide displacement forecasting. Recently, Deep Learning algorithms, such as Long Short-Term Memory (LSTM) networks and Gated Recurrent Unit Neural Networks (GRU) (Jiang et al., 2022), demonstrate superior performance. These models consider historical displacement, rainfall, and reservoir water level data, providing accurate and stable predictions. While much literature focuses on Three Gorges Reservoir landslides, there is a growing interest in applying AI to forecast landslide displacement in diverse global regions. Studies explore novel approaches, such as Random Forests for predicting landslide velocity and evaluating the performance of various DL models in different landslide cases (Krkač et al., 2017; Nava et al., 2023).

6. The Return overview on ML&DL

6.1 Summary statistics and assessment of ML and DL usage

An initial review of the learning examples (LEs) from all work packages (WPs) was conducted to determine whether they describe approaches based on machine learning (in its broader sense, encompassing all data-driven processes) or deep learning.

The results of this review activity were summarized in the following table (**Errore. L'origine riferimento non è stata trovata.**), where each LE was described with the following information:

- Institution developing/proposing the LE
- ID of the paper
- Bibliographic information (Short reference, Full reference, D.O.I.)
- Type of ground instability
- Learning technique
- Predisposing factors (if any)
- Preparatory factors (if any)
- Triggering factors (if any)
- Input data
- Output data
- Constrains
- Notes

Table 1 – List of the Learning examples used for the issuing of the present deliverable

Institution	L.E.	BIBLIOGRAPHY	TYPE OF GROUND INSTABILITY	TECHNIQUE	
	ID of the paper	D.O.I		ML	DL
UNIPD	CA_UNIPD_P14	https://doi.org/10.1007/s10346-023-02104-9	slow landslides		x
UNIBO	CA_UNIBO_Bologna2	https://doi.org/10.1016/j.enggeo.2013.10.014	subsidence	x	
UNIBO	CA_UNIBO_AppenninoER2	https://doi.org/10.1029/2012JF002367	fast landslides	x	
UNIFI	CA_UNIFI_Guidonia	https://doi.org/10.1080/10106049.2022.2113455	sink hole	x	
UNIPD	CA_UNIPD_Dolomiti_1	https://doi.org/10.5194/nhess-22-1395-2022	slow and fast landslides	x	
UNIBO	CA_UNIBO_AltaValCamonica2	https://doi.org/10.1029/2019JF005513	Fast landslides	x	
UniBA	CA_UniBA_RegionePuglia1	n.a.	Sinkholes	x	
UniBA	CA_UniBA_FossaBradanica1	https://doi.org/10.1007/978-3-642-31445-2_88	Slow and fast landslides	x	

UNINA	CA_UNINA_Napoli_frane_3	https://doi.org/10.3390/rs12152505	slow landslides, fast landslides	x	x
UNINA	CA_UNINA_Napoli_sinkhole	https://doi.org/10.1007/s11069-022-05279-x	sinkholes	x	
UNINA	CA_UNINA_Santucci_et_al_2013	http://dx.doi.org/10.1016/j.soildyn.2013.07.011	soil liquefaction	x	
UNINA	CA_UNINA_Santucci_et_al_2014	https://doi.org/10.1007/s11069-014-1229-x	soil liquefaction	x	
UNIPA	CA_UNIPA_Frana di Cerda 1	https://doi.org/10.1016/j.enggeo.2018.01.016	slow landslides	x	
UNIPA	CA_UNIPA_Frana di Cerda 2	https://doi.org/10.1007/978-3-030-21359-6_21	slow landslides	x	
UNIPA	CA_UNIPA_IMERA-TORTO 1	https://doi.org/10.1080/17445647.2023.2198148	rotational/translational landslides	x	
UNIPA	CA_UNIPA_IMERA-TORTO 2	https://doi.org/10.1080/17445647.2020.1805807	rotational/translational landslides	x	
UNIPA	CA_UNIPA_MESSINESE IONICO 1	https://doi.org/10.5194/nhess-15-1785-2015	debris flow	x	
UNIPA	CA_UNIPA_MESSINESE IONICO 2	https://doi.org/10.1016/j.geomorph.2017.03.025	debris flow	x	
UNIPD	CA_UNIPD_Delta_Po_2	https://doi.org/10.1029/2010JB008122	subsidence	x	
UNIGE	CA_UNIGE_PiemonteLiguria	n.a.	landslides (no differentiation)	x	
UNIROMA	SAPIENZA_Roma_sinkhole	https://doi.org/10.1080/19475705.2021.1978562	sinkhole	x	

As a result, a total of 21 LEs were considered that report techniques and methods related to artificial intelligence, including machine learning techniques loosely related to AI, such as regression on empirical datasets, as well as fully fledged DL applications. The selected LEs cover most of the processes considered in WP2 and WP3, as it can be appreciated from the summary plots in Figure 2 on the left. The right side of the figure shows the distribution of different techniques related to ML and DL used in the same LEs list.

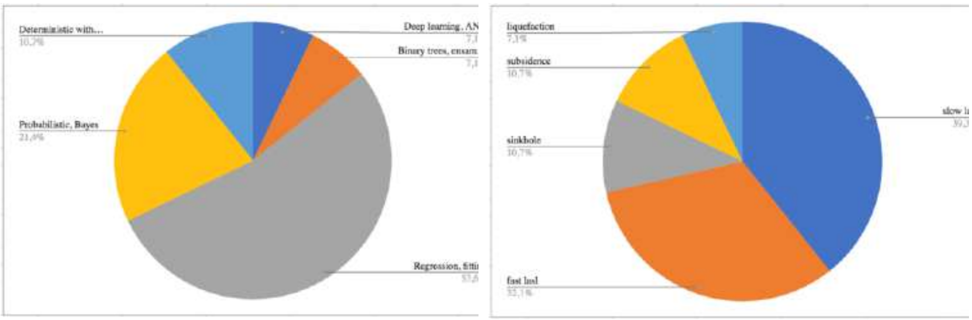

Figure 2 – Statistics of selected learning examples and their usage of ML and DL techniques. Left: percentage of AI methods used; right: percentage of coverage of different ground displacement processes in the selected LE set.

6.1.1 Slow and fast-moving landslides:

As reported in the following table (**Errore. L'origine riferimento non è stata trovata.**), ML and DL applications were observed to be widely used, particularly for estimating forecasts of displacement in the case of slow-moving landslides.

