




## Editorial

# Preface to the Special Issue “Rainfall Thresholds and Other Approaches for Landslide Prediction and Early Warning”

Samuele Segoni <sup>1,\*</sup>, Stefano Luigi Gariano <sup>2</sup> and Ascanio Rosi <sup>1</sup><sup>1</sup> Department of Earth Sciences, University of Firenze, Via La Pira 4, 50121 Florence, Italy; ascanio.rosi@unifi.it<sup>2</sup> CNR-IRPI—Research Institute for Geo-Hydrological Protection of the Italian National Research Council, 06127 Perugia, Italy; stefano.luigi.gariano@irpi.cnr.it

\* Correspondence: samuele.segoni@unifi.it



**Citation:** Segoni, S.; Gariano, S.L.; Rosi, A. Preface to the Special Issue “Rainfall Thresholds and Other Approaches for Landslide Prediction and Early Warning”. *Water* **2021**, *13*, 323. <https://doi.org/10.3390/w13030323>

Academic Editor: Yi Jun Xu

Received: 22 January 2021

Accepted: 26 January 2021

Published: 28 January 2021

**Publisher’s Note:** MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



**Copyright:** © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

Landslides are frequent and widespread destructive processes causing casualties and damage worldwide [1,2]. The majority of the landslides are triggered by intense and/or prolonged rainfall [3]. Therefore, the prediction of the occurrence of rainfall-induced landslides is an important scientific and social issue. To mitigate the risk posed by rainfall-induced landslides, landslide early warning systems (LEWS) can be built and applied at different scales as effective non-structural mitigation measures [4]. Usually, the core of a LEWS is constituted of a mathematical model that predicts landslide occurrence in the monitored areas [5–7]. In the last decades, rainfall thresholds have become a widespread and well-established technique for the prediction of rainfall induced landslides, and for the setting up of prototype or operational LEWS at regional scale [8–11]. A rainfall threshold expresses, with a mathematical law, the rainfall condition that, when reached or exceeded, is likely to trigger one or more landslides in a given area. Rainfall thresholds can be defined with relatively few parameters and are very straightforward to operate, because their application within LEWS is usually based only on the comparison of monitored and/or forecasted rainfall with the identified critical conditions. Because of these advantages, the technique of rainfall thresholds has received growing attention from the early 1980s of the last century to present. To date, rainfall thresholds have become the most widespread method to develop (operational or prototypal) regional scale warning systems irrespective of physical settings, landslide characteristics, and technological level of the countries financing research programs and applications [10,11].

Despite that, the technique is still affected by some limitations, making the topic a prolific research field for the landslide community. Among the most cogent research trends: the evaluation and reduction of possible sources of uncertainties [12,13]; the reduction of the false alarm rate committed by the models [14]; the strife for improving quantity and quality of input data [15]; the definition of standardized and objective methods of analysis [16,17]; the comparison between different possible rainfall parameters to identify the optimal ones for each case of study [18]; the attempts to enhance the performances of the thresholds by the joint use of instrumental monitoring [19]; the combination of rainfall thresholds into more complex forecasting systems combining different techniques, among which landslide susceptibility zonation [20,21] and antecedent soil conditions analyses [22]; the tests with hydrological parameters instead of the classical rainfall parameters [23,24]; the experiments on the exportability of consolidated models to completely different test sites [25].

In this wide panorama of open research questions, the present special issue can contribute to the advancement of the state of the art, as some of the aforementioned criticalities are tackled in the papers collected. Indeed, this special issue collects contributions about recent research advances or well-documented applications of rainfall thresholds, as well as other innovative methods for landslide prediction and early warning. All contributions are focused on the development of LEWS or are preparatory studies on forecasting models with the perspective of future operational implementations.

