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SEISMIC RISK OF SLOPES CONSIDERING UNCERTAINTIES IN GEOTECHNICAL VARIABLES

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Abstract

The dynamic interaction between soil and slopes plays an important role in seismic risk assessment. This study aims to evaluate such interaction from a probabilistic perspective by integrating seismic records propagated through random soil profiles. The main objective is to characterize the seismic response of slopes under varying subsoil conditions and to quantify the impact on possible risk scenarios. The methodology consists of generating random soil profiles and simulating the propagation of seismic waves by means of the equivalent linear analysis to obtain signals at surface level. These signals are used to assess the response of a slope via Newmark's methodology. Then, statistical cloud analysis is used to relate intensity measures and dynamic soil properties to main slope response parameters. Preliminary results indicate that incorporating variability in soil profiles significantly affects the seismic response, highlighting the importance of accounting for probabilistic uncertainty. This approach not only advances the understanding of soil-slope interaction under seismic loading, but also provides a robust computational framework for integrating probabilistic methods into landslide risk assessment.

Keywords: Slope stability, non-linear effects, seismic risk, time-dependent risk assessments.

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1 INTRODUCTION

The dynamic response of soil to seismic actions is a highly nonlinear phenomenon involving multiple random variables [1]. This complexity arises not only from the characteristics of the seismic event, such as the type of rupture, depth of the earthquake, and distance to the epicentre, but also from local site conditions and the mechanical properties of the medium through which seismic waves propagate. In particular, these waves significantly alter the dynamic properties of the soil at low shear strain levels [2], with such variation being more pronounced in near-surface layers. Therefore, proper modelling of the seismic response of shallow soils must consider both the nonlinearities of the medium and the randomness of the involved variables.

This characterization is especially relevant for slope stability analysis, where the accelerations transmitted from the soil profile to the base of the slope are critical for calculating permanent displacements, as described by the Newmark method [3]. This method, widely used in seismic landslide hazard assessment, is based on the analogy of a rigid block that slides when the acceleration exceeds a threshold resistance to sliding. However, most studies implementing this approach assume deterministic subsoil conditions, which may underestimate or overestimate the dispersion of the induced displacement. In this regard, incorporating the propagation of seismic signals through random soil profiles enables more realistic estimates of surface motion, which directly impacts better prediction of the slope's dynamic performance.

Based on this premise, this study proposes a probabilistic framework to analyse the dynamic interaction between the soil and the slope, considering the variability of geotechnical profiles. It begins with a detailed site characterization, using geotechnical data derived from extensive investigations conducted in Bogotá, Colombia, to generate synthetic soil profiles that are statistically compatible with the observed data. Actual seismic records, selected from Colombian Geological Survey, SGC [4] databases, are then propagated through these profiles using equivalent linear dynamic analyses. The resulting surface signals are used as input for a simplified slope model, whose dynamic response is analysed using the Newmark method.

In addition, statistical tools such as cloud analysis [5] are employed to establish causal relationships between intensity measures (IMs), dynamic soil properties, and slope response parameters (Engineering Demand Parameters, EDPs). This allows for identifying the variables that represent the dynamic response of the soil-slope system and for deriving fragility functions that incorporate the uncertainty of both seismic hazard and geotechnical media.

This work not only contributes to the understanding of soil-slope interaction under seismic loading but also provides a robust tool for integrating probabilistic methods into seismic landslide risk assessment, with direct applications in the design and management of critical infrastructure located in unstable areas.

2 PROBABILISTIC SOIL MODEL

A probabilistic soil model is used in geotechnical applications to consider the spatial [6] and temporal [7] variability of soil properties. The objective is to measure how these uncertainties influence the dynamic response of the slope. The randomness of soil properties (e.g. stiffness and damping) are simulated using statistics methods and laboratory tests. As commented above, this paper adopts the computational framework presented in Zapata-Franco et al., 2023, which allows for:

a) Random generation of the dynamic features of the modelled soil profile (G_i, ρ_i, ξ_i and h_i stand for shear modulus, density, damping and layer thickness, respectively).
b) Introduce a ground motion record at the bedrock level of a probabilistically simulated soil profile.
c) Estimate the stiffness degradation and increase of damping of each soil layer based on the equivalent linear method.
d) Calculate the resulting ground motion at the surface, after propagating through the soil profile, considering the degradation of soil properties.
e) The resulting ground motion estimated in the previous step could act at the base of a civil infrastructure (Building, bridge, slope, etc).

A schematic representation of these steps can be seen in Figure 1. The main objective of this research is to investigate the causal relationship between IMs, which characterize the wave propagated through the soil, and EDPs, which reflect slope stability. This approach enables a more comprehensive understanding of how site-specific dynamic properties influence slope behaviour under seismic loading.

