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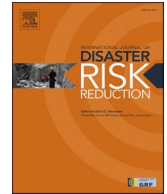
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Implications of landslide runout modeling for vulnerability assessment: Benchmarking from a case study in the andean region

Miguel Angel Alvarez Jaimes^a, Daniel Camilo Roman Quintero^{b,c,*} ,
Jose David Ortiz Contreras^b, Diego Fernando Bedoya Rios^d ,
Mauricio Alberto Tapias Camacho^b

^a Universidad Industrial de Santander, Escuela de Ingeniería Civil, Cl. 9 #27 (680006), Bucaramanga, Colombia

^b Universidad Nacional de Colombia, Departamento de Ingeniería Civil y Agrícola, Carrera 30 Calle 45-03 (111321), Bogotá, Colombia

^c Delft University of Technology, Department of Water Management, Building 23 Stevinweg 1, (2628 CN), Delft, the Netherlands

^d Fundación Universitaria Agraria de Colombia, Escuela de Ingeniería Civil, Calle 170 # 54a – 10 (110911), Bogotá, Colombia

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ABSTRACT

The vulnerability to landslides depends on both the susceptibility of the exposed elements and the intensity of the landslide, which is commonly characterized by its motion mechanism. This study proposes a quantitative evaluation framework to assess the implications of using different models for predicting the landslide runout distance (LRD) on vulnerability, estimated through two distinct vulnerability functions. The analysis focuses on a debris flow that impacted a major highway in the Colombian Andes. The event, with a triggered volume of 340 m³, a runout of 84 m, and a vertical drop of 42 m, serves as a benchmark for evaluating model performance. The findings provide insights into the influence of material type, flow regime, and model uncertainty on LRD and vulnerability estimates. Empirical methods enabled rapid assessments but exhibited high variability (LRD errors up to 120 %). Analytical models, particularly the sliding block model, offered a balance between simplicity and physical realism, overestimating LRD by 14 % without calibration while also providing velocity estimates. Multidimensional (2D/3D) models, though resource-intensive, best reproduced the observed behavior; the 3D model closely matched the measured runout when calibrated with high-friction parameters and GIS-derived inputs. A benchmarking analysis using the Analytic Hierarchy Process (AHP) identified the sliding block model as the most effective overall, combining accuracy, functionality, and usability. These results highlight that model selection should align with the intended application: empirical models for rapid screening, analytical models for design purposes, and multidimensional models for detailed vulnerability assessments.

1. Introduction

Landslides are processes typically starting in a source area, and with effects often extending far beyond. Specifically, the processes occurring on slopes just before movement begins, commonly referred to as pre-failure or initiation processes [1,2], define the extent of

* Corresponding author. Delft University of Technology, Department of Water Management, Building 23 Stevinweg 1, (2628 CN), Delft, the Netherlands.

E-mail address: dromanquintero@tudelft.nl (D.C. Roman Quintero).

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the source area and are well understood in many situations. In contrast, post-failure mechanisms remain subject to significant uncertainty and can vary depending on slope conditions and other factors related to the material involved.

In some cases, landslides deform so slowly that potential damage countermeasures can be implemented in time to ensure the safety of affected infrastructure and populations [3,4]. Conversely, many landslides evolve into fast, flow-like movements that suddenly impact areas several meters or even kilometers away from the source, often without providing sufficient time for warning [5–8]. This is particularly true for shallow landslides, commonly triggered by rainfall or earthquakes and often playing a central role in catastrophic scenarios [9–12].

In this regard, special attention has been paid to large and catastrophic landslides, but smaller landslides, which are more common, are usually overlooked [13,14]. These landslides are particularly relevant in tropical countries, which often experience a bimodal hydrological regime [15]. As a result, relatively small landslides frequently occur in susceptible areas even twice a year.

In fact, in the case of Colombia (South America), it has been estimated that the cumulative impact of these smaller landslides accounts for the majority of economic losses among all natural hazards [16]. Small to medium-sized landslides typically mobilize between 10^2 m³ and 10^3 m³ of material, making them potentially harmful [2]. Commonly observed along highways and critical infrastructure, particularly in the northern Andes, these events are responsible for significant infrastructure damage and economic losses [14].

The landslide runout distance (LRD), representing the total longitudinal extent affected by landslide displacement, serves as a measure of the exposure of elements to landslides. The level of exposure or vulnerability is often estimated differently for infrastructure, such as buildings or highways, or for persons in the affected area and is a function of both the susceptibility of the element and the intensity of the landslide event [17–21].

LRD can be assessed using two main approaches: empirical models and analytical models [22]. Empirical models are practical and relatively easy-to-use tools that exploit statistical relationships (e.g. between the triggered volume, slope inclination, and the LRD). In contrast, analytical models derive mathematical formulations based on physical principles to estimate the LRD.

Within analytical modeling, two main strategies are commonly employed. One is based on the laws of classical mechanics and treats the flowing material as a rigid block sliding down a slope [22]. The other applies the laws of continuum mechanics, particularly mass and momentum conservation, to analyze the kinematics of flowing materials composed of a mixture of solid phases (e.g. soil, rock) and fluid phases (e.g. water, air). An additional category involves alternative modeling strategies such as Cellular Automata, the Material Point Method and the Distinct Element Method [23–25].

When it comes to modeling LRD, several mathematical tools have been made available to practitioners in international guidelines [26,27]. In fact, free and open-source software solutions are now accessible and are suitable for both practical and scientific applications [28,29]. Nonetheless, despite the wide range of tools available for LRD estimation, there is ongoing debate about which models and theoretical approximations are most appropriate for different circumstances [30]. In particular, assessing landslide vulnerability requires the evaluation of LRD and, in some cases, its velocity and flow depth [20,21]. This key point may require intensive analysis for small to medium-sized landslides as the resources needed to apply each model vary significantly depending on the chosen approach. In fact, the importance of the fair estimation of LRD on vulnerability estimations extent from quantitative landslide risk assessment [31], to the correct hazardous zone delineation for the design of risk mitigation strategies [32,33].

Therefore, this study aims to propose a quantitative methodological evaluation framework to analyze the implications of using different landslide runout modeling strategies on landslide vulnerability assessments. We focus on a well-documented case study of a small to medium-sized debris flow in the northeastern Andean region, representative of typical landslide scenarios affecting critical infrastructure. The evaluation compares empirical, analytical, and multidimensional (2D/3D) models in terms of their predictive accuracy, computational demands, and practical usability following an Analytical Hierarchy Process. By benchmarking model outputs against observed runout distances and examining implementation requirements, this study provides evidence-based guidance for

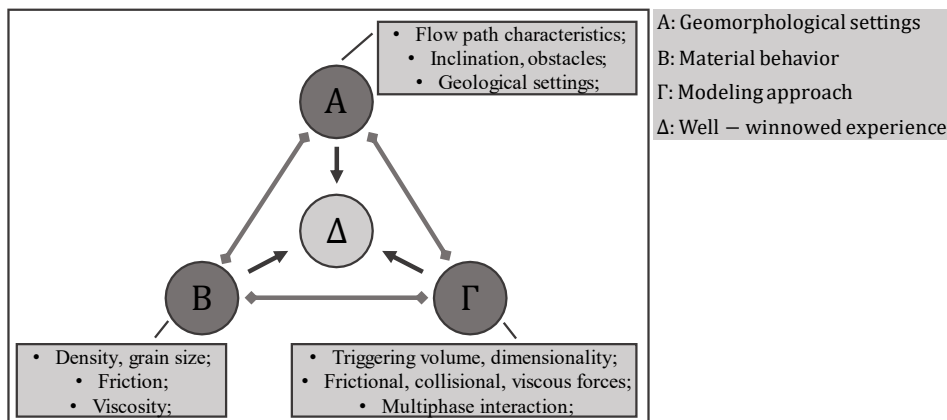


Fig. 1. Methodological approach linking geomorphological settings, observed material behavior through empirical approaches, and modeling strategies based on problem conceptualization and idealization, aimed at gaining well-winnowed experience in landslide runout and vulnerability assessment. Adapted from Burland (2012) [34].

selecting appropriate modeling approaches tailored to specific contexts of landslide vulnerability assessment, thereby impacting on risk management, and road resilience enhancement.