Table 2 - List of the LEs describing learning processes for landslide phenomena

Institution	L.E.	TYPE OF GROUND INSTABILITY	TECHNIQUE		MODELS
	ID of the paper		ML	DL	
UNIPD	CA_UNIPD_P14	slow landslides		x	MLP, LSTM, GRU, CNN
UNIBO	CA_UNIBO_AppenninoER2	fast landslides	x		One-Dimensional Bayesian Probability, Two-Dimensional Bayesian Probability
UNIPD	CA_UNIPD_Dolomiti_1	slow and fast landslides	x		random forest and XGBoost
UNIBO	CA_UNIBO_AltaValCamonica2	Fast landslides	x		Intensity Duration Function
UniBA	CA_UniBA_FossaBradanica1	Slow and fast landslides	x		Linear regression
UNINA	CA_UNINA_Napoli_frane_3	Slow and fast landslides	x	x	the artificial neural network (ANN), generalized boosting model (GBM), random forest (RF), and maximum entropy (MaxEnt)
UNIPA	CA_UNIPA_Frana di Cerda 1	slow landslides	x		quantitative correlation (trial and error procedure and least square method foe best fit)
UNIPA	CA_UNIPA_Frana di Cerda 2	slow landslides	x		quantitative correlation (trial and error procedure and least square method foe best fit)
UNIPA	CA_UNIPA_IMERA-TORTO 1	rotational/translational landslides	x		Multivariate adaptive regression splines (MARS) method
UNIPA	CA_UNIPA_IMERA-TORTO 2	rotational/translational landslides	x		multivariate adaptive regression splines (MARS) method
UNIPA	CA_UNIPA_MESSINESE IONICO 1	debris flow	x		binary logistic regression (BLR)
UNIPA	CA_UNIPA_MESSINESE IONICO 2	debris flow	x		binary logistic regression (BLR)
UNIGE	CA_UNIGE_PiemonteLiguria	landslides (no differentiation)	x		Logistic multiple regression

While a combination of complex DL models such as Long-short term memory and Gated Recurrent Units were employed, signifying their capability in handling sequential data and temporal dependencies crucial in understanding landslide dynamics, the application of some lesser complex models also saw nice usage, such as Multilayer Perceptrons suggesting their effectiveness in scenarios where less complex modeling suffices or where data limitations preclude the use of more sophisticated approaches. For fast landslides, distinct methodologies are employed. For instance, in the Emilia-Romagna study, Bayesian probabilistic models are used, highlighting their strength in dealing with uncertainty and providing deterministic outcomes (i.e., the occurrence or absence of landslides) under specific rainfall conditions. This approach is indicative of a shift towards probabilistic risk assessment in landslide studies, offering an understanding of landslide triggers and their likelihood under varying environmental conditions. Moreover, the table also indicates studies reflecting the application of Random Forest and XGBoost algorithms in the context of both slow and fast landslides, which suggests the usage of ensemble methods known for their high accuracy and ability to handle a variety of data types and distributions. These methods, characterized by their robustness and generalization capabilities, are particularly valuable in the complex, multifactorial analysis inherent in landslide susceptibility and risk assessment.

6.1.2 Subsidence:

The table of LEs also reflects a diverse application of methodologies in understanding and predicting subsidence movements.

Table 3 - List of the LEs describing learning processes for subsidence

Institution	L.E.	TYPE OF GROUND INSTABILITY	TECHNIQUE		MODELS
	ID of the paper		ML	DL	
UNIBO	CA_UNIBO_Bologna2	subsidence	x		Kriging
UNIPD	CA_UNIPD_Delta_Po_2	subsidence	x		the kriging stochastic interpolator

For example, in Bologna, a Kriging geostatistical method was employed for its ability to create spatially continuous surfaces from discrete data points, making it highly suitable for modeling subsidence across varied geologies and thicknesses of soil layers, as well as groundwater levels. This technique's strength lies in its capacity to interpolate and predict values in unmeasured locations, thereby offering a comprehensive spatial understanding of subsidence patterns. Adding to this study, the Persistent Scatterers Interferometry (PSI) technique was also used for subsidence mapping. Despite not using any particular ML model, this presents the opportunity to use PSI-derived products that detect and measure ground movements over time in creating ML-driven forecasting models to enhance predictive accuracy and provide more granular insights into subsidence risk. These models can integrate PSI data with other relevant variables, such as soil moisture content, geological characteristics, and anthropogenic factors, to develop more comprehensive and dynamic subsidence models.

6.1.3 Sinkholes:

In the context of sinkhole research, Les (**Errore. L'origine riferimento non è stata trovata.**) indicate a diverse use of methodologies and data types. For instance, the Maximum Entropy algorithm (MaxEnt) was employed in one study, leveraging parameters like lithology, land use, and various geological and hydrological factors, along with InSAR ground motion displacement rates, to create susceptibility zoning and risk assessment maps. Another approach involved a multi-criteria method, focusing on geomorphological features such as lithology, faults, and hydrology, to assess sinkhole susceptibility, which adds the benefits of experts' opinions. Additionally, a frequency ratio method was applied in a study that incorporated an array of factors including aqueduct and sewer system densities, groundwater depth, and anthropogenic influences, aiming to update sinkhole inventories and susceptibility assessments.

Table 4 - List of the LEs describing learning processes for sinkholes

Institution	L.E.	TYPE OF GROUND INSTABILITY	TECHNIQUE		MODELS
	ID of the paper		ML	DL	

UNIFI	CA_UNIFI_Guidonia.pdf	sinkhole	x		Maximum Entropy algorithm (MaxEnt)
UniBA	CA_UniBA_RegionePuglia1	sinkhole	x		Multi-criteria approach
UNINA	CA_UNINA_Napoli_sinkhole	sinkhole	x		frequency ratio
UNIROMA	SAPIENZA_Roma_sinkhole	sinkhole	x		multivariate logistic regression

6.1.4 Soil liquefaction:

Although ML applications were not prevalent in soil liquefaction (Table 5) in our LE examples, we do, however, see wide applications moving forward with the data and information the current LE examples provide. ML models, such as neural networks or ensemble methods like Random Forests, can be trained to predict soil liquefaction occurrence using a range of input features, including geotechnical properties (derived from standard penetration tests, cone penetration tests, and shear wave velocity measurements) and seismic data (like peak ground acceleration and Arias Intensity). Beyond mere occurrence prediction, these models could be leveraged to estimate the extent of ground deformation resulting from liquefaction, providing valuable insights for infrastructure risk assessment and urban planning. Additionally, incorporating historical data on past liquefaction events allows for temporal analysis, aiding in the understanding of changing risk profiles over time.

Table 5 - List of the LEs describing learning processes for liquefaction

Institution	L.E.	TYPE OF GROUND INSTABILITY	TECHNIQUE		MODELS
	ID of the paper		ML	DL	
UNINA	CA_UNINA_Santucci_et_al_2013	soil liquefaction	x		4-parameters Beta probability distribution
UNINA	CA_UNINA_Santucci_et_al_2014	soil liquefaction	x		log-normal probability distribution, 4-parameters Beta probability distribution

6.2 ML and DL applications within LEs

This section shortly describes the ML/DL-related technology used in the listing of selected LEs adopted for the Spoke VS2 as a whole (Table 1). Here, the focus is not on the specific tool derived at parameter-level stage (see related DVs) but on the overall use. The aim is to give a synoptic view of what is included in the selected learning set with respect to the available methods and tools present in the recent but vast literature on the subject and to set the stage for the subsequent derivation of rationales specifically centered on ML/DL in the form of LE-specific toolchains (Section 6.1).

