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On disasters evacuation modeling: From disruptive to slow-response decisions☆

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ABSTRACT

Decision-making evacuation modeling for natural hazards has always been complex due to the uncertainty of variables affecting it. One of the most relevant existing assumptions for this kind of simulation is the use of sigmoid distributions (e.g., Rayleigh) to represent the evacuation times. We found some disadvantages in using this type of probability distribution for slow-response disasters (i.e., geological hazards applications), where there may be a non-negligible delay time between the beginning of the disaster and the consequent evacuation. For that reason, we developed and fitted a displaced sigmoid distribution to the results of a landslide evacuation simulation, i.e., applied to the 2008 disaster of Chaitén in southern Chile. We considered a Rayleigh distribution with a shape factor and a (proposed) displacement factor for predictions. The results suggest considering a displacement when using the Rayleigh distribution to represent slow-response evacuations. We also provide a detailed discussion about the time-dependent factors that may influence this displacement.

1. Introduction

Heavy rainstorms are one of the most recurrent and serious natural disasters we face. The heavy rain induced by heavy rainstorms or even by sudden strong precipitation in couple of hours known as flash floods, have the characteristics of high frequency, strong explosiveness, wide range of impact, which result in high intensity of disasters triggered. These characteristics can easily induce instability in mountainous slopes, endangering inhabitants and affecting the environment. When this phenomenon strikes, it is subjected to several consequences such as the uplifting effect of the mountainous terrain, and in some cases the displacement of the isotherm curve, factors that often increases the intensity of the heavy rainfall, affect the slope texture, therefore increasing the possibility of geological disasters in the mountainous terrain on the windward slope allowing mobilization of unconsolidated material.

Chaitén, one of the areas that has been studied by our research group, is located in the southern part of Chile, in Los Lagos Region, a mountainous region of the Andes, with a great number of inhabitants and recurrent tourists. It is also a region with a complex geological environment and frequent geological disasters. This province has a typical warmth and temperate climate, and heavy rainfall occurs throughout the year in Chaitén. The Köppen-Geiger classification in Chaitén is oceanic, where the average temperature

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is 7.8 °C and the average annual precipitation reaches 4995 mm. Precipitation varies from 342 mm between the driest and wettest months, and the difference between the lowest and highest temperatures throughout the year is about 9.2 °C. The highest and lowest relative humidity are measured in June (91.34%) and January (80.26%) respectively, and the wettest and driest days per month are on August (22.07 days) and February (12.37 days) respectively. Additionally, in this part of the Andes, geological hazards such as collapse, landslides and mudslides are easily induced in areas where geological and environmental conditions are relatively fragile, causing serious causalities and property losses, with non-consolidated volcanic ashes.

One of the main concerns regarding to disasters like landslides (and any other) is how people perceive the associated risks and in what manner it can affect their evacuation decisions. When a strong and disruptive landslide take place, several factors can influence a no-notice evacuation where people decide to evacuate immediately after the occurrence of the disaster [1]. Nevertheless, when inhabitants have enough time to make an informed decision they can underestimate the associated risks and extend their evacuation departure times [2]. The Rayleigh distribution function was first proposed for modeling evacuation times by Tweedie et al. [3]; and it has been widely used so far for this purpose.

In slow-response (non-disruptive) disasters the assumption that this distribution may accurately represent the evacuation modeling process can be blurred. For that reason, this paper seeks to extend the Rayleigh distribution by adding a displacement parameter, in order to generalize its application not only for disruptive, but also for slow-response events. In particular, we analyze the displaced distribution to better represent an evacuation triggered by landslide and lahar caused (11 days after) by the Chaitén volcanic eruption in 2008. So mainly two research questions guide this work: (i) Can a displaced Rayleigh distribution better represent a slow-response evacuation process?, and (ii) What are the principal dynamic variables that can be considered when modeling landslides triggered by heavy rainstorms?

The remainder of the paper is organized as follows. Section 2 introduces the main complexities in the representation of heavy rainstorm triggered landslides. Section 3 discuss about the principal time-dependent variables involved on the prediction of landslides. Section 4 introduces the main approaches used to modeling disasters evacuation times (e.g., Rayleigh distribution), whereas Section 5 presents the non-linear programming model for fitting the (proposed) displaced Rayleigh distribution. Section 6 shows the main results of the fitting process and its practical implications. Finally, Section 7 concludes.

2. Complexity in heavy rainstorm triggered landslide representation

The complexity and variability of heavy rainstorms and the lack of systematic theory increase the difficulties of this kind of landslide disasters study. In general, rainstorm landslides are characterized by high rainfall intensity, short duration (few hours), and liquid precipitations above the isothermal curve, a determinant factor that affects the consistency of the snow-covered slope, resulting in mud and rock flows. In the study of rainstorm landslides, many scholars have analyzed the characteristics of landslides. Because the characteristics of landslides are influenced by the internal and external complexities of mechanical mechanisms given by conditioning and triggering factors, the landslide structures and surface morphologies are quite different. It is generally believed that the main influencing factors include potential energy conditions, material sources, ground sports fields and hydrodynamic conditions [4], triggered by an external cumulus [5].

In the aspect of landslide material sources, the rainstorm induced landslide is basically the unconsolidated Quaternary Residual Soil strata and the fully weathered shallow earth landslides. The thickness of the landslide is generally less than 2 m [6]. In terms of landslide triggers, results indicated that the rainstorm is the most important factor, the number of landslides generates 70–80% of the total [7–10], and it can be described as rainfall induced landslide (RIL) [11]. In addition, some research have analyzed the impact factors of such landslides through methods such as comprehensive analysis and monitoring, considering as the main factors the storms, high winds, vegetation, landforms, formation lithology, structures, slope structures and human engineering activities [12–14].

For the occurrence of rainstorm induced landslides, the formation mechanism is the key to monitoring, early warning and forecasting the rainstorm landslides, and it is of great significance in predicting the temporal and spatial distribution of landslides during winter season (Sidle, 2006). In terms of the theory of formation mechanism, on one hand, the rainstorm eroded the slope by way of slope runoff, resulting in soil erosion [5,15].

Based on the research on the mechanism of the rainfall induced landslides, the research on predictive rainstorm induced landslides is also deepening [16–18]. Current research on prediction of rainstorm landslide is usually based on empirical statistical models. Empirical models mainly analyze the rainfall characteristics that induce the occurrence of landslides, especially the rainfall intensity, duration, and cumulative rainfall, and obtains the intensity-duration curve (I-D curve) or the critical value of cumulative rainfall to determine the possibility of landslides. There are two main methods for determining the landslide rainfall threshold, one is the infinite slope model [8,19], and the other one is to use the threshold curve [20].

The threshold curve method was first proposed by Caine [20]. It mainly describes the impact of rainfall intensity and duration on landslides. We found also that Guzzetti et al. [21] made an improvement to Caine's model and obtained a new global rainfall threshold curve using 2185 landslide events. In recent years, many scholars have carried out multi-technical statistical analysis of rainfall and landslide data, proposed warning thresholds for landslides in different regions and formed different statistical models and perspectives. Some research such as Yin et al. [4] pointed out that geological conditions and landslide types were factors that affect the threshold of rainfall [22]. Liu & Yin [23] proposed that it should be considered the impact of rock and soil fissures. When rainfall intensity is greater than a certain value, sufficient precipitation will seep into the depth of the slope through cracks.

