Landslide '25 EAGE

Landslide25_17

A nation-wide nowcasting system for Italy combining rainfall thresholds and risk indicators

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SUMMARY

Regional- and national-scale landslide warning systems are usually based on rainfall thresholds that forecast the possibility of landslide occurrence over wide spatial units called alert zones (AZs). This work proposes a substantial improvement of the stateof- the-art by combining the rainfall threshold outcomes with a set of spatially explicit risk indicators aggregated at the municipality level. The combination of these two different techniques is performed by means of a dynamic matrix, which was purposely calibrated to provide an output in the form of five possible levels of risk (from R0 to R4), which are connected to the growing intensity of expected impacts and a pre-defined confidence in issuing warnings without omitting alarms. Italy (about 300,000 km2) is used as a case study, producing a set of rainfall thresholds differentiated for 150 AZs and providing a specific calibration of the dynamic risk matrix for each of them. The verification of the matrix outputs was satisfactory as no AZs experienced landslides at the R0 level; only two of them had more than 10% of landslides at the R1 level, and most of the AZs had more than 90% of the landslides in the R2 to R4 risk classes. A comparison with a nation-wide dataset of very severe hydrogeological disasters further corroborated the consistency of the model outputs with real scenarios, as most part of the impacts occurred in places and times when the matrix outputs were at the highest levels. The proposed Methodology represents a reliable improvement for state-of-the-art territorial warning systems, as it brings two main advances: the spatial resolution is greatly improved, as the basic spatial unit for warning is downscaled from AZs to municipalities (whose average extension, in Italy, is about 1770 and 38 km2, respectively); second, the outputs can better address the needs of landslide emergency management, as the warning are specifically addressed to small areas based on the expected impacts (since risk indicators are used in the dynamic matrices), rather than on the mere probability of landslide occurrence.

Introduction. Italy, a country with complex geomorphological and climatic characteristics, is particularly vulnerable to landslides (Gariano & Guzzetti, 2016). To manage this risk, Territorial Landslide Early Warning Systems (TLEWS, Piciullo et al., 2018) are crucial. TLEWS traditionally rely on rainfall thresholds applied across large spatial units (Guzzetti et al., 2020). While this method is easy to implement and interpret, making it useful for civil protection authorities, it lacks spatial precision, often issuing alerts across broad areas without clear differentiation of local risk. The spatial assessment of landslide hazard has been usually assessed through Landslide Susceptibility Maps (LSMs), more recently enhanced through machine learning (Reichenbach et al., 2018). However, these susceptibility maps focus on spatial forecasting, while rainfall thresholds mainly focus on temporal triggers.

More recently, the combination of susceptibility maps and rainfall thresholds through hazard matrices has gained popularity (Wang et al., 2020; Palau et al., 2022; Pradhan et al., 2019; Auflič et al., 2016; Dikshit et al., 2020). Despite that, some issues are still open. A key open issue is determining the optimal dimension of spatial units, meeting the needs of civil protection authorities but without reducing the prediction accuracy. Additionally, using susceptibility maps alone to represent spatial forecasting does not fully address operational needs for landslide risk management. Indeed, a relevant risk level takes place only if a hazardous process interacts with exposed elements (e.g., buildings, infrastructure). Then, the matrix calibration procedure must maximise the effectiveness and provide an objective, quantitative, yet easily understandable meaning to the resulting warning classes.

This research addresses these limitations by implementing a prototype national-scale TLEWS for Italy that integrates rainfall thresholds and spatial risk indicators. It enhances the resolution by issuing alerts at the municipal level (average area: 38 km²), compared to the Alert Zones (AZs, average area: thousands km²) used in Italy, and uses a dynamic matrix approach to merge spatial and temporal predictions into actionable risk scenarios. The proposed methodology leads to alert levels with quantitative significance, thereby increasing the system's reliability and reducing false alarms.

Methodology. The methodology was applied across the entire Italy, covering approximately 300,000 km² and 170 AZs. Of these, 150 AZs are mountainous or hilly and prone to landslides, while 20 flat AZs (in alluvial plains) were excluded from the analysis. Rainfall data were collected from over 3000 automatic rain gauges, using hourly records from 2010 to 2019. For landslide data, an inventory of approximately 10,500 landslides was automatically generated using a data mining algorithm, which scrapes online news sources for geo-referenced and date-stamped landslide reports.

