International Journal of Geosciences, 2023, 14, 1146-1159
https://www.scirp.org/journal/ijg
ISSN Online: 2156-8367
ISSN Print: 2156-8359

The SNAKE System: CEMADEN's Landslide Early Warning System (LEWS) Mechanism

Marcio Roberto Magalhães de Andrade[1*], Cassiano Antonio Bortolozo[1], Adenilson Roberto Carvalho[1], Harideva Marturano Egas[1], Klaifer Garcia[1], Daniel Metodiev[1], Tulius Dias Nery[1], Carla Prieto[1], Tristan Pryer[2], Silvia Midori Saito[1], Graziela Scofield[1]

[1]CEMADEN—National Center for Monitoring and Early Warning of Natural Disasters, General Coordination of Research and Development, São José dos Campos, Brazil
[2]Department of Mathematical Sciences, University of Bath, Bath, UK
Email: *marcio.andrade@cemaden.gov.br

How to cite this paper: de Andrade, M.R.M., Bortolozo, C.A., Carvalho, A.R., Egas, H.M., Garcia, K., Metodiev, D., Nery, T.D., Prieto, C., Pryer, T., Saito, S.M. and Scofield, G. (2023) The SNAKE System: CEMADEN's Landslide Early Warning System (LEWS) Mechanism. *International Journal of Geosciences*, **14**, 1146-1159.
https://doi.org/10.4236/ijg.2023.1411058

Received: October 7, 2023
Accepted: November 27, 2023
Published: November 30, 2023

Copyright © 2023 by author(s) and Scientific Research Publishing Inc.
This work is licensed under the Creative Commons Attribution International License (CC BY 4.0).
http://creativecommons.org/licenses/by/4.0/
Open Access

Abstract

In Brazil, the prominent climate-induced disasters are floods and mass movements, with the latter being the most lethal. The spate of major landslide events, especially those in 2011, catalyzed the creation of CEMADEN (National Center for Monitoring and Early Warning of Natural Disasters). This article introduces one of CEMADEN's pivotal systems for early landslide warnings and traces its developmental timeline. The highlighted SNAKE System epitomizes advancements in digital monitoring, forecasting, and alert mechanisms. By leveraging precipitation data from pluviometers in observed municipalities, the system bolsters early warnings related to potential mass movements, like planar slides and debris flows. Its deployment in CEMADEN's Situation Room attests to its suitability for overseeing high-risk municipalities, attributed primarily to its robustness and precision.

Keywords

Natural Disasters, Landslide Early Warning System (LEWS), SNAKE System, CEMADEN, Brazil

1. Introduction

The disaster risks in Brazil stemming from excessive rainfall primarily manifest as floods and mass movements, such as landslides [1] [2]. In fact, landslides are the deadliest hazard in the country [3]. Notably, a significant landslide event in the mountainous region of the state of Rio de Janeiro took place in 2011, resulting in over 900 deaths and 300 missing individuals [4]. Following this tragedy, the Brazilian government established the National Center for Monitoring and Early Warning of Natural Disasters (CEMADEN) in 2011.

Other severe landslide events include those in the Itajaí Valley, Santa Catarina, in 2008, which caused over 130 deaths and displaced thousands [5]. Recent events in Petrópolis, Rio de Janeiro, in early 2022, led to over 240 fatalities [6] [7]. Furthermore, a large-scale disaster struck Recife, the capital of Pernambuco, in May 2022, causing more than 130 deaths [8]. Given the high fatality rates linked to mass movements, the study and prediction of landslides have become paramount across several scientific domains.

CEMADEN, in particular, emphasizes the need to understand and predict landslides. Their research ranges from slope stability studies [9] [10] to integrating various methods to address the issue [11] [12] [13] and even software development for data analysis [14] [15] [16].

Mass movements can take various forms, including planar slides, rotational slides, debris flows, and rockfalls. The rapid nature of some of these processes makes evacuations challenging once initiated. Hence, the best strategy is often preemptive evacuation based on predictive data. Despite the availability of rainfall data, accurately predicting the onset of certain movements, such as planar slides, remains a challenge.

Mitigating such events requires structural interventions like drainage, containment, and stabilization on vulnerable slopes. Yet, a reliable Alert System, a non-structural measure, is equally crucial. This system should have a precise threshold to provide timely alerts for evacuations.

Post the Rio de Janeiro disaster, the Brazilian Government bolstered its protection, civil defense, and early warning systems [17]. In collaboration with the Japanese government, they also sought to enhance their capacity for landslide risk assessment, urban expansion plans, and disaster prevention strategies. This cooperative effort involved multiple Brazilian ministries.

This collaboration birthed the Project for Strengthening National Strategy of Integrated Natural Disaster Risk Management (GIDES) from 2013 to 2017. This project focused on pilot municipalities such as Blumenau, Petrópolis, and Nova Friburgo. A key component of the project was leveraging Japanese expertise in landslide early warning systems. CEMADEN subsequently introduced a method reminiscent of Japan's, termed the Shared Method, which relied on a critical threshold and support lines [18].

The ultimate goal is the integration of new methodologies to amplify computerized monitoring, forecasting, and alert systems. This study aims to harmonize monitoring with risk management actions, linking reference lines to prevention and response measures at various governance levels.

This article's primary objective is to introduce the system developed by CEMADEN for early landslide warnings. The SNAKE System described enhances computerized monitoring and alert issuance. It assists in determining critical rainfall thresholds for alerts and better informs evacuation decisions. A case study from Petrópolis exemplifies the method's operational efficacy.

