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PREDICTION OF RAINFALL-INDUCED SHALLOW LANDSLIDES AT A GEOGRAPHICAL SCALE USING DEEP LEARNING: AN APPLICATION TO THE LIGURIA REGION (NW ITALY)

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EXTENDED ABSTRACT

Le frane superficiali pluvio-indotte rappresentano una tipologia di instabilità di versante molto diffusa in paesaggi collinari e montani. Tali fenomeni possono produrre impatti significativi sull'ambiente e sulla società, causando ingenti danni a infrastrutture, edifici, zone agricole e aree boschive, costituendo una importante fonte di rischio. Per tali ragioni, le attività di ricerca finalizzate a migliorare la previsione delle frane superficiali riveste grande importanza nell'ambito delle strategie di mitigazione del rischio geo-idrologico e dello sviluppo di sistemi di allertamento a supporto delle attività di protezione civile. Tuttavia, la previsione di queste peculiari instabilità del terreno risulta piuttosto difficoltosa a causa della loro natura complessa, tra cui l'assenza di indicatori geomorfologici precursori. La previsione spazio-temporale delle frane superficiali innescate dalle piogge si basa generalmente sull'applicazione di approcci empirici, fisicamente basati e stocastici, la cui scelta dipende principalmente dalla scala di analisi e dalla tipologia, numerosità e qualità dei dati a disposizione.

Nel presente studio viene presentato un *framework* probabilistico per la previsione spazio-temporale a scala geografica di frane superficiali pluvio-indotte. L'approccio metodologico proposto si articola in due fasi principali. Nella prima fase, basata su un'analisi statistica e su metodi di *deep learning*, l'occorrenza delle frane viene modellata come un esperimento casuale di Bernoulli con esito binario (*i.e.*, frana e non frana). Utilizzando il catalogo storico ITALICA (*ITAlian rainfall-induced LandslIdes CAtalogue)* delle frane superficiali indotte da pioggia avvenute in Italia e un dataset pluviometrico ventennale raccolto dai pluviometri della rete nazionale di Protezione Civile, viene stimata la probabilità di innesco delle frane nell'intorno di ciascun pluviometro. Nella seconda fase, tale probabilità, basata unicamente sulla pioggia, viene spazializzata e combinata con la suscettibilità, ossia la variabile spaziale che descrive la propensione al dissesto del territorio in base alle caratteristiche geo-ambientali. Per tale scopo, sono state utilizzate unità di mappatura della suscettibilità da frana disponibili in bibliografia. L'operazione di spazializzazione è stata effettuata utilizzando due tecniche di modellazione geometrica differenti: un approccio deterministico basato sulla tassellazione di Voronoi e un modello stocastico implementato tramite il software MUSE (*Modeling Uncertainty as a Support for Environments*).

Il framework probabilistico di previsione spazio-temporale delle frane superficiali è stato testato sull'intera regione Liguria durante un evento pluviometrico significativo verificatosi nei primi giorni di marzo 2018. Entrambi gli approcci si sono dimostrati affidabili nel prevedere l'occorrenza di frane superficiali a scala geografica, consentendo di mappare l'evoluzione spazio-temporale della probabilità di innesco di frane durante l'evento meteorologico analizzato. I risultati ottenuti dimostrano che l'integrazione delle informazioni geologico-geomorfologiche con le variabili meteorologiche può rappresentare un approccio efficace anche per applicazioni su scale geografiche. L'approccio proposto può rappresentare un utile strumento di supporto alle attività di Protezione Civile nella previsione e gestione di potenziali scenari di impatto al suolo in seguito ad eventi idro-meteorologici.

ABSTRACT

The present work addresses the implementation of a probabilistic framework for the spatio-temporal prediction of rainfall-induced shallow landslides at geographic scales. The methodological approach consists of two main phases. In the first phase, based on statistical analysis and machine learning, landslide occurrence is modelled as a Bernoulli experiment. Using a historical catalogue of rainfall-induced shallow landslides in Italy and a 20-year pluviometric dataset collected from the rain gauges of the national civil protection network, the probability of rainfall-induced landslide initiation is estimated at locations where rainfall data are available. In the second phase, the rainfall-based probability is spatialized and coupled with landslide susceptibility, a spatial variable that accounts for the influence of geological and geomorphological characteristics of the territory. Two techniques were used: a deterministic approach based on the Voronoi tessellation and a stochastic model implemented using the MUSE (Modeling Uncertainty as a Support for Environments) software. The coupled spatio-temporal forecasting model was tested over the entire Liguria region during a significant rainfall event that occurred in early March 2018. The outcomes showed that integrating both temporal and spatial variables is effective in forecasting rainfall-induced shallow landslides.

Keywords: *deep learning, prediction, rainfall, shallow landslides, susceptibility, stochastic framework, Voronoi diagram*

INTRODUCTION

Fast-moving rainfall-induced shallow landslides (SLs) are widespread types of mass movement in hilly and mountainous environments that typically mobilize thin (generally < 5 m) soil layers (Hungr *et alii*, 2014). These events are mainly triggered by intense and/or prolonged rainfall, which causes progressive soil saturation and a subsequent reduction in shear strength, ultimately leading to failure, which often develops along the interface between the soil cover and the underlying bedrock (Crosta & Dal Negro, 2003; Larsen, 2008; Harp *et alii*, 2009). Once the first failure has occurred, which is frequently sudden and without precursory signs of movement, the displaced mass can reach high speeds (> 5 m/s) and travel long distances, giving rise to dangerous and destructive phenomena such as debris avalanches, debris flows, and debris floods (Hungr *et alii*, 2014).