Landslide-triggering rainfall thresholds follow a power-law relationship: $I=\alpha D^\wedge\beta$, where I is intensity (mm/h), D is duration (hours), and α and β are empirical parameters. Each AZ was analyzed by combining rainfall and landslide data to identify the most critical rainfall conditions. The goal was to minimize false alarms (FA) and missed alarms (MA) while keeping the number of correct alarms (CA) constant. A base threshold was defined to detect 95% of known landslides. To establish multi-level alert thresholds, the base curve was shifted upward, maintaining the same β but increasing α, resulting in a moderate criticality threshold with ≤1 FA/year and a high criticality threshold with ≤0.1 FA/year (i.e., 1 FA per decade).

Instead of traditional LSMs, the Landslide Risk Index (LRI) developed by Segoni & Caleca (2021) was used. This combines susceptibility maps with land consumption data to reflect both the spatial landslide predisposition and the presence of exposed anthropogenic elements. Then the Average Landslide Risk (ALR) was calculated in each municipality as the mean value of susceptibility in correspondence with anthropic elements. It represents a measure of how hazardous is on average the portion of the territory where anthropic elements are located.

The translation of temporal predictions (rainfall thresholds) and spatial characterization (risk indicators) into a real-time risk evaluation occurs through a 3x3 matrix (Figure 1). This matrix combines three possible levels of spatial propensity to landslide impacts (S0, S1, S2) with three possible levels of rainfall severity

(T0, T1, T2), which reflect the three levels of temporal hazard. Matrix calibration is a key point of the methodology, as it attributes a specific meaning to each resulting risk class in terms of the expected risk scenario. Each AZ is calibrated independently to reflect the peculiar relationship between hillslope processes and rainfall forcing. ALR, originally represented by continuous values (0-100), is reclassified into 3 classes (S0, S1, S2). Calibration consists of defining the optimal ALR breakpoint values between the S0-S1 and S1-S2 classes. Specifically, the S0-S1 breakpoint value is defined so that no landslide occurred in class R0. The S1-S2 breakpoint value is defined so that at least 90% of landslides occur in classes R2, R3, or R4, and less than 10% in class R1. This scenario-based calibration allows defining risk classes that are not merely qualitative and better suited for a possible operational use of the dynamic matrix, where R0 and R1 are considered safe scenarios with different degrees of confidence.

	S0	S1	S2
T0	R0	R1	R2
T1	R1	R2	R3
T2	R2	R3	R4

Figure 1 *Dynamic matrix used for spatiotemporal landslide forecasting: S = spatial component (three classes, S0, S1 and S2); T = temporal component (three classes: T0, T1 and T2); R = forecasted risk levels (five classes: R0, R1, R2, R3 and R4).*

The dynamic risk matrices were validated by comparing them with a comprehensive dataset of hydrogeological disasters that caused national emergency declarations by the Italian government, collected by Gatto et al. (2023). The overlapping period for validation was 2013-2019, containing 96 events that affected a total of 9059 municipalities. The main objective was to verify the consistency between predicted high-risk municipalities (R3 and R4) and those that actually suffered significant hydrogeological impacts.

Results. 127 thresholds were established to cover 150 AZs, with 20 flat AZs excluded. For some AZs with data scarcity, thresholds were grouped (27 AZs in 11 groups) or transferred from nearby AZs. The calibration criterion imposed for the moderate criticality level (maximum 1 FA/year) was met by 92.7% of the 127 thresholds. For the high criticality level (maximum 1 FA every 10 years), the criterion was met in 87.3% of cases. Although some thresholds slightly exceeded these criteria (e.g., 9 thresholds with 1.1 FA/year for moderate criticality, 19 thresholds with max 0.5 FA/year for high criticality), the calibration was generally considered effective in minimizing the impact of FA especially considering the national scale of the work.

Mapping the ALR index for Italian municipalities (excluding flat areas) reveals that half of the municipalities fall into class S2 (maximum risk propensity), while the remaining half is almost equally distributed between classes S1 (26%) and S0 (24%).

In total, 127 matrices were identified to characterize 150 AZs. A first reliability check verified the adherence of data distribution to the imposed calibration requirements. The results were very satisfactory: all AZs met the R0 requirement (no landslide occurred with an R0 alert level). Furthermore, 125 out of 127 matrices (98.4%) met the R1 requirement, meaning less than 10% of landslides occurred with an R1 alert level (which means at least 90% of landslides occurred in R2, R3, or R4 alert levels). Most matrices (95 out of 127, equal to 74.8% of the total) demonstrated reliability above 95%, with less than 5% of landslides in AZs falling into class R1. Only 2 matrices (1.6%) showed reliability below 90% (Figure 2).

Regarding the validation, no significant hydrogeological disasters occurred when/where a municipality was at risk level R0. Only 3% of occurrences happened at level R1, while the vast majority (97%) of occurrences were recorded at risk levels R2 (18%), R3 (41%), and R4 (38%). This demonstrates that, for most municipalities affected by hydrogeological disasters with significant impacts (those that triggered national emergency declarations), the TLEWS would have correctly predicted high-risk levels.

