International Soil and Water Conservation Research 10 (2022) 547–556

Contents lists available at ScienceDirect

International Soil and Water Conservation Research

journal homepage: www.elsevier.com/locate/iswcr

Original Research Article

Natural disaster in the mountainous region of Rio de Janeiro state, Brazil: Assessment of the daily rainfall erosivity as an early warning index

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ARTICLE INFO

Article history:
Received 15 October 2021
Received in revised form
8 February 2022
Accepted 13 February 2022
Available online 7 April 2022

Keywords:
Daily rainfall erosivity
Rainfall hazards
Brazilian mountainous regions
Rainfall warning system

ABSTRACT

Rainfall erosivity is defined as the potential of rain to cause erosion. It has great potential for application in studies related to natural disasters, in addition to water erosion. The objectives of this study were: i) to model the R_{day} using a seasonal model for the Mountainous Region of the State of Rio de Janeiro (MRRJ); ii) to adjust thresholds of the R_{day} index based on catastrophic events which occurred in the last two decades; and iii) to map the maximum daily rainfall erosivity (R_{maxday}) to assess the region's susceptibility to rainfall hazards according to the established R_{day} limits. The fitted R_{day} model presented a satisfactory result, thereby enabling its application as a R_{day} estimate in MRRJ. Events that resulted in R_{day} > 1500 MJ ha^{-1}.mm.h^{-1}. day^{-1} were those with the highest number of fatalities. The spatial distribution of R_{maxday} showed that the entire MRRJ has presented values that can cause major rainfall. The R_{day} index proved to be a promising indicator of rainfall disasters, which is more effective than those normally used that are only based on quantity (mm) and/or intensity (mm.h^{-1}) of the rain.

1. Introduction

Rainfall erosivity is an index that encompasses the impacts caused by the raindrops impact and the energy dissipated on the soil surface. It was proposed and defined by Wischmeier and Smith (1958) as the product between the kinetic energy of raindrops and the maximum rainfall intensity in 30 consecutive minutes (I_{30}), designated as EI_{30}. Its calculation requires rainfall data recorded with a temporal resolution ≤15-min. However, such records are difficult to access and obtain, usually due to an insufficient number of stations in developing countries (Mello et al., 2015).

To develop a model for estimating daily rainfall erosivity (R_{day}) based on daily rainfall data is essential to better understand the role of extreme rainfall on natural disasters (Mello et al., 2020) since daily rainfall data is much more accessible and spatially distributed than those with temporal resolutions ≤15-min. Therefore, a model to estimate R_{day} was initially proposed by Richardson et al. (1983), with the inconvenience of having to fit different models for each month. In addition, these models tend to underestimate the R_{day} (Angulo-Martínez & Beguería, 2009). To overcome these limitations, Yu and Rosewell (1996) proposed a mathematically more advanced approach by introducing a sinusoidal function to model the seasonality of rainfall erosivity. This approach can estimate R_{day} considering the period of the year (biweekly or monthly periods). This is a hypothesis that considers that the same precipitation can generate different R_{day} according to the period of year, which is relevant in regions with a seasonal climate.

The increase in the frequency and intensity of extreme rainfall in Brazil, combined with the high degree of susceptibility of the population in risk areas has triggered rainfall disasters (Fernandes & Rodrigues, 2018; Amorim and Chaffe, 2019; Mello et al., 2020), with a high number of fatalities (CEPED, 2013). The geomorphological and pedological characteristics associated with changes in land use (especially deforestation of the Atlantic Forest) (Freitas et al., 2012) and the high intensity of the rainfall (Brito et al., 2016) are the key factors to rainfall disasters in mountainous

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https://doi.org/10.1016/j.iswcr.2022.02.002

regions in Brazil (Mello et al., 2020).

One of the regions most affected by rainfall disasters is the mountainous region of the Rio de Janeiro state (MRRJ) (Brasil, 2012; Freitas et al., 2012; Oliveira et al., 2016). In January/2011, landslides were triggered by extreme rainfalls, causing the so-called "mega-disaster" in this region. A total of 23 municipalities were affected, and seven of these were declared in a emergency situation (Cardozo & Monteiro, 2019). Petrópolis, Teresópolis, and Nova Friburgo municipalities recorded the highest number of victims. The most significant impacts in Nova Friburgo occurred in the urban area, whereas the rural areas were the most affected in the other two municipalities (Busch & Amorim, 2011; Cardozo & Monteiro, 2019). Official reports indicated 918 fatalities, 22,604 displaced, and 8795 homeless across the region (Freitas et al., 2012). This event was the worst natural disaster in Brazil's history (Cardozo & Monteiro, 2019).

Some authors have assessed the efficiency of the early warning system (EWS) indexes in reducing risks from rainfall. However, due to the difficulty in obtaining and combine all the variables involved with landslides in an index that can be used as an early warning, indexes have been applied focusing on the extreme rainfall and the human and material damages (Xu et al., 2014; Calvello et al., 2015; Oliveira et al., 2016). Some indexes have been widely used in Brazil and the world, such as the accumulated rainfall in the last 24, 48, 72, and 96 h, rainfall intensity (mm h^{-1}), or even such variables evaluated simultaneously. Nevertheless, some of these indexes have shown to be inefficient. An example of this was the rainfall disasters in Campus do Jordão county in Serra da Mantiqueira (southeastern Brazil) in the year 2000. This event was caused by an accumulation of rain below the limit previously established in 72 h (Mendes et al., 2018). Another example, it was the index used by the *Alerta-Rio*, as 20 false alerts were issued for the four warning zones of the city between 2010 and 2013.

Mello et al. (2020) proposed the use of R_{day} as a rainfall index as EWS for the Serra da Mantiqueira region (SMR), in Minas Gerais state (Southeast Brazil). Although this index has shown efficiency, it lacks a complementary spatial analysis using data from several stations with rain records every 15-min, as they used data from only one station with this characteristic. This aspect makes it possible to better understand the genesis of extreme events in regions with a strong orographic influence, which the researchers did not properly characterize. In this direction, the purpose of this study is to fit a seasonal R_{day} model for the MRRJ. Based on this index, the main objective was to improve R_{day} as an index, which could be applied coupled with the EWS for rainfall disasters in this region in Brazil.

2. Material and methods

2.1. The mountainous region of Rio de Janeiro state (MRRJ)

The MRRJ is located in Serra do Mar region, in southeast Brazil. In geomorphological terms, it is inserted in the Reverse Plateau unit (Garcia and Francisco, 2013), characterized by mountainous and steep relief, with altitudes ranging from 400 to 2350 m (Fig. 1). The predominant soils are the Cambisols, which are shallow, moderately permeable, with a high silt/clay ratio, low natural fertility, and with the formation of crusts that constraints the infiltration if the vegetation cover is scarce or absent (Pinto et al., 2018).

The geographical location of the three municipalities severely impacted by rainfall hazards is in Fig. 1, as well as the location of the Brazilian National Water Agency (ANA) rain gauge stations and the National Center for Monitoring and Early Warning of Natural Disasters (CEMADEN) automatic rain gauges used in this study.

The municipalities of Petrópolis (792 km^2), Teresópolis (773 km^2) and Nova Friburgo (936 km^2) were focused in this study because they are the most representative municipalities in the population, and they were more prone to rainfall hazards in recent decades (Coelho Netto et al., 2013). The population of these three municipalities is predominantly urban (approximately 90%), totaling approximately 645,000 inhabitants (296,000, 166,000 and 183,000 in Petrópolis, Teresópolis, and Nova Friburgo, respectively) (IBGE, 2010; Cardozo & Monteiro, 2019; Coelho Netto et al., 2013). Its economy is geared towards industry, agriculture, and tourism (Coelho Netto et al., 2013).

The MRRJ climate is generally characterized as Cwb (according to the Köppen climate classification), with dry winters and rainy summers. The annual average temperatures are around 16 °C (Coelho Netto et al., 2013) and the summer accounts for 70% of the rainfall between October and March. The winters are cool and dry (Dourado et al., 2012). The rainfall pattern in the MRRJ is driven by frontal systems; convective rains in the summer; South Atlantic Convergence Zone (SACZ); orographic effects; tropical and subtropical cyclones; surface water temperature of the Subtropical Atlantic Ocean; and maritimity (Reboita et al., 2010).

