Sensor-based slope stability prediction using a digital twin and AI-driven stability forecasting

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Keywords: Mems, Digital twin, land slope, Machine Learning, IA.
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Abstract
The need for better geological risk management techniques has increased due to the frequency and severity of natural disasters like floods and landslides, which are being caused by urbanization and climate change. Such management has always depended on limited simulations and static models derived from historical data. But more dynamic methods for modelling physical situations in real time and predicting future events are now available thanks to recent developments in digital technology, especially Digital Twins (DT). The use of DT in landslide prediction is examined in this work, with an emphasis on the use of inexpensive sensors in real-time monitoring of vital environmental factors such ground movement, pore water pressure, and volumetric water content. The research was conducted on a test site located on the Feo di Vito hill within the University of Reggio Calabria, a geologically vulnerable area. The proposed system integrates real-time environmental monitoring with advanced modeling and predictive techniques, ultimately supporting early risk detection and response. Results highlight the potential of this approach to enhance forecasting accuracy and responsiveness, offering an effective, scalable, and low-cost decision-support tool for mitigating landslide risk in vulnerable areas.

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1. Introduction

Climate change, increasing urbanization, and the rise in extreme weather events are making natural hazards such as floods and landslides more frequent and severe. These events can cause extensive damage to human life, the environment, and critical infrastructure.
Rainfall-induced landslides are a major geological hazard, especially in tropical and subtropical regions, leading to significant loss of life and infrastructure damage. The infiltration of precipitation leads to rapid changes in water content and other conditions—such as increased soil weight, changes in pore water pressure (PWP), and ground deformation—that can severely compromise slope stability and trigger landslides.
Traditionally, hydrogeological risk management systems have relied on static models based on historical data from past events. However, advances in digital technologies have introduced innovative tools, such as Digital Twins (DTs), that can replicate the physical conditions of a given area in real time and simulate predictive scenarios based on dynamic variables like rainfall, soil saturation, and ground movement.
A Digital Twin is a virtual representation of a physical product, system, or process that enables real-time monitoring, simulation, analysis, and decision-making (Grieves, 2014). The key feature of a Digital Twin is its ability to bridge the physical and virtual worlds, providing a simulated environment in which hypotheses can be tested, scenarios modelled, and outcomes predicted—without direct interference with the actual physical object (Li & Duan, 2024).
The concept of the Digital Twin was introduced by Michael Grieves in 2002 at the University of Michigan in the context of Product Lifecycle Management (PLM). The original model was based on three core components: the physical space, the virtual space, and the flow of data and information between them (Grieves & Vickers, 2016)
The term "Digital Twin" first appeared in a draft of NASA's technology roadmap (Shafto et al., 2010), and was later adopted by the U.S. Air Force to support the design and maintenance of aircraft (Tuegel et al., 2011, Gockel et al., 2012).
The use of Digital Twins offers several key advantages: reducing errors and inefficiencies, accelerating prototyping, improving safety through remote monitoring, and cutting costs, since updates and testing occur entirely in a virtual environment (Singh et al., 2021).
DT technology is now widely applied across many industries (Singh et al., 2022), including aerospace (Li et al., 2021, Ferrari & Willcox, 2024), construction (El Jazzar et al., 2020; Sacks et al., 2020; Tuhaise et al., 2023), cultural heritage (Barrile & Fotia, 2022; Barrile et al., 2011), oil and gas (Bo et al., 2020; Priyanka et al., 2022; Shen et al., 2021), healthcare (Elayan et al., 2021; Sun et al., 2023) and agriculture (Elayan et al., 2021; Sun et al., 2023; Barrile et al., 2021).
In the field of hydrogeological risk, Digital Twins enable enhanced event forecasting, better emergency management, and more effective mitigation planning. These models can incorporate detailed representations of landscapes, river basins, infrastructure, and weather systems—all with the goal of monitoring high-risk conditions in real time and predicting imminent hazards. In particular, DTs play a crucial role during the forecasting phase, using meteorological predictions to assess slope stability and anticipate landslide risks.
This study aims to predict slope stability by analyzing various hydrological, meteorological, and vegetation-related variables.
The first section presents the results obtained through the use of a slope-specific Digital Twin—a virtual model that simulates and monitors the terrain's behavior in real time. This is followed by an analysis of hydrological predictions, which are fundamental for understanding how moisture, precipitation, and

