Soils and Rocks
An International Journal of Geotechnical and Geoenvironmental Engineering
www.soilsandrocks.com
ISSN 1980-9743
ISSN-e 2675-5475

Critical threshold curves for landslides in Rio de Janeiro city via long term rainfall monitoring

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Article

Keywords
Landslide
Critical threshold
Landslide prediction
Long term rainfall monitoring
Early-warning system

Abstract

The city of Rio de Janeiro, Brazil, regularly experiences landslides triggered by rainfall. To enhance our understanding of critical thresholds, this study analyses two datasets over a period of 24 years (1999 to 2022): rainfall events, from data obtained from 33 city-installed rain gauges and an inventory of landslide occurrence reports from the Geo-Rio Foundation. The dataset comprises 7,019 significant rainfall events, of which 6,481 resulted in landslides. A total of 6,671 landslides occurred during the analyzed period, a total of 14,402 technical inspections were conducted after slope instability assessments were requested by the population. In addition to evaluating rainfall values that lead to landslides, the study analyses the impact of Geo-Rio's slope-stabilization efforts and population growth in landslide-prone areas. Computational techniques were used to manipulate and classify the data, revealing zone-dependent thresholds. A strong correlation is identified between landslide events, rainfall intensity and accumulated rainfall (96-hour period). The results underscore the necessity to improve Rio de Janeiro's early-warning system, considering both rainfall intensity and 96 hours of accumulated rainfall data to predict landslides, with implications for future slope stabilization efforts and urban planning in landslide-prone areas.

1. Introduction

Critical threshold curves for landslides are among the most important tools used by specialists to forecast the rainfall levels that can trigger landslides. Globally, it is estimated that 17.1% of the land area is susceptible to landslides and 8.2% of the world's population resides in those regions (Mondini et al., 2023). Several relevant global methodologies which have been proposed to support early-warning systems (Caine, 1980; Tatizana et al., 1987; Larsen & Simon, 1993; Aleotti, 2004; Chien-Yuan et al., 2005; Guzzetti at al., 2007; Tiranti & Rabuffetti, 2010; Castro et al., 2012; Rosi t al., 2019; Ehrlich et al., 2021). These methodologies include various empirical threshold procedures based on combinations of commonly used rainfall parameters, such as duration (D, min), intensity (I, mm/h) and cumulative rainfall over the antecedent period (A_{96}, mm/96hs and A_{60}, mm/60hs).

In general, the critical threshold curves for landslides have been proposed based on two main approaches:

a) Empirical thresholds, which rely on historical data correlating rainfall with landslides. This approach is widely used and incorporates various pluviometry parameters, such as antecedent rainfall type, duration, intensity, and accumulated rainfall. Among these parameters, the rainfall intensity versus duration is most commonly applied (Caine, 1980; Tatizana, et al. 1987; Larsen & Simon, 1993; Aleotti, 2004; Chien-Yuan et al., 2005; Guzzetti at al., 2007; Tiranti & Rabuffetti, 2010; Castro et al., 2012; Ehrlich et al., 2021; Chaves et al., 2017; Guidicini & Iwasa, 1976; Kanji et al., 2003; Liu et al., 2024; Metodiev et al., 2018; Parizzi et al., 2010).
b) Physically-based thresholds, based on numerical models that examine the relationship between rainfall, pore pressure and slope stability (Wu & Siddle, 1995; Pack et al., 1998; Baum et al., 2005; Montrasio & Valentino, 2008; Meena et al., 2020; Mondini et al., 2023; Montoya-Araque & Montoya-Noguera, 2024). These numerical models combine a hydrological model with a slope stability model. However, due to the complexity of developing these models, which require detailed knowledge of soil conditions and field tests, this methodology is less commonly employed.

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Submitted on October 1, 2025; Final Acceptance on October 3, 2025; Discussion open until May 31, 2026.
Editor: Renato P. Cunha
https://doi.org/10.28927/SR.2026.015725

Rosi et al. (2019), motivated by the 2011 catastrophic landslides in Rio de Janeiro's mountainous region, developed MaCumBa (Massive CUMulative Brisk Analyser), a semi-automated method for defining rainfall intensity–duration thresholds for landslide initiation. Using over 3,000 events (2008–2017) with rainfall data, they assessed thresholds through correct alarms (*CA*), false alarms (*FA*), missed alarms (*MA*), and Positive Predictive Value (*PPV*). Three thresholds (moderate, high, very high) were proposed for Petropolis, Teresopolis, and Nova Friburgo. Despite satisfactory performance, the moderate threshold produced excess FA, highlighting the need for expanded datasets to improve reliability of early-warning systems.

Salles (2023) analyzed governance policies and landslide occurrences in Brazilian municipalities (2000–2019), using reports from 722 events. Three variables were defined: annual landslides per municipality, clustered landslides, and rainfall duration. Applying a Poisson pseudo-maximum likelihood estimator with high-dimensional fixed effects (*PPML-HDFE*), the study identified correlations between governance policies and landslide frequency, distribution, and rainfall intensity. A Landslide Risk Index (*LRI*) based on rainfall Intensity–Duration modeling was also proposed. However, the study did not incorporate geomorphology, topography, or geotechnical factors. Findings suggest regions with intense rainfall histories are more prone to landslides.

Mendonça et al. (2020) analyzed the Quitandinha river basin (Petropolis, Brazil) using landslide records and rainfall data (2003–2009) to define rainfall thresholds. The region's hydrogeological conditions promote infiltration through soil and fractures in bedrock. Using the chi-squared contingency coefficient, they identified 24 h and 96 h accumulated rainfall as the most significant triggers. Considering both periods together improved prediction compared to each individually. The methodology estimated probabilities for at least one, three, or five landslides occurring, depending on rainfall intensity.

Recent advances highlight the growing role of statistical methods and *AI* in landslide prediction. He et al. (2024) reviewed *AI* applications in landslide detection, susceptibility, and displacement forecasting. They examined machine learning, deep learning, hybrid models, performance testing, and graphical user interfaces (*GUIs*). The study emphasized *GUIs*, which integrate complex algorithms into user-friendly platforms, as valuable tools for landslide risk assessment and early warning systems.

Vanani et al. (2024) applied fuzzy techniques, artificial neural networks (*ANN*), and multivariate regression to map landslide susceptibility in northern Tehran. They analyzed spatial landslide distribution in relation to topographic, seismic, lithologic, hydrologic, vegetation, and human activity factors. Results showed strong correlations between controlling factors, landslide area, and density, offering insights into sliding mechanisms. Among the tested models, *ANN* performed best, effectively assessing landslide susceptibility under diverse triggers, including seismic, lithological, hydrological, and topographical conditions.