Commentato [FC1]: Remember to link papers (e..g. Nava et al 2023) with tools as reported by other Tasks and WPs (for each paper more than one tool can exist, with a specific filled form)

The study of Nava et al. (2023) [WP3_P15_PD_3_WP3] utilizes a multivariate forecasting approach to forecast future landslide displacement in four different landslides. The comparative analysis not only seeks to identify the most effective model but also contributes valuable insights into the nuanced relationships between rainfall, reservoir water level changes, and landslide dynamics. This nuanced understanding is crucial for advancing the precision and reliability of future landslide displacement predictions, enhancing our ability to proactively address and mitigate the impact of these natural hazards. The findings of this research will serve as a precious aid when implementing a DL-based landslide early warning system (LEWS).

The study of Modoni et al. (2013) [WP2: Scheda CA WP2 UNIBO Bologna; WP3: BO_4_WP4] utilizes a comprehensive modeling approach to examine the causes and consequences of land subsidence in Bologna, Italy. The primary focus is on subsidence triggered by extensive groundwater withdrawal, a significant hazard in the region. The analysis incorporates various factors, including the geological, hydrogeological, and geotechnical properties of the soil, along with topographical changes and fluctuations in the groundwater regime. The input data is an extensive collection of geological surveys, hydrogeological data, satellite records, and topographical measurements, leading to a spatial analysis output that maps subsidence patterns. The study specifically uses ordinary Kriging as a geostatistical method for interpolating the subsidence data, effectively capturing the progressive deformation of the ground surface over time. This research is important in understanding the type of mass movement (subsidence) induced by groundwater extraction.

Berti et al. (2012) [WP2: Scheda CA WP2 UNIBO Appennino Emiliano-Romagnolo] focuses on developing a model to predict landslides triggered by rainfall in the Emilia-Romagna Region, Italy. This model, based on a Bayesian statistical approach, considers a variety of factors, including rainfall duration, intensity, and total amount, while also taking into account the historical landslide archive and daily rainfall data. The trigger in this study is rainfall, with particular emphasis on understanding its role in inducing landslides. The input data comprises over 4,000 historical landslide events and rainfall measurements from a network of rain gauges. The output is a probabilistic assessment of landslide likelihood under varying rainfall conditions. This research significantly advances the understanding of landslide triggers, particularly the complex relationship between rainfall characteristics and landslide occurrences, providing valuable insights for regional landslide warning systems.

Berti et al. (2020) [WP2: Scheda CA WP2 UNIBO ValCamonica] performed a study in the Dimai Basin, Dolomite region, Italy, which aimed to decipher and predict debris flow occurrences based on rainfall thresholds. Centered on rainfall as the primary trigger, the work focuses on the hazards of debris flows, particularly those initiated by surface runoff. The primary trigger investigated is rainfall, and the hazard addressed is debris flows. An important aspect of the modeling process is the use of intensity-duration functions, which are critical in understanding the relationship between rainfall characteristics and debris flow initiation. The study examines factors like rainfall intensity and duration, catchment hydrology, and the physical characteristics of the catchment area. The methodology involves a synthesis of field data collection, hydrological modeling, and analysis of rainfall-runoff relationships, employing tools such as the kinematic wave approximation and the Soil Conservation Service Curve Number (SCS-CN) method. The input data consists of detailed rainfall records and catchment monitoring data, leading to outputs that precisely define rainfall thresholds for the initiation of debris flows.

Bianchini et al. (2022) [WP2: Scheda CA WP2-Guidonia-Bagni di Tivoli; WP4: FI_4_WP4] utilizes machine learning, specifically the Maximum Entropy (MaxEnt) algorithm, to model and predict sinkhole risks in the Guidonia-Bagni di Tivoli plain. The main hazard addressed is sinkholes, a type of ground collapse, with the model triggered by the occurrence of these geological phenomena. The study considers various factors including lithology, land use, soil characteristics, fault settings, hydrography, groundwater levels, and satellite InSAR data. The input data comprises a detailed sinkhole inventory and several geo-environmental factors, while the output is a comprehensive risk map indicating sinkhole susceptibility, vulnerability, and exposure.

Another aspect was towards landslide susceptibility, particularly fast- and slow-moving landslides such as in the Veneto region of Italy. The study by Meena et al. (2022) [WP2: Scheda CA WP2 - Dolomiti 1 UNIPD; WP3: WP3_P14_PD_1_WP3; WP4: PD_1_WP4] focused on the role of conditioning factor selection in landslide susceptibility modeling. The work is centered around landslides, examining how different environmental and anthropogenic factors such as topography, hydrology, geology, and human activities (land cover, roads) influence the occurrence and prediction of these events. The model employs machine learning techniques like Random Forest and XGBoost, along with statistical methods like frequency ratio and evidence belief function, to analyze input data comprising a comprehensive landslide inventory and various conditioning factors. The output is a set of landslide susceptibility maps, showcasing the variation in predictive accuracy based on the chosen factors. This study underscores the importance of meticulous factor selection in enhancing the reliability of landslide susceptibility assessments.

Another set of studies related to landslide susceptibility was made by Di Napoli et al. (2020) [WP3: WP3_P3_NA_6_WP3; WP4: NA_9_WP4] in their attempt to evaluate landslide risks related to wildfires in the Camadoli and Agnano hills of Naples, Italy. They utilize a method that combines earth-observation techniques and machine learning to model the susceptibility of landslides post-wildfires. The primary trigger for this machine learning model is the occurrence of wildfires, with the ensuing hazard being the increased likelihood of landslides in these burnt areas. Important input factors considered in the study include terrain attributes like slope angle, aspect, and curvature, as well as environmental factors like the topographic wetness index and land use, while the output is a landslide susceptibility map. The algorithms used include artificial neural networks (ANN), generalized boosting model (GBM), random forest (RF), and maximum entropy (MaxEnt).

Tufano et al. (2022) [WP2: Scheda CA WP2 UNINA Napoli; WP4: NA_5_WP4] focused on assessing and predicting sinkhole susceptibility in Naples, particularly in response to anthropogenic activities. Specific on sinkholes caused by human activities like service line damage were emphasized. The study incorporates a range of factors, including cavity-roof collapse, rainfall events, and various infrastructural elements like aqueduct and sewer system densities. The input data consists of an updated sinkhole inventory, encompassing 458 events recorded between 1880 and 2021, with a detailed analysis of 270 new events from 2010 to 2021. The model utilizes the Frequency Ratio method to establish the probability of sinkhole occurrences, considering the spatial relationship between sinkholes and various predisposing factors. The output of the study is a sinkhole susceptibility map of Naples, categorizing different areas based on their susceptibility levels.

The paper by Teatini et al. (2011) [WP2: Scheda CA WP2 - Delta Po UNIPD; WP3: WP3_P13_PD_2_WP3; WP4: PD_2_WP4] explores the significant land subsidence in the Po Delta region of Italy, primarily attributed to the compaction of Holocene sediments. The study combines radar Interferometric Point Target Analysis (IPTA) with aerial and satellite imagery, seismic surveys, and data from core samples to understand the current and historical subsidence patterns. The analysis identified a correlation between subsidence rates and the age of the sedimentary layers, particularly the highly compressible Holocene deposits that form the top 30–40 meters of the earth's surface in this region. The findings indicate that the compaction of these late Holocene sediments is the primary driver of the current land subsidence, providing valuable insights into the subsidence processes affecting other modern deltas formed during the same geological epoch.