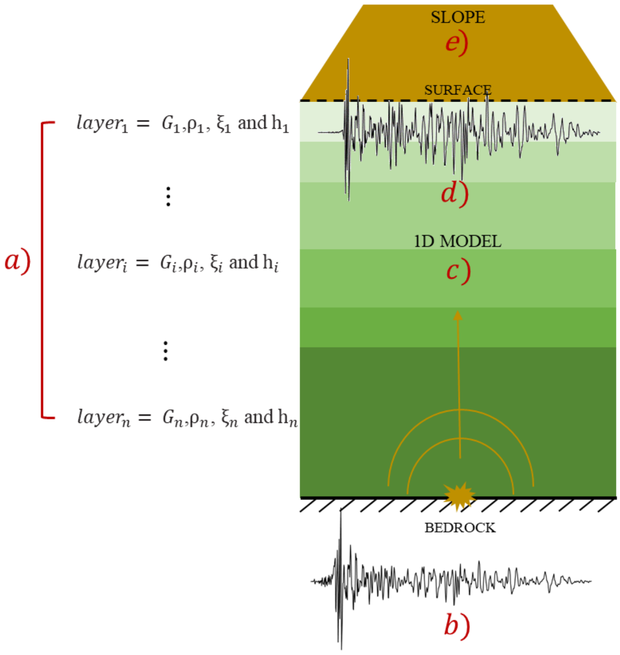

Figure 1: Computational framework diagram

These steps have been applied after generating samples of soil profiles affected by ground motion records randomly selected from a seismic database. It is preferable that these records were acquired at seismic stations where the rock comes to the surface.

3 PROBABILISTIC SOIL MODEL

3.1. Case of study: Bogotá Microzonation

Since 1993, Bogotá's Mayor Office has conducted seismic microzonation studies to enhance infrastructure design and identify zones with similar seismic behaviour [9]. As a result, a seismic zonation map has been developed, dividing the city into six main zones and 16 subzones based on factors such as bedrock depth, soil characteristics, ground thickness, fundamental period, and site effects.

This study focuses on lacustrine soils, the city's most significant deposit type, characterized by soft clays with interbedded sand, ash, and peat, with thicknesses ranging from 50 m to over 300 m. These soils exhibit fundamental vibration periods from 1.1 s to 5.8 s and shear-wave velocities from 140 m/s to 340 m/s, depending on depth. Notably, strong amplification at long periods (2–2.5 s) occurs due to the basin's shape and soft soil conditions.

Out of more than 20 studied sites, 10 are located in lacustrine zones. Table 1 presents the characteristics of these stations, including location, deposit thickness, number of layers, vibration periods, maximum amplitudes, and average shear-wave velocities, along with median values for each parameter.

Soil Profile	Station name	Latitude	Longitude	Length (m)	Number of layers	Fundamental period (T_i)			Max Amp.	Vs_{avg} (m/s)
						T_1 (s)	T_2 (s)	T_3 (s)		
1	CBANC	4.7085	-74.0789	50	11	1.5	1.2	0.5	14.1	136
2	CEING	4.7835	-74.0459	130	19	2.8	1.1	0.4	10	186
3	CUAGR	4.7541	-74.0527	130	16	2.6	1	0.6	13	201
4	CBOG1	4.6418	-74.0803	180	21	2.6	1.2	0.4	13.3	279
5	CCORP	4.7619	-74.0937	250	21	3.6	1.5	0.9	11.6	275
6	CJABO	4.6664	-74.0993	275	21	3.8	1.7	1.1	15.1	287
7	CNINO	4.6959	-74.093	225	21	3.5	1.4	0.9	22.4	260
8	CAVIA	4.6854	-74.1188	360	21	5.3	1.8	0.9	7.5	274
9	CFLOD	4.7297	-74.1464	500	21	5.8	2.4	1.5	9.2	344
10	CTIEM	4.6943	-74.1559	425	21	4.9	1.9	0.9	11.1	345
			$\bar{X}$	237.5	21	3.55	1.45	0.9	12.3	274.5

Table 1: Summary of the main features of Lacustrine soils profile.

In the following section, the random generation process to simulate statistically compatible soil profiles is briefly explained with data provided in Table 1.

3.2. Application of the Toro's model to a Lacustrine soil type

The probabilistic framework used in this research employs the Toro's model to generate random soil profiles [10]. This model incorporates three main elements: i) information describing the random stratigraphy at the site; ii) the median wave velocity profile; iii) the dispersion of the Vs with depth and the correlation between consecutive layers.