Tzampoglou et al. (2025) investigated correlations between landslides and geotechnical indexes, such as grain size, plasticity, liquid limit, geomorphology, geological strength, and uniaxial compressive resistance, in southwestern Cyprus. Based on Geological Survey data, 1,936 landslides were recorded, including 529 active and 1,407 inactive. Using the Frequency Ratio method and advanced machine learning (Random Forest and Shapley Additive Explanations), the study found that incorporating geotechnical indexes significantly improved the predictive accuracy and effectiveness of landslide hazard assessment.

The city of Rio de Janeiro, in Southeast Brazil, is characterized by three main massifs, Tijuca, Pedra Branca, and Gericino, interspersed with coastal plains and valleys. Pedra Branca reaches the highest elevation at 1,025 m. Geologically, the area is dominated by granitoid and gneiss rocks. Mountainous slopes, typically steeper than 30°, consist of residual soils a few centimeters to several meters thick over fractured bedrock. The landscape features colluvium at slope bases, residual soils on mid to upper slopes, and exposed rock outcrops at hilltops, while plains and valleys are filled with alluvial and colluvial deposits.

The Geo-Rio Foundation, a municipal institution integrating geotechnical, geological, and meteorological expertise, is responsible for risk management, public geotechnical works, supervision of private construction, and mineral exploration in Rio de Janeiro. To support planning, the city was subdivided into 11 geotechnical regions, encompassing 163 districts grouped by topography, geology, and land use. This framework enables site-specific evaluation and prioritization of interventions. Figure 1 depicts the 11 sub-regions and the spatial distribution of 33 rain gauges.

Table 1 presents the total area, as well as the areas of medium and high susceptibility to landslides for each sub-region (refer to Figure 1), according to studies conducted by Geo-Rio. Most landslides involved residual soils and were characterized by shallow failures. However, some deep-seated landslides and rockfalls have also been reported.

Figure 2 shows accumulated monthly rainfall considering the average value identified in 33 rain gauges installed across Rio de Janeiro City. Considering the geological, geomorphological, and topographical attributes of Rio de Janeiro, coupled with its substantial rainfall records, the region is notably vulnerable to landslides. This is exacerbated by the city's unplanned urban expansion. Rain plays a pivotal role as the primary catalyst for these movements. The rainy season extends from October to April, which is when most landslide occurrences are recorded. As rainwater infiltrates the soil, it can elevate the groundwater table, diminishing soil resistance due to the increase in pore pressure (Lacerda et al., 2017). In areas where the rock face is fractured, water infiltration through these cracks facilitates the dislodging of rock fragments and destabilizes larger rock blocks.

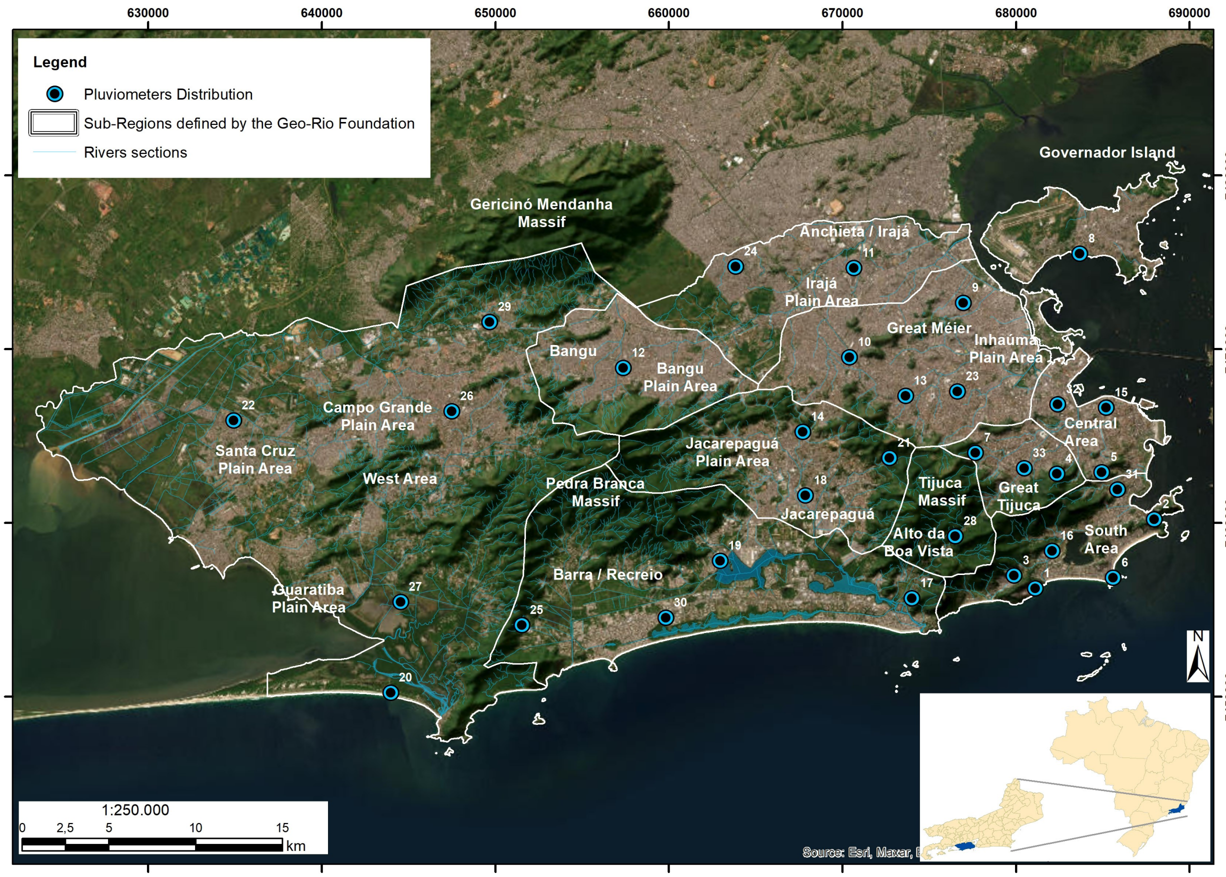

Figure 1. Morphology, rain gauge distribution and sub-regions in Rio de Janeiro.