Moreover, besides scientific advances, the development of the recent literature highlights the interest, by an international audience, of new case studies, new approaches, new objectives (reliable results before establishing an operational LEWS). In this regard, the special issue collects case studies from three continents and a wide range of countries: Bhutan, China, India, Italy, Slovenia, Taiwan, and a site across Democratic Republic of Congo, Uganda, Rwanda, and Burundi. This allows accounting for very different climatic and geological settings, two relevant factors in the definition of critical rainfall conditions for landslide initiation. Moreover, the papers account for scales of application ranging from the local scale to the national scale. An interesting advance, useful especially in data-scarce regions, is represented by the use of satellite-based rainfall estimates and freely available global landslide catalogues in the calculation of the thresholds. Interestingly, contributions focused on different approaches useful in landslide analyses (e.g., numerical modeling, susceptibility and hazard analysis) are also proposed in this special issue to cover a broad spectrum of studies.

To better address the readers towards the content of the special issue, a short summary of each published paper is provided hereafter.

- In the paper by Yang and co-authors [26], the authors presented the Runout modeling of the Yining landslides (China), made using DAN-W software. Triggering factors of the landslide have been identified in a combination of snow melt and geological setting of the slopes. The numerical model was calibrated using field survey and laboratory tests results and allowed the researchers to estimate the velocity of the landslide, which reached a maximum of 20.5 m/s and to estimate the duration of the paroxysmic event in 22 s. The outcomes of this paper showed the importance of slope monitoring, since landslide triggering can be a quick event, leaving no time for countermeasure operations once the landslide started its mobilisation.
- Dikshit and co-authors [27] investigated the rainfall conditions that can lead to landslide triggering in the Chukha Dzongkhag area (Bhutan) and defined a rainfall threshold based on E-D (cumulative rainfall-duration) relationship. They also discovered that 10 days and 30 days antecedent rainfall play an important role in the occurrence of landslides in the investigated area.
- Abraham and co-authors [28] try to define empirical rainfall thresholds for the Idukki area in India, to set the first step to establish a landslide early warning system. Two types of thresholds have been defined: (i) classical I-D (mean rainfall intensity-duration) thresholds, (ii) threshold based on short (1 day) and long duration rainfall (from 3 to 40 days). One of the main outcomes of the paper is the clear importance of antecedent rainfall (30 and 40 days before failure) in the triggering of landslides for the investigated area.
- Using satellite-based rainfall estimates from TMPA 3B42 Real-Time v.7 and information on 184 dated landslides in the period 2001–2019, Monsieus and co-authors [29] applied the modified antecedent rainfall–susceptibility threshold approach (previously proposed by the same authors [30]) to calculate and validate regional rainfall thresholds in a data-scarce region: the western branch of the East African Rift. The method was here tested and improved by means of newly available regional-scale susceptibility data: a regional model and a continental model. The main methodological novelty is the stratified selection of data linked to the lowest landslide-triggering antecedent rainfall values. A statistical analysis on the effect of outliers in small datasets on the estimation of parameter uncertainties with bootstrapping statistical technique is a valid methodological corollary to this work.
- The contraposition between empirical and physically-based thresholds includes different methods (the first ones are defined using past rainfall and landslide data, the latter integrate stability analyses and hydrogeological modeling) and applications (the first ones are mostly applied at a regional scale, while the second ones are mainly used at a local scale). Bordoni and co-authors [31] present a comparison between thresholds defined with the two methods using landslide and rainfall data collected in the period 2000–2018 in the Oltrepò Pavese, in Northern Italy. They used the CTRL-T tool [17] to define the empirical thresholds and the TRIGRS model [32] to calculate the physically-based thresholds. After validating both

thresholds against an independent dataset, the authors observed that the physically-based thresholds discriminate better than empirical thresholds the landslide triggering and non-triggering rainfall events. This is due mostly to the fact that the adopted physically-based model considers the antecedent soil hydrological conditions, which are known to have a primary role in slope instability.

