Landslides
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Likelihood of landslide occurrences for definition of rainfall thresholds applied to the Quitandinha river basin, Petrópolis, Brazil

Abstract As increased pore pressure due to rainwater infiltration is the primary triggering factor for landslides, rainfall is normally established as the first condition that allows definition of the predictability of their occurrence over the short term for a determined location. It is therefore common to propose landslide occurrence predictions based on awareness of accumulated background rainfall from historic data analysis. This paper proposes that landslide occurrence be predicted by quantitatively estimating their probabilities based on accumulated rainfall during a pair of time frames (e.g., 24 and 72 h) prior to the event, with selection determined by statistical dependence readings. This method was applied to the Quitandinha river basin region in the municipality of Petrópolis, Brazil, using background data from 2003 to 2009. It was observed that landslide occurrence presented the highest relevance level with the two accumulated rainfall periods of 24 and 96 h, and it was possible to estimate the probability of occurrence of at least one, three, or five landslides depending on the accumulated rainfall rates during these time frames.

Keywords Mass movement · Landslide · Statistics · Rainfall thresholds · Pluviometry

Introduction

Mass movements on a slope occur due to preparatory causal factors which make the slope susceptible to movement and thereby tend to place it in a marginally stable state and trigger causal factors which initiate movement (Popescu 1994). Preparatory causes include ground conditions, geomorphological processes and anthropogenic alterations, and physical environmental processes (e.g., rainfall, earthquake), whereas triggering factors include the last three only (Popescu 1994). In this text, the term "landslide" is used to designate the different types of mass movements (fall, topple, slide, spread, flow, and time-dependent slope deformation without a well-defined rupture surface) involving soil and/or rock (Cruden and Varnes 1996; Hungr et al. 2014), focusing on those triggered by increased pore pressure as a result of rainwater infiltration.

The rate of disasters associated to landslides triggered by rainfall has significantly increased in quantity and magnitude of impact over time, even when underestimated due to association with other events such as floods, storms, or earthquakes (Petley 2012; Hernández-Moreno and Alcántara-Ayala 2017). Considering such underestimation in recording, the International Disaster Database (EM-DAT 2019), which uses the criterion of a minimum of ten fatalities for an event to be included in the database, recorded a total of 206 landslides causing 10,671 fatalities during the period 2009–2019 worldwide. In Brazil, official records from 1991 to 2012 indicate that 699 landslide disasters occurred across 388 municipalities during that period, causing 535 deaths and affecting approximately 5 million people (CEPED-UFSC 2013). Similarly to what occurs on a global level, these quantities are, however, understated as many landslide disasters recorded in different sources (e.g., EM-DAT 2019 and CEPED-UFSC 2013) have been incorrectly attributed to flood or flash flood events.

To lessen the consequences of landslides on society, both structural and non-structural actions should be taken. The former, such as retaining walls and drainage, are physical interventions which prevent landslides from occurring or control their trajectory, while non-structural actions help to prevent the presence of elements which may suffer impacts from the landslide (Vaciago 2013) and/or reduce their vulnerability, lessening the consequences (Popescu and Sasahara 2009).

Notable among non-structural actions is the warning system, comprising a set of measures to generate and disseminate information among the population and the relevant authorities in sufficient time for the possible damages caused by the disaster to be reduced. Operation of such systems is based on the identification, measurement, and monitoring of landslide precursor elements (Calvello et al. 2014).

Particularly in tropical regions, due to their high levels of precipitation, landslides are usually triggered by rainfall events (Guidicini and Iwasa 1977), with water infiltration of the soil increasing its pore pressure and reducing the shear strength of the potentially unstable material (Terzaghi 1950; Lacerda 2004). In these cases, the pore pressure is indirectly related to the cumulative antecedent rainfall which, when it reaches a certain level known as the rainfall threshold, renders the slope unstable, thereby causing the landslide. The literature presents different parameters used for rainfall threshold definition, such as rainfall intensity duration—most used—and antecedent rainfall considering cumulative values over different periods of time, second most used (Segoni et al. 2018). Owing to their geological, geotechnical, and climatic characteristics, each location is subject to different rainfall observation periods, which are more relevant in terms of the occurrence of landslides. There are different methods and tools to set such thresholds, based on empirical or statistical observations of background physical parameter and landslide series.

Within statistics, there are methods to determine the degree of dependence between two variables—one is known as the chi-squared (χ^2) test (Cramér 1946) and measures the distance between observed and expected values for the joint relative frequencies of two variables, where the expected values are hypothetical and obtained on assuming that the variables are independent. The greater the distance, the closer the association between the two variables, and therefore, if the observed and expected values are

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sufficiently close to each other, the variables may be considered as independent. Using this test, it is possible to discover which pair of accumulated rainfall periods is more closely associated with the occurrence or non-occurrence of landslides.

This article presents a methodology to find the most appropriate pair of accumulated rainfall observation periods for the purpose of considering estimated probability curves for landslide likelihood according to precipitation levels, which may be used to define rainfall thresholds. It describes application of the method in the Quitandinha river basin in the municipality of Petrópolis, situated in the mountainous region of Rio de Janeiro state, Brazil, which has an extensive history of disasters associated to high-severity landslides. The parameters used for rainfall threshold definition in the present work are antecedent rainfall combining two time frames.

Rainfall thresholds

As mentioned before, rainfall is the most significant triggering cause of landslides, and therefore, its measurement and observation is one of the most widely used tools to determine thresholds (Terlien 1998; Martelloni et al. 2012). A rainfall threshold is defined as the precipitation value at which there is a stipulated likelihood of landslide (Guzzetti et al. 2007). To find this threshold, one needs to rely on the correlation between landslide occurrence and the rainfall which triggers it (Calvello et al. 2014).