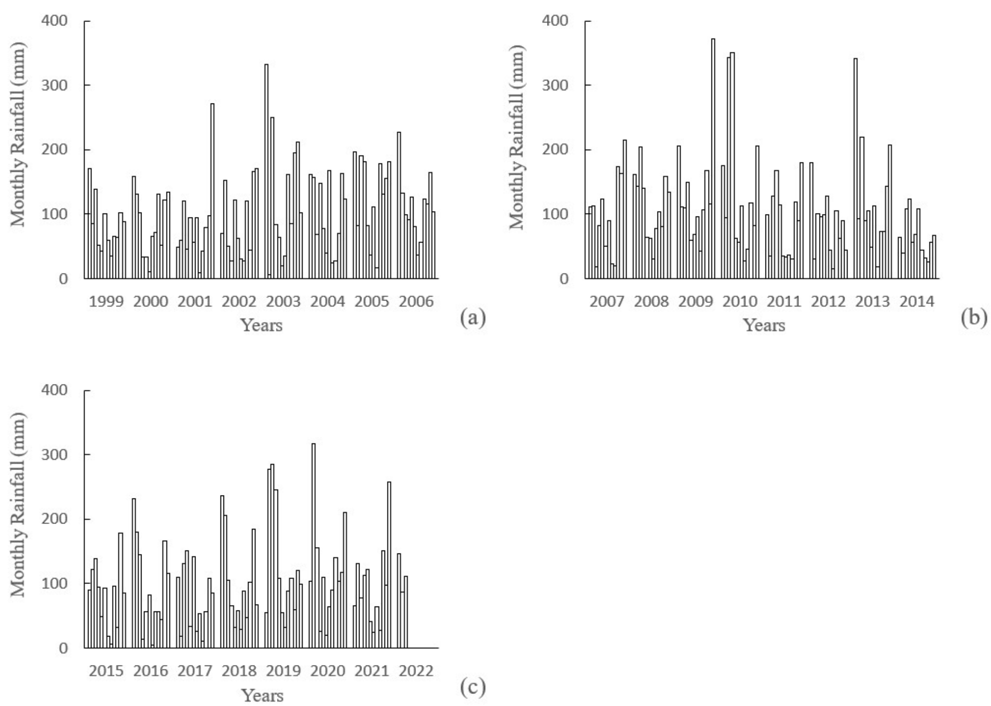

Figure 2. Monthly rainfall for periods: (a) 1999 to 2006; (b) 2007 to 2014; and (c) 2015 to 2022.

Table 1. Total area and the areas of susceptibility to landslides for the different regions of Rio de Janeiro City, according to Geo-Rio.

Region	Total area (km²)	Susceptible areas (km²)	Susceptible areas (%)
Anchieta/Iraja	82.4	24.7	30
Alto da Boa Vista	33.3	33.3	100
Bangu	68.4	16.4	24
Barra/Recreio	177.0	37.2	21
Central area	30.6	9.2	30
Great Meier	112.0	43.7	39
Great Tijuca	27.7	18.6	67
Governador Island	17.3	11.9	69
Jacarepagua	96.6	31.9	33
South area	53.2	35.1	66
West area	499.0	144.7	29
Total	1197.5	406.7	34

Table 2. Criteria for early warning alarms for rainfall-induced landslide occurrences (D'Orsi, 2012).

Period (hours)	Probability of occurrence vs. accumulated rainfall (mm)		
	Medium	High	Very High
1	25 - 50	50 - 80	> 80
24	85 - 140	140 - 220	> 220
96	142 – 220 and 25 – 50 mm/24h	220 – 300 and 50 – 100 mm/24h	> 300 and > 100 mm/24h

Table 3. Classification of a rainfall event (Ehrlich et al., 2021).

Category of mass movement	number of landslide occurrences km² of susceptible area (NNL)
Non-landslides event	**NNL = 0**
I	$0 < NNL \leq 0.2$
II	$0.2 < NNL \leq 0.4$
III	$0.4 < NNL$

The city has an impressive history of landslides associated with significant rainfall events (Ehrlich et al., 2021). These occurrences present numerous challenges to the population, spanning from property destruction to loss of life. The city has witnessed significant incidents, the latest major ones being in April 2010, claiming over 60 lives.

Through studies on the correlations between rainfall and geotechnical accidents on the city's slopes, Geo-Rio developed the ALERTA RIO System (Geo-Rio Foundation, 1996). Implemented in 1996, Table 2 outlines the criteria used by city authorities to activate early warning alarms for rainfall-induced landslide occurrences. This system relies on short-term weather forecasts and data from the automatic rain gauges installed in 33 locations across Rio de Janeiro (D'Orsi et al., 2005). Heretofore, the criteria used by ALERTA RIO have been based on accumulated rainfall. Calvello et al. (2015) assessed the effectiveness of the correlation models and rainfall thresholds employed by ALERTA RIO to issue landslide warnings. The study indicated that, while the adopted criteria successfully kept the number of missed alerts low, they also generated a significant number of false alerts across the city. The authors suggested that the system's performance could be enhanced by implementing zone-specific thresholds.

Ehrlich et al. (2021) defined threshold rainfall curves for different categories of events based on the number of landslide occurrences per km² of susceptible area (*NNL*) in each specific region of the city (Table 3). Critical thresholds in Rio de Janeiro City were obtained by analyzing landslide occurrences documented in the Geo-Rio Foundation's inventory and rainfall measurements collected from 33 rain gauges across the city (Figure 1).

The Geo-Rio inventory covers a 24-year period, from 1999 to 2022. However, the study by Ehrlich et al. (2021) focused specifically on events in Rio de Janeiro between 1998 and 2002, as well as from 2010 to 2012. This timeframe was selected to assess the impact of slope stabilization efforts by the Geo-Rio Foundation and the effects of population growth in areas highly vulnerable to landslides during that period. Over the broader span from 1999 to 2022, the city underwent various urban improvement programs under multiple administrations, which were accompanied by significant geotechnical investment (Figure 3) and steady population growth in certain regions (Figure 4). The study emphasizes how rainfall patterns, infrastructure investment, and population growth have had different impacts across the city's sub-regions. A strong correlation was identified between landslide events, rainfall intensity and accumulated rainfall (96-hour period).

Building on the empirical approach of previous studies that correlate rainfall with landslides using historical data, the goal of this study is to refine the critical rainfall thresholds for the city of Rio de Janeiro. This work aims to improve upon earlier research (D'Orsi et al., 2005; Calvello et al., 2015; Bonnard & Noverraz, 2001; Campbell, 1975; D'Orsi, 2012; Martins et al., 2016) in several significant key respects:

- The present work covers the full 24-year period (from 1999 to 2022) in which rainfall data and technical reports were systematically collected in the city;
- In the presence of 7,019 significant rainfall events and 6,671 landslide occurrences from 14,402 technical reports, the results are more statistically reliable;
- Computational techniques were employed throughout, including the process of extracting information from the raw rainfall data and the technical reports, a task that was previously carried out by hand;
- A new quantitative indicator (Δ_b defined in the Methodology section) is proposed here, in order to analyze which period of accumulated rainfall (24, 48, 96, or 720 hours) is more reliable in predicting the possibility of catastrophic events, considering different periods of time and sub-regions of the city;
- The much larger dataset allowed a more comprehensive examination of each of the 11 sub-regions, separately;
- The impact of geotechnical investment and population grown was evaluated along the full 24-year period.