3.2.1. Random stratigraphy at the site

The results of the geotechnical investigations carried out in Bogotá have been used to characterize the random stratigraphy at the site. The "Layering Model" has been employed [10], which allows to consider that as the layer is deeper, it becomes thicker. Thus, for each layer and respective depth from the soil profiles depicted in Figure 2, a cloud of transition points has been statistically parametrized. The following power law has been adopted:

$$\lambda(h) = C_3[h + C_1]^{-C_2} \tag{1}$$

where λ is the layer boundary rate (i.e. the inverse of the thickness of the layer, 1/m) and h is the depth in the middle point of the layer in m. The estimation of the values C1, C2 and C3 is carried out by using the capabilities of the Monte Carlo method to minimize multi-dimensional functions; Figure 2 shows this statistical parametrization. Using the regression line, and by considering the dispersion of the data, the geometrical random features of the stratigraphy have been considered in the generated soil profiles.

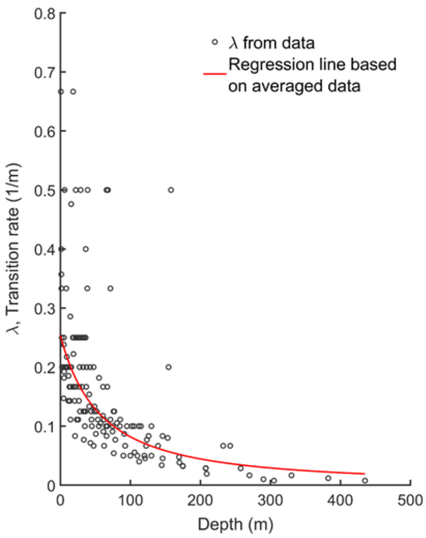

Figure 2. Transition rates by considering direct values

3.2.2. The median wave velocity profile at the site

Figure 3 shows wave velocity soil profiles at low shear strains (< 10-3 %) for the selected locations (thinner gray lines) and its corresponding median value. Two main conclusions can be drawn from these profiles: i) the deeper, the higher the shear wave velocity; ii) the deeper, the thicker the layer, which confirms the conclusions reached in Toro et al [10]. Both features should be considered when generating random samples of the profile.

The median velocity profile shown in Figure 3 has been used to generate random soil profiles. Due to the cumulative process associated with lacustrine deposits, it has been observed that a log-normal distribution parametrizes adequately the aleatory character of shear wave velocities [11]. This distribution has been adopted in the sampling process of this variable.

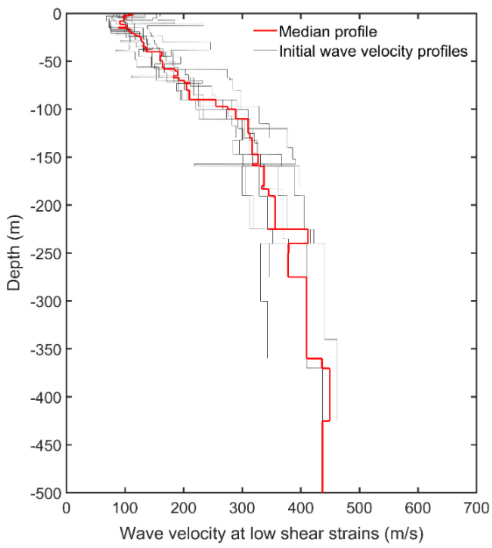

Figure 3: Wave velocity soil profiles at low shear strains.

3.2.3. Deviations of the velocity in each layer and correlation between consecutives layers

From the base profiles shown in Figure 3, it has been estimated how the standard deviation changes with depth. In the analysed case, it can be observed that this variable tends to decrease with depth. This feature has been incorporated in the random generation of profiles. Another important aspect observed in soil profiles is related to the spatial correlation between closer layers; the closer the layers the higher the correlation [12]. This implies that widely separated layers tend to be less correlated. It has been assumed that the correlation between adjacent soil layers decreases with distance by means of the following conditions:

$$\rho_{i,j} = \begin{cases} i = j & \rho_{i,j} = 1 \\ i = j \pm k & \rho_{i,j} = 1 - \dfrac{k}{r} \geq 0 \end{cases} \quad (2)$$

where k is a number related to the position of a layer belonging to the same profile; r is a coefficient associated to the rate of correlation between adjacent layers. In this research, r has been fixed to 100/3.

3.2.4. Probabilistic simulation of soil profiles

Based on the description of the probabilistic features that must meet the soil profiles, one-thousand statistic realizations of them have been performed via Monte Carlo simulation. Figure 4 (A-B) shows the random set of one-thousand shear wave velocity soil profiles that have been employed in the development of the probabilistic framework proposed in this research. It is worth mentioning that these soil profiles correspond to low shear strains; it is worth mentioning that they correspond to low shear strains.