2. Materials and methods

Estimating landslide vulnerability of exposed elements in flow-like processes, is closely linked to the adopted landslide run-out modeling strategy, which should reflect well-winnowed experience in identifying the key factors governing landslide flow and deposition. In this context, the present study is based on the methodological approach illustrated in Fig. 1, derived from the theory proposed by Burland (2012) [34].

The methodological approach illustrated in Fig. 1 highlights the considered relationships between: (i) the geomorphological setting of the specific case, including the geological context of the landslide, slope inclination, presence of obstacles along the flow path, and general path characteristics; (ii) the material behavior evaluated from laboratory and field measurements; and (iii) the modeling strategy, considering different levels of process idealization.

2.1. Case study

The study focuses on a landslide event located on the Colombian northeastern Andean region, specifically in Girón city in the metropolitan area of Bucaramanga, capital city of the Santander region. Fig. 1 shows the location of the event within the study area, including the failure, transit and deposition zones affected by the landslide. The event affected a national highway connecting Lebrija-Giron and an international airport.

The landslide is recorded in the inventory of the Colombian Geological Survey under code number 34197, within the *Sistema de Información de Movimientos en Masa* (SIMMA). It corresponds to a landslide triggered for the first time between September 2009 and April 2011, involving a volume between 100 m³ and 1000 m³, which partially closed the highway. Since then, coinciding with an observed return period of ten years, the same location experienced a similar landslide reactivation in 2020, triggering a similar volume of material and with similar impacts. This particular event is a slide developing as a debris flow, similar to more than 75 % of the inventoried landslides in the region according to SIMMA. Moreover, despite the specific properties of the material involved, the landslide's impacts and dimensions are close to the median of the events recorded in this subregion of the northeastern Andes, making it relevant to the present study [14].

Fig. 2 shows the progression of the landslide scarp and the affected area over time. All displacements occurred within the regolith of weathered sandstones from the Girón Formation, on a structural hill at an elevation of approximately 920 m above sea level.

An on-site inspection for reconnaissance and material sampling was carried out. Fig. 3 shows frontal and aerial views of the landslide site, taken in August 2018, before the landslide reactivation.

It was observed that both the deposits and the source area consist of an abundant soil matrix composed mainly of sandy particles, along with some boulders and coarser fragments. Disturbed samples of the soil matrix were collected to characterize the soil material, from the places indicated in Fig. 3. At the same locations, the material density was estimated using the sand cone test.

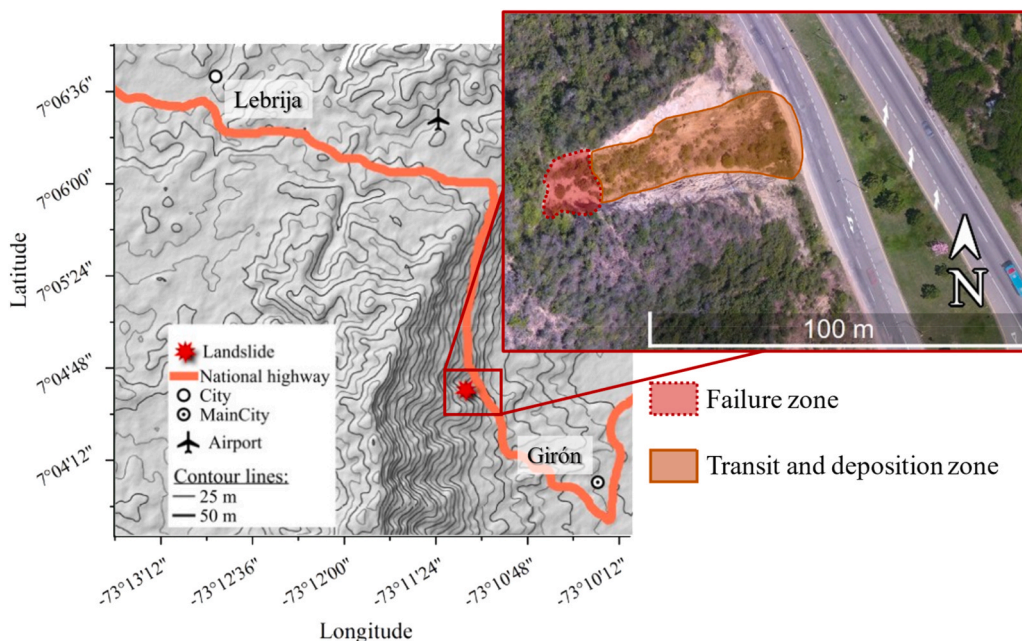


Fig. 2. Location of the case study and aerial image of the studied landslide within the municipalities of Lebrija and Girón, Colombia.



Fig. 3. Time-line showing the development of the studied landslide starting from left to right: October 2009, April 2011, October 2017, and August 2020.

Index property investigations revealed that the soil is predominantly coarse-grained: a sandy soil with finer silty particles. Atterberg limit tests on the fine fraction of the samples indicated a low-plasticity silt, with a plasticity index of 4.1 %, a plastic limit of 20.4 %, and a liquid limit of 24.5 %.

Regarding the flow-type characteristics of the landslide, specific features suggest a high level of interaction among soil particles in the debris flow, which indicates a highly frictional behavior [35,36]. The dense deposits found at the landslide's toe are evidence of this high interaction among the particles. A vertical cut, about 1.5 m high, was made when the affected highway lane was being cleared, exposing this condition. The dense frictional flow is further supported by the sand cone tests performed at three different locations within the landslide-affected area. These tests yielded mean dry density values of 1.52 g/cm^3 at the main scarp, 1.41 g/cm^3 in the transit zone, and 1.48 g/cm^3 in the deposition zone, resulting in an overall mean density of 1.46 g/cm^3 .

According to literature, the internal friction angle of soil materials with similar characteristics to the case study ranges between 30° and 35° [37], and recent technical reports in the area confirm this [38,39]. Moreover, shear resistance was tested on remolded samples using conventional direct shear tests. The samples were consolidated under saturated conditions to reach the field-measured density, and a pre-cut was applied obtaining a value of 30.85° , which mirrors the residual shear strength.

2.2. Morphometrical measurements

Morphometric data was obtained using a Terrestrial Laser Scanner (TLS), specifically a Riegl VZ-400® model. It consists of a topographical station mounted on a tripod (see Fig. 4b), equipped with a LiDAR scanner integrated with a Nikon D700 photo camera,

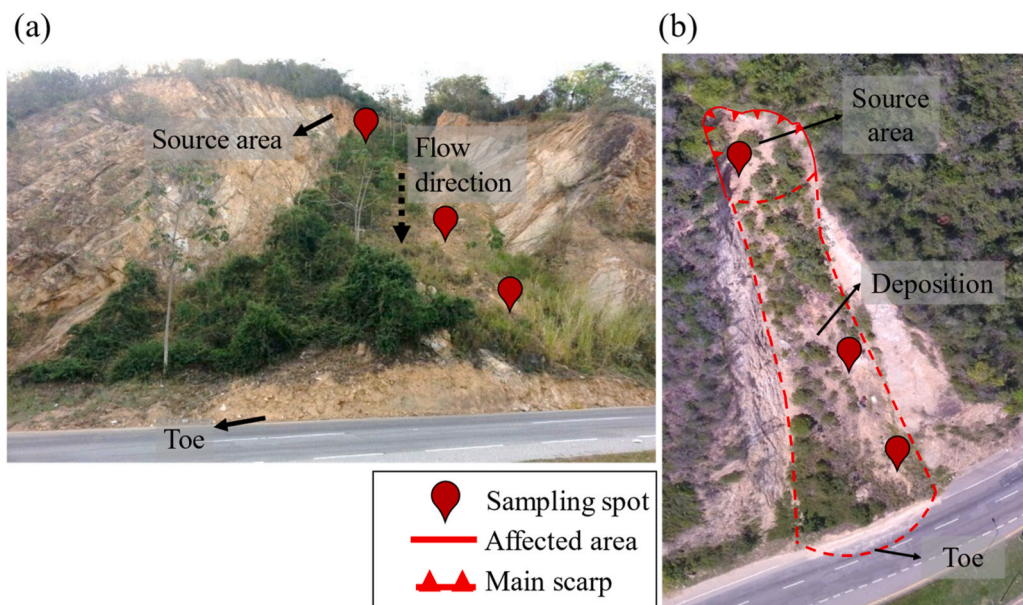


Fig. 4. Landslide case study: (a) Frontal view taken in front of the toe of the landslide deposits (b) Aerial view of the landslide identifying the failure zone, its deposit zone and its toe.