Nova Friburgo has been hit by the highest rainfall amount throughout the state of Rio de Janeiro, with an annual average of 2500 mm in the highest areas, decreasing progressively towards the north (N) as the altitudes decrease (Cardozo & Monteiro, 2019; Coelho Netto et al., 2013). The average annual rainfall in Teresópolis also varies in the North-South direction (from 2200 to 1500 mm), and in Petrópolis (from 1900 to 1000 mm). The rainiest period occurs between December and February, when the monthly average rainfall varies between 340 and 240 mm in the highest altitudes in the southern MRRJ, and between 240 and 150 mm in the northern (Coelho Netto et al., 2013).

2.2. Rainfall erosivity calculation (EI_{30})

Datasets of rainfall from 68 automatic rain gauges provided by CEMADEN with a 10-min temporal resolution (Fig. 1) were used to calculate EI_{30}, using the available period between 2014 and 2020. The following equations were used to calculate EI_{30}:

$$ke_d = 0.29 \cdot [1 - 0.72 \cdot \exp(-0.082 \cdot i_d)] \quad (1)$$

$$E_d = Ke_d \cdot P_d \quad (2)$$

$$\mathrm{KE} = \left(\sum_{d=1}^{n} E_d \right) \quad (3)$$

$$EI_{30} = KE \cdot I_{30} \quad (4)$$

Equation (1) allows calculating the kinetic energy per mm of rain (ke_d) per time interval "d" ($MJ.ha^{-1}$. mm^{-1}), in which i_d is the rainfall intensity ($mm.h^{-1}$) (McGregor & Mutchler, 1976). In equation (2), E_d is the kinetic energy ($MJ.ha^{-1}$), and P_d is rainfall depth (mm), both in the "d" time interval. Thus, the kinetic energy of the event is obtained by the sum of the kinetic energy (E_d) calculated for each time interval (KE, $MJ.ha^{-1}$) (Equation (3)), where "n" corresponds to the number of the time interval "d". Finally, the EI_{30} calculation for the event ($MJ.ha^{-1}.mm.h^{-1}$) (Equation (4)) is made by multiplying KE by the 30-min maximum rainfall intensity (I_{30}) ($mm.h^{-1}$).

Two conditions were considered to separate individual erosive events: $KE > 3.6$ MJ ha^{-1} (De Maria, 1994); and $I_{30} \geq 13.3$ mm h^{-1} (Xie et al., 2002). Nevertheless, EI_{30} is not necessarily synonymous with R_{day}, since a single rain event can have a duration greater than one day, or more than one erosive event may occur on the same

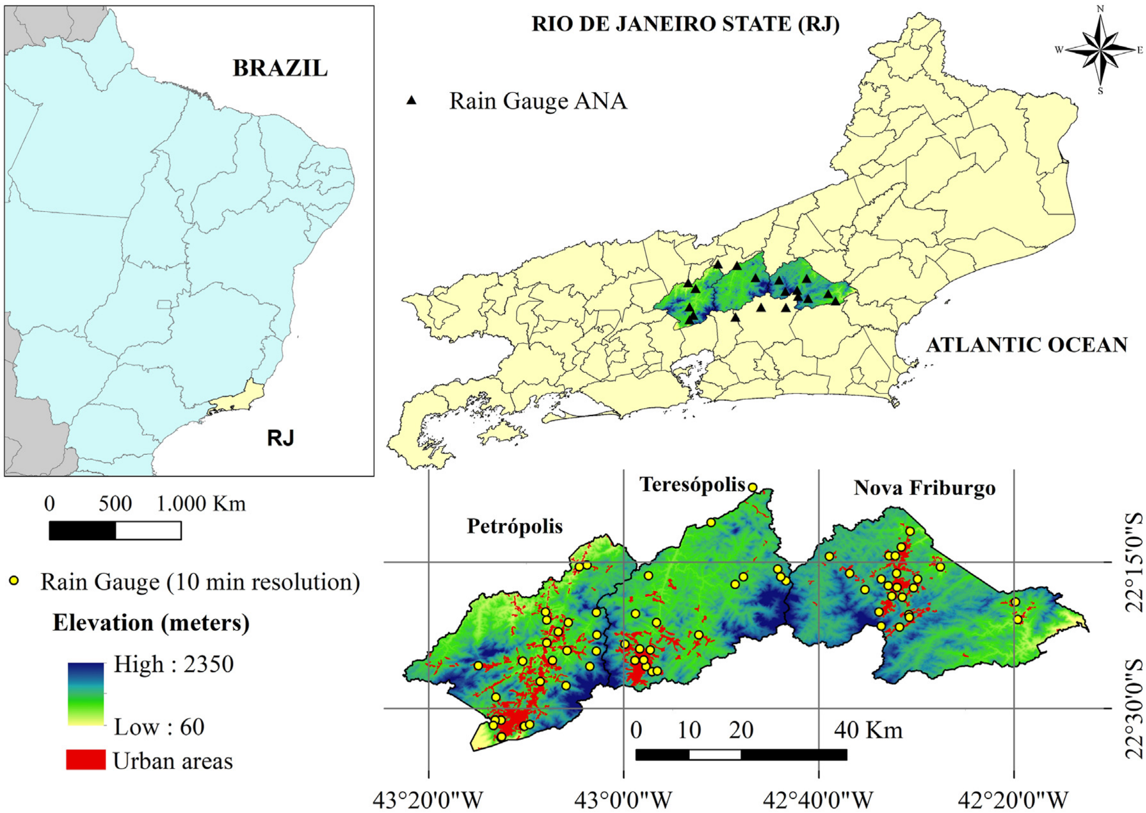

Fig. 1. Geographical location of MRRJ, highlighting Nova Friburgo, Petrópolis, and Teresópolis municipalities, the CEMADEN automatic rain gauges, and the ANA rain gauges.

day. Therefore, three situations are possible to define R_{day} (Xie et al., 2016; Mello et al., 2020):

Type I: a day with only one rain event ($R_{day} = EI_{30}$ of the event);

Type II: a day with multiple rain events separated by > 6 h (R_{day} = sum of the EI_{30} of each event in the day); and.

Type III: a day with rainfall event that lasts over 24 h ($R_{day} = KE$ considering the 24-h interval with the highest total rainfall multiplied by the highest I_{30} for their calculation).

2.3. Seasonal model for estimating R_{day}

A seasonal R_{day} model was fitted based on the study by Yu and Rosewell (1996):

$$R_{day} = \alpha \cdot [1 + \eta \cos(2\pi fj - \omega)] \cdot P_{day}{}^{\beta} \tag{5}$$

In which j is the fortnight of the year (ranging from 1 to 24); f = 1/24; η, α, ω and β are the fitted parameters. The η parameter is related to the amplitude in the variation of the α parameter; ω is the parameter related to the fortnight with the highest accumulated rainfall erosivity; β is a parameter considered for modeling the non-linearity of daily rainfall and respective erosivity (Richardson et al., 1983). In the MRRJ, the first half of January has the highest accumulated total erosivity (based on seven years of recording); $\omega = \pi/6$.

The model parameters were estimated using the least squares method considering the R_{day} and the respective daily rainfall observed in the 68 automatic rain gauges. For this, we split the dataset (rainfall erosive events) into two groups: one for fitting the daily rainfall erovisity model (equation (5)) and the other for analyzing the model's performance. For the latter, approximately 37% of the data were used, being randomly chosen according to the number of erosive events distributed in daily rainfall classes (<15 mm; 16–20 mm; 21–30; 31–40 mm; 41–50 mm; 51–75 mm; 76–100; >101 mm).

Two precision statistics were adopted (Angulo-Martínez & Beguería, 2009):

i) Nash-Sutcliffe Efficiency Coefficient (C_{NS}) (Nash & Sutcliffe, 1970):

$$C_{NS} = 1 - \frac{\sum_{i=1}^{N}(E_{oi} - E_{ei})^2}{\sum_{i=1}^{N}(E_{oi} - \overline{E_o})^2} \tag{6}$$

ii) P_{bias} that measures the trend of estimates, and is calculated by:

$$P_{bias} = \frac{\sum_{i=1}^{N}(E_{oi} - E_{ei})}{N} \tag{7}$$

2.4. Natural disaster rainfall-based alert indexes

2.4.1. Previous rainfall indexes

Brooks and Stensrud (2000) defined that a rainfall event is classified as intense when the precipitation intensity is ≥ 25.4 mm h^{-1}. Groisman et al. (2001) established that intense and very intense rainfall can be separated using a fixed threshold of 50.8 and 101.6 mm/day, respectively, or the values corresponding to the 90th and 99th percentiles. In investigating the occurrence of extreme events in the United States, Groisman et al. (2012) considered four classes of precipitation: moderately intense (12.7–25.4 mm/day), intense (25.4–76.2 mm/day), very intense

(76.2–154.9 mm/day), and extreme intense (>154.9 mm/day); the latter is related to floods, property damage, accidents, and fatalities.