Additionally, it is important to assess the need for enhancing the city's early warning system by establishing zone-specific rainfall thresholds. Variations in factors such as topography, vegetation, geological and geotechnical characteristics, and occupation patterns among sub-regions

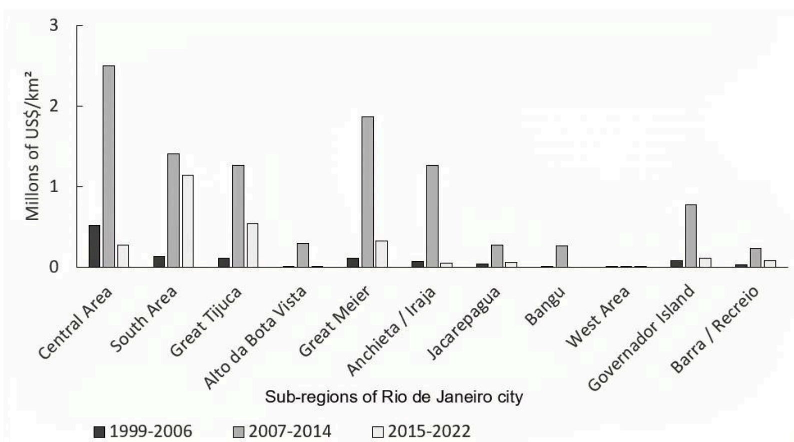

Figure 3. Investment in slope stabilization per susceptibility (millions of dollars/km^2) for each of the 11 sub-regions of the city of Rio de Janeiro (Geo-Rio Foundation, 1996).

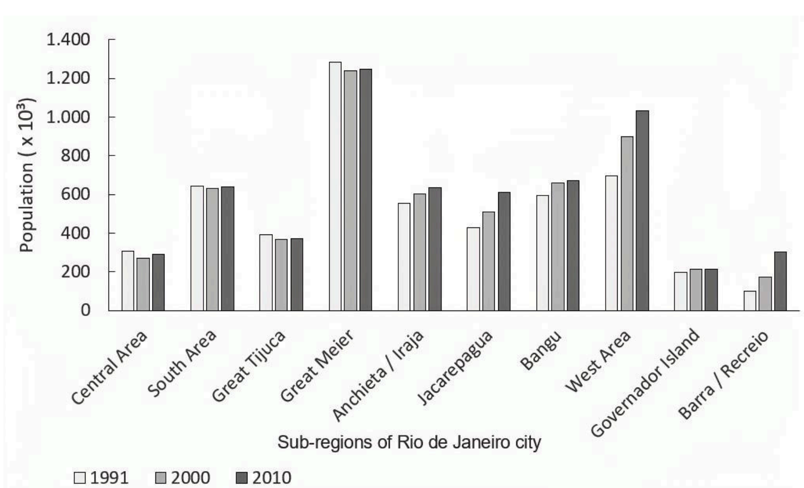

Figure 4. Resident population in Rio de Janeiro sub-regions (Pereira Passos Institute, 2024).

suggest that landslide susceptibility to rainfall may differ uniquely across these areas.

2. Materials and methods

Due to the large amount of information collected, it was necessary to adopt a procedure that could bring efficiency and speed in the analysis of the data obtained. Among the available alternatives, we chose to work with computational techniques, which involved statistics, databases, expert systems, and data visualization techniques. The study methodology using computational techniques was developed in stages, using the Python programming language (Lutz 2013). The first action involved formulating an algorithm which was capable of automatically extracting the relevant information contained in the occurrence reports and the existing database of rain gauge (data ingestion).

Given the presence of 33 existing rain gauges, there was a vast amount of rainfall data available for each year. For the rain database, the algorithm extracted data on the amount of rain recorded every 15 minutes (in mm) and the respective recording times, corresponding to each of the 33 rain gauges distributed throughout the city of Rio de Janeiro. Relevant rainfall periods were defined for each of the rain gauge, assuming rainfall intensities greater than 10 mm as being relevant. To define the duration of these relevant rainfall events, their commencement was defined as the moment in which the rainfall presented an intensity equal to, or greater than, 1 mm. To determine the end of the relevant rainfall period, a rain intensity value of less than 1 mm was considered if it remained below 1 mm for less than 6 consecutive hours. If the rainfall picked up again, a new event was recognized, and the cycle recommended. Applying these criteria, a total of 7,019 noteworthy rainfall events were recorded between 1999 and 2022.

In addition to identifying relevant rainfall periods, an inventory of landslide reports from the Geo-Rio Foundation was thoroughly reviewed to ensure that only those linked to rainfall-triggered landslides were included. These reports, generated by Geo-Rio technicians, assessed the hazardous conditions associated with each landslide event. The inventory includes details such as the location, date, and time of the occurrences, as well as factors like the type and density of land use, the instability processes involved in the mass movement, and any human actions that may have exacerbated the event. Additional information provided in the reports included the volume and nature of the mobilized material, geological conditions, vegetation cover, slope geometry, drainage conditions, and any pre-existing stabilization works, along with their type and condition. Each report was carefully verified to ensure accuracy, particularly regarding the location and date of the events. The reports were then categorized by landslide type, material mobilized, and land use in the affected areas. After processing the data, the information was organized according to the sub-regions defined by Geo-Rio (D'Orsi 2012).

Figure 5 depicts a schematic representation of the statistical method employed to identify a critical threshold. This approach involves establishing a straight line (I vs. A) on a log-log graph, below which 85% of the landslides corresponding to a specific category of rainfall event (as detailed in Table 3) were recorded. It is based on the normal probability model (Devore 2011), where the upper limit of 85% of the rainfall events associated with a given category of landslides (D'Orsi 2012), can be expressed by Equation 1, as presented below:

$$Log\left(I_{85\%}\right) + n\,Log\left(A_{85\%}\right) = Log\left(b_{85\%}\right) \tag{1}$$

The 85% probability of occurrence was used as the reference, to prevent the warnings from being discredited by frequent false alerts. The proposed criterion aimed to ensure that warnings were only issued when there was a strong likelihood of landslide events, allowing local populations to seek a safe place (Ehrlich et al. 2021).

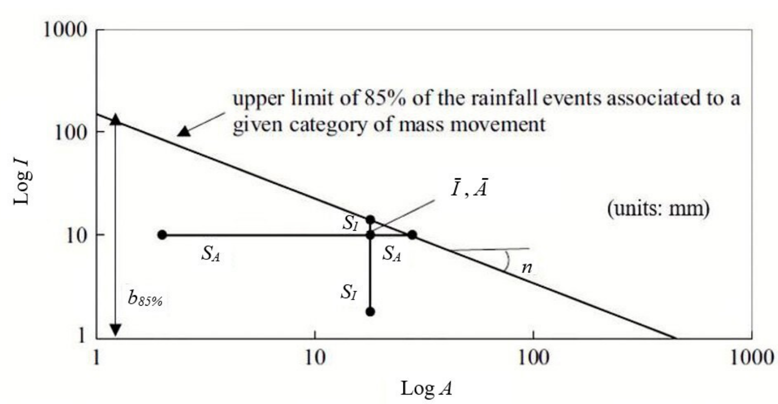

Figure 5. Determination of the critical pairs of *I* and *A* values (Ehrlich at al., 2021).