The study of early warning systems for heavy rainstorm induced landslides is still relatively blank. Because landslides caused by rainstorm are characterized by strong explosiveness, wide distribution, location uncertainty, and strongly bounded to geological parameters, traditional single landslide warning systems have no advantage in terms of warning time and warning range. Therefore, it

is necessary to develop regional and multi-stage early-warning landslide systems for such landslides.

3. Time-dependent variables for landslide disaster modeling

The aforementioned factors involved in landslide generation are several. These parameters are based on topographic/geological aspects of the territory, the geology, geotechnics, hydrology, vegetation, weather, and human intervention towards territory which can be summarized as conditioning and triggering factors. All of these are considered disequilibrium factors [12]. Some of these parameters have a stronger incidence in material equilibrium. Among the factors with more relevance for landslides we find slope, elevation, rock or soil type, precipitation, previous landslide occurrence and seismicity, which can be seen in Table 1.

The combination of critical factors that a massive landslide may cause come from the intrinsic conditions of the territory. These formerly mentioned factors such as topography and slope, among others, together with the combination and high exposure to flash and heavy rains in a short period and/or high intensity earthquakes, are triggering factors for landslide generation.

At a local level, variables such as the change in the 0 °isotherm curve may induce liquid precipitation in snow zones, triggering landslides at any given time during the year []. A critical instability condition for landslides is found in high slope angles, e.g., greater than 55° [25] of mountainous terrain made of meteorized sedimentary and fractured rocks under heavy rain, seismicity or volcanic eruptions. According to Hauser [26]; it is estimated the existence of a landslide occurrence threshold of 60 mm/day in summer time in the Metropolitan and pre-andinians zones due to geotechnical characteristics of soils and their behavior under heavy rain.

According to Cruden & Varnes [27]; and as shown in Table 2, the speed of occurrence for material movement is variable from displacements in m/s for rock fall or collapse (extremely fast), to mm/year for lateral extensions or gliding cases (extremely slow). Landslide processes have the difficulty of being exposed and visible for all surrounding areas affected by a potential risk, therefore the possibility for an early evacuation decreases without a general warning (zones, infrastructure, or individuals), having as a reference the difference between imminent risk from a volcanic eruption, visible for most of the exposed zone. A way to warn higher risk and exposure zones is the zonification of sectors with higher susceptibility to occurrence of such movements. This, along with continuous meteorological monitoring is part of a major proposition such as an early warning system for landslides. Critical and high exposure zones may count on active sensors for monitoring.

We consider the concept of slow-response to those situations where landslides run from fast to moderate speed. By this, there is a possibility for exposed systems or individual risk evaluation. Critical factors that perpetuate equilibrium may maintain in constant activity a slow speed landslide, keeping unnoticed to the exposed population. This situation changes when the area under movement become involved in a seismic activity, increasing its acceleration and then the displacement velocity [28] or the intense volcanic activity, triggering seismicity in all surrounding area, fast snow melting, pyroclastic and lahars flows, or volcanic alluviums [29], causing a series of landslides through runoff fluvial channels that may end up in total evacuation, as seen in the 2008 volcanic eruption of Chaitén city in southern Chile [30].

The 2008 eruption of the Chaitén volcano in the southern part of Chile was from such magnitude and intensity (VEI 4–5) that resulted in the evacuation of the whole Chaitén city as a consequence of the overflow of the Blanco river and the disappearance of the southern zone, located 12 kms from the apical zone of the volcano. The eruption presented an explosive and ash emission phase that lasted 2 weeks, generating deposits of nearly 1 km^3 of pyroclastic materials [31]. This disaster left evidence of several flaws at governmental level with respect to disaster management as the relocation and recovery phases were poorly planned and highly erratic [32]. Several days after the eruption, heavy rainstorms displaced the non consolidated accumulated material from the eruption, through the drainage network causing lahars and floods in near valleys (see Fig. 1), leaving Chaitén city inhabitable and severely damaged [33].

4. Modeling disaster evacuation times

Following Gaiha et al. [35]; the frequency of occurrence and human or economic losses from natural hazards are strongly correlated and constantly increasing. As a result, the effect of these variables is strong enough to affect people's perception as a way to contribute to disaster risk reduction. Indeed, there exists a correlation between the capacity of saving lives through effective evacuations and the technological capability for future threat prediction [36].

Inaccurate or erroneous forecasting, besides the consequences already covered, could bring substantial effects in any of the different disaster response stages, such as the restoration of complex systems like the electric power system or transport networks, among others. For instance, we can see how congestion in transport networks under stress (as in an evacuation) may prevent the timely dispatch of mobile emergency generators used for restoring electricity in priority demand sectors [37], and the prolonged absence of essential services such as electricity could seriously affect individuals' awareness [38]. If the evacuation forecast is not accurate, and

Table 1
Critical parameters and importance level in landslide generation at local and regional scale [24].

Characteristics	Rock fall	Sliding	Flow	Regional scale
Elevation and shape	High	Critical	High	High
Slope	Critical	Critical	Critical	High
Rock type	Critical	High	Critical	High
Dough removal activities	Critical	Critical	Critical	High
Precipitation	Critical	Critical	Critical	High
Seismicity	Critical	Critical	Critical	High

Table 2
Removal rate scale [27].

Class	Description	Speed (m/s)	Typical speed
1	Extremely fast	5	5 m/s
2	Very fast	0.05	3 m/min
3	Fast	$5 \cdot 10^{-4}$	1.8 m/h
4	Moderate	$5 \cdot 10^{-6}$	13 m/month
5	Slow	$5 \cdot 10^{-8}$	1.6 m/year
6	Very slow	$5 \cdot 10^{-10}$	16 mm/year
7	Extremely slow	$< 5 \cdot 10^{-10}$	<16 mm/year