Dolif and Nobre (2012) defined an extreme event for the city of Rio de Janeiro as one that causes a precipitated accumulation >50 mm in any interval of 24 h. This threshold is the one used by the World Meteorological Organization (WMO) in the "Severe Weather Information Centre" (http://severe.worldweather.org/rain/), applied in intense precipitation prediction models (Pristo et al., 2018). Still, regarding the city of Rio de Janeiro, a system called *Alerta-Rio* has been applied since April/2010. However, despite its good performance in predicting extreme events and alerting the population to these, its implementation cost is high since it is based on rain intensity data derived from meteorological radars.

Despite the difficulty of establishing a single value as an alert index, it is known that precipitation is one of the factors that most triggers natural disasters (Guzzetti et al., 2007). In addition, the forecast of this variable can be made 48 or even 72 h in advance (Oliveira et al., 2016), providing enough time for the authorities to assess the event and warn the population of imminent risks. Thus, precipitation has been used to compose the majority of EWS.

2.4.2. Application of the R_{day} as an EWS

R_{day} thresholds are proposed as an index to be used in the EWS. These thresholds were established through the joint analysis of the R_{day} values, which concomitantly caused rainfall hazards with the respective consequences observed in eight events that hit the MRRJ in the last two decades.

Maximum daily rainfall erosivity (R_{maxday}) (Mello et al., 2020) map was developed to identify areas more vulnerable to rainfall hazards. It is based on the maximum daily rainfall observed in at least 22 years since it is the minimum period to characterize the rainfall erosivity pattern for a given region (Wischmeier & Smith, 1978). Its mapping was developed by means kriging techniques, considering the highest rainfall values observed in the MRRJ in the last three decades (1990–2019).

The R_{day} index definition is based on (Mello et al., 2020): i) detailed survey of the events which caused natural disasters, characterizing, in this order, fatalities, homeless, and damage in the infrastructure; ii) other indexes were used for comparative purposes when establishing R_{day} thresholds. Thus, R_{day} intervals were proposed for MRRJ according to the occurrences and the respective R_{day}, linking these intervals to the consequences registered, and comparing them with other existing indexes.

The indexes used in this study for comparison purposes are those used by *Alerta-Rio*, operated by the Geotechnical Foundation of the municipality of Rio de Janeiro (*GEO-Rio*), and those presented by Oliveira et al. (2016), who studied the precipitation thresholds that caused rainfall hazards in the Nova Friburgo municipality (Table 1). The established indexes can be based on a relationship between rainfall and landslides or through statistical analysis (Calvello et al., 2015). The intervals that consider a period of 24 and 72 h is presented in Table 1. Both indexes consider the rainfall duration; Alerta Rio 1 h, 24 h, and 72 h, while Oliveira et al. (2016) 24 h, 48 h, and 72 h. Besides, both indexes proposed a classification warning according to the magnitude of the rain; Alerta Rio defined "Mean," "High," and "Very High" warning, linking them to the respective duration and an interval of the rainfall depth. Oliveira et al. (2016) created three levels, A, B, and C, which are associated with the respective duration and rainfall depth. Similar to Alerta Rio, these levels indicate the concern with the rainfall impact, increasing from A to C.

Table 1
Precipitation limits currently adopted as warning indexes in Rio de Janeiro state.

Duration (hours)	Alert level according to accumulated rainfall (mm) – Alerta Rio		
	Mean	High	Very high
1	25–50	50–80	>80
24	85–140	140–220	>220
72	140–220	220–300	>300
Criteria	**Accumulated rainfall (mm)** (Oliveira et al. 2016)		
	24h	**48h**	**72h**
A	50	60	100
B	50	75	120
C	75	120	150

3. Results

3.1. Daily rainfall erosivity modeling in the MRRJ

Based on 68 CEMADEN stations, 5101 rainfall events with $I_{30} \geq 13.3$ mm h^{-1} (the first step for split rainfall erosivity events) were identified between 2014 and 2019 in MRRJ, with the lowest observed amount of 6.7 mm. However, some of these events are not erosive according to the kinetic energy (KE > 3.6 MJ ha^{-1}). Therefore, the second step consisted of separating those that are erosive. From the 5101 events, 3698 were classified as erosive events, i.e., KE > 3.6 MJ ha^{-1}, corresponding to 72.5% of the studied events. The number of erosive and non-erosive events and the frequency and respective class of R_{day} in MRRJ are presented, respectively, in Fig. 2(a) and (b).

Table 2 shows the number and percentage of erosive events, the percentage of observed erosivity, and the average I_{30} (mm.h^{-1}) for each rainfall class.

The classification of erosive events in terms of their type is: 83% Type I; 11.6% Type II; and 5.4% Type III.

To apply the R_{day} model, it is fundamental to establish a minimum daily rainfall that potentially can triggers a rainfall erosive event. Fig. 2a shows that all 898 events <13 mm were not classified as erosive. However, 126 events in the 13–15 mm interval (25.2%) were erosive, which allows us to infer that the minimum precipitation depth to be considered erosive is within this interval, bearing in mind that some 13 mm events were erosives.

Erosive events had the following characteristics: i) they are generated by rainfall ≥13 mm; ii) all rainfall events ≥22 mm are erosive; iii) approximately half of the erosive events (1848 out of 3698 events) occur for rainfall ≥31 mm; and iv) despite representing approximately 50% of the total number of erosive events, rainfall ≥31 mm corresponds to 78.6% of the total observed rainfall erosivity over MRRJ.

3.2. Seasonal R_{day} model for MRRJ

The fitted seasonal model for MRRJ presented the following structure:

$$R_{day} = 3.3888 \cdot \left[1 + 0.4659 \cdot \cos\left(\frac{2 \cdot \pi \cdot j}{24} - \frac{\pi}{6}\right)\right] \cdot Pday^{1.2028} \quad (8)$$

This model describes the inter-daily annual seasonality of R_{day} by estimating the parameters "α", "η" and "β" (3.3888; 0.4659; 1.2028; respectively). An important detail is that the fitted parameters spatially represent the MRRJ since it was determined based on data from 68 rain gauge stations with precipitation data recorded every 10 min.

The precision statistics associated with calibration ($C_{NS} = 0.51$; $P_{bias} = -0.56$) and validation ($C_{NS} = 0.50$; $P_{bias} = -2.22$) demonstrate satisfactory results for the R_{day} model, especially when

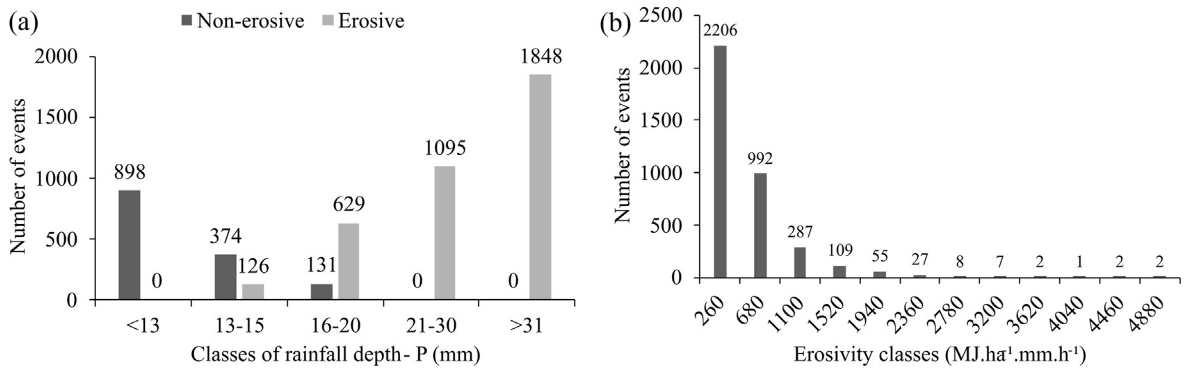

Fig. 2. The number of erosive and non-erosive events (2014–2019) per rainfall classes (a) and frequency of R_{day} observed in MRRJ (b).