To obtain this envelope for each category of event, the corresponding Intensity and Accumulated Rainfall average values ($\bar{I}, \bar{A}$) were determined, and the standard deviations (S_I, S_A) were, subsequently calculated. The intercept between the intensity axis and the envelope was called $b_{85\%}$ and the angular coefficient of this straight line was called n. Analyses were carried out by considering accumulated values of rainfall for 24hs, 48hs,

96hs and 720hs, in each of the 11 sub-regions defined by the Geo-Rio Foundation. Those accumulated values were measured considering a total rainfall value during a specific period before the corresponding relevant rainfall event (Figure 6). The period of the rainfall event was considered to be the most relevant interval of precipitation, as measured by rain gauges immediately after the landslide, according to the Geo-Rio report.

The analysis was carried out considering each of the geological regions defined by the Geo- Rio Foundation for Rio de Janeiro City, as well as each of the categories of landslides (Tables 1 and 3). In addition to correlations between landslide events and Intensity and Accumulated rainfall, correlations based on Intensity and Duration of rainfall were also analyzed.

For each of the 11 sub-regions defined by the Geo-Rio Foundation, the evaluation of the most relevant periods of accumulated rainfall were verified using the following procedure. A high Δ_b indicates a more effective separation between categories for the corresponding analysis period (i.e., 24 h, 48 h, 96 h, and 720 h). Greater separation implies that the accumulated value considered is a more relevant factor in landslide triggering. Studies were also carried out considering the correlation between rainfall intensity and duration. The results of the analysis, considering non-landslide events and Category I, should be regarded as more representative, due to the smaller amount of landslide data associated with Categories II and III.

$$\Delta_b = \frac{\left(b_i - b_{i-1}\right)}{b_{i-1}} \tag{2}$$

Where: Δ_b represents the relative difference between the category of mass movement; b_i is the $b_{85\%}$ for a given category of mass movement; and b_{i-1} is the $b_{85\%}$ for the antecedent category of mass movement.

Moreover, the relationship between the number of landslides per susceptibility area (*NNL*) and IA^n, defined as the product of hourly rainfall intensity and accumulated rainfall, was assessed for each independent event across 11 sub-regions of Rio de Janeiro.

3. Analysis and results

3.1 Volume of material in a landslide, effects and types of human intervention and occupation:

The analysis of the Geo-Rio reports indicates that the greatest number of landslides (90%) occurred in places where there was human intervention, which may or may not have been favorable to stability. As shown in Figure 7, most

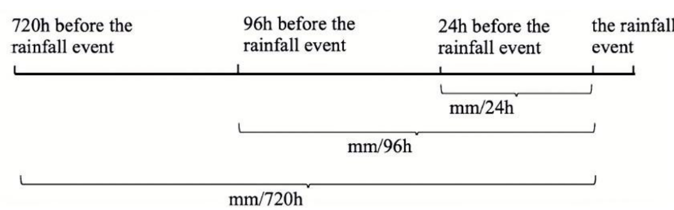

Figure 6. Accumulated rainfall corresponding to a rainfall event (Ehrlich at al., 2021).

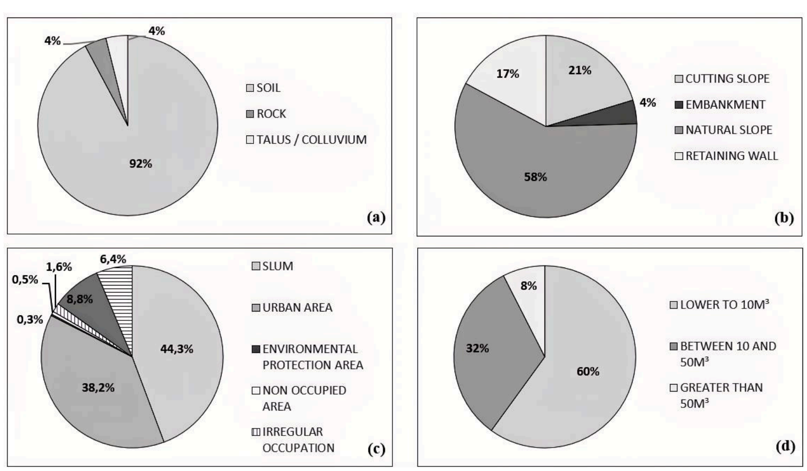

Figure 7. Incidence of landslides by type of material (a), terrain (b), occupation (c), and landslide volume (d).

of the occurrences took place in urban areas with irregular settlements, such as slums, slum interfaces and other non-regular settlements (about 55%). Notice that, in these areas, interventions were often implemented without technical support. The most common type of event involved landslides on natural slopes (58%), with the majority mobilizing soil masses (92%). Over the entire study period, most landslides were relatively small: 60% had volumes under 10 m^3, 32% ranged between 10 and 50 m^3, and 8% exceeded 50 m^3. It has previously been suggested that shallow landslides are typically triggered by short, intense storms (Campbell, 1975; Lumb, 1975; Brand et al., 1984; Cancelli & Nova, 1985; Cannon & Ellen, 1985; Polloni et al., 1992; Wieczorek, 1996; Morgan et al., 1997; Crosta, 1998; Corominas & Moya, 1999; Guzzetti et al., 2007; Bordoni et al., 2015), while deep-seated landslides are more influenced by long-term variations in annual rainfall (Bonnard & Noverraz, 2001). In 2010, however, there was a notable increase in the frequency of larger landslides. During this period, 49% of landslides had volumes under 10 m^3, 36% ranged from 10 to 50 m^3, and 15% exceeded 50 m^3. This pattern corresponded with an unusually high total rainfall of 1,621 mm during the rainy season from October 2009 to March 2010, significantly above the 24-year average of 810 mm (see Figure 2).

3.2 Relationship between rainfall and landslides

Figure 8 presents the Δ_b evaluation, incorporating data from all regions of Rio de Janeiro City. Given the larger dataset, the non-landslide event category was employed to determine the n value, resulting in a value of 0.6, which was assumed in all the analyses. The assessments included the evaluation of different periods of accumulated rainfall (24hs, 48hs, 96hs, and 720hs) as part of the IA^n procedure, also considering analysis which considered rainfall intensity and duration (ID^n). In the figure, a more efficient separation between the categories (high Δ_b values) is observed in the IA^n procedure compared to ID^n. This suggests that accumulated rainfall values demonstrate a stronger correlation than rainfall duration.

Figure 9 shows the Δ_b evaluation for each of the 11 sub-regions defined by the Geo-Rio Foundation. The figure indicates the results of the analyses for the evaluation of the most relevant periods of accumulated rainfall (24hs, 48hs, 96hs, and 720hs) covering the periods from 1999 to 2006, 2007 to 2014, and 2015 to 2022. The study was conducted considering only non-landslide events and Category I of mass movement, due to the limited amount of data associated with Categories II and III, resulting in a less representative analysis when considering that data. An n value of 0.6 was assumed in all analyses.