- Lin and co-authors [33] presented the definition of SWI-D (soil water index-duration) thresholds to define the condition of landslide triggering in Taiwan. In this paper, besides the classical rainfall thresholds, the authors proposed an approach based on the definition of soil water content, calculated by the use of a 3-layers tank model, where each tank represents a soil layer, from ground surface to the bedrock. Results of the work highlighted that the water content of the deeper layer is more relevant in the triggering of large landslides and therefore that their initiation is more related to long rainfall events rather than shorter ones.

- This study proposed by Dikshit and co-authors [34] presents a landslide hazard assessment in a 180 km long road corridor in Bhutan, combining (i) rainfall thresholds based on daily rainfall amount and 30-days antecedent rainfall; (ii) temporal probability analysis of landslide triggering using a Poisson probability model; (iii) landslide susceptibility map developed with the AHP (Analytical Hierarchy Process) method. The study gains relevant knowledge for the strategic infrastructure analyzed, and poses the basis for further developments of the research towards an operational landslide warning system in the area.

- He and co-authors [35] defined four groups of national rainfall thresholds for landslide occurrence in China based on 771 landslide events occurred in the period 1998–2017. In particular, they used the satellite precipitation product produced by the NOAA's (National Oceanic and Atmospheric Administration) Climate Prediction Center Morphing technique (CMORPH) and calculated both rainfall event–duration (E–D) and normalized (by mean annual precipitation) (EMAP–D) rainfall thresholds. Moreover, they defined thresholds for rainy season and non-rainy season, and thresholds for short ( $<48$  h) and long ( $\geq 48$  h) durations. The main findings retrieved from the results are that: (i) the slope of the thresholds for long durations is larger than that for short durations, and (ii) the thresholds in the non-rainy season are generally lower than those in the rainy season.

- The study proposed by Abraham and co-authors [36] faces the operational difficulties encountered when trying to establish a regional scale I-D threshold in an area monitored by a sparse rain gauge network at daily temporal resolution. The paper investigates the sensitivity of the results to different model configurations adopted in selection of the rain gauges, in defining the rainfall intensity and in dividing the area into smaller sub-zones. After a comparative validation, the authors conclude that in their case of study, selecting the rain gauge based on maximum average intensity performs better than choosing the nearest rain gauge.

- Abraham and co-authors [37] applied in a sub-Himalayan test site in India a state-of-the-art rainfall threshold model called SIGMA [38,39], which is based on statistical anomalies observed in varying time-windows of antecedent rainfall to account for both shallow and deep-seated landslides. The application is interesting because SIGMA was purposely developed for an Italian test site affected by both kinds of landslides and was conceived to be operated using rainfall measurements at daily temporal resolution: this is the first reported attempt to apply it in other geographical climatic settings. Results are encouraging since a quantitative and comparative validation shows that the effectiveness of the model is higher than other approaches based on I-D and E-D thresholds.

- Given that a recent validation of the prototype landslide early warning system in Slovenia highlighted the need to define new reliable rainfall thresholds, Jordanova and co-authors [40] addressed this task taking advantage of a consolidated tool [17] that allows the automated calculation and validation of empirical, frequentist thresholds at different non-exceedance probabilities. Other than new national thresholds (compared with other regional, national, and global thresholds), the authors determined additional thresholds for two different environmental classifications: the first based on three classes of mean

annual rainfall and the second based on four lithological units. Through these additional analyses, two findings are observed: (i) the area with the highest mean annual rainfall has the highest thresholds, which indicates the landscape adaptation to higher average rainfall; (ii) the areas characterized by rocks prone to weathering have the lowest thresholds signal that the lithology influences landslide occurrence conditions.

The contributions collected in the special issue "Rainfall Thresholds and Other Approaches for Landslide Prediction and Early Warning" provide interesting understanding and new perspectives on the very wide topic of rainfall thresholds for landslide prediction. The different aspects covered in this special issue demonstrate that the definition, validation, and application of rainfall thresholds are complex tasks which require detailed data and rigorous methods. The research contributions deal with both empirical and physically-based approaches, use different sources for landslide and rainfall data and are implemented in different study areas with diverse temporal scales.