which has a resolution of 12 MP. The scanner samples a dot cloud consisting of between 6 and 8 million points at each station, with a range of up to 250 m. The precision of measurements derived from the point cloud, such as digital elevation models, ranges between 3 mm and 5 mm. Specifically, as shown in Fig. 4a, the terrestrial laser scanner was positioned on three stations in front of the landslide body to cover the entire area affected by the landslide.

Every point in the dot cloud is associated with an elevation and a relative position compared to the scanning position. Coordinates and the elevation of each point were retrieved by linking this information to the integrated GPS data.

Morphometric data compatible with diverse numerical modeling strategies were obtained by generating longitudinal and transversal profiles. The initial and final conditions, the landslide runout distance (LRD) and any other morphometrical parameters needed for modeling purposes, were estimated from the central profile displaying the maximum distance reached by the debris flow.

The landslide volume in most cases was estimated using simple cubature calculations based on the measured profiles, except for the 3D modeling approach. However, further details about this aspect will be given in subsequent sections. Fig. 5 shows the initial and final conditions of material depth (h) and distance from the landslide crown. These conditions will be used later to compare the performance of different models. As a general rule, all models will start from the same initial position.

2.3. Modeling the landslide runout distance

2.3.1. Geometrical approximations

Two different models based on geometrical approximations were used [14]. These approaches exploit the relationship between landslide magnitude and runout distance. The landslide magnitude is assumed to be equivalent to the triggered volume (V), commonly described by the three characteristic distances shown in Fig. 6: landslide width (W_R), depth (D_R) and length (L_R). Thus, the volume was estimated with $V = \left(\frac{1}{6}\pi D_R W_R L_R\right) f_{exp}$, where f_{exp} is an expansion factor, which was assumed as 1.5.

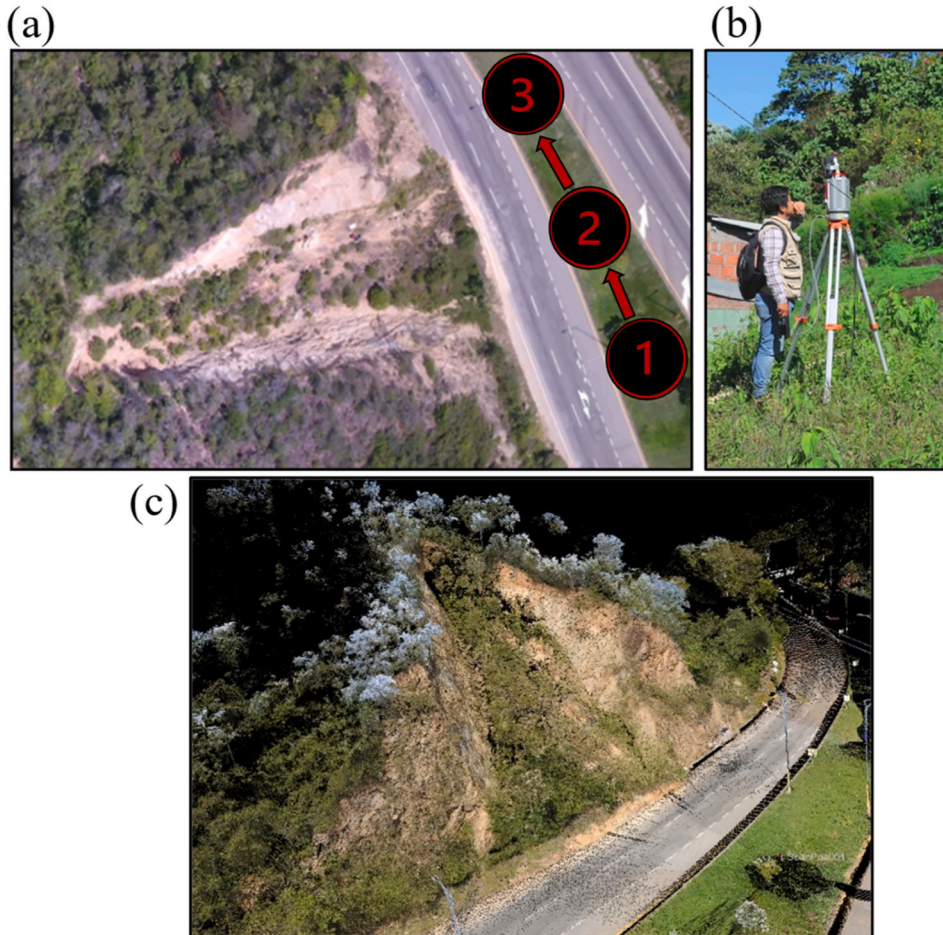


Fig. 5. Topographical campaign carried out on the studied landslide site: (a) consecutive topographical stations in front of the main landslide scarp (b) execution of the topographical survey using a Riegl VZ-400® station (c) Dot cloud product of the survey derived from the point and image processing.

In these models, the landslide runout (L) is defined as the horizontal distance affected by the material displacement. It is the horizontal projection of the line joining the crown of the landslide with its toe, as illustrated by the red dashed line in Fig. 6. The angle of the line is known as the reach angle and is related to the maximum drop height (H), by the equation $\alpha = \tan^{-1}(H/L)$ [40].

Two empirical relationships exploiting the relationship between L and V, were applied here. The first one, proposed by Corominas (1996) [40], is the logarithmic relationship depending also on H: $\log(H/L) = a + b \log(V)$. The second empirical relationship was developed for the study area, and was proposed by Roman Quintero et al. (2024) [14]. It only depends on V as an input variable, $L = a + bV$. The coefficients a and b are shown in Table 1.

In both cases, L was transformed from the horizontal projection, into the ground surface distance (LRD) supposedly affected by the landslide according to each model.

2.3.2. Machine learning model

A Random Forest (RF) model was built to assess L in the case study. RF is a machine learning technique that employs decision tree theory to capture relationships within a dataset, typically exhibiting relatively low bias [41]. This approach is used to predict a target variable using predictor variables through a collection of randomly generated decision trees, in either regression or classification contexts.

Since the Random Forest technique uses a large number of decision trees, the resulting model has a set of general parameters known as hyperparameters. The hyperparameters were calibrated by varying parameters and testing model error. Specifically, the training sample was varied among four values: 0.55, 0.632, 0.70, and 0.8. Meanwhile, the minimum leaf split was varied between 1 and 122. The error metric utilized was the Out-of-Bag Error (OOBE), which is the average error in prediction obtained by analyzing its performance on the training dataset. The optimal hyperparameters used here correspond to 80 % sample size, and 23 minimum leaf split, leading to $OOBE = 0.1746$.