In Figure 9a, for the 1999-2006 period, it can be seen that, in general, 96 hours of accumulated rainfall led to the more efficient separation between the categories for most of the sub-regions, except for the southern area and Governador Island, both of which had a relevant value at 48hs accumulated rainfall; the western area had a relevant value at 24hs accumulated rainfall. Considering the 2007 to 2014 period (Figure 9b), 96hs accumulated rainfall continued to be the relevant pluviometry reference for most sub-regions, except for the southern area, Great Tijuca and the western area, with 48hs accumulated rainfall, and Bangu and Governador Island with 24hs accumulated rainfall being the most relevant ones. For the 2015-2022 period (Figure 9c), 96hs accumulated rainfall remained the best reference for most sub-regions, except for Alto da Boa Vista and the western area, where analyses indicate 24hs of accumulated rainfall, and Governador Island and Barra/Recreio, where 48hs of accumulated rainfall was the best reference.

As presented in Figure 9, in the Alto da Boa Vista sub-region for the first period analyzed (1999-2006), 96hs accumulated rainfall was the most relevant period, as previously mentioned,

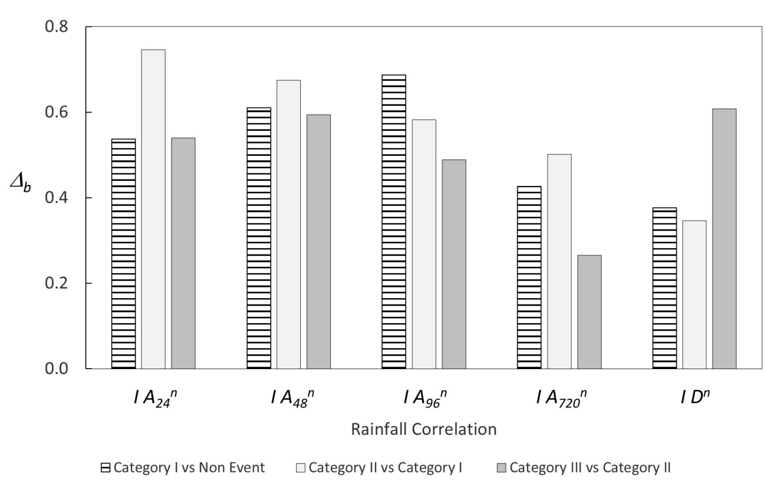

Figure 8. Δ_b evaluation considering landslide categories and procedures.

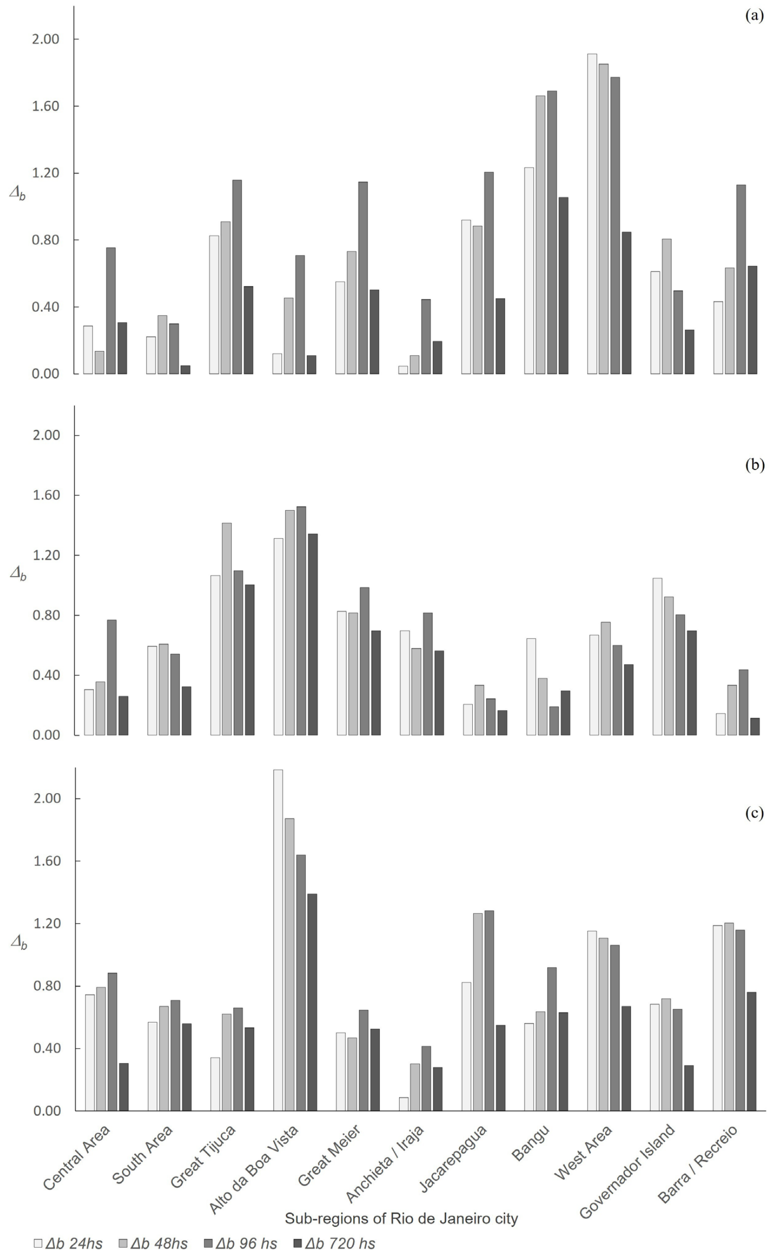

Figure 9. Most relevant period of accumulated rainfall for each of the 11 sub-regions of the city of Rio de Janeiro, considering: (a) 1999 to 2006; (b) 2007 to 2014 and (c) 2015 to 2022.

indicating similar behavior to most other sub-regions over this period. However, from the second period of analysis, the Alto da Boa Vista sub-region started showing gradual change, reaching the last period studied with 24hs accumulated rainfall period as the most relevant for triggering landslides. It should be noted that this region has experienced a considerable increase in population occupation in recent years (Figure 4), which may have led to a greater possibility of occurrences and notifications, due to the anthropic presence, as well as an increase in the susceptibility of landslide occurrences promoted by this occupation.

Figure 10 shows, in a log-log graph, the relationship between I (mm/h) and A (mm/96hs) associated with different categories of landslide events, considering data from the entire monitoring period (from 1999 to 2022) and all regions of Rio de Janeiro City. As previously mentioned, given the larger dataset, the non-landslide event category was employed to determine the n value, resulting in a value of 0.6, which was assumed in all categories of event. Figure 10 exhibits a large data dispersion relating to both non-event and event results. Additionally, Figure 11 displays the critical threshold curves on a natural scale.