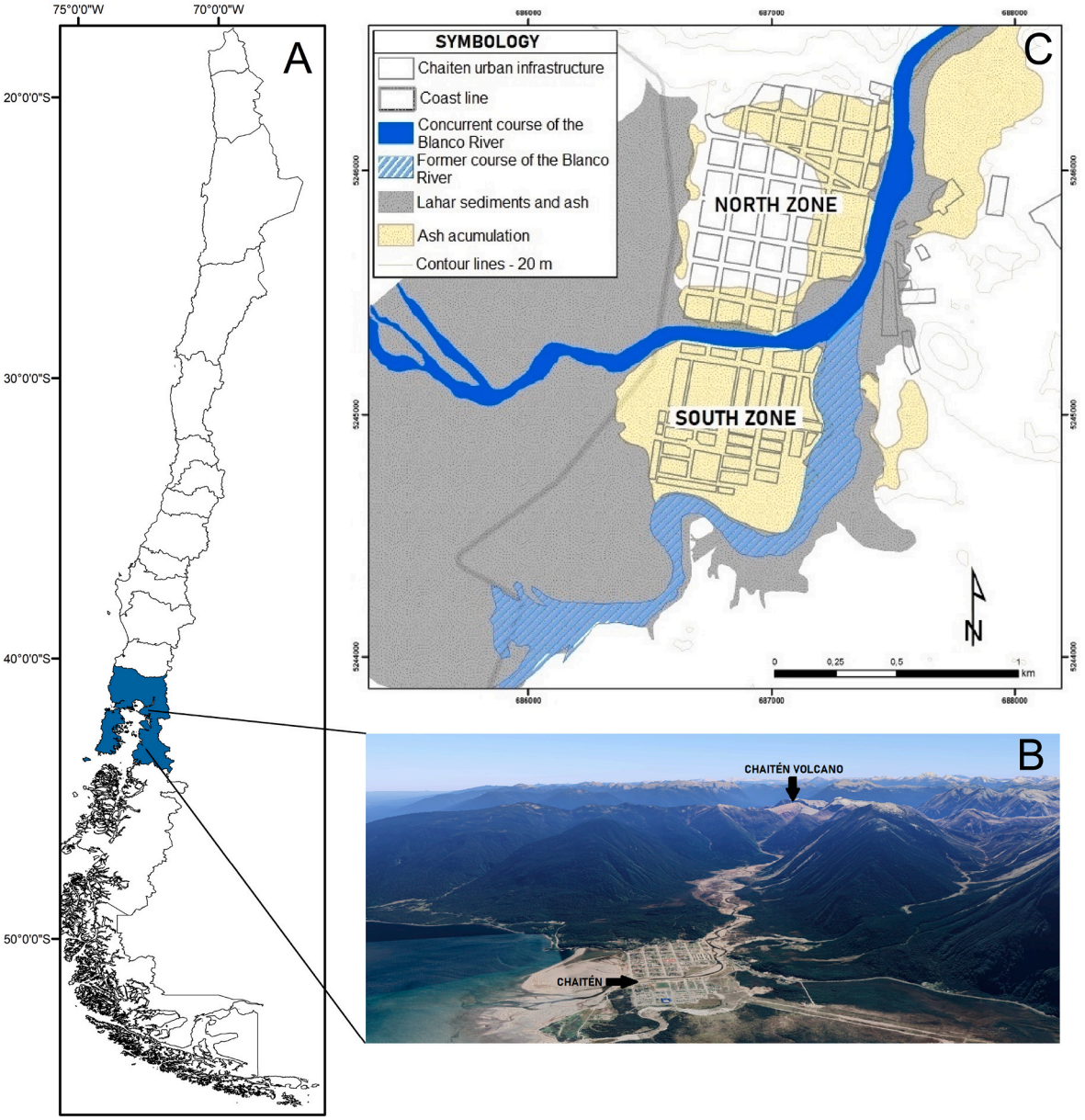


Fig. 1. A) Maps of Chile and Los Lagos Region; B) Distance (12 km) from Chaitén and the volcano; and C) Map of ash and lahars deposits before the 2008 Chaitén volcanic eruption, based on INFRACON [34].

no consideration was given to traffic congestion, routes assigned to mobile emergency generators would result in low overall performance in terms of support, with significant losses.

Regarding recent literature, several research works have aimed towards modeling and optimization of concerning aspects of population evacuation under emergency such as route selection, global situation evaluation, among others [39–41]. Here, a relevant point is how the decision-making process has been modeled given that present literature has centered evacuation representation in a few behavioral variables [42], deriving into the utilization of assumptions such as bounded rationality and economically effective decisions [43].

In some research, the evacuation starting point (or departure time) has been represented through the Rayleigh cumulative distribution function (CDF) –shown in Fig. 2– given that it properly represents typical evacuation data, as mentioned in Beloglazov et al. [44]; for a wildfire evacuation simulation.

In the work of Mas et al. [45]; a Rayleigh distribution was used since it was found that it had an accurate fitting to an earthquake-based surveyed data. In the research of Mas et al. [46]; the authors used the same probability distribution for departure times in a Peruvian tsunami simulation, based on the same criteria as before. Another case where the Rayleigh distribution was considered was the evacuation modeling of Solís & Gazmuri [47]; due to the sigmoid shape of the distribution and its domain. The works of Wang et al. [48]; Takabatake et al. [49,50] also consider the Rayleigh distribution to model departure times in tsunami evacuations.

Expression (1) shows the mathematical definition of the Rayleigh CDF, where β is a scale parameter related to the expected value (μ), and t the elapsed time from the moment when the disaster began (in case of an evacuation). One interesting point in the works mentioned above is that all of them based their analysis and assumptions for the use of the Rayleigh distribution on Tweedie et al. [3]. However, this last research was developed as a methodology for estimating the evacuation time near a nuclear energy plant in Oklahoma in the year 1980.

$$F(t|\beta) = 1 - e^{\left(\frac{-t^2}{2\beta^2}\right)} \tag{1}$$

According to Tweedie et al. [3]; there are some crucial assumptions when using this distribution. The first one is related to the fact of modeling evacuation time through a probability distribution. The second assumption, and more relevant for this research, is related to departure times (preparation time before evacuation), because total evacuation time depends directly on this. This last point triggers one of our research questions: When the initial time for a disaster evacuation should be considered? That is, When should the first person start evacuating (considering all the people exposed to a threat)? Maybe, in high-impact and immediate-response disasters, like earthquakes, this assumption could be addressed with a lower level of detail since the resulting differences could be just a matter of seconds, which does not necessarily represent an outstanding displacement of the sigmoid curve.

On the other hand, on slow-response disasters like landslides, volcanic eruptions, or hurricanes, the scenario might be different since the people exposed to danger have even more time for making decisions since these events can be categorized as non-disruptive. As a consequence of the available time, an important displacement of the curve proposed by a Rayleigh distribution may occur. This displacement is represented by the parameter d on (2), which represents our proposed, displaced Rayleigh distribution function

$$F(t|\beta, d) = 1 - e^{\left(-\frac{(t-d)^2}{2\beta^2}\right)}. \tag{2}$$

As mentioned in Section 1, this paper seeks to demonstrate that a displaced Rayleigh distribution could provide a more accurate fitting to evacuation data when compared to a non-displaced one (or the displaced distribution with $d = 0$). The displaced distribution will

