Probabilistic Analysis of the Obstruction of Water Sources Due to the Occurrence of Rainfall-Triggered Mass Movements

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Abstract. This paper presents a methodology for the probabilistic estimation of the obstruction of water streams generated by shallow mass movements triggered by rainfall. The study focuses on the Ovejas River, a tributary stream of the Medellín River, in the jurisdiction of the municipality of San Vicente in the department of Antioquia (Colombia). The occurrence of a mass movements was evaluated by deterministic and probabilistic methods based on the automation of processes of Geographic Information Systems (GIS) and spatial modeling. The spatial distribution of the mass movement hazard was estimated in terms of Factor of Safety (FoS) values by the deterministic method with physical basis SLIDE (Slope - Infiltration - Distributed Equilibrium), which allows the hazard zonation by calculating a FoS for rainfall-induced mass movements with different return periods. The rainfall regimes of the study area are estimated by means of a simple scaling Log Normal Model. On the other hand, the Probability of Failure (PF) analysis was performed under Rosenblueth's punctual estimates method (PEM), which allows incorporating the uncertainty of the soil parameters. Subsequently, the resulting zones with high hazard that could detach and reach the Ovejas River channel are identified as sources for runout modeling by means of the Flow R model, thus estimating the extent of mass movement in probabilistic terms. In all the analyzed scenarios, the sliding material from the critical stability zones has a high probability of spreading to the riverbed of the main river. This analysis makes possible to identify those areas of the riverbed that should be analyzed with more detail and require possible intervention for the protection of the riverbed.

1. Introduction
The greatest percentage accumulated for loss of life and infrastructure destroyed by natural hazards corresponds to mass movements and floods respectively [1]. Mass movements and floods are the two natural phenomena that generate the most severe risks in Colombia. Mass movements are often caused by diverse geographic and physiographic features and are triggered by both natural as well as anthropogenic factors [2]. As an example, in the last six years, there have been three major events of extreme impacts in the country, such as the avalanche of Salgar - Antioquia in 2015 [3], devastating mudslides in the city of Mocoa - Putumayo in 2017 [4] and in 2021 heavy rain caused severe flooding in the municipality of Dabeiba - Antioquia in [5]. These disasters occur by the combination of heavy rainfall, mass movements, and torrential floods on areas of high vulnerability. Generally, the risk evaluated in these phenomena is the risk of exposed people and infrastructure. However, when there is no directly exposed population, there are other types of risks, such as water shortages due to streams obstruction, or the reduction or suspension of hydroelectric generation of small hydroelectric plants. The study of the vulnerability to the obstruction of channels due to mass movements triggered by rainfall is...
a necessity in many countries, since it will allow the local authorities to manage the critical areas of the riverbeds and mitigate the risk in this type of infrastructure that requires a hydroelectric catchment on the rivers.

Recently, a methodology has been proposed for mass movements assessment causing river channel obstruction using the deposition height with a geometrical method based on slope gradient (Z), that reflects the potential and kinetic energies involved with the movement of soil mass, which can be used as an indicator of the mass movement intensity [2,6].

The proposed methodology uses the physically based deterministic method, called SLIDE (Slope - Infiltration - Distributed Equilibrium), which allows the hazard zonation by calculating a FoS for rainfall-induced mass movements with different return periods. Additionally, the failure probability is calculated by Rosenblueth punctual estimates method that allows incorporating the uncertainty of soil parameters and an estimation of mass movement propagation in probabilistic terms using the Flow R model.

2. Materials and Methods

In this study, the chosen stream corresponds to the Ovejas River, which contributes its flow to a small hydroelectric plant, nowadays in design phase by the company that owns the project. The hydroelectric project basin is above the elevation of 2176 meters above sea level with an area of about 77 km². The highest slopes occur in some areas of the upper part of the basin, reaching up to 67%. Figure 1 shows general location.

![Figure 1. General location. The green point is the catchment of the Ovejas River hydroelectric project.](image)

2.1. Sources of information

Cartographic information, soil characterization and 0.5 m pixel resolution Lidar topographic information of the study area were obtained from the detailed pre-feasibility studies provided by the company that owns the project. This information was complemented with information of the study area obtained from
the watershed management plan of Aburra River [7]. The rainfall data were acquired through the portal of the Institute of Hydrology, Meteorology and Environmental Studies - IDEAM.

2.2. Hazard zonation and annual probability of failure due to shallow mass movements. The mass movement hazard was evaluated by two methods. The deterministic model that estimates the safety factor for rainfall-induced mass movements called SLIDE (Slope - Infiltration - Distributed Equilibrium) was used. Additionally, the probabilistic punctual estimates method PEM was applied to incorporate the uncertainty on the soil geomechanics parameters. Figure 2 summarizes the development methodology applied for the execution of the work.