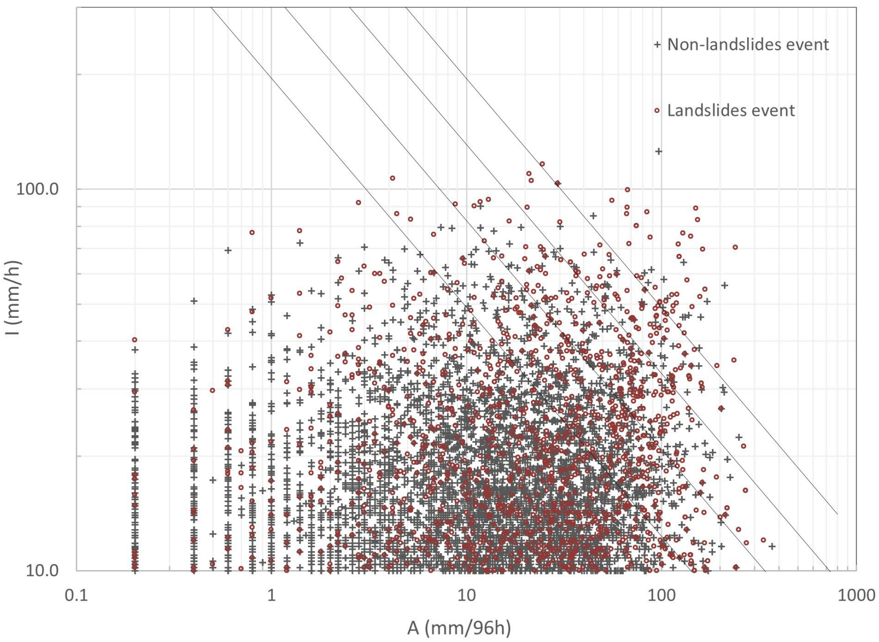

Figure 10. Critical threshold curves, in log-log graph, corresponding to 85% occurrence probability of landslide events in Rio de Janeiro City from 1999 to 2022.

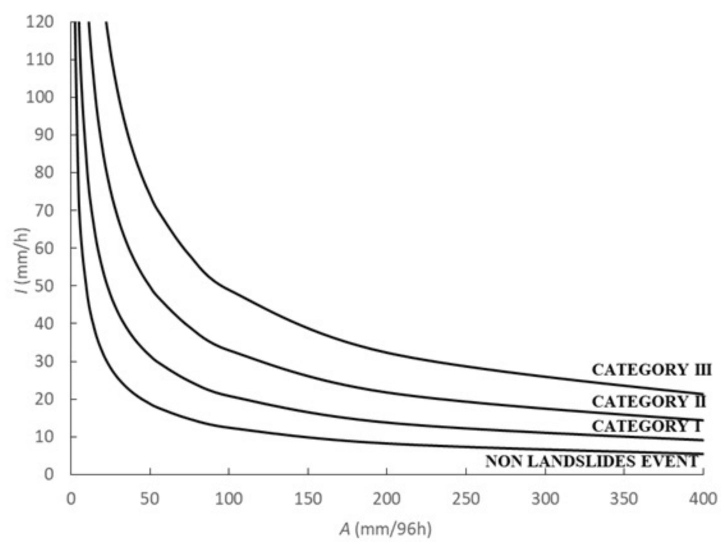

Figure 11. Critical threshold curves, in natural scale, corresponding to 85% occurrence probability of landslide events in Rio de Janeiro City from 1999 to 2022.

Figure 12 presented the relationship between the number of landslide occurrences per area of susceptibility (*NNL*) and the product of the hourly rainfall intensity (mm/h) and the accumulated rainfall for 4 days (mm/96hs), expressed for IA^n, for each independent event and the 11 sub-regions analysed in Rio de Janeiro City. The analyses were carried out considering both the total period studied, from 1999 to 2022, and the periods 1999 to 2006, 2007 to 2014 and 2015 to 2022, revealing significant differences between the results of each sub-region. Such behavior was expected, as the sub-regions present differences in topography, vegetation, geological-geotechnical characteristics and, mainly, density and characteristics of occupation.

In Figure 12, it is observed that, from 1999 to 2022, the western area appears to be the most stable, while the central area is the one that requires the least amount of rainfall for

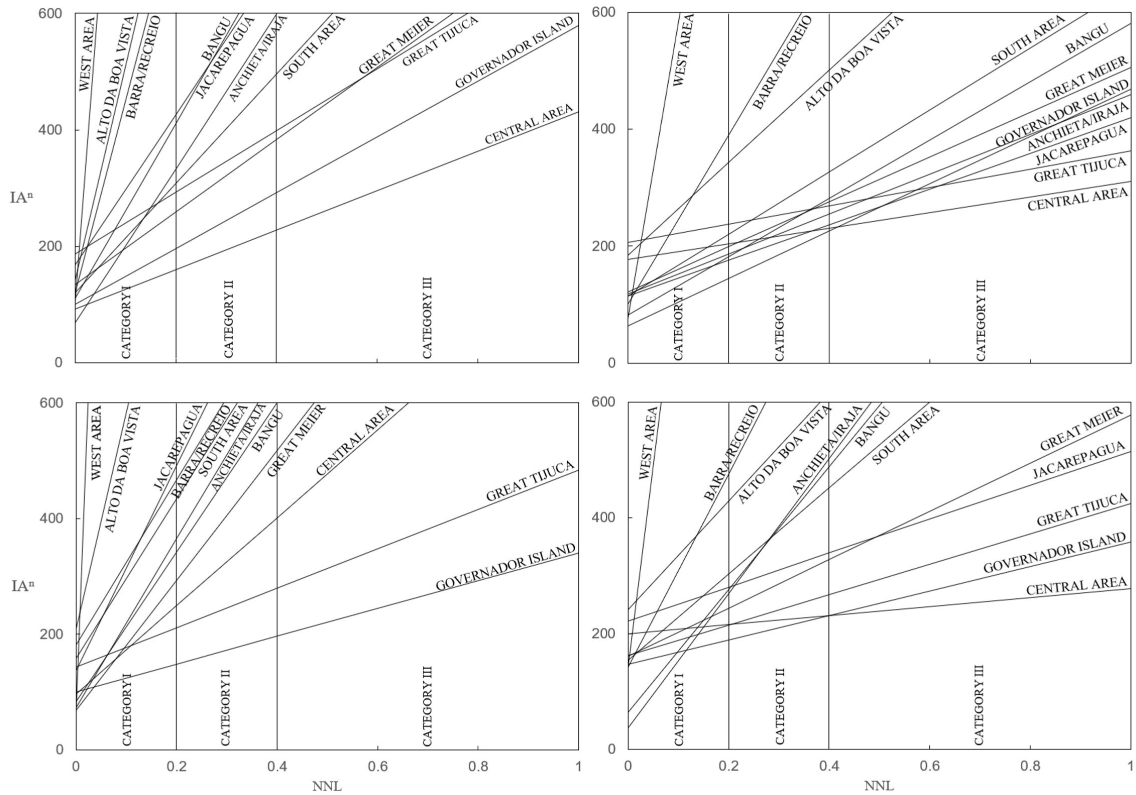

Figure 12. Relationship between number of landslide occurrences per km^2 of susceptible area (*NNL*) and the average values of IA^n for each of the 11 sub-regions of the Rio de Janeiro, considering: (a) 1999 to 2006; (b) 2007 to 2014; (c) 2015 to 2022 and (d) 1999 to 2022.