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This contribution has been peer-reviewed.

runoff affect slope instability. The study also explores the use of data-driven models that rely on collected variables to predict the Factor of Safety (FOS)—a critical parameter for assessing slope security and landslide risk.
Finally, the paper outlines the operational framework of the Digital Twin system, which leverages low-cost sensors to collect real-time data. This approach ensures continuous, scalable, and cost-effective monitoring of slope conditions, opening the door to more proactive and intelligent risk management.

2. Materials and methods

2.1 Study area

The study area is located in the city of Reggio Calabria, in South Italy. The city is collocated on the slopes of Aspromonte mountain and is separated from Sicily Island by the Strait of Messina. Unfortunately, the city and its hinterland are characterized by a hilly and mountainous landscape, with a complex geology that can accentuate the risk of landslides and flooding
The first experimentation of this approach was applied in the hilly reliefs in the locality of Feo di Vito, Reggio Calabria, an area located within the Mediterranean University of Reggio Calabria, precisely in the part that hosts the Faculty of Agriculture, as shown in the following figure, figure 1. This area already subject to studies to monitor slope stability (Barrile et al., 2014).

Figure 1. Study area.

In order to provide a more scientific framework, next figure (figure 2) shows the pedologic region of the study area (ARSSA, 2003). In detail, the soils in the study area fall within soil province 6.9 characterized by steep and steep slopes. the texture is medium-textured with neutral or subalkaline reaction, high surface stoniness.

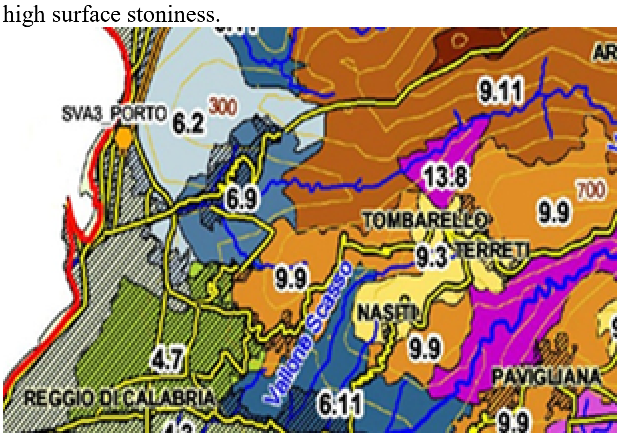

Figure 2. Pedologic region of the study area.

2.2 Mems and sensors

For this study, several sensors were strategically installed across the slope to continuously monitor key geotechnical and hydrological parameters, including volumetric water content (VWC), soil temperature, and pore water pressure. These values are fundamental variable in managing geotechnical hazard and ensuring slope stability. VWC refers to the volume of water retained by the soil pore system; higher VWC values are correlated to reduction in matric suction and a decreasing in soil shear strength. Soil temperature regulates several dynamics, in particular phase changes (e.g., freeze-thaw cycles) which can alter pore structure and soil’s permeability, in turn influencing the movement and retention of water inside the soil matrix
The sensors were distributed both horizontally, to capture spatial variations across the slope surface, and vertically, to assess how soil conditions evolve with depth.
All sensors are connected to a centralized microcontroller system that collects data at regular intervals, storing it for long-term analysis and transmitting it in real time to a monitoring platform. This system supports the visualization of data through interactive dashboards, which allow for real-time trend analysis, threshold-based alert generation, and historical data evaluation.
The following table, table 1, summarizes the sensors utilized for the experiment.