SLs represent a significant threat to people and infrastructures, resulting in severe potential risk scenarios (Papathoma-Köhle *et alii*, 2015; Galve *et alii*, 2016). However, predicting the occurrence of these mass movements is not an easy task due to their complex nature, which requires considering both rainfall-related triggering features (*e.g.*, intensity and duration) and terrain conditions (*e.g.*, geology, geomorphology, land use, and geotechnical characteristics), namely predisposing factors. Various approaches for the spatio-temporal forecasting of rainfall-induced SLs are available in the literature. The choice of the most suitable approach primarily depends on the scale of analysis, the available data, and the objectives of the study, with a main distinction between empirical, physically-based, and stochastic approaches (Corominas *et alii*, 2014). Empirical methods are based on the statistical analysis of past rainfall and landslide events and aim to define curves (*e.g.*, intensity-duration or cumulative-duration) that identify rainfall thresholds separating triggering from non-triggering conditions (Guzzetti *et alii*, 2008; Peruccacci *et alii*, 2017; Segoni *et alii*, 2018). Physically-based methods are based on the use of laws that allow the simulation of slope failure preparatory processes (*e.g.*, rainfall infiltration and subsurface groundwater flow) (Baum *et alii*, 2010). They are more suited to slope-scale stability analyses when geotechnical and geometrical properties are known, although they are also successfully implemented for the spatial prediction of landslides over large areas (*i.e.*, at basin scale), and the results can be expressed either in deterministic or probabilistic terms (Salciarini *et alii*, 2008; Salvatici e*t alii*, 2018; Raimondi *et alii*, 2023; Cui *et alii*, 2024). Methods based on probabilistic frameworks are designed to handle systems influenced by random variables and data uncertainty, returning results expressed in probabilistic terms. These approaches, which also include the use of neural networks and machine learning, are particularly effective in contexts characterized by natural variability, such as the prediction of landslides triggered by precipitation (Mondini *et alii*, 2023, 2025).

This work presents a new probabilistic framework for the spatio-temporal prediction of rainfall-induced SLs at the geographical scale. The proposed modelling approach involves the integration of a rainfall-based probability of landslide triggering, estimated using neural networks, with the landslide susceptibility of the terrain. To this end, the probability of landslide occurrence based on precipitation data was spatialized and coupled with landslide susceptibility using two different spatial distribution modelling approaches: the Voronoi diagram (Okabe *et alii*, 2009) and the MUSE software (Modeling Uncertainty as a Support for Environment) (Miola, 2025; Miola *et alii*, 2022). The proposed approach was tested using the Liguria region as a demonstration area by considering a rainfall event that occurred in early March 2018.

MATERIALS AND METHODS

Theoretical framework

In this study, the occurrence of a rainfall-induced SL was modelled as a Bernoulli trial with a binary outcome, namely landslide occurrence (value 1) and non-occurrence (value 0) (Mondini *et alii*, 2025). Specifically, the probability of a landslide event (F), conditioned by rainfall events (R) and geoenvironmental terrain conditions, expressed in terms of susceptibility (*S*), can be estimated according to the function *P(F|R,S)* (Eq. 1). Assuming that rainfall events are not related to a static susceptibility and considering that the latter is locally constant and time-invariant, susceptibility was treated as a scaling factor, and the equation (1) can be expressed as *P(F|R)·S* (Eq. 2). Consequently, the implementation of the forecasting model involves a first step in which a fully connected neural network is used to determine the rainfall-based landslide-triggering probability, which is then multiplied by susceptibility to obtain a spatio-temporal prediction.

Neural Network model configuration

The first phase of this study involved the construction of a fully connected neural network to estimate the probability of occurrence of rainfall-induced SLs given rainfall conditions (*i.e.*, the probability of the success in a Bernoulli trial). The procedure consisted of initially defining the network structure, followed by a learning phase (training and validation) to optimize the connection weights, and concluding with a testing phase to evaluate its performance. The fully connected neural network developed for this work consists of an input layer with 75 variables and a hidden structure of 9, 7, and 5 neurons, followed by binary output layer. Interconnections between layers are established such that each neuron receives a linear combination of the values from the previous layer, with each connection modulated by a specific weight parameter. Additionally, a bias term is introduced, conceptually acting as the weight of a virtual neuron with a constant value of 1. During the learning phase, weights and biases are updated using backpropagation (Buscema, 1998) and gradient descent (Bottou *et alii*, 1991). The goal is to minimize the difference between the network's predicted output values and the actual target, thus modifying both the weights and the bias. After receiving the weighted input every neuron applies an activation function (in this work, ReLu was chosen for the deep layers) to calculate its output, which serves as the input for the next layer, while the Sigmoid activation function was used for the output layer. Rainfall time series were obtained from the network of 4,031 rain gauges deployed across Italy by Regional and Provincial administrations and by the Italian Civil Protection Department, which covers the hourly time interval between 2002 and 2020 corresponding of a total of 184,080 hours. In the absence of data gaps, time series spanning 793 hours (corresponding to the 30 days preceding the forecast) were developed. From these, 75 variables were derived, which describe, at an hourly resolution, the cumulative rainfall over the first 72 hours and, subsequently, the total cumulative duration relating to the interval between the 73rd and 792nd hour (*i.e.*, antecedent rainfall prior to the last three days) (Mondini *et alii*, 2025). Moreover, the mean annual precipitation associated with each rain gauge was used. For information on rainfall-induced SLs, data available in the ITAlian rainfall-induced LandslIdes CAtalogue (ITALICA) database were used (Peruccacci *et alii*, 2023). Before deep learning processing, SLs were preselected to include only the ones with a maximum temporal uncertainty of 6 hours, located within 10 km of an active rain gauge that recorded significant precipitation in the previous 72 hours. To address the marked disproportion in the rainfall record, where non-landslide hours exceed 99.9% compared to hours with events (<0.1%), the deep networks were trained using an imbalance ratio of 5:1. This choice represents a compromise between the need to preserve the inherent asymmetry of the physical process (as not every rainfall event triggers a landslide) and the technical limitations of deep learning models in handling highly imbalanced datasets