There are two methods for rainfall threshold definition: statistical, normally used when there is a database on the occurrence of landslides and hydrological aspects such as rainfall; and physically based, which study landslide occurrence using physical models (Terlien 1998). Statistical thresholds may be based on accumulated rainfall over a specific time frame, or on the rainfall duration-frequency ratio, as shown by certain studies such as Lumb (1975), Caine (1980), Crozier (1989), Kim et al. (1992), Reichenbach et al. (1998), Wang and Sassa (2003), Dahal and Hasegawa (2008), Brunetti et al. (2010), and Martelloni et al. (2012). Thresholds based on physical characteristics are described in the works of Weyman (1973), Okimura and Kawatani (1987), Anderson and Kemp (1991), Terlien (1996), Papa et al. (2013), Alvioli et al. (2014, 2018), Napolitano et al. (2016), and Marin and Velásquez (2020).

There is no standardized rainfall threshold applicable to all cases—due to the natural and anthropogenic conditions of each location (climate, relief, slope dimensions, geohydrology, vegetation, forms of land occupation, etc.), the mechanical behavior of slopes will be different during and after rainfall (Intrieri et al. 2012; Chen et al. 2017). Therefore, each location will have its specific rainfall thresholds, based on the better correlation found between precipitation and landslide occurrence (Guidicini and Iwasa 1977; Glade et al. 2000; Guzzetti et al. 2007; Martelloni et al. 2012). Each location has its own rainfall thresholds and more appropriate time frames for observation.

Based on Segoni et al. (2018), rainfall thresholds are defined worldwide using different temporal resolutions, most commonly hourly and daily data. All thresholds used for early warning purposes must be based on at least hourly time resolution data, considering that a coarser time resolution involves many uncertainties that may lead to errors such as false or missed alarms (Gariano et al. 2020). In areas where finer time resolution data are not available, as in our case, daily measurements may be only used for preliminary early warning works with research purposes, considering that the thresholds need to be improved with the finest time resolution data to be applied. According to Guzzetti et al. (2007), for a warning system to function efficiently, rainfall threshold definition is as important as the manner in which such events are observed in terms of the accumulated rainfall time frames considered. In line with what is observed in the literature, therefore, combined use of two different periods of rainfall will reveal enhanced results in terms of landslide occurrence likelihood for application in warning systems.

Study area

The site considered for this study is the Quitandinha river basin, with an area of 12.81 km^2 and estimated population of over 80,000 (Brazilian Geographical and Statistics Institute – IBGE 2019), in the municipality of Petrópolis, in the mountainous region of Rio de Janeiro state (Fig. 1). In this area, as throughout the aforementioned mountainous region, there is a high frequency of disasters associated to landslides, with significant human and material losses (Guerra 1995; Avelar et al. 2013; da Silva et al. 2016). Precipitation levels in this catchment may be represented by the pluvial measurements collated by the National Scientific Computation Laboratory (LNCC) weather station situated at the following geographical coordinates: latitude 22° 31′ 43″ S and longitude 43° 12′ 45″ W. Considering the extension of the study area and its geographical conformation, one could say that rainfall distribution in the study area is well represented by its measurements.

The municipality of Petrópolis is situated in a predominantly hilly area (Avelar et al. 2013), with average altitude 845 m and steep slopes varying from 30° to 90° (Guerra 1995; Guerra et al. 2007; da Silva et al. 2016). The study area falls between the Bingen and Santo Aleixo geological units (ICMBIO 2009), characterized by extremely rugged terrain and the presence of extensive faults, fractures, and discontinuities in the impermeable rock layer (Guerra 1995; Rosi et al. 2019) enabling water percolation, as evidenced by waterholes forming on natural and artificial slopes in the region (Costa Nunes and Fernandes 1990). Soil on the bedrock is not very thick due to the steep declivities hampering the formation of deep layers (Guerra et al. 2007), and rocky outcrops are abundant (Avelar et al. 2013). Such mountainous relief in an area so close to the sea occasions a drop in temperature and renders the moist atmosphere unstable, causing rainfall (Rosi et al. 2019). The regional climate, according to the Köppen classification (Alvares et al. 2013), is Cfb—mesothermal, humid with mild summers, also known as tropical altitude climate, with average annual precipitation of 1929 mm (CLIMATE-DATA 2019), saturating the ground which, in turn, is of high hydraulic conductivity (Avelar et al. 2013).

Urban occupation has occurred in an irregular, disorganized manner in some areas of the city, allowing many to build their homes on sites susceptible to landslides (Guerra 1995; Rosi et al. 2019). There are records of deforestation in Petrópolis since the end of the nineteenth century (Guerra et al. 2007), which have contributed to the slope instability due to felling and root removal (Avelar et al. 2013), overload from occupation, waste discharge and watercourse alterations brought about by impermeabilization of the ground, and alteration of the relief (Stein et al. 1990).

Most frequently observed landslides in the first district of Petrópolis, in which the study area is situated, are shallow translational landslides of layers which, in the main, vary between 0.5