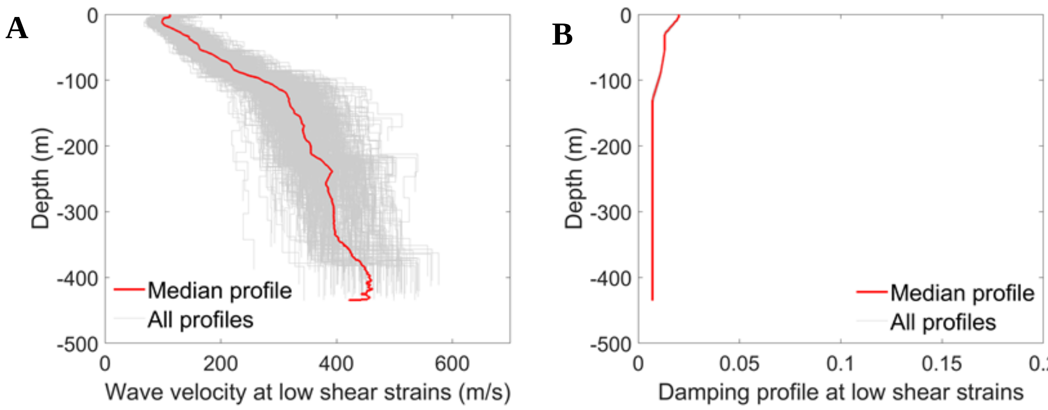

Figure 4. Probabilistic shear wave velocity profiles

The damping properties at low shear strains have been obtained by using degrading curves for the soil types analysed. In general, these values vary in a narrow band between 1-1.2 %. Another important variable influencing the dynamic properties of the simulated soil profiles is density. This has been considered as random variable by using the relationship proposed in Nakamura, 1989:

$$\gamma = 8.32 \cdot \log_{10} Vs - 1.61 \cdot \log_{10} Z \quad (3)$$

where Z is the depth in m. Figure 5 depicts the random set of density profiles after applying equation (3).

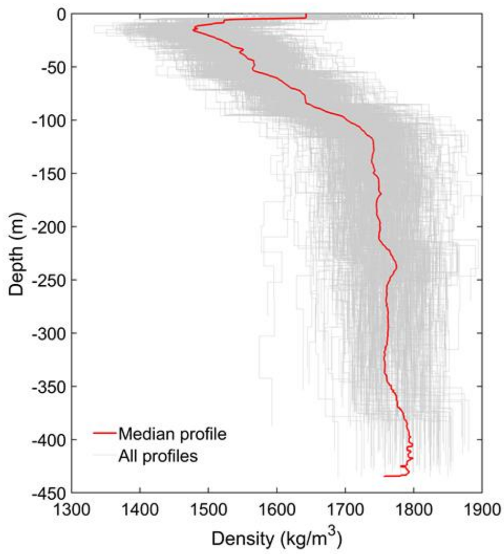

Figure 5: Probabilistic soil profiles for density

Once the probabilistic set of soil profiles has been generated, it is necessary to characterise the seismic hazard at the site. It has been done by considering ground motion records acquired in seismic stations. Then, using both soil profiles and records, the probabilistic propagation of seismic waves can be performed.

4 SEISMIC HAZARD CHARACTERIZATION

The analysis of earthquake-induced ground vibrations has gained increasing relevance not only in regions with high seismic hazard but also globally. As noted by [14], earthquakes with magnitudes around 5.5 Mw, which represent energy levels comparable to those released by non-tectonic geological processes, can occur almost anywhere in the world. Therefore, understanding the seismic response of the ground is essential for reliable seismic risk assessments.

For this study, a comprehensive compilation of ground motion records in Colombia has been carried out, covering events with moment magnitudes greater than 4.0 Mw that occurred between 1993 and 2017. To better capture the seismogenic characteristics relevant to the Bogotá region, an algorithm has been developed to identify seismic records from stations located nearest to a given study point within Colombian territory.

Once the representative events for the study area have been selected, the ground motions were amplitude-scaled following the methodology presented in [8]. As shown in Figure 7A, these scaled motions exhibit high spectral ordinates at the bedrock level. However, it is important to highlight that the soil profile, particularly in lacustrine deposits, acts as a natural filter, attenuating the response at short periods due to its relatively high stiffness. Consequently, the spectral ordinates obtained at the surface (Figure 7B) reflect a more realistic seismic demand, consistent with observed local site effects.