Sensor	**Variable**	**Measurements time interval**
YL-69	Volumetric water content (VWC) Soil moisture	5-10 minutes
DS18B20	temperature	5 minuti
GEOTECH PVT	Pore Pressure (PWP)	1 hour

Table 1. sensors used for the experiment.

The sensors used were placed on the top of the slope at different pro-depths 0.1 m, 0.5 m, 1 m, 2 m, 4 m and 6 m. In contrast, GEOECH PVT electronic piezometers (Figure 3) were installed at four different depths: 6 m, 9 m, 15 m and 23 m.

Figure 3: Piezometer

2.3 Digital twin creation

Regarding slope stability, DT could be seen such as a realistic virtual replica of a slope, created in order to simulate, analyze and forecast the behaviour of the slope under different conditions. This digital replica integrates geotechnical, environmental and hydrological information with data from multiple sources, including field surveys, monitoring data and meteorological conditions, to provide a complete and dynamic representation of the slope.
A parametrically adjustable virtual environment was also created, starting from a three-dimensional base model and using the modeling software Rhinoceros (McNeel & Associates, 1993), together with the visual programming tool Grasshopper (Davidson, 2021) and the Firefly plugin, in order to integrate data collected from the MEMS sensors.
Data from Mems are used as input in Rhinoceros 3D, which through the Grasshopper plug-in allows the prediction of the hydrological Variables (VWC and PWP) for seven consecutive days.
In this virtual environment modelled with Grasshopper, a 3D model of the area under study was created. This model can be modified based on the coordinates of the nodes, which represent the points in three-dimensional space used to define the geometry of the virtual terrain.
The Firefly plugin powers the model by sending sensor data to the Grasshopper environment, allowing changes in the real world to be processed in real time (or using stored data) within the virtual world. In this way, the virtual environment reproduces real conditions.
Node coordinates represent points in three-dimensional space that define the geometry of the virtual terrain.
Data collected by sensors and weather forecasts, such as precipitation (P) and temperature (T) are used, together with other variables explained ahead, to calculate variables such as the Factor of Safety (Fos), which helps assess the stability of the terrain.
Next, for the simulation of the landslide we will use the Unreal Engine graphics engine, developed by Epic Games.
To work directly in the two environments in a fluid way, we will install the Rhino Inside Unreal plugin on both Rhinoceros 3D and Unreal Engine. Rhino Inside Unreal creates a direct connection between the two software, allowing the visualization of the Rhinoceros 3D models within the Unreal Engine interface.

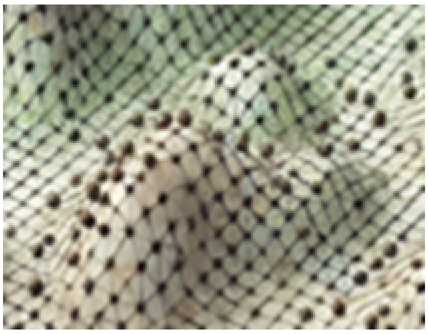

Figure 4: example of Node and sensor distribution

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The predicted VWC and PWP values, along with predictions of climate and vegetation variables, are used as inputs to data-driven models to predict Fos (factor of safety).
VWC and PWP values are modeled using both sto-ric measurements and forecasts of precipitation (P), air temperature (T). Historical and forecast metereological data are retrieved from Online resources. Meteorological data together with Leaf Area Index (LAI) are used as input in Rhinoceros 3D to predict hydrological variables. The LAI is a measure of leaf area per unit land area and is an essential parameter for the study of forest and agricultural cover.
Subsequently, the simulation of the landslide phenomenon will be carried out using the Unreal Engine graphics engine, developed by Epic Games, famous for its high-performance real-time rendering capabilities and support for complex interactive environments.
To ensure seamless integration and workflow between the modelling and simulation environments, we will install the Rhino Inside Unreal plugin on both Rhinoceros 3D and Unreal Engine. This plugin establishes a direct connection between the two software platforms, allowing Rhinoceros 3D models to be visualized and manipulated directly within the Unreal Engine interface—eliminating the need for manual exporting or file conversion processes. This connection significantly improves efficiency and maintains model fidelity throughout the workflow.
For online visualization and remote interaction, we will use Pixel Streaming, a native feature of Unreal Engine. Pixel Streaming allows the simulation of the 3D model—specifically, the area of interest affected by the landslide—to be broadcast in real time directly to a standard web browser. This makes it possible to view and interact with the simulation remotely, without the need for specialized software or powerful local hardware.
Methodology is resumed in the following figure (figure 5)