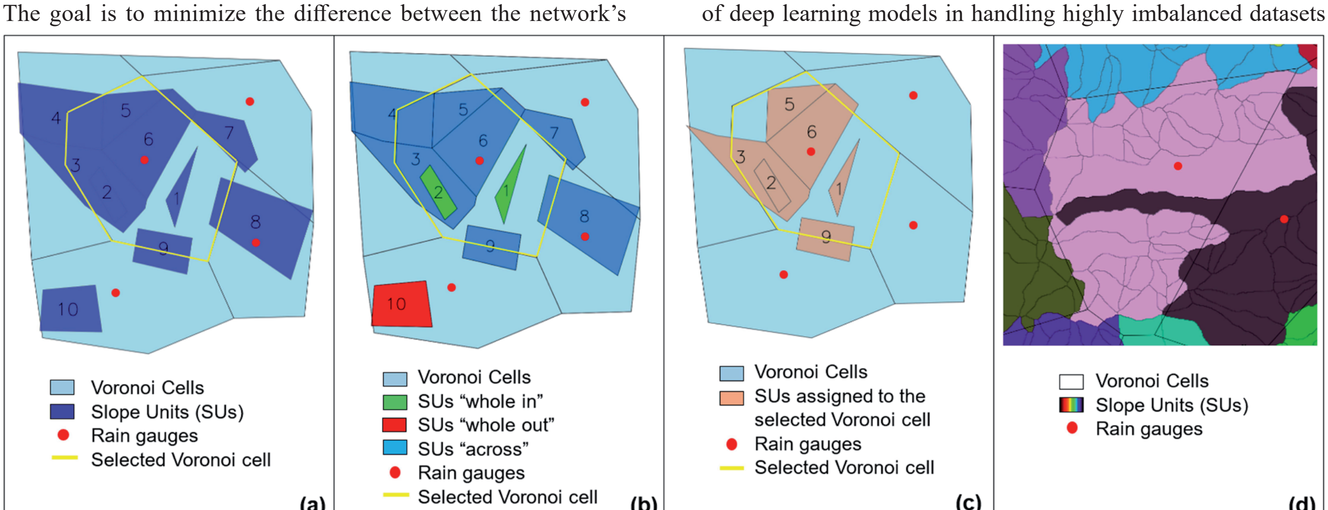

Fig. 1 - Representative sketches describing the procedure developed to assign the SUs to the Voronoi cells: a) Voronoi diagram with overlapping SUs and rain gauges; b) SU classification as "whole in", "whole out", and "across"; c) SUs that fall for more than 50% of their area within the selected Voronoi cell; d) Example showing SUs assigned to their respective Voronoi cells

(Mondini *et alii*, 2025). The dataset used to approximate the relationship between rain and SLs using the neural network was divided into two subsets: approximately 80% of the data was used for the training and validation phase while the remaining 20% was used for the testing phase. The performance of the model was evaluated using the AUC (Area Under the Curve) of the ROC (Receiver Operating Characteristic) curve, a tool used for binary classification problems. The resulting AUC was equal to 0.90, while the best trade-off (or ideal threshold) was around 0.20.

Spatial modeling

The second phase of this work involved incorporating susceptibility information into the neural network model. This step is essential because susceptibility describes local geoenvironmental terrain information that influences a slope's response to rainfall. For this purpose, the testing area was divided into the slope unit (SU) divisions proposed by Alvioli *et alii* (2020). Slope units (SUs) represent a mapping-unit division commonly used in landslide susceptibility mapping. They consist of a polygonal subdivision of the terrain based on topographic, morphological, and hydrological conditions, structured to maximize geomorphological homogeneity within each unit and geomorphological heterogeneity between neighboring units (Alvioli *et alii*, 2020). To spatialize the point-based landslide probability of occurrence, two different approaches were applied: a deterministic model based on Voronoi diagrams, and a stochastic model developed using the MUSE software (Miola, 2025; Miola *et alii*, 2022).