The study by Cama et al., (2017) [WP2: Scheda CA WP2 UNIPA MESSINESE IONICO; WP4: PA_3_WP4] predicts debris flow susceptibility in areas where direct evidence of such events is scarce due to vegetation or weathering concealing past occurrences. Debris flows are characterized as rapid mass movements prompted by storm rainfalls. To address the lack of reliable landslide inventories necessary for susceptibility assessment, the paper explores model transferability, where a model is calibrated in one area (source) to predict debris flows in another (target). The research presents a comparison of predictive performances using three different criteria for factor selection during model calibration. Binary logistic regression was employed for this purpose. Two distinct areas in Messina province, the Itala and Saponara catchments, which suffered severe debris flow events in 2009 and 2011, respectively, were chosen for the study. The findings highlight that while a model may fit well in its calibration zone, its performance can be poor when applied to a target area. However, models calibrated with a well-chosen set of variables in the source area provided robust and accurate predictions for the debris flows in the Saponara catchment in 2011, using only data available after the Itala event in 2009.

The paper titled by Cama et al. (2015) [WP2: Scheda CA WP2 UNIPA MESSINESE IONICO; WP4: PA_3_WP4] addresses the predictive challenges posed by storm-triggered debris flows in the Mediterranean, particularly when previous models based on past events are used to forecast future occurrences. Emphasizing that past patterns are critical for predicting future scenarios, the study focuses on the Itala torrent catchment in Sicily, Italy, where two significant storm events in 2007 and 2009 led to debris flows, with 73 and 616 occurrences respectively. A logistic regression model was developed using predictors from digital elevation and geological maps. The model's validity was tested through self-validation and chrono-validation methods. These methods allowed a comparison of the model's ability to predict 2009 debris flows based on 2007 data and vice versa. Although both predictions showed acceptable performance, differences in predictor selection between the models indicated the influence of non-linear relationships between the triggers' intensity and the resulting slope responses, as well as the spatial variability of the storms within the catchment area.

The paper by Martinello et al. (2023) [WP3: WP3_P15-PA_2_WP3_eng] investigates how the choice of mapping units influences the accuracy and effectiveness of landslide susceptibility models. The study uses multivariate adaptive regression splines (MARS) to analyze the relationship between various predictors and an inventory of 1608 rotational/translational landslides. Four types of mapping units were compared: standard grid cells (PX), contributing area-controlled slope units (5000_SLU), parameter-free multiscale slope units (PF_SLU), and a new type that combines hydrological partitioning with landform classification (LCL_SLU). Additionally, different slope unit (SLU) modeling strategies were tested on these mapping units, including pixel score zoning and re-modelling, as well as factor-based SLU re-modelling. The study concluded that the LCL_SLUs, which utilize zoned pixel-based score deciles for regression, provided the most reliable results, striking a balance between the high accuracy but scattered predictions from pixel-based models and the smooth but less accurate predictions from hydrologic SLU-based models, achieving an outstanding ROC_AUC of 0.95.

The paper by Martinello et al. (2021) [WP3: WP3_P15-PA_2_WP3_eng] tackles the crucial issue of choosing the right mapping units for landslide susceptibility modeling. The research employs MARS (Multivariate Adaptive Regression Splines) to analyze landslide susceptibility, drawing from a significant dataset of 12 predictors and 1608 cases. The study develops a pixel-based model, which is then applied across 10 different types of slope units generated by combining two half-basin (HB) and four landform classification (LCL) coverages. The main goal is to determine the most effective approach, which was found to be the integration of HB and LCL, as it outperformed simple HB classifications while maintaining most of the predictive power of the pixel-based model.

The paper titled Rosone et al. (2018) [WP2: Scheda CA WP2 UNIPA FRANA CERDA (PA); WP3: WP3_P15_PA_5_WP3_eng] analyzes the horizontal displacements and reactivation mechanisms of a large landslide within the Varicoloured Clay formation in Sicily, initially triggered by an earthquake in September 2002. To understand the impact of rainfall on landslide reactivation, a three-year monitoring program from 2008 to 2011 measured rainfall, pore water pressures, and deep and superficial displacements. The data identified three distinct landslides with varying directions and rates of movement, reactivated by increased pore water pressures during autumn 2009 to spring 2010. The study demonstrates the significant role of pore water pressures in slope stability and the correlation between displacement rates and cumulative rainfall over five months. Using simple models with three parameters to predict horizontal displacements, the study effectively forecasted displacement rates from September 2010 to May 2011, closely matching the actual measurements.

The research detailed in by Rosone et al. (2020) [WP2: Scheda CA WP2 UNIPA FRANA CERDA (PA); WP3: WP3_P15_PA_5_WP3_eng] examines the mechanisms behind the reactivation of a large landslide in Cerda, Sicily, Italy, with a focus on the effects of rainfall. The study is grounded in extensive field investigations aimed at evaluating the geotechnical characteristics of the landslide material, complemented by a three-year monitoring program that tracked rainfall, pore water pressures, and both deep and superficial displacements. The investigation revealed three separate landslides within the main area, each evolving at different rates and directions, highlighting the crucial influence of pore water pressures on slope stability. The research applied a conceptual and simplified model to one of these landslides to predict the time evolution of displacements in relation to pore water pressures, factoring in viscous forces on the slip surface under infinite slope conditions. The model's predictions closely matched the actual displacement measurements, thereby confirming its validity.

The technical note by Santucci de Magistris et al. (2013) [WP4: NA_2_WP4] discusses the establishment of a peak ground acceleration (PGA) threshold for defining liquefaction exclusion criteria, which is a common component in seismic codes and recommendations. The note presents a rational approach to setting this threshold and identifies a PGA limit of 0.09 g. This value is the outcome of a statistical analysis of background data that has been traditionally used to generate verification charts for assessing the liquefaction problem.

The paper by Santucci de Magistris et al. (2014) [WP2: Scheda CA WP2 Emilia; WP4: NA_2_WP4] critically examines the peak ground acceleration (PGA) threshold used in seismic codes for liquefaction exclusion. The authors developed a database of liquefaction case histories to conduct statistical analyses, which led to identifying a PGA threshold below which liquefaction is unlikely to occur, regardless of site conditions. The determined threshold value ranges between 0.07 to 0.1 g. This value was then evaluated in the context of the 2012 Emilia seismic events in Italy, known for numerous liquefaction occurrences at relatively low PGA values. Consequently, the study suggests that seismic codes should consider setting a PGA threshold at a lower probability level, specifically around 1%, to better prevent liquefaction risks.