Table 2
Percentage of erosive events and total erosivity for different rainfall classes.

Rainfall (mm)	N°. of events	% of Events	% of accumulated EI_{30} ($MJ.ha^{-1}.mm.h^{-1}$)	Average I_{30} ($mm.h^{-1}$)
<15	126	3.4	0.5	26.1
16–20	629	17.0	5.2	25.6
21–30	1095	29.6	15.7	29.0
31–40	679	18.4	16.1	34.5
41–50	428	11.6	14.9	39.6
51–75	497	13.4	24.3	42.5
76–100	125	3.4	10.2	45.6
>101	119	3.2	13.1	46.2

Table 3
Summary of the rainfall hazards observed in the MRRJ in the last two decades and respective estimated R_{day}.

Date (DD/MM/Year)	Municipality	Displaced	Fatalities	Number of affected	R_{day} ($MJ\ ha^{-1}\ mm.h^{-1}\ day^{-1}$)	Area**	P24 (mm)	P72 (mm)	*Alerta-Rio*
December 24, 2001	Petrópolis	5017	38	10230	3125.4	Urban	220.1	220.1	Very high
December 18, 2002	Teresópolis	253	14	9200	1293.5	Rural	105.7	171.6	Mean
February 04, 2005	Nova Friburgo	249	0	1050	1788.9	Rural	134.6	170	Mean
November 29, 2006	Teresópolis	248	3	1751	1198.7	Urban	110.5	169.6	Mean
November 29, 2006	Nova Friburgo	545	8	6800	2578.2	Rural	208.8	223	High
January 04, 2007	Petrópolis	525	3	30000	1133.9	Rural	92.2	163.6	Mean
January 04, 2007	Nova Friburgo	4196	11	80000	2238.4	Rural	162.3	395.9	High
January 04, 2007	Teresópolis	229	2	1500	1851.3	Rural	138.6	160.1	Mean
January 12, 2011	Petrópolis	7144	71	*	900.1	Rural	76.1	80.3	No hazards
January 12, 2011	Nova Friburgo	5317	429	*	2594.6	Urban	183.5	201.8	High
January 12, 2011	Teresópolis	15837	392	*	1962.8	Rural	145.5	249.8	High
April 06, 2012	Nova Friburgo	2371	5	10162	1875.1	Urban	173	176.5	High
January 15, 2016	Petrópolis	523	34	152277	1682.4	Urban	128.2	221.4	Mean
January 15, 2016	Teresópolis	144	0	102372	1016.7	Rural	84.2	130.5	No hazards

* Official sources did not account for an approximate number per municipality, but it is known that more than 1,000,000 people were affected across the region. ** Areas more impacted (urban and rural).

considering that this estimate is made based only on daily rainfall and the period of the year.

Fig. 3a and b represent the fitted model applied to the events (1368 events) separated exclusively for validation. The regression in Fig. 3a means a relationship between estimated R_{day} values by the fitted model in function of rainfall depth (red triangles). Through this fitting, one can observe that the model could capture the seasonality effect on daily rainfall erosivity, i.e., different Rday values were estimated with the same precipitation depth, meaning that these events occurred in different seasons of the year.

In Fig. 3b, it is possible to verify that the estimated R_{day} values fitted reasonably well to the observed ones. However, over-estimation and understation values can be seen, respectively, for the lowest and the highest values.

Fig. 4 shows the model fitting graphs for MRRJ considering different classes of I_{30}. It can be seen in Fig. 4a that the model tends to overestimate R_{day} for $I_{30} < 25$ mm h^{-1}. On the other hand, the model's performance is superior for the I_{30} between 25 and 50 mm h^{-1} (Fig. 4b), and between 51 and 75 mm h^{-1} (Fig. 4c), with good precision. However, the model underestimates R_{day} for the greatest I_{30} class (Fig. 4d).

3.3. Relation between R_{day} and rainfall hazards in MRRJ

To relate R_{day} values and the most significant rainfall hazards provoked by rainfall in MRRJ, maps of it were developed (Fig. 5 – left columns). For comparing purposes, a map using the EWS developed by Alerta-Rio was also developed (Fig. 5 – right column), which allows observing how Rday is more sensitive and complete than the previous alert index.

All three municipalities had R_{day} > 1500 MJ $ha^{-1}.mm.h^{-1}.day^{-1}$ at some point, and these events have always been linked to disasters that culminated in thousands of people affected (fatalities, displaced, homeless, injured people), as further depicted in Table 3.

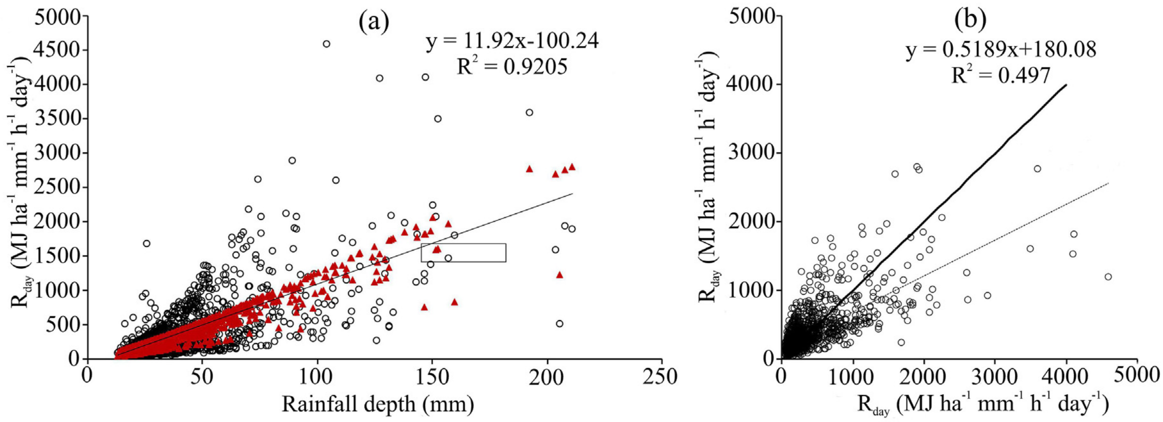

Fig. 3. Behavior of the R_{day} by the seasonal model applied to the validation data.