Some important aspects were not covered in this special issue: the topic of landslide initiation is still open for new ideas and innovations. However, we think that this collection of manuscripts could be useful for the community involved in operational prediction of landslides and landslide early warning at all levels [41], from the academic sector to the practitioners and end-users.

**Author Contributions:** Conceptualization, investigation, writing—original draft preparation, and writing—review and editing, S.S., S.L.G., A.R. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Conflicts of Interest:** The authors declare no conflict of interest.

## References

1. Pereira, S.; Zêzere, J.L.; Quaresma, I.; Santos, P.P.; Santos, M. Mortality patterns of hydro-geomorphologic disasters. *Risk Anal.* **2015**, *36*, 1188–1210. [[CrossRef](#)] [[PubMed](#)]
2. Froude, M.J.; Petley, D.N. Global fatal landslide occurrence from 2004 to 2016. *Nat. Hazards Earth Syst. Sci.* **2018**, *18*, 2161–2181. [[CrossRef](#)]
3. Sidle, R.C.; Ochiai, H. Landslides: Processes, prediction, and land use. *Water Resour. Monogr.* **2006**. [[CrossRef](#)]
4. Segoni, S.; Piciullo, L.; Gariano, S.L. Preface: Landslide early warning systems: Monitoring systems, rainfall thresholds, warning models, performance evaluation and risk perception. *Nat. Hazards Earth Syst. Sci.* **2018**, *18*, 3179–3186. [[CrossRef](#)]
5. Calvello, M. Early warning strategies to cope with landslide risk. *Rivista Italiana di Geotecnica* **2017**, *2*, 63–69. [[CrossRef](#)]
6. Intrieri, E.; Gigli, G.; Casagli, N.; Nadim, F. Brief communication "Landslide Early Warning System: Toolbox and general concepts". *Nat. Hazards Earth Syst. Sci.* **2013**, *13*, 85–90. [[CrossRef](#)]
7. Intrieri, E.; Gigli, G.; Mugnai, F.; Fanti, R.; Casagli, N. Design and implementation of a landslide early warning system. *Eng. Geol.* **2012**, *147–148*, 124–136. [[CrossRef](#)]
8. Guzzetti, F.; Peruccacci, S.; Rossi, M.; Stark, C.P. The rainfall intensity-duration control of shallow landslides and debris flows: An update. *Landslides* **2008**, *5*, 3–17. [[CrossRef](#)]
9. Segoni, S.; Piciullo, L.; Gariano, S.L. A review of the recent literature on rainfall thresholds for landslide occurrence. *Landslides* **2018**, *15*, 1483–1501. [[CrossRef](#)]
10. Piciullo, L.; Calvello, M.; Cepeda, J.M. Territorial early warning systems for rainfall-induced landslides. *Earth-Sci. Rev.* **2018**, *179*, 228–247. [[CrossRef](#)]
11. Guzzetti, F.; Gariano, S.L.; Peruccacci, S.; Brunetti, M.T.; Marchesini, I.; Rossi, M.; Melillo, M. Geographical landslide early warning systems. *Earth-Sci. Rev.* **2020**, *200*, 102973. [[CrossRef](#)]
12. Gariano, S.L.; Melillo, M.; Peruccacci, S.; Brunetti, M.T. How much does the rainfall temporal resolution affect rainfall thresholds for landslide triggering? *Nat. Hazards* **2020**, *100*, 655–670. [[CrossRef](#)]
13. Peres, D.J.; Cancelliere, A.; Greco, R.; Bogaard, T.A. Influence of uncertain identification of triggering rainfall on the assessment of landslide early warning thresholds. *Nat. Hazards Earth Syst. Sci.* **2018**, *18*, 633–646. [[CrossRef](#)]
14. Rosi, A.; Segoni, S.; Canavesi, V.; Monni, A.; Gallucci, A.; Casagli, N. Definition of 3D rainfall thresholds to increase operative landslide early warning system performances. *Landslides* **2020**, 1–13. [[CrossRef](#)]