2.2.1 SLIDE (Slope – Infiltration – Distributed Equilibrium). Slope stability is estimated by a deterministic model, applying the methodology presented by Liao et al. [8]. This model highlights the destabilizing forces by the water down-flow and the contribution of partial saturation to the shear strength of the soil. Factor of safety (FoS) of a slope is the ratio of resisting forces to driving forces. A relation between the rainfall amount and the final expression of FoS has been set up and translated into a simple mathematical formulation of model SLIDE as shown in Equation 1 [8].

\[ FS = \frac{\cot \beta \cdot \tan \phi \cdot \left[ \Gamma + m_n (n_w - 1) \right] + C \cdot \Omega}{\Gamma + m_n n_w} \]  
\[ \Gamma = G_s \cdot (1 - n) + n \cdot S_r \]  
\[ n_w = n \cdot (1 - S_r) \]  
\[ \Omega = \frac{\sin 2\beta \cdot H \cdot Y_w}{2} \]

Where \( \beta \) is the slope angle (°), \( H \) is the soil depth (m) which is explained in 2.2.2, \( \phi \) is the friction angle (°), \( C \) is the soil cohesion (Kpa), \( G_s \) the specific gravity of soil (N/m³), \( n \) is the porosity, \( S_r \) is degree of saturation (%) and \( m \) initial dimensionless thickness.

The finite slope grid is conceptualized as a water balance tank that simultaneously accounts for water gain from rainfall infiltration and seepage inflow as well as the water loss due to outflow and evapotranspiration through the grid. The hourly intensities are estimated from 1h to 24 hours for the return periods. The initial value of \( m \) was derived by calculation of water balance at each time-step based on Equation 5. [8].
In the area of interest there are no mechanisms of movement corresponds to superficial resampled to obtain an elevation model with a spatial resolution of 10 m. This is because the physical parameters obtained from the information characterized by 𝑥, 𝜃, 𝑀𝑖𝑛 𝑇, 𝐻. cos 𝜋, 𝐷𝑡.

\[
\begin{align*}
    m_1 &= 0 \\
    O_t &= K \cdot \sin \beta \cdot m_t \cdot H \cdot \cos \beta \cdot \Delta t \\
    \Delta m_t &= \frac{(I_t - O_2)}{n.H.(1 - S_p)} \\
    m_{t+1} &= m_t + \Delta m_t
\end{align*}
\]

(5)

Where \( t \) is time, \( \Delta t \) is time step (1 hour), \( m_1 \) is initial value of m, and \( m_t \) is calculated at each time-step. \( O_t \) represents the water outlet of a finite portion of a slope of finite length \( L \), \( I_t \) is rainfall intensity, and \( K \) is the significance of a global drainage capability due to both the intrinsic soil permeability and the presence of numerous preferential down-flow ways.

The estimation of soil depth is based on the behavior of the soil in relation to the slope of the terrain, high slopes imply less soil accumulation. The model of the soil susceptible to sliding is represented by the following equation [9].

\[
H = (h_{\text{max}} - h_{\text{min}}) \times \left\{ \left[ 1 - \frac{1}{\tan(\theta_{\text{lim}})} \right] \times \tan(\theta(a \times x)) \right\} + h_{\text{min}}
\]

(6)

Where \( H \) Soil depth (m), \( h_{\text{max}} \) Soil depth maximum (m), \( h_{\text{min}} \) Soil depth minimum (m), \( \theta \) slope value (°), \( \theta_{\text{lim}} \) slope value threshold for which higher values imply that the depth of soil susceptible to sliding is minimal/negligible or even null (according to the analysis of the distribution of the slopes \( \theta_{\text{lim}} = 35^\circ \)), \( a \) Dimensionless parameter that controls the curvature of the terrain (0.04 for tropical soils), \( x \) Horizontal distance of a considered point to the nearest drainage (m). Table 1 shows the necessary parameters obtained from the information characterized by hydroelectric project owner.

| Table 1. Soil parameters for mass movement assessment. |
|------------------------------------------------------|
| C’ (kPa) | \( \varphi \) (°) | Sr (%) | K (m/s) | h min (m) | h max (m) |
|----------|----------------|--------|--------|----------|----------|
| Antioquia batholith   | 12    | 30     | 38.49  | 1.60E-07 | 1.2      | 6        |
| Alluvial deposits     | 9.5   | 30     | 41.65  | 5.00E-06 | 1        | 6        |
| Colluvial deposits    | 5     | 21     | 52.07  | 5.00E-07 | 1        | 4        |

For the application of the infinite slope methodology, the Lidar elevation model of 0.5 m was resampled to obtain an elevation model with a spatial resolution of 10 m. This is because the physical mechanism of movement corresponds to superficial mass movements with rupture surfaces parallel to the surface of the slopes.