2. Empirical Thresholds for Critical Rainfall That Trigger Landslides

Rainfall-induced landslides are triggered when specific thresholds—defined by factors like precipitation, soil moisture, or hydrological conditions—are met or exceeded [19]. Empirical thresholds for critical daily or hourly rainfall and preceding precipitation that can trigger landslides are determined by examining rainfall events known to have caused landslides. This is especially useful when the exact date, time, and prior precipitation data are accessible [20]. These thresholds are typically derived by plotting the lower bounds of precipitation conditions known to have caused landslides, using Cartesian, semi-logarithmic, or logarithmic coordinates [21].

In numerous instances, landslides are influenced not just by the specific rainfall event leading to the landslide but also by prior rainfall. Empirical precipitation thresholds considering these preparatory conditions recognize that preceding rains can affect groundwater levels and soil moisture, which in turn act as precursors to slope failures. This preceding rainfall data can be crucial in predicting potential landslide occurrences, offering a direct method to set a threshold based on past rainfall patterns. When leveraging antecedent rainfall data to forecast landslides, a key challenge is specifying the exact accumulation period for the precipitation. While literature reviews show variation in the selected periods, it's commonly observed that periods of 3 to 4 days are considered—owing to soil studies that have indicated soil moisture dissipation beyond this timeframe. The observed variability across different studies can often be traced back to differing lithological, morphological, pedological, vegetative, climatic, and meteorological conditions—all of which can contribute to slope instability.

The impact of antecedent rainfall generally diminishes as time passes from the primary, triggering rainfall event. In light of this [22], drawing from [23], introduced a method with a diminishing value to calibrate antecedent rainfall, often referred to as "effective rainfall".

3. Methods for Landslide Prediction—Shared Method

Landslide risk alerts typically hinge on rainfall accumulation thresholds. When rainfall surpasses this operational threshold, a warning system is activated, swiftly alerting residents and emergency services about potential landslides [24] [25]. Such a proactive strategy is pivotal, not only for minimizing property damage but, more crucially, for preserving lives. The predictive methodology employed within the SNAKE System is termed the Shared Model. This model represents a hybrid approach, incorporating elements from two foundational methods: the statistical framework by [26] and the hydrological principles underpinning Tank Model [27].

In their study, [26] formulated an empirical method based on the rainfall events from January 22/23, 1985. These events precipitated widespread landslides in the Serra do Mar Mountain Range, specifically within Cubatão in the State of

São Paulo. The authors contend that the cumulative rainfall over four consecutive days (termed "antecedent rainfall") critically preconditions the landscape for potential landslides. As this period unfolds, the terrain's shear resistance wanes, while external active forces intensify, amplifying the landslide risk. Consequently, short-term precipitation becomes a possible landslide trigger, colloquially termed "triggering rainfall". Accordingly, [26] determined their thresholds by juxtaposing the 96-hour cumulative rainfall (x-axis) against the 1-hour rainfall accumulation (y-axis).

In contrast, the Tank Model by [27] is a hydrological blueprint crafted for runoff analysis. This model conceptualizes a multi-tiered tank system, spanning one to three stages. Each stage mirrors flow conditions on both the slope and in the valley. The volume held by each tank is a function of the accumulated rainfall and the interval post the rain event. Herein, the notion of the "rainfall half-life" emerges as central. It demarcates the duration required for the rainfall's saturation effect to halve. This half-life parameter (T) encapsulates critical insights into soil infiltration, runoff, and water retention attributes, facilitating a regional adaptation rather than a location-specific one. This parameter's exact value can be ascertained through myriad means: scouring relevant literature, orchestrating lab experiments, or sifting through data from the CEMADEN soil moisture observation network. As a result, the adjusted effective rainfall, incorporating the half-life, is computable via the ensuing equation [28]:

$$R_w = \sum a_{1i} \times R_{1i} \tag{1}$$

where we have utilized the following notation:

R_w: Effective rainfall (mm).

a_{1i}: Reduction coefficient for i hours before ($a_{1i} = 0.5^{i/T}$).

i: Number of hours of antecedence of the hourly rainfall considered in relation to the current moment (hours).

T: Half-life, both for short-term and long-term rainfall (hours).

R_{ij}: Volume of i-hour rainfall before the current moment (mm).

The Shared Model employs a statistical framework that utilizes antecedent rainfall to gauge disaster risk. It achieves this through two distinct configurations of effective rainfall computation, as illustrated in Equation (1): one configuration with a half-life of 72 hours and another with a half-life of 90 minutes. With every new measurement from rain gauge stations, the effective rainfall is recalculated. This dynamic approach facilitates continuous monitoring of risk levels using thresholds, which will be elucidated subsequently. To establish these thresholds, an intimate understanding of the monitored region is essential, primarily derived from historical rainfall data and past disaster records.

3.1. Definition of Homogeneous Blocks and Corresponding Rain Gauges

Setting up thresholds can be an expensive process, especially when dealing with many stations. Moreover, there are instances where the available disaster records are insufficient to determine individual thresholds for every station. A potential solution to this is to group stations that share similar characteristics.

Figure 1 illustrates an example of such a grouping. This classification should consider the variations in triggering conditions influenced by factors like precipitation, topography, geology, soils, vegetation, land use, and vulnerabilities. Ideally, unique thresholds should be designated for each valley or slope. However, when there are shared characteristics such as topography, geology, vegetation, and climate, a singular threshold can be practically applied across multiple slopes and valleys. As a result, regions with comparable event probabilities (both in terms of primary causes and triggers) are zoned and evaluated using the same risk criteria. In the absence of distinct variations in event likelihood, areas are determined based on the municipal scale.

3.2. Rainfall Series with Landslide Events

The subsequent step is to gather and systematize rainfall data related to events. This data is sourced from historical disaster records, which include documents like Civil Defense reports, forms, newspaper articles, and more, as well as from interviews. Additionally, it's crucial to consult data from the closest automatic rain gauge located in the risk zone of the reported incident or disaster. For each documented event, essential attributes are recorded: the type of process, the geographic coordinates of the event's epicenter, date and time of the occurrence, the name and code of the nearest automatic rain gauge, and the distance between this rain gauge and the location of the event.