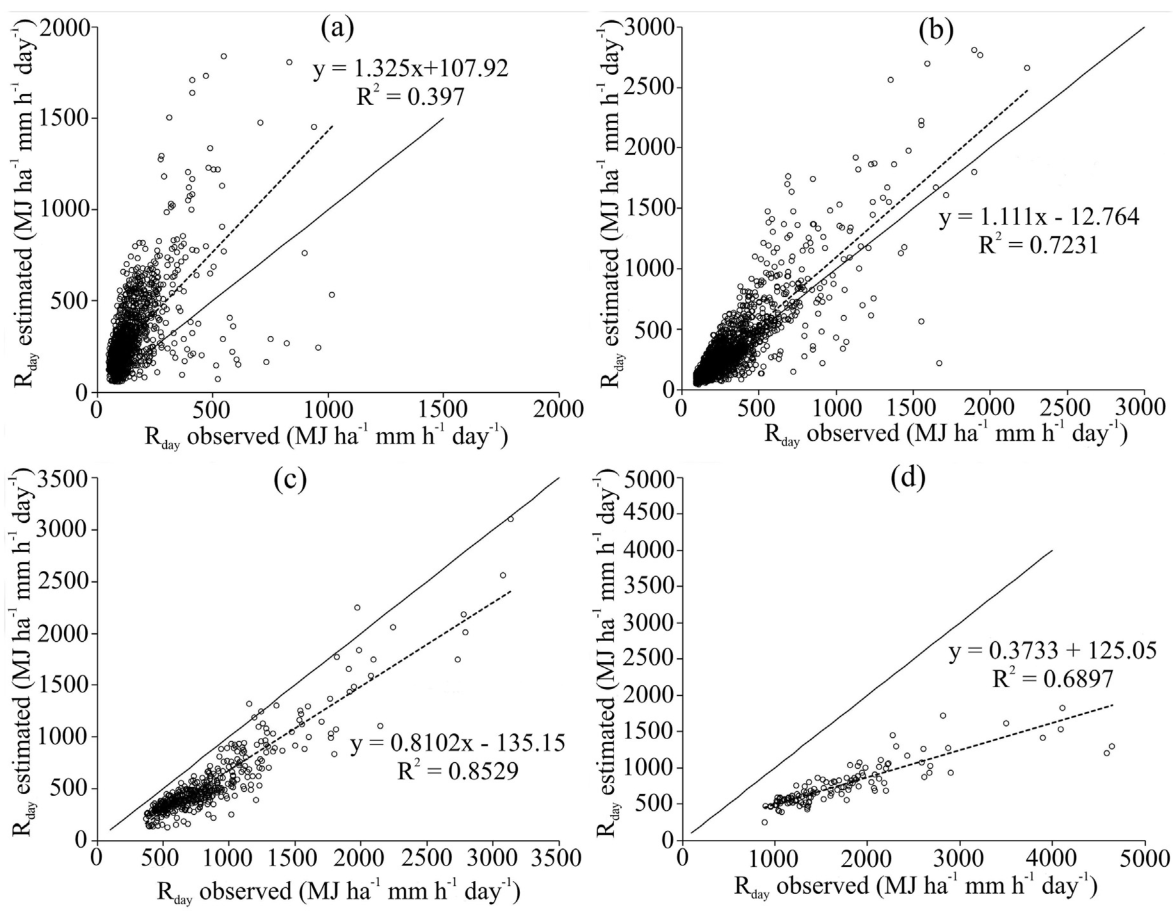

Fig. 4. Model fitting for different I_{30} classes (a. $I_{30} < 25$; b. $25 \leq I_{30} \leq 50$; c. $51 \leq I_{30} \leq 75$; and d. $I_{30} > 75$).

This table has as purpose of presenting the most impacting rainfall hazards in MRRJ between 2001 and 2016, respective impacts and risk classification (EWS) according to Alerta-Rio, taking the greatest precipitation in 24 h or 72 h, i.e., the worst situation (Table 1). Also, the disasters were presented according to the most affected (urban or rural), and the respective R_{day} was calculated using the fitted model.

The R_{day} estimates can be useful to analyze whether a given region can be hit by R_{day} that causes rainfall hazards. In addition, the development of R_{maxday} maps can be used as a tool to identify the most vulnerable areas to rainfall hazards. These maps can also be helpful in planning and managing the reduction of impacts caused by very erosive rains, which occur in mountainous regions of southeastern Brazil. The spatial distribution of R_{maxday} in MRRJ is presented in Fig. 6 and was prepared using the maximum daily precipitation observed in the last 30 years (1990–2019).

The highest R_{maxday} values ($\geq$2500 MJ $ha^{-1}.mm.h^{-1}.\ day^{-1}$) were estimated in southern Petrópolis, eastern Teresópolis, and the

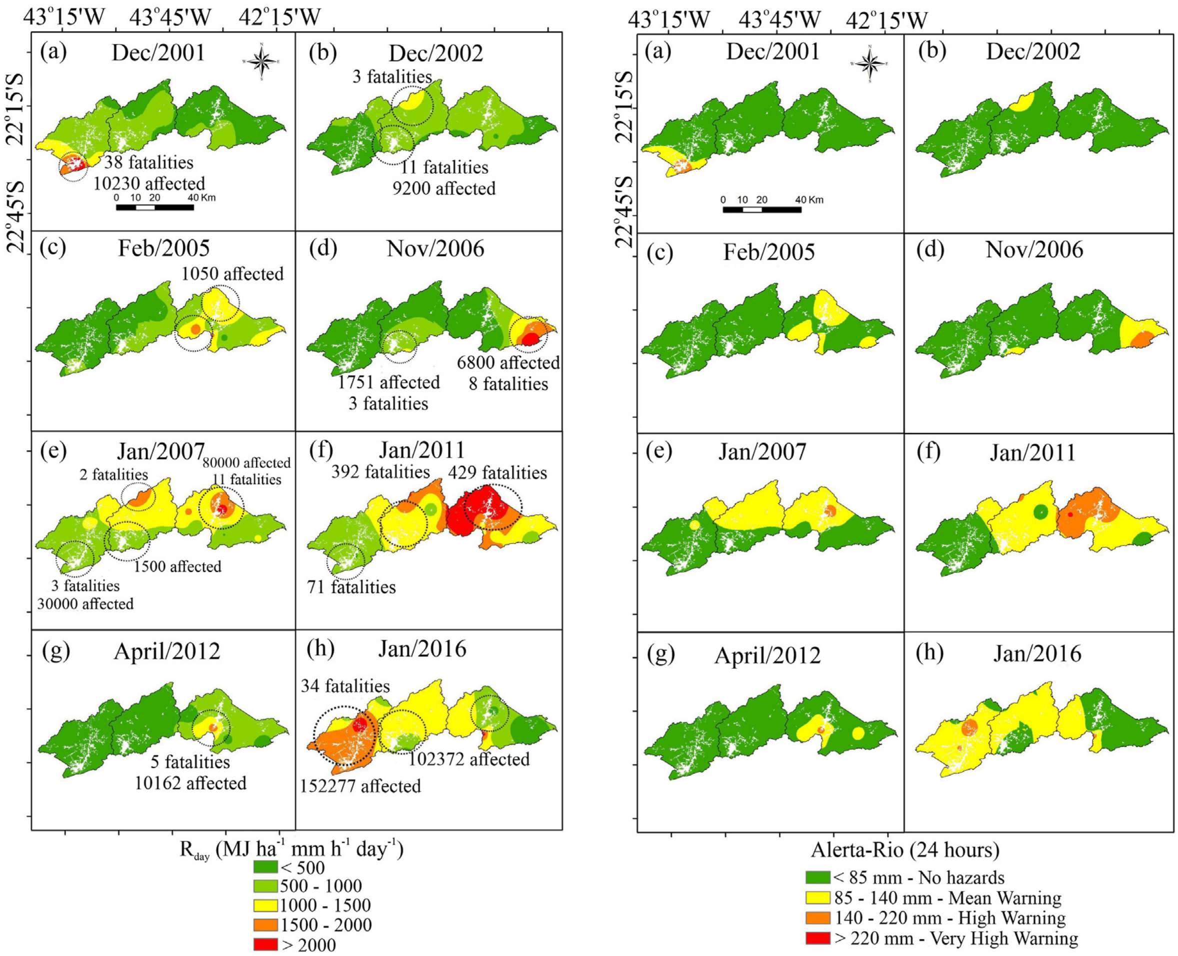

Fig. 5. Maps of the most severe rainfall hazards in MRRJ (see Table 3) and respective R_{day} values (maps in left column) and using *Alerta-Rio* (maps in right column).

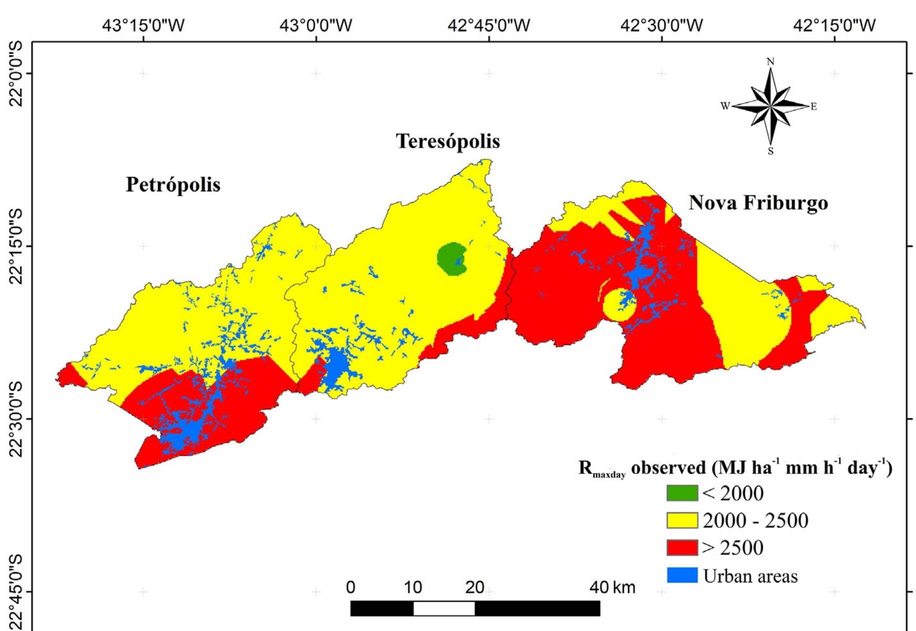

Fig. 6. R_{maxday} mapping for the MRRJ considering the last three decades.

largest part of the Nova Friburgo, matching with the highest altitudes. The urban areas of Petrópolis and Nova Friburgo are inserted in these regions, and Teresópolis is in a region where 2000 < $R_{max-day}$ < 2500 MJ ha^{-1}.mm.h^{-1}. day^{-1}. These high values are explained based on the combination of the effects of orographic rainfall events due to altitude and proximity to the Atlantic Ocean. Therefore, these are the most vulnerable areas to rainfall hazards in MRRJ.