Specifically, a regression-based Random Forest method was used to forecast H/L, with V serving as the predictor. The implementation of this technique was carried out using a freely available open-source algorithm in R (see documentation in the CRAN network, Package 'randomForest'). The training dataset used here is the same as that used by Corominas (1996), which consists of 204 landslide events with triggered volumes ranging from approximately $0.5 \cdot 10^1 \text{ m}^3$ to $5 \cdot 10^7 \text{ m}^3$. The ratios H/L range between 0.06 and 1.09. Finally, the model's performance was tested against a dataset of 49 landslides (including this case study), by comparing the relative error between the observed LRD and the predicted one.

2.3.3. Sliding block model

A sliding block model was used, treating the landslide as a rigid body. This model applies Newton's second law and the principle of work to simulate a block sliding down a path. The block is accelerated by gravity and slowed down by friction. We used a mathematical formulation expressed in equation (1) to represent the change in the block's kinetic energy as it moves down [22].

$$d\left(\frac{mu^2}{2}\right) = mg(\sin \beta - \cos \beta \tan \phi_{bed})dL \quad (1)$$

In equation (1), m is the block's mass, g is the acceleration of gravity, β is the inclination angle of the flow path, dL is the differential element of the sliding path where the velocity is intended to be estimated, and ϕ_{bed} is the friction angle between the landslide material and the slip plane, estimated from a direct shear test.

The model parameters are shown in Table 2. Note that the friction angle, ϕ_{bed} , was assumed to be equal to the residual friction angle of the material, derived from laboratory tests.

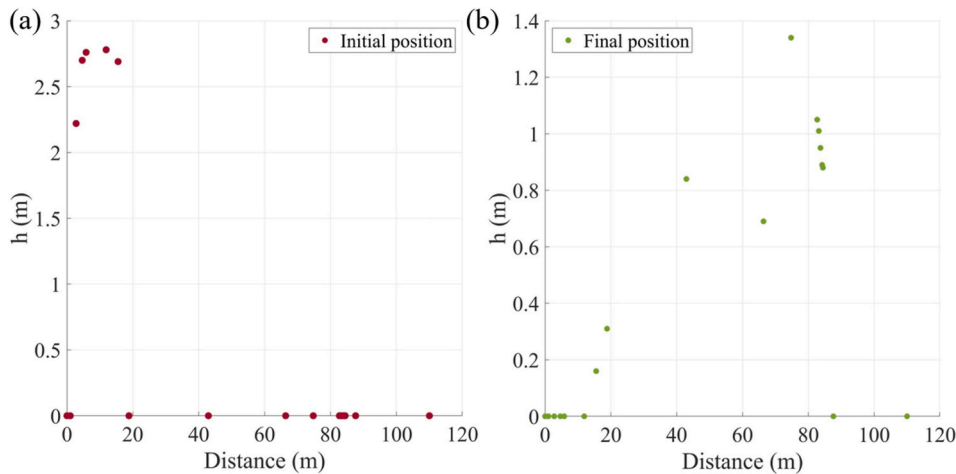


Fig. 6. Measured soil depths in a central profile for the (a) initial position and (b) final position of the Giron landslide.

Table 1

Model coefficients for the empirical geometrical approximations models of Corominas (1996) $\log(H/L) = a + b \log(V)$ and Roman Quintero et al. (2024) $L = a + bV$.

Equation	a	b
Corominas (1996)	-0.047	-0.085
Roman Q. et al. (2024)	172.16	$5.00 \cdot 10^{-4}$

The sliding block model was solved twice to estimate the landslide runout distance in this case. First, it was solved for the inclined section, as shown in Fig. 7, and then it was solved for the horizontal section representing the highway. The final velocity from the inclined section was used as the initial velocity for the horizontal part. The landslide runout distance was measured when the sliding block came to a stop on the horizontal section. It is noteworthy that the model underwent no further calibration.

2.3.4. Two-dimensional mass flow modeling

The model proposed by Iverson and Denlinger (2001), grounded in the theory of continuum mechanics for mixtures [42], was used here. Derived from a generalized set of equations encompassing the propagation of mass in all directions, this model specifically regards the primary momentum directions as parallel to the flow path surface.

The kinematics of the studied debris flow indicated a main momentum direction parallel to the slope inclination. The model was therefore simplified to account for velocity and momentum in that direction only. In this case, the model set of physical parameters are listed in Table 3. The friction angle at the base and the internal friction angle were considered to be equal. The solid and fluid fractions and the fluid viscosity were considered as suggested in literature for debris flows modeling [43,44].

It is worth noting that the model rigorously solves a one dimensional mass-momentum problem. Nonetheless, it provides information in two dimensions; the velocity component parallel to the main flow direction and the flow depth perpendicular to the main flow direction.

Furthermore, the parameters ensuring numerical stability and utilized for solving the model are listed in Table 4. A workstation with 32 GB of RAM and a 4-core Intel XEON processor was used.

2.3.5. Three-dimensional mass flow modeling

The three-phase, multidimensional model available in the r.avaflow package was used to simulate the multidimensional mass flow in the case study [45]. The model provides flow depth, perpendicular to the flow direction, and depth-averaged velocities in two components parallel to the flow direction, and perpendicular to each other.

The model was applied with a high-resolution, 30 cm Digital Elevation Model (DEM) derived from the topographical campaign. We used field observations and geomorphological analysis to create a raster map that defined the starting volume and location of the flowing mass. Using the r.avaflow platform, we solved the mass and momentum conservation equations with an explicit numerical scheme to simulate the landslide flow [46].

The initial velocity was set to zero, assuming a sudden release from rest. To solve the system, the multi-core computation mode with task parallelization was enabled, which allowed for multiple simulations varying key parameters, such as the viscosity of the fluid phase or friction coefficients, to explore their influence on flow dynamics.

Validation was performed by comparing the final simulated extent with the observed footprint of the event, using spatial overlap metrics and volumetric differences.

It is worth noting that, in this case the model solves the system of equations in two dimensions. Nonetheless, it provides three-dimensional information, including two velocity components parallel to the flow direction and the flow depth perpendicular to it.

For the three-dimensional analysis, the initial conditions related to the geometry of the slope were analyzed directly from the Digital Elevation Model derived from LiDAR topography results, and the initial dimensions of the triggered mass were estimated automatically by an integrated routine in r.avaflow, directly from this very detailed information.

Fig. 8 show the initial conditions of the material depth extrapolated from the morphometrical dispositions within the DEM; the contour lines represent the elevations above sea level of the terrain surface sampled in the area, indicating the vertical drop of the movement.

Three sets of parameters were used to calibrate the model and test the model performance in order to analyze the case study, varying two of the most important parameters: the solid/fluid fraction and the internal/basal friction angle. Table 5 summarizes the parameters used for each model.

The model parameters include phase-specific properties such as internal and basal friction angles ϕ_{int} and ϕ_{bed} , respectively. In this

Table 2

Physical parameters used in the sliding block model approach.

Parameter	Value
Friction angle, ϕ_{bed} (°)	30.85
Inclination of the slope, β (°)	34.60
Gravitational acceleration, g (m/s ²)	9.81
Initial velocity, u_i (m/s)	0

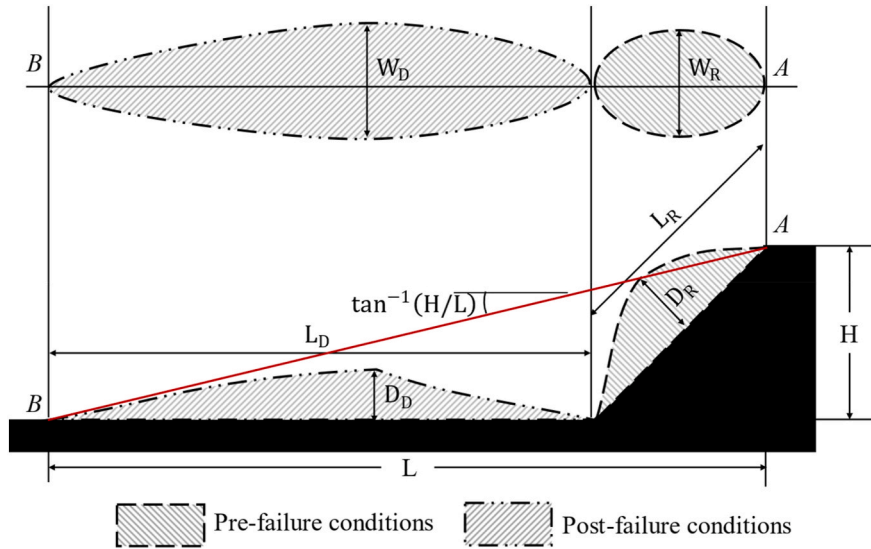


Fig. 7. Scheme with typical distances characterizing the morphometry of landslides in pre-failure and post-failure conditions. Adapted from [27].

