LANDSLIDE SUSCEPTIBILITY IN RIO GRANDE DO SUL: COULD PAST LANDSLIDES INDICATE AREAS AFFECTED IN MAY 2024?

Renata Pacheco Quevedo[1], *Daniel Andrade Maciel*[2], *Clódis de Oliveira Andrades Filho*[3,4], *Lorenzo Fossa Sampaio Mexias*[4], *Guilherme Garcia de Oliveira*[4], *Pâmela Boelter Herrmann*[4], *Fabio Corrêa Alves*[5], *Thomas Glade*[1]

[1]Department of Geography and Regional Research, University of Vienna, 1010 Vienna, Austria, renata.pacheco.quevedo@univie.ac.at, thomas.glade@univie.ac.at, [2]Earth Observation and Geoinformatics Division, National Institute for Space Research, 12227010 São José dos Campos, São Paulo, Brazil, daniel.maciel@inpe.br; [3]Institute of Geoscience, Federal University of Rio Grande Do Sul, 91509-900 Porto Alegre, Rio Grande do Sul, Brazil, clodis.filho@ufrgs.br, [4]Postgraduate Program in Remote Sensing, Federal University of Rio Grande Do Sul, 91509-900, Porto Alegre, Rio Grande do Sul, Brazil, lorenzo.mexias@ufrgs.br, g.g.oliveira10@gmail.com, pamelaboelter@gmail.com, and [5]Center of Humanities - CEHU, Federal University of Western Bahia, 47810-047, Barreiras, Bahia, Brazil, fabio.alves@ufob.edu.br

ABSTRACT

The Mega Disaster that occurred in May 2024, reaching Rio Grande do Sul (RS), Brazil, resulted in more than 15,000 landslides, affecting nearly 18,000 km^2. In this study, we generated a landslide susceptibility map based on historical landslide data (1995-2017) and assessed its capacity to forecast the 2024 landslides. Based on the Random Forest algorithm, we modelled landslide susceptibility for the entire RS with a high overall accuracy of 0.964. The retrospective evaluation using the 2024 landslide inventory considered two sets: i) polygon centroids, and ii) points by pixels. In the first approach, our model correctly classified 69% of the landslides in susceptible areas. The second analysis classified 31% of the points in very high susceptibility areas. Furthermore, when comparing the landslide areas, our model correctly classified most of the landslide rupture zones (79%). Finally, we highlight the need to consider landslide zones for updating susceptibility maps.

Key words – *Natural hazard, disaster, Random Forest, modelling, Brazil.*

1. INTRODUCTION

Natural hazards are occurring more frequently and with a higher magnitude over the world [1], mainly due to climate change and anthropic activities [2]. Disasters caused by floods and landslides have increased over tenfold in the last 50 years [2]. Specifically in Brazil, floods and rainfall-induced landslides caused at least 13,000 casualties between 1948 and 2023 [3].

The Mega Disaster that occurred in May 2024 affected more than 400 municipalities in the *Rio Grande do Sul* (RS) state. Although the floods received more attention due to their impact on big cities, such as the capital, *Porto Alegre* [4], almost the entire Meridional Plateau Escarpment was affected by landslides. The efforts carried out by the voluntary research team, coordinated by the LATITUDE group[1] from the Federal University of *Rio Grande do Sul* resulted in the mapping of more than 15 thousand landslides in the region, representing 90% of the target area [5]. This number is expected to increase as further analyses are conducted.

The landslide-affected region covers an area of approximately 18,000 km^2, distributed in the Meridional Plateau Escarpment. We analysed the previous landslides that occurred in the state (between 1995 and 2017) and aimed to assess if the susceptibility map could indicate the areas most affected in 2024. In addition, we validated the susceptibility mapping by considering each part of the landslide polygons (initiation, propagation, and deposition).

2. MATERIAL AND METHODS

2.1. Study Area

The RS is the southernmost state in Brazil, which presents a total area of 281,730 km^2, with altitude varying between 1 m to nearly 1,400 m (Figure 1). The central-northern region of RS is characterised by the Meridional Plateau, composed of volcanic rock sequences from the *Serra Geral* Group, that overlies the aeolian sandstones from the *Botucatu Formation* [6]. The transition between the Plateau and the *Depressão Central* region is marked by a steep Escarpment, which concentrates most of the landslides that occur in the state.