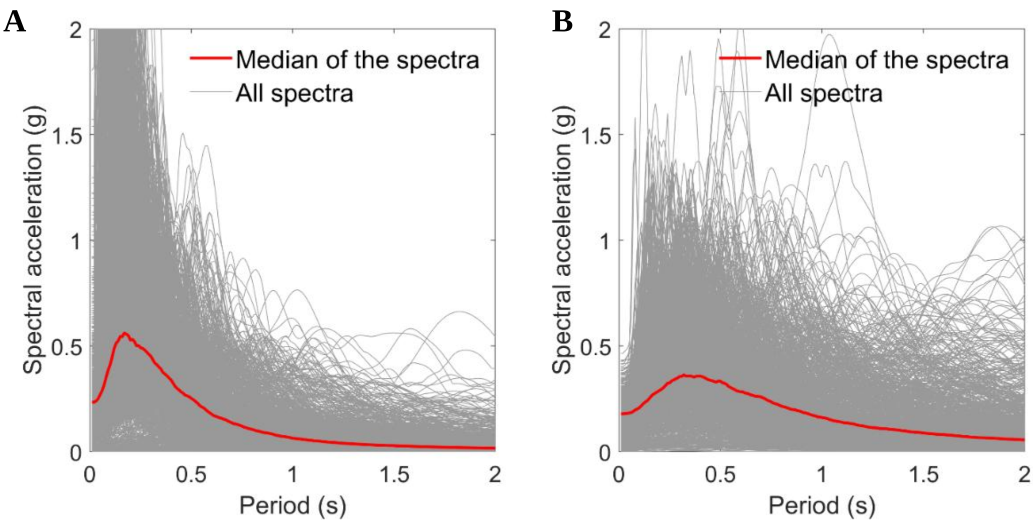

Figure 6**A)** Spectra of ground motion records acting at bedrock level. **B)** Spectra of the resulting ground motions at the surface after the propagation process.

5 DEGRADATION OF SOIL PROPERTIES

Depending on the soil type and depth, the mechanical properties of the soil can be highly modified due to the pass of seismic waves. In this respect, it is a common practice to use simplified 1D soil models to 3D finite-element representations. However, the higher the complexity of the model the higher the computational time involved in solving the dynamic problem. In addition, due to the boundary conditions related to the reflection of the seismic waves, it is sometimes necessary to develop large soil models, which significantly increase the number of finite elements.

In order to tackle the computational effort related to 3D models, simplified soil representations are widely used to estimate the dynamic response of large simulations. One of the most employed is the 1D model, in which the soil layers are considered as Kelvin-Voigt solids. This model is represented by a purely viscous damper and elastic spring connected in parallel. It allows a good approximation of the dynamic response of a soil volume. Moreover, this model has been extended to consider nonlinearities associated to the stiffness degradation of the soil, and the consequent increase in damping due to shear strains. It can be achieved by means of the linear equivalent method [15]. The 1D model becomes an ideal candidate to include uncertainties via Monte Carlo simulations.

Using the methodology described above, the propagation of seismic waves through the soil profiles is carried out. Figure 7 shows in grey the one-thousand nonlinear wave velocity profiles after the degradation process whilst the red one shows the median profile.

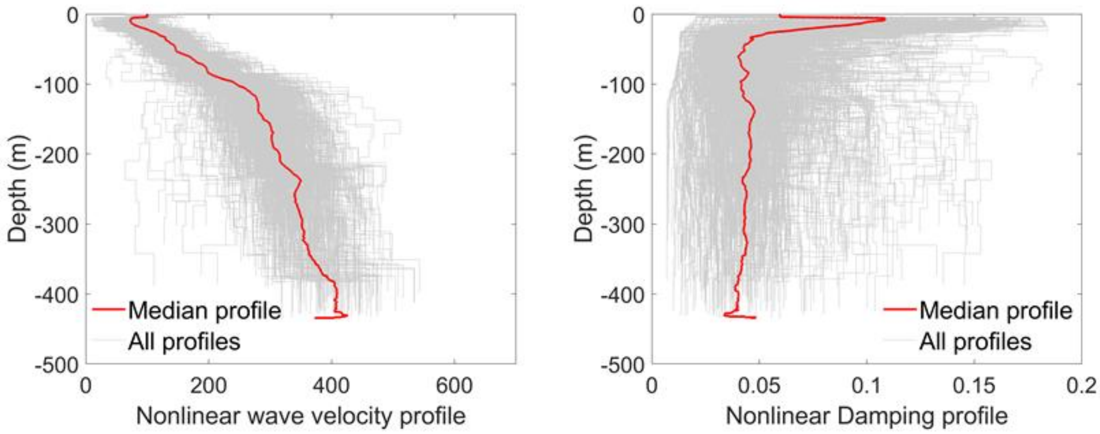

Figure 7:**A)** Nonlinear Vs of the one-thousand profiles. **B)** Nonlinear damping of one-thousand profiles

6 INTENSITY MEASURES AND ENGINEERING DEMAND PARAMETERS

The relationship between IM and EDPs can be employed to estimate the expected risk of systems. For instance, from a set of IM-EDP pairs, one can derive fragility functions according to the so-called 'cloud analysis' approach [5].