Table 3

Input physical parameters for the bidimensional flow model.

Parameter	Value
Friction angle at the base, ϕ_{bed} (°)	30.85
Internal friction angle, ϕ_{int} (°)	30.85
Solid volume fraction, v_s	0.6
Fluid volume fraction, v_f	0.4
Mix density, ρ (kg/m ³)	1462
Fluid viscosity, μ (Pa · s)	0.1

Table 4

Parameters ensuring numerical model stability used for simulation with the bidimensional model.

Parameter	Value
Number of nodes (–)	8800
Mesh step (m)	0.0125
Time step (s)	0.001
Number of corrective cycles (–)	3
Max. Number of iterations (–)	1000
Admissible error: flow depth (m)	0.0001
Admissible error: flow velocity (m/s)	0.0005

way, the residual shear strength angle was analyzed along with literature values for the peak shear strength angle. The solid and fluid densities (ρ_s , ρ_f respectively), fluid shear elastic limit (τ_Y) and fluid viscosity (ν), were assumed from literature and preliminary calibration [45].

The initial volume fractions for the solid and fluid (α_s and α_f , respectively) were assigned according to the dominant material type and estimated saturation conditions within a range of values previously proposed in literature and according to the grain size distribution analysis carried out in the present study [45].

A total of 592 time steps ($n_{out} = 592$) were executed to simulate 9 s of physical time, enabling a detailed representation of flow evolution, kinetic energy, and the spatial distribution of solid and fluid phases. The number of active cells per time step (n_{sum}) and CFL values (~ 0.37) indicate numerically stable performance using the explicit NOC-TVD scheme, without requiring adaptive mesh refinement.

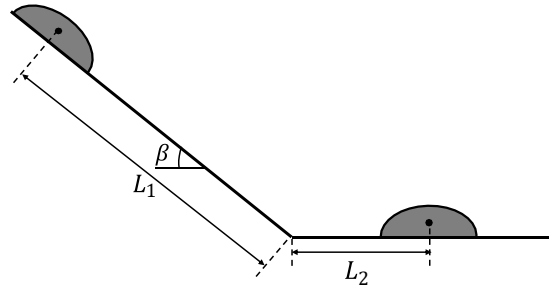


Fig. 8. Schematic representation of the domain simulated with the sliding block model composed by two sections: an inclined section representing the slope part and a horizontal section representing the highway acting as a deposition zone.

Table 5

Physical parameters used for the tridimensional mass flow model in three different model runs: model 1 using residual friction angle, model 2 using peak friction angle and model 3 using peak friction angle with greater solid/fluid volume fraction.

Parameter	Model 1	Model 2	Model 3
Friction angle at the base, ϕ_{bed} ($^{\circ}$)	30.85	35.0	35.0
Internal friction angle, ϕ_{int} ($^{\circ}$)	30.85	35.0	35.0
Solid volume fraction, α_s	0.6	0.6	0.9
Fluid volume fraction, α_f	0.4	0.4	0.1
Solid density, ρ_s ($kg\ m^{-3}$)	2700	2700	2700
Fluid density, ρ_f ($kg\ m^{-3}$)	1400	1400	1400
Fluid phase elastic limit, τ_Y (Pa)	10	10	10
Kinematic fluid viscosity, ν ($m^2\ s^{-1}$)	10^{-3}	10^{-3}	10^{-3}

2.4. Evaluation of the LRD modeling strategies

2.4.1. Landslide vulnerability assessment

A basic model performance metric was calculated by assessing the Relative Error (RE) between the observed and modeled LRD, defined as $RE = (LRD_{obs} - LRD_{mod})/LRD_{obs}$.

Additionally, the vulnerability of the exposed elements was estimated according to the outcome of each model to further evaluate the implications of estimating LRD with different modeling strategies. The adopted vulnerability model is presented in equation (2), and is referred to here as Function 1 [20]. This model is relevant to the study as, while developed in international contexts, it is proposed for use in the Colombian guideline for landslide hazard, vulnerability, and risk assessment [20,27].

$$V = \begin{cases} \frac{1}{2} \left(\frac{I}{1-S} \right)^2, & I \leq 1-S \\ 1 - \frac{1}{2} \left(\frac{1-I}{S} \right)^2, & I > 1-S \end{cases} \quad (2)$$

V , I and S are the vulnerability, landslide intensity and susceptibility of the exposed elements. The landslide intensity was estimated as $I = L_A/W_{TR}$, where L_A is the distance affecting the highway from the LRD estimation, and W_{TR} is the total roadway width, which is 35 m in this case. For comparison, vulnerability was also evaluated as $V = I \cdot S$, referred to here as Function 2 [21].

The susceptibility was assessed differently for the road structure and persons. For the road it was estimated as $S_R = 3/W_{ER}$, where 3 is the minimum road width required for a vehicle to be able to continue its way and W_{ER} is the paved roadway available in the studied section, 24 m in this case. Conversely, for persons it was assumed the model proposed by Uzielli et al. (2008) [21]: $S_P = 1 - (\xi_{PDN})(1 - \xi_{GDP})(1 - \xi_{AGE})$. The model considers three factors: the population density factor (ξ_{PDN}), the income factor (ξ_{GDP}) and the age factor (ξ_{AGE}). Only ξ_{AGE} was neglected. In turn, ξ_{PDN} and ξ_{GDP} were assumed as 0.11 and 0.05, respectively, according to population information in the studied region. Thus, the susceptibility values of road structure and persons were estimated as $S_R = 0.13$ and $S_P = 0.16$.

2.4.2. Analytical Hierarchy Process framework

To compare the strengths and weaknesses of different landslide runout models, the Analytic Hierarchy Process (AHP) was used. This method, developed by Saaty (1980), allows for the evaluation of each model based on five categories that consider both its predictive accuracy and the practical effort needed for implementation [47].

The method is based on structured pairwise comparisons between criteria or categories, allowing the decision-maker to express

judgments about the relative importance of each category or criterion.

The categories and criteria used to evaluate the modeling strategies are described in Table 6. The final composite score was evaluated as $\Gamma = \mathbf{M}\mathbf{v}_c$, where Γ is a score vector ranking the models under evaluation, $\mathbf{v}_c$ is the relative importance vector comparing the categories and the criteria evaluating the models, and $\mathbf{M}$ is the pairwise performance score of the models within each category under evaluation. $\mathbf{v}_c$ was estimated from expert judgement and $\mathbf{M}$ was estimated from the performance of every model against every category.

3. Results

3.1. Comparative analysis of runout modelling

Fig. 9 shows the final conditions of the landslide mass derived from site observations in the studied case, and also the final modeled conditions using all different modeling strategies. Apart from the empirical model by Roman Quintero et al. (2024), based on geometrical approximations, all models calculated the LRD around the observed one with a relative error of $\pm 20\%$. Table 7 summarizes the estimated LRDs, RE, required computational time (T) and different key parameters required for the estimation.