The climate is classified as a humid subtropical ocean climate without a dry season, with temperate summer (Cfb) in the northern portion of the state, i.e., the highest areas. The lowest areas present a humid subtropical ocean climate without a dry season, with a hot summer (Cfa) [7]. The state is composed of the biomes Pampa (63%), native grasslands, and Atlantic Forest (37%), Semideciduous Seasonal Forests and Mixed Ombrophilous Forests [8].

The complex geomorphological natural characteristics combined with different rainfall regimes and increasing trends in precipitation [9], result in many landslide-prone areas throughout the state. In 22 years, at least 1,211 landslides were recorded in the Meridional Plateau Escarpment (Figure 1A, B, C, and D) [10]. Although this number represents a big record, the extreme event that occurred in May 2024 was the only one responsible for at least 15,094 landslides [5].

[1]LATITUDE - Sensoriamento Remoto Geológico, Geomorfológico e Dinâmicas da Paisagem

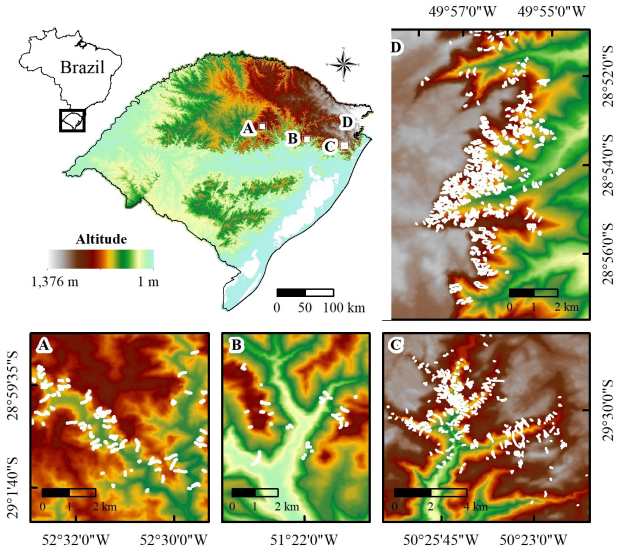


Figure 1: *Rio Grande do Sul* state and landslides recorded between 1995 and 2017 (white polygons). A) *Fão* river valley, B) *Forromeco* stream valley, C) *Rolante* river basin, D) *Rocinha* river valley.

2.2. Methods

In this study, we used the landslides recorded between 1995 and 2017 to generate a Random Forest-based susceptibility map for the RS state, aiming to assess whether this map could predict the areas affected by the 2024 extreme event. Since the *Rocinha* river valley is in the Meridional Plateau Escarpment, but specifically in Santa Catarina state, we considered the RS limits with a 3 km buffer as our study area.

The landslide inventory was composed of 1,211 landslides, represented by 15,580 points. For representing non-landslide samples, we randomly selected the same number of points in the entire state, considering areas without any landslide record in our inventory. The total sample set (nearly 31,000 points) was randomly split into training (70%) and validation (30%) samples.

The landslide conditioning factors comprehended terrain data derived from NASADEM [11] with 30 m spatial resolution. Therefore, we selected seven morphometric parameters: i) altitude, ii) convergence index, iii) plan curvature, iv) profile curvature, v) slope, vi) Topographic Position Index (TPI), and vii) Topographic Ruggedness Index (TRI). The modelling process was carried out using the Random Forest algorithm [12]. We run the model using the R randomForest package [13], setting 500 trees (*ntree*=500) and three variables for the splits (*mtry*=3) as the hyperparameters.

A second validation was carried out through a retrospective evaluation of the susceptibility map [14], considering the landslides that occurred in 2024 (Figure 2). For that, we considered all the 15,094 landslides in two different sets: i) sample set composed of landslide centroids (15,094 points), and ii) all pixels found inside the landslide polygons (324,500 points).