Using the open-source software GRASS GIS, a Voronoi tessellation was first generated using the rain gauges as input vector points. This resulted in a Voronoi diagram in which each cell has a specific value of landslide occurrence probability associated with the rain gauge contained within it (Figure 1a). Subsequently, a code was developed to assign the SUs contained within the Voronoi cells. The developed script implements a set of logical rules that determine whether a SU is "whole in", "whole out", or "across" the reference Voronoi cell (Figure 1b, c). If the slope unit is "whole in" the cell, it is assigned to that Voronoi cell; if it is "whole out", it is not associated with that cell (Figure 1b, c). For the SUs classified as "across", the procedure calculates the portion of the area falling within the cell; if this area exceeds 50%, the SU is assigned to that cell, otherwise it is associated with another cell in the diagram (Figure 1b, c, d).

By using the MUSE software, a stochastic model was created using a geostatistical framework. This contributed to predicting rainfall probability in the unsampled locations, starting from a discrete set of sampled values. The latter consists of all the probability observations derived from the rain-gauge network. The proposed model adopts a probabilistic approach based on Sequential Gaussian Simulations (SGS) (Gòmez-Hernàndez & Srivastava, 2021) on an unstructured geometric support, built as polygonal mesh in which each irregular polygon corresponds to a SU (Miola *et alii*, 2025). Such a stochastic simulation process relies on spatial covariance laws (*i.e.*, variograms); in this case, a 2D directional variography analysis is performed to estimate existing spatial dependence structures between samples. As a result of the stochastic process over 10 simulations, each SU contains 10 equiprobable rainfall-probability values. The estimated values enabled the building of cumulative probability distribution functions, from which the main statistical moments are computed (*i.e.*, Q1, mean, median, Q3 and 95th percentile).

Finally, to calculate the combined probability of landslide occurrence, namely that conditioned by rainfall and terrain susceptibility (Eq. 2), a relational database was created using Structured Query Language (SQL). The database includes the following input data: (*i*) the value of susceptibility associated with each SU and its corresponding ID number, (*ii*) the IDs of the selected rain gauges from the regional network, and (*iii*) the rainfall-based probability of landslide occurrence for each rain gauge, obtained from the neural network; for the model developed with the MUSE software, the mean rainfall-based probability was used.

General setting of the testing area

The Liguria Region is located in northwestern Italy, bordering France to the west, Piedmont and Emilia-Romagna to the north, and Tuscany to the east, while facing the Ligurian Sea to the south, with a coastline of approximately 350 km (Figure 2). This narrow strip of land, approximately 5400 km^2 in area, is characterized by peculiar geological, geomorphological, and climatic features. The territory of Liguria is almost entirely mountainous and hilly, accounting for about 98% of the total area (Gorziglia *et alii*, 2006), with the highest elevations exceeding 2000 m a.s.l. The few flat areas consist of small alluvial-coastal plains; the largest of which is associated with the Centa River (Savona Province, approximately 45 km^2).

This hilly-mountainous landscape in close proximity to the sea is the result of the Ligurian Alps and the Northern Apennines orogenic belts, formed during the closure of the Mediterranean Mesozoic Tethyan basins. The two belts originated during the Cretaceous and Cenozoic and are linked to subduction and continent-continent collision stages, which caused the progressive stacking of tectonic units upon each other (Carminati & Doglioni, 2012).

Three main groups of tectonic units can be distinguished from a paleo-geographical point of view (Molli *et alii*, 2010; De Carlis *et alii*, 2013): Paleo-European continental units (Eastern Provençe domain, Briançonnais domain and Pre-Piedmont domain), oceanic units (Ligurian and Ligurian-Piedmont domains), and Adriatic continental units (Tuscan Nappe). These

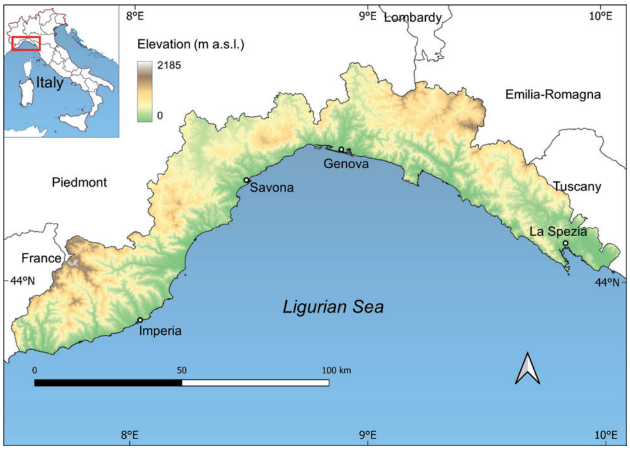

Fig. 2 - Location and relief map of the testing area (derived from 5 m cell-size Digital Elevation Model, source: Geoportale Regione Liguria)

tectonic units are covered by post-orogenic Neogene–Quaternary sedimentary sequences (*e.g.*, the Tertiary Piedmont Basin). This geological context results in a considerable lithological variety. Large areas of the western, eastern and central sectors of the region are broadly characterized by calcareous-marly and arenaceous turbiditic rocks, as well as sedimentary rocks such as limestones, dolomites, sandstones and conglomerates. Towards the central-western sectors, the bedrock is dominated by metamorphic rocks, such as serpentinites, gneisses, amphibolites, basalts and schists. Alluvial and marine deposits fill the main valley floors, while debris deposits widespread outcrop along the slopes.