The study by Esposito et al. (2021) [WP2: Scheda CA WP2 UNIROMA ROMA (SINKHOLE)] offers a methodology designed to aid in the management of underground pipelines in Rome, which are frequently jeopardized by spontaneous sinkhole formations due to the upward migration of pre-existing subterranean voids. This approach combines sinkhole susceptibility assessment, employing multivariate logistic regression based on extensive stratigraphic data, with advanced A-DInSAR satellite image processing. The A-DInSAR processing, enhanced by specially developed algorithms, produces maps indicating the density of subsiding reflectors that could potentially precede sinkhole collapses. These maps, when integrated with susceptibility assessments, identify critical 'hotspots' for further detailed examination. The validity of this method is substantiated by the recent sinkhole occurrences in Rome, demonstrating the efficacy of combining separate data sets to generate precise and targeted information for risk management and preventive measures.

Pepe et al. (2013) [WP2: Scheda CA WP2_UNIBA Regione Puglia; WP3: WP3_P12-BA_3_WP3_eng, WP3_P13-BA_3_WP3_eng, WP3_P15-BA_3_WP3_eng] outlined the importance of increasing sinkholes in the town of Altamura, situated in the Murge plateau of inland Apulia, Italy. Sinkholes, specifically those related to underground quarries in built-up urban areas were focused on this work. These quarries, largely used for extracting calcarenite—a local rock used for building purposes—have become increasingly destabilized due to abandonment and weathering, leading to surface-level sinkhole formation. The study documents sinkholes that have occurred since 2006, with a particular focus on their impact on urban and construction areas. In response, the local authority implemented new building codes in 2008, requiring detailed geological studies in at-risk areas to mitigate hazards. The study identifies anthropogenic activities, notably quarrying, as key triggers for sinkhole formation. The research incorporates a variety of factors such as cavity presence and depth, lithotypes, land use, hydrography, and seismicity, although tectonics and seismic data are less emphasized. Utilizing comprehensive input data like geophysical surveys, topographic information, and historical sinkhole records, the study outputs GIS-based models highlighting sinkhole susceptibilities. The mass movement central to this research is sinkhole formation due to subsurface void collapses, often exacerbated by human activities.

Lazzari et al. (2013) [WP2: Scheda CA WP2_UNIBA Fossa Bradanica; WP3: WP3_P8-BA_2_WP3_eng, WP3_P13-BA_2_WP3_eng, WP3_P15-BA_2_WP3_eng] details a study on landslide triggering and local rainfall thresholds in the Bradanic Foredeep region of Basilicata, Southern Italy. The research aims to establish empirical triggering thresholds for landslides, primarily triggered by short, intense storms characteristic of the Mediterranean climate. Addressing the hazard of landslide occurrences (both fast and slow landslides), the study examines factors like rainfall intensity and duration, though it finds no significant correlation between antecedent rainfall and critical rainfall events. The study made use of the least squares method to fit a line to the empirical rainfall data, represented in terms of rainfall duration (D) and mean intensity (I). Additionally, Kernel Density Estimation was applied to these data points, fitting the results with a Gaussian function to determine the probability density function of the distribution of differences in D (duration). The study further used the Frequentist method to establish local ID thresholds. It identified three specific thresholds – T50, T10, and T5 – which correspond to 50%, 10%, and 5% exceedance probabilities, respectively. By analyzing a catalog of 97 rainfall events linked to landslides over 85 years, the study successfully establishes local rainfall intensity-duration (ID) thresholds for predicting landslides.

Bovolenta et al. (2016) [WP2: Scheda CA WP2 UNIGE LiguriaPiemonte; WP3: WP3_P14-GE_1_WP3_eng, WP3_P15-GE_1_WP3_eng; WP4: GE_1_WP4] details a comprehensive GIS-based landslide susceptibility assessment in the Liguria and Piedmont regions of North-Western Italy, using a logistic multiple regression approach. This study is distinctive for its thorough consideration of geomorphologic, geological, climatic, and anthropogenic factors, including the impact of infrastructure. The model, calibrated across these diverse regions, produces maps indicating landslide probabilities, complemented by error maps and statistical coefficients like the Akaike Information Criterion (AIC) and the R^2 correlation coefficient. These outputs not only offer probabilities of landslide occurrence but also quantify the relative

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influence of each factor, aiding in effective risk assessment and mitigation planning in these geologically diverse areas.

7. Rationale for the usage of ML and DL in mass wasting processes

7.1 Rationale based on LEs

In this section, we propose LE-level toolchains related specifically to the application of ML and/or DL methods to the selected processes and environments. The definition of the toolchain design follows standard block-diagram recommendations and stems from the structure of the LE-derived process-based forms of WP2 and WP3 that have produced the set of available tools. Specifically, the block units always include an input and an output data component. Furthermore, to adequately address the recommended conceptual and logical scheme of application of machine learning methods, blocks related to pre-processing, processing, and post-processing are included (see below). Quite often, the pre-processing stage encompass several different types of data cleaning and data transformation methods that are not discussed nor described here, as they are explicitly accounted for in WP2, WP3, and WP4 process/parameter/stage deliverables. Almost in all cases, the post-processing includes some form of accuracy assessment and/or of validation of results, before generating outputs in various form.

When relevant to the described toolchain, as each operational block may be founded on existing state-of-the-art open-source technology, we specify the used or the available toolsets, libraries, and codes, in white-filled link boxes.

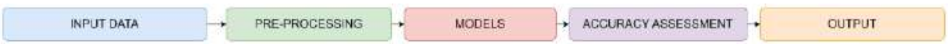

Figure 3 – A general workflow of the toolchain with modules for the input data, pre-processing prior to modelling, model selection, accuracy assessment of the outputs, and reporting final outputs.

The following flowcharts delineate a structured methodology applied in geohazard analysis in the form of a VS2 toolchain. The toolchains are meant to be specific but replicable to similar conditions. For this reason, where suitable, more than one LE is used to generate a single toolchain that may serve as a unique solver for the specific problem of analysis. Several toolchains are outlined, each tailored to address specific processes and analysis steps. For each case, input data, pre-processing steps, models used, accuracy assessment, and expected output are indicated.

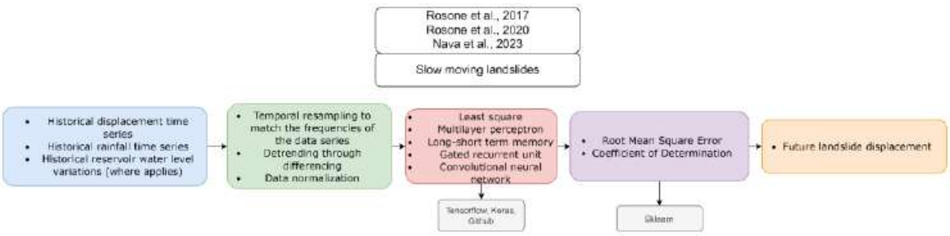

Figure 3 – Toolchain for slow moving landslide displacement forecasting (Rosone et al. 2018, 2020; Nava et al., 2023).