We also estimated the closeness of the relationship between areas with landslide occurrence and susceptibility classes using the Frequency Ratio (FR) method. This method

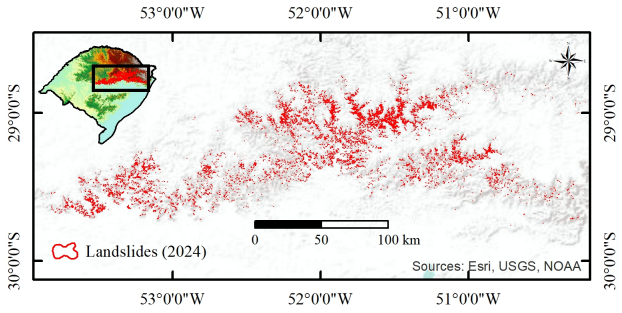


Figure 2: Inventory of landslides occurred in May 2024, composed of 15,094 polygons.

calculates the correlation between landslide locations with each analysed class, in which values greater than 1 represent a higher correlation [15]. With that, analysed the correlation between the 2024 landslides and the susceptibility classes generated with the past inventory, to understand the reliability of the landslide susceptibility map. The FR is calculated as follows:

$$FR = \frac{LA_i/A_i}{\sum LA_t otal \sum A_{total}} \quad (1)$$

where FR represents the Frequency Ratio; LA indicates the landslide area in each susceptibility class i; A_i is the total area of class i; LA_{total} is the landslide area; A_{total} is the total analysed area.

Finally, we analysed the landslide areas (initiation, propagation, and deposition) and assessed which parts were more classified as susceptible. For that, we split the complete sample set (218,540 points) into three parts according to the altitude in each landslide polygon. Due to the high number of landslides that occurred in 2024, this automatic split into three parts aimed to approximate the different landslide areas. Here, the lower third (lowest altitude of each landslide) represents the deposition area; the upper third (highest altitude) represents the rupture area, and the intermediate third corresponds to the propagation area.

3. RESULTS

3.1. Model's evaluation and susceptibility mapping

The most important conditioning factors were TRI (terrain heterogeneity estimation), altitude, and TPI (difference between a given pixel altitude and their neighbour pixels). In this specific context, profile curvature was the least important variable. The susceptibility model reached a high overall accuracy of 0.964 (Table 1).

Statistical metric	RF	Statistival metric	RF
PPR	0.973	Sensitivity	0.953
NPR	0.956	Specificity	0.975
OA	0.964	AUC	0.990

RF: Random Forest, PPR: Positive Prediction Rate, NPR: Negative Prediction Rate; OA: Overall Accuracy

Table 1: Model prediction performance metrics.

In the susceptibility map, approximately 92% and 3% of the entire study area were classified with very low and low susceptibility, respectively (Figure 3). The remaining 5% were considered susceptible to landslides. Among them, an area of 5,665 km^2 was classified as very high susceptibility

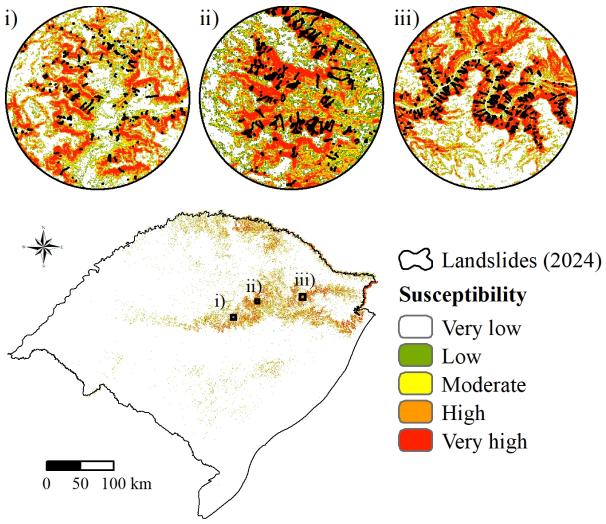


Figure 3: Susceptibility map for the RS state, according to past landslides (1995 to 2017). Zoom areas present the susceptibility overlaid with the landslides that occurred in 2024.

3.2. Landslides in May 2024

The 15,094 landslides that occurred in May 2024 were analysed through centroids and points. Considering the centroid sample set, 10,345 landslides (69%) were found in susceptible areas (Table 2). Among them, 5,238 landslides (35%) are in very high susceptible areas, 3,218 (21%) in high susceptibility, and 1,889 (13%) in moderate susceptibility.

Susceptibility	Centroids	FR	Points	FR
Very high	5,238 (35%)	10.63	100,116 (31%)	13.04
High	3,218 (21%)	7.12	64,577 (20%)	7.57
Moderate	1,889 (13%)	7.73	41,169 (13%)	7.84
Low	1,905 (13%)	7.68	43,590 (13%)	7.33
Very low	2,844 (19%)	0.38	75,048 (23%)	0.33
Total	15,094		324,500	

FR: Frequency Ratio

Table 2: Validation of the susceptibility map according to the landslides occurred in 2024.