landslide occurrences. These results indicate that the early alarm system for Rio de Janeiro should be improved by specifying zone-dependent thresholds. For each region, the determined relationship between the number of landslide occurrences (*NNL*) and the product of the IA^n may give support to the new criteria. Considering the 2015 to 2022 period. Considering the 2015 to 2022 period, the western area still appears to be the most stable and Governador Island is the one that requires the least amount of rainfall for landslide occurrences. It should be noted that the Central Zone received the highest amount of geotechnical investment, followed by the Great Meier (refer to Figure 3). The interventions carried out in these sub-regions have led to a reduced susceptibility to landslides due to rainfall. When comparing the earlier (1999 to 2022) and more recent (2015 to 2022) periods, a significant increase in rainfall is required to trigger landslides in these sub-regions. Conversely, the growth in population (see Figure 4) may have heightened susceptibility to landslides due to rainfall in the Barra/Recreio sub-region.

4. Conclusion

Data analyses, based on landslide occurrences from an inventory provided by the Geo-Rio Foundation and rainfall measurements from the 33 rain gauges installed across the city, spanned a 24-year period from 1999 to 2022. This comprehensive dataset, comprising 7,019 significant rainfall events and 6,671 landslide occurrences drawn from 14,402 technical reports, posed a challenge for global analysis. Computational techniques, including statistics, databases, expert systems, and data visualization, were essential for processing the data and conducting the analyses.

Analyses based on Geo-Rio reports indicate that, in Rio de Janeiro, the number of landslide incidents was higher in areas where human intervention occurred, whether these interventions were technically supervised. Furthermore, a higher percentage of landslides took place in subnormal agglomerate areas (slums), which are generally located in regions more susceptible to landslides. In most cases, the volume of soil mobilized by these landslides was small, typically less than 10 m^3.

The extensive dataset allowed for a detailed analysis of the distinct characteristics of each of the 11 sub-regions in Rio de Janeiro City. Over the entire period from 1999 to 2022, rainfall intensity, combined with 96-hour accumulated rainfall, proved to be the most effective for distinguishing threshold rainfall curves across different event categories. For the more recent period (2015–2022), 96-hour accumulated rainfall remained the most reliable indicator for most sub-regions, except in Alto da Boa Vista and the western area, where 24-hour accumulated rainfall provided better results, and in Governador Island and Barra/Recreio, where 48-hour accumulated rainfall was the best reference.

Significant differences were found in the established relationships between the number of landslide occurrences per area of susceptibility (*NNL*) and rainfall for each sub-region. Variations in factors such as topography, vegetation, geological and geotechnical characteristics, and occupation patterns among sub-regions make landslide susceptibility unique to each area. The results show that the western area appears to be the most stable, while the central area, Governador Island and Great Tijuca are those that require the least rainfall to trigger landslides.

Interventions in the Central Zone and Greater Meier sub-regions, which received the highest levels of geotechnical investment, have significantly reduced rainfall-induced landslide susceptibility. A comparison of the earlier (1999 to 2015) and more recent (2015 to 2022) periods reveals that much higher rainfall levels are now required to trigger landslides in these sub-regions. Conversely, population growth in the Barra/Recreio sub-region may have increased susceptibility to rainfall-induced landslides.

The criteria currently used by city authorities to activate early warning alarms for rainfall-induced landslides through the ALERTA RIO System depends on a single standard for the entire city, based on accumulated rainfall. The findings of the present study highlight the need to improve the system by implementing zone-specific rainfall thresholds. While the current approach has effectively reduced missed alerts, it has also produced a significant number of false alarms across the city. The results of the present study could offer more accurate references for issuing landslide warnings.

Acknowledgements

The authors would like to thank the Geo-Rio Foundation for providing access and permission to use their database. Financial support for this study was provided by the following Brazilian funding agencies: CNPq, CAPES, FAPERJ and MCTI/INCT-REAGEO.

Declaration of interest

The authors have no conflicts of interest to declare. All co-authors have observed and affirmed the contents of the paper and there is no financial interest in reporting.

Authors' contributions

Desirée Christine de Oliveira e Silva: conceptualization, data curation, methodology, formal analysis, writing – original draft. Karina Livramento do Santos: data curation, methodology, software, writing – original draft. Maurício Ehrlich: conceptualization, methodology, formal analysis, resources, supervision, validation – review & editing. Francesco Noseda: formal analysis, supervision, validation – review & editing.

Data availability

The datasets generated analyzed in the course of the current study are available from the corresponding author upon request.

Declaration of use of generative artificial intelligence

This work was prepared without the assistance of any generative artificial intelligence (GenAI) tools or services. All aspects of the manuscript were developed solely by the authors, who take full responsibility for the content of this publication.

List of symbols and abbreviations

A	Accumulated rainfall
$\bar{A}$	Average accumulated rainfall
A_{24}	Accumulated rainfall in 24hs
A_{48}	Accumulated rainfall in 48hs
A_{60}	Accumulated rainfall in 60hs
A_{96}	Accumulated rainfall in 96hs
A_{720}	Accumulated rainfall in 720hs
AI	Artificial intelligence
ANN	Artificial neural networks
CA	Correct alarm
CAPES	Coordination for the personal improvement on university education
CNPq	National council for scientific and technological development
COPPE	Coordination of graduate and research programs in engineering
D	Rainfall duration
FA	False alarm
FAPERJ	Research support foundation of Rio de Janeiro state
Geo-Rio	Geotechnical Institute Foundation of Rio de Janeiro city
GUIs	Graphical user interfaces
HDFE	High-dimensional fixed effects
I	Rainfall intensity
$\bar{I}$	Average rainfall intensity
INCT-REAGEO	Geotechnical institute for slope and plain rehabilitation
LRI	Landslide risk index
MA	Missed alarm
MCTI	Ministry of Science, Technology and Innovation
NNL	Number of landslide occurrences per km^2 of susceptible area
PPV	Positive predictive value
PPML	Poisson pseudo-maximum likelihood estimator

S_A	Standard deviation of accumulated rainfall
S_I	Standard deviation of rainfall intensity
$b_{85\%}$	Intercept of the intensity axis with the envelope of I–A pairs marking the upper limit of 85% of rainfall events for a given landslide category (log–log scale)
$b_i\ b_{85\%}$	for a given category of landslide
$b_{i-1}\ b_{85\%}$	for antecedent category of landslide
n	Angular coefficient of the envelope of I–A pairs representing the upper limit of 85% of rainfall events for a given landslide category in log–log space
Δ_b	relative difference between the category of landslide

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