The Rosone et al. (2018, 2020) and Nava et al. (2023) case studies utilize historical monitoring data for predicting future landslide displacement through regression-based deep learning neural networks. The targets of this workflow are monitored slow moving landslides. The models are designed to handle stationary time series as inputs, with the landslide displacement as the target variable. Exogenous variables, such as rainfall and, where applicable, water level changes, drive the landslide accelerations. To facilitate modeling, cumulative displacement and water level data can be differenced to derive instantaneous changes. A temporal resampling process, involving upsampling, interpolation, and downsampling, is applied to standardize the row displacement data into time series with consistent time steps. If necessary, the rainfall time series can be downsampled by summation. Once all the time series share the same frequency, steps with no data are removed, and outliers are filtered out. Subsequently, the processed data series are inputted into the MLP, LSTM, or GRU models, as outlined in the open-source code available on GitHub at https://github.com/lorenzonava96/Landslide-Displacement-Forecasting-using-seven-Deep-Learning-architectures-and-monitoring-data/tree/main/Codes. Accuracy assessment involves employing Root Mean Square Error and R2 metrics, comparing predicted versus measured displacement in a calibration year.

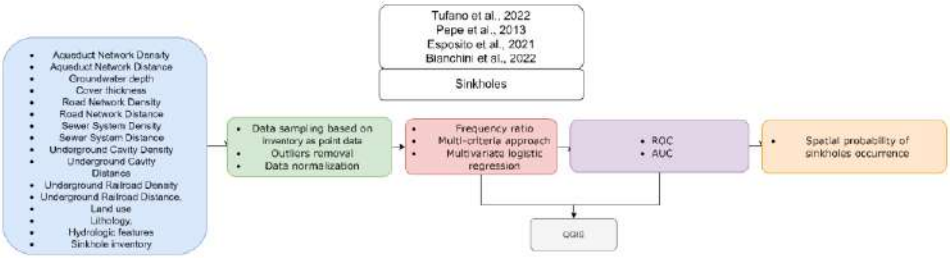

Figure 4 – Toolchain for spatial probability of sinkholes occurrence (Pepe et al., 2013; Bianchini et al., 2022; Esposito et al., 2021; Tufano et al., 2022).

The susceptibility analysis for sinkholes (Pepe et al., 2013; Bianchini et al., 2022; Esposito et al., 2021; Tufano et al., 2022) utilize ML models as the predictive models. This approach leverages the Frequency Ratio method, a spatial analysis technique, to predict sinkhole susceptibility based on the spatial distribution of contributing factors derived from input maps. In this methodology, historical data and spatial information are amalgamated to assess the likelihood of sinkhole occurrences. The model is configured to handle map-based input data. The sinkhole susceptibility is identified as the target variable, and the FR model considers various exogenous factors to formulate predictions. These factors encompass Aqueduct Network Density, Aqueduct Network Distance, Groundwater depth, Cover thickness, Road Network Density, Road Network Distance, Sewer System Density, Sewer System Distance, Underground Cavity Density, Underground Cavity Distance, Underground Railroad Density, Underground Railroad Distance. The FR method, tailored for spatial analysis, assesses the spatial distribution of factors related to sinkhole occurrences. Preprocessing involves preparing the spatial data and sampling for the FR model. This may include scaling or normalizing the input features, handling missing values, and ensuring consistent map resolutions. The model is then trained using historical sinkhole data, allowing it to discern and generalize patterns from the input data. The outcome of the FR model is a susceptibility map, highlighting areas with an elevated likelihood of sinkhole formation based on the frequency of relevant factors observed in the training data. The performance of the model can be assessed using appropriate metrics, such as the area under the curve (AUC) and receiver operating characteristic (ROC) curve.

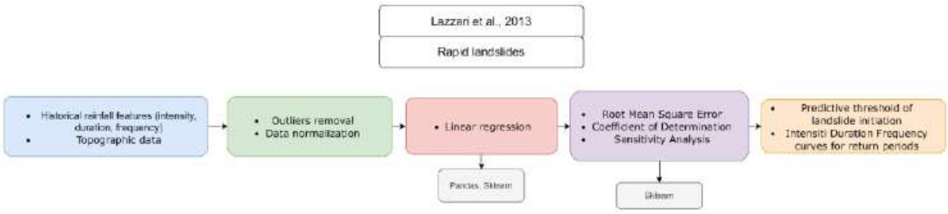

Figure 5 – Toolchain for intensity duration frequency curves (Lazzari et al., 2013)

The study case Lazzari et al. (2013) on rainfall intensity-duration (ID) relationships adopts a statistical frequentist approach inspired by Brunetti et al. (2010). It explores a power-law relationship between rainfall mean intensity and event duration. Following log transformation, a linear equation is fitted to log-transformed rainfall conditions, akin to a power-law in linear coordinates. Differences between the logarithm of event intensity and the fitted value are calculated for each event. The probability density function (PDF) of these differences is determined through Kernel Density Estimation and fitted with a Gaussian function. Using a sufficient amount landslide-triggering rainfall events in the Bradanic Foredeep region (1924–2009), three local ID thresholds (50%, 10%, 5%) are determined. Normalizing intensity with mean annual rainfall (MAP) refines the "intensity–duration" approach, emphasizing regional climatic conditions. This methodology offers a comprehensive framework for deriving rainfall thresholds for landslide susceptibility, incorporating statistical and regional climatic considerations.

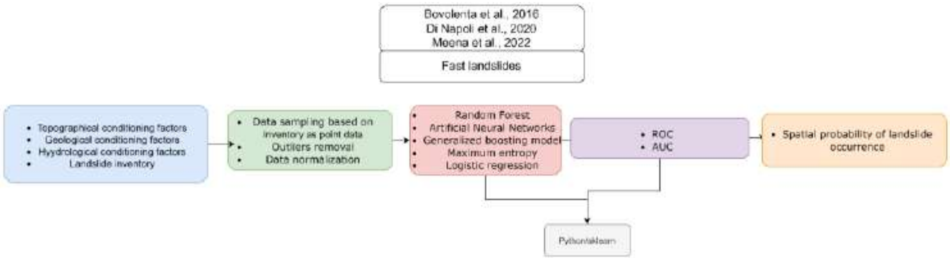

Figure 6 – Toolchain for spatial probability of landslide occurrence (Bovolenta et al., 2016; Di Napoli et al., 2020; Meena et al., 2022)

Three study cases (Bovolenta et al., 2016, Di Napoli et al., 2020, and Meena et al., 2022) describe the procedure to produce landslide susceptibility map. These approaches leverage ML models to predict landslide susceptibility based on the distribution of predisposing and factors derived from input maps. In this methodology, historical data and spatial information are amalgamated to assess the likelihood of landslide occurrences. The model is configured to handle map-based input data. The landslide susceptibility is identified as the target variable, and the RF model considers various exogenous factors to formulate predictions. These factors encompass topographical, geological and hydrological conditioning factors. The RF and XGBoost methods, tailored for spatial analysis, assess the spatial distribution of factors related to landslides occurrences. Preprocessing involves preparing the spatial data and sampling for the models. This may include scaling or normalizing the input features and handling missing values. The model is then trained using historical landslide data, allowing it to discern and generalize patterns from the input data. The outcome of the models is a susceptibility map, highlighting areas with an elevated likelihood of landslide occurrence based on of relevant factors observed in the training data. The performance of the model can be assessed using appropriate metrics, such as the area under the curve (AUC) and receiver operating characteristic (ROC) curve.