According to the landslide points, 64% (205,862) were found in susceptible areas, being 31% located in very high susceptibility. Since the high susceptibility class occupied nearly 1.8% of the total study area, the FR showed that this class concentrated most landslides that occurred in 2024.

The analysis considering landslide mechanical areas showed that 42% of the points represented the deposition area, 31% the propagation area, and 27% the rupture zone (Table 3). It is noteworthy that 79% of the rupture points were well classified in susceptible areas, mainly very high susceptibility class (47%). On the other hand, deposition samples were mostly misclassified in areas with low or very low susceptibility (51%).

Susceptibility	Rupture	Propagation	Deposition
Very high	42,032 (47%)	34,376 (34%)	23,693 (18%)
High	18,771 (21%)	22,258 (22%)	23,553 (17%)
Moderate	9,638 (11%)	13,353 (13%)	18,188 (13%)
Low	7,324 (08%)	12,249 (12%)	24,017 (18%)
Very low	10,964 (12%)	18,755 (19%)	45,329 (34%)
Total	88,729	100,991	134,780

Table 3: Distribution of landslide for susceptible classes, considering mechanical areas.

4. DISCUSSION

The generation of landslide susceptibility maps aims, in general, to estimate "where" future landslides are most likely to occur [16]. Evaluating these types of maps is of utmost importance [17], as they can be used for disaster risk management and territorial planning. When applied in practice, susceptibility maps can help to determine areas with (or without) occupation restrictions and because of that the validation and identification of the most suitable model is important [18]. In this sense, we generated a landslide susceptibility map using past inventory (1995 – 2017) available in the study area and carried out a double evaluation of the model prediction performance [19] using: i) 30% of the samples not used to calibrate the model, and ii) a retrospective assessment with landslides occurred in 2024.

In the first evaluation, the model prediction performance reached very high accuracy values (i.e., greater than 0.95). It is noteworthy that the high accuracy reached by our model can be associated with the restricted area of the inventories compared to the total analysed area (0.01% of the RS territory). In addition, the retrospective assessment showed that our landslide susceptibility map was capable of identifying susceptible areas that covered more than 60% of the landslides that occurred in 2024.

Specifically, our model covered most of the rupture and transport areas, with 79% and 69%, respectively. Different from the results found by Ozturk et al. [20], in which the model performed better considering landslide toe area, here considered as deposition area. The lower performance related to the deposition areas was expected since the previous landslide inventory was made after 2020, when most of the landslide deposition areas were no longer visible in remote sensing images, remaining only rupture and transport zones.

Despite the limitations found regarding the deposition areas, we emphasise that the best performance of our model for rupture and transport areas can provide information about the morphology of the affected areas. Evaluating the landslide mechanical areas, such as the rupture and deposition morphometric patterns [21], can provide useful information on the study of landslides in RS. Therefore, there is a need to segment the susceptibility modelling and mapping according to the landslide mechanical areas, aiming to highlight the different patterns and better conditioning factors.

5. CONCLUSIONS

The more frequent occurrence of extreme events related to natural hazards, such as landslides, indicates the increasing necessity of society's adaptation. In this study, we explored the capacity of susceptibility maps to indicate landslide-prone areas. Our susceptibility map was generated using an inventory of events that occurred between 1995 and 2017 and was assessed using the 2024 landslides. This retrospective assessment is used to evaluate landslide susceptibility suitability for forecasting prone-areas and its utility for territorial planning. The results showed that our model was capable of correctly predicting most landslides that occurred in 2024. Even though the 2024 Mega Disaster in Rio Grande do Sul was responsible for 12.5 times more landslides than all the previous inventory, our model based on 1,211 landslides correctly classified 10,345 landslides (69%) in susceptible areas. Furthermore, our study highlights the importance of considering landslide mechanical areas (rupture, propagation, and deposition) in the analysis process. The lack of deposition area mapping in the previous landslide inventory was verified in the outputs, which presented a better performance when considering rupture and transition zones. These findings demonstrate the value of refining susceptibility models by incorporating more detailed mechanical area analysis. This approach could significantly enhance the ability to predict future landslides and improve territorial planning, contributing to disaster risk management. For future studies, we suggest carrying on landslide susceptibility modelling considering not only each mechanical zone but also the mass movement type.

6. ACKNOWLEDGEMENTS

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