The models applying the Random Forest and Corominas (1996) underestimate the LRD by 17.9 % and a 9.5 %, respectively. In turn, the model presented by Roman Quintero et al. (2024) overestimates the LRD by 122.6 %. The outcome of such models may range within an Inter Quartile Range (IQR) of about 100 % of the observed LRD, as shown in Fig. 10.

Conversely, analytical models show better performance in LRD prediction, as seen in Fig. 9. First, in the case of the sliding block model, it overestimated the observed LRD in about 14 %. However, even if the application of this model requires some extra information compared to the empirical models, it is still relatively easy to apply, without needing very sophisticated tools for assessing LRD.

Second, in the case of the bidimensional mass flow model, a total of 10 s were simulated and it came to rest after 7.64 s at a distance of 86.32 m, overestimating the observed LRD by about 3 %. In this case, due to the complexity of the physical and numerical requirements of the model, the implementation is more challenging than the previous applications; the computational time exceeded 24 h to solve the numerical simulation.

Third, in the case of the three-dimensional mass flow model, three different model configurations were tested. From Fig. 9 and Table 7 show that model 3 reached a RE overestimating LRD only by 0.71 %. Models 1 and 2 overestimated LRD by 18.7 % and 12.5 %, respectively. An accurate estimation of triggered volume and flow path was fundamental for this modeling strategy. However, in the case of this model, r.avaflow presents a convenient numerical solver, implementing parallel computing and reducing simulation times, completing every simulation in approximately 200 s each [2,17,20,36].

3.2. Vulnerability analysis and model evaluation

Fig. 11 presents the difference between the vulnerability calculated with the observed LRD and the vulnerability estimated through vulnerability Function 1 and Function 2, using the LRD from each tested model. The vulnerability of the highway and persons estimated with the observed LRD corresponds to $V_R = 0.0427$ and $V_P = 0.0466$, respectively (see Fig. 12).

Empirical models severely overestimate and underestimate observed vulnerability conditions. In turn, the sliding block and three-dimensional models 1 and 2 overestimated vulnerability by around 15 % and 30 %, with vulnerability Function 1, and around 4 % and

Table 6

Categories proposed for the evaluation of different modeling alternatives in the assessment of the LRD.

Category	Description	Criteria
Complexity	It evaluates the complexity of the models from a physical, mathematical, and conceptual standpoint.	• User training level required; • Required parameters and calibration needs; • Unidimensional model; • Multidimensional model.
Applicability	It evaluates the ease of application of the model, specifically how straightforward it is to apply it in a case study.	• Software availability; • Ease of implementation; • Application scale; • Experimental data availability.
Accessibility	It assesses how easily users can obtain and use the model and the results derived from its application.	• Model licensing; • Operating system compatibility; • Source code availability; • Technical support
Requirements	It evaluates the basic requirements needed to access and use the model.	• Required data; • Internet access; • Interface and compatibility; • Computational capacity.
Functionality	It evaluates the functional performance of the model, focusing on its predictive behavior and associated uncertainties.	• Uncertainty in model output; • Error in the simulated LRD; • Overestimation of LRD; • Underestimation of LRD.

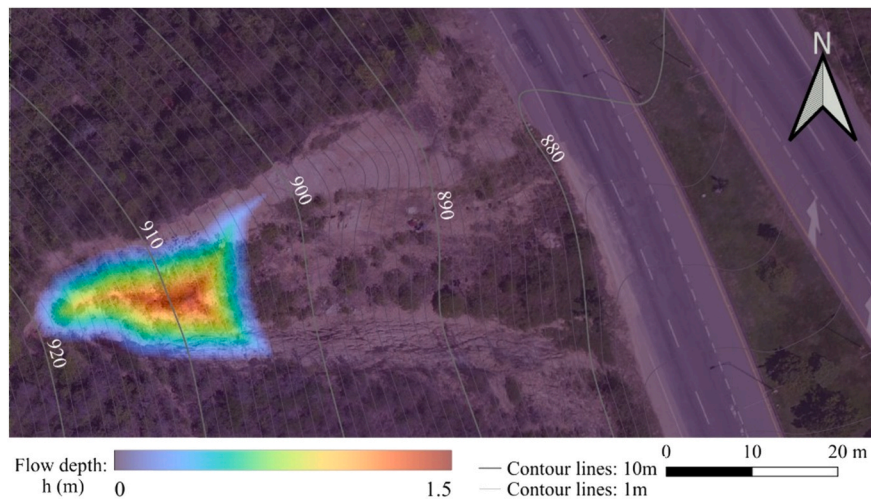


Fig. 9. Initial conditions estimated for the simulation of the runout distance in the case study.

Table 7

Different modeled landslide runout distance (LRD), its relative error (RE) compared to the landslide case and computational time (T) required. Key parameters are listed for comparative purposes (S) stands for Simplified and (D) for detailed.

Model	LRD (m)	RE (%)	T (s)	Key parameters
Random Forest	69.0	-17.86	<1	Triggered volume; (S) flow path
Corominas (1996)	76.0	-9.52	<1	Triggered volume; (S) flow path
Roman Quintero et al. (2024)	187.0	122.62	<1	Triggered volume; (S) flow path
Sliding block model	95.8	14.00	<1	Friction angle; slope inclination; (S) flow path
Bidimensional model	86.0	2.38	>86400	Friction angle; solid/fluid fraction; mix density; fluid viscosity; (S) flow path
Tridimensional: Model 1	99.7	18.69	~200	Friction angle; solid/fluid fraction; solid/fluid density; fluid phase elastic limit; kinematic fluid
Tridimensional: Model 2	94.5	12.5	~200	viscosity; (D) flow path
Tridimensional: Model 3	84.6	0.71	~200	

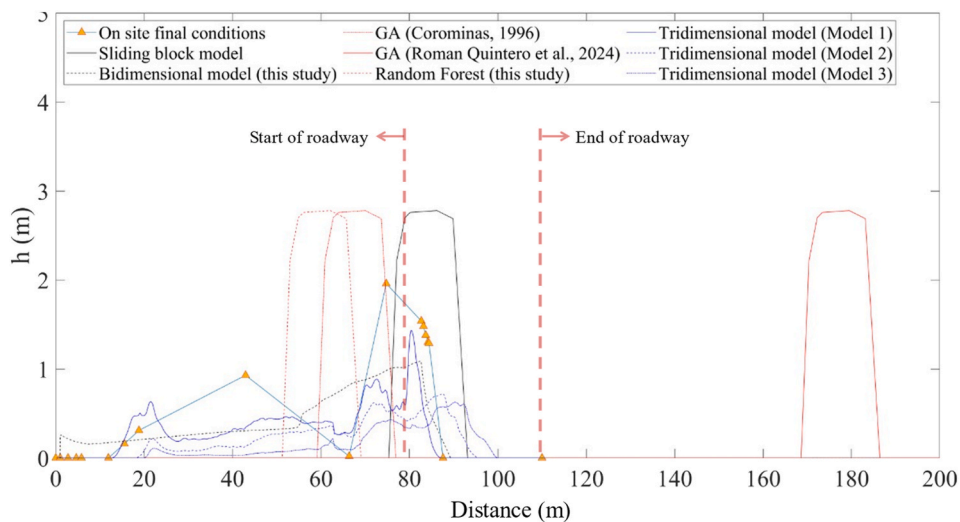


Fig. 10. Comparison of the final position and the resulting runout distance between actual and simulated flow depths using: the sliding block model, the bidimensional model, the Geometric Approximations (GA), the Random forest model and three simulations based on the tridimensional approach.