The rainfall scenarios in the slope stability model are represented by the rainfall intensity values \( (I_t) \). In the area of interest there are no meteorological stations with available Intensity Duration Frequency - IDF curves, so these curves were estimated. The simple scaling methodology Log Normal Model was used [10]. The expression corresponding to the simple scaling is summarized as Equation 7.

\[
I_{d,q} = \frac{E[I_{dref}]^2}{E[I_{dref}]^2} \exp \left( \phi_q \cdot \sqrt{\ln \frac{E[I_{dref}]^2}{E[I_{dref}]^2} \left( \frac{d}{d_{\text{ref}}} \right)^\theta} \right)
\]

(7)

Where \( I_{d,q} \) is the maximum intensity for a duration \( d \) for a non-exceedance probability (mm/h), \( I_{dref} \) maximum intensity of a reference duration (mm/h), \( E[I_{dref}] \) expected value (mm/h), \( \phi_q \) quantile for a non-exceedance probability \( q \) from the standard Normal distribution (mm/h), \( \theta \) = scaling exponent.
Considering that there is no availability of annual series of maximum 24-hour rainfall and that there are annual series of maximum daily precipitation, the data obtained in the previous paragraph are increased by 11% [10]. With the information collected on maximum daily precipitation for each station, the intensities were estimated for durations from 1h to 24 hours for return periods of 2.33, 25 and 100 years. Spatial interpolation for rainfall distribution in the study area was performed using the inverse distance weighted IDW interpolation method.

2.2.2 Annual Probability of failure (APF) by punctual estimates method (PEM). The probability of failure is determined as the probability that the values considered as limits are equaled or exceeded. Once the values of FoS were obtained through the stability analysis for the determined scenarios of rainfall as a triggering factor, the FoS were estimated for each of the analyzed scenarios considering uncertainty criteria of the existing soil parameters for the determination of the PF by PEM [11].

The PEM states that with an F function that depends on n variables that are not correlated with each other, the mean and standard deviation estimates can be obtained for the function F using the following formulas [2].

\[
\bar{F} = \frac{1}{2^n} \sum_{i=1}^{2n} (f_i)
\]

\[
\sigma[F] = \frac{1}{2^n} \sum_{i=1}^{2n} \left( f_i - \bar{F} \right)
\]

The \(f_i\) values are obtained by applying the F function and independent variables by alternately substituting the values of those variables with \(X_j \pm \sigma_j\) when \(j = 1, 2, ..., n\), giving the \(2n\) values of \(f_i\). To perform the calculation, combinations of values are obtained for the maximum and minimum punctual estimates of each independent variable. Therefore, separate \(2n\) analyses are required. By assuming a triangular distribution, values are calculated at the extremes of the independent variables [2].

The failure probabilities are the probability of the security factor (FoS) having a value lower than the unit in the saturated and unsaturated condition respectively, calculated based on the reliability index (\(\beta\)) as [12]:

\[
\beta = \frac{\left( E[F_{FS}] - 1 \right)}{\sigma[F_{FS}]}
\]

Where \(E[F_S]\) is the usual value (deterministic method) of the FoS calculated with the mean parameters of the independent variables y \(\sigma[F_{FS}]\) is the standard deviation of the FoS estimated considering the standard deviation of soil parameters such as cohesion (C), friction angle (\(\phi\)) and permeability (K).

Table 2 presents the average values and standard deviation of the soil parameters to calculate the deviation of the FoS and subsequent PF. For permeability, a Coefficient of Variation (CV) of 50% was used, based on typical ranges in slope stability analysis [12].

| Geological Units          | C (kPa)  | \(\phi\) (°) | Sr (%) |
|---------------------------|---------|---------------|--------|
| Antioquia batholith       | 12 ± 4  | 30 ± 3        | 38.49  |
| Alluvial deposits         | 9.5 ± 2.3 | 30 ± 2       | 41.65  |
| Colluvial deposits        | 5 ± 3   | 21 ± 6        | 52.07  |

Table 2. Soil parameters to calculate probability of failure.

The probability of failure is given by the portion of the area under the unit frequency distribution curve (probability density function) of the corresponding FoS with values less than 1.1. This was determined
from the normal probability distribution with mean 0 and standard deviation 1. Combining the results of the PEM with the reliability index determines $P_F$ of a system [12].