6.1. Intensity measures

An instrumental IM is a parameter extracted from a ground motion record to characterize seismic hazard [16]. In this article, a set of 18 IMs have been employed. They have been summarized in Table 2; further details on how to calculate them can be found in Vargas-Alzate et al., 2022.

Intensity Measure	Variable
Spectral acceleration at T_1	$Sa(T_1)$
Spectral velocity at T_1	$Sv(T_1)$
Spectral displacement at T_1	$Sd(T_1)$
Average spectral acceleration	$AvSa$
Average spectral velocity	$AvSv$
Average spectral displacement	$AvSd$
Equivalent velocity at T_1	$VE(T_1)$
Average equivalent velocity	$AvVE$
Peak ground acceleration	PGA
Peak ground velocity	PGV
Peak ground displacement	PGD
Specific Energy Density	SED
Arias intensity	I_A
Characteristic intensity	I_C
Root mean of the velocity	vel_{RMS}
Root mean of the acceleration	acc_{RMS}
Cumulative Absolute Velocity	CAV
Fajfar intensity	I_F

Table 2: Intensity measures

6.2. Engineering demand parameters

The Newmark method [3] is widely used in earthquake engineering to evaluate the stability of slopes or structural systems subjected to dynamic loads. In particular, this method estimates the permanent displacements, δN, induced by seismic events through a simplified sliding block approach. Its application as an engineering demand parameter lies in its ability to provide a direct measure of the accumulated response of a system to a specific ground motion record, accounting for both the intensity and duration of the shaking.

In this study, the method has been applied to a slope with a height of H=25m and an inclination of β=45º, while the soil is characterized by a unit weight γ=17 kN/m³, effective cohesion c′=30 kPa, and effective friction angle ϕ′=18º. These parameters are used to calculate the critical acceleration employing Eq. (4) [18], defined as the minimum threshold of seismic acceleration required to initiate movement in the slope:

$$ac = (FS - 1)g \cdot \sin\alpha \tag{4}$$

where FS is the safety factor, g denotes gravitational acceleration, and α represents the thrust angle, defined as the inclination from the horizontal to the center of gravity of the leading block in the potential landslide mass. FS has been calculated by using the Taylor's method [19,20], which is summarized in Figure 8.

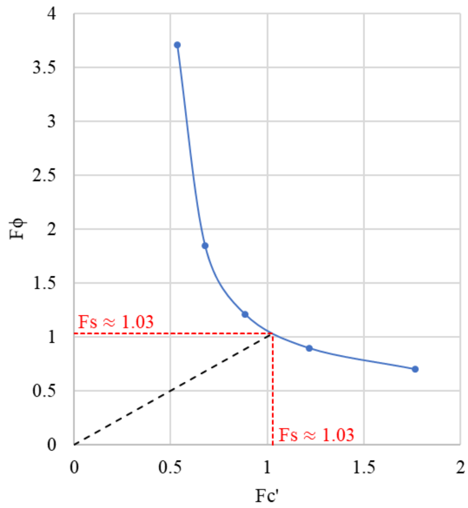

Figure 8 Estimation of FS based on the Taylor's method [19,20]

Once this acceleration is known (ac = 0.021 g), the time intervals where ground acceleration exceeds this threshold are integrated using the Newmark method, yielding the cumulative displacement of the slope. This displacement, known as the Newmark displacement, has been taken as EDP, particularly useful in fragility assessments and probabilistic seismic risk analyses. It allows for the evaluation of post-earthquake stability of the slope and the definition of acceptable performance thresholds in terms of permanent displacements, which is essential for the design of mitigation and protection measures in infrastructure projects exposed to seismic hazards.

6.3. Cloud analysis based on IM-EDP pairs

Cloud analysis requires to calculate the best fit curve between a set of IM-EDP realizations in the log-log space. The resultant curve is used to estimate the median of a parametric statistical distribution, given an IM value. The variability of this parametric distribution is estimated as the logarithmic standard deviation of the regression. In this way, the probability of exceeding a certain damage threshold given an IM value can be calculated. In the following, variables described in section 6.1 are used as IMs and δN as EDP. The objective is to find the most correlated bivariate distribution. Figure 9 shows the bivariate distribution between IMs and δN. From this figure, it can be seen that the Specific Energy Density, SED, is the most efficient IM to predict the response in slopes by considering the Newmark's approach. It is worth mentioning that this variable is highly employed in early warning systems at a regional scale [21].