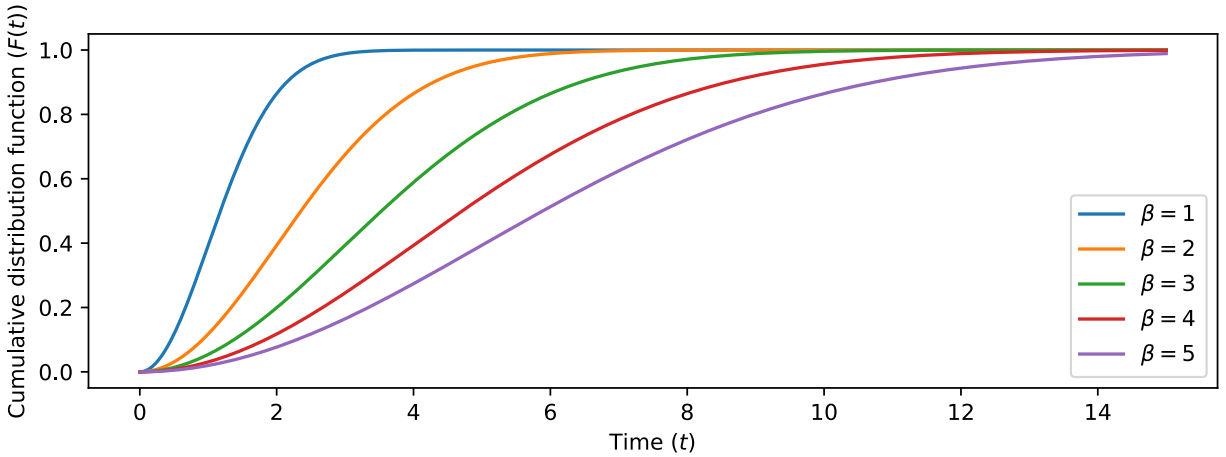


Fig. 2. Rayleigh cumulative distribution function for different values of β (scale parameter).

extend previous research efforts by generalizing its application for different disasters (disruptive and slow-response) by setting a displacement parameter (d). We approach this problem by developing and solving a non-linear optimization model minimizing the error between the displaced Rayleigh distribution and a set of existing evacuation data. Data used for this research was obtained from Favereau et al. [51]; where a multi-method simulation model was developed to represent the 2008 Chaitén evacuation caused by a heavy rainstorm triggered landslide (after a volcanic eruption).

The decision-making process considered on Favereau et al. [51] was based on the risk homeostasis theory [52] and some psychosocial factors found in Favereau et al. [53]. The risk homeostasis theory deals with human decision-making processes which are modeled and decomposed under a comparison transition stage between a certain level of risk perception and risk acceptance, always looking for an equilibrium (homeostasis) between both. This equilibrium is reached through decisions taken, which will increase or decrease the risk levels. Despite that this theory was proposed in the context of the automobile accident field, it was demonstrated in Favereau et al. [51] that it could be adapted to other fields like disasters (evacuations), particularly a landslide evacuation triggered by a volcanic eruption. Fig. 3 shows the simplified homeostatic process for evacuation decision-making on disasters.

Fig. 4 shows the main results obtained in the multi-method simulation of Favereau et al. [51] based on the risk homeostasis theory. It is essential to mention the scarce information available from real evacuation processes (Chaitén volcanic eruption in southern Chile, 2008). However, it is possible to see the accurate representativeness of the simulated curve against the real estimated evacuation curve.

As Fig. 4 depicts, and even though the results obtained have a sigmoid appearance, a small percentage (3%) of evacuated people remain in the site until 100 h after the eruption of the Chaitén volcano. Based on the latter, this research's primary motivation was finding if the Chaitén evacuation could have been modeled using just a probability distribution. Then a natural question arises: What would have been the right moment for starting the evacuation curve? If there is enough available real data, the answer is easy: Carry out a statistical process for fitting the Rayleigh distribution parameters. However, as it happens in most cases, such information does not exist. Hence the errors induced by estimating the evacuation times from a Rayleigh distribution could be significant.

5. Rayleigh distribution fitting

As mentioned in Section 4, one of the objectives of this research is the fitting of a Rayleigh distribution, minimizing the mean squared error (MSE), to the results obtained on Favereau et al. [51]. For this, a non-linear programming model is proposed.

Let $i \in \mathcal{N}$ be the elements of the set of evacuation times (based on the simulation results), $d \in \Delta \subseteq \mathcal{N}$ the elements of the set of possible departure times (curve displacement). s_i denotes the percentage of evacuees in the simulation for each time $i \in \mathcal{N}$. $\widehat{s}_{id}$ denotes the percentage of evacuees in each time i as a function of departure time d. σ_d is the mean squared error based on the prediction $\widehat{s}_d$ for each departure time d, and β_d is the scale factor associated with the prediction $\widehat{s}_d$ for each departure time d. Based on this, the following non-linear optimization model is proposed

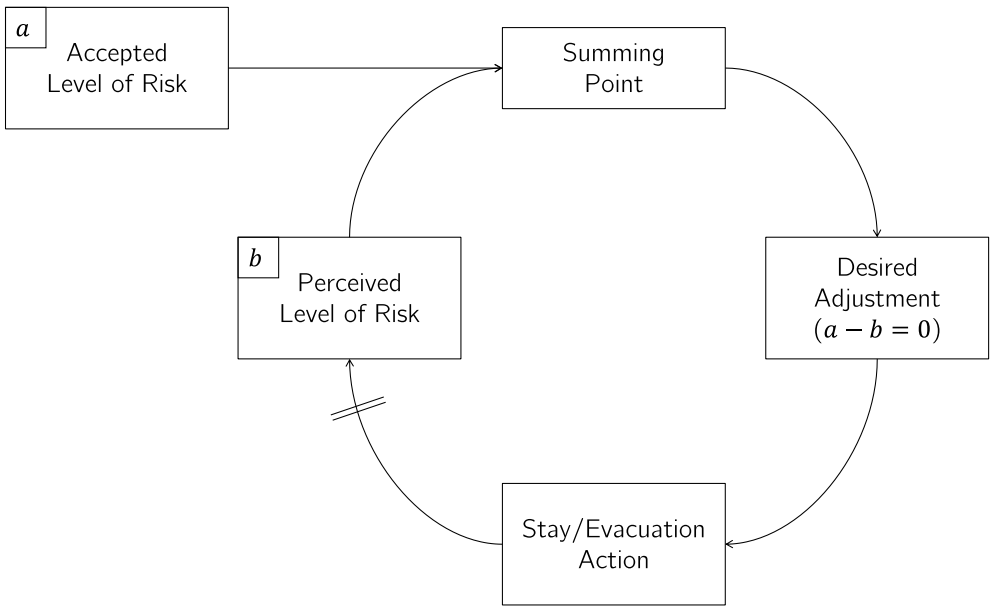


Fig. 3. Simplified homeostatic risk model process [51].