Having access to precise data is critically important. The effective rainfall for a series of events is determined by the exact timing (down to the hour and minute) of the occurrence, with the greatest possible precision (in this context, every 10

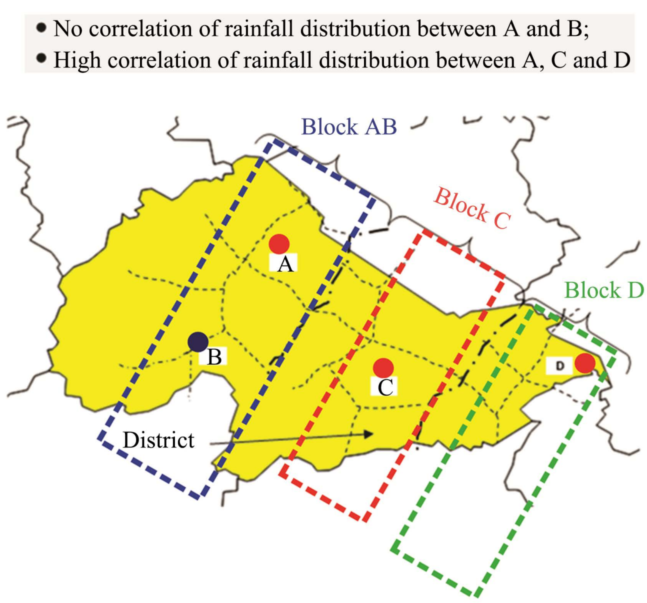

Figure 1. Example of definition of blocks for threshold calculation, according to criteria of physical environment and pluviometric correlation.

minutes). This precision takes into account the current data collection intervals of both automatic rain gauges and weather radars. For past events, an exhaustive data search from public institutions is often mandatory. This is because it might not always be possible to clearly identify the type of event (for example, distinguishing between a planar landslide and a debris flow) or to pinpoint the exact moment the event took place. Additionally, it's ideal for the events to occur within a 3 km radius from the rain gauges.

3.3. Calculation of the Threshold (Critical Line—CL)

The effective rainfall values obtained from monitoring, as calculated using Equation (1), are employed to set warning thresholds. Consequently, each rainfall station possesses a time series comprising two values: effective rainfall over 72 hours and over 90 minutes. Within this time series, specific points of interest are chosen, which are then factored into threshold determination. The selection of these points hinges on disaster records, with varying criteria for records in proximity to disasters as opposed to those without disasters.

The most straightforward scenario is the selection of values adjacent to disasters. In such cases, the last measurement taken before the event is picked. When determining values to represent instances without disasters, it's preferable to opt for values closely mirroring those that instigate events, accentuating the borderline value. To achieve this, a differentiation between rainy periods was established, selecting the apex of each such period. A rainy period is defined as a continuous sequence of measurements, both preceded and succeeded by a minimum span of 24 hours devoid of any positive rainfall records. From all the measurements within a rainy period, the chosen value is the one that yields the highest outcome when subjected to Equation (2):

$$D = \left(W_{72h}\right)^2 + \left(W_{1.5h}\right)^2 \tag{2}$$

where we denote:

D: Relevance for selection.

W_{72h}: Calculated value for 72 h effective rain.

$W_{1.5h}$: Calculated value for the effective rain of 90 minutes.

3.4. Drawing the Threshold: Critical Line and Support Lines

Once all the rainfall series for a specific block have been plotted, the threshold (or critical line) must be established. This line should optimally differentiate the rainfall series associated with events from those without any events. Ideally, it should delineate the safe zone from the unsafe zone with maximum accuracy.

In Brazil, alarms are dispatched to the Municipal Civil Defense bodies, who are charged with implementing mitigation strategies. Given that these entities necessitate time to mobilize and initiate response measures, auxiliary lines are also delineated. To this end, the historical rainfall data of the region is leveraged. Each auxiliary line is crafted such that, even during bouts of intense rainfall, there exists an hour-long interval prior to measurements surpassing the ensuing upper boundary. Consequently, **Figure 2** serves as a hypothetical representation of the critical and auxiliary lines. The auxiliary lines, designated as Very High Probability of Events Line (VHP), High Probability of Events Line (HP), and Moderate Probability of Events Line (MP), are formulated based on the maximum recorded 3-hour, 2-hour, and 1-hour rainfall, respectively, across all the rainfall series.

In **Figure 3**, we illustrate a real-world example of a set of Critical and Support Lines for the city of Florianópolis, situated in the state of Santa Catarina, in the southern part of Brazil. In the depicted figure:

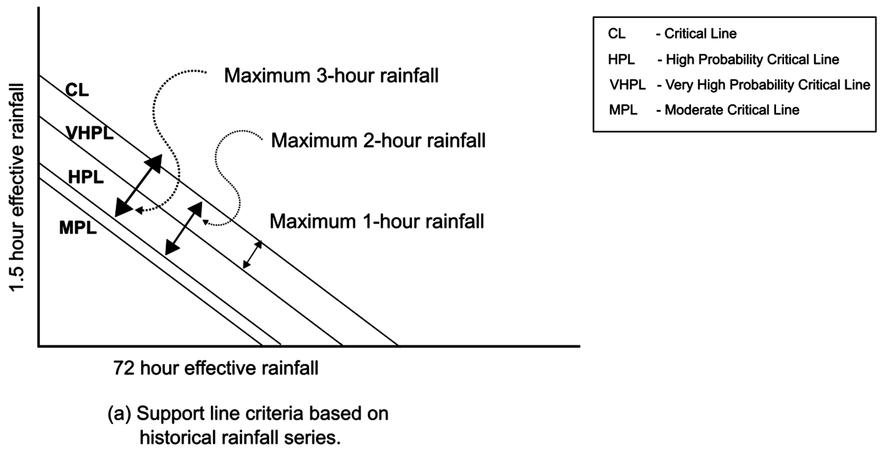

Figure 2. Schematic of critical and support lines.