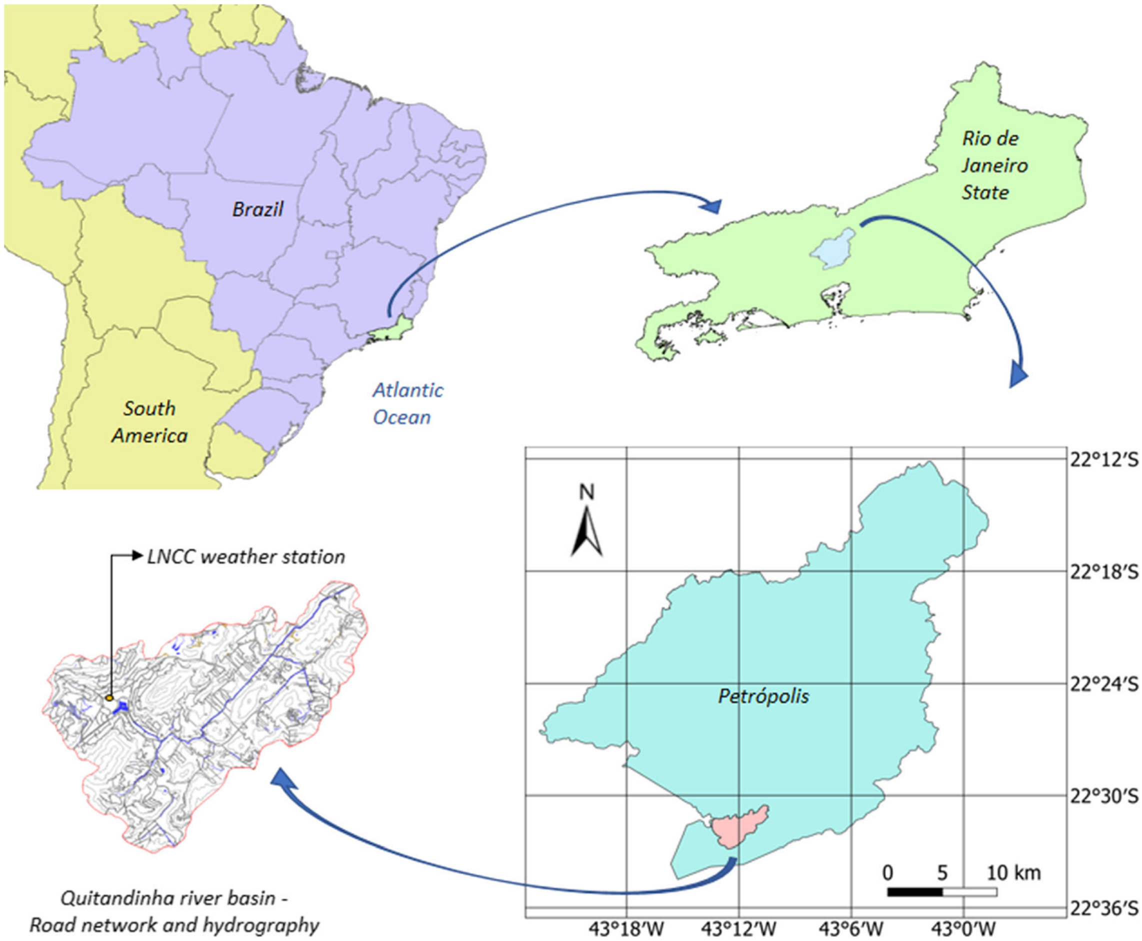

Fig. 1 Location of Quitandinha river basin

and 2 m in thickness (Nakawaza and Cerri 1990; Augusto Filho 1992; Avelar et al. 2013). According to Varnes (1978), translational landslides are characteristic of areas with relatively fine soil layers on a stable surface, and travel on a practically flat surface.

Methodology

The proposed study methodology consists of analyzing data on landslide occurrence and accumulated rainfall recorded over two previous time frames, and determining the most relevant pair of time frames for the rainfall thresholds. For this pair, landslide occurrence probabilities are calculated according to accumulated rainfall values. The relevance of an accumulated rainfall time frame pair against others will be determined by the contingency coefficient calculated using the chi-squared method (Cramér 1946). This coefficient measures the level of dependence between two variables. For the purposes of this study, the variables, whose dependence needs to be evaluated, are the occurrence or non-occurrence of landslides and the accumulated rainfall during two time frames. The procedures adopted, and summarized in Fig. 2, are discussed below.

a) Selection of time frames>

Each pair of time frames analyzed involves one short period close to the time of the landslide, and a longer period of accumulated rainfall observation; for example, short period of 24 h prior to the event, and long period of 48 h, this latter including the first period.

b) Accumulated rainfall bands>

For each of these rainfall time frames, disjunct and complimentary bands of accumulated rainfall are considered (e.g., 10–20 mm and 20.1–40 mm). Then, the number of days in which each of these bands occurred within each period (of 24 h, for example) is calculated. By combining two periods, we obtain the number of days in which two bands of accumulated rainfall occurred. For example, the number of days on which the 10–20 mm accumulated rainfall band over 24 h occurred at the same time that there was 20.1–40 mm in 48 h was 125.

c) Observed values>

For a chosen pair of rainfall time frames (N_1,N_2), we compute the observed value in each combination of rainfall bands as $o_{N_1,N_2}(x, y)$ which is number of days with accumulated rainfall within the bands (x, y) specified for the pair of time frames (N_1,N_2) and $o_{N_1,N_2}(r, x, y)$, where