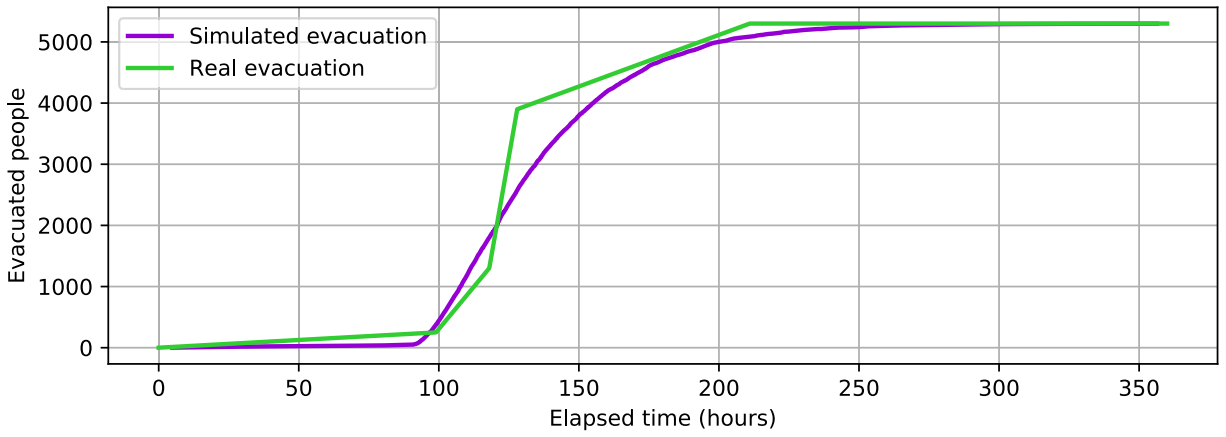


Fig. 4. Main results obtained in Favereau et al. [51].

$$
\begin{aligned}
\underset{\boldsymbol{\sigma},\widehat{\boldsymbol{s}},\boldsymbol{\beta}}{min} \quad & \mathbf{1}^{\top}\boldsymbol{\sigma} \\
\text{s.t.} \quad & \sigma_d = \frac{\sum_{i\in\mathcal{N}} (s_i - \widehat{s}_{id})^2}{|\mathcal{N}|} \forall d \in \Delta \\
& \widehat{s}_{id} = 100 \cdot \left(1 - e^{-\frac{(t-d)^2}{2\beta_d^2}}\right) \qquad \forall d \in \Delta, i \in \mathcal{N} : i \geq d \\
& \widehat{s}_{id} = 0 \qquad\qquad\qquad\qquad\quad \forall d \in \Delta, i \in \mathcal{N} : i < d \\
& \widehat{\boldsymbol{s}} \in \mathbb{R}_{+}^{\mathcal{N}\times\Delta} \\
& \boldsymbol{\beta} \in \mathbb{R}_{+}^{\Delta}.
\end{aligned}
\tag{3}
$$

Here the objective function (3) minimizes the sum of MSEs from all predictions in order to find the parameters that better fit to real data. Constraints (3) compute the MSE for each departure time d. We choose this metric of error because it is differentiable in any point, and it does not indeterminate in any of them, compared to another kind of error measures such as the Root Mean Squared Error (RMSE), which in some cases it indeterminates itself when the argument of its squared root is 0.

Constraints (3) and (3) compute the predictions of the variables $\widehat{s}_{id}$. Here, it is important to note that when $i < d$ the variable takes a value of 0, while when $i \geq d$ the variable takes a value associated with a displaced Rayleigh distribution. This is what makes it possible to have a displacement (d hours) of the obtained curve. Constraints (3) and (3) correspond to the nonnegative nature of variables.

This model was solved through Ipopt solver (Interior Point Optimization), as it is recommended for non-linear optimization problems.

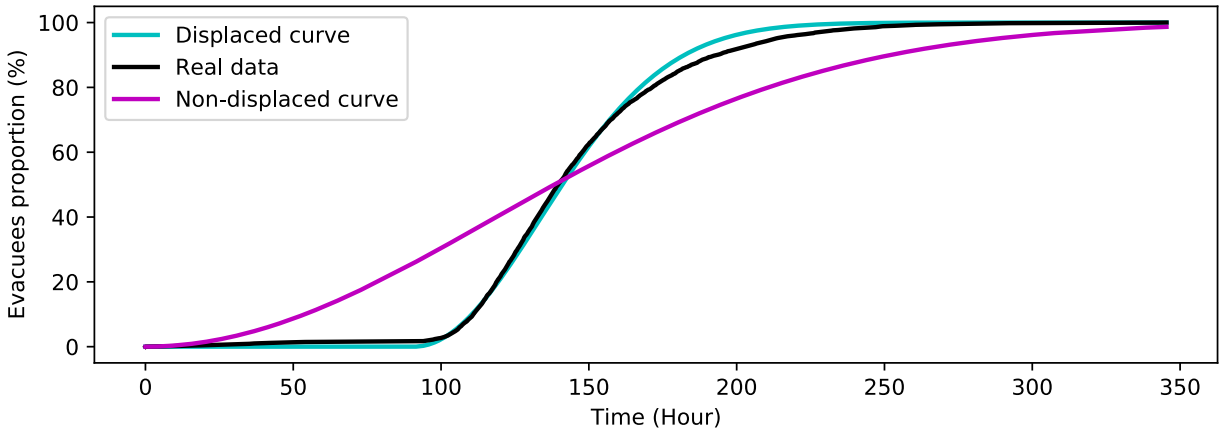


Fig. 5. Rayleigh distribution fitting.

6. Analysis of results

The main result from this research comes from the comparison between the observed results in the simulation and the Rayleigh distribution that has the lowest error. As Fig. 5 depicts, the results obtained through the optimization model (cyan curve) greatly resembles the results obtained in the simulation (black curve); in fact, the MSE is 4.5. Furthermore, the magenta curve in Fig. 5 shows the best possible fit (in terms of MSE) of a non-displaced Rayleigh distribution. Here it is clear to note that if a displacement of the distribution had not been considered, then the best possible prediction of the evacuation times would not be very accurate.

In this case, it is very relevant to consider the value of d (90.8 h, approximately), which provides concrete evidence to the questions formulated at the beginning of this article. This entails that the Rayleigh distribution parameters that resemble most of the simulation results are different from 0. Thus, if we had used the Rayleigh distribution for modeling the evacuation decision-making process in the case presented by Favereau et al. [51]; considering as the initial time the start of the eruption (0 h), the results obtained would have been far from the reality, as the magenta curve shows in Fig. 5.

On the other hand, it is interesting to analyze what happens with the MSE for different departure times. In Fig. 6 we can observe how the error decreases as the departure time (d) in the optimization model is reached. We clearly see that the minimum is located at the point where the optimal solution of the problem is found (Fig. 5).

With respect to practical results for this research, it is known that several factors affect the comprehension of risk by individuals exposed to it. Factors such as knowledge, trust, sense of community, experiences, proximity to the disaster zone, among others, has been identified as the main precursors in individuals decision making under natural hazards [53]. As expected, these factors may also affect the probability of perceived damage with respect to evacuation cost-benefit, and those who consider evacuation as high cost, could simply decide not to evacuate [54]. Factors such as the sense of community and previous experiences play a key role as those who have a higher social attachment to their residence zone, or those who haven't had significant previous experiences in disasters could be potentially prone to estimating a lower damage probability in future events.

The evacuation model determined for each phenomenon depends on the knowledge of the phenomenon previously obtained through monitoring, forecasts and during its occurrence, for cases with greater uncertainty of information, risk profiles could be used. In the case of a tsunami, the amount of existing data before and during the event allows knowing with greater certainty the intensity and time of arrival of the water to the coast, unlike an earthquake or an eruption, where at the beginning of the phenomenon, the maximum level of risk to which the nearby population is exposed is unknown, which coincides with the maximum degree or peak of the phenomenon (or a set of them). According to Vega & Díaz [55]; risk is the result of the product between the Vulnerability Index and the Intrinsic Threat Index, the latter is dependent on the probability of occurrence by the weighted sum of intensity, duration, accumulation and extension, so that each natural phenomenon studied is capable of generating different manifestations in combination with its own characteristics or in cumulative effect with another phenomenon.