Nova Friburgo is the municipality with the highest R_{maxday} values. Thus, it is the most vulnerable to fatalities, damage to infrastructure, economy, and society in general. On the other hand, it is observed that practically all of the MRRJ presented R_{maxday} values > 2000 MJ ha^{-1}.mm.h^{-1}. day^{-1}, which is higher than the previously established index (1500 MJ ha^{-1}.mm.h^{-1}. day^{-1}), allowing classifying this region as very vulnerable to fatalities, homelessness, and infrastructure damages.

4. Discussion

4.1. General aspects of R_{day} in MRRJ

Despite the lower frequency of erosive events in the last three precipitation classes (Table 2; P ≥ 51 mm), these are the most expressive events in terms of erosivity, representing 47.6% of the total rainfall erosivity for the region. This fact demonstrates that only an erosive rain event can easily trigger natural disasters in the region. Thus, the study of these events is essential for analyzing the occurrence of natural disasters and a more practical index for issuing warning signs for natural disasters.

In MRRJ, there is a predominance of type I events due to the fact that the Serra do Mar is close to the Atlantic Ocean, increasing the presence of air humidity, leading to orographic and convective rains, which are generally of short to medium duration. Mello et al. (2020) for Mantiqueira Range region, southeast Brazil, also observed the dominance of type I, which is linked with the pattern of rainfall in tropical regions in summer. Most erosive events are associated with convective rains, characterized as local events of short duration and high intensity, increasing the *KE* values, as well as the maximum values for I_{30}. These rains are common in the summer, justifying the predominance of Type I. Despite the high magnitude of the total precipitation, events classified as Type III generally present lower I_{30} values since they come from high-duration frontal systems and less intensity than convective rains. However, several rainfall hazards are associated with this type of event since they are responsible for soil saturation, increasing the susceptibility to landslides and floods. It is also known that the variability in precipitation intensity during these frontal events is small, so that Type III events do not tend to overestimate R_{day} even with a higher amount of precipitation (Xie et al., 2016). Also, the South Atlantic Convergence Zone (SACZ) can hit the Southeast Brazil in summer, being responsible for several consecutive rainy days, and can therefore be highlighted as a potential source for types II and III.

Because a rainfall of 13 mm generated some erosive rains, this value is considered more appropriate as a threshold for erosive rainfall in MRRJ. This value is similar to those suggested by Xie et al. (2002), who conducted a study to characterize the erosive thresholds of the rains (from 11.9 to 12.8 mm), as well as Xie et al. (2016), who considered 12.0 mm as the most appropriate for eastern China, and Wischmeier and Smith (1978) suggested 12.7 mm for the United States. Mello et al. (2020) observed that none of the studied events smaller than 12 mm was erosive, while some events with precipitation equal to 13 mm were classified as erosive in the Mantiqueira Range region.

4.2. Seasonal R_{day} model for MRRJ

Mello et al. (2020) fitted values of "α", "η" and "β" for Mantiqueira range region equal to 1.8524, 0.2827, and 1.2950, respectively. Comparing these values with those fitted for the MRRJ, it seems that the "α" parameter, which is responsible for the R_{day} annual variation, is intrinsic to each region and did not show any similarity. "β" models the non-linearity variation between rainfall and rainfall erosivity (Wang et al., 2017; Yang & Yu, 2015), and therefore the value for MRRJ is similar to that for Mantiqueira range region. It is directly related to the rainfall patterns. Finally, "η" is the parameter that models the amplitude of the interannual variation of "α" and is not similar to the value for the Mantiqueira range region. Yu and Rosewell (1996) and Xie et al. (2016) fitted this model for eastern China and Australia, respectively, and found values equal to 0.2686, 0.5412 and 1.7265; and 0.535, 0.306 and 1.46 for "α", "η" and "β", respectively, as mean parameters of the respective studied regions. Wang et al. (2017) also fitted a similar model in a subtropical region of China and found "α" varying from 1.04 to 3.12, "η" from 0.13 to 0.74, and "β" from 1.16 to 1.46. Therefore, it is recommended that each geographical region has its own fitted model since the parameters are associated with the respective rainfall pattern.

The behavior of the fitted model for MRRJ is similar to those found by Xie et al. (2016) and Mello et al. (2020), who found that this model shows an overestimation behavior for the lowest R_{day} values and produces better results for more intense rainfall events, which generate higher erosivity values. Despite the similarity of the results, Xie et al. (2016) and Mello et al. (2020) did not relate the model's performance to I_{30} behavior. In general, the model fits reasonably well to MRRJ, since the predominant I_{30} class in the region is 25–75 mm h^{-1} (Fig. 4).

4.3. R_{day} and rainfall hazards in MRRJ: application of R_{day} and comparison with previous indexes

In this section, it is highlighted the main impacts of the rainfall hazards and respective R_{day}, which enable us to propose thresholds for R_{day} in MRRJ (Table 3), and to compare it with the previous existent. Petrópolis county was hit by a rainfall event in 2001 (220.1 mm in 24 h) impacting the urban area, causing 38 fatalities (R_{day} > 3000 MJ ha^{-1} mm h^{-1} day^{-1}). Similarly, the Teresópolis county was hit by rainfall in 2002 that resulted in R_{day} ranging from 500 to 1000 MJ ha^{-1}.mm.h^{-1}. day^{-1} in most part of its area. These events led to 11 fatalities and more than 9200 habitants affected. In the northern area, R_{day} reached 1500 MJ ha^{-1}.mm.h^{-1}. day^{-1} and caused people to be buried by landslides. The R_{day} values in the urban area of Nova Friburgo in 2005 ranged from 500 to 1500 MJ ha^{-1}.mm.h^{-1}. day^{-1} affecting 1050 inhabitants, and leaving 249 homeless. The R_{day} values in the rural area were between 1500 and 2000 MJ ha^{-1}.mm.h^{-1}. day^{-1}. The municipalities of Nova Friburgo (545 homeless and eight fatalities), and Teresópolis (with 248 homeless and three fatalities) were severely affected again in 2006. In this year, the R_{day} values covered all the classes, with the highest values > 2000 MJ ha^{-1}.mm.h^{-1}. day^{-1}. The years of 2007 and 2011 had the highest R_{day} values and the greatest spatial coverage, resulting in 16 fatalities and 111,500 inhabitants affected.

The rainfall disaster that occurred in 2011 deserves special attention, since it was the worst observed in Brazil (Cardozo & Monteiro, 2019). This disaster not only caused a high number of fatalities, but also significant economic losses and damages. Petrópolis, Teresópolis and Nova Friburgo recorded the highest number of victims in MRRJ. The greatest impact in Nova Friburgo was observed predominantly in the urban area, while in the other two municipalities were on the rural areas (Busch & Amorim, 2011;

Cardozo & Monteiro, 2019). The R_{day} values in Nova Friburgo exceeded 2500 MJ $ha^{-1}.mm.h^{-1}$. day^{-1}, and the entire urban area presented values varying from 1500 to >2000 MJ $ha^{-1}.mm.h^{-1}$. day^{-1}, which resulted in 434 fatalities (47% overall) (Cardozo et al., 2018; Cardozo & Monteiro, 2019). On the same day, the total number of homeless in Teresópolis reached 15,837 inhabitants, and it is estimated that more than 1 million people were affected in the three municipalities.