The mountain peaks of the Alps and the Northern Apennines constitute the main drainage divide, separating the Tyrrhenian flank of the chains from the Po flank, which exhibits pronounced asymmetry. The southern maritime side shows slopes ranging from steep to very steep, directly reaching the coastline, while the northern flank descends more gently toward the Po Plain. Both the morphology and hydrography of the drainage basins are strongly controlled by the Plio-Quaternary tectonic evolution (Boni *et alii*, 1980), often showing V-shaped valleys carved by steep main watercourses, generally oriented perpendicular to the coastline, which is predominantly high and rocky and characterized by the alternation of promontories, rocky cliffs, and small pocket beaches. Human activity has extensively modified the landscape through the construction of urban settlements in lowland areas (*i.e.*, alluvial-coastal plains) and agricultural terraces for cultivation purposes on slopes. However, over the years, the progressive reduction in the availability of flat areas suitable for urban expansion has given rise to intense urbanization even on slopes.

The climate of the region is overall of the Mediterranean-type, although the concurrent effect of several geographic factors, such as the mitigating action of the sea, the distribution

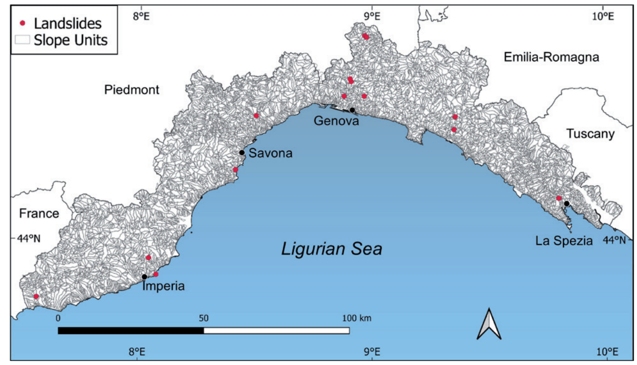

Fig. 3 - Location of the shallow landslides triggered during the selected demonstration period according to the ITALICA database

of altitudes, morphological features and the orographic effect due to the mountain relief, produce a wide spectrum of microclimates (Frattiani & Acquaotta, 2006). According to the Köppen-Geiger classification, the coastal zones are characterized by a hot temperate climate (Csa), with hot and dry summers, while the inner hilly sectors show a transition to a sub-coastal temperate climate (Cs). The northern sector facing the Po Plain is characterized by a sub-continental temperate climate (Cf), while at elevations higher than 1000 m a.s.l., a continental temperate climate (Cf) occurs. Intense or prolonged rainfall often occurs during autumn and winter seasons, acting as the primary triggering factor of SLs.

Given the rainfall regime and the inherent geological, morphological, and land-use features of slopes, SLs are recurrent natural hazards that can give rise to significant risk scenarios, as witnessed by the severe events that have affected several areas of the region in recent decades (Brandolini *et alii*, 1999; Guzzetti *et alii*, 2004; Cevasco *et alii*, 2015; Cevasco *et alii*, 2017; Giordan *et alii*, 2017; Roccati *et alii*, 2018).

Model validation

To test the developed procedure, the period between 8 and 14 March 2018 was selected, during which significant rainfall triggered 14 SLs across the Liguria region according to the ITALICA database (Figure 3), most of which occurred on 11 March.

For each landslide, information on the location and initiation time, expressed in hours and minutes, was extracted from the inventory. The creation of relational databases for both models resulted in the extraction of 168 databases, each with 7022 rows corresponding to the total amount of SUs in Liguria, with each one representing an hourly time step.

To evaluate the predictive capability of the developed models, graphs showing the hourly evolution of the combined probability of landslide occurrence were used for each SU in which a SL was observed during the selected time interval. The hourly rainfall intensity recorded at the nearest rain gauge, and the landslide triggering period were added to the graphs.

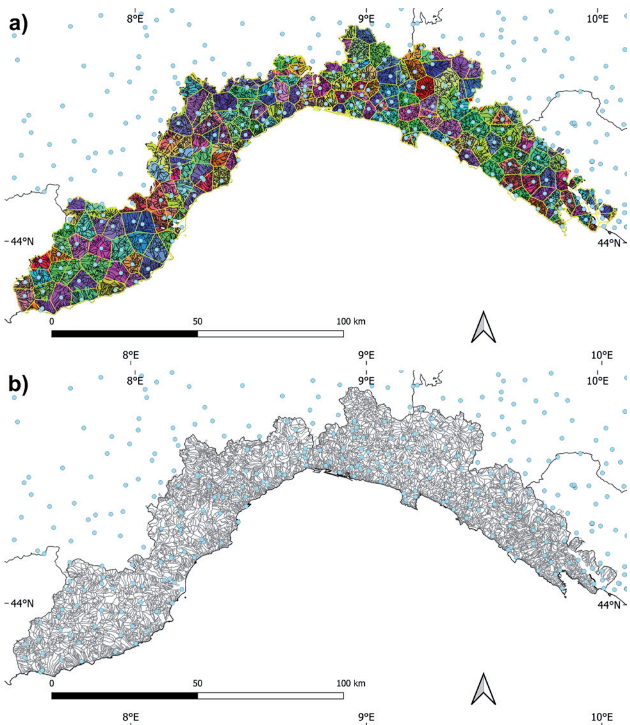

Fig. 4 - Spatial frameworks derived from the Voronoi method (a) and the MUSE software (b) (in both panels, blue points denote the locations of rain gauges)

RESULTS

Geometrical frameworks

In Figure 4, the geometrical models that allowed the spatialization of the rainfall-conditioned landslide probability obtained from the neural network are shown. Concerning the Voronoi method, the geometrical framework resulted in 236 clusters of SUs (Figure 4a), whereas, using the MUSE software, a polygonal mesh of the Ligurian territory consisting of 7022 irregular cells, each corresponding to a SU, was obtained (Figure 4b).