The case of Chaitén represents a volcanic event with significant ash deposits that shortly after are mobilized by heavy rains as a lahar, as detailed in the section Time-dependent variables, which means that when modeling the evacuation, the effect of the risk variables must be considered, as evidenced by the displacement of the Rayleigh curve. In addition, there may be a moment when the phenomena become cumulative and the hazard manifests itself by increasing its magnitude significantly, increasing its threat level [55] in a short period of time. From the above, it is inferred that for the occurrence of some phenomenon and its possible combination of effects after the event, a specific risk profile is required to estimate the displacement of the Rayleigh curve that models the evacuation of the population, which could be obtained through the calculation of the risk.

Results shown previously could help to understand that evacuation decision-making modeling could have a significant displacement in slow-response disasters. Obviously, these displacement should be related to the physical dynamics of the disaster (guided by the detailed discussion on Sections 2 and 3), the social characteristics of the environment and the psychological characteristics of the inhabitants in danger. It was also proved that the selection of the initial moment of the evacuation (in the Chaitén study case), did not coincide with the exact moment when the eruption started, but approximately 90 h later (Fig. 5).

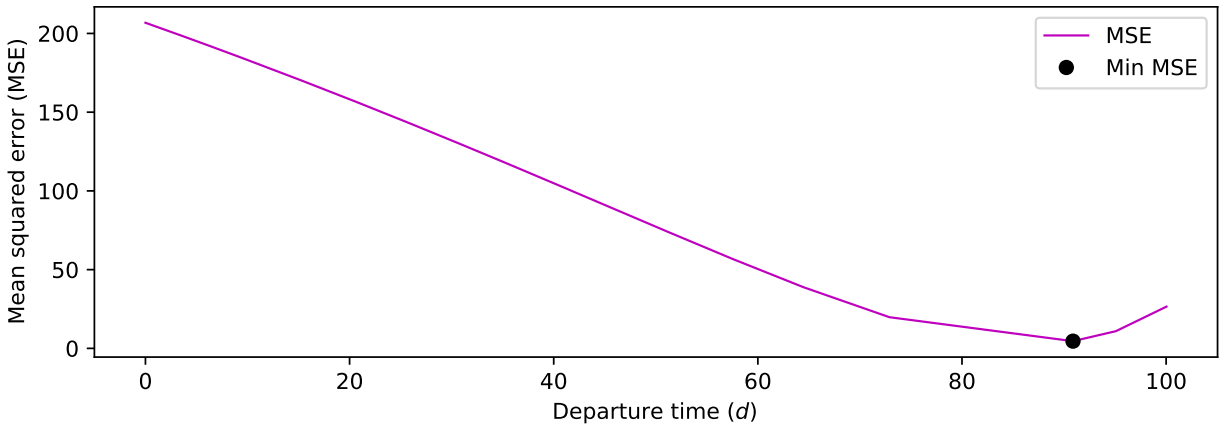


Fig. 6. Mean squared error for each departure time (d).

In the Chaitén case, it was approximately in that moment (90 h after the beginning) when the eruption increased its intensity and consequently caused a landslide by the overflow of the Blanco river. Therefore the population affected became aware of what was happening; most of them were able to observe that there was an eruption of almost 20 km high in progress. Then, the question that comes to mind is what is the reason (triggering factor) for which just a few people decided to evacuate before 90 h from the initial event starting point? We have already seen that many factors influence such decisions, therefore thinking that the decision of not evacuating is a consequence of the still low intensity of the disaster could lead to certain errors.

On the other side, what is clear now is that it is necessary to understand that the determination of the initial moment in an evacuation process is not trivial, and if it is done incorrectly, it could lead to serious consequences for risk management institutions, and worst, for people directly affected by the disaster. Therefore, information flows and behavioral responses seem relevant to the risk communication. Misleading or inaccurate information, mainly in social media or informal sources, impose serious challenges because it could lead to more spatio-temporal uncertainty and difficulties in the coordination and planning of evacuation processes [56].

7. Conclusions

Heavy rainstorms on movement-susceptible lands represent one of the riskiest scenarios for the generation of mass removals. Both sensors and real time monitoring of meteorological variables could be an important asset when developing an early warning system. Issuing early warnings during a disaster is of the utmost importance for properly handling and managing the evacuation processes of people under risk. As the literature and the results of this research suggest, these evacuation processes can be represented with sigmoid curves, and particularly using the Rayleigh distribution.

From the experience of the Chaitén eruption, it can be inferred that the characteristics of the natural hazard, together with its effect over time or with other phenomena, have a direct impact on the risk to which the population is exposed. Bearing in mind that the magnitude of the risk may increase suddenly due to the properties of the phenomenon itself itself, risk profiles could be necessary to approach the displacement obtained from the modeling of the evacuation through a Rayleigh distribution.

It was possible to fit a displaced Rayleigh distribution function through a non-linear optimization model that seeks to minimizing the MSE. The results obtained from this curve were compared and validated against results obtained in the multi-method simulation developed in Favereau et al. [51] based on the risk homeostasis theory.

Based on the results obtained through this research, it is possible to identify the warning at the moment of modeling the decision-making process related to evacuation when facing a disaster. Despite that Rayleigh distribution has been used in some research for modeling evacuation decision-making under disruptive events, we should consider an extension of this approach by adding a displacement parameter. This has an important implication, mainly related with the generalization of the application of the Rayleigh distribution for modeling evacuation times. This removes the restriction of the application of the Rayleigh distribution only for disruptive events and allows to have a more accurate forecast on evacuation times in any type of disaster (disruptive and non-disruptive). This also has important implications in terms of evacuation planning, as it can serve as a support tool for decision-making by risk management entities.

Considering the aforementioned, both questions stated at the beginning of the paper can be answered:

1. Regarding to the research question that makes reference to when people make the decision to evacuate under slow-response disasters, many psychosocial factors influence such decision and, eventually, getting close to the risk homeostasis theory an answer could be reached out but, just by using a Rayleigh distribution (with no displacement) could derive to serious errors, especially when there is a lack of information associated with real evacuations.
2. With respect to the research question that makes reference to obtaining a displaced sigmoid curve, we concluded that this could be obtained when using a fitted curve to the results of some simulation model that considers an evacuation decision, with a psychological or social base, and if possible, with empirical data.

Finally, it would be interesting in the near future to determine a way to identify the starting point in an evacuation process, or in other words, to determine what the displacement of the curve will be. Notwithstanding that risk homeostasis theory contributed with evidence for a particular case, there is still a lot of work to do related to calibration and standardization of the model developed in Favereau et al. [51]; something which may provide substantial advantages at the moment of determining displacements.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] L. Zheng, Y. Guo, S. Peeta, B. Wu, Impacts of information from various sources on the evacuation decision-making process during no-notice evacuations in campus environment, J. Transport. Saf. Secur. 12 (2020) 892–923, https://doi.org/10.1080/19439962.2018.1549643, arXiv:10.1080/19439962.2018.1549643.