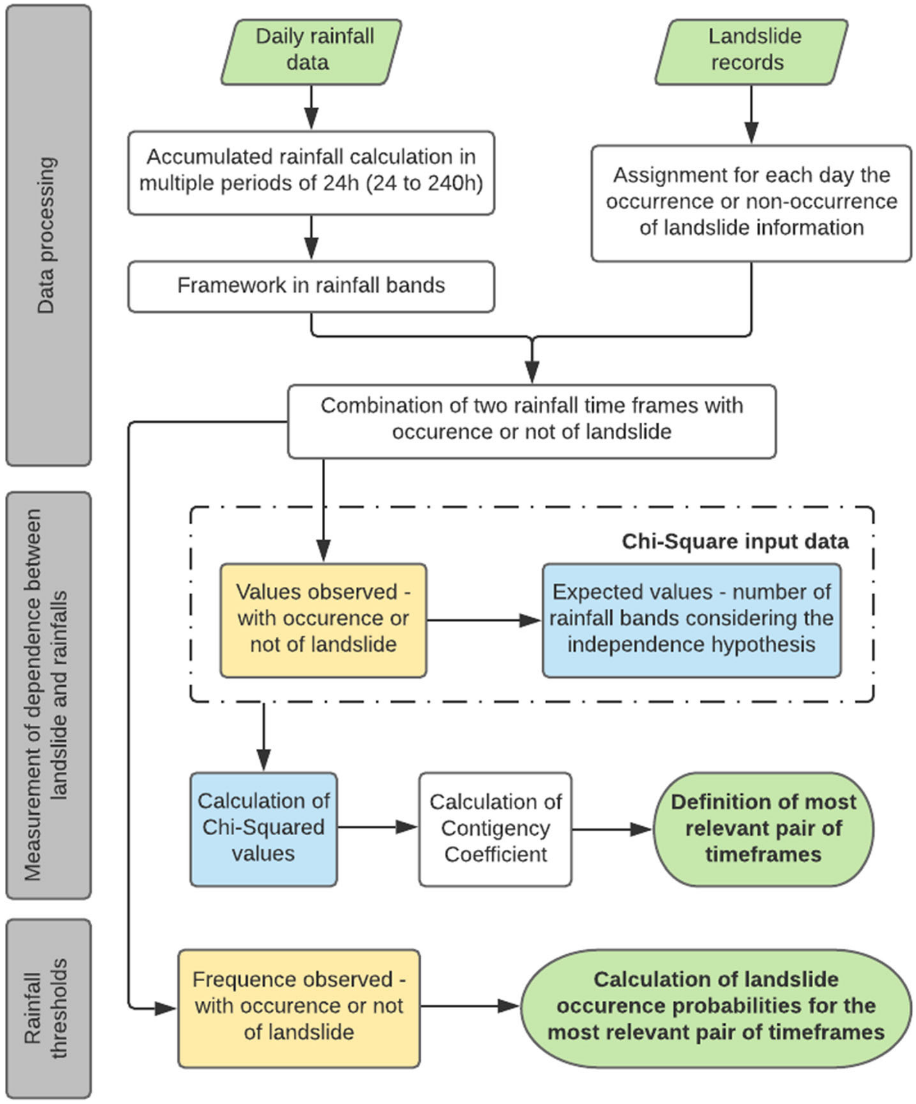

Fig. 2 Workflow to determine the most relevant pair of accumulated rainfall time frames and landslide occurrence probabilities

$r = 0$ or 1, such that $o_{N_1,N_2}(1,x,y)$ is the number of days with landslides and accumulated rainfall within the bands (x, y) specified for the pair of time frames (N_1, N_2), and $o_{N_1,N_2}(0,x,y)$ is the number of days without landslides and accumulated rainfall within the bands (x, y) specified for the pair of time frames(N_1, N_2).

d) Expected values>

The expected value would be that obtained in the case of total independence between accumulated rainfall bands and the occurrence or not of landslides. For a chosen pair of rainfall time frames (N_1,N_2), we compute the expected value in each combination of rainfall bands as:

$$e_{N_1,N_2}(r,x,y) = \frac{o_{N_1,N_2}(x,y)\, W_{N_1,N_2}(r)}{T} \tag{1}$$

where $r = 0$ or 1, $W_{N_1,N_2}(1)$ is the total number of days with landslides for the pair of time frames, (N_1, N_2), $W_{N_1,N_2}(0)$ is the number of days without landslides for the pair of time frames (N_1, N_2), and T is the total number of days for the periods considered.

e) Chi-squared>

Chi-squared measures degree of dependence, and provides an outcome based on the difference between observed $o(x, y)$ and expected values $e(x, y)$. Using all observed and expected values for time frame pairs, a double entry table is devised (Table 1), where chi-squared is calculated by Eq. (2) (Cramér 1946).

$$\chi^2_{(a-1)} = \sum_r \sum_{(x,y)} \frac{\left(o_{N_1,N_2}(r,x,y) - e_{N_1,N_2}(r,x,y)\right)^2}{e_{N_1,N_2}(r,x,y)} \tag{2}$$

where χ^2 is the chi-squared measure of dependency for the time frame pair (x, y), and a is the number of lines in the table, equivalent to the number of accumulated rainfall bands.

f) Contingency coefficient>

The Pearson contingency coefficient (Blaikie 2014), obtained from the chi-squared value (Eq. (2)), provides values of association between the two events studied, varying between 0 and 1, where 0 is total independence between the events and approximates to 1 as the dependency between the events increases (Cramér 1946). Values higher than 0.3 can be considered as results expressing the existence of dependency between the two events. We observe that the contingency tables considered all have the same dimension; therefore, for comparison purposes, it is not necessary to work with a standardized contingency coefficient. The Pearson contingency coefficient is defined as:

$$C = \sqrt{(\chi 2/(\chi 2 + T))} \tag{3}$$

g) Probability of landslide occurrence>

Following the definition of a more relevant pair of time frames for the occurrence of landslides, the occurrence probabilities can be calculated based on the number of days on which a condition of accumulated rainfall was observed, and the number of those days on which a landslide occurred (Eq. (4)). This probability can be estimated for the occurrence of different numbers of landslides, characterizing different states of emergency.

$$q_{N_1,N_2}(x,y) = \frac{r_{N_1,N_2}(x,y)}{P_{N_1,N_2}(x,y)} \tag{4}$$

where $q_{N_1,N_2}(x,y)$ is the probability of landslide occurrence, given that rainfall is predicted for the periods N_1 and N_2, respectively, within bands x and y; $r_{N_1,N_2}(x,y)$ is the number of periods in which landslides occurred when in N_1 hours, there was a rainfall rate in band x and in N_2 hours, there was a rainfall rate in y; and $P_{N_1,N_2}(x,y)$ is the number of periods of N_1 hours in which the rainfall total fell within band x, and in N_2 hours, the rainfall total fell within band y.

A correction procedure was adopted in calculating probabilities, under which the function $q_{N_1,N_2}(x,y)$ would necessarily increase; i.e., despite the contrary being mathematically possible, this value was not permitted to be reduced with increased rainfall. If this happened, the value of $q_{N_1,N_2}(x,y)$ was replaced to be equal to the value calculated for the immediately preceding rainfall band.

Based on periods of greater relevance, landslide occurrence probability graphs were drafted based on the combination of accumulated rainfall bands, devised using MatLab software assisted by cubic spline interpolation, which transforms the function into polynomials of up to third order, thereby smoothing the curve.