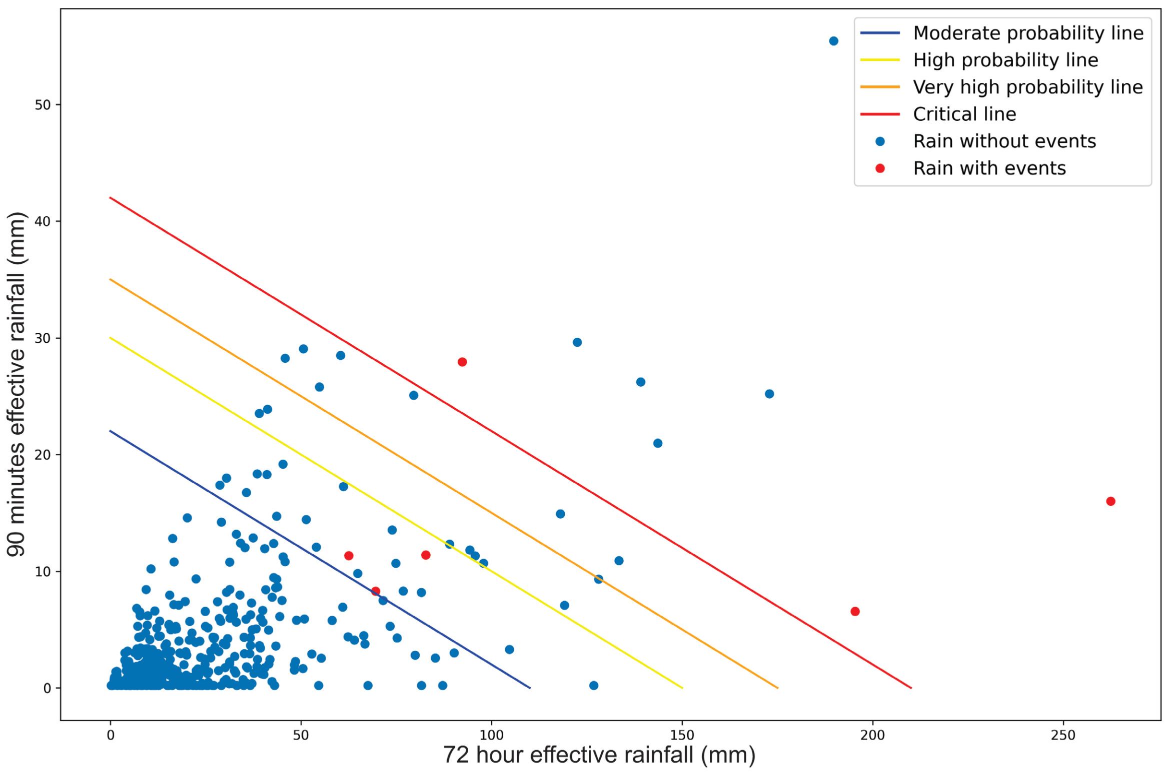

Figure 3. Critical and support lines for Florianópolis city (Santa Catarina state). Station 420540702A.

- The blue line represents the Moderate Probability of Events Line (MP).
- The yellow line corresponds to the High Probability of Events Line (HP).
- The orange line denotes the Very High Probability of Events Line (VHP).
- The red line stands for the Critical Line (CL).

Blue points indicate rainfall that did not result in landslides, while red points are tied to events that triggered such landslides. A discernible pattern is that all logged events transpire after the alert lines. Three events occur shortly after the MP alert line. Such alerts are especially vital in Brazil, where a large number of events arise from marked anthropogenic impacts on the stability of inhabited slopes. This instability often stems from subpar construction methods and inadequately planned drainage systems. These incidents, being smaller in scale, pose prediction challenges due to the high variability of influencing factors, both spatially and over time. Such inconsistency is largely attributed to the ever-evolving nature of slope habitation.

Furthermore, three events showcasing significant rainfall accumulation are evident, all of which transpire post the Critical Line. Events with such considerable accumulations inherently carry a more destructive capability and present heightened risks to human life.

4. SNAKE Curve

To determine if the effective rainfall in the current series has entered the unsafe zone, we construct the "Cobra Curve". This process involves plotting the effective rainfall with half-lives of 1.5 and 72 hours using real-time data from the pluviometer as new measurements become available. These data points are presented on the same graph, juxtaposed with the Critical Line (CL) and the support lines: Very High Probability of Events Line (VHP), High Probability of Events Line (HP), and Moderate Probability of Events Line (MP). As an example, **Figure 4** illustrates this for the city of Petrópolis, in the state of Rio de Janeiro, during the rainy season of 2021/2022 (from 10/01/2021 to 03/31/2022).

The dynamic progression of the Cobra Curve aids in discerning if it has reached or surpassed the support lines (VHP, HP, and MP). In essence, this curve provides a visual representation not only of how the effective rainfall from the current series encroaches into the unsafe zone (by meeting or exceeding the threshold lines) but also how it stands in relation to the support lines and the critical line itself. As a result, when a specific pluviometer registers rainfall, the trajectory of the Cobra Curve relative to that rainfall can be closely monitored. Upon reaching each support line, the system dispatches a notification to the Operational Room operators. Armed with this information, alongside other vital parameters like weather forecasts and historical disaster events, they can relay alerts to the State and/or Municipal Civil Defense, enabling mitigation efforts or potential evacuation of populations from high-risk zones.