[2] A.M. Sadri, S.V. Ukkusuri, P. Murray-Tuite, H. Gladwin, How to evacuate: model for understanding the routing strategies during hurricane evacuation, J. Transport. Eng. 140 (2014) 61–69, https://doi.org/10.1061/(ASCE)TE.1943-5436.0000613.

[3] S.W. Tweedie, J.R. Rowland, S.J. Walsh, R.P. Rhoten, P.I. Hagle, A methodology for estimating emergency evacuation times, Soc. Sci. J. 23 (1986) 189–204, https://doi.org/10.1016/0362-3319(86)90035-2.

[4] Q. Yin, Y. Wang, Z. Tang, Mechanism and dynamic simulation of landslide by precipitation, Geol. Sci. Technol. Inf. 21 (1) (2002) 75–78.

[5] G. Wieczorek, Landslides: Investigation and Mitigation. Chapter Landslide Triggering Mechanisms. (Pp. 76–90). Transportation Research Board, National Research Council, Special Report, 1996.
[6] C.-W. Lin, W.-S. Chang, S.-H. Liu, T.-T. Tsai, S.-P. Lee, Y.-C. Tsang, C.-L. Shieh, C.-M. Tseng, Landslides triggered by the 7 august 2009 typhoon morakot in southern taiwan, Eng. Geol. 123 (2011) 3–12, https://doi.org/10.1016/j.enggeo.2011.06.007. Reconnaissance of Extreme Natural Disasters of Morakot Typhoon, Taiwan.
[7] C. Prieto, Inestabilidades y erosión de laderas asociadas a riadas: geología y prevención de riesgos por inundaciones, Instituto Geológico y Minero de España (1985) 117–192.
[8] R.M. Iverson, Landslide triggering by rain infiltration, Water Resour. Res. 36 (2000) 1897–1910, https://doi.org/10.1029/2000WR900090. https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2000WR900090.
[9] S.-W. Kim, K.-W. Chun, K. Otsuki, Y. Shinohara, M. Kim, M. Kim, D. Lee, J.I. Seo, B. Choi, Heavy rain types for triggering shallow landslides in South Korea, J. Fac. Agric. Kyushu Univ. 60 (2015) 243–249, https://doi.org/10.5109/1526323.
[10] S.W. Kim, K.W. Chun, M. Kim, F. Catani, B. Choi, J.I. Seo, Effect of antecedent rainfall conditions and their variations on shallow landslide-triggering rainfall thresholds in South Korea, Landslides 18 (2021) 569–582.
[11] I. Fustos, P. Moreno-Yaeger, D. Vasquez, B. Morales, A. Silva, E. Ramirez, Evaluation of rainfall-induced landslides triggering using a multidisciplinary approach, Univ. Sci. 25 (2020) 277–298, https://doi.org/10.11144/Javeriana.SC25-2.eorl.
[12] A. Hauser, Remociones en masa en Chile (versión actualizada), Servicio Nacional de Geología y Minería, Subdirección Nacional de Geología (59) (2000) 9–90.
[13] T. Pánek, Recent progress in landslide dating: a global overview, Prog. Phys. Geogr. 39 (2014) 168–198, https://doi.org/10.1177/0309133314550671.
[14] T. Pánek, Landslides and quaternary climate changes—the state of the art, Earth Sci. Rev. 196 (2019) 102871, https://doi.org/10.1016/j.earscirev.2019.05.015.
[15] T. Bayer Altın, E. Gökkaya, Assessment of landslide-triggering factors and occurrence using morphometric parameters in geyraz basin, tokat, northern Turkey, Environmental Earth Sciences 77 (2018) 126.
[16] M. Lazzari, M. Piccarreta, Landslide disasters triggered by extreme rainfall events: the case of montescaglioso (basilicata, southern Italy), Geosciences 8 (2018), https://doi.org/10.3390/geosciences8100377.
[17] D. Ren, L. Leslie, M. Lynch, Trends in storm-triggered landslides over southern California, Journal of Applied Meteorology and Climatology 53 (2014), https://doi.org/10.1175/JAMC-D-12-0253.1.
[18] M. Polemio, O. Petrucci, Rainfall as a Landslide Triggering Factor: An Overview of Recent International Research, 2000, pp. 1219–1226.
[19] P. Frattini, G. Crosta, R. Sosio, Approaches for defining thresholds and return periods for rainfall-triggered shallow landslides, Hydrol. Process. 23 (2009) 1444–1460, https://doi.org/10.1002/hyp, 7269, https://onlinelibrary.wiley.com/doi/pdf/10.1002/hyp.7269.
[20] N. Caine, The rainfall intensity: duration control of shallow landslides and debris flows, Geogr. Ann. Phys. Geogr. 62 (1980) 23–27.
[21] F. Guzzetti, S. Peruccacci, M. Rossi, C.P. Stark, The rainfall intensity-duration control of shallow landslides and debris flows: an update, Landslides 5 (2008) 3–17.
[22] X. Jian-ming, Study on the threshold valves of rainfall of landslide hazards for early-warning and prediction in zhejian province, Geol. Sci. Technol. Inf. 22 (2003) 101–105.
[23] L.-L. Liu, K.-L. Yin, Analysis of rainfall infiltration mechanism of rainstorm landslide, Yantu Lixue/Rock and Soil Mechanics 29 (2008) 1061–1066.
[24] M. Arenas, E. Opazo, A. Alfaro, J. Fernández, N. Garrido, C. Jara, M.P. Marín, N. R Sepúlveda, V. Sepúlveda, Methodological Guide for Susceptibility Mapping for Landslide at Regional Level, Technical Report SERNAGEOMIN, 2017.
[25] R. Van Zuidam, Aerial Photointerpretation in Terrain Analysis and Geomorphologic Mapping, ITC Books VII-6, 1985.
[26] A. Hauser, Flujos de barro en la zona preandina de la región metropolitana: características, causas, efectos, riesgos y medidas preventivas, Rev. Geol. Chile 24 (1985) 75–92.
[27] D. Cruden, D. Varnes, Landslides: Investigation and Mitigation, 1996.
[28] D.K. Keefer, Landslides caused by earthquakes, GSA Bulletin 95 (1984) 406–421, 10.1130/0016-7606(1984)95<406:LCBE>2.0.CO;2, https://pubs.geoscienceworld.org/gsabulletin/article-pdf/95/4/406/3419326/i0016-7606-95-4-406.pdf.
[29] Y. Miyabuchi, F. Maeno, S. Nakada, The october 16, 2013 rainfall-induced landslides and associated lahars at izu oshima volcano, Japan, J. Volcanol. Geoth. Res. 302 (2015) 242–256, https://doi.org/10.1016/j.jvolgeores.2015.07.012.
[30] T.C. Pierson, J.J. Major, l. Amigo, H. Moreno, Acute sedimentation response to rainfall following the explosive phase of the 2008-2009 eruption of chaitén volcano, Chile, Bull. Volcanol. 75 (2013) 723.
[31] L. Lara, R. Calderon, Peligro y riesgo específico asociado al volcán chaitén: perspectiva geológica de la vulnerabilidad en el entorno de un volcán activo, Magallania 43 (2015) 27–35, https://doi.org/10.4067/S0718-22442015000300003.
[32] C. Sandoval, C. Boano, C. González-Muzzio, C. Albornoz, Explorando potenciales vínculos entre resiliencia y justicia ambiental, Magallania 43 (3) (2015) 37–49.
[33] L. Lara, The 2008 eruption of the chaitén volcano, Chile: a preliminary report, Andean Geol. 36 (2009), https://doi.org/10.4067/S0718-71062009000100009.
[34] S. Infracon, Estudio de Riesgo de Sismos, Volcanismo, Remoción en Masa, Inundación por Desborde de Cauces y Canales y Maremotos para Ocho Localidades de la Comuna de Chaitén, Informe Final, Technical Report SUBDERE, 2012.
[35] R. Gaiha, K. Hill, G. Thapa, V.S. Kulkarni, Chapter 23-have natural disasters become deadlier? in: A.M. Balisacan, U. Chakravorty, M.-L.V. Ravago (Eds.), Sustainable Economic Development Academic Press, San Diego, 2015, pp. 415–444, https://doi.org/10.1016/B978-0-12-800347-3.00023-6.
[36] R.R. Thompson, D.R. Garfin, R.C. Silver, Evacuation from natural disasters: a systematic review of the literature, Risk Anal. 37 (2017) 812–839, https://doi.org/10.1111/risa.12654. https://onlinelibrary.wiley.com/doi/pdf/10.1111/risa.12654.
[37] S. Lei, J. Wang, C. Chen, Y. Hou, Mobile emergency generator pre-positioning and real-time allocation for resilient response to natural disasters, IEEE Transactions on Smart Grid 9 (2018) 2030–2041, https://doi.org/10.1109/TSG.2016.2605692.
[38] J. Burger, M. Gochfeld, Health concerns and perceptions of central and coastal New Jersey residents in the 100days following superstorm sandy, Sci. Total Environ. 481 (2014) 611–618, https://doi.org/10.1016/j.scitotenv.2014.02.048.
[39] N. Dash, H. Gladwin, Evacuation decision making and behavioral responses: individual and household, Nat. Hazards Rev. 8 (2007) 69–77, https://doi.org/10.1061/(ASCE)1527-6988(2007)8:3(69).
[40] S. Jumadi Carver, D. Quincey, Abm and gis-based multi-scenarios volcanic evacuation modelling of merapi, AIP Conference Proceedings 1730 (2016), 050005. doi:10.1063/1.4947401, https://aip.scitation.org/doi/pdf/10.1063/1.4947401.
[41] S. Li, J. Zhuang, S. Shen, A three-stage evacuation decision-making and behavior model for the onset of an attack, Transport. Res. C Emerg. Technol. 79 (2017) 119–135, https://doi.org/10.1016/j.trc.2017.03.008.
[42] M.K. Lindell, C.S. Prater, Critical behavioral assumptions in evacuation time estimate analysis for private vehicles: examples from hurricane research and planning, J. Urban Plann. Dev. 133 (2007) 18–29, https://doi.org/10.1061/(ASCE)0733-9488(2007)133:1(18).
[43] M. Busogi, D. Shin, H. Ryu, Y.G. Oh, N. Kim, Weighted affordance-based agent modeling and simulation in emergency evacuation, Saf. Sci. 96 (2017) 209–227, https://doi.org/10.1016/j.ssci.2017.04.005.
[44] A. Beloglazov, M. Almashor, E. Abebe, J. Richter, K.C.B. Steer, Simulation of wildfire evacuation with dynamic factors and model composition, Simulat. Model. Pract. Theor. 60 (2016) 144–159, https://doi.org/10.1016/j.simpat.2015.10.002.
[45] E. Mas, A.F.I. Suppasri, K. Koshimura, Agent-based simulation of the 2011 great east Japan earthquake/tsunami evacuation: an integrated model of tsunami inundation and evacuation, J. Nat. Disaster Sci. 34 (2012) 41–57, https://doi.org/10.2328/jnds.34.41.
[46] E. Mas, B. Adriano, S. Koshimura, An integrated simulation of tsunami hazard and human evacuation in la punta, Peru, J. Disaster Res. 8 (2013) 285–295.
[47] I.A. Solís, P. Gazmuri, Evaluation of the risk and the evacuation policy in the case of a tsunami in the city of iquique, Chile, Nat. Hazards 88 (2017) 503–532.
[48] H. Wang, A. Mostafizi, L.A. Cramer, D. Cox, H. Park, An agent-based model of a multimodal near-field tsunami evacuation: decision-making and life safety, Transport. Res. C Emerg. Technol. 64 (2016) 86–100, https://doi.org/10.1016/j.trc.2015.11.010.
[49] T. Takabatake, T. Shibayama, M. Esteban, H. Ishii, G. Hamano, Simulated tsunami evacuation behavior of local residents and visitors in kamakura, Japan, International Journal of Disaster Risk Reduction 23 (2017) 1–14, https://doi.org/10.1016/j.ijdrr.2017.04.003.