Nova Friburgo was again affected by similar natural disasters in 2012, however, unlike in 2011, they impacted the region in a more isolated way. R_{day} values ranged from 500 to 2000 MJ $ha^{-1}.mm.h^{-1}$. day^{-1}, resulting in five fatalities, 2371 homeless and more than 10,000 affected inhabitants. In analyzing the year 2016 (Fig. 5), it is observed that there was a considerable spatial range of the R_{day} values, with emphasis on the municipality of Petrópolis (34 fatalities, 523 displaced people, and 152,277 inhabitants affected). The fact that the number of victims decreased after the 2011 disaster compared to the number of victims in the years 2012 and 2016 indicates that the public policies, mainly the creation of structures such as CEMADEN, the Technical Support and Emergency Task Force at the National Secretariat for Civil Defense and the National Force of Brazilian Health System (SUS) had a positive effect on the protocols associated with natural disaster management.

Based on these data, it is possible to suggest some thresholds and possible impacts related to them. However, such thresholds do not necessarily mean that impacts, especially fatalities, may occur, since the system for protecting the population from these events is currently more structured than in the past. Therefore, we have: (i) R_{day} > 1500 MJ $ha^{-1}.mm.h^{-1}$. day^{-1} presents a “very high” possibility of fatalities; “very high” number of homeless people; and “very high” possibility of social, economic and infrastructure damages. In these cases, the alert system must be activated immediately and the rescue teams must be properly prepared; (ii) 1000 < R_{day} <1500 MJ $ha^{-1}.mm.h^{-1}$. day^{-1} shows “high” possibility of fatalities, “very high” possibility for homeless people, and “high” possibility of causing damage to infrastructure and economy; (iii) 500 < R_{day} <1000 MJ $ha^{-1}.mm.h^{-1}$. day^{-1} “medium” possibility of fatalities in the urban area and “low” possibility in the rural area, “medium” impact in terms of homelessness, and “medium to low” possibility of causing damage to the infrastructure and economy; (iv) R_{day} < 500 MJ $ha^{-1}.mm.h^{-1}$. day^{-1} shows “very low” possibility of fatalities, “low” number of homeless people, and “low” possibility of economic and infrastructure losses.

According to the classification presented by *Alerta-Rio*, only one event of all the eight extreme events which caused great human and economic losses, or 14 if the municipalities are considered separately (Table 3), could be classified as “very high” risk, five as “high”, six as “medium” and two were not classified, meaning they were not considered as causing natural disasters.

Among these events, the 3rd largest rainfall accumulated in 24 h (183.5 mm) was the cause of the “mega-disaster” observed in MRRJ. According to the *Alerta-Rio* classification, this event would be classified as “high” risk (not “very high” risk as R_{day}). Although this event was the 3rd largest in terms of precipitation accumulated in 24 h, it presented the 2nd highest R_{day} value (2594 MJ $ha^{-1}.mm.h^{-1}$. day^{-1}). This demonstrates how the proposed index is more comprehensive as a warning of natural disasters.

Considering the two events that were not classified by the *Alerta-Rio* since the accumulated precipitation in 24 h was below 85 mm, it is observed that these events had R_{day} values close to 1000 MJ $ha^{-1}.mm.h^{-1}$. day^{-1}, which caused 71 fatalities. The other event, although no fatality was observed, affected more than 100 thousand inhabitants and left 144 families homeless. The alert system would have been triggered when applying $R_{day,}$ and much of the impact would have been minimized.

Among the three criteria studied by Oliveira et al. (2016), criterion A is the least restrictive. Of the events presented in Table 3, only one (occurred on Jan-12, 2011) in the municipality of Petrópolis is not considered to cause landslides, when the precipitation accumulated in 72 h is analyzed. The same result is obtained for criterion B.

Criterion C constraints the occurrence of landslides. The event that hit Petrópolis in January 12, 2011 was discarded as a cause of landslides in criteria A and B, as well as the event of Jan-15, 2016) in Teresópolis. These two events are the same that are not classified by *Alerta-Rio*, and together they affected thousands of people. Oliveira et al. (2016) emphasize that thresholds established for the most restrictive criteria do not separate events with landslides from those without landslides but are identified together with multiple disasters.

Comparing both early warning indexes (Fig. 5) spatially, one can observe a sensitivity of the Rday index, especially in the rainfall hazards in which fatalities were observed. Examples are the events of 2001, 2006, 2007, 2011, and 2016. The Alerta-Rio index would emit a “high” warning in all these years, while Rday displays an “every high” warning for fatalities. Call attention 2011 event, the most severe rainfall hazard in Brazil. In this case, only a tiny spot would be warned as a “very high” warning, being the most significant part of the most affected area receiving a “high” warning. Otherwise, Rday would emit a “very high” possibility for fatalities in most of this area. We can see that more than 400 people died because of this event. In this direction, the event of 2016 would be understood as a “mean” warning using Alerta-Rio, whereas Rday would emit a “very high” warning (34 fatalities + more than 150,000 people displaced). Therefore, proposing Rday as a new early warning index proved to be more sensitive and more accurate with the impacts provoked by the rainfall because this index encompasses more information regarding the nature of heavy rainfall. Besides, it is easy to calculate and apply as a warning index for the MRRJ.

It should be noted that the occurrence of natural disasters in a region is inevitable since they depend on climatic variables. However, the consequences caused by these events not only depend on climatic factors, but also on political, social, and economic factors. Thus, an effective EWS must comprise four main components: knowledge of risk, monitoring, communication structures and efficient alerts, and lastly precautions, all of which need application of efficient public policies.

5. Conclusions

R_{day} addresses fundamental physical aspects associated with precipitation, its energy, as well as the mean and maximum intensities over a 30-min time interval, being more sensitive than those which have been used in Brazil. Considering warning indices based only on the total rainfall or intensity of rainfall has not been shown to be sufficient to understand the complex dynamics of an extreme rainfall event, as its consequences are not only caused by water accumulation, but mainly by the dissipation of accumulated energy. R_{day} values can integrate national databases on the most vulnerable areas and specify risk management strategies and disaster response approaches, especially in places with the highest concentrations of exposed people. Further conclusions are:

a) The R_{day} model had superior performance of other studies with the same model and can be applied to additional studies related to rainfall disasters in Brazil.
b) All events with R_{day} > 1500 MJ $ha^{-1}.mm.h^{-1}$. day^{-1} would fatally impact the region, and therefore areas historically

affected by these events should be considered more prone to natural disasters.

c) Using the fitted model for R_{day} estimates, it was found that the municipality of Nova Friburgo, and the south of the municipality of Petrópolis are very vulnerable to natural disasters from the climatic point of view, with the highest R_{maxday} values.

d) January was historically the period with the highest daily erosivity values, in which all precipitation events used for developing the R_{maxday} map occurred in the first or second half of this month.

Conflict of interest

None.

Declaration of competing interest

None.

Acknowledgments

We acknowledge the Coordination of Superior Level Staff Improvement – CAPES [grant number 88882.306661/2018–01]; the National Council for Scientific and Technological Development – CNPQ [grant number 301556/2017-2] for supporting and funding this work.

References

Angulo-Martínez, M., & Beguería, S. (2009). Estimating rainfall erosivity from daily precipitation records: A comparison among methods using data from the Ebro basin (NE Spain). *Journal of Hydrology, 379*(1–2), 111–121.

Brito, T. T., Oliveira, J. F., Jr., Lyra, G. B., Gois, G., & Zeri, M. (2016). Multivariate analysis applied to monthly rainfall over Rio de Janeiro state, Brazil. *Meteorology and Atmospheric Physics, 129*, 469–478.

Brooks, H. E., & Stensrud, D. J. (2000). Climatology of heavy rain events in the United States from hourly precipitation observations. *Monthly Weather Review, 4*, 1194–1201. https://doi.org/10.1175/1520-0493(2000)12860;1194:cohrei62;2.0.co;2

Busch, A., & Amorim, S. N. D. (2011). *A Tragédia da Região Serrana do Rio de Janeiro em 2011: Procurando respostas*. Brasília: ENAP.