It is worth noting that the Shared Method is adept at guiding decision-making during both prolonged and intermittent rainfall scenarios. It not only aids in the

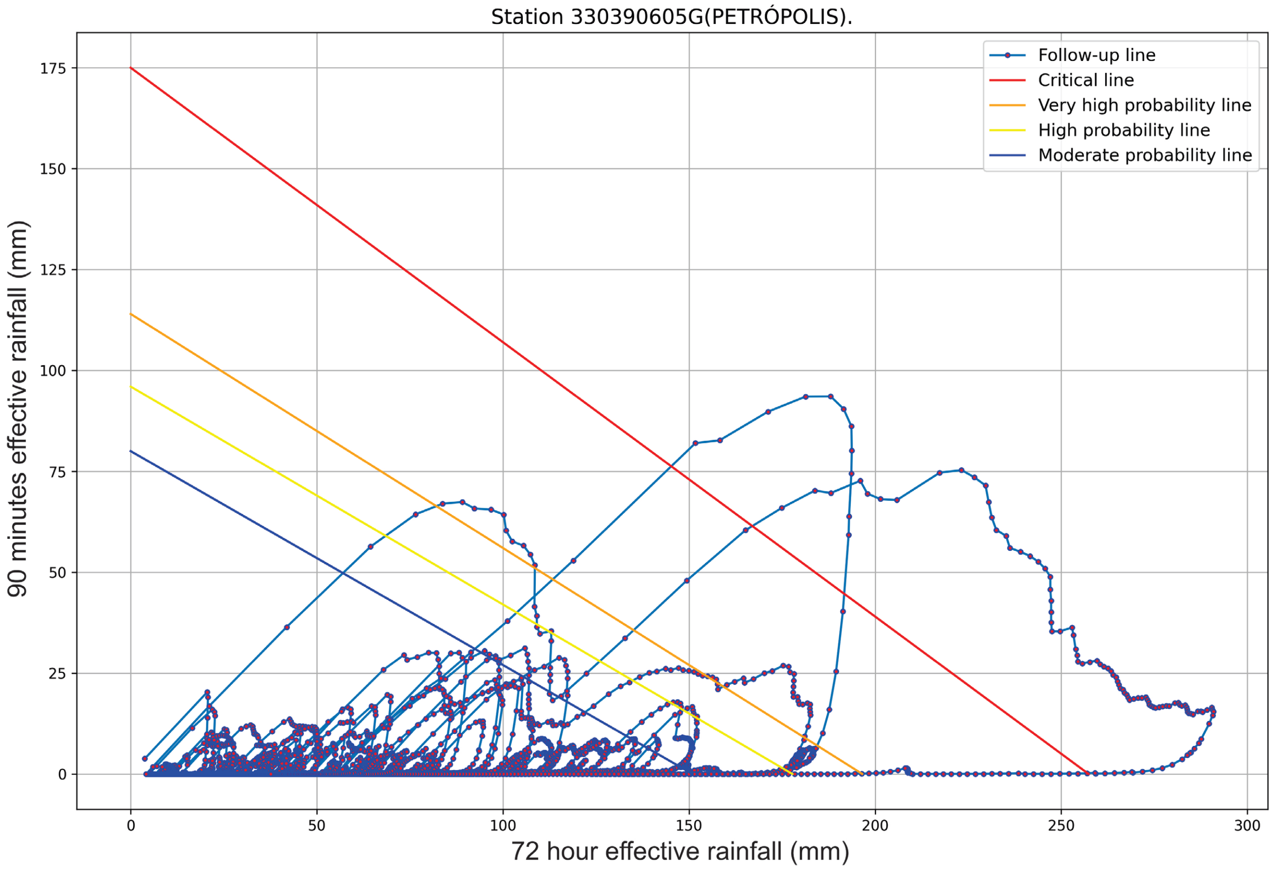

Figure 4. Cobra curve for Petrópolis (Rio de Janeiro state) for the rainy period of 2021/2022.

issuance of alerts and alarms but also offers insights for the coordination of evacuation mobilizations and demobilizations.

5. The SNAKE System

Leveraging the cobra curve method, the SNAKE System was devised to serve the following purposes:

- Monitor the cobra curve during rainfall within a municipality;
- Adjust the Critical Line and support lines upon the emergence of new incidents in pilot municipalities;
- Enable the retrospective simulation of the cobra curve's behavior during past events.

The SNAKE System, now integrated within the CEMADEN platform, consists of four distinct modules, each with its specific access:

1) **Data Loading Module**: Tasked with pulling data from the CEMADEN database.

2) **Calculation Module**: This section manages rainfall sequencing, drawing out features like peak rainfall, accumulated rainfall, and the like. It also runs a range of half-life calculations on the received precipitation data.

3) **Alert Level Monitoring Module**: At set intervals, this module keeps tabs on the alert level of every station and municipality, thereby activating the me-

chanism for alert issuance and transmitting vital data.

4) **Alert Emitter Module**: Triggered by the alert level monitoring module, this module is designated to assemble and dispatch alerts to contacts already listed in the system.

The operations conducted by these modules occur seamlessly, hidden from the user, and are executed on the machine hosting the application server. As previously highlighted, the alert emitter module holds the charge of relaying alerts to the pertinent bodies. The criteria for issuing these alerts are outlined in the subsequent table (**Table 1**).

In summary, an alert is triggered whenever the cobra curve intersects any of the critical lines as delineated in **Table 1**. Should the cobra curve reverse its trajectory and cross any of these critical lines in the opposing direction, a CESSAR alert will be dispatched.

6. Real Case Application—Petrópolis/RJ

In this section, we illustrate the practical application of the system using a real-world event. We focus on the significant incident of February 15, 2022, in Petrópolis, a city within the state of Rio de Janeiro. On this day, the city faced a torrential rain event, leading to devastating floods and landslides. This calamity resulted in the tragic death of over 240 individuals. The area hardest hit was Morro do Centenário, where a landslide at 21:30 UTC led to the obliteration of roughly 50 houses and the grievous loss of nearly 100 lives.