[50] T. Takabatake, T. Shibayama, M. Esteban, H. Ishii, Advanced casualty estimation based on tsunami evacuation intended behavior: case study at yuigahama beach, kamakura, Japan, Nat. Hazards 92 (2018) 1763–1788.
[51] M. Favereau, L.F. Robledo, M.T. Bull, Homeostatic representation for risk decision making: a novel multi-method simulation approach for evacuation under volcanic eruption, Nat. Hazards 103 (2020) 29–56.
[52] G.J.S. Wilde, The theory of risk homeostasis: implications for safety and health, Risk Anal. 2 (1982) 209–225, https://doi.org/10.1111/j.1539-6924.1982.tb01384.x. https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1539-6924.1982.tb01384.x.
[53] M. Favereau, L.F. Robledo, M.T. Bull, Analysis of risk assessment factors of individuals in volcanic hazards: review of the last decade, J. Volcanol. Geoth. Res. 365 (2018) 57–64, https://doi.org/10.1016/j.jvolgeores.2018.10.009.
[54] E.E. Doyle, J. McClure, D. Paton, D.M. Johnston, Uncertainty and decision making: volcanic crisis scenarios, International Journal of Disaster Risk Reduction 10 (2014) 75–101, https://doi.org/10.1016/j.ijdrr.2014.07.006.
[55] L. Vega, F. Díaz, Evaluación integral del riesgo volcánico del cerro machín, Colombia, Invest. Geográficas (2013) 66–78.
[56] E. Du, X. Cai, Z. Sun, B. Minsker, Exploring the role of social media and individual behaviors in flood evacuation processes: an agent-based modeling approach, Water Resour. Res. 53 (2017) 9164–9180, https://doi.org/10.1002/2017WR021192. https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1002/2017WR021192.