Application of method to study area

This method was applied to data on the number of landslides and accumulated daily rainfall between first of 1 January 2005 and 16 May 2009 across the study area. Daily rainfall data were used because of temporal resolution of the rain gages at the weather station. Landslide occurrence data used in the study were obtained from municipal civil defense records. Table 2 presents a summary of the data obtained.

In this case, the short time period was fixed at 24 h, with the longer periods of 48, 72, 96, 120, 144, 168, 192, 216, or 240 h. Accumulated rainfall in these periods was classified into the following bands: 10 –20 mm; 20.1–40 mm; 40.1–60 mm; 60.1–80 mm; 80.1–100 mm; 100.1–120 mm; 120.1–140 mm. As stated by Segoni et al. (2018), good temporal precision of a landslide depends on data source. Despite numerous advances in cataloging of landslides, some errors can be expected when these data are not directly obtained by researchers. In the present case study, no accumulated rainfall periods with less than 10 mm of rain over 24 h, 20 mm in 48 h, and 40 mm in 72 h were considered as it was deemed that reports of landslides triggered by rainfall lower than these values were not reliable.

For the purposes of this study, landslide occurrence times were considered as 0 h (zero hour) on the days that they were registered. The previous accumulated rainfall levels for each landslide occurrence are calculated as explained in Fig. 3.

Subsequently, for the pair of time frames considered most relevant, according to the Pearson contingency coefficient (Eq. (3)), the probabilities of occurrence of at least 1, at least 3, and at least 5 landslides were calculated and graphically represented for each combination of two accumulated rainfall bands, applying Eq. (4) for the observed data.

Results and analysis

The contingency coefficient values found for the pair of time frames 24 h and 48–240 h are shown in the graph at Fig. 4. Initially, observation indicates that all contingency coefficients present values in excess of 0.3, meaning that the landslides observed are dependent on rainfall for the pairs of time frames considered. The contingency coefficient applied for 48 h as the short period and 72–240 h as the long period (0.551–0.656) is lower than the values for 24 h (0.629–0.776). Increased contingency coefficients can be observed up to the pair 24 –96 h (C = 0.771), from which the value decreases at first and returns to grow only surpassing its value at 24 –96 h on the time frame 24 –216 h (C = 0.773) and 24 –240 h (C = 0.776). Although the contingency coefficients for 24 –216 h and 24 –240 h are higher, it was considered that the longer 96-h period should be selected to pair up with the short 24-h period to estimate the probability of landslide occurrence due to two facts: firstly, the existence of a notable difference in contingency coefficients between the longer time frame of 96 h and neighboring choices for the longer time frame; secondly, the higher coefficients for the longer time frames of 216 h and 240 h are very close to that of 96 h and then the difference is not significant (difference of 0.005).

The probabilities for this pair of time frames are presented in the graphs at Figs. 5, 6, and 7, obtained from the MatLab software. The color scale indicates the probability variations with accumulated rainfall over the time frames, and the black lines show the iso-probability curves of 0.25, 0.5, 0.75, and 1 of landslide occurrence. Comparison of the three graphs enables evaluation of variations in the probability of landslide occurrences with the spatial density of these events considering what, in turn, represents different disaster scenarios. The graphs in Figs. 5, 6, and 7 were

Table 1 Example of chi-squared test input data for the pair of time frames of 24 × 48 h

Observation periods		Values observed		Total
24 h	48 h	Days with landslides	Days without landslides	
10–20	20–40	20	105	125
20–40	20–40	9	68	77
10–20	40–60	5	38	43
20–40	40–60	2	24	26
40–60	40–60	4	16	20
10–20	60–80	7	13	20
20–40	60–80	2	10	12
40–60	60–80	1	10	11
60–80	60–80	1	13	14
10–20	80–100	3	5	8
20–40	80–100	2	7	9
40–60	80–100	2	3	5
60–80	80–100	1	2	3
80–100	80–100	2	6	8
10–20	100–120	1	8	9
20–40	100–120	0	2	2
40–60	100–120	1	0	1
60–80	100–120	0	2	2
80–100	100–120	0	1	1
100–120	100–120	1	4	5

respectively formulated for densities in excess of 8, 23, and 40 landslides per 100 km², in approximate values. The comparison shows that for the same combination of rainfall bands, the lower the spatial density of landslides, the higher the probability of one occurring. Based on 200 mm of cumulative rainfall over 96 h, and 120 mm over 24 h, the probability of at least five landslides occurring in the study area is 100%, indicating that in the case of such extreme rainfall events, generalized landslides are expected to occur. The variation in distance between the iso-probability curves in a single graph indicates that the ratio between the increases in probability and rainfall levels is not constant. The way we arrive at the variation of this ratio may be useful for establishing threshold levels for intermediate states of warning systems.

As previously stated, the most common mass movements observed in the study area are shallow landslides, generally varying between 0.5 and 2 m in thickness (Avelar et al. 2013). Movements of this nature normally occur during intense, short-duration rainfall, with the removal of the most superficial part of the soil on the bedrock or stable ground (Brönnimann et al. 2013; Chen et al. 2017). It is possible that

Table 2 Quantitative summary of data considered between 1 January 2005 and 16 May 2009

Data	Quantity
Total days	1597
Days with rainfall	561
Landslides recorded	420
Days with at least 1 landslide	133
Days with at least 3 landslides	32
Days with at least 5 landslides	19
Average of landslides per day with landslide	3.16
Average daily accumulated rainfall on rainy days (mm)	22.5

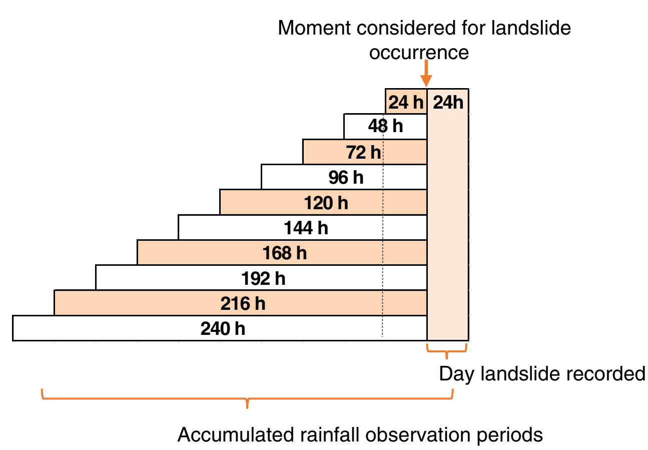

Fig. 3 Some summary data on accumulated rainfall periods and occurrence of landslides