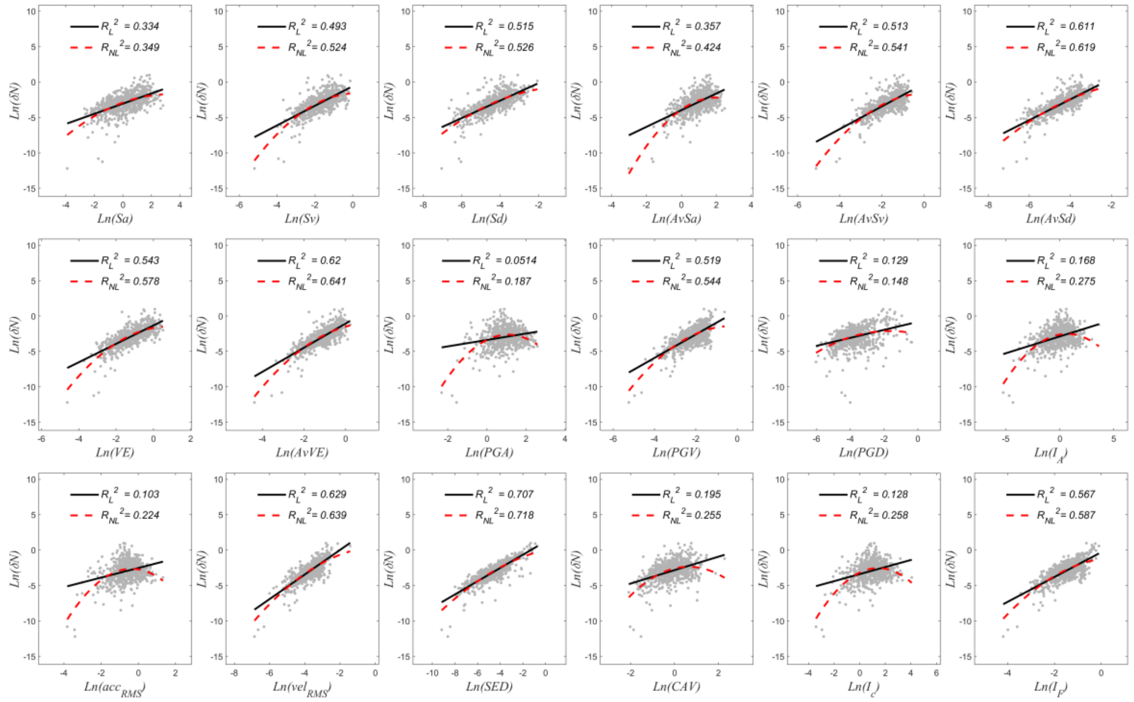

Figure 9 IM-EDP pairs for identifying the most efficient IM

7 CONCLUSIONS

This study analysed the seismic performance of slopes by incorporating soil variability into a probabilistic framework and evaluating the resulting permanent displacements using the Newmark method. A set of random soil profiles was generated to simulate the propagation of seismic waves to the surface, where the response of a representative slope was assessed. The dynamic behaviour of the soil was captured using the equivalent linear method, allowing for a realistic characterization of ground motion amplification.

The relationship between intensity measures (IMs) and slope response, quantified through Newmark displacements, was examined using statistical cloud analysis and nonlinear regression. Results show that the Specific Energy Density, SED, is the most efficient IM to predict the response in slopes by considering the Newmark's approach. Future research should aim at analysing the extent to which the predictive ability of vector-valued IMs increases compared to scalar-based IMs, such as those analysed in this research. Once these improved arrangements have been identified, the derivation of fragility will be more accurate.

These findings highlight the importance of accounting for local soil conditions and probabilistic variability in slope stability assessments. The proposed approach enables a more robust estimation of seismic-induced displacements and may support future developments in landslide risk analysis. Further research could explore 3D models to improve prediction accuracy and generalize the methodology to other slope configurations.

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REFERENCES

[1] D. Pitilakis, C. Petridis, Fragility curves for existing reinforced concrete buildings, including soil–structure interaction and site amplification effects, Eng Struct 269 (2022) 114733. https://doi.org/10.1016/j.engstruct.2022.114733.