Calvello, M., D'Orci, R. N., Piciullo, L., Paes, N., Magalhães, M., & Lacerda, W. A. (2015). The Rio de Janeiro early warning system for rainfall-induced landslides: Analysis of performance for the years 2010–2013. *Internatinal Journal Disaster Risk Reduction Reduct, 12*, 3–15. https://doi.org/10.1016/j.ijdrr.2014.10.005

Cardozo, C. P., Lopes, E. S., & Monteiro, A. M. V. (2018). Shallow landslide susceptibility assessment using SINMAP in Nova Friburgo (Rio de Janeiro, Brazil). *Revista Brasileira de Cartografia, 4*, 1206–1230. https://doi.org/10.14393/rbcv70n4-46139

Cardozo, C. P., & Monteiro, A. M. V. (2019). Assessing social vulnerability to natural hazards in Nova Friburgo. In *Rio de Janeiro mountain region* (Vol. 2, pp. 71–83). Brazil: REDER.

CEPED. (2013). *Atlas Brasileiro de Desastres naturais: 1991-2010* (2nd ed.). Santa Catarina: Ceped.

Coelho Netto, A. L., Sato, A. M., Avelar, A. S., Vianna, L. G. G., Araújo, I. S., Ferreira, D. L. A., Lima, P. H., Silva, A. P. A., & Silva, R. P. (2013). January 2011: The extreme landslide disaster in Brazil. In C. Margottini, P. Canuti, & K. Sassa (Eds.), *Landslide science and practice* (pp. 377–384). Heidelberg: Springer.

De Maria, I. C. (1994). Cálculo da erosividade da chuva. In *Instituto Agronômico de Campinas. Manual de programas de processamento de dados de campo e de laboratório para fins de experimentação em conservação do solo*. IAC-SCS.

Dolif, G., & Nobre, C. (2012). Improving extreme precipitation forecasts in Rio de Janeiro, Brazil: Are synoptic patterns efficient for distinguishing ordinary from heavy rainfall episodes? *Atmospheric Science Letters, 3*, 216–222. https://doi.org/10.1002/asl.385

Fernandes, L. G., & Rodrigues, R. R. (2018). Changes in the patterns of extreme rainfall events in southern Brazil. *International Journal of Climatology, 38*, 1337–1352. https://doi.org/10.1002/joc.5248

Freitas, C. M., Carvalho, M. L., Ximenes, E. F., Arraes, E. F., & Orlando, J. (2012). Vulnerabilidade socioambiental, redução de riscos de desastres e construção da resiliência: Lições do terremoto no Haiti e das chuvas fortes na Região Serrana, Brasil. *Ciência & Saúde Coletiva, 17*, 1577–1586. https://doi.org/10.1590/S1413-81232012000600021

Groisman, P. Y., Knight, R. W., & Karl, T. R. (2001). Heavy precipitation and high streamflow in the contiguous United States: Trends in the twentieth century. *Bulletin of the American Meteorological Society, 82*, 219–246. https://doi.org/10.1175/1520-0477(2001)082<0219:HPAHSI>2.3.CO;2

Groisman, P. Y., Knight, R. W., & Karl, T. R. (2012). Changes in intense precipitation over the central United States. *Journal of Hydrometeorology, 1*, 47–66. https://doi.org/10.1175/JHM-D-11-039.1

Guzzetti, F., Peruccacci, S., Rossi, M., & Stark, C. P. (2007). Rainfall thresholds for the initiation of landslides in central and southern Europe. *Meteorology and Atmospheric Physics, 98*, 239–267. https://doi.org/10.1007/s00703-007-0262-7

IBGE. (2010). *Census*. http://www.ibge.gov.br/home/estatistica/populacao/censo2010/default.shtm. (Accessed 17 January 2020).

McGregor, K. C., & Mutchler, C. K. (1976). Status of the R-factor in northern Mississippi. In T. J. Toy, G. R. Foster, & K. G. Renard (Eds.), *Soil erosion: Prediction and control* (pp. 135–142). Soil Conservation Society America.

Mello, C. R., Alves, G. J., Beskow, S., & Norton, L. D. (2020). Daily rainfall erosivity as an indicator for natural disasters: Assessment in mountainous regions of southeastern Brazil. *Natural Hazards, 103*, 947–966. https://doi.org/10.1007/s11069-020-04020-w

Mello, C. R., Ávila, L. F., Viola, M. R., Curi, N., & Norton, L. D. (2015). Assessing the climate change impacts on the rainfall erosivity throughout the twenty-first century in the Grande River Basin (GRB) headwaters, southeastern Brazil. *Environmental Earth Sciences, 73*, 8683–8698. https://doi.org/10.1007/s12665-015-4033-3

Mendes, R. M., Andrade, M. R. M., Tomasella, J., Moraes, M. A. E., & Scofield, G. B. (2018). Understanding shallow landslides in Campos do Jordão municipatily – Brazil: Disentangling the anthropic effects from natural causes in the disaster of 2000. *Natural Hazards and Earth System Sciences, 18*, 15–30. https://doi.org/10.5194/nhess-18-15-2018

Nash, J. E., & Sutcliffe, J. V. (1970). River flow forecasting through conceptual models part I: A discussion of principles. *Journal of Hydrology, 10*, 282–290.

Oliveira, N. S., Rotunno Filho, O. C., Maton, E., & Silva, C. (2016). Correlation between rainfall and landslides in Nova Friburgo, Rio de Janeiro—Brazil: A case study. *Environmental Earth Sciences, 75*, 1358. https://doi.org/10.1007/s12665-016-6171-7

Pinto, L. C., Mello, C. R., Norton, L. D., Poggere, G. C., Owens, P. R., & Curi, N. (2018). A hydropedological approach to a mountainous Clayey Humic Dystrudept in the Mantiqueira range. *Southeastern Brazil. Scientia Agricola, 75*, 60–69. https://doi.org/10.1590/1678-992x-2016-0144

Pristo, M. V. J., Dereczynski, C. P., Souza, P. R., & Menezes, W. F. (2018). Climatologia de chuvas intensas no município do Rio de Janeiro. *Rev. Bras. Meteorol., 4*, 615–630.

Reboita, M. S., Gan, M. A., Rocha, R. P., & Ambrizzi, T. (2010). Regimes de precipitação na América do Sul: Uma revisão bibliográfica. *Revista Brasileira de Meteorologia, 2*, 185–204. https://doi.org/10.1590/S0102-77862010000200004

Richardson, C. W., Foster, G. R., & Wright, D. A. (1983). Estimation of erosion index from daily rainfall amount. *Transactions of the ASABE, 26*, 153–156. https://doi.org/10.13031/2013.33893

Wang, Y., Tan, S., Liu, B., & Yang, Y. (2017). Estimating rainfall erosivity by incorporating seasonal variations in parameters into the Richardson model. *Journal of Geographical Sciences, 27*, 275–296. https://doi.org/10.1007/s11442-017-1376-6

Wischmeier, W. H., & Smith, D. D. (1958). Rainfall energy and its relationship to soil loss. *Transactions - American Geophysical Union, 39*, 285–291. https://doi.org/10.1029/TR039i002p00285

Wischmeier, W. H., & Smith, D. D. (1978). *Predicting rainfall erosion losses: A guide to conservation planning*. Washington: USDA.

Xie, Y., Liu, B., & Nearing, M. A. (2002). Practical thresholds for separating erosive and non-erosive storms. *Transactions of the ASAE, 45*, 1843–1847. https://doi.org/10.13031/2013.11435

Xie, Y., Yin, S., Liu, B., Nearing, M., & Zhao, Y. (2016). Models for estimating daily rainfall erosivity in China. *Journal of Hydrology, 535*, 547–558. https://doi.org/10.1016/j.jhydrol.2016.02.020

Xu, L., Meng, X., & Xu, X. (2014). Natural hazard chain research in China: A review. *Natural Hazards, 70*, 1631–1659. https://doi.org/10.1007/s11069-013-0881-x

Yang, X., & Yu, B. (2015). Modelling and mapping rainfall erosivity in new south Wales, Australia. *Soil Research, 53*, 178–189. https://doi.org/10.1071/SR14188

Yu, B., & Rosewell, C. J. (1996). Rainfall erosivity estimation using daily rainfall amounts for South Australia. *Australian Journal of Soil Research, 53*, 721–733. https://doi.org/10.1071/SR9960721