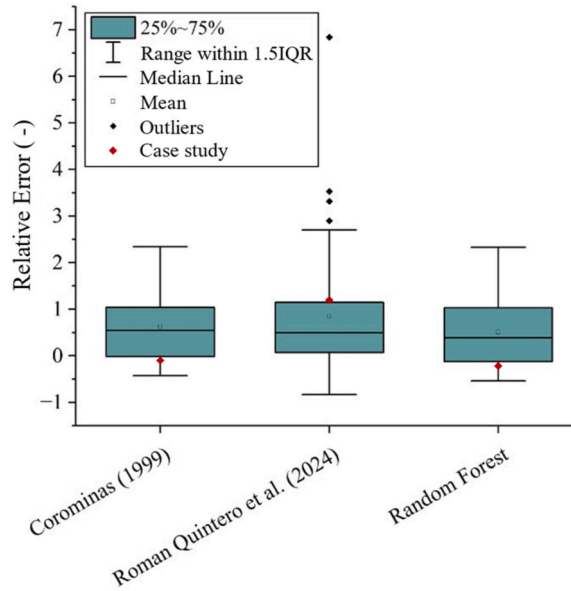


Fig. 11. Distribution of the Relative Error in the estimation of the Landslide Runout Distance by using three different empirical models.

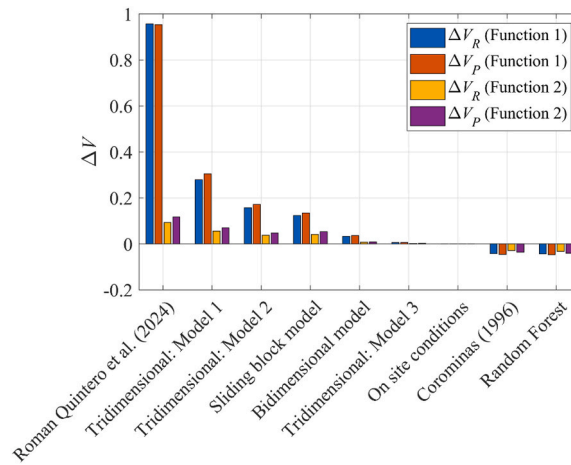


Fig. 12. Difference in vulnerability values for roads (V_R) and persons (V_P) evaluated from modeled LRD, and the vulnerability value with observed on-site conditions (baseline = 0), using vulnerability Functions 1 and 2. Positive values indicate an overestimation of vulnerability, while negative values indicate underestimation.

12 % with vulnerability Function 2. The two-dimensional model and three-dimensional model 3 showed the best performances, overestimating vulnerability by less than 3 % with both vulnerability Functions 1 and 2.

Table 7 presents the evaluation results of each model based on the criteria defined in Section 2.4, which are represented in matrix **M**. Regarding the Complexity and Applicability criteria, the evaluation indicates that models requiring fewer parameters receive higher scores, with the geometrical approximations and random forest models in the first places and the three-dimensional model ranked at last. In terms of applicability, multidimensional models receive the lowest scores, particularly the two-dimensional model, due to its demanding computational time and other requirements.

Concerning Accessibility, the two-dimensional model again scores lowest, due to the unavailability of a public numerical implementation. In contrast, for the other models, numerical solver availability is relatively straightforward.

For the Requirements criterion, empirical models clearly show advantages. The model by Roman Quintero et al. (2024) leads in this category, receiving nearly 30 % of the total score, as it only requires the triggered volume to produce an estimate.

Finally, regarding Functionality, analytical models stand out, showing better performance. In particular, the three-dimensional flow model (Model 3) slightly overestimates the LRD. Conversely, empirical models are penalized more heavily, specially due to their tendency to over- or under-estimate results. However, the model by Roman Quintero et al. (2024), despite significantly

overestimating LRD, is penalized less severely.

Furthermore, the importance of the criteria was also evaluated. The results are briefly summarized in Table 8, representing v_c . Clearly, the most important characteristics of a model are those related to its Functionality, which accounts for up to 49 % of the total score. This criterion, in fact, addresses more than just model accuracy. On one hand, it encourages the controlled overestimation of LRD, which provides a conservative estimate of vulnerability. On the other hand, it strongly discourages any underestimation of LRD, as this could lead to false negatives and potentially catastrophic consequences.

However, other factors, particularly those in the Requirements and Applicability categories, also play a significant role in model evaluation. Notably, applicability and requirements receive equal weighting, as both contribute to assessing a model's feasibility for practical use.

Table 9 shows the final evaluation (Γ , as defined in Section 2.4) of every model according to every category. The sliding block model achieves the highest overall score, despite overestimating LRD and vulnerability. The model demonstrates clear advantages in applicability and accessibility, which help balance its relatively minor lack of accuracy. In second place, is the three-dimensional model, ranking just below the sliding block model. Although it achieves very high accuracy, its scores for complexity, applicability, and requirements are particularly low. The tested two-dimensional model's score drops into the same range as the empirical models. This is due to its lack of accessible code or software and low applicability, which is driven by the long computational times required for simulation. Empirical models based on geometrical approximations complete the ranking. The model by Roman Quintero et al. (2024) performed closest to the two-dimensional model, while the models by Corominas (1996) and Random Forest critically underestimated the LRD and resulting in zero vulnerability values, are in the last places (see Table 10).

4. Discussion

4.1. Effects of modeling strategies on landslide runout estimation

Results outlined an overall evaluation framework for LRD modeling approaches, including both empirical and analytical methods. On one hand, Empirical models based on geometrical approximations provide straightforward means to estimate LRD, requiring only limited input data such as the landslide volume and, in some cases, the potential fall height. Their main advantages lie in simplicity, broad applicability, and minimal data requirements. However, these benefits come at the cost of considerable variability, with a standard relative error of 78 %. Among the tested approaches, the model by Corominas (1996) produced estimates closer to the observed LRD but underestimated the runout, suggesting that the landslide would not reach the road. The Random Forest model, trained on data from Corominas (1996), reproduced a similar level of variability yet resulted in an even stronger underestimation. Conversely, the model by Roman Quintero et al. (2024) substantially overestimated the LRD, even covering the entire road structure. Despite these discrepancies, such deviations that overestimate LRD, remain valuable for identifying areas that warrant further, more detailed analyses.

On the other hand, the analytical LRD modeling results suggest that the granular nature of the debris material plays a key role in controlling the frictional flow regime [2,36], and consequently, the overall debris flow behavior and deposition patterns. Using the residual shear strength angle as input consistently produced low relative errors across all analytical strategies. Moreover, the 3D model indicated that increasing the solid fraction yielded the most accurate results, emphasizing the dominant influence of solid content and interparticle interactions on LRD.

A major advantage of analytical approaches is their ability to estimate coupled flow depth and velocity, a feature unavailable in empirical models. Although not explored in detail here, this capability is particularly useful for designing mitigation measures and evaluating vulnerability, such as defining safe inundation zones [17,20]. Specifically, 2D and 3D mass-flow models capture spatial variations in flow depth within the computational domain, providing valuable insights for estimating dynamic pressures on structures (e.g., walls or check dams) and delineating safe corridors for evacuation [32,33]. However, the effort and expertise required increase substantially from simple empirical models to multidimensional analytical approaches. These latter methods demand specialized hardware, a solid understanding of the underlying physics and mechanics, and advanced numerical modeling skills.

Table 8

Pairwise performance score matrix ($\mathbf{M}$) evaluating the six different modeling strategies in the application of the case study according to the defined five different criteria.

Model	Criteria				
	Complexity	Applicability	Accessibility	Requirements	Functionality
GA-Corominas (1996)	21.89 %	28.77 %	19.50 %	20.64 %	5.85 %
GA-Roman et al. (2024)	21.89 %	25.43 %	19.50 %	29.75 %	8.44 %
Random Forest	21.89 %	14.39 %	19.50 %	20.64 %	5.85 %
Sliding block	14.22 %	16.05 %	18.33 %	13.05 %	23.70 %
Bidimensional	11.23 %	5.12 %	7.81 %	9.41 %	26.15 %
Tridimensional	8.87 %	10.24 %	15.34 %	6.53 %	30.01 %

Table 9
Relative importance vector (v_c) evaluating the five criteria under consideration in the present study.