[2] D.V. Okur, A. Ansal, Stiffness degradation of natural fine grained soils during cyclic loading, Soil Dynamics and Earthquake Engineering 27 (2007) 843–854. https://doi.org/10.1016/j.soildyn.2007.01.005.

[3] N.M. Newmark, Effects of Earthquakes on Dams and Embankments, Géotechnique 15 (1965) 139–160. https://doi.org/10.1680/geot.1965.15.2.139.

[4] SGC, Sistema de Consulta de la Amenaza Sísmica de Colombia, Colombian Geological Survey (2020). https://amenazasismica.sgc.gov.co/ (accessed November 28, 2021).

[5] F. Jalayer, R. De Risi, G. Manfredi, Bayesian Cloud Analysis: Efficient structural fragility assessment using linear regression, Bulletin of Earthquake Engineering 13 (2015) 1183–1203. https://doi.org/10.1007/S10518-014-9692-Z.

[6] E.H. Vanmarcke, Probabilistic Modeling of Soil Profiles, Journal of the Geotechnical Engineering Division 103 (1977) 1227–1246. https://doi.org/10.1061/AJGEB6.0000517.

[7] S.R. Carrière, D. Jongmans, G. Chambon, G. Bièvre, B. Lanson, L. Bertello, M. Berti, M. Jaboyedoff, J.-P. Malet, J.E. Chambers, Rheological properties of clayey soils originating from flow-like landslides, Landslides 15 (2018) 1615–1630. https://doi.org/10.1007/s10346-018-0972-6.

[8] A.M. Zapata-Franco, Y.F. Vargas-Alzate, L.G. Pujades, R. Gonzalez-Drigo, Improved intensity measures considering soil inelastic properties via multi-regression analysis, Front Earth Sci (Lausanne) 11 (2023). https://doi.org/10.3389/feart.2023.1214536.

[9] FOPAE, Procesamiento e interpretación de señales de la red de acelerógrafos de Bogotá 2009 - 2011, Bogotá, 2011.

[10] W.J. Silva, N. Abrahamson, G. Toro, C. Constantino, Description and validation of the stochastic ground motion model, Pacific Engineering and Analysis, 1996.

[11] G.R. Toro, Uncertainty in Shear-Wave Velocity Profiles, J Seismol 26 (2022) 713–730. https://doi.org/10.1007/s10950-022-10084-x.

[12] M.E. Angelini, G.B.M. Heuvelink, Including spatial correlation in structural equation modelling of soil properties, Spat Stat 25 (2018) 35–51. https://doi.org/10.1016/j.spasta.2018.04.003.

[13] Y. Nakamura, A method for dynamic characteristics estimation of subsurface using microtremor on the ground surface, Railway Technical Research Institute/Tetsudo Gijutsu Kenkyujo 30 (1989) 25–33.

[14] A. Coburn, R. Spence, Earthquake Protection, John Wiley & Sons, Ltd, Chichester, UK, 2002. https://doi.org/10.1002/0470855185.

[15] D. Assimaki, E. Kausel, A. Whittle, Model for Dynamic Shear Modulus and Damping for Granular Soils, Journal of Geotechnical and Geoenvironmental Engineering 126 (2000) 859–869. https://doi.org/10.1061/(ASCE)1090-0241(2000)126:10(859).

[16] G.M. Atkinson, S.I. Kaka, Relationships between Felt Intensity and Instrumental Ground Motion in the Central United States and California, Bulletin of the Seismological Society of America 97 (2007) 497–510. https://doi.org/10.1785/0120060154.
[17] Y.F. Vargas-Alzate, J.E. Hurtado, L.G. Pujades, New insights into the relationship between seismic intensity measures and nonlinear structural response, Bulletin of Earthquake Engineering 20 (2022) 2329–2365. https://doi.org/10.1007/s10518-021-01283-x.
[18] S. Figueras Vila, A. Macau Roig, X. Goula Suriñach, M. Gonzalez Díaz, Aplicación del método de newmark para elestudio de los movimientos de ladera activados por terremotos en andorra, in: VI Simposio Nacional Sobre Taludes y Laderas Inestables, Valencia, 2005.
[19] J.T. Christian, G.B. Baecher, D. W. Taylor and the Foundations of Modern Soil Mechanics, Journal of Geotechnical and Geoenvironmental Engineering 141 (2015). https://doi.org/10.1061/(ASCE)GT.1943-5606.0001249.
[20] D.W. Taylor, Fundamentals Of Soil Mechanics, John Wiley (1948).
[21] S.K. Sarma, K.S. Yang, An evaluation of strong motion records and a new parameter A_{95}, Earthq Eng Struct Dyn 15 (1987) 119–132. https://doi.org/10.1002/eqe.4290150109.