Spatio-temporal landslide forecast

Figure 5 depicts some representative maps of the spatio-temporal prediction of SLs across the Liguria region obtained with the two geometric methods. Specifically, the time frames at 13:00 UTC within the interval spanning from 10 to 12 March 2018 were selected. Overall, the results from both spatio-temporal landslide prediction models indicate that, during the selected testing period, the highest combined probability of landslide occurrence was recorded on 11 March 2018, especially in the western sector of Liguria Region. The SUs located along the coastal areas generally exhibit lower probability of landslide occurrence than those located inland. Furthermore, the combined probability values obtained using the Voronoi method were found to be generally higher than those of the model developed with the MUSE software. In the Voronoi-based model, some anomalous SU clusters maintained constant value throughout the period of analysis. This is caused by malfunctioning rain gauges, for which the neural network-derived probability is always zero, resulting in a null combined probability.

Model predictive capability

Figures 6 and 7 show some representative graphs used to assess the predictive performance of the developed spatio-temporal landslide forecasting models. In each graph, the orange and green curves represent the temporal distribution of the combined probability of landslide occurrence, obtained using the Voronoi method (Figure 6) and the MUSE software (Figure 7), respectively. The blue bars represent hourly precipitation, while the red lines indicate the SL triggering period within the corresponding SU. All curves start from non-zero initial values, as both the neural network-derived probability and the susceptibility associated with the SUs are always positive. The results were satisfactory, as the models produced non-zero probabilities of occurrence for all observed SLs. The graphs show that most SLs occur along the ascending branch of the combined probability curves, whereas only a limited number of events occur beyond the maximum probability peaks predicted by the models. A comparison of the curves obtained using the two spatialization methods shows that the Voronoi-based model produces relatively higher probabilities than the MUSE-based model. The ascending branches of the curves, up to the maximum combined probability, highlight the presence of noise, likely due to the breakdown of the quasi-stationarity condition following the onset of precipitation. In particular, the curves obtained using

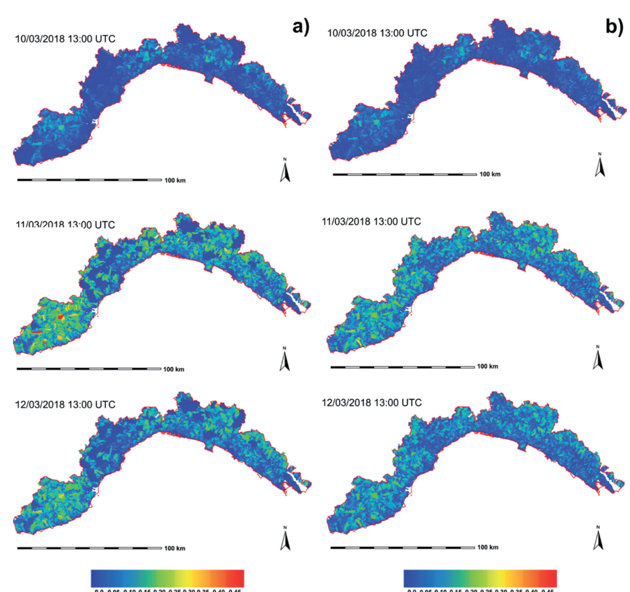

Fig. 5 - Maps showing the spatial distribution of the combined probability of landslide occurrence for the time frames at 13:00 UTC within the interval spanning from 10 to 12 March 2018: (a) Voronoi method; (b) MUSE software