Criteria	Evaluation
Complexity	8 %
Applicability	16 %
Accessibility	11 %
Requirements	16 %
Functionality	49 %

Table 10
Final evaluation metric (Γ) of the different modeling strategies implemented in the present study.

Ranking	Model	Evaluation
1	Sliding block	19.83 %
2	Tridimensional	19.64 %
3	Bidimensional	16.90 %
4	Roman et al. (2024)	16.79 %
5	Corominas (1996)	14.53 %
6	Random Forest	12.31 %

4.2. Landslide runout modeling and vulnerability assessment

This study goes beyond comparing relative errors (RE) in LRD estimation by examining how different modeling strategies influence vulnerability assessments for road infrastructure and exposed individuals. Two vulnerability functions relating susceptibility to landslide intensity were tested: a piecewise quadratic (Function 1) and a linear one (Function 2). Both performed similarly when vulnerability was underestimated; however, Function 1 was markedly more sensitive to LRD overestimations, producing higher vulnerability estimates, particularly with the model proposed by Roman Quintero et al. (2024). This feature makes it more sensitive to uncertainties linked to LRD modeling, a desired characteristic yielding conservative results as the landslide hits the road.

Vulnerability and risk analysis of landslides remains challenging due to their complex, diverse nature and the fragmented treatment of initiation, runout, and consequence models, which limits method transferability and consistency. Frameworks such as the third-generation Multimodal Method (MM3) address these issues by integrating initiation, runout, and vulnerability components, combining physically based groundwater modeling, dynamic runout with rockfall fragmentation, and intensity-dependent vulnerability functions [31,48–50]. Analytical runout models like r.avaflow, DAN3D, and RAMMS-DF, based on continuum mechanics and Voellmy–Salm rheology, generate hazard intensity metrics (i.e. runout distance, flow depth, velocity, and impact pressure) directly linked to vulnerability [51,52]. However, parameter calibration remains a key limitation: site-specific tuning is often required [51,53], reducing model transferability across geological contexts (e.g., Alps vs. Andes). Ongoing research aims to relate frictional properties to intrinsic material characteristics or fluctuation energy to enhance generalization [53,54]. Overall, the analytical models tested here resulted in a controlled overestimation of landslide vulnerability, regardless of the dimensionality adopted by the modeling strategy.

In contrast, empirical models provide simpler, data-efficient tools for preliminary or large-scale vulnerability assessment. They rely on geometric correlations derived from regional inventories (e.g. fall height–runout ratios or landslide length normalized by area) and even incorporate parameters like slope curvature and upslope contributing area [14,48]. The models tested here showed the highest variability, with REs within an interquartile range reaching up to ~ 100 % of LRD. In fact, these models either largely overestimated the observed vulnerability conditions or underestimated them, resulting in null vulnerability assessments.

Given the complexity and uncertainty inherent in landslide processes and their runout estimations, rigorous landslide vulnerability and risk assessments must explicitly propagate uncertainty through the full modeling chain, from initiation (e.g., triggering factors) to runout (morphometrical/rheological variables) and vulnerability (damage functions). In this context, two clear paths emerge: (1) narrowing model output variability, particularly for empirical models, and (2) assessing uncertainties underlying modeling strategies. The Monte Carlo approach, implemented in frameworks like MM3, enables uncertainty propagation to produce probabilistic, scenario-based risk estimates [31]. However, such methodologies rely on parametric probabilistic assumptions driving the functions behind Monte Carlo simulations, an aspect that has been scarcely studied and requires rigorous evidence to statistically validate its applicability to these processes. For instance, exploring non-parametric approaches, such as the Generalized Method of Moments, could provide an alternative or complement to the aforementioned parametric methods.

5. Conclusions

This study presents a comprehensive evaluation of landslide runout modeling approaches (namely empirical, analytical, and multidimensional) applied to a well-documented debris flow event. The landslide, involving approximately 340 m^3 of low-plasticity sandy soil and rocks, shows evidence of a dense, high-frictional flow regime, with a measured runout distance of 84 m and a vertical drop of 42 m. The vulnerability of people and infrastructure was assessed through two different functions (i.e. a piece-wise quadratic

function and a linear function) using each model's predicted landslide runout distance (LRD). Model performance was benchmarked against observed data and evaluated through a multi-criteria Analytical Hierarchy Process (AHP) framework.

Empirical models, such as those by Corominas (1996) and Roman Quintero et al. (2024), proved useful for rapid screening but showed significant variability and inconsistent predictions, with estimated runout distances underestimating and overestimating the observed runout by up to 120 %. A Random Forest approach, while overall efficient (OOBE = 0.17), still displayed a wide uncertainty and underestimated runout by about 18 %, leading to zero vulnerability estimations in this case, highlighting the limitations of these data-driven methods when detached from physical constraints.

Analytical models, particularly the sliding block model, offered a strong compromise by estimating runout with moderate overestimation (+14 %) and providing valuable flow velocity data, critical for the design of mitigation measures. Though conservative, such overestimation is could be admissible in this context.

The two-dimensional model achieved near-perfect accuracy at the cost of high computational demand, while the three-dimensional r.avaflow simulation delivered the most robust results when calibrated with high-friction parameters and GIS integration, supporting precise runout estimations.

In this particular studied case, on-site evidence and model estimations suggest an important role of frictional contacts on landslide runout and deposition. This may explain the overall good performance of the sliding block model when compared with the other two analytical models.

Finally, the AHP framework facilitated a balanced comparison across the models' evaluation criteria (i.e. functionality, complexity, accessibility, applicability and requirements), ranking highest the sliding block model, overall due to its strong functionality and practical accessibility. While empirical models may still be suitable for rapid assessments, and 2D/3D models for high-stakes, site-specific design, this study reaffirms that a balance between simplicity and functionality, such as rapid but accurate LRD predictions and low output uncertainty, outweighs extreme simplicity or extreme complexity in some applications.

In summary, the choice of LRD model must be aligned with the intended purpose.

- **Empirical modeling** displays high uncertainties in LRD estimations, serving for quick or preliminary assessments when lacking physically related input data. These models can be integrated into national or regional scale early warning systems or used for nationwide hazard mapping due to their low data requirements.
- **Sliding block model** balances accuracy and efficiency with few data requirements, displaying an optimal trade-off between model's evaluation criteria in high frictional and small to medium-sized debris flows. Its simplicity makes it ideal for quickly designing initial, conservative mitigation structures (like retention barriers) where rapid prototyping is needed.
- **Multidimensional simulations** are suited for high-impact zones, requiring detailed spatial planning and material characterization but delivering realistic LRD and vulnerability approximations. The detailed outputs (velocity, depth) can be used to generate dynamic evacuation routes or to define precise safety factors for specific structures (like bridges).

As the field evolves, multidisciplinary collaboration is essential to close the gap between empirical simplicity and analytical depth, ensuring context-appropriate, transparent, and defensible landslide susceptibility and vulnerability assessments.

CRediT authorship contribution statement

Miguel Angel Alvarez Jaimes: Writing – review & editing, Writing – original draft, Visualization, Validation, Investigation, Formal analysis, Data curation. **Daniel Camilo Roman Quintero:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Jose David Ortiz Contreras:** Writing – original draft, Visualization, Validation, Investigation, Formal analysis, Data curation. **Diego Fernando Bedoya Rios:** Writing – original draft, Validation, Supervision, Investigation, Formal analysis. **Mauricio Alberto Tapias Camacho:** Writing – review & editing, Writing – original draft, Supervision, Resources, Methodology, Funding acquisition, Formal analysis, Conceptualization.

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Declaration of competing interest

The authors report there are no competing interests to declare.

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interdisciplinary insights into landslide runout distances in Colombia's North-East Andean region.

To promote further research, the authors encourage interested researchers to explore the **open-access Colombian landslide inventory**, freely available at: <https://simma.sgc.gov.co>.

Data availability

Data will be made available on request.

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