Figure 5 showcases the SNAKE System's reaction for the São Sebastião Pluviometer (Code 330390604G) on that fateful day. This figure depicts the city's Critical and Support lines. The follow-up curve, represented by the blue line, is populated with blue data points, each indicating measurements taken at 10-minute intervals. The spacing between these points serves as a metric for rainfall intensity. Evidently, the rain's intensity was alarming, resulting in rapid accumulation. The SNAKE system dispatched a Moderate Probability alert at 19:30 UTC as the curve exceeded this delineation. A mere 10 minutes later, at 19:40 UTC, a High Probability alert was sent out due to the substantial rainfall accumulation over this short time frame, pushing past both the High and Very High probability thresholds.

Table 1. Transition rules for alert issuance.

Status	Alert Issued
Exceed the MPL ↑	*Moderate*
Exceed the HPL ↑	*High*
Exceed the VHPL ↑	*Very High*
Regressed to MPL ↓	*Cease Moderate*
Regressed to HPL ↓	*Cease High*
Regressed to VHPL ↓	*Cease Very High*

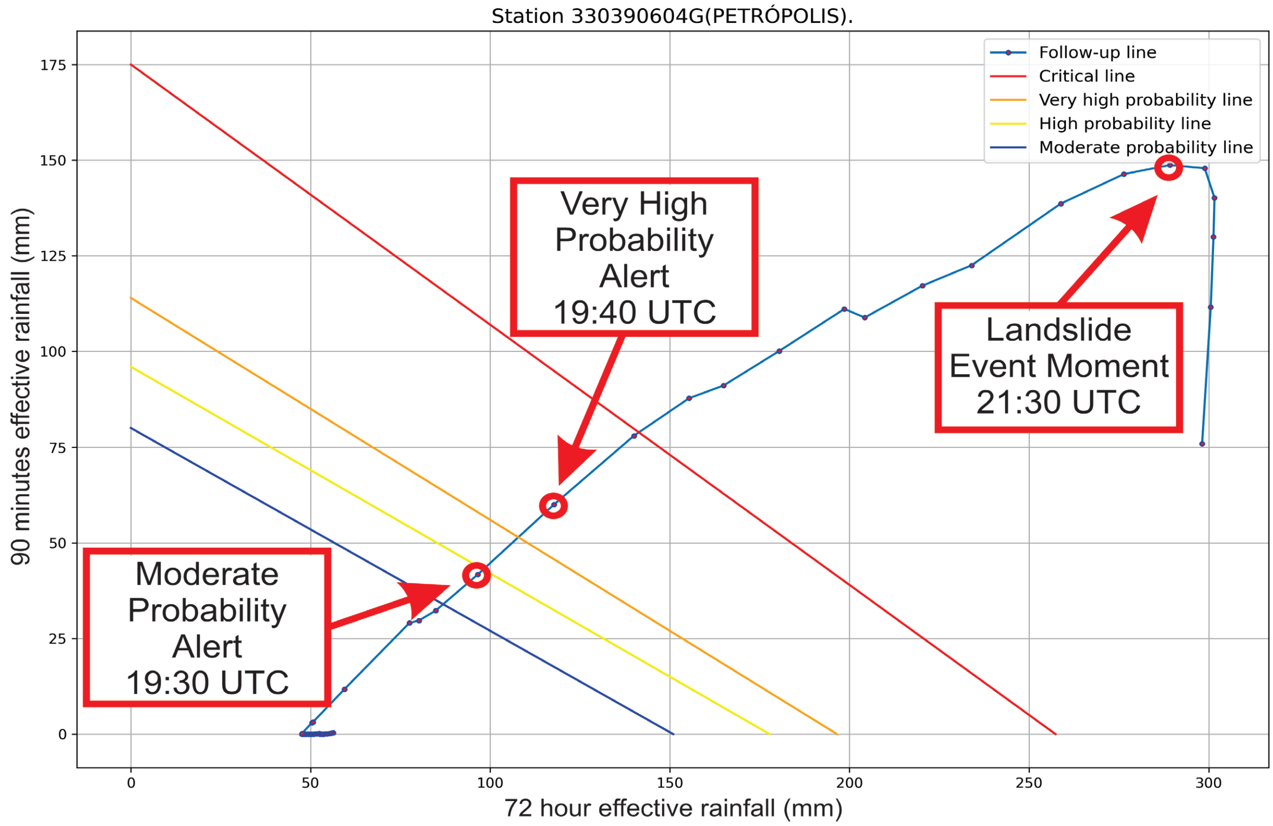

Figure 5. Cobra curve generated by the SNAKE System for the city of Petrópolis (State of Rio de Janeiro) on February 15, 2022. Highlighted are the moments of alert issuance by the system and the timing of the occurrence at Morro do Centenário.

Reflecting on this case study, the SNAKE system's first alert was conveyed 2 hours before the disaster, while the Very High Probability alert was sent 1 hour and 50 minutes prior to the catastrophe. These timelines emphasize the SNAKE system's considerable promise in enhancing CEMADEN's alert dissemination efforts.

7. Conclusions

CEMADEN has introduced the SNAKE System to monitor risk conditions in selected cities, leveraging the critical and support lines of the Shared Method. The system utilizes precipitation data from pluviometers stationed in pilot municipalities. Its primary objective is to alert authorities about potential risks of mass movement processes, such as planar slides and debris flows, thereby enabling the proactive evacuation of residents from vulnerable areas.

Each crossing of the critical and support lines signifies an operational stage for CEMADEN, guiding the issuance of alerts. It also dictates specific actions—whether inspection or evacuation—to be undertaken by the Civil Defense, in collaboration with the local population. The efficacy of this method, as showcased in CEMADEN's Operations Room, confirms its robustness and suitability for monitoring high-risk municipalities. Notably, it offers clear and objective output for the operators, ensuring timely and effective response.