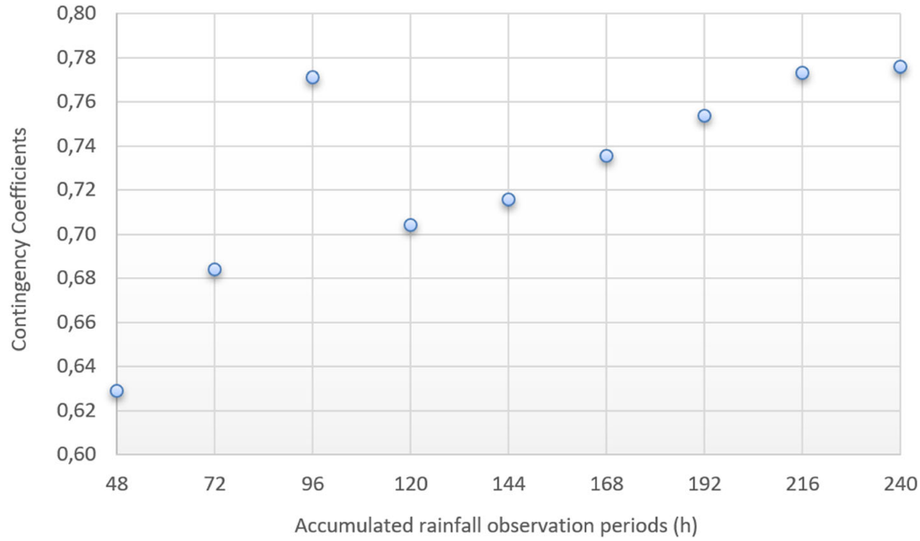

Fig. 4 Contingency coefficients (C) identified in the chi-squared (χ^2) tests for the 24-h period associating to other accumulated rainfall time frames (48–240 h) and landslide occurrence

increased pore pressure may be due to not only slope surface water infiltration but also water infiltration percolating through existing fractures in the rock, characteristic of areas with ground faults and fractures (Brönnimann et al. 2013). Lacerda (2004) highlights the importance of hydrogeology in slope stability, presenting a case in which piezometers located in the bedrock showed a delayed response to the rainfall, where only in the third day after a raining event, the piezometer in the decomposed granite and granite began to rise and they continued to rise even after the rain stopped. Rosi et al. (2016) highlights the combination of prior rainfall and water infiltration in rock with fractures as a significant factor in the triggering of landslides.

According to Costa Nunes and Fernandes (1990), in a study of geological influence on landslides in Petrópolis, the base rock mass in the region of this municipality is significantly fractured,

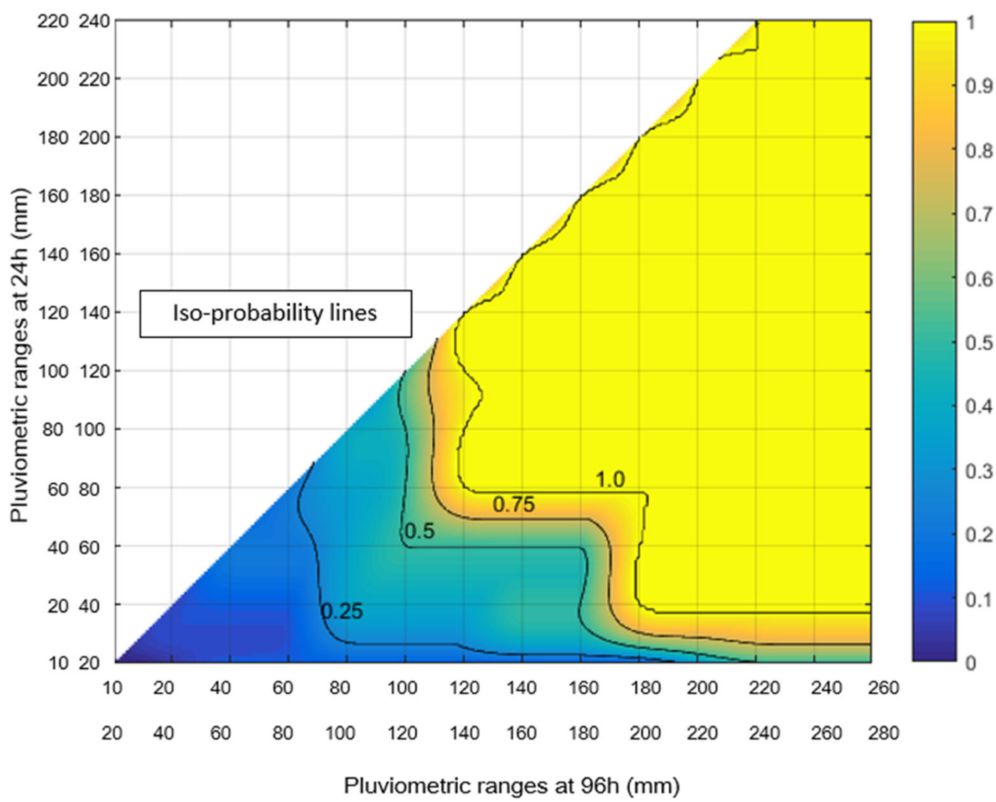

Fig. 5 Probabilities of at least one landslide occurring across different accumulated rainfall bands