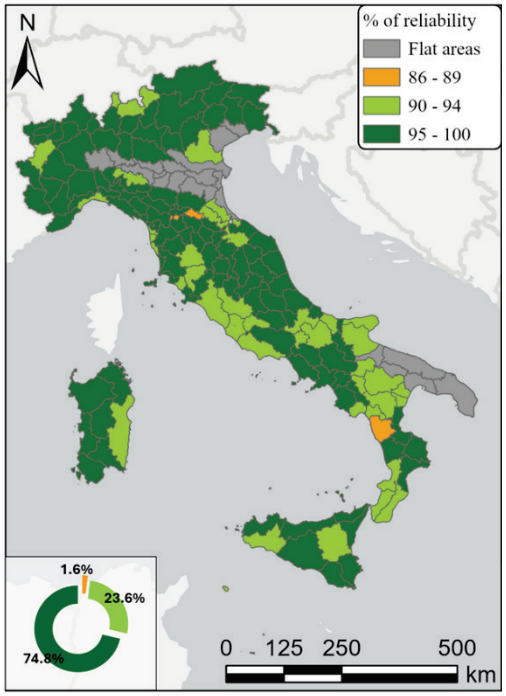

Figure 2 *Italian AZs classified by the reliability of their risk matrix (dark green for reliability equal or higher than 95%, light green for reliability between 90 and 94%, orange for the reliability below 90%).*

An example of the operational application of the TLEWS proposed in this work is shown in Figure 3. The state-of-the-art alert-zones output of the warning system based on rainfall thresholds (Figure 3a) can be visually compared to the upgraded warning system introduced in this work (Figure 3b), in which risk matrices combine rainfall thresholds outputs with municipality-based risk indicators. This simulation represents an hindcast of the extreme rainfall event of 10–13/10/2014, during which over 100 mm of rain fell on the central-eastern part of the Liguria region. The approach based on dynamic risk matrices produces a more granular definition of landslide risk, allowing a better assessment of specific risks levels and setting priorities concerning operational responses.

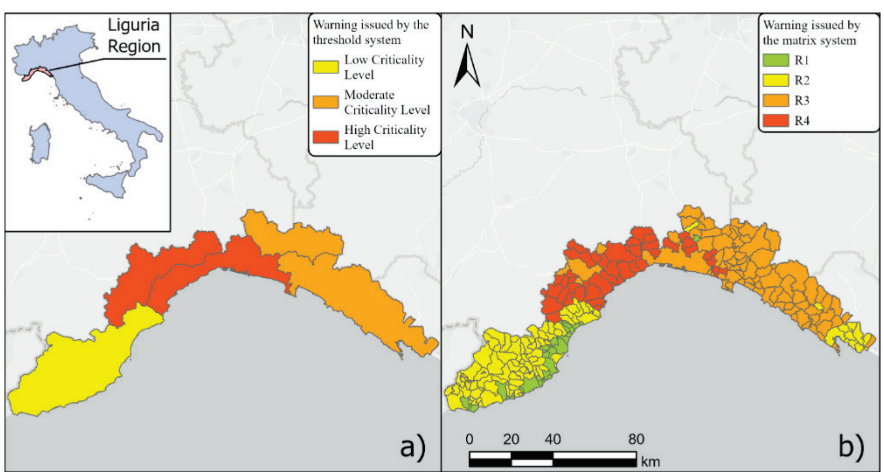

Figure 3 *Spatial resolution as showcased by the rainfall event that occurred on 10–13/10/2014 over the Liguria region, hindcasted by the warning system based on rainfall thresholds (a), and on risk matrices (b).*

Conclusions. This work has outlined a prototype national landslide early warning system for Italy, successfully integrating two methodologies traditionally considered distinct: rainfall thresholds for temporal prediction and spatial risk indicators.

The basic spatial unit for alerts has been reduced from AZs to municipalities. This represents a notable operational advance, considering that the average size of AZs in Italy is approximately 1770 km², while that of municipalities is about 38 km². This spatial refinement allows civil protection authorities to receive more precise indications for their territory. The integration of risk indicators into dynamic matrices allows focusing on the spatial interference between landslide-susceptible areas and exposed elements (primarily buildings and infrastructure), providing a scenario corresponding to actual risk. The results of the national-scale validation were very positive: most impacts occurred in locations and times when matrix outputs were at the highest levels (38% R4, 41% R3, 18% R2).

Further details about this research can be found in Segoni et al. (2025).

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