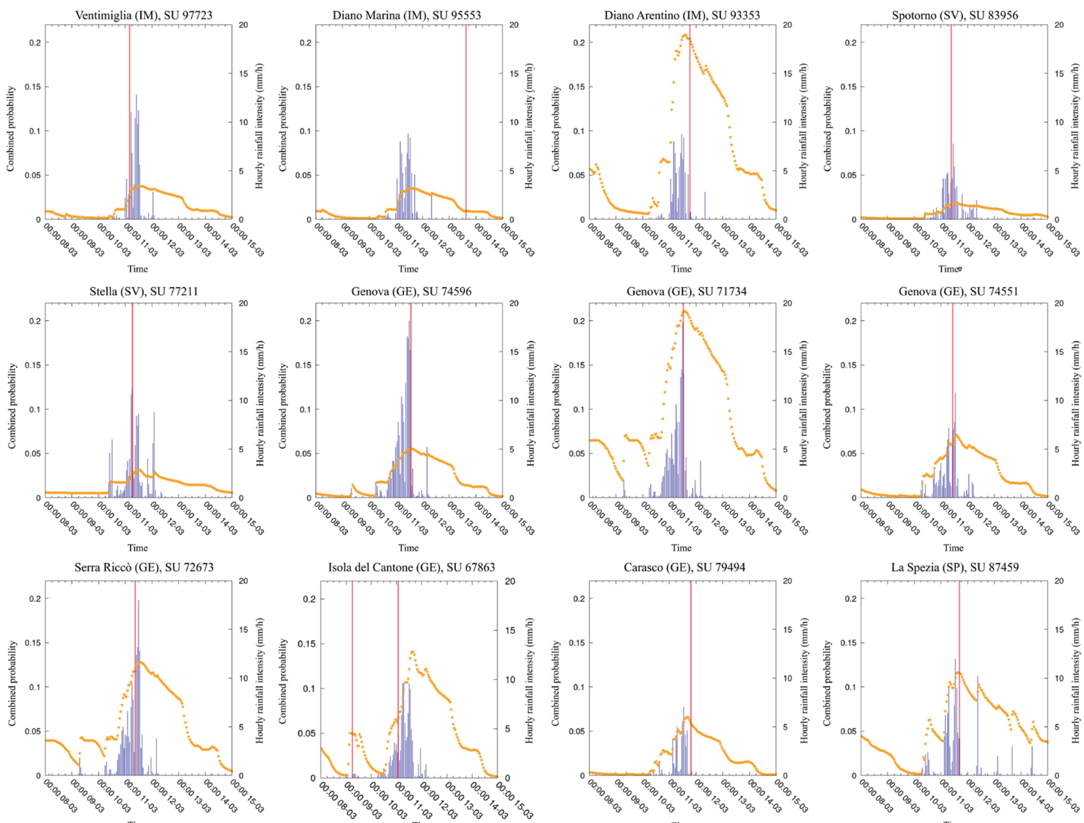

Fig. 6 - Temporal evolution of the combined probability of landslide occurrence during the validation period (from 00:00 UTC on 08 March 2018 to 00:00 UTC on 14 March 2018) obtained using the Voronoi method (blue bars indicate hourly rainfall intensity while red bars indicate the observed landslide triggering period; each graph indicates the SU in which a SL was observed; rainfall data were retrieved from Liguria Region (https://ambientepub.regione.liguria.it/SiraQualMeteo/script/PubAccessoDatiMeteo.asp))

the MUSE software exhibit noisier ascending branches than those obtained with the Voronoi method. Conversely, descending portions produced by both models are more regular. Furthermore, although the combined probability of landslide occurrence tends to decrease over time due to rainfall attenuation, the model results maintain good predictive performance.

DISCUSSION AND FINAL REMARKS

This work presented a methodology designed to support civil protection activities in predicting and managing potential ground-impact scenarios deriving from hydro-meteorological events. Such activities involve the activation of procedures required to safeguard populations and property exposed to landslide risk. Indeed, the proposed models appeared to be effective in predicting the occurrence of SLs at the geographic scale, based on estimates from local territorial units.

By applying the two spatial distribution models (*i.e.*, the deterministic Voronoi method and the stochastic method implemented using the MUSE software), it was possible to map in detail the evolution of landslide-triggering probability throughout the meteorological event that affected the Liguria Region from 8 to 14 March 2018. A comparison between the outputs obtained by using the two proposed methods shows that both approaches generally captured the variation in landslide occurrence probability over the course of the rainfall period; however, a notable discrepancy is observed in the calculated absolute probability values. The Voronoi-based model typically produces higher absolute probability values than the MUSE-based model values, as illustrated in figure 5. Since both models strongly depend on individual rain gauges and are equally affected by any instrument errors or malfunctions, this difference can be explained by the different methodologies employed to spatially distribute the data. Indeed, in the Voronoi-based model, a constant value is assigned to the area of influence of each rain gauge, so that all SUs within the same Voronoi cell share the same probability. By contrast, the MUSE software employs a stochastic approach to estimate the variable at unsampled points via a probabilistic distribution, producing averaged and more variable values, particularly in regions far from rain gauges. A test in the GIS environment was performed to compute a general statistic on the differences map