15. Battistini, A.; Rosi, A.; Segoni, S.; Lagomarsino, D.; Catani, F.; Casagli, N. Validation of landslide hazard models using a semantic engine on online news. *Appl. Geogr.* **2017**, *82*, 59–65. [\[CrossRef\]](#)
16. Segoni, S.; Rossi, G.; Rosi, A.; Catani, F. Landslides triggered by rainfall: A semi-automated procedure to define consistent intensity–duration thresholds. *Comput. Geosci.* **2014**, *63*, 123–131. [\[CrossRef\]](#)
17. Melillo, M.; Brunetti, M.T.; Perruccacci, S.; Gariano, S.L.; Roccati, A.; Guzzetti, F. A tool for the automatic calculation of rainfall thresholds for landslide occurrence. *Environ. Model. Softw.* **2018**, *105*, 230–243. [\[CrossRef\]](#)
18. Leonarduzzi, E.; Molnar, P. Deriving rainfall thresholds for landsliding at the regional scale: Daily and hourly resolutions, normalisation, and antecedent rainfall. *Nat. Hazards Earth Syst. Sci.* **2020**, *20*, 2905–2919. [\[CrossRef\]](#)
19. Abraham, M.T.; Satyam, N.; Bulzinetti, M.A.; Pradhan, B.; Pham, B.T.; Segoni, S. Using Field-Based Monitoring to Enhance the Performance of Rainfall Thresholds for Landslide Warning. *Water* **2020**, *12*, 3453. [\[CrossRef\]](#)
20. Segoni, S.; Tofani, V.; Rosi, A.; Catani, F.; Casagli, N. Combination of rainfall thresholds and susceptibility maps for dynamic landslide hazard assessment at regional scale. *Front. Earth Sci.* **2018**, *6*, 85. [\[CrossRef\]](#)
21. Palau, R.M.; Hürlimann, M.; Berenguer, M.; Sempere-Torres, D. Influence of the mapping unit for regional landslide early warning systems: Comparison between pixels and polygons in Catalonia (NE Spain). *Landslides* **2020**, *17*, 2067–2083. [\[CrossRef\]](#)
22. Wicki, A.; Lehmann, P.; Hauck, C.; Seneviratne, S.I.; Waldner, P.; Stähli, M. Assessing the potential of soil moisture measurements for regional landslide early warning. *Landslides* **2020**, 1–16. [\[CrossRef\]](#)
23. Bogaard, T.; Greco, R. Invited perspectives: Hydrological perspectives on precipitation intensity–duration thresholds for landslide initiation: Proposing hydro-meteorological thresholds. *Nat. Hazards Earth Syst. Sci.* **2018**, *18*, 31–39. [\[CrossRef\]](#)
24. Marino, P.; Peres, D.J.; Cancelliere, A.; Greco, R.; Bogaard, T.A. Soil moisture information can improve shallow landslide forecasting using the hydrometeorological threshold approach. *Landslides* **2020**. [\[CrossRef\]](#)
25. Rosi, A.; Canavesi, V.; Segoni, S.; Dias Nery, T.; Catani, F.; Casagli, N. Landslides in the mountain region of Rio de Janeiro: A proposal for the semi-automated definition of multiple rainfall thresholds. *Geosciences* **2019**, *9*, 203. [\[CrossRef\]](#)
26. Yang, L.; Wei, Y.; Wang, W.; Zhu, S. Numerical Runout Modeling Analysis of the Loess Landslide at Yining, Xinjiang, China. *Water* **2019**, *11*, 1324. [\[CrossRef\]](#)
27. Dikshit, A.; Sarkar, R.; Pradhan, B.; Acharya, S.; Dorji, K. Estimating Rainfall Thresholds for Landslide Occurrence in the Bhutan Himalayas. *Water* **2019**, *11*, 1616. [\[CrossRef\]](#)