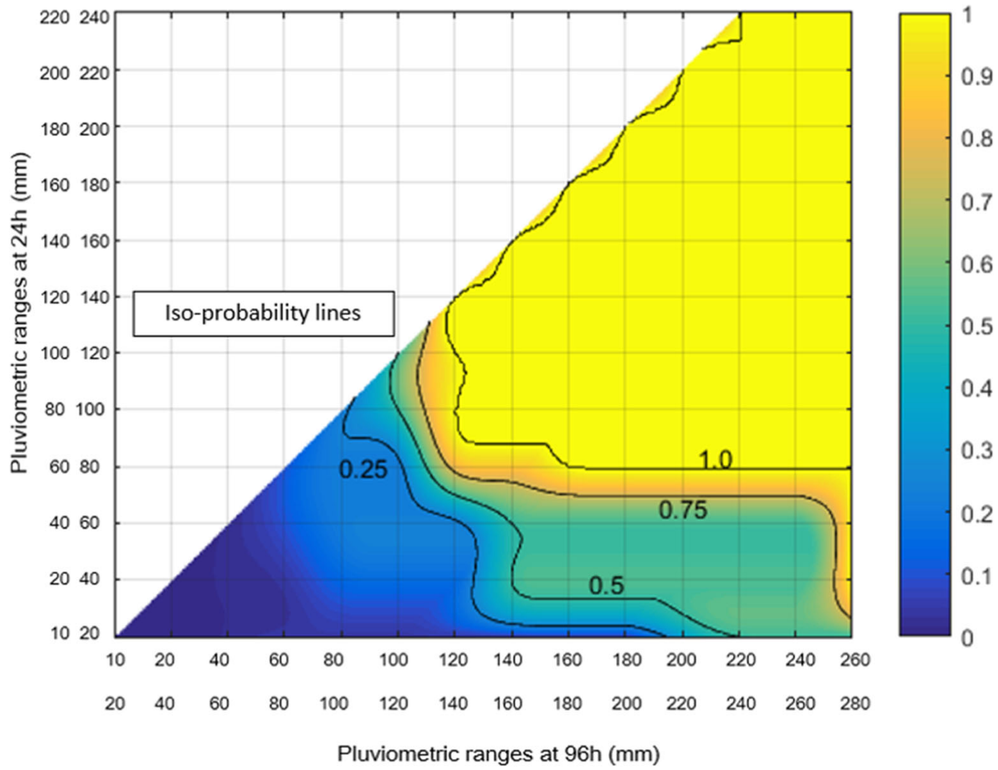

Fig. 6 Probabilities of at least three landslides occurring across different accumulated rainfall bands

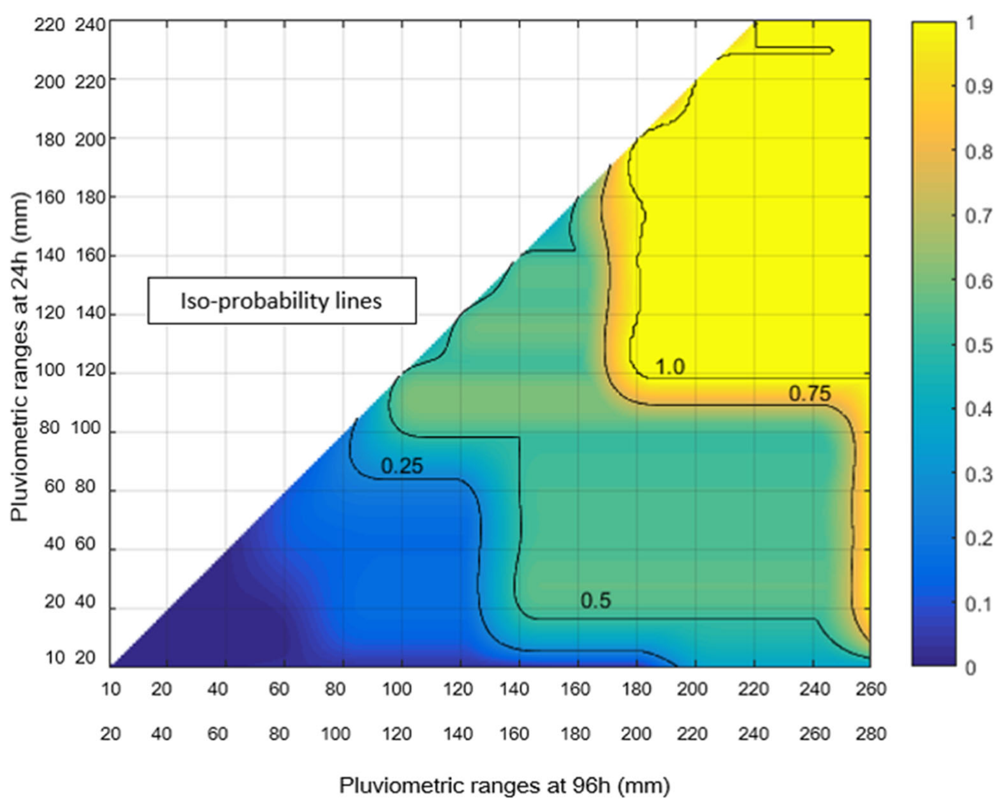

Fig. 7 Probabilities of at least five landslides occurring across different accumulated rainfall bands

with millimeter- or centimeter-wide faults extending for kilometers, and going down to hundreds of meters—saturated by circulating water—evidenced by waterholes at the base of slopes there. Figure 8 shows a schematic section of this representative slope model, using Monte Florido as an example for its typical configuration within the 1st district of Petrópolis, which covers the study area. These authors cite the artesian soil-rock contact condition as a natural piezometric consequence of the local geology, having a destabilizing effect on the soil layer base, leading to a reduction in shear strength due to increased pore pressure. According to these authors, such conditions may explain the occurrence of landslides even under low intensity rainfall conditions, given that the bases of these soil layers are already conditioned by pore pressure induced by water flow through the fractures. The presence of aquifers between the rocks would be capable of generating significant pore pressures at the base of soil cover on the rock, reducing shear strength at such points and causing saturated soil to undergo landslides triggered even by low intensity rainfall. There would be, therefore, two processes of pore pressure increase—by the multiple and extensive rock fractures, and by infiltration into the ground mass.