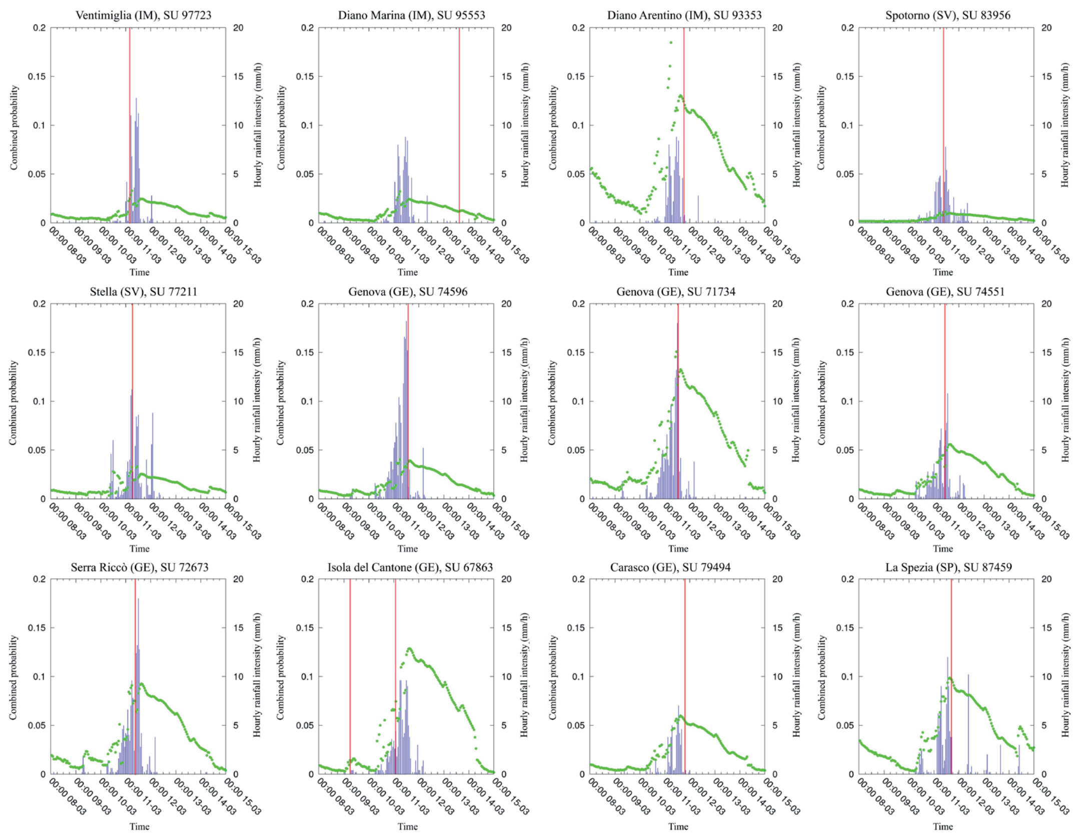

Fig. 7 - Temporal evolution of the combined probability of landslide occurrence during the validation period (from 00:00 UTC on 08 March 2018 to 00:00 UTC on 14 March 2018) obtained using the MUSE software (blue bars indicate hourly rainfall intensity while red bars indicate the observed landslide triggering period; each graph indicates the SU in which a SL was observed; rainfall data were retrieved from Liguria Region (https://ambientepub.regione.liguria.it/SiraQualMeteo/script/PubAccessoDatiMeteo.asp))

(*i.e.*, mean of estimates on the stochastic model and the forecast associated at Voronoi tessellation) as a global screening metric. Considering the spatial results transferred to the common same geometry (*i.e.*, the polygonal SU mesh), for the same time frame (8th March 2018 at 00:00), statistical values indicate that the two methods are highly comparable and numerically equivalent, except for localized divergences evident in the spatial representation (Figure 8). In this case, the basic statistics indicate a range of variability of the quadratic differences of 0.07, with a mean of 0.004, a median of 0.002, and an RMSE of 0.06.

A detailed examination of the graphs used to assess the performance of the two spatio-temporal landslide prediction models (Figure 6 and 7) revealed the key drawbacks and advantages of the two spatialization methods. The Voronoi-based model has shown high effectiveness in areas with a dense rain gauge network. Its main operational vulnerability lies in the quality of input vector data. Indeed, a malfunctioning rain gauge or erroneous rainfall data can prevent the calculation of trigger probabilities for all SUs within the affected Voronoi cell. Consequently, this can result in information gaps in landslide prediction. This limitation may be managed by introducing quality control strategies on rain gauges measurements, such procedures aimed at excluding anomalous measurement points during the generation of the Voronoi tessellation. The MUSE-based model exhibits some data dispersion along the ascending

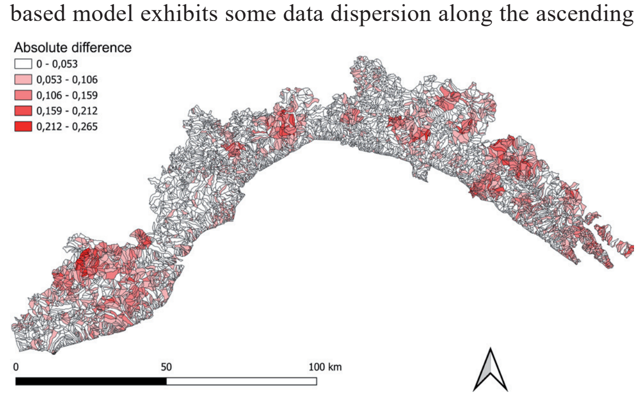

Fig. 8 - Spatial distribution map of absolute differences between the two results obtained from (1) Voronoi-based tessellation and (2) the stochastic approach on the SU polygonal mesh (by MUSE). Results refer to the time frame: 8th March 2018 at 00:00

branch of the regression curve during major increases in rainfall (Figure 7). This behaviour is due to the model's sensitivity to stationarity breaks caused by the onset of rainstorms, which directly influence the variographic analysis. However, this limitation can be mitigated through expert supervision during variogram configuration. Overall, the obtained results suggest that integrating geological-geomorphological information with meteorological variables can provide an effective approach suitable for geographic scale applications. Extending the analysis to a twenty-year timeframe would enable further validation of the obtained spatio-temporal SL predictions. At the same time, scaling up both spatially and temporally poses considerable challenges regarding computational resources and data management.

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Data availabilty statement

Rainfall data are the property of the regional governments of Italy and should be obtained from them.

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