

EGU21-1623

<https://doi.org/10.5194/egusphere-egu21-1623>

EGU General Assembly 2021

© Author(s) 2022. This work is distributed under the Creative Commons Attribution 4.0 License.



## **Towards the effective use of Artificial Neural Networks for accessing rainfall thresholds for rainfall-induced landslides, a study based on in-situ and satellite merged rainfall data**

**Luísa Vieira Lucchese<sup>1</sup>**, Guilherme Garcia de Oliveira<sup>2</sup>, and Olavo Correa Pedrollo<sup>1</sup>

<sup>1</sup>Instituto de Pesquisas Hidráulicas, Universidade Federal do Rio Grande do Sul, Porto Alegre, Brazil

([luisa.lucchese@ufrgs.br](mailto:luisa.lucchese@ufrgs.br))

<sup>2</sup>Departamento Interdisciplinar, Universidade Federal do Rio Grande do Sul, Tramandaí, Brazil

Rainfall-induced landslides have caused destruction and deaths in South America. Accessing its triggers can help researchers and policymakers to understand the nature of the events and to develop more effective warning systems. In this research, triggering rainfall for rainfall-induced landslides is evaluated. The soil moisture effect is indirectly represented by the antecedent rainfall, which is an input of the ANN model. The area of the Rolante river basin, in Rio Grande do Sul state, Brazil, is chosen for our analysis. On January 5<sup>th</sup>, 2017, an extreme rainfall event caused a series of landslides and debris flows in this basin. The landslide scars were mapped using satellite imagery. To calculate the rainfall that triggered the landslides, it was necessary to compute the antecedent rainfall that occurred within the given area. The use of satellite rainfall data is a useful tool, even more so if no gauges are available for the location and time of the rainfall event, which is the case. Remote sensing products that merge the data from in situ stations with satellite rainfall data are increasingly popular. For this research, we employ the data from MERGE (Rozante et al., 2010), that is one of these products, and is focused specifically on Brazilian gauges and territory. For each 12.5x12.5m raster pixel, the rainfall is interpolated to the points and the rainfall volume from the last 24h before the event is accumulated. This is added as training data in our Artificial Neural Network (ANN), along with 11 terrain attributes based on ALOS PALSAR (ASF DAAC, 2015) elevation data and generated by using SAGA GIS. These attributes were presented and analyzed in Lucchese et al. (2020). Sampling follows the procedure suggested in Lucchese et al. (2021, in press). The ANN model is a feedforward neural network with one hidden layer consisting of 20 neurons. The ANN is trained by backpropagation method and cross-validation is used to ensure the correct adjustment of the weights. Metrics are calculated on a separate sample, called verification sample, to avoid bias. After training, and provided with relevant information, the ANN model can estimate the 24h-rainfall thresholds in the region, based on the 2017 event only. The result is a discretized map of rainfall thresholds defined by the execution of the trained ANN. Each pixel of the resulting map should represent the volume of rainfall in 24h necessary to trigger a landslide in that point. As expected, lower thresholds (30 - 60 mm) are located in scarped slopes and the regions where the landslides occurred. However, lowlands and the plateau, which are areas known not to be prone to landslides, show higher rainfall thresholds, although not as high as expected (75 - 95 mm).

Mean absolute error for this model is 16.18 mm. The inclusion of more variables and events to the ANN training should favor achieving more reliable outcomes, although, our results are able to show that this methodology has potential to be used for landslide monitoring and prediction.