Analysis of the probability graphs indicates a considerable variation on altering the 96-h accumulated rainfall band, while the 24-h band remains constant, or varying the 24-h band, while the 96-h band remains constant, indicating the influence of two rainfall periods in the landslide probability estimate. Consequently, one must consider the two periods of rainfall to define rainfall thresholds for a warning system. It can also be noted that the probability estimate is highly influenced by the minimum number of landslides to which it is related.

The typical geology of the region and inherent geohydrological mechanisms involved in landslide occurrence are in line with the findings of this study, which demonstrates significant dependence on landslides occurring over two combined time frames, one short and one long. Validation of this hypothesis, in which the applicable time frames were 24 h and 96 h, is outside the objective of this study and can be assessed by numerical modeling and geotechnical instrumentation. Furthermore, use of a higher temporal rainfall resolution, in order to put in practice rainfall thresholds in early warning systems, must be encouraged.

Conclusions

This paper has presented a statistical method to determine the pair of accumulated rainfall time frames most closely associated with the occurrence of landslides, based on a series of background data on accumulated rainfall and landslides. Once this pair is defined, it can be applied in the form of observation periods to gage the likelihoods of landslide occurrence in given accumulated rainfall and, thereafter, define rainfall thresholds.

Applying this method to the Quitandinha river basin in the municipality of Petrópolis (mountainous region of Rio de Janeiro State, Brazil), considering data from January 2005 to May 2009, and following the criteria explained in the "Results and analysis" section, the pair of time frames presenting the highest relevance level was 24–96 h. This pair can be understood by hydrogeological conditions in the region, which cause increases in pore pressure on soil-rock contact, responsible for shallow landslides—predominant in the region—occurring due to direct water infiltration into the soil surface and water flowing through the multiple, extensive, and deep fractures in the bedrock. Observation of variations in the likelihoods for this pair of time frames shows firstly that observing two periods together provides a better result than just one, and that once an acceptable landslide probability value is defined, this type of graph will provide rainfall thresholds for warning systems. Furthermore, it is evident that the probability calculation also varies with the spatial density of expected landslides, which, consequently, represents different disaster scenarios. For future work, it is worth investigating the effect of rainfall in time frames longer than 10 days on dependence between landslide occurrence and rainfall.

Observation of significant variations in landslide likelihoods with accumulated rainfall demonstrates that early warning system

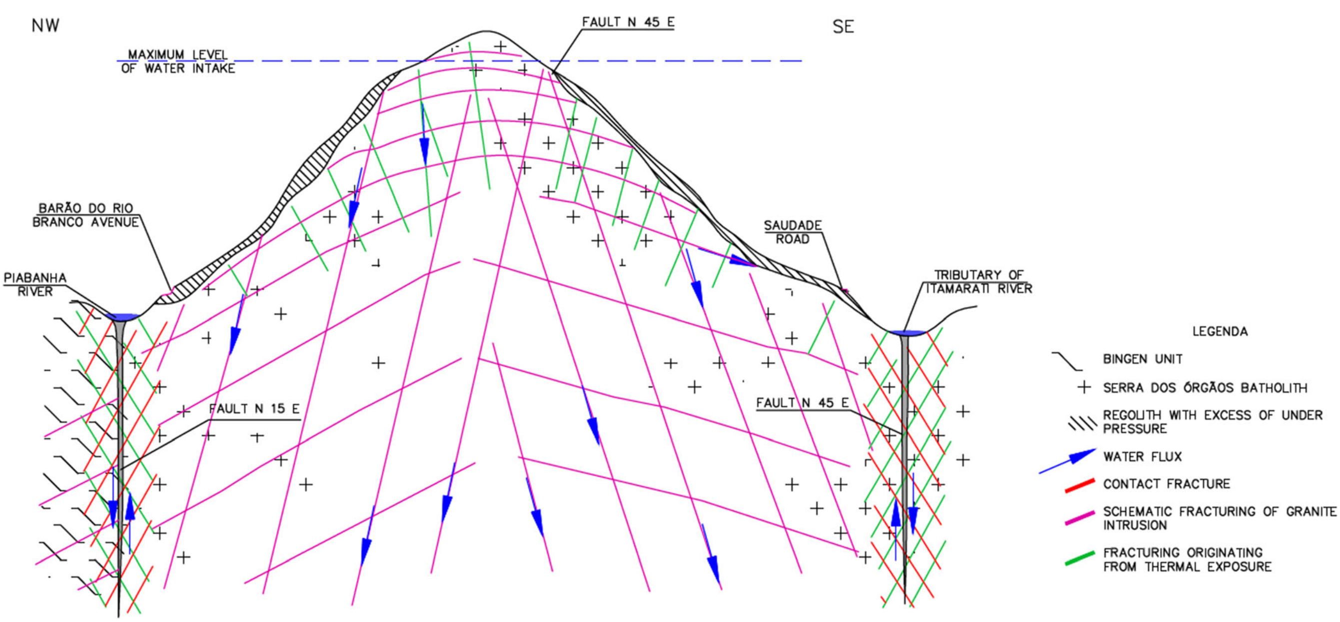

Fig. 8 Representative model of the Monte Florido slopes. Adapted from Costa Nunes and Fernandes (1990)

rain thresholds should not be defined based on a single time period. Results such as these will enable public administrators to define such thresholds based on an acceptable mass probability values for landslide occurrence. Encouragement must be given to use higher temporal resolutions of rainfall gages and landslide reports, at least hourly in scale, in order to put the rainfall thresholds in practice in early warning systems.

As the anthropogenic conditions for landslides may vary over time according to land occupation and use, along with execution of structural risk reduction actions, rainfall thresholds may also vary, requiring verification of the validity of likelihood results against to date-accumulated rainfall figures. It will therefore be necessary to conduct future studies along the same line to add more recent data.

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