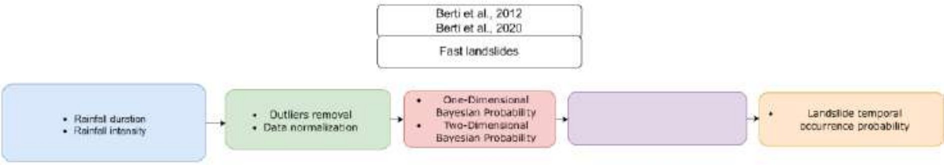

Figure 7 – Toolchain for landslide temporal occurrence probability (Berti et al., 2012, 2020)

The study cases Berti et al.,2012 and Berti et al., 2020 on rainfall-Induced landslide analysis shows that rainfall data duration and intensity are fundamental in understanding the triggering mechanisms of fast landslides. After preprocessing, the workflow employs Bayesian probability methods in one and two dimensions to predict the temporal occurrence probability of landslides. This probabilistic approach is key for anticipating landslides and implementing early warning systems. These workflows collectively highlight the application of various statistical and machine learning techniques to assess and predict geohazard risks, each tailored to specific types of ground movement phenomena and informed by a combination of geological, hydrological, and environmental data.

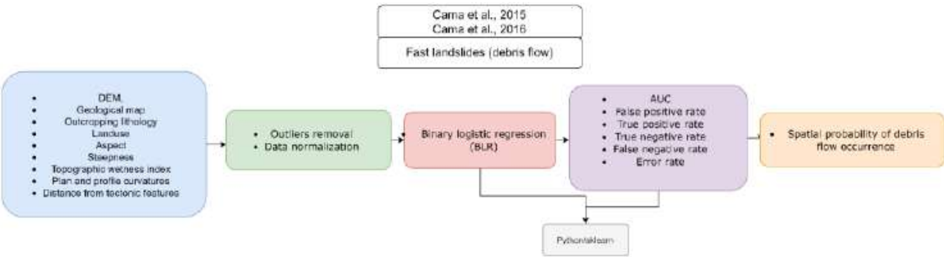

Figure 8 – Toolchain for spatial probability of debris flow occurrence (Cama et al., 2015, 2016)

The study cases Cama et al., 2015; Cama et al., 2016 focuses on fast landslides, beginning with inputs from Digital Elevation Models (DEM), geological maps, and other geomorphological factors. The Binary Logistic Regression model trained on this data aims to predict the spatial probability of occurrence of fast landslides, providing crucial insights for hazard mitigation and emergency planning.

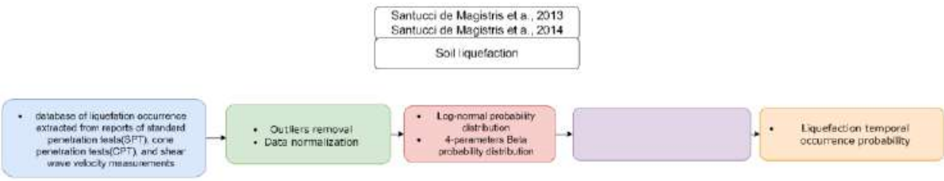

Figure 9 – Toolchain for liquefaction temporal occurrence probability (Santucci de Magistris et al., 2013, 2014).

The study cases De Magistris et al., 2013; De Magistris et al., 2014 focuses on soil liquefaction potential, beginning with inputs from a database of historical liquefaction, SPT, and CPT tests. After preprocessing, the workflow uses probability distribution functions to establish the relationship between the inputs and the occurrence of soil liquefaction. The final output is landslide temporal occurrence probability.

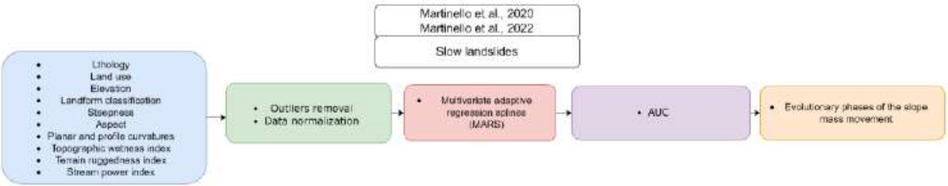

Figure 10 – Toolchain for evolutionary phases of slow landslides movement (Martinello et al., 2020, 2022)

The study cases Martinello et al., 2020; Martinello et al., 2022 focuses on analyzing slow landslides using various input parameters such as lithology, land use, and several topographical indexes (elevation, steepness, curvature, etc.). These inputs are first processed to remove outliers and normalized. The methodology employs Multivariate Adaptive Regression Splines (MARS), a non-parametric regression technique that captures complex nonlinear relationships between variables. The model's performance is assessed using the Area Under the Receiver Operating Characteristic curve (AUC), which evaluates the predictive accuracy. The output is a characterization of the evolutionary phases of slope mass movement.

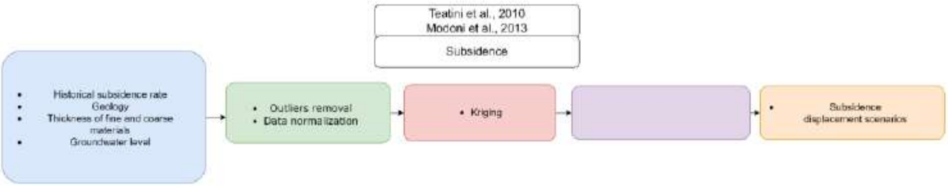

Figure 11 – Toolchain for subsidence displacement scenarios (Teatini et al., 2010; Modoni et al., 2013)

The study cases Teatini et al., 2010; Modoni et al., 2013 utilizes a workflow starting with key input factors for subsidence analysis: historical subsidence rate, geology, thickness of fine and coarse materials, and groundwater level. These inputs undergo preprocessing steps, including outliers' removal and data normalization, to ensure data quality and comparability. The workflow then applies the geostatistical technique of Kriging, which interpolates and predicts values in unmeasured locations, culminating in the generation of subsidence displacement scenarios. This model aids in understanding the spatial distribution and potential future occurrences of ground subsidence.

7.2 Rationale from general cases

From the experience learned from the LEs analysis and the larger set of knowledge coming from an internal Task-related state-of-the-art review, as well as from the shared knowledge within the entire VS2 group, it is possible to attempt a first preliminary generalization step that distills some of the selected toolchains into larger-scope, general-purpose toolchains that will form the conceptual and logical basis for the parts of PoC which are related to machine learning and deep learning techniques applied to ground instability detection, measurement, monitoring, modelling, and forecasting.

Among them, we have selected only a few relevant ones according to what has emerged from the work of Task and DV2.3.4.