Future work to be undertaken will focus on developing more sophisticated methods for defining the Critical Line and support lines, aiming to enhance the system's precision and its ability to accurately represent the actual conditions of the monitored areas.

Acknowledgements

The authors thank the Japan International Cooperation Agency (JICA) for all support and assistance during the realization of the project. Additionally, CAB thanks to the Conselho Nacional de Desenvolvimento Científico e Tecnológico (CNPq) for the Postdoctoral Scholarship (grant 152269/2022-3) and for the Research Fellowship Program (grant 383480/2023-0). All authors thank FINEP (Financiadora de Estudos e Projetos) for financing the REDEGEO project (Carta Convite MCTI/FINEP/FNDCT 01/2016), responsible for the PCD Geo network installation and maintenance.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Marengo, J.A., Alcântara, E., Cunha, A.P., Seluchi, M., Nobre, C.A., Dolif, G., Goncalves, D., De Assis Dias, M., Cuartas, L.A., Bender, F., Ramos, A.M., Mantovani, J.R., Alvalá, R.C. and Moraes, O.L. (2023) Flash Floods and Landslides in the City of Recife, Northeast Brazil after Heavy Rain on May 25-28, 2022: Causes, Impacts, and Disaster Preparedness. *Weather and Climate Extremes*, **25**, Article ID: 100545. https://doi.org/10.1016/j.wace.2022.100545

[2] Sousa, I.A., Bortolozo, C.A., Mendes, T.S.G., Andrade, M.R.M., Dolif, G., Metodiev, D., Pryer, T., Howley, N., Simoes, S.J.C. and Mendes, R.M. (2023) Development of a Soil Moisture Forecasting Method for a Landslide Early Warning System (LEWS): Pilot Cases in Coastal Regions of Brazil. *Journal of South American Earth Sciences*, **131**, Article ID: 104631. https://doi.org/10.1016/j.jsames.2023.104631

[3] Debortoli, N.S., *et al.* (2016) Índice de Vulnerabilidade aos Desastres Naturais no Brasil, no contexto das Mudanças Climáticas. In: Teixeira, B.S., Orsini, J.A.M. and da Cruz, M.R., Eds., *Modelagem Climática e Vulnerabilidades Setoriais à Mudança do Clima no Brasil*, MCTI, Brasília, Vol. 1, 321-386.

[4] De Assis Dias, M.C., *et al.* (2018) Estimation of Exposed Population to Landslides and Floods Risk Areas in Brazil, on an Intra-Urban Scale. *International Journal of Disaster Risk Reduction*, **31**, 449-459. https://doi.org/10.1016/j.ijdrr.2018.06.002

[5] Marengo, J.A., Jones, R., Alves, L. and Valverde, M. (2009) Future Change of Temperature and Precipitation Extremes in South America as Derived from the PRECIS Regional Climate Modeling System. *International Journal of Climatology*, **29**, 2241-2255. https://doi.org/10.1002/joc.1863

[6] Puente, B., Brasil, F. and Alpaca, N. (2022) Tragédia em Petrópolis completa três meses neste domingo. CNN Brasil, Rio de Janeiro. https://www.cnnbrasil.com.br/nacional/tragedia-em-petropolis-completa-tres-meses-neste-domingo

[7] Bortolozo, C.A., Andrade, M.R.M., Mendes, T.S.G., Egas, H.M., Moraes, M.A.E., Pryer, T., Prieto, C.C., Metodiev, D., Simões, S.J.C. and Mendes, R.M. (2022) The Tragedy of Morro do Centenário in Petrópolis—RJ, Brazil (February 15, 2022): Landslide Complexity Analyzed from a Multidisciplinary Perspective. *The AGU* 2022 *Fall Meeting*, Chicago, 12-16 December 2022, NH15B-07. https://agu.confex.com/agu/fm22/meetingapp.cgi/Paper/1122883

[8] Andrade, M.R.M., Bortolozo, C.A., Mendes, R.M. and Metodiev, D. (2023) Interpretação da Variação da Umidade do Solo Monitorado Pela PCD Geotecnica Ur12 Cohab II no Evento Meteo-rológico de Maio de 2022 em Recife/PE. In: III Encontro Nacional de Desastres, 2023, Niteroi. Anais do III Encontro Nacional de Desastres.

[9] Mendes, R.M., De Andrade, M.R.M., Graminha, C.A., Prieto, C.C., De Ávila, F.F. and Camarinha, P.I. (2017) Stability Analysis on Urban Slopes: Case Study of an Anthropogenic-Induced Landslide in São José dos Campos, Brazil. *Journal of Geotechnical Engineering*, **36**, 599-610. https://doi.org/10.1007/s10706-017-0303-z

[10] Mendes, R. and Filho, M. (2015) Real-Time Monitoring of Climactic and Geotechnical Variables during Landslides on the Slopes of Serra do Mar and Serra da Mantiqueira (São Paulo State, Brazil). *Engineering*, **7**, 140-159. https://doi.org/10.4236/eng.2015.73012

[11] Bortolozo, C.A., Mendes, T.S.G., Motta, M.F.B., Simoes, S.J.C., Pryer, T., Metodiev, D., Andrade, M.R.M., Moraes, M.V., Paula, D.S., Bastos, N.J., Pampuch, L.A., Mendes, R.M. and Moraes, M.A.E. (2023) Obtaining 2D Soil Resistance Profiles from the Integration of Electrical Resistivity Data and Standard Penetration Test (SPT) and Light Dynamic Penetrometer (DPL) Resistance Tests—Applications in Mass Movements Studies. *International Journal of Geosciences*, **14**, 840-854. https://doi.org/10.4236/ijg.2023.149045