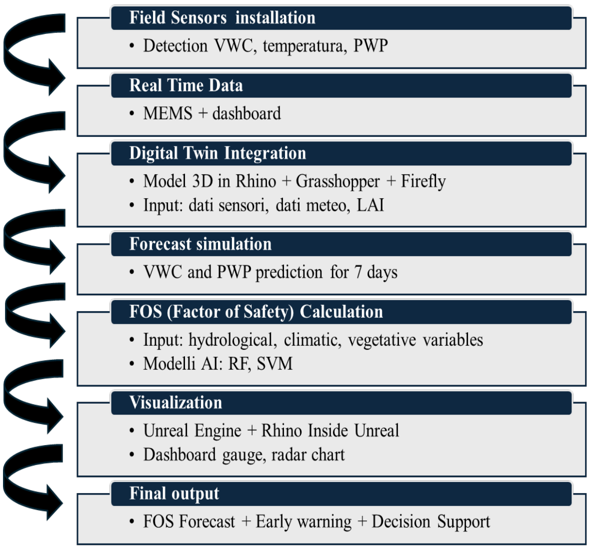


Figure 5: proposed methodology

2.4 Data-based model

A validated numerical slope model was defined in (Piciullo et al., 2022). The model was used to calculate FOS using six different 1-year period datasets: 4 belonging to the past and 2 to the future. The time-dependent input variables used are divided into meteorological and vegetation. They are P, T, Leaf Area Index.
Daily and forecasted data of P and T were obtained from different sources, such as satellite data and online repositories.
The trends of the variables examined are summarized in the following figure (figure 6).

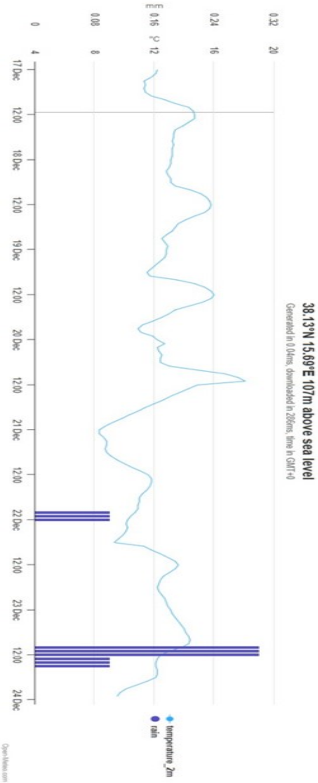


Figure 6: trends of climatic variables.

2.5 Data-based IA model for slope stability prediction

The next step involved training data-driven model to predict FOS through the incorporation of different variables.
This was obtained with the aim of defining the relationship between FOS and meteorological, hydrological and vegetation variables.
Different Data-driven models were considered for FOS forecasting:

- Linear Regression,
- Polynomial Regression,
- Random Forest (RF),
- Bayesian Ridge,
- Multilayer Perceptron,
- Support Vector Machine (SVM)

The best scores were achieved from RF and SVM.
SVM finds the optimal hyperplane that best separates data points of different classes in a high-dimensional space. This hyperplane is chosen to maximize the margin between the classes, which helps improve generalization on unseen data. SVM can handle both linear and non-linear classification problems. SVM is known for its robustness, especially in high-dimensional spaces, and is widely used in areas such as image recognition, bioinformatics, and text classification.
RF, instead, works by building a large number of decision trees during training and outputting either the mode (for classification) or the mean (for regression) of their predictions.
The key idea behind Random Forest is to improve accuracy and reduce overfitting by combining the predictions of multiple decision trees. Each tree is trained on a random subset of the data and at each split, a random subset of features is considered.