2.3. Estimation of landslide propagation with Flow-R

In addition to the probability of occurrence and the magnitude of a mass movements, determining its dynamics is one of the most important tasks during the hazard assessment and zonation. In this methodology the use of the Flow-R model is proposed. This is a spatially distributed empirical model developed under Matlab® which was developed at the University of Lausanne. Application of the model requires two distinctive steps based on a digital elevation model (DEM), in one hand the source areas are first identified by means of morphological and user-defined criteria, and then the sliding material also known as debris flows are propagated from these sources based on frictional laws and flow direction algorithms [13]. The model sets normalized or absolute values for the assessed initial source areas. When normalized, the values never exceed 1, and thus get close to a notion of spatial probability. Two types of algorithms are involved in the propagation assessment. One is spreading algorithms controlling the path and the spreading of the debris flows and friction laws determining the runout distance. The methods chosen for the analysis are:

- The simplified limited friction model selected is based on the maximum possible deflection distance, which is characterized by a minimum angle of travel.
- For the evaluation of the susceptibility of debris flows, the Holmgren version algorithm was chosen since it allows to reproduce most of the other flow direction algorithms. Moreover, it is the only algorithm that allows parameterizing of the spreading.

3. Results and discussions

As a variable in the proposed methodology, the rainfall intensities for each return period were estimated. Figure 3 shows the rainfall intensity maps with a duration equal to the estimated basin concentration time of 3 hours, simulating the gradual saturation of the material hour by hour. The highest intensities are found towards the south and southeast of the study area.

![Figure 3. Rainfall intensities for the basin concentration time (3 hours)](image)
From the rainfall intensities for each return period, the mass movements hazard is estimated by the deterministic methodology according to the FoS values (Figure 4). The moderate and high hazard zones are distributed mainly in soils susceptible to mass movements of greater soil depth, where higher rainfall events progressively affect soil saturation and its possible failure, highlighting the influence of topographic features on the stability of the terrain. It is important to highlight that although slopes are a factor that probably have a high degree of influence, they do not control the hazard zonation and they are affected by soil parameters, including the soil depth susceptible to sliding.

Figure 4. Hazard zonation in terms of FoS.

From the zonation by FoS and applying the probabilistic methodology of PEM for each return period, the APF is estimated for each of the return periods analyzed. Figure 5 shows that as the return period increases, the annual probability of recurrence is lower, with very high annual failure probability with values greater than 2% for the 2.33-year return period.
Figure 5. Hazard zonation in terms of APF.

For the propagation assessment, mass movements source areas were considered as those areas with FoS<1.1. These sources for each return period are shown in the Figure 6.

Figure 6. Sources identified for mass movements assessment.

As mentioned in the methodology, the propagation probability was estimated using the Flow R model. This probability is associated with the probability that the material removed from the source areas may reach the Ovejas River channel. The Figure 7 shows the estimated trajectories of the sliding mass emerging from the sources identified by the different scenarios analyzed.
As can be seen in the previous figure, estimated sliding mass trajectories for each return periods 2.33, 25 and 100 years have high probabilities of spreading to the Ovejas riverbed. Once the results of the runout of the mass movement were obtained in probabilistic terms, we analyzed Ovejas River longitudinally to know those areas of the channel that should be analyzed with greater attention and require a possible intervention for the protection of the riverbed. Figure 8 shows the longitudinal axis of the channel. The color scale corresponds to the propagation probabilities, and each line with a different return period.

For nearest areas of the sources of material detachment (abscissae 100 and 300 and 500 and 700m), there is a high probability that the material will reach the riverbed in the Ovejas River in the return periods analyzed. The section of the river between 500 and 700m is the most likely to be affected because
it is the area with the highest number of sources with FoS<1.1. These critical areas should be managed to mitigate the vulnerability of the intake works in the channel.

4. Conclusions

In this work, a comprehensive methodology for hazard assessment of water shortage due to the obstruction of water sources by the occurrence of mass movements using deterministic and probabilistic methods was presented. This methodology evaluates the spatial distribution of the hazard in terms of Factor of Safety (FoS) and Annual Probability of Failure (APF) values, identifying high hazard zones that may detach sliding material and generate obstructions in the rivel channel.

The identified sources have a high probability of extending into the river channel and generating possible obstructions. This would imply a shortage in water catchment, which could be reflected in the reduction of power generation by small hydroelectric plants or a shortage of water supply in a community’s aqueduct.

This methodology turns out to be a useful tool for specialists when designing mitigation measures that contribute to the reduction of economic losses or choosing possible locations for the construction of new infrastructures considering exclusion criteria. It allows the development of protocols in the event of a disaster and the planning of the territory.

Acknowledgments
This study is framed within the guidelines and products of the research program “Vulnerability, resilience and risk of communities and supplying basins affected by landslides and avalanches”, code 1118-852-71251, project “Functions for vulnerability assessment due to water shortages by landslides and avalanches: micro-basins of southwest Antioquia”, contract 80740-492-2020 held between Fiduprevisora and the Universidad de Medellín, with resources from the National Financing Fund for science, technology and innovation, “Francisco José de Caldas”.

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