7.2.1 Ground displacement mapping with ML/DL

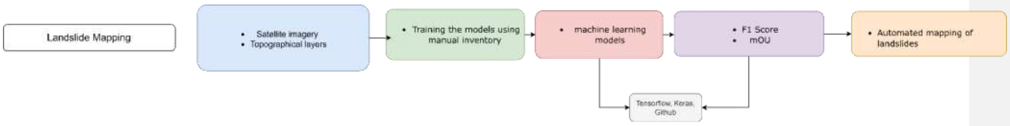

Figure 12 – General toolchain for automated mapping of landslides.

Ground displacement mapping may be in general done or improved greatly by recurring to a series of standard ML and DL tools such as those employing optical, multi-spectral, and/or SAR images acquired by any available platform at a suitable scale. In all cases, input data requires ancillary information (such as DEMs) to improve classification, a training ground-truth set, and the images to be used. ML and/or DL methods to be applied for the mapping can be tailored to pixel, cluster, patch, or segmentation scale, depending on needs and input data accuracy. After training and testing of the models, accuracy assessment methods are mandatory, in the form of standard scores (F1-score, Accuracy, etc.). Output metrics depend on the application type. For building risk scenarios with further analysis, the use of a scaled, continuous probability output (either normalized or absolute) is recommended. Analysis and modelling can be easily implemented due to the availability of a number of validated and open-source libraries, code-examples, and toolboxes (see examples in the toolchain).

7.2.2 Ground displacement susceptibility with ML/DL

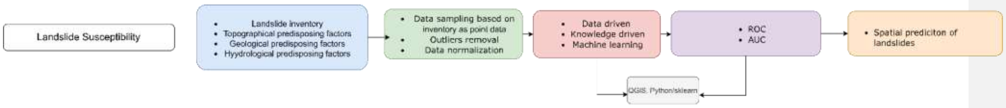

Figure 13 – General toolchain for spatial prediction of landslides.

The susceptibility of a tract of land of being subject to ground displacements is nowadays computed with standard and widely accepted methods belonging to the broader AI realm. Among them, multi-variate ML and DL methods are frequently used, also in terms of ensemble combinations. The proposed general-purpose toolchain mirrors this established procedure, starting from the input datasets that must include all available predisposing (see WP2 Tasks) and preparatory (see WP3 Tasks) factors. A relevant and reliable mapping of ground truth must also be available (see Mapping Toolchain and WP2 Tasks). The data pre-processing may often be supported by ML techniques with special reference to those useful to apply dimensionality reduction and parameter selection. Analysis mainly consists in training and testing the model until a desired level of accuracy is reached, in an iterative process connecting pre-processing, processing, and post-processing. Accuracy estimation is not only based on metrics such as F1-score but also on graphical supports such as ROC curves and derivations. As in the case of mapping, output depends on operational needs. For building risk scenarios with further analysis, the use of a scaled, continuous probability output (either normalized or absolute) is recommended. Analysis and modelling can be easily implemented due to the availability of a number of validated and open-source libraries, code-examples, and toolboxes (see examples in the toolchain).

7.2.3 Ground displacement forecasting with ML/DL

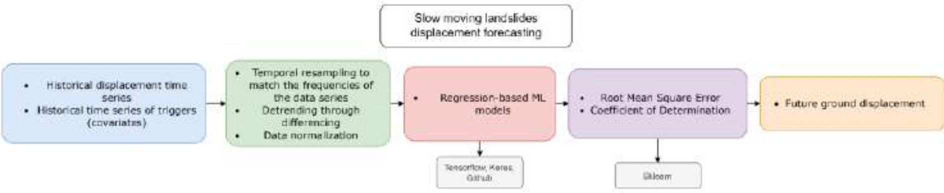

Figure 14 – General toolchain for ground displacement forecasting.

Efficient forecasting of ground displacements can be achieved or significantly enhanced through the application of regression machine learning (ML) and deep learning (DL) tools. These tools utilize historical monitoring data such as displacement and triggering covariates. Following model training and testing, the application of accuracy assessment methods, including standard scores like root-mean square error (RMSE), and coefficient of determination R^2, becomes mandatory. The implementation of analysis and modeling is facilitated by the availability of validated and open-source libraries, code examples, and toolboxes, as demonstrated in various examples within the toolchain.

8 Conclusions

By providing practical toolchains for the integration of AI methodologies into mass movement hazard mitigation, the document contributes to defining a framework for the implementation of ML and DL methods in ground displacement risk mitigation and assessment. This implementation should empower decision-makers with data-driven insights, facilitating more informed choices in areas such as land-use planning, infrastructure development, and emergency response, treated by other Return Spokes with special reference to TS1, TS2, TS3. Moreover, the document should also facilitate interdisciplinary collaboration, bridging the gap between domain-specific knowledge and advanced data analytics. This collaborative approach ensures a holistic and comprehensive perspective in hazard assessment and management and makes it possible a smoother transition between conceptual modelling and logical/physical implementation of procedures in a PoC software. Crucially, the document does not merely address present challenges but acts as a forward-looking guide, preparing for future developments in ML applied to mass movements risk assessment.

The review carried out within the Task underlined the following gaps. Deep learning (DL) applications in the domain of mass movements, encompassing processes like landslides, subsidence, soil liquefaction, sinkholes and submarine landslides, reveals a significant gap in current research and tool development, as per the available learning examples. Mass movements, characterized by complex and dynamic behaviors influenced by geological, climatic, and topographical factors, pose challenges that DL could potentially address. The scarcity of DL in this context may limit the possible outcomes of the predictive models, potentially impeding our ability to anticipate and mitigate the impact of these events on population and infrastructure. Moreover, the deficiency in machine learning (ML) applications tailored specifically for submarine landslides highlights a critical gap in our ability to understand and mitigate the risks associated with these underwater events. Submarine landslides, challenging to study due to limitations in traditional data collection methods in underwater environments, could benefit significantly from ML's analytical capabilities. Initiatives should prioritize interdisciplinary collaboration between oceanographers, geologists, and data scientists to create robust ML models, coupled with explorative surveys to gather more data that can be capitalized for processing and interpreting submarine landsliding events effectively. Increasing collaborations and funding support for projects can address these unique challenges, thereby accelerating the development and integration of ML applications in this specific domain.

The absence of comprehensive ML/DL tools for multi-hazard assessment and runout estimation in the available dataset of LEs, as well as the building of risk scenarios, represents a critical gap in our ability to address natural hazards related to mass movements effectively and should be addressed in the next project phase. Current limitations in available tools and data hinder our capacity to synoptically evaluate the complex interplay of multiple hazards and accurately estimate their potential risk with the help of developed AI methods. The lack of dedicated tools for constructing risk scenarios further impedes our ability to develop robust mitigation strategies. A suite of integrated tools is essential for assessing the cascading effects of various hazards, understanding their combined impact, and formulating effective risk management plans. These aspects will be covered by WP4 tasks, which offers a possible framework for multi-hazard evaluation and risk scenario building through the implementation of toolchains loops. This, however, does not imply that AI-related methods that could be potentially used will be covered in a second project phase. Our recommendation, on this issue, is to take into account possible ML and DL methodologies, potentially of impact on runout and multi-hazard assessment, during the PoC implementation phase, by recurring to the content of this document and of the relevant cited literature.

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