3. Results

Unlike common practices that rely on empirical threshold values and displacement monitoring for slow-moving landslides, the proposed approach is characterized by its exclusive reliance on hydrological and meteorological parameters. This paper presents the implementation of a Digital Twin model of a slope system, capable of replicating hydrological behavior as a function of vegetation characteristics and dynamically varying meteorological inputs. The Digital Twin was developed using Rhinoceros 3D and Unreal Engine, and integrated data from low-cost in-situ sensors alongside meteorological datasets derived from ERA raster files. These inputs are processed by a numerical model that simulates the slope's hydrological response and estimates its Factor of Safety (FOS). While sensor deployment presents limitations, such as potential issues with measurement accuracy, material durability, and real-time data transmission, the predictive model compensates by enabling hydrological forecasting.
FOS estimations are generated through data-driven models, and although not all sources of uncertainty in the physical system are captured, the application of a machine learning techniques model contributes to enhanced predictive performance.
To facilitate interpretation and operational use, the dashboard was designed to present both hydrological and geotechnical forecast variables in a clear and intuitive manner. While the Factor of Safety (FOS) values are inherently easy to interpret, the meaning of hydrological variables such as Volumetric Water Content (VWC) and pore water pressure (PWP) becomes relevant only when contextualized against historical measurements taken at corresponding locations and depths. To this end, forecasted hydrological variables are displayed using a radar chart (figure 7), which allows users to assess the relative magnitude of each variable in a compact visual format.Figures and Tables.

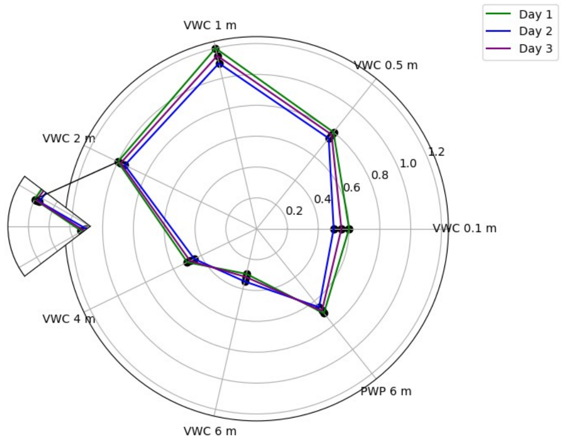


Figure 7: Radar chart of VWC.

On the other hand, gauge indications are used to depict the predicted FOS values (Figure 8), where each gauge corresponds to a one-day forecast. This method makes it easier to quickly and easily evaluate slope stability across brief time periods, which is essential for early warning applications.