28. Abraham, M.T.; Pothuraju, D.; Satyam, N. Rainfall Thresholds for Prediction of Landslides in Idukki, India: An Empirical Approach. *Water* **2019**, *11*, 2113. [\[CrossRef\]](#)
29. Monsieurs, E.; Dewitte, O.; Depicker, A.; Demoulin, A. Towards a Transferable Antecedent Rainfall—Susceptibility Threshold Approach for Landsliding. *Water* **2019**, *11*, 2202. [\[CrossRef\]](#)
30. Monsieurs, E.; Dewitte, O.; Demoulin, A. A susceptibility-based rainfall threshold approach for landslide occurrence. *Nat. Hazards Earth Syst. Sci.* **2019**, *19*, 775–789. [\[CrossRef\]](#)
31. Bordoni, M.; Corradini, B.; Lucchelli, L.; Valentino, R.; Bittelli, M.; Vivaldi, V.; Meisina, C. Empirical and Physically Based Thresholds for the Occurrence of Shallow Landslides in a Prone Area of Northern Italian Apennines. *Water* **2019**, *11*, 2653. [\[CrossRef\]](#)
32. Baum, R.L.; Savage, W.Z.; Godt, J.W. *TRIGRS—A Fortran Program for Transient Rainfall Infiltration and Grid-Based Regional Slope-Stability Analysis, Version 2.0*; Open-File Report, 1159; US Geological Survey: Reston, VA, USA, 2008.
33. Lin, G.W.; Kuo, H.L.; Chen, C.W.; Wei, L.W.; Zhang, J.M. Using a Tank Model to Determine Hydro-Meteorological Thresholds for Large-Scale Landslides in Taiwan. *Water* **2020**, *12*, 253. [\[CrossRef\]](#)
34. Dikshit, A.; Sarkar, R.; Pradhan, B.; Jena, R.; Drukpa, D.; Alamri, A.M. Temporal Probability Assessment and Its Use in Landslide Susceptibility Mapping for Eastern Bhutan. *Water* **2020**, *12*, 267. [\[CrossRef\]](#)
35. He, S.; Wang, J.; Liu, S. Rainfall Event–Duration Thresholds for Landslide Occurrences in China. *Water* **2020**, *12*, 494. [\[CrossRef\]](#)
36. Abraham, M.T.; Satyam, N.; Rosi, A.; Pradhan, B.; Segoni, S. The Selection of Rain Gauges and Rainfall Parameters in Estimating Intensity–Duration Thresholds for Landslide Occurrence: Case Study from Wayanad (India). *Water* **2020**, *12*, 1000. [\[CrossRef\]](#)
37. Abraham, M.T.; Satyam, N.; Kushal, S.; Rosi, A.; Pradhan, B.; Segoni, S. Rainfall Threshold Estimation and Landslide Forecasting for Kalimpong, India Using SIGMA Model. *Water* **2020**, *12*, 1195. [\[CrossRef\]](#)
38. Martelloni, G.; Segoni, S.; Fanti, R.; Catani, F. Rainfall thresholds for the forecasting of landslide occurrence at regional scale. *Landslides* **2012**, *9*, 485–495. [\[CrossRef\]](#)
39. Segoni, S.; Rosi, A.; Fanti, R.; Gallucci, A.; Monni, A.; Casagli, N. A regional-scale landslide warning system based on 20 years of operational experience. *Water* **2018**, *10*, 1297. [\[CrossRef\]](#)
40. Jordanova, G.; Gariano, S.L.; Melillo, M.; Perruccacci, S.; Brunetti, M.T.; Jemec Auflič, M. Determination of Empirical Rainfall Thresholds for Shallow Landslides in Slovenia Using an Automatic Tool. *Water* **2020**, *12*, 1449. [\[CrossRef\]](#)
41. Calvillo, M.; Devoli, G.; Freeborough, K.; Gariano, S.L.; Guzzetti, F.; Kirschbaum, D.; Nakaya, H.; Robbins, J.; Stähli, M. LandAware: A new international network on Landslide Early Warning Systems. *Landslides* **2020**, *17*, 2699–2702. [\[CrossRef\]](#)