[12] Bortolozo, C.A., Motta, M.F.B., Andrade, M.R.M., Lavalle, L.V.A., Mendes, R.M., Simões, S.J.C., Mendes, T.S.G. and Pampuch, L.A. (2019) Combined Analysis of Electrical and Electromagnetic Methods with Geotechnical Soundings and Soil Characterization as Applied to a Landslide Study in Campos do Jordão City, Brazil. *Journal of Applied Geophysics*, **161**, 1-14. https://doi.org/10.1016/j.jappgeo.2018.11.017

[13] Lavalle, L.V.A., Bortolozo, C.A., Pacheco1, T.C.K.F., Andrade, M.R.M., Motta, M.F.B., Mendes, R.M., Metodiev, D., Guedes, M.R.G. and Porsani, J.L. (2018) Evaluation Methodology for Obtaining Geotechnical Parameters Using Electrical Resistivity. *First Break*, **36**, 55-58. https://doi.org/10.3997/1365-2397.n0112

[14] Bortolozo, C.A., Souza, I.A., Andrade, M.R.M., Mendes, T.S.G., Dolif, G., Pryer, T., Simões, S.J.C., Mendes, R.M. and Metodiev, D. (2022) The Development of a Landslide Alert System Based on the Prediction of Soil Moisture in Critical Cities in Brazil—Preliminary Results with the Cemaden's Observation Network. *The AGU* 2022 *Fall Meeting*, Chicago, 12-16 December 2022, NH42C-0437. https://agu.confex.com/agu/fm22/meetingapp.cgi/Paper/1120182

[15] Ashby, B., Bortolozo, C.A., Lukyanov, A. and Pryer, T. (2021) Adaptive Modelling of Variably Saturated Seepage Problems. *Quarterly Journal of Mechanics and Applied Mathematics*, **74**, 55-81. https://doi.org/10.1093/qjmam/hbab001

[16] Lavalle, L.V.A., Stabile, R.A., Bortolozo, C.A., Mendes, R.M., Garcia, J.V.C., Motta, M.F.B., Andrade, M.R.M., Pacheco, T.C.K.F. and Metodiev, D. (2018) Environmental Data Observation System—Solam for Analysis and Interpretation of Soil Moisture Variation and Precipitation Indexes. *International Journal of Geosciences*, **9**, 658-667. https://doi.org/10.4236/ijg.2018.911039

[17] BRASIL (2012) Lei N˚ 12.608, de 10 de abril de 2012. Institui a Política Nacional de Proteção e Defesa Civil—PNPDEC, Brasília. Manual Técnico Para Ela-boração, Transmissão E Uso De Alertas De Risco De Movimentos De Massa. https://antigo.mdr.gov.br/images/stories/ArquivosDefesaCi-vil/ArquivosPDF/Volume2-ManualTecnicoparaElaboracaoTransmissaoeUsodeAler-tas_CEMADEN.pdf

[18] CEMADEN Centro Nacional de Monitoramento e Alertas de Desastres Naturais (2018).

[19] Guzzeti, F., Peruccacci, S., Rossi, M. and Stark, C.P. (2008) The Rainfall Intensity-Duration Control of Shallow Landslides and Debris Flows: An Update. *Landslides*, **5**, 3-17. https://doi.org/10.1007/s10346-007-0112-1

[20] Jamaludin, S. and Ali, F. (2011) An Overview of Some Empirical Correlations between Rainfall and Shallow Landslides and Their Applications in Malaysia. *Electronic Journal of Geotechnical Engineering*, **16**, 1429-1439.

[21] Guzzetti, F., Peruccacci, S., Rossi, M. and Stark, C.P. (2007) Rainfall Thresholds for the Initiation of Land-Slides in Central and Southern Europe. *Meteorology Atmospheric Physics*, **98**, 239-267. https://doi.org/10.1007/s00703-007-0262-7

[22] Ministry of Land, Infrastructure and Transport MLIT and Infrastructure Development Institute Japan (2004) Guidelines for Development of Warning and Evacuation System against Sediment Disaster in Developing Countries.

[23] Crozier, M.J. (1986) Landslides: Causes, Consequences and Environment. Croom Helm, London, 245 p.

[24] Moraes, M.V., Pampuch, L.A., Bortolozo, C.A., Mendes, T.S., Andrade, M.R.M. and Metodiev, D. (2023) Thresholds of Instability: Precipitation, Landslides, and Early Warning Systems in Brazil. *International Journal of Geosciences*, **14**, 895-912. https://doi.org/10.4236/ijg.2023.1410048

[25] Metodiev, D., Andrade, M., Mendes R., Moraes, M., Konig, T., Bortolozo, C., Bernardes, T., Luiz, R. and Coelho, J. (2018) Correlation between Rainfall and Mass Movements in North Coast Region of Sao Paulo State, Brazil for 2014-2018. *International Journal of Geosciences*, **9**, 669-679. https://doi.org/10.4236/ijg.2018.912040

[26] Tatizana, C., Ogura, A.T., Cerri, L.E.S. and Rocha, M.C.M. (1987) Modelamento numérico da análise de correlação entre chuvas e escorregamentos aplicado às encostas da Serra do Mar no município de Cubatão. *Anais do Congresso Brasileiro de Geologia de Engenharia* 5, São Paulo, Vol. 2, 237-248.

[27] Suzuki, M., Fukushima, Y., Takei, A. and Kobashi, S. (1979) The Critical Rainfall for the Disasters Caused by Debris Movement. *Journal of Japan Society of Erosion Control Engineering*, **31**, 1-7. (In Japanese)

[28] Yano, K. (1990) Study of the Method for Setting Standard Rainfall of Debris Flow by the Reform of Antecedent Rain. *Journal of the Japan Society of Erosion Control Engineering*, **43**, 3-13.