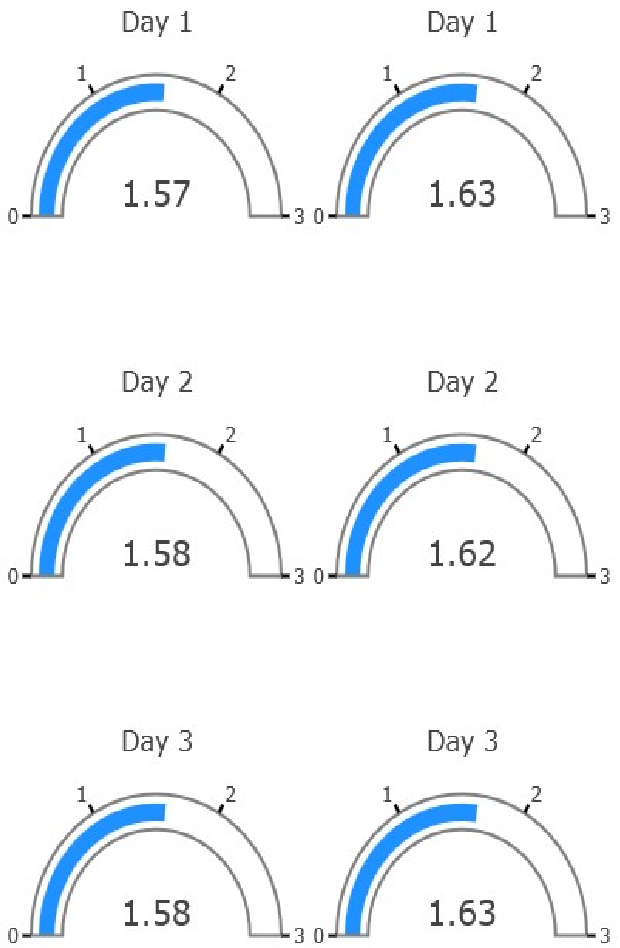
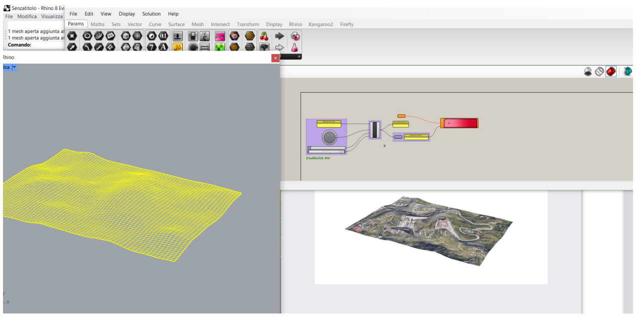


Figure 8: gauge charts of FOS forecast.

Users can also monitor the temporal evolution of all forecasted variables by using the dashboard's time series graphs. Real-time observations from in-situ sensors are superimposed on predicted hydrological parameters to enable direct comparison. When significant differences between expected and observed values are found, this configuration facilitates anomaly detection and the use of quality control measures. The dashboard offers a powerful tool for well-informed decision-making in landslide early warning systems by combining forecast models, historical data, and real-time monitoring into a single visual interface.
Finally, the last figure (Figure 9) shows a digital twin of a spatial area, obtained by parametric modeling tools within the integrated working environment between Grasshopper and Rhinoceros.



4. Conclusion

Hydrogeological risk is among the most significant environmental threats globally, exacerbated by climate change, which has increased the frequency and intensity of extreme weather events. Among these, landslides brought on by rainfall are a major threat to infrastructure and people, underscoring the urgent need for creative risk monitoring, forecasting, and management solutions.
In order to better handle the complexity of landslide events, the current study suggested an integrated strategy that combines inexpensive sensors, digital twin models, and data-driven modeling tools. It was possible to create a system that could dynamically estimate the factor of safety (FOS) and provide easily comprehensible risk forecasts through interactive dashboards by processing important hydrological variables like volumetric water content (VWC) and pore water pressure (PWP) and using predictive machine learning models.
These results demonstrate that, even in regions with limited financial or technical resources, the utilization of scalable and easily accessible technology in conjunction with the capacity to deliver real-time updated forecasts can be a useful tool for reducing hydrogeological risk. However, there are still several obstacles to overcome, like the requirement for precise model calibration and the reliance on the quality, density, and consistency of field data.
In the future, the established system might be improved even more by incorporating satellite observations and growing the sensor network, which would allow for a multi-scale view of the phenomena and wider territory coverage. The use of increasingly sophisticated AI algorithms that can adapt to changing inputs could increase system resilience and prediction accuracy even more. This strategy might be transformed into an operational tool for the early protection of people and infrastructure by simultaneously integrating predictions directly with early warning systems and emergency management platforms in collaboration with civil protection agencies. A key component of sustainable land management may eventually be the incorporation of such technology into more comprehensive territorial